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The Effect of Investor Relations on Income Objectives and Meeting Expectations

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Doctor of Philosophy

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An abstract of
a dissertation submitted to the Faculty of the Graduate School of Emory
University in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Business

2009

Abstract

The Effect of Investor Relations on Income Objectives and Meeting Expectations

By: Marcus Kirk

Over a quarter of publicly listed firms employ National Investor Relations Institute (NIRI) members. Yet we know little about the impact of investor relations (IR) for these firms. I examine the role of professional IR in achieving income objectives and influencing managers' financial reporting decisions to meet those objectives. I find companies with NIRI members as employees (IR firms) are more likely to meet analyst forecasts and have smoother earnings. I also find that IR firms rely less on accrual or earnings management to meet analyst forecasts and more on expectations management. Finally, I document that IR firms receive a greater market premium than non-IR firms for meeting analyst expectations. The evidence suggests that while IR may increase the pressure to meet expectations, it also relieves the pressure on firms to use earnings management to meet these expectations.

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I. INTRODUCTION

This paper investigates the role of professional investor relations (IR) in achieving income objectives and in influencing managers' financial reporting decisions to meet those objectives. Broadly speaking, income objectives are earnings patterns that managers want to attain. Yet IR activities can alter the incentives managers face to meet these objectives. For example, increased media coverage, analyst following, forecast accuracy, and forecast precision are identified in the IR literature as measureable objectives of a successful IR program. However, Brown and Caylor (2005) argue that these attributes are also linked to the pressure to meet analyst forecasts. Additionally, academics and regulators have expressed concern that the pressures to meet earnings expectations and a close relationship between managers and analysts may be eroding financing reporting quality (Levitt, 1998; Jensen et al., 2004). This raises the question: are firms with professional IR more sensitive to achieving income objectives and are these firms more likely to engage in earnings management to meet these objectives?

I refer to IR as the specialized function within a firm that integrates activities related to communications with investors and analysts. This role is staffed by professional IR employees, often senior managers or vice-presidents, who report directly to top management. Professional IR programs develop relationships with investors and analysts, and gather market intelligence used in management's strategic decision making. IR influences financial reporting choices and the pressure to meet income objectives through this central position in the organizational chart and its influence over disclosure policy, analyst relations, firm valuation, and investor clientele.

To capture this professionalized IR role within firms, I use the membership directory of the National Investor Relations Institute (NIRI), the professional membership organization for IR in the United States. I examine publicly listed firms over 2001 – 2006 that employ at least one NIRI member over this period (IR firm). I match these IR firms with a control group of firms without a NIRI member (non-IR firms) using propensity score matching.

I provide evidence that IR firms achieve many of the benefits cited by practitioners as the measurable outcomes of IR (Mahoney and Lewis, 2004; Rosenbaum, 1994). Specifically, I find IR firms have more analysts who produce more accurate earnings forecasts with less forecast dispersion. IR firms also have greater levels of institutional investor ownership, disclosure, liquidity, and reduced information asymmetry between investors. These results are consistent with Bushee and Miller's (2007) findings with small firms hiring IR consultants. However, Bushee and Miller (2007) find no significant results for larger firms. My evidence extends Bushee and Miller (2007) and suggests that larger firms may be able to achieve similar outcomes from IR but choose to implement their IR strategy by employing professional IR members instead of hiring external consultants. Although consistent with IR strategies, these outcomes are also linked to increased pressure to meet expectations.

Consistent with this increased pressure, I find that IR firms are more likely to meet or beat the most recent analyst consensus forecast, doing so 71% of the time compared to 64% for non-IR control firms. IR firms also have a smoother earnings path. However, I do not find that IR firms are more likely to meet other income objectives such as avoiding losses or beating the prior year's earnings. The results are consistent with

Brown and Caylor (2005) who document that meeting analyst expectations is the preeminent benchmark investors care about in terms of stock market consequences. Graham et al. (2005) also find the two dominant motivations to smooth earnings relate to investors' and analysts' perceptions and preferences.

However, I find that although the evidence suggests IR firms face more pressure to meet expectations and are more likely to meet expectations, they are less likely to use accrual or real earnings management to meet analyst forecasts. Specifically, IR firms rely less on income increasing accruals or abnormally low R&D to meet analyst forecasts. I investigate the potential explanation that IR firms are more likely to manage expectations through earnings guidance or a closer relationship with analysts. I find evidence that IR firms are more likely to relieve the pressure to meet analyst expectations through expectations management than are non-IR firms, consistent with recent literature that argues managers make tradeoff decisions between accrual management, real management, and expectations management (Matsumoto, 2002; Zang, 2007; Brown and Pinello, 2007; Bartov and Cohen, 2008).

The increased ability of IR firms to play this "game of nods and winks" with analysts (Levitt, 1998) could increase investor skepticism and alter investor reactions to meeting or missing expectations. On one hand, I find that IR firms receive a greater market premium than non-IR firms for meeting expectations based on market-adjusted returns over the year. Notably, only the IR firms receive the premium in my sample. On the other hand, the stock market reaction for missing expectations at the time of the announcement is more negative for IR firms compared to non-IR firms. There is no relative difference for meeting expectations.

Finally, I investigate the level of earnings management of IR firms versus non-IR firms in a different setting: loss avoidance. With an income objective of non-negative earnings, managers are unable to move the benchmark through other means (i.e. unlike analyst forecasts). I find no evidence that IR firms are more or less likely than non-IR firms to engage in either accrual or real earnings management to avoid reporting a loss. This suggests IR firms do not focus on this benchmark incrementally more or less than non-IR firms.

This study provides evidence that professional IR may increase managers' sensitivity to income objectives related to the preferences of investors and analysts. IR is also associated with outcomes that increase the pressure to meet analyst expectations. Though IR firms are more likely to meet these expectations, their financial reporting quality is not compromised. Rather, IR firms rely less on earnings management and more on expectations management to achieve this benchmark. This evidence raises the question: does the earnings expectations/guidance game erode the quality of financial reporting? Or does IR help firms to relieve the pressure to use accrual or real cash flow adjustments to beat expectations? IR firms' relationship with analysts also shapes the way investors assess meeting or missing earnings forecasts. Collectively this evidence suggests that IR may improve a firm's financial reporting quality when meeting analyst forecasts by substituting expectations management for earnings management. However, future research may consider if a cost of IR's relationship with analysts and use of expectations management is a breakdown of the role analysts play in the capital market as independent research providers.

In the next section, I provide information on the background and role of IR. Section 3 develops my hypotheses. Section 4 describes the sample and research design, section 5 presents the results, section 6 provides additional analyses, and section 7 offers concluding remarks.

II. THE ROLE OF INVESTOR RELATIONS

IR has grown from a peripheral component of the CFO's responsibility in the 1980s to a full-time professionalized function (Useem, 1993). The National Investor Relations Institute has over 4,300 members in 2008 with over a quarter of publicly listed firms over 2001 – 2006 employing a NIRI member.

Over time, the IR position has become more demanding and has developed into a full-time professionalized operation that directly reports to the CEO and/or the CFO (Rosenbaum, 1994). Almost 90% of the respondents in a NIRI membership survey report directly to the CFO, CEO, president, or chairman (NIRI, 2005). This direct reporting relationship provides a channel through which the IR function influences the corporate decision making process. For example, IR manuals explicitly recommend gathering market intelligence "including shareholder and institutional investor feedback on their views of the company, its strategies and value-creating status," and measuring its impact by the "extent management uses the feedback in its critical decision making" (Mahoney and Lewis, 2004). Many individual activities can be classified as IR. However, in this paper I define IR as the professionalized function within a firm that centralizes activities related to communication with investors and analysts. This integrated approach spans many functional areas within a firm, reports directly to executive management, and engages in activities such as setting disclosure policy, investor targeting, analyst relations, and market intelligence.

Despite the proliferation of IR in US companies and its potential influence over major topics in the accounting literature, there is little academic research that investigates the effects of IR.[1] An exception is Bushee and Miller (2007) which investigates the role of IR consultants hired by small firms. Their study finds that smaller firms, after hiring an IR consultant, experience increases in press releases, media coverage, liquidity, analyst following, and institutional investor ownership. However, they do not find increases in these key objectives of IR when larger firms hire IR consultants.

A potential reason for this non-result is that larger firms may choose to implement IR strategies through a different mechanism than smaller firms: economies of scale may induce them to internally employ professional IR staff. Following the evidence for smaller firms in Bushee and Miller (2007) and key objectives cited in the IR literature, I expect firms employing professional IR staff to have greater levels of disclosure, analyst following, institutional investor ownership, and liquidity as well as an improved information environment and reduced information asymmetry. These objectives are consistent with economic theory linking financial reporting and disclosure to capital market consequences (Healy and Palepu, 2001).

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[1] The extant literature typically references "investor relations" in terms of the AIMR database introduced by Lang and Lundholm (1993) that contains evaluations of firm disclosures along three dimensions: "annual published information", "quarterly and other published information", and "investor relations and related aspects." The "investor relations" category includes access to management, responsiveness to questions, and frequency and content of presentations to analysts. This definition is restrictive, as a professionalized IR function within a firm influences many aspects of a firm's communications including activities in the annual and quarterly information categories. Reflecting this broad scope, NIRI defines IR as: "…a strategic management responsibility that integrates finance, communication, marketing and securities law compliance to enable the most effective two-way communication between a company, the financial community, and other constituencies, which ultimately contributes to a company's securities achieving fair valuation."

Disclosure is a core part of the IR process – 80% of NIRI's members participate in the firm's disclosure committee, which rises to 90% in firms with a market cap over $10 billion (Brennan and Tamarowski, 2000; NIRI, 2005). IR activities include directing the annual report, MD&A, interim reports and other publications, conference calls, and press releases. Attracting sell-side analysts is another strategy of IR to reach a broader audience and improve the information environment of the firm (Lang, Lins and Miller, 2003). IR professionals build relationships with analysts through organizing webcasts, meetings, and presentations (Francis et al., 1997). The IR literature consistently claims a key objective of IR is to target institutional investors and in particular longer term investors (Farragher et al., 1994; Mahoney and Lewis, 2004). Confirming the importance of these strategies, IR professionals cite increases in the number of analysts, institutional investors, and disclosure as measureable objectives of a successful IR program (Mahoney and Lewis, 2004).

Additionally, IR is closely related with the firm's information environment and stock market characteristics. The accuracy and dispersion of analyst forecasts reflect the firm's information environment as they reveal the precision and certainty of investors when assessing a firm's business operations (Lang et al., 2003). An improved information environment is also related to a reduction in information asymmetry between investors and an increase in liquidity (Leuz and Verrecchia, 2000). Previous literature has used the bid-ask spread, trading volume, and the probability of informed trading (PIN) as measures of liquidity and proxies for information asymmetry (Leuz and Verrecchia, 2000; Brown et al., 2004). Analysts and institutional investors also have a preference for liquid stocks to facilitate trading (Irvine, 2003). Complementing the theoretical justifications for these measures, IR professionals cite decreased standard deviation of analyst forecasts and bid-ask spread; and increased analyst forecast accuracy and trading volume as measures of IR performance (Mahoney and Lewis, 2004; Marcus 2005).

III. THEORY AND HYPOTHESES

I define income objectives broadly as the earnings patterns that managers have a preference to achieve, which can include attaining targets and earnings characteristics. In this paper, I investigate four income objectives that the academic literature suggests are important to both investors and managers: meeting analyst expectations (Brown et al., 1987), avoiding losses (Burgstahler and Dichev, 1997), increasing earnings (Barth et al., 1999), and smoothing earnings (Ronen and Sadan, 1981). There are at least two reasons why firms with IR will be more likely to exhibit specific earnings patterns. First, the goals associated with a professional IR strategy, such as analyst following, may increase the pressure on management to meet earnings targets. Second, the relationship an IR program develops with capital market participants enhances bilateral communication, which opens a conduit where analysts' and investors' preferences and expectations flow directly to the CEO/CFO and become more salient. Former SEC Chairman, Arthur Levitt, highlighted the potential problem from this relationship: "Too many corporate managers, auditors, and analysts are participants in a game of nods and winks. In the zeal to satisfy consensus earnings estimates and project a smooth earnings path, wishful thinking may be winning the day over faithful representation" (Levitt, 1998).

Brown and Caylor (2005) find that, since the mid-90s, meeting analyst expectations is the most important benchmark that investors reward (punish) firms for meeting (missing). They argue that meeting analyst forecasts has become the predominant target because of increased media coverage, more analyst following, and temporal increases in the accuracy and precision of analyst forecasts – the same variables that IR seeks to influence and the ones that are cited as measurable outcomes of a successful IR program. Thus the increased accuracy and precision of investor expectations from an improved information environment may also lead to increased pressure to meet these expectations.

Prior research suggests managers also have incentives to avoid losses (Burgsthaler and Dichev, 1997) and beat last periods' earnings (Barth et al., 1999). Despite, Brown and Caylor's (2005) evidence that investors care less about these targets since the mid-90s, surveyed financial executives report that meeting earnings from the same quarter last year is at least as important as meeting analyst forecasts with avoiding losses the third most important earnings target (Graham et al., 2005).

CFOs cite two dominant motivations for smooth earnings, which relate to the perceptions and preferences of investors and analysts: (1) analysts and investors believe smooth earnings represent less volatile, and thus less risky, business environments; and (2) smooth earnings make it easier for analysts and investors to predict future earnings (Graham et al., 2005). Analysts' and investors' preferences are more important for firms whose managers issue guidance and have a larger number of analysts. Although virtually all CFOs indicate they prefer a smooth earnings path holding cash flows constant (Graham et al., 2005), firms with IR will be more likely to engage in earnings smoothing because of IR activities that increase the number of analysts, provide earnings guidance, and directly bring the preferences of investors and analysts to the CFO/CEO.

Overall, I expect firms with IR to be more likely to meet income objectives and have smoother earnings because of the increased pressure to meet expectations. In addition, managers with professionalized IR will be more sensitive to satisfying the preferences of investors and analysts.

H1: Firms with IR are more likely to meet income objectives.

The increased pressure to meet expectations also results in an increased pressure to manage earnings through manipulating accruals, cash flows, or both (Jensen et al., 2004). This is consistent with cynics who believe that instead of IR enabling long-term focus, it creates an atmosphere of “slavish catering to Wall Street” where management becomes too involved with the short-term earnings game at the cost of long-term investors (Shilling, 2004). This atmosphere could be indirectly created through the pursuit of other objectives. For example, an objective of IR is to increase disclosures such as management forecasts yet Kasnik (1999) finds that managers who issue forecasts feel pressure to meet those forecasts and engage in accrual management to manage earnings towards them.

Survey evidence also suggests financial executives feel meeting short-term expectations is important and are willing to manipulate real activities to meet these expectations, even though the manipulation has deleterious effects on future cash flows (Graham et al., 2005). Roychowdhury (2006) finds empirical evidence that firms manipulate sales, R&D, SG&A, and inventory production to avoid losses. IR activities and the increased salience of analysts’ expectations can create an atmosphere of shorttermism that fosters myopic behavior and influences real investment decisions. For example, Cheng et al. (2005) find firms that frequently issue earnings guidance are associated with underinvestment in R&D. Also increasing the level of disclosure is associated with an increase in "transient" investors, who encourage R&D cuts to meet short-term expectations (Bushee, 1998; Bushee and Noe, 2000). This leads to my second hypothesis.

H2: Firms with IR will be more likely to use accrual and real earnings management to meet income targets.

IV. SAMPLE AND RESEARCH DESIGN

Sample

I use employment of a National Investor Relations Institute member as a proxy for professional IR. NIRI is the association of IR professionals. Corporate Membership in NIRI costs $475 and requires that the individual be "actively engaged in the practice of IR and/or corporate communication at the time of the application as an employee of a corporation listed on a public stock exchange (or of a company that is planning to list)."[2]

To identify firms with members of NIRI on their staff, I gather the names and companies from NIRI's *Who's Who in Investor Relations* membership directory. This directory is now only available on-line with the membership list updated daily and no historical record. I use this on-line version to construct a list of companies in December

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[2] NIRI offers four other membership categories: Counselor Member, Service Provider Member, Affiliation Profession Member and Academic Member. It's unlikely that I mistakenly attribute one of these members to a CRSP/COMPUSTAT firm as the organizations listed for these members are not listed in the CRSP/COMPUSTAT population: small consulting firms, obvious news outlets (e.g. Newswire), small law firms, or universities.

2007 with NIRI members. I combine this current membership information with an archived hard copy of the *2001/2002 Who's Who in Investor Relations* membership directory to classify firms into two major categories based on the presence of a NIRI member over a period of several years, specifically 2001 – 2006. The first category, *IR firms*, includes firms that had a NIRI member in 2001 and also have a NIRI member in 2007. The second category, *non-IR firms*, includes firms that existed during 2001–2006 but do not have a NIRI member associated with them in either 2001 or in the current list. Firms that did not exist for 2001–2006 or that had a NIRI member in only one of the 2001 archived list or the current list were not included in the analysis. Table 1 shows my sample includes 1,008 IR firms and 2,683 non-IR firms.[3]

The benefits of this classification method are that examining firms with or without a persistent IR presence over a six-year period increases my confidence in separating IR firms from non-IR firms. Also, it is unclear how long it takes for the establishment of IR to have its full effect on the firm, complicating a time-series analysis. If a firm establishes a professionalized IR function with no formal IR activities previously being performed, it may take months and maybe years for the full effects to take place. For example, outcomes such as analyst following and institutional ownership may take longer to be realized as they depend on prior action such as increases in disclosure and liquidity (Bushee and Miller, 2007).

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[3] I validate my measure by randomly sampling 50 IR and 50 non-IR firms. First, I examine IR activities from the IR literature that firms have direct control over: conference calls and press releases. I find IR firms host a conference call in 92% of the firm-years with a mean of 5.2 per year; and non-IR firms host a conference call in 57% of the firm-years with a mean of 2.5 per year. I find that over 2001 – 2006, the mean number of press releases for IR firms is 421 and the mean press number of releases for non-IR firms is 118. Second, I also examine if the firm has a key executive listed in Lexis Nexis Corporate Affiliations under the IR sub-section. I find 23 of 50 (46%) IR firms have a key executive listed under IR and 2 of the 50 (4%) non-IR firms have a key executive listed.

Estimation Method

The purpose of my analysis is to identify the effects of IR. The main econometric problem is selection bias; managers choose to implement IR meaning IR firms will be non-randomly different from non-IR firms. To take into account the endogeneity of the IR choice, I use propensity score matching methodology (PSM) – a nonparametric technique used in the economics (Dehejia and Wahba, 2002; Smith and Todd, 2001), finance (Lee and Wahal, 2004; Hillion and Vermaelen, 2004; Cooper et al., 2005) and accounting literatures (Armstrong et al., 2010; Chen and Johnston, 2008). PSM seeks to allow causal inference in nonexperimental settings by constructing a suitable control group of firms similar to the target group in all relevant characteristics (Rosenbaum and Rubin, 1983).

The basic intuition of PSM is to create two portfolios of firms, IR and matched non-IR, whose control variables at the portfolio level are nearly identical. I can then more plausibly attribute the difference in mean outcome variables between the portfolios to the presence of IR.

PSM offers four benefits relative to traditional econometric techniques. First, PSM avoids imposing a linear functional form on the relation among the outcome, treatment, and control variables inherent in linear regression models. Second, it allows the effect of treatment variables to vary across firms. For example, it accommodates that the effect of IR may be different for firms with different underlying characteristics. Third, it accommodates a high number of matching variables circumventing the 'curse of dimensionality'.[4] Fourth, it avoids the need for exclusion restrictions or joint normality of

[4] The traditional matching procedure in the accounting literature is to match on a subset of the characteristics dimension by dimension (e.g. size, industry); however, the curse of dimensionality does not

the error terms to identify the model. See Appendix A for a more detailed description of PSM.

I use the nearest-neighbor algorithm to generate my sample of matched non-IR control firms using the following steps.

Step 1: I estimate a firm's propensity to have IR using a logit model that regresses the endogenous choice variable, IR, against a control vector, X, of firm and industry characteristics determining the selection choice.

Step 2: The predicted probabilities from the model are the propensity scores: PR(IR=1 | X) = P(X). I match each IR firm to the non-IR firm with the closest propensity score, within 0.01, to form a sample of IR and matched control firms within the same year.[5]

Step 3: Repeat step 2 for each year t. I match by year because time effects likely have an impact during my sample time period.[6]

Step 4: Pool the years together to obtain a total sample of an equal number of IR firm-years and matched non-IR control firm-years over the period 2001–2006.

There are a number of reasons why PSM controls for self-selection bias in this setting (Rubin, 1974; Rosenbaum and Rubin, 1983) and allows for an effective test of the

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need many variables to quickly become a problem. For example, Lang et al. (2006) attempt to create a matched sample for firms that cross-list based on only three variables: past sales growth, industry, and year. They state: "ideally, we would like to match on size as well as growth because both could affect the characteristics of accounting data. However, it is quite difficult to get a good match on size and growth simultaneously" and that they are unable to "match on all factors that might affect the characteristics of accounting data." Propensity score matching offers a solution to these problems.

[5] I impose the restriction that the propensity score of the matched firm has to be within 0.01 of the propensity score of the IR firm to reduce the risk of a poor match. IR firms without a non-IR match within the 0.01 caliper are not used. I also match with replacement which abstracts from ordering effects, increases the quality of the match and reduces bias (Caliendo and Kopeinig, 2008). I investigate the sensitivity of the results to this design choice in Section VI.

[6] For example, scandals in the investment banking industry led to the Global Settlement; SOX shifted the cost-benefit tradeoffs between earnings management and expectation management (Bartov and Cohen, 2008; Koh et al., 2008); and intertemporal changes occurred in media coverage, analyst following, analyst accuracy and forecast precision (Brown and Caylor, 2005).

effect of IR. First, the choice variable is binary. Second, outcomes and control characteristics are measured in the same way using the same databases for both groups. Third, IR and non-IR firms are from the same economic environment in terms of U.S. publicly traded firms. Fourth, there is a large pool of control firms which facilitates a good distributional match of control characteristics at the portfolio level. Finally, there is a rich set of relevant observable data available on these firms.

Overall, successfully matching firms based on propensity score creates two portfolios, IR and non-IR firms, that have nearly identical distributions of the control variables. These portfolios have on average similar size, performance, growth, leverage, capital market transactions, competitive environment, exchange listing, industry, and other characteristics highly correlated with these measures. The assumption underlying PSM is that, on average, two portfolios balanced in terms of these control variables would have the same estimated non-IR outcomes. For example, two portfolios of firms identical on these characteristics would also be expected to have similar average analyst following. I can then attribute the difference in the mean outcome variables, e.g. number of analysts, to the presence of IR. This means after matching there is no need to adjust for differences in the control variables between IR and non-IR firms and I can focus on differences in outcome measures. I present evidence on the effectiveness of the matching algorithm in the next section.

Outcome Variables

My analyses require measures relating to income objectives and earnings management. A detailed description of variable measurement is provided in Appendix B.

I use stock return data from CRSP, financial data from COMPUSTAT, analyst data from I/B/E/S, institutional investor data from Thomson Financial 13-f filings, capital market transaction data from SDC, and management earnings guidance from the First Call Company Issued Guidelines database.

I use several variables related to income objectives: meeting analyst expectations, avoiding losses, meeting last year's earnings, and projecting a smooth income path. MEDEST is the median consensus forecast immediately prior to the earnings announcement.[7] MBE is an indicator variable equal to one if a firm meets or beats analyst forecasts based on MEDEST. MBE ALL YEARS is an indicator variable equal to one if a firm meets or beats MEDEST in all six years during my sample period. I capture whether a firm attempts to avoid losses by an indicator variable, SUSPECT NI, equal to one if a firm's net income before extraordinary items (NIBE) divided by total assets is equal to or greater than 0 and less than 0.05 (Roychowdury, 2006). I capture meeting or beating last year's earnings by an indicator variable, MB LAST YEAR, equal to one if NIBE is equal to or greater than the previous year's NIBE. I define SMOOTHNESS as the ratio of a firm's standard deviation of annual NIBE divided by beginning total assets, to the standard deviation of CFO divided by beginning total assets calculated over the period 2001 – 2006 (Leuz et. al, 2003; Francis et al., 2004). A lower value of SMOOTHNESS indicates smoother earnings.

[7] I use the median consensus forecast from the adjusted summary file and the adjusted actual earnings. I choose this specification as the ensuing analyses relate prior analyst expectations and actual realizations of earnings to the current period. Even using the unadjusted data requires multiple adjustments to align prior periods with the current period. For consistency and ease of exposition throughout the paper, I use adjusted data for analyst forecasts, earnings, stock prices, and shares outstanding. I recognize using an indicator variable for meeting or beating expectations with adjusted data is sensitive to rounding issues from future events such as stock splits (Doyle et al, 2006). However, this effect is likely to be mitigated in my setting as the six-year period shortens the time available for multiple stock splits which will have the greatest influence on the data. Also, the results examining the propensity to meet or beat expectations are robust to using unadjusted forecasts.

I estimate abnormal accruals, AB AA, by using the Jones model estimated cross-sectionally for each sample year and two-digit SIC code with at least 10 observations.[8] Specifically, I estimate:

$$\frac{Accruals_{\,t}}{Assets_{\,t-1}} = \alpha + \beta_1 \frac{1}{Assets_{\,t-1}} + \beta_2 \frac{\Delta Sales_{\,t}}{Assets_{\,t-1}} + \beta_3 \frac{PPE_t}{Assets_{\,t-1}} + \varepsilon \qquad (1)$$

I include a constant as an additional control for heteroskedasticity and an omitted size variable (Kothari et al., 2005). Combining propensity score matching with this model is similar in spirit to the performance matching recommended in Kothari et al. (2005). However, propensity score matching permits me to match on multiple variables beyond the ROA and industry membership match used in Kothari et al. (2005) to compare relative levels of abnormal earnings management between my IR and matched non-IR control firms. I also create an indicator variable, POSAA, equal to one if the abnormal accruals are positive.

Graham et al. (2005) finds that the most prevalent real earnings management strategy CFOs use to meet desired earnings targets is to decrease discretionary spending such as R&D. The accounting treatment for R&D requires that most R&D costs be fully expensed immediately although the earnings and cash flow benefits may be many years in the future. This creates a perverse incentive where cutting R&D can directly help managers meet short-term earnings goals at the expense of future cash flows. Following Gunny (2005) and Zang (2007), I calculate the normal level of R&D expenditures by estimating the following model cross-sectionally for each industry-year with at least 10 observations:

[8] When estimating abnormal accruals and abnormal real earnings management, I exclude banks and financial institutions (SIC codes between 6000 and 6999), utilities (SIC codes between 4800 and 4999), and other regulated industries (SIC codes between 4000 and 4499) as these models do not apply to firms in these industries.

$$\frac{RD_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{RD_{t-1}}{Assets_{t-1}} + \beta_2 \frac{Funds_t}{Assets_{t-1}} + \beta_3 TobinsQ_t + \beta_4 \frac{Capex_t}{Assets_{t-1}} + \varepsilon_t \qquad (2)$$

where Funds is NIBE plus R&D and depreciation expense. Abnormal R&D, AB RD, is the residual from this model and NEGRD is an indicator variable equal to one if AB RD is negative. Zang (2007) performs validity tests that provide support that the abnormal R&D estimated by equation (2) captures real earnings management decisions.

V. EMPIRICAL RESULTS

Propensity Score Matching

The selection of control variables in the first stage is critical to remove selection bias. I choose several control variables that accounting theory and empirical evidence suggest are related to income objectives, earnings management, expectation management, analyst following, *and* the decision to establish IR.[9] I estimate a logit model using the lagged value of control variables as regressors and including all IR and non-IR firms with available data.[10] Table 2 shows the descriptive statistics for the observations used in the propensity score estimation.

I use the log of market value of equity, LOG MVE, and the log of total assets, LOG ASSETS, to control for size effects as staffing IR may represent a relatively fixed

[9] Characteristics related to the outcome variables but not related to the IR decision do not need to be controlled for because they will be randomly distributed between the IR and non-IR firms. For example, while length of operating cycle is related to earnings attributes such as accrual quality (Dechow and Dichev, 2002; Francis et al, 2004), it is unlikely to itself be a determinant of establishing IR. Empirically, it will already partly be balanced between the IR and non-IR firms because of its correlation with other conditioning variables such as industry. As expected, the difference in means for length of operating cycle between the IR and matched non-IR sample results is insignificant with a p-value of 0.94. In section VI, I explore whether additional variables of interest are also balanced between the two portfolios. I avoid including extraneous variables in the propensity score estimation as it can decrease the quality of the matches and increase the variance (Caliendo and Kopeinig, 2008). In addition, variables that may be influenced by IR should not be incorporated into the estimation of the propensity score as this could undermine the interpretability of the estimated effects (Bryson, 2002; Heckman et al., 1998).
[10] The independent variables Financing Activity and M&A Activity are not lagged.

cost that is subject to economies of scale. Size is also related to many outcome variables of interest such as analyst following, information environment, capital market pressures, meeting earnings targets, and earnings management.

I include return on assets, ROA, as a proxy for the performance of the firm. Better performing firms tend to be more forthcoming in terms of disclosure (Miller, 2002). However, poorer performing firms may face more questions about their performance and require IR to satisfy this demand. Performance may also be related to abnormal accruals and abnormal real earnings management activities (Kothari et al., 2005). While the indicator variable LOSS will also capture performance, Brown (2001) argues managers of firms with recent losses are less likely to feel pressure to meet analyst forecasts. I include the market-to-book ratio, MB, as a proxy for growth opportunities. Incentives to meet earnings targets are greater for high growth firms as the market reaction to earnings announcements (Collins and Kothari, 1989) and the negative reaction to missing earnings expectations (Skinner and Sloan, 2002) are greater for firms with growth opportunities.

I include a litigation indicator variable, LITIGATION, as firms in highly litigious industries may have a greater need to manage communications with investors and analysts. I include dummy variables for debt or equity issuance, FINANCING ACTIVITY, and merger and acquisition activity, M&A ACTIVITY, as I expect firms engaged in recent capital market transactions will have greater incentives to care about stock price.

I include the gross margin of the firm, MARGIN, to capture the firm’s product market competitiveness. I expect the higher a firm’s gross margin, the less likely it will need IR as it has less product market pressures from competitors based on substitutable products. I include leverage, LEVERAGE, as firms with more reliance on equity in their capital structure may be more likely to establish IR to cater to this audience.

I include the log of the age of the firm, LOG AGE, as the need to establish IR may be related to the life cycle of a firm. I include the log of the number of shares outstanding, LOG SHARES, as this will be correlated with the number of shareholders and shares available to trade in the market which will increase the demand for IR. Lastly, I include exchange dummies, year dummies, and 2-digit SIC industry dummies as proxies for structural barriers and industry- and time-specific effects related to establishing IR or to variation in the outcome variables. I use robust standard errors clustered at the firm level.

Table 2 shows the results from estimating the model. LOG MVE is positive and significant. ROA is negative while LOSS is positive and significant indicating that poorer performing firms are more likely to have IR. Firms that are from more litigious industries, that are actively accessing the capital market for financing, that are active in the M&A market, and that are older are more likely to establish IR. Firms with higher MARGIN are less likely to have IR. NYSE firms are more likely to have IR than AMEX firms.

Overall, the model has good in-sample predictive power of establishing IR. The McFadden's pseudo R-squared is 0.31, and 80% of the observations are correctly classified compared to a base rate of 69%. Figure 1 shows the propensity score distribution for the IR and non-IR firms from the model. Two features are of interest. First, the probability distribution between the IR and non-IR firms again highlights the predictive power of the model. Second, although highly skewed, the propensity score distribution for the non-IR firms has a long tail that provides a large region of common support for the IR firms to be matched against non-IR control firms.

Table 3 presents the characteristics of the IR and matched non-IR control firms before and after using nearest neighbor matching with replacement.[11] Column two shows the means of the IR firms. Columns three and four report the means of the non-IR sample after matching and the t-statistics of the difference compared to the IR sample. Columns five and six report means of the non-IR firms before matching and t-statistics of the difference compared to the IR sample. Before matching, IR firms and non-IR firms differ both statistically and economically in almost every dimension, confirming the need to explicitly control for the choice to implement IR.

Table 3 shows that after matching, nearly all control variable characteristics of the non-IR firms have moved closer to the IR firm values. The IR and matched non-IR firms differ insignificantly at the portfolio level in terms of size, assets, loss, ROA, MB, leverage, litigation, financing activity, M&A activity, gross margin, shares outstanding, exchange listing, and most major industry classifications. Age and the Wholesale Trade industry are statistically different (but with an arguably small economic difference) between the two samples with the IR firms being slightly older and more likely be in the Wholesale Trade industry. Figure 2 shows graphs of the control variable distributions between the two portfolios. The graphs show that in addition to balancing the means, the matching has done a decent job of balancing even irregular distributions. Overall, the

[11] Overall, 5,546 IR firm-year observations are matched with 1,998 non-IR firm-year observations: 709 non-IR firm-year observations are used only once, 507 are used twice, and 298 are used three times. The most times a non-IR firm-year observation is used as a match is 25. To mitigate potentially misleading standard errors, I use standard errors adjusted for multiple matches as well as clustering by matched firms. In section VI, I investigate the sensitivity of the results to this design choice.

propensity score matching has worked successfully in terms of balancing the control variables.

IR, Analyst Following, Institutional Ownership, and Stock Market Characteristics

Table 4 presents evidence on the relationship between IR and objectives claimed by IR practitioners. IR firms have a greater number of analysts and are more likely to have an analyst than non-IR firms. Column two is the number of IR firm-years that were successfully matched with non-IR firm-years. Column three shows IR firms have an average of 9.00 analysts versus 5.44 analysts for the matched non-IR control firms in column four. Columns five and six present the difference between the IR and matched non-IR control firms and the associated t-statistics based on robust standard errors clustered by firm.

The results show IR firms have a significantly greater amount of institutional investors and larger percentage of their shares outstanding held by institutional investors. IR firms have over 200 institutional investors on average, 73% more than the 124 of non-IR firms. Institutional investors hold 63% of the shares of IR firms compared to 41% of comparable non-IR firms.[12] Reflecting a concern for high quality, relevant disclosures, IR firms are also 11 days quicker on average at issuing an earnings announcement from the end of the fiscal year.

IR's influence also extends to a firm's stock market characteristics. IR firms' mean closing bid-ask spread scaled by share price is 0.54% compared to 0.72% for non-IR firms; and IR firms show a greater amount of daily share turnover than non-IR firms:

[12] The number of analysts and institutional investor data are set to zero for years that the firm is publicly traded but there are no data on the firm in I/B/E/S or the Thomson Financial 13-f filings.

0.77% versus 0.68%. In addition, the Probability of Informed Trades (PIN) metric, a proxy for a firm's level of information asymmetry (Brown et al., 2004), is significantly lower for IR firms versus non-IR firms.[13] The spread, turnover, and PIN results are consistent with IR professionals reducing information asymmetry between investors and increasing liquidity to increase the attractiveness of the stock to analysts and institutional investors.

Overall, the results complement and extend Bushee and Miller's (2007) findings on IR consultants and provide support that firms staffed with NIRI professionals achieve outcomes frequently cited in the IR literature as core components of an IR strategy. As opposed to Bushee and Miller's (2007) non-result in larger firms, I find this result in a sample of larger firms by using a measure of professionalized internal IR. This suggests despite not facing the same visibility problems as smaller firms, larger firms are able to achieve similar outcomes from IR but choose to implement their IR strategy by employing professional IR members instead of hiring external consultants.

Income Objectives

In this section, I examine the relationship between IR and income objectives. Table 5 shows the results from the propensity score matching. IR firms are more likely to meet or beat analyst earnings expectations, doing so 71% of the time compared to 64% for the non-IR sample. IR firms are also more likely to meet or beat analyst expectations in all 6 years during the sample period: 22% of IR firms met expectations in all six years compared to 14% of non-IR firms.

[13] PIN is available from Professor Stephen Brown's website: http://userwww.service.emory.edu/~sbrow22

On the other hand, IR firms do not appear more likely than non-IR firms to beat last year's earnings or avoid losses. There is no difference in the likelihood of having small positive net income between IR firms and non-IR firms. Against my expectations, IR firms appear less likely to meet last year's earnings (63% versus 66%).

The results also show that IR firms have a smoother earnings path than non-IR firms. This is consistent with managers of IR firms being more sensitive to the perceptions and preferences of analysts and investors; although the ultimate effect on financial reporting quality is unclear. On one hand, Chaney and Lewis (1995) and Demski (1998) argue that smoothness is desirable if managers use their private information about future income to smooth transitory fluctuations. On the other hand, managerial intervention to transform an inherently variable or unpredictable earnings path into a smooth or predictable one through earnings management reduces the information quality of earnings (Leuz et al, 2003; Francis et al, 2004).

Overall, this suggests that IR firms are more sensitive to the income objectives that are most strongly related to the preferences of analysts and where investors react the most strongly in terms of stock market consequences for meeting or missing the benchmark (Brown and Caylor, 2005).

Earnings Management to Meet Analyst Expectations

In this section I examine whether IR firms are more likely to use accrual and/or real earnings management when meeting analyst expectations. To assess whether managers use accrual management to meet analyst expectations, I first rescale estimated abnormal accruals from equation (1) to a per share basis. I define abnormal accruals per share as: $AB\ AA\ PS_t = \frac{AB\ AA_t * Assets_{t-1}}{Shares_t}$ where Shares is the number of shares used to compute adjusted EPS. Next, I adjust realized EPS for AB AA PS and compute the proportion of firm-years that could not have met the consensus analyst forecast without the use of abnormal accruals (Koh et al., 2008). I define MBE ACC as an indicator variable equal to one if the abnormal accrual adjusted EPS met or beat the consensus analyst forecast.

Table 6, Panel A, shows 51% of the IR firm-years that met analyst expectations based on actual EPS (MBE=1) did not meet expectations based on the abnormal accrual adjusted EPS (MBE ACC=0). This is a significantly lower proportion compared to the 57% of non-IR firm-years that met analyst forecasts only with the assistance of income increasing abnormal accruals.

To assess whether managers use real management to meet analyst expectations, I use a similar analysis to accrual management. To investigate whether IR firms are more or less likely to decrease R&D to meet analyst expectations, I adjust actual earnings for abnormal R&D. I first rescale estimated abnormal R&D from equation (2) to a per share basis. I define abnormal R&D per share as: $AB\ RD\ PS_t = \frac{AB\ RD_t * Assets_{t-1}}{Shares_t}$. Next, I adjust reported EPS for AB RD PS and compute the proportion of firm-years that could not have met the consensus analyst forecast without abnormally low R&D.[14] I create an indicator variable, MBE RD, equal to one if the abnormal R&D adjusted EPS met or beat the consensus analyst forecast and 0 otherwise.

[14] This treatment ignores tax effects of R&D investment and thus the proportions of IR and non-IR firms may be overstated. However, the matching algorithm will tend to balance the influence of tax effects between the IR and matched non-IR samples mitigating the concern that tax effects will be substantially influencing the comparison between the IR and matched non-IR control firms. Section VI (table 11) shows that the effective tax rate is not statistically different between IR and matched non-IR control firms.

Table 6, Panel B, shows 44% of the IR firm-years that met analyst expectations based on actual EPS (MBE=1) did not meet expectations based on the R&D adjusted EPS (MBE RD=0). This is a significantly lower proportion compared to the 51% of non-IR firm-years that met analyst forecasts only with the assistance of abnormal R&D.

I also examine whether this result could reflect concurrent differences in investment opportunities, although I expect the matching procedure will have mostly controlled for these differences. Specifically, I investigate another measure of investment, capital expenditures, with a different accounting treatment than R&D: these investments are capitalized and have little effect on current income. If the differences in relative abnormal R&D are attributable to differences in incentives to invest instead of accounting treatment, I expect to also find differences in capital spending.

I estimate the normal level of CAPEX spending by estimating the following equation cross-sectionally for each industry-year with at least 10 observations:

$$\frac{CAPX_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{CAPX_{t-1}}{Assets_{t-1}} + \beta_2 \frac{Funds_t}{Assets_{t-1}} + \beta_3 TobinsQ_t + \beta_4 \frac{PPE_t}{Assets_{t-1}} + \varepsilon_t \qquad (3)$$

AB CAPX is the residual from this model and NEGCAPX is indicator equal to one if AB CAPX is negative. I compare the likelihood of NEGCAPX within the firm-years relying on R&D management and find no significant difference between the IR and non-IR firms.[15] This suggests the differences are due to the accounting for R&D and not unspecified factors correlated with the classification.

Overall, it appears that IR firms are associated with factors that increase pressure to meet analyst expectations (number of analysts, forecast accuracy, forecast dispersion,

[15] The average coefficients on lagged CAPX, FUNDS, TOBINSQ, and PPENT are positive and significant with an average adjusted R^2 of 61%. The differences between IR and the matched non-IR firms are also insignificant if I use AB CAPX or abstain from using the CAPX model and instead use an indicator variable = 1 if the firms increases CAPX relative to last year.

etc.) and are more likely to meet those expectations. However, they are less likely to manage accruals or real activities in order to meet those expectations.

Expectations Management

In this section I explore a potential explanation for why IR firms appear less likely to use accruals management or real earnings management when meeting analyst forecasts. Analyst forecasts differ from other earnings benchmarks as they are a soft benchmark that potentially can be influenced by the firm. Specifically, instead of managing earnings, firms can also manage expectations to move the benchmark (Matsumoto, 2002; Brown and Pinello, 2007). Bartov and Cohen (2008) also argue that firms may trade off between expectations management, accrual management, and real earnings management.

Firms with IR may be better positioned to manage analysts' forecasts to beatable numbers through forecast guidance and a closer relationship with analysts. The issue of earnings guidance is frequently cited within the IR literature and the business press is replete with examples tying IR to this expectations management game: "Despite regulations on 'fair disclosure', companies still play warmer-now, colder-now with analysts who want to check their numbers against the investor relations department" (Financial Times, 2008).

NIRI conducts annual surveys specifically on earnings guidance practices. These surveys show that a majority of NIRI corporate members issue guidance and believe it is necessary; although recent surveys have shown a slight decline in overall guidance in an attempt to lessen the pressures to meet short-term expectations. Despite the controversy over guidance Louis Thompson, NIRI's former president and CEO, notes that, "a strong majority of companies [NIRI corporate members] still believe analysts and investors need some direction from the company to avoid increased stock price volatility" NIRI (2004).

I examine expectations management using three different methods. First, I compare characteristics consistent with expectations management. Second, I use a variation of the expectations management model used in Koh et al. (2008). And third, I compare situations where the results are more or less likely to be affected by expectations management (Bartov and Cohen, 2008).

In table 7, Panel A, I present results for activities consistent with expectations management. IR firms are nearly twice as likely as non-IR control firms to issue earnings forecasts during the fiscal year as captured by the CIG database: 59% vs. 31% of firm-years. [16] I next examine the characteristics of analyst forecasts at two points in time: (1) the beginning of the forecast period based on the month after the prior year's earnings announcement and (2) immediately before the current year's earnings announcement. At the beginning of the forecast period, IR and non-IR firms are just as likely to meet or beat analyst expectations. In addition, IR firms are only weakly more likely to have lower forecast dispersion and higher forecast accuracy at the beginning of the year where dispersion is measured by the coefficient of variation of analyst forecasts and accuracy is $\frac{|Actual\ \ Earnings\ _{t} - MEDEST_t|}{Price\ _{t-1}} * -100$ with higher values signifying greater accuracy.[17]

[16] Ajinkya, Bhojraj, and Sengupta (2005) conclude that the CIG database is a comprehensive source of management forecasts after performing two small sample tests (in 1997 and 2000) and finding about 2.5 times more CIG forecasts compared to a similar keyword search in Factiva (formerly Dow Jones News Retrieval Service).

[17] The result that IR and non-IR firms have a difference in the accuracy and dispersion of analyst forecasts *at the beginning of the period* also disappears in two separate additional analyses in section VI: controlling for concurrent changes in disclosure and matching without replacement.

On the contrary, IR firms are more likely to meet the most recent consensus earnings forecast. Analyst forecasts for IR firms immediately prior to the earnings announcement are also more accurate with less dispersion than non-IR firms. In untabulated analysis, I find that IR firms experience a greater decrease in forecast dispersion (p=0.01) and increase in forecast accuracy (p=0.07) over the year than non-IR firms, implying IR firms provide more information guiding analysts towards earnings. This suggests that these differences between IR and non-IR control firms at the time of the earnings announcement are not due to innate differences in their information environments. Instead, IR firms are more likely to walk-down analyst estimates reducing dispersion and uncertainty throughout the year (Richardson et al., 2004). Also consistent with a steady walk-down effect is that IR firms have lower forecast revision volatility compared to non-IR firms where revision volatility is the standard deviation of the month-to-month changes in the median consensus forecast.

Second, I use an annual version of the model in Koh et al. (2008) to estimate a firm's expected annual earnings forecast. Specifically, I estimate the following equation cross-sectionally for each sample year and four-digit SIC code with at least 10 observations:

$$\frac{(Actual_{\,t} - Actual_{\,t-1})}{Price_{\,t-1}} = \alpha + \beta_1 \frac{(Actual_{\,t-1} - Actual_{\,t-2})}{Price_{\,t-1}} + \varepsilon \tag{4}$$

where Actual is the adjusted earnings per share reported in I/B/E/S and price is split-adjusted. From the model, the firm's expected annual forecast is: $E(Actual_t) = Actual_{t-1} + \left[\hat{\alpha} + \widehat{\beta_1}\left(\frac{Actaul_{\,t-1} - Actual_{\,t-2}}{Price_{\,t-1}}\right)\right] * Price_{t-1}$. To only use data available to analysts at the time they make their forecast, I use parameter estimates from the prior period when determining the expected forecast to avoid introducing forward-looking bias. I define MBE DOWN as an indicator variable equal to one if the firm's earnings met or beat the expected annual forecast.

Panel B shows the results comparing suspect firm-years based on whether actual earnings met or exceeded a firm's expected forecast. I follow Koh et al. (2008) and define "suspect" firm-years as those years where a firm's annual earnings met or beat MEDEST but did not meet or beat the firm's expected annual forecast (MBE=1 and MBE DOWN=0). Consistent with expectations management, I find that 47% of IR firms relied on downward guidance to meet expectations compared to 42% of matched non-IR firms.

Third, panel C splits the sample into firm-years that are most likely or least likely to be affected by expectations management based on Bartov and Cohen (2008). The cases most likely affected by expectations management are those where the firm's actual earnings would not have met analyst expectations at the beginning of the year (MBE BEG=0) but ended up meeting or beating analyst expectations prior to the earnings announcement (MBE=1) scaled by the number of firms with MBE BEG =0. The cases least likely to be affected by expectations management are those where the firm's actual earnings would have met analyst expectations at the beginning of the year (MBE BEG=1) but ending up missing analyst expectations prior to the earnings announcement (MBE=0) scaled by the number of firms with MBE BEG=1.

The results show in the cases most likely affected by expectations management, 58% of IR firms missing initial expectations end up meeting the final consensus forecast compared to 48% of non-IR firms. In cases less likely to be affected by expectations management, only 17% of IR firms meeting initial expectations ending up missing the final consensus forecast compared to 21% of non-IR firms.

Overall, the evidence suggests that although IR may increase the pressure to meet analyst expectations, IR firms are more likely to relieve this pressure through expectations management. Moreover, IR's use of expectations management appears to act as a substitute for accrual or real earnings management to meet analyst expectations.

Stock Market Reaction to Meeting/Missing Analyst Expectations

Prior literature suggests there is a market premium for meeting expectations that exists even if the expectations are met through earnings or expectations management (Kasznik and McNichols, 2002; Bartov et al., 2002). IR firms may or may not exhibit such a premium. On one hand, Kasznik and McNichols (2002) find that firms that consistently meet expectations exhibit the premium even after controlling for the information content of future earnings performance. On the other hand, Koh et al. (2008) find the market premium to meeting expectations has decreased after the recent accounting scandals and SOX. They attribute this decrease to increased investor skepticism surrounding meeting analyst expectations. IR firms may also arouse investor cynicism over meeting expectations because of an IR firm's closer relationship with analysts.

I examine the relationship between meeting expectations and stock returns using stock returns cumulated over two periods in time: (1) from two trading days after the prior year's earnings announcement until one trading day after the current year's earnings announcement, and (2) from the day of until one trading day after the current year's earnings announcement. I estimate the following regression model based on Kasznik and

McNichols (2002) and Koh el al. (2008) after matching IR and non-IR firms based on propensity score and having non-missing information for Forecast Error, MBE and CAR:

$$CAR_t = \alpha + \beta_1 Forecast\ Error_t + \beta_2 MBE_t + \beta_3 IR_t$$
$$+\beta_4 IR_t * Forecast\ Error_t + \beta_5 IR_t * MBE_t + \varepsilon \quad (5)$$

where CAR is the cumulative return over the relevant period adjusted by subtracting the CRSP value-weighted market index; and Forecast Error is the difference between actual EPS and the median consensus forecast at the beginning of the period starting in the month after the prior year's earnings announcement. I use robust standard errors clustered by firm.

Table 8 shows that the market-adjusted returns are significantly related with meeting expectations for IR firms after controlling for the information in current earnings (MBE + IR*MBE in Panel B). This is consistent with IR firms receiving a market premium for meeting expectations. Surprisingly, this premium is concentrated only in the IR firms. There is no evidence that non-IR firms receive a premium for beating expectations (β_2) and the market premium difference between IR and non-IR firms (β_5) is statistically significant. Potentially, if the impetus behind an IR firm's smoother earning path is to create a more informative signal of future performance, the information content in meeting expectations, and thus the market premium, may also be related to IR. I leave the exploration of this result for future work.

In the short-window setting, the returns for both IR firms and non-IR firms are related to meeting/beating analyst expectations. However, there is no difference in the CAR for meeting expectations between IR and non-IR firms (Panel B: IR + IR*MBE).

Instead, it appears that investors punish IR firms more severely for missing expectations than matched non-IR firms (β_3). [18]

Overall, the results suggest that IR firms receive a premium for MBE and that this premium is greater for IR firms than for matched non-IR firms. In particular, the premium to MBE is solely concentrated within the IR firms in my sample. However, IR firms are asymmetrically punished for missing rather than rewarding for meeting/beating analyst expectations based on the short-window investor reaction on the earnings announcement date. Investors may expect IR firms to be more adept at the expectations management game and view missing final expectations as incrementally more negative for IR firms relative to non-IR control firms.

Earnings Management to Avoid Losses

In the analyst expectations analysis, managers have an option besides earnings management to meet the income benchmark. In this section, I examine a different income objective where firms are unable to move the benchmark. I use the setting introduced in Roychowdhury (2006) where he finds firms are likely to engage in real activities management in order to avoid losses.

In addition to R&D, I introduce two other real earnings management measures from the literature that capture ways managers can manipulate real activities to increase short-term earnings but potentially have negative effects on future cash flows. First, managers can produce more goods than is necessary to meet demand. Overproduction can increase earnings by lowering the cost of goods sold by spreading out fixed costs

[18] If I use 3-day CAR that also includes the day before the announcement [-1,+1] or define Forecast Error relative to the consensus median forecast prior to the earnings announcement, the results are qualitatively unchanged.

over more items, however, it creates excess inventories to be sold later and greater inventory holding costs. I follow Roychowdhury (2006) and Zang (2007) and estimate the normal level of production costs by estimating the following model cross-sectionally for each industry-year with at least 10 observations:

$$\frac{Prod_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{1}{Assets_{t-1}} + \beta_2 \frac{Sales_t}{Assets_{t-1}} + \beta_3 \frac{\Delta Sales_t}{Assets_{t-1}} + \beta_4 \frac{\Delta Sales_{t-1}}{Assets_{t-1}} + \varepsilon_t \qquad (6)$$

where Prod is COGS + ΔInventory. AB PROD is the residual from this model and POSPROD is an indicator variable equal to one if AB PROD is positive.

Second, managers can temporarily increase sales through offering price discounts or providing more lenient credit terms. While additional sales increase current earnings, price discounts and more lenient credit imply that cash flow from operations will be lower in the current period for a given level of sales. I follow Roychowdhury (2006) and estimate the normal level of cash flows by estimating the following model cross-sectionally for each industry-year with at least 10 observations:

$$\frac{CFO_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{1}{Assets_{t-1}} + \beta_2 \frac{Sales_t}{Assets_{t-1}} + \beta_3 \frac{\Delta Sales_t}{Assets_{t-1}} + \varepsilon_t \qquad (7)$$

where CFO is cash flow from operations. NEGCF is an indicator variable equal to one if the residual from this model is negative.

I estimate the following logit regression similar to Roychowdhury (2006):

$$(Prob\ EM_t = 1) = f(\alpha + \beta_1 IR_t + \beta_2 Suspect\ NI_t + \beta_3 IR_t * Suspect\ NI_t + \varepsilon) (8)$$

Where EM is one of the binary accrual or real earnings management variables: POSAA, NEGRD, POSPROD, or NEGCF.

Table 9 shows the coefficients on the real earnings management variables are all positive and significant consistent with Roychowdhury (2006)'s evidence that firms engage in real earnings management to avoid losses. The coefficient on the abnormal accrual variable is insignificant. In addition, none of the coefficients on the interaction term are statistically significant indicating that IR firms do not appear more or less likely than matched non-IR firms to engage in real earnings management to avoid losses. A caveat is that the small number of firms with suspect earnings may decrease the power of the test. Overall, IR firms show no relative proclivity for meeting hard earnings targets such as avoiding losses and no evidence that they are more or less likely to engage in real earnings management to avoid losses.

VI. ADDITIONAL ANALYSES

Survivorship

My classification of firms into the categories *IR firms* and *non-IR firms* requires the firm to be alive in both 2001 and 2006. While this method has many advantages in my setting, it also implicitly restricts an analysis of potential survivorship differences between IR and non-IR firms. In this section, I provide an exploratory analysis of the survival implications of firms with IR using two comparisons: (1) all IR and non-IR firms classified in 2001; (2) a matched sample of IR and non-IR firms classified in 2001.

First, as in the previous analysis, I use the NIRI membership data from the *2001/2002 Who's Who in Investor Relations* membership directory to classify firms into two categories (*IR firms* and *non-IR firms*) based on the presence of a NIRI member in 2001. These firms are then matched to CRSP/COMPUSTAT. Table 10, panel A, shows the survivorship rates of these firms over 2001 – 2006. There are 2,603 IR firms in 2001 (column two) and 4,702 non-IR firms in 2001 (column three). Of these initial firms, there are only 1,993 IR firms and 2,698 non-IR firms left with CRSP/COMPUSTAT data by

2006. Figure 3, panel A, shows this represents a survival rate of 77% for IR firms and 57% for non-IR firms. However, as this paper shows, there is a significant selection bias as to whether a firm makes an investment in professional IR. Table 10, panel B, confirms that IR and non-IR firms in 2001 are significantly different on almost every dimension. Thus, the difference in survivorship rates could be attributed to initial differences in size, profitability, exchange, financing activity, and others.

In the second comparison, I control for initial differences in these variables by using the model introduced in Section V (Propensity Score Matching) to create a matched sample of IR and non-IR firms in 2001. Overall, I match 1,583 IR firms with 1,583 non-IR firms in 2001 based on nearest-neighbor propensity score matching. Table 10, panel B, shows that the firm characteristics of the IR and matched non-IR control sample are economically and statistically indistinguishable. However, table 10, panel A, and figure 3, panel B, still show evidence of a difference in survivorship rates between IR and non-IR over the ensuing six years.

Table 10, panel C, investigates how the firm characteristics of the surviving IR and matched non-IR firms change over these six years. In 2001, the matching has worked and the sets of IR and non-IR firms are virtually identical. But by 2002, both market-to-book and financing have become statistically different between the two groups. Despite the differing survivorship rates, the match holds on most variables until 2006 where seven variables become statistically different between the remaining IR and non-IR firms. The variables that differ the most consistently across 2002-2006 are market-to-book, financing, and M&A activity. This suggests that IR firms may have characteristics that enhance the long-term viability of the firm through maintaining a higher stock price and access to financing.

Overall, this analysis underscores the choices in my primary analysis to form my sample of IR and non-IR firms each year instead of an initial sample formation, as well as requiring IR and non-IR firms to exist for the entire period to ensure comparable economic environments. However, the analysis of survivorship rates and characteristics suggests potential avenues for future research by using a time-series setting to study the evolution of IR versus non-IR firms and the influence of IR on a firm's chance of survival.

The Effect of Matching on Additional Variables of Interest

In this section, I provide an additional layer of comfort that shows the effect of propensity score matching on additional variables of interest that were not included in the first-stage estimation. Technically, characteristics related to the outcome variables but not to the IR decision do not need to be controlled for because they will be randomly distributed between the IR and non-IR firms. In addition, even if these variables potentially are related to the outcome variables and the IR decision (in that case, these variables could be thought of as examples of unobservable attributes), the use of a rich data set in the first stage will mitigate any potential bias as it is likely that the variables will mostly be balanced between the IR and matched non-IR firms because of their correlation with the vector of firm and industry characteristics used in the first stage.

Table 11 presents seven other variables of interest for the IR and non-IR firms before and after using nearest neighbor matching. Three of the variables (length of operating cycle, net working capital, and the standard deviation of daily returns over the fiscal year) differ both statistically and economically between the IR and non-IR firms before matching. Although none of these variables are included in the first-stage regression, table 11 shows that after matching the difference in means between the IR and matched non-IR control firms is insignificant for all the variables.

The Effect of IR Incremental to the Change in Disclosure

In this section I examine whether the documented influence IR has on the outcome measures is solely a result of IR increasing the firm's disclosures or if IR has a significant impact on the other outcome variables beyond this increase in disclosure. To examine whether IR has an incremental effect beyond the increase in disclosure, I estimate regression models where I control for the difference in whether a firm issues an earnings forecast during the fiscal year. I form a pooled sample of IR firms with their matched non-IR control firms and estimate the following regression:

$$Outcome_t = \alpha + \beta_1 IR_t + \beta_2 Any\ MEF_t + \varepsilon \tag{9}$$

where Outcome is the outcome variable of interest and Any MEF is an indicator variable equal to one if the firm issued an earnings forecast during the fiscal year. I use robust standard errors clustered by firm.

Table 12 shows results from controlling for the concurrent change in disclosure. Columns two to six contain the summary results from the previous tables while columns seven and eight show the difference and t-statistic after controlling for Any MEF. Overall, the results are largely consistent with the previous results. However, the differences in column six are also typically lower than column four. Combined this suggests that IR strategies have a direct effect on the outcomes incremental to disclosure changes; although, disclosure is one of avenues through which IR strategies operate.

The variables that were significant in the previous analyses but no longer significant after controlling for the change in disclosure are smoothness, forecast dispersion and accuracy at the beginning of the period (end of the period is still significant), forecast revision volatility, and the percentage of firms relying on expectation management to meet analyst expectations. With the exception of smoothness, these variables are those where disclosure is likely to be the main venue through which IR exerts its influence. This is particularly true considering the post Reg-FD sample period of the study. An interesting future extension of the paper would be to examine how Reg-FD affected the methods and effectiveness of IR strategies.

Matching With / Without Replacement

In this section I examine the sensitivity of the results to the choice of matching with or without replacement when performing the propensity score matching. In the matching algorithm there are many choices. One is whether to match with or without replacement. In the preceding analyses I matched with replacement which abstracts from ordering effects, increases the quality of the match and reduces bias (Caliendo and Kopeinig, 2008). This is important in this study as the propensity score distribution is different for the IR and non-IR firms. Figure 1 shows that there is a wide range of propensity scores for both IR and non-IR firms meaning that a potential match can be found for many IR firms. Though, the IR firms begin to dramatically outnumber the non-

IR firms as the propensity scores increase leading to throwing away potentially matchable IR firms when not allowing replacement.

However, matching without replacement can provide the benefit of not requiring an adjustment to the standard errors used for statistical tests to account for using the same firm in multiple matches. In the previous analyses I use standard errors adjusted for multiple matches as well as clustering standard errors by matched firms. Besides limiting the available data, matching without replacement is also sensitive to the order in which observations get matched.

I repeat the preceding analyses but by matching without replacement. I still impose the restriction that the propensity score of the matched firm has to be within 0.01 of the propensity score of the IR firm to reduce the risk of a poor match. I also randomly order the observations before matching to eliminate order effects.

Table 13, panel A, shows the characteristics of the IR and matched non-IR control firms after using nearest neighbor matching *without* replacement. The number of matched firm-years has decreased 36% from 5,546 with replacement to 3,564 without replacement potentially reducing the power of the tests. Column two shows the means of the IR firms. Columns three and four report the means of the non-IR sample after matching and the t-statistics of the difference compared to the IR sample. The matching procedure has again performed successfully as the IR and matched non-IR control firms differ insignificantly at the portfolio level for all the conditioning variables.

Table 13, panel B and C, re-estimate the main results but matching without replacement. While the number of observations is lower, the results are generally consistent with those previously reported in the paper. Smoothness, forecast dispersion/accuracy at the beginning of the period, forecast revision volatility, and the interaction term IR*MBE in the long-window stock market reaction test were significant in the main analysis but no longer significant after matching without replacement. On the other hand, SUSPECT NI (avoiding a loss), MBE – beginning (meeting expectations at the beginning of the period), and the coefficients on MBE and IR in the long window stock market reaction test become significant when previously they were statistically insignificant.

Overall, this section shows that the main results are robust to the research design choice of matching with or without replacement. The least robust results from the main analyses appear to be the effect on income smoothing and forecast revision volatility as the initially significant results on these variables also become insignificant after controlling for concurrent changes in disclosure.

VII. CONCLUSION

Using a sample of 1,008 firms with NIRI members during 2001 – 2006 I provide evidence on the decision to establish IR and the effect of IR on income objectives and the financial reporting decisions to meet expectations. My empirical analyses show that IR firms have substantially stronger information environments in terms of analyst coverage and forecasts, disclosure, and information asymmetry. IR firms also have more institutional investors and higher liquidity. This evidence suggests IR is able to substantially influence the communications between management and investors even in a sample of larger firms within a rich disclosure environment such as the U.S.

However, enhancing communications with investors also increases the pressure to meet expectations. Consistent with an increased concern for analyst and investor perceptions, IR firms are more likely to meet analyst forecasts and have smoother earnings. In spite of this, the focus on meeting analysts' expectations does not appear to degrade these firms' financial reporting quality. Instead, IR firms rely less on accrual or real earnings management and more on expectations management to meet expectations. This suggests that despite increasing the pressure to meet expectations, professional IR is able to relieve this pressure through other channels which may have a beneficial impact on the financial reporting of firms when meeting analyst expectations.

IR firms' ability at the expectations management game does not diminish the market premium to meeting expectations found in prior research (Kasnik and McNichols, 2002; Bartov et al., 2002). On the contrary, in my sample, the market premium is not only higher for IR firms compared to non-IR firms but also is observed only within the IR firms. However, investors appear to asymmetrically punish IR firms for missing expectations at the time of the earnings announcement based on 2-day abnormal returns. The stock market reaction for missing expectations is more negative for IR firms than non-IR firms while there is no relative difference for meeting expectations.

One implication of these results is that managers may increasingly employ professional IR staff to manage earnings expectations due to increased scrutiny and negative perceptions over earnings management after the recent accounting scandals, Enron, and SOX (Koh et al., 2008; Bartov and Cohen, 2008). The result of this shift may increase the proportion of firms meeting expectations and relieve pressure on managers to use accrual or real earnings management to meet expectations. However, it may also have a negative effect on the capital market system by affecting the credibility of analyst forecasts.

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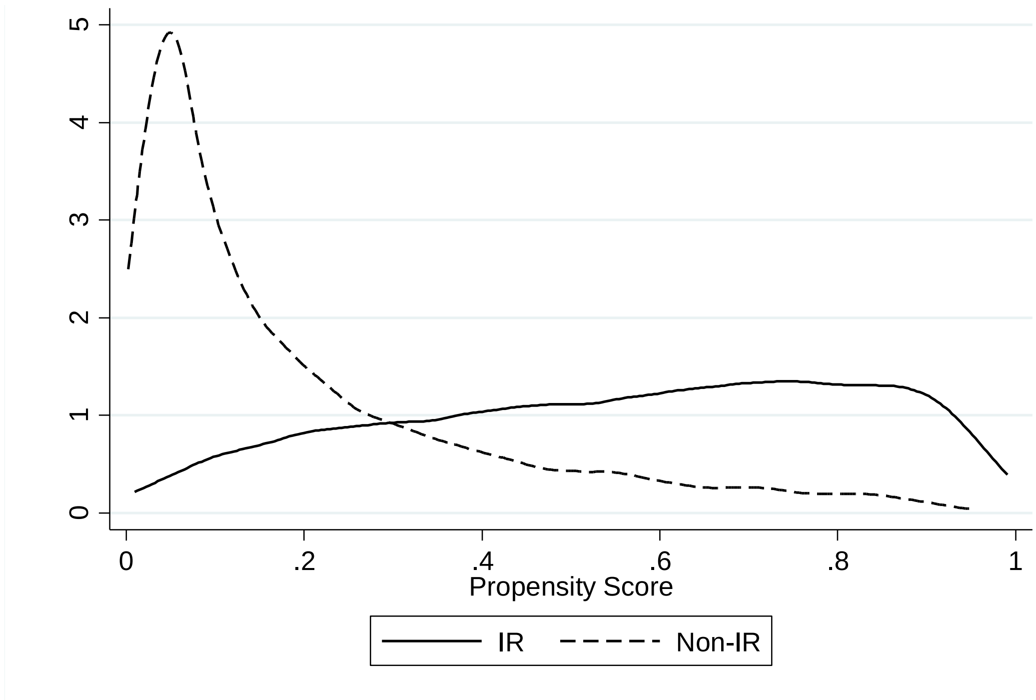
FIGURE 1
Propensity Score Density for IR and Non-IR Firms



This figure shows the propensity score distribution (i.e. predicted probabilities) for the IR and non-IR firms from the logit regression: Prob (IR=1) = f(β_1Log MVE + β_2Log Assets + β_3Loss + β_4ROA + β_5MB + β_6Leverage + β_7Litigation + β_8Financing Activity + β_9M&A Activity + β_{10}Margin + β_{11}Log Shares + β_{12}Log Age + β_{13}NYSE + β_{14}NASDAQ + 2-digit SIC Industry dummies). An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **Log MVE** is the log of market value of equity; **Log Assets** is log of total assets; **LOSS** is an indicator variable equal to one if net income before extraordinary items (NIBE) is negative; **ROA** is NIBE divided by total assets; **MB** is market value of equity divided by book value of equity; **Leverage** is (long-term debt + short-term debt) divided by total assets; **Litigation** is an indicator variable equal to one if a firm is in the following industries pharmaceuticals/biotechnology (SIC codes 2833–2836, 8731–8734), computers (3570–3577, 7370–7374), electronics (3600–3674), or retail (5200–5961); **Financing Activity** is an indicator variable equal to one if a firm issued common equity or debt in year t–1, t, or t+1; **M&A Activity** is an indicator variable equal to one if a firm engaged in mergers and acquisitions in year t–1, t, or t+1; **Margin** is (Sales – Cost of Goods Sold) / Sales for the year; **Log Shares** is the log of common shares outstanding; **Log Age** is the log of the number of years the firm has been listed on CRSP; **NYSE (NASDAQ)** are indicator variables equal to one if a firm is listed on NYSE (NASDAQ).

FIGURE 2
Control Variable Distributions between IR and Matched Non-IR Firms

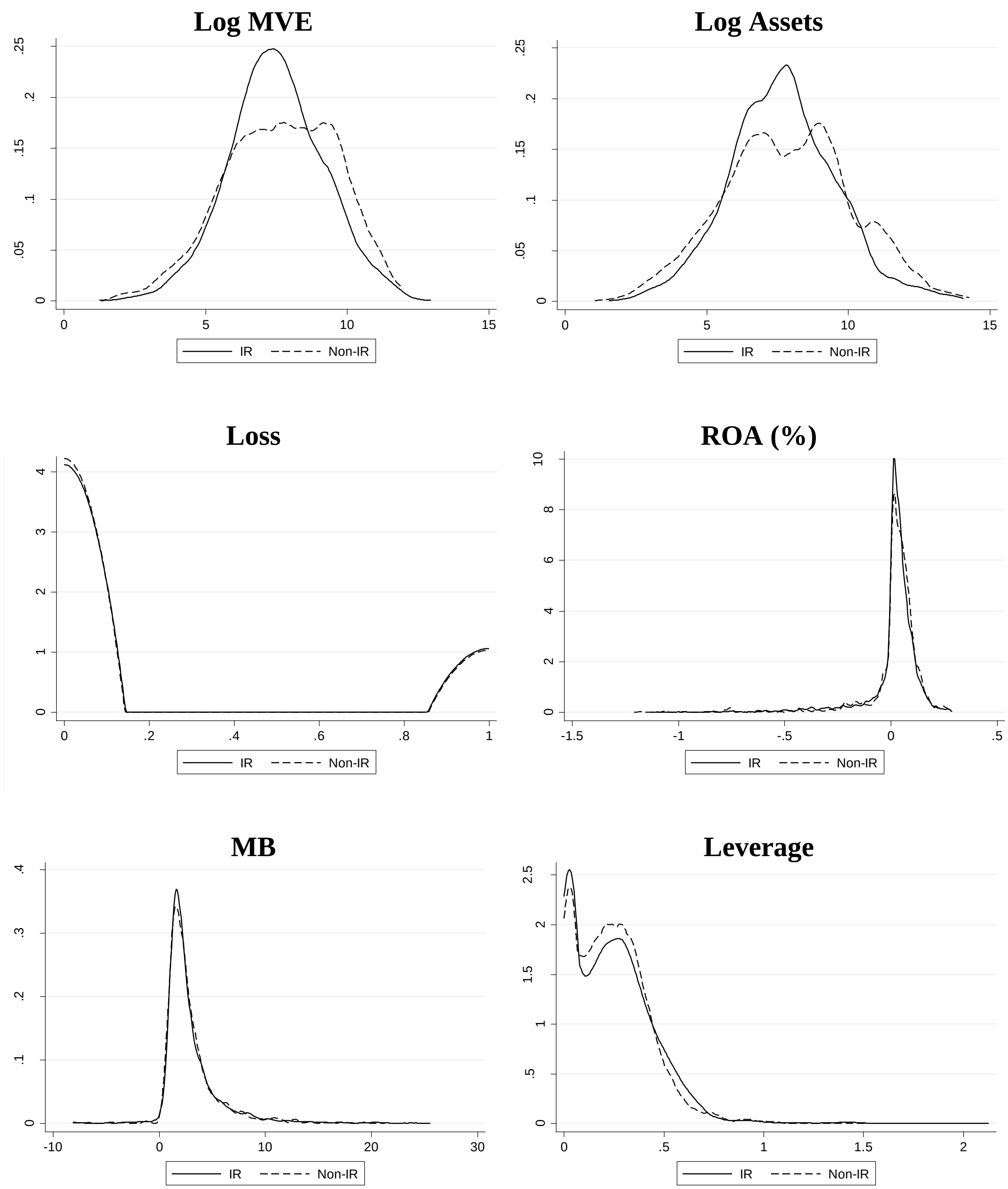
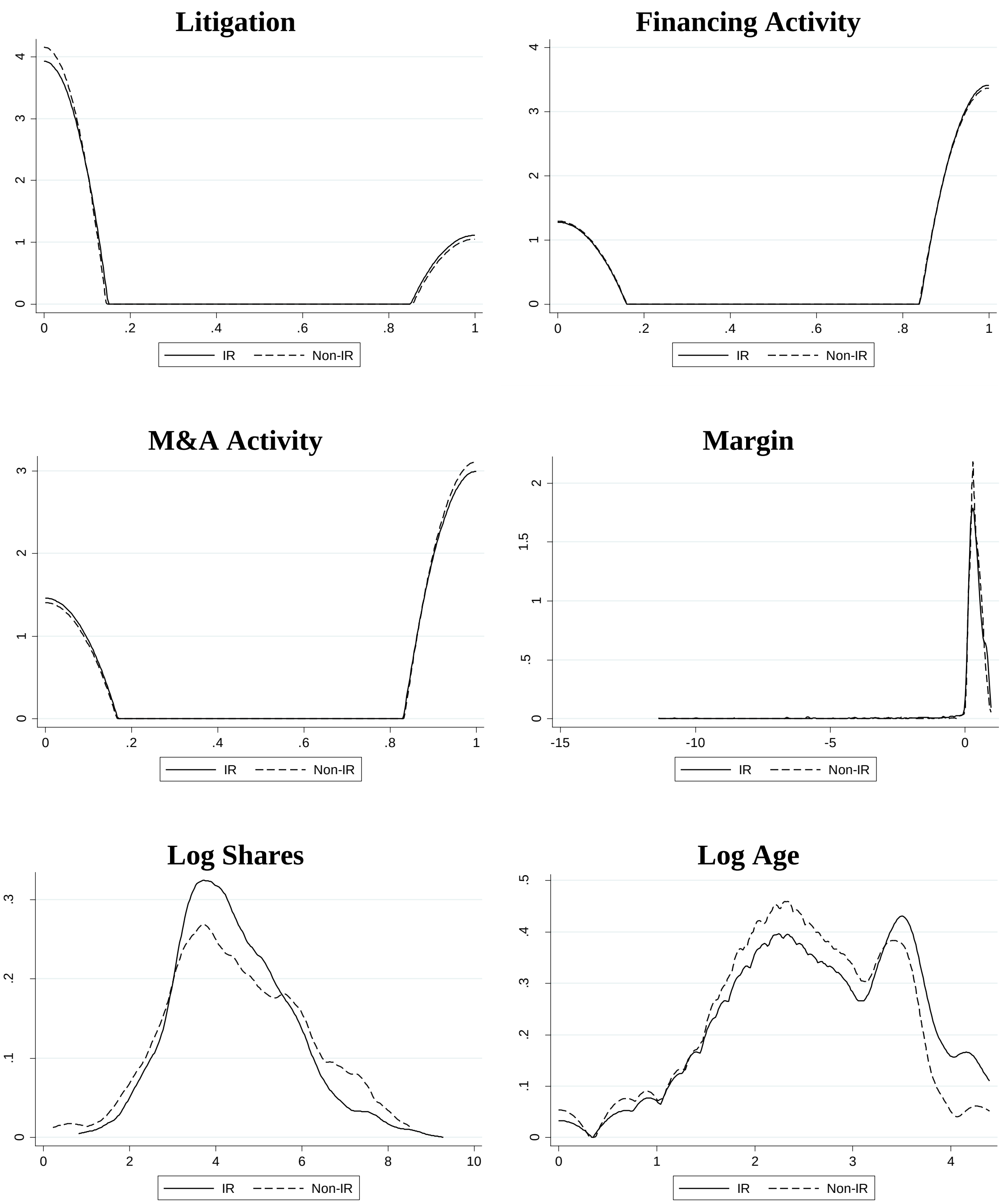


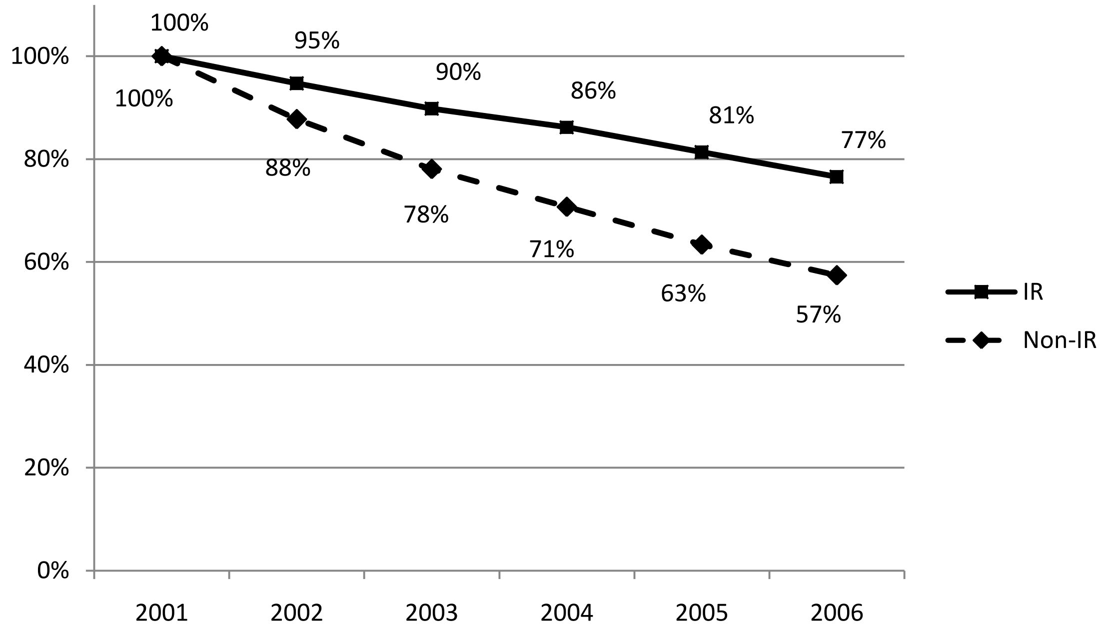
FIGURE 2 (continued)
Control Variable Distributions between IR and Matched Non-IR Firms



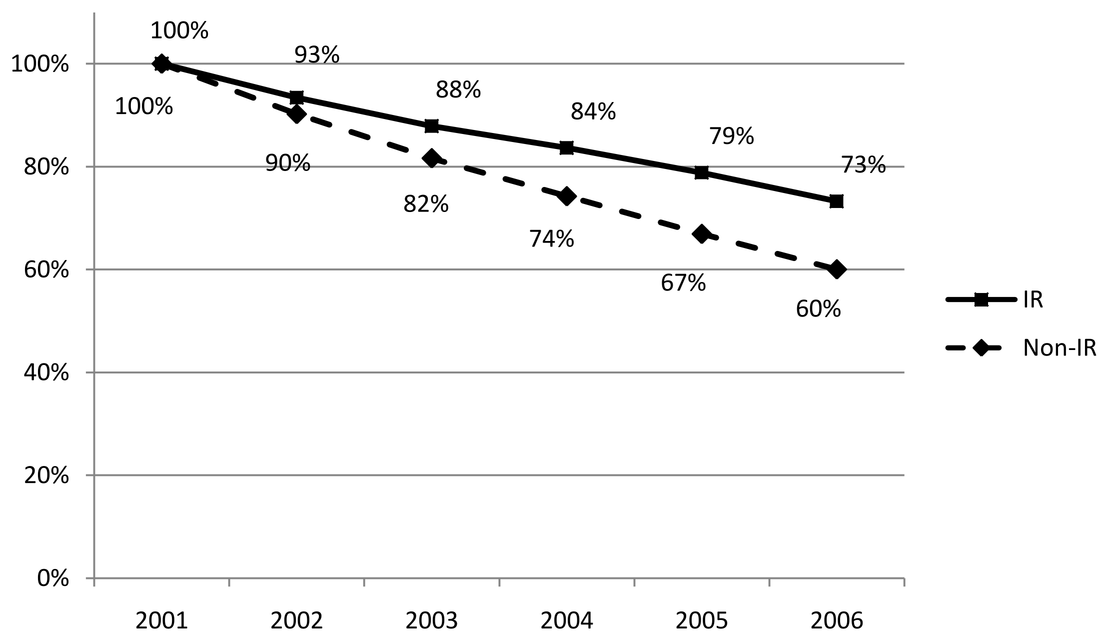
The sample consists of 5,561 IR and 5,561 matched non-IR firm-year observations from 2001 to 2006. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. The IR sample includes IR firms. The matched non-IR sample includes only those non-IR firms that were matched on a one-to-one basis with the IR firms using nearest-neighbor matching. This presents the distributions of control variables used in estimating the propensity score between the IR and the matched non-IR sample.

FIGURE 3
Survivorship Rates of IR and Non-IR Firms

Panel A: % of IR and Non-IR Firms Surviving from 2001



Panel B: % of IR and Matched Non-IR Firms Surviving from 2001



Panel A shows the percentage of IR and unmatched non-IR firms classified in 2001 that survived through 2006. Panel B shows the percentage of IR and matched non-IR firms classified in 2001 that survived through 2006. Matching was done through nearest neighbor propensity score matching.

TABLE 1
Sample Selection

	Unique Firms
Firms with CRSP/COMPUTSTAT data in 2001	7,305
Firms with CRSP/COMPUTSTAT data in 2002	6,877
Firms with CRSP/COMPUTSTAT data in 2003	6,582
Firms with CRSP/COMPUTSTAT data in 2004	6,580
Firms with CRSP/COMPUTSTAT data in 2005	6,506
Firms with CRSP/COMPUSTAT data in 2006	6,506
Firms with CRSP/COMPUSTAT data in all years 2001 through 2006	4,671
Firms with a NIRI member (IR firms) in both 2001 and 2006	1,008
Firms without a NIRI member (Non–IR firms) in both 2001 and 2006	2,683
Total firms in sample	3,691

NIRI (National Investor Relations Institute) members and their associated firms are hand–coded from NIRI's annual *Who's Who in Investor Relations* membership directory.

TABLE 2
Descriptive Statistics and Logit Propensity Score Regression

	Descriptive Statistics			Logit Propensity Score Regression		
Variable	**Mean**	**Median**	**SD**	**Sign**	**Coef**	**Z-stat**
Log MVE	5.91	5.82	2.21	+	0.65	8.29***
Log Assets	6.28	6.20	2.24	+	–0.07	–1.02
Loss	0.25	0.00	0.44	+/–	0.34	3.84***
ROA	–0.00	0.02	0.16	+/–	–1.14	–4.26***
MB	2.55	1.85	2.65	+/–	–0.01	–0.91
Leverage	0.21	0.16	0.20	+/–	0.45	1.71*
Litigation	0.23	0.00	0.42	+	0.37	1.98***
Financing Activity	0.46	0.00	0.50	+	0.47	5.24***
M&A Activity	0.53	1.00	0.50	+	0.13	1.69**
Margin	0.34	0.38	0.64	–	–0.08	–1.63**
Log Shares	3.34	3.21	1.59	+	0.00	0.00
Log Age	2.44	2.40	0.87	+/–	0.28	4.56***
NYSE	0.38	0.00	0.48	+/–	0.82	3.12***
NASDAQ	0.54	1.00	0.50	+/–	0.29	1.14
2–digit SIC Industry dummies					y	
Year dummies					y	
N					18,127	
McFadden's Pseudo R^2					0.31	
% Classified correctly					79.72%	
Base rate					68.69%	

TABLE 2 (continued)
Descriptive Statistics and Logit Propensity Score Regression

Table 2:

This table shows (1) **Descriptive Stats** – the characteristics variables included in the logit regression model as determinants of a firm's decision to establish Investor Relations; (2) **Logit Propensity Score Regression** – the results of the logit regression with IR as the independent variable: Prob (IR=1) = f(β_1Log MVE + β_2Log Assets + β_3Loss + β_4ROA + β_5MB + β_6Leverage + β_7Litigation + β_8Financing Activity + β_9M&A Activity + β_{10}Margin + β_{11}Log Shares + β_{12}Log Age + β_{13}NYSE + β_{14}NASDAQ + 2-digit SIC Industry dummies). The sample consists of 18,127 firm-year observations from 2001 – 2006 with data available for the propensity score model and where the firm existed in the CRSP/COMPUSTAT database for the entire period. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on one-tailed tests if the sign is predicted and two-tailed otherwise. Z-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **Log MVE** is the log of market value of equity; **Log Assets** is log of total assets; **LOSS** is an indicator variable equal to one if net income before extraordinary items (NIBE) is negative; **ROA** is NIBE divided by total assets; **MB** is market value of equity divided by book value of equity; **Leverage** is (long-term debt + short-term debt) divided by total assets; **Litigation** is an indicator variable equal to one if a firm is in the following industries pharmaceuticals/biotechnology (SIC codes 2833–2836, 8731–8734), computers (3570–3577, 7370–7374), electronics (3600–3674), or retail (5200–5961); **Financing Activity** is an indicator variable equal to one if a firm issued common equity or debt in year t–1, t, or t+1; **M&A Activity** is an indicator variable equal to one if a firm engaged in mergers and acquisitions in year t–1, t, or t+1; **Margin** is (Sales – Cost of Goods Sold) / Sales for the year; **Log Shares** is the log of common shares outstanding; **Log Age** is the log of the number of years the firm has been listed on CRSP; **NYSE (NASDAQ)** are indicator variables equal to one if a firm is listed on NYSE (NASDAQ).

TABLE 3
IR and Non-IR Firm Descriptive Statistics Before and After Matching

(1)	(2)	(3)	(4)	(5)	(6)
	IR	**Non-IR After Match**		**Non-IR Before Match**	
Variable	**Mean**	**Mean**	**T-stat**	**Mean**	**T-stat**
Characteristic Variables					
Log MVE	7.50	7.67	–1.54	5.78	20.03***
Log Assets	7.69	7.87	–1.37	6.18	16.33***
Loss	0.20	0.20	0.48	0.26	–4.23***
ROA (%)	1.06	1.55	–0.85	–0.47	3.60***
MB	3.01	2.89	0.92	2.45	6.59***
Leverage	0.24	0.24	0.45	0.20	5.18***
Litigation	0.22	0.20	0.81	0.22	0.20
Financing Activity	0.73	0.72	0.25	0.43	17.93***
M&A Activity	0.67	0.69	–0.74	0.52	9.55***
Margin	0.30	0.28	0.65	0.34	–1.82*
Log Shares	4.40	4.49	–0.97	3.24	17.74***
Log Age	2.66	2.46	3.60***	2.37	8.06***
Stock Exchange					
NYSE	66.08%	67.98%	–0.76	35.29%	14.33***
AMEX	2.02	1.73	0.52	8.58	–6.94***
NASDAQ	31.90	30.29	0.66	56.13	–11.72***
	100.00%	100.00%		100%	

TABLE 3 (continued)
IR and Non-IR Firm Descriptive Statistics Before and After Matching

(1)	(2)	(3)	(4)	(5)	(6)
	IR	Non-IR After Match		Non-IR Before Match	
Variable	Mean	Mean	T-stat	Mean	T-stat
Major Industry					
Agriculture	0.11%	0.04%	0.78	0.08%	0.23
Mining	4.13	6.13	–1.57	4.65	–0.61
Construction	1.15	0.90	0.47	1.11	0.10
Manufacturing	41.16	42.35	–0.40	38.34	1.41
Transportation/ Comm. / Utilities	11.56	12.64	–0.46	8.71	2.07**
Wholesale Trade	3.53	2.04	2.00**	3.74	–0.28
Retail Trade	5.79	4.35	1.18	5.42	0.40
Finance, Ins. & Real Estate	18.16	17.67	0.21	23.22	–3.05***
Services	14.41	13.88	0.29	14.73	–0.23
	100.00%	100.00%		100.00%	

This table show the descriptive statistics for the IR firms; Non-IR Before Match firms – all non-IR firms before matching them by propensity score with IR firms; Non-IR After Match firms – only those non-IR firms that were matched on a one-to-one basis with the IR firms using nearest-neighbor matching. The sample consists of 18,127 firm-year observations from 2001 – 2006 with data available for the propensity score model and where the firm existed in the CRSP/COMPUSTAT database for the entire period. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on one-tailed tests if the sign is predicted and two-tailed otherwise. T-statistics (or Z-statistics for exchange and industry) are based on heteroskedasticity–consistent standard errors clustered by firm. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **Log MVE** is the log of market value of equity; **Log Assets** is log of total assets; **LOSS** is an indicator variable equal to one if net income before extraordinary items (NIBE) is negative; **ROA** is NIBE divided by total assets; **MB** is market value of equity divided by book value of equity; **Leverage** is (long-term debt + short-term debt) divided by total assets; **Litigation** is an indicator variable equal to one if a firm is in the following industries pharmaceuticals/biotechnology (SIC codes 2833–2836, 8731–8734), computers (3570–3577, 7370–7374), electronics (3600–3674), or retail (5200–5961); **Financing Activity** is an indicator variable equal to one if a firm issued common equity or debt in year t–1, t, or t+1; **M&A Activity** is an indicator variable equal to one if a firm engaged in mergers and acquisitions in year t–1, t, or t+1; **Margin** is (Sales – Cost of Goods Sold) / Sales for the year; **Log Shares** is the log of common shares outstanding; **Log Age** is the log of the number of years the firm has been listed on CRSP. The major industry groupings are based on the following SIC codes: Agriculture (700–999), Mining (1000–1499), Construction (1500–1999), Manufacturing (2000–3999), Transportation/ Communication/ Utilities (4000–4999), Wholesale Trade (5000–5199), Retail Trade (5200–5999), Financial/Insurance/Real Estate (6000–6999), Services (7000–9998).

TABLE 4
Analyst Following, Institutional Ownership, and Stock Market Characteristics

(1) Variable	(2) N	(3) IR	(4) Non-IR Control	(5) Diff	(6) T-stat
# analysts	5,561	9.00	5.44	3.56	15.41***
Any analyst following	5,561	0.92	0.82	0.10	11.85***
% institutional investors	5,561	0.63	0.41	0.22	26.45***
# institutional investors	5,561	214.81	124.49	90.32	17.77***
Days to earnings announcement	5,452	38.29	49.22	– 10.93	–19.83***
Probability of informed trading	5,237	0.14	0.18	– 0.04	–22.62***
Mean bid-ask spread	5,380	0.54%	0.72%	– 0.18%	–10.40***
Mean daily share turnover	5,521	0.77%	0.68%	0.09%	5.04***

This table shows the differences in the mean outcome variables between IR firms and the matched non–IR control firms that were matched on a one–to–one basis by propensity score based on a "nearest neighbor" with replacement matching algorithm and a 0.01 caliper. The column N is the number of successfully matched IR-firm years with non-IR firm-years. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on two-tailed tests. T-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. The column IR and Non-IR Control are the mean measures of the variable for the IR firms and matched non-IR control firms respectively. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **# analysts** is the number of analysts in the median consensus earnings forecast immediately prior to the earnings announcement; **Any analyst following** is an indicator variable equal to one if a firm has one or more analysts; **% (#) institutional investors** are the percentage of shares outstanding held by institutions and number of institutions holding shares as of the 13-f filing report immediately prior to the fiscal year-end date; **Days to earnings announcement** is the number of days after the fiscal year end until the earnings announcement based on COMPUSTAT; **Probability of informed trading (PIN)** is the mean quarterly probability of informed trading measure over the fiscal year; **Mean bid-ask spread** is the mean daily (Closing Ask – Closing Bid) / Price over the fiscal year; **Mean daily share turnover** is the mean daily turnover divided by shares outstanding for the fiscal year. The number of analysts and institutional investor variables are set to zero for years where the firm is publicly traded but there is no analyst data in I/B/E/S or institutional investor data in Thomson Financial 13-f filings.

TABLE 5
Differences in Income Objectives

Variable	Sign	N	IR	Non-IR Control	Diff	T-stat
Income objective: meet analyst expectations						
MBE	+	5,067	0.71	0.64	0.07	6.34***
MBE ALL YEARS	+	4,414	0.22	0.14	0.09	5.36***
Income objective: avoid reporting a loss						
SUSPECT NI (%)	+	5,560	2.37	2.53	–0.16	–0.49
Income objective: meet last year's earnings						
MB LAST YEAR	+	5,560	0.63	0.66	– 0.03	–3.04###
Income objective: report a smooth earnings path						
SMOOTHNESS	–	4,951	1.06	1.11	–0.05	–1.53*

This table shows the differences in the mean outcome variables between IR firms and the matched non–IR control firms that were matched on a one–to–one basis by propensity score based on a "nearest neighbor" with replacement matching algorithm and a 0.01 caliper. The column N is the number of successfully matched IR-firm years with non-IR firm-years. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on one-tailed tests if the sign is predicted and two-tailed otherwise. ### denote statistical significance at the 0.01 level against the predicted direction. T-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. The column IR and Non-IR Control are the mean measures of the variable for the IR firms and matched non-IR control firms respectively. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **MBE** is an indicator variable = 1 if a firm's actual annual earnings are greater than or equal to the median consensus forecast, and 0 otherwise; **MBE ALL YEARS** is an indicator variable = 1 if a firm's actual annual earnings are greater than or equal to the median consensus forecast in each year from 2001 to 2006, and 0 otherwise; **SUSPECT NI** is an indicator variable = 1 if a firm's net income before extraordinary items (NIBE) divided by total assets is greater than or equal to zero and less than 0.005, and 0 otherwise; **MB Last Year** is an indicator variable = 1 if a firm's NIBE is greater than or equal to last year's NIBE, and 0 otherwise; **Smoothness** is the ratio of a firm's standard deviation of annual NIBE divided by beginning total assets, to the standard deviation of CFO divided by beginning total assets calculated over the period 2001 – 2006.

TABLE 6
Earnings Management to Meet Analyst Expectations

	IR	**Non-IR Control**	**Diff**	**T-stat**
Panel A: Accrual Management				
# firms MBE = 1	2,526	2,242		
# firm MBE = 1 & MBE ACC=0	1,282	1,288		
% relying on accrual management	50.75%	57.45%	–6.70%	4.10***
Panel B: Real Earnings Management Through Abnormally Lower R&D				
# firms MBE = 1	2,243	2,032		
# firms MBE = 1 & MBE RD=0	982	1,038		
% relying on R&D management	43.78%	51.08%	–7.30%	4.08***
% of NEGCAPX where MBE = 1 & MBE RD=0	61.41%	61.49%	–0.08%	–0.03

This table shows the proportion of firms relying on accrual management or R&D earnings management out of the number of firms meeting or beating analyst expectations. The firms are subdivided into IR firms and the matched non–IR control firms that were matched on a one–to–one basis by propensity score based on a "nearest neighbor" with replacement matching algorithm and a 0.01 caliper. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on two-tailed tests. T-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. The column IR and Non-IR Control represent the IR firms and the matched non-IR control firms. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **MBE** is an indicator variable equal to one if a firm's actual annual earnings per share are greater than or equal to the median consensus forecast; **MBE ACC** is an indicator variable equal to one if a firm's earnings per share adjusted for abnormal accruals per share are greater than or equal to the median consensus forecast. Abnormal accruals are calculated using the Jones (1991) model estimated annually for each 2-digit SIC code. **MBE RD** is an indicator variable equal to one if a firm's earnings per share adjusted for abnormal R&D per share are greater than or equal to the median consensus forecast. Abnormal R&D is calculated by estimating the following model annually for each 2-digit SIC code: $\frac{RD_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{RD_{t-1}}{Assets_{t-1}} + \beta_2 \frac{Funds_t}{Assets_{t-1}} + \beta_3 TobinsQ_t + \beta_4 \frac{Capex_t}{Assets_{t-1}} + \varepsilon_t$. **NEGCAPX** is an indicator variable equal to one if a firm's abnormal capital expenditures are negative. Abnormal capital expenditures are calculated by estimating the following model annually for each 2-digit SIC code: $\frac{CAPX_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{CAPX_{t-1}}{Assets_{t-1}} + \beta_2 \frac{Funds_t}{Assets_{t-1}} + \beta_3 TobinsQ_t + \beta_4 \frac{PPE_t}{Assets_{t-1}} + \varepsilon_t$.

TABLE 7
Expectations Management to Meet Analyst Expectations

Variable	N	IR	Non-IR Control	Diff	T-stat
Panel A: Firm Characteristics Consistent with Expectations Management					
Any management earnings forecast	5,561	0.59	0.31	0.28	19.18***
MBE – beginning	5,067	0.50	0.50	0.00	–0.51
MBE	5,067	0.71	0.64	0.07	6.34***
Forecast dispersion – beginning	4,629	0.11	0.12	–0.01	–1.90*
Forecast dispersion	4,644	0.05	0.07	–0.02	–6.67***
Forecast accuracy – beginning	5,045	–2.02	– 2.20	0.18	1.88*
Forecast accuracy	5,044	– 0.52	– 0.80	0.28	6.85***
Forecast revision volatility	4,937	0.06	0.07	–0.01	–2.04**
Panel B: Proportion Relying on Expectations Management					
# firms MBE = 1		1,298	1,214		
# firm MBE = 1 & MBE DOWN=0		607	511		
% relying on expectations management		46.76%	42.09%	4.67%	2.21**

TABLE 7 (continued)
Expectations Management to Meet Analyst Expectations

Variable	N	IR	Non-IR Control	Diff	T-stat
Panel C: Cases Consistent/Inconsistent with Expectations Management					
Cases likely affected by expectations management		57.66%	47.93%	9.73%	6.09***
Cases less likely affected by expectations management		16.92%	20.89%	–3.97%	3.48***

This table shows expectations management between between IR firms and the matched non–IR control firms that were matched on a one–to–one basis by propensity score based on a "nearest neighbor" with replacement matching algorithm and a 0.01 caliper. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on two-tailed tests. T-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. Panel A shows the differences in the mean outcome variables between IR firms and the matched non–IR control firms. The column N is the number of successfully matched IR-firm years with non-IR firm-years. The column IR and Non-IR Control are the means of the variable for the IR firms and matched non-IR control firms. **Any management earnings forecast** is an indicator variable equal to one if a firm issued earnings guidance during the year. Meeting expectations, forecast dispersion and accuracy are based on the consensus forecast at two points in time: (1) immediately before the current year's earnings announcement, and (2) the beginning of the annual forecast period starting the month after the prior year's earnings announcement. **MBE** is an indicator variable equal to one if a firm's actual annual earnings per share are greater than or equal to the median consensus forecast. **Forecast accuracy** is –100 * |Actual EPS – Median Forecast EPS | divided by beginning of year price; **Forecast dispersion** is the standard deviation of mean earnings forecast divided by the absolute value of the mean earnings forecast; **Forecast revision volatility** is the standard deviation of month-to-month changes in the median forecast from the month after the prior year's earnings announcement to before the earnings announcement. Panel B shows the proportion of firms relying on expectations management out of the number of firms meeting or beating analyst expectations. **MBE DOWN** is an indicator variable equal to one if a firm's annual earnings are greater than or equal to the expected earnings forecast where the expected forecast is estimated using a variation of the Matsumoto (2002) model. Panel C shows the proportion of firms in cases like and less likely to be affected by expectations management (Bartov and Cohen, 2008). Cases likely to be affect by expectations management are cases where **MBE**=1 and **MBE – beginning** =0 scaled by **MBE – beginning** =0. Cases less likely to be affected by expectations management are cases where **MBE**=0 and **MBE – beginning** =1 scaled by **MBE**=1.

TABLE 8
Stock Market Reaction to Meeting/Missing Analyst Expectations

Variables	CAR [EA_{t-1} + 2, EA_t +1]		CAR [EA_t, EA_t + 1]	
	Coef	**T-stat**	**Coef**	**T-stat**
Panel A: $CAR_t = \alpha + \beta_1 FE_t + \beta_2 MBE_t + \beta_3 IR_t + \beta_4 IR_t * FE_t + \beta_5 IR_t * MBE_t + \varepsilon$				
Forecast error	1.72	7.48***	–0.03	–1.07
MBE	0.01	0.96	0.02	10.76***
IR	–0.01	–0.65	–0.01	–4.12***
IR*Forecast error	0.05	0.15	0.01	0.32
IR*MBE	0.03	1.85*	0.01	3.57***
Constant	0.09	10.15***	–0.01	–6.01***
N	9,730		9,730	
R^2	0.03		0.03	

Panel B: F-tests of Significance

	Coef	F-stat	Coef	F-stat
MBE + IR*MBE=0	0.04	12.16***	0.03	200.17***
IR + IR*MBE=0	0.02	6.09**	0.00	0.06

TABLE 8 (continued)
Stock Market Reaction to Meeting/Missing Analyst Expectations

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Table 8:

This table shows 4,865 IR firms and 4,865 matched non–IR control firms that were matched on a one–to–one basis by propensity score based on a "nearest neighbor" with replacement matching algorithm and a 0.01 caliper. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on two-tailed tests. T-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. The OLS regression model:

$$CAR_t = \alpha + \beta_1 Forecast\ Error_t + \beta_2 MBE_t + \beta_3 IR_t + \beta_4 IR_t * Forecast\ Error_t + \beta_5 IR_t * MBE_t + \varepsilon$$

is estimated for two periods. CAR[Ea_{t-1}+2, EA_t+1] is the market adjusted stock return beginning two trading days after the prior year's earnings announcement and ending one trading day after the current year's earnings announcement. CAR[EA_t, EA_t+1] is the market adjusted stock return from the day of and one trading day after the current year's earnings announcement. The market adjusted return is calculated by subtracting the CRSP value-weighted market index including distributions. **Forecast error** is earnings per share in year t minus the median consensus forecast at the beginning of the period starting in the month after the earnings announcement in year t-1 deflated by share price at the beginning of the year. **MBE** is an indicator variable = 1 if a firm's actual annual earnings are greater than or equal to the median consensus forecast immediately prior to the earnings announcement, and 0 otherwise. **IR** is an indicator variable =1 if a firm is an IR firm, and 0 otherwise.

TABLE 9
Earnings Management to Avoid Losses

Variables	POSAA		NEGRD		POSPROD		NEGCF	
	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat
IR	–0.17	–2.94***	–0.20	–3.56***	–0.08	–1.05	0.05	0.75
Suspect NI	0.19	0.62	0.56	1.64*	0.76	2.46***	0.62	2.19**
IR*Suspect NI	–0.18	–0.49	–0.48	–0.25	–0.01	–0.03	0.13	0.35
Constant	0.32	9.08***	0.54	14.55***	0.03	0.73	–0.45	–12.73***
N	6,590		6,590		6,590		6,590	
Pseudo R^2	0.00		0.00		0.00		0.00	

TABLE 9 (continued)
Earnings Management to Avoid Losses

Table 9:

This table shows 3,295 IR firms and 3,295 matched non–IR control firms that were matched on a one–to–one basis by propensity score based on a "nearest neighbor" with replacement matching algorithm and a 0.01 caliper. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on two-tailed tests. T-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. The logit regression $(Prob\ EM_t = 1) = f(\alpha + \beta_1 NIRI + \beta_2 SUSPECT_{NI} + \beta_3 NIRI * SUSPECT\_NI + \varepsilon)$ is estimated for four independent variables where EM is POSAA, NEGRD, POSPROD, or NEGCF. Abnormal accruals are calculated using the Jones (1991) model estimated annually for each 2-digit SIC code. **POSAA** is an indicator variable equal to one if a firm's abnormal accruals are positive. Abnormal R&D is calculated by estimating the following model annually for each 2-digit SIC code: $\frac{RD_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{RD_{t-1}}{Assets_{t-1}} + \beta_2 \frac{Funds_t}{Assets_{t-1}} + \beta_3 TobinsQ_t + \beta_4 \frac{Capex_t}{Assets_{t-1}} + \varepsilon_t$. **NEGRD** is an indicator variable equal to one if a firm's abnormal R&D is negative. Abnormal production is calculated by estimating the following model annually for each 2-digit SIC code: $\frac{Prod_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{1}{Assets_{t-1}} + \beta_2 \frac{Sales_t}{Assets_{t-1}} + \beta_3 \frac{\Delta Sales_t}{Assets_{t-1}} + \beta_4 \frac{\Delta Sales_{t-1}}{Assets_{t-1}} + \varepsilon_t$ where Prod is Cost of Goods Sold + ΔInventory. **POSPROD** is an indicator variable equal to one if a firm's abnormal production is positive. Abnormal cash flow from operations (CFO) is calculated by estimating the following model annually for each 2-digit SIC code: $\frac{CFO_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{1}{Assets_{t-1}} + \beta_2 \frac{Sales_t}{Assets_{t-1}} + \beta_3 \frac{\Delta Sales_t}{Assets_{t-1}} + \varepsilon_t$. **NEGCF** is an indicator variable equal to one if abnormal CFO is negative. **IR** is an indicator variable equal to one if a firm employs a NIRI member. **SUSPECT NI** is an indicator variable equal to one if a firm's net income before extraordinary items (NIBE) divided by total assets is greater than or equal to zero and less than 0.005.

TABLE 10
Exploratory Survivorship Analysis

(1)	(2) IR	(3) Non-IR	(4) IR	(5) Non-IR Control
Panel A: Mortality Rate of IR and Non-IR Firms				
Firms with CRSP/COMPUSTAT data in 2001	2,603	4,702	1,583	1,583
# Firms still with data in 2002	2,465	4,126	1,479	1,428
# Firms still with data in 2003	2,338	3,670	1,391	1,292
# Firms still with data in 2004	2,243	3,324	1,324	1,175
# Firms still with data in 2005	2,118	2,978	1,248	1,059
# Firms still with data in 2006	1,993	2,698	1,160	950
Panel B: Firm Characteristics as of 2001				
Log size	6.58	4.50***	5.83	5.83
Log Assets	6.72	5.12***	6.15	6.12
Loss	0.31	0.39***	0.33	0.35
ROA	-0.03	-0.08***	-0.04	-0.04
MB	3.21	2.18***	2.79	2.76
Leverage	0.24	0.22**	0.22	0.23
Litigation	0.27	0.22***	0.26	0.28
Financing	0.61	0.27***	0.51	0.52
M&A	0.65	0.41***	0.60	0.61
Margin	0.27	0.27	0.27	0.25
Log Shares	3.86	2.61***	3.38	3.36
Log Age	2.08	1.93***	1.94	1.90
Exchange				
NYSE	47.02	26.25***	36.58	37.02
AMEX	5.31	12.21***	6.32	7.20
NASDAQ	47.67	61.54***	57.11	55.78

TABLE 10 (continued)
Exploratory Survivorship Analysis

Panel C: IR and Non-IR Firm Characteristics Through Time for a Sample Matched in 2001

	2001		2002		2003		2004		2005		2006	
	IR	Non-IR	IR	Non-IR	IR	Non-IR	IR	Non-IR	IR	Non-IR	IR	Non-IR
Log size	5.83	5.83	5.89	5.80	5.71	5.64	6.24	6.19	6.48	6.39	6.59	6.46*
Log assets	6.15	6.12	6.18	6.15	6.24	6.22	6.34	6.37	6.50	6.49	6.63	6.58
Loss	0.33	0.35	0.41	0.38	0.35	0.36	0.30	0.30	0.22	0.24	0.23	0.24
ROA	–0.04	–0.04	–0.08	–0.07	–0.06	–0.06	–0.03	–0.02	–0.00	–0.00	0.00	0.00
MB	2.79	2.76	2.59	2.30***	1.98	1.83**	2.96	2.66***	2.86	2.74	2.96	2.63***
Leverage	0.22	0.23	0.23	0.23	0.23	0.22	0.22	0.21	0.21	0.20	0.21	0.19*
Litigation	0.26	0.28	0.27	0.28	0.26	0.27	0.25	0.26	0.25	0.26	0.25	0.26
Financing	0.51	0.52	0.51	0.47**	0.56	0.47***	0.57	0.48***	0.57	0.48***	0.49	0.41***
M&A	0.60	0.61	0.57	0.55	0.57	0.53**	0.58	0.54**	0.62	0.55***	0.53	0.47***
Margin	0.27	0.25	0.29	0.29	0.30	0.29	0.31	0.33	0.32	0.36	0.32	0.38*
Log Shares	3.38	3.36	3.45	3.43	3.50	3.49	3.57	3.55	3.67	3.64	3.77	3.68
Log Age	1.94	1.90	2.18	2.13	2.35	2.30	2.47	2.44	2.59	2.54*	2.69	2.65*
Exchange												
NYSE	36.58	37.02	39.10	38.17	41.45	40.37	42.33	42.16	43.37	42.14	43.59	42.84
AMEX	6.32	7.20	5.91	6.90	6.09	6.47	6.03	6.47	5.58	6.29	5.20	6.26
NASDAQ	57.11	55.78	54.99	54.93	52.46	53.16	51.64	51.38	51.05	51.57	51.21	50.90

TABLE 10 (continued)
Exploratory Survivorship Analysis

Table 10:

This table shows the exploratory survivorship analysis. Panel A shows the number of IR and unmatched non-IR firms classified in 2001 which continue to have available data through 2006 (columns two and three). In addition, columns four and five show the number of IR and matched non-IR firms classified in 2001 that survived through 2006. Matching was done on a one-to-one basis using nearest neighbor propensity score matching based on the logit regression: Prob (IR=1) = f(β_1Log MVE + β_2Log Assets + β_3Loss + β_4ROA + β_5MB + β_6Leverage + β_7Litigation + β_8Financing Activity + β_9M&A Activity + β_{10}Margin + β_{11}Log Shares + β_{12}Log Age + β_{13}NYSE + β_{14}NASDAQ + 2-digit SIC Industry dummies). Panel B shows the descriptive statistics for the IR firms and unmatched non-IR firms classified in 2001 (columns two and three) and the IR firms with matches and their matched non-IR firms in 2001 (columns four and five). Panel C shows the descriptive statistics from 2001 – 2006 for the IR and matched non-IR firms based on matching these firms initially in 2001. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **Log MVE** is the log of market value of equity; **Log Assets** is log of total assets; **LOSS** is an indicator variable equal to one if net income before extraordinary items (NIBE) is negative; **ROA** is NIBE divided by total assets; **MB** is market value of equity divided by book value of equity; **Leverage** is (long-term debt + short-term debt) divided by total assets; **Litigation** is an indicator variable equal to one if a firm is in the following industries pharmaceuticals/biotechnology (SIC codes 2833–2836, 8731–8734), computers (3570–3577, 7370–7374), electronics (3600–3674), or retail (5200–5961); **Financing Activity** is an indicator variable equal to one if a firm issued common equity or debt in year t–1, t, or t+1; **M&A Activity** is an indicator variable equal to one if a firm engaged in mergers and acquisitions in year t–1, t, or t+1; **Margin** is (Sales – Cost of Goods Sold) / Sales for the year; **Log Shares** is the log of common shares outstanding; **Log Age** is the log of the number of years the firm has been listed on CRSP; **NYSE (NASDAQ)** are indicator variables equal to one if a firm is listed on NYSE (NASDAQ).

TABLE 11
Other IR and Non-IR Firm Descriptive Statistics Before and After Matching

Variable	IR Mean	Non-IR After Match Mean	Non-IR After Match T-stat	Non-IR Before Match Mean	Non-IR Before Match T-stat
Characteristic Variables					
Length of operating cycle	4.96	4.94	0.34	5.27	–6.00***
Altman's Z-score	4.06	4.22	–0.61	4.03	0.16
Net working capital	533.95	562.53	–0.17	262.57	3.32***
Herfindahl index	0.09	0.09	0.97	0.09	0.14
SD ret (*100)	2.53	2.47	0.94	3.03	–10.18***
Net operating assets	1.44	1.60	–1.25	1.57	–1.61
Effective tax rate	0.18	0.21	–1.64	0.19	–0.54

This table shows the differences in the mean outcome variables between IR firms and the matched non–IR control firms that were matched on a one–to–one basis by propensity score based on a "nearest neighbor" with replacement matching algorithm and a 0.01 caliper. The column N is the number of successfully matched IR-firm years with non-IR firm-years. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on two-tailed tests. T-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. The column IR Mean, Non-IR After Match, and Non-IR Before Match are the mean measures of the variable for the IR firms, matched non-IR control firms, and all non-IR firms respectively. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **Length of operating cycle** is the log of days receivable plus days in inventory; **Altman's Z-score** is 1.2(Net Working Capital / Total Assets) + 1.4(Retained Earnings / Total Assets) + 3.3(EBIT / Total Assets) + 0.6(MVE / Total Liabilities) + 1.0(Sales / Total Assets); **Net working capital** is current assets minus current liabilities; **Herfindahl index** is $\sum_i$ (Sales$_i$/Industry Sales)^2 for all i in the 2–digit SIC industry; **SD ret** is the standard deviation of daily returns over the fiscal year; **Net operating assets** is shareholders equity – cash and marketable securities + total debt deflated by lagged sales; **Effective tax rate** is federal income taxes / (net income before extraordinary items + federal income taxes + minority interest – extraordinary items and discontinued operations – equity in earnings of unconsolidated subsidiaries).

TABLE 12
The Effect of IR Incremental to the Change in Disclosure

(1) Variable	(2) N	(3) IR	(4) Non-IR Control	(5) Diff	(6) T-stat	(7) Diff	(8) T-stat
Analyst Following, Institutional Ownership, and Stock Market Characteristics							
# analysts	5,561	9.00	5.44	3.56	15.41***	2.32	10.03***
Any analyst following	5,561	0.92	0.82	0.10	11.85***	0.05	5.29***
% institutional investors	5,561	0.63	0.41	0.22	26.45***	0.16	18.70***
# institutional investors	5,561	214.81	124.49	90.32	17.77***	67.40	13.30***
Days to earnings announcement	5,452	38.29	49.22	– 10.93	–19.83***	–8.19	–14.76***
Probability of informed trading	5,237	0.14	0.18	– 0.04	–22.62***	–0.03	–14.51***
Mean bid-ask spread	5,380	0.54%	0.72%	– 0.18%	–10.40***	–0.11%	–5.64***
Mean daily share turnover	5,521	0.77%	0.68%	0.09%	5.04***	0.06%	3.24***
Differences in Income Objectives							
MBE	5,067	0.71	0.64	0.07	6.34***	0.02	2.34**
MBE ALL YEARS	4,414	0.22	0.14	0.09	5.36***	0.05	3.40***
SUSPECT NI (%)	5,560	2.37	2.53	-0.16	–0.49	0.23	0.66
MB LAST YEAR	5,560	0.63	0.66	-0.03	–3.04###	–0.03	–2.81###
SMOOTHNESS	4,951	1.06	1.11	–0.05	–1.53*	0.00	0.15

TABLE 12 (continued)
The Effect of IR Incremental to the Change in Disclosure

(1) Variable	(2) N	(3) IR	(4) Non-IR Control	(5) Diff	(6) T-stat	(7) Diff	(8) T-stat
Earnings Management to Meet Analyst Expectations							
% relying on accrual management	4,768	50.75%	57.45%	–6.70%	4.10***	–7.30	4.40***
% relying on R&D management	4,275	43.78%	51.08%	–7.30%	4.08***	–9.00%	5.01***
Expectations Management to Meet Analyst Expectations							
MBE – beginning	5,067	0.50	0.50	0.00	–0.51	–0.01	–0.66
MBE	5,067	0.71	0.64	0.07	6.34***	0.02%	2.34**
Forecast dispersion – beginning	4,629	0.11	0.12	–0.01	–1.90**	0.01	1.08
Forecast dispersion	4,644	0.05	0.07	–0.02	–6.67***	–0.01	–3.10***
Forecast accuracy – beginning	5,045	–2.02	– 2.20	0.18	1.88*	–0.02	–0.19
Forecast accuracy	5,044	– 0.52	– 0.80	0.28	6.85***	0.12	2.92***
Forecast revision volatility	4,937	0.06	0.07	–0.01	–2.04**	–0.00	–0.13
% relying on exp mgmt	2,512	46.76%	42.09%	4.67%	2.21**	3.17%	1.49
Cases likely affected by exp mgmt	5,060	57.66%	47.93%	8.84%	6.09***	4.87%	3.02***
Cases less likely affected by exp mgmt	5,074	16.92%	20.89%	– 3.97%	3.48***	0.68%	0.60

TABLE 12 (continued)
The Effect of IR Incremental to the Change in Disclosure

Table 12:

This table shows the differences in the mean outcome variables between IR firms and the matched non–IR control firms that were matched on a one–to–one basis by propensity score based on a "nearest neighbor" with replacement matching algorithm and a 0.01 caliper. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on two-tailed tests. T-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. Columns two to six are reported previously in the paper. The column IR and Non-IR Control are the mean measures of the variable for the IR firms and matched non-IR control firms respectively. Columns seven and eight report the difference between IR and non-IR control firms after controlling for the concurrent change in disclosure. Columns seven and eight are based on the β_1 estimate from estimating the following regression after forming a pooled sample of the IR and non-IR control firms: $Outcome_t = \alpha + \beta_1 IR_t + \beta_2 Any\_MEF_t + \varepsilon$. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **# analysts** is the number of analysts in the median consensus earnings forecast immediately prior to the earnings announcement; **Any analyst following** is an indicator variable equal to one if a firm has one or more analysts; **% (#) institutional investors** are the percentage of shares outstanding held by institutions and number of institutions holding shares as of the 13-f filing report immediately prior to the fiscal year-end date; **Days to earnings announcement** is the number of days after the fiscal year end until the earnings announcement based on COMPUSTAT; **Probability of informed trading (PIN)** is the mean quarterly probability of informed trading measure over the fiscal year; **Mean bid-ask spread** is the mean daily (Closing Ask – Closing Bid) / Price over the fiscal year; **Mean daily share turnover** is the mean daily turnover divided by shares outstanding for the fiscal year. The number of analysts and institutional investor variables are set to zero for years where the firm is publicly traded but there is no analyst data in I/B/E/S or institutional investor data in 13-filings. **MBE** is an indicator variable = 1 if a firm's actual annual earnings are greater than or equal to the median consensus forecast; **MBE ALL** is an indicator variable = 1 if a firm's actual annual earnings are greater than or equal to the median consensus forecast in each year from 2001 to 2006; **SUSPECT NI** is an indicator variable = 1 if a firm's net income before extraordinary items (NIBE) divided by total assets is greater than or equal to zero and less than 0.005; **MB Last Year** is an indicator variable = 1 if a firm's NIBE is greater than or equal to last year's NIBE; **Smoothness** is the ratio of a firm's standard deviation of annual NIBE divided by beginning total assets, to the standard deviation of CFO divided by beginning total assets calculated over the period 2001 – 2006. **% relying on accrual management** is the proportion of firm-years where MBE=1 but where the earnings per share adjusted for abnormal accruals per share are less than the median consensus forecast. Abnormal accruals are calculated using the Jones (1991) model estimated annually for each 2-digit SIC code. **% relying on R&D management** is the proportion of firm-years with MBE=1 but where the earnings per share adjusted for abnormal R&D per share are less than the median consensus forecast. Abnormal R&D is calculated by estimating the following model annually for each 2-digit SIC code: $\frac{RD_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{RD_{t-1}}{Assets_{t-1}} + \beta_2 \frac{Funds_t}{Assets_{t-1}} + \beta_3 TobinsQ_t + \beta_4 \frac{Capex_t}{Assets_{t-1}} + \varepsilon_t$. **Any_MEF** is an indicator variable equal to one if a firm issued earnings guidance during the year. Meeting expectations, forecast dispersion and accuracy are based on the consensus forecast at two points in time: (1) immediately before the current year's earnings announcement, and (2) the beginning of the annual forecast period starting the month after the prior year's earnings announcement. **Forecast accuracy** is –100 * |Actual EPS – Median Forecast EPS | divided by beginning of year price; **Forecast dispersion** is the standard deviation of mean earnings forecast divided by the absolute value of the mean earnings forecast; **Forecast revision volatility** is the standard deviation of month-to-month changes in the median forecast from the month after the prior year's earnings announcement to before the earnings announcement. **% relying on exp mgmt** is the proportion of firms with MBE=1 but where the earnings per share were less than the expected earnings forecast where the expected forecast is estimated using a variation of the Matsumoto (2002) model. Cases likely to be affected by expectations management are cases where **MBE**=1 and **MBE – beginning** =0 scaled by **MBE – beginning** =0. Cases less likely to be affected by expectations management are cases where **MBE**=0 and **MBE – beginning** =1 scaled by **MBE**=1.

TABLE 13
Matching Without Replacement

(1) Variable	(2) IR Mean	(3) Non-IR After Match Mean	(4) Non-IR After Match T-stat
Panel A: IR and Non-IR Firm Descriptive Statistics After Matching			
Characteristic Variables			
Log MVE	6.88	6.92	–0.54
Log Assets	7.07	7.08	–0.12
Loss	0.24	0.23	0.48
ROA (%)	–0.05	–0.01	–0.06
MB	2.79	2.86	–0.73
Leverage	0.22	0.22	0.45
Litigation	0.22	0.23	–0.43
Financing Activity	0.63	0.63	–0.38
M&A Activity	0.63	0.63	–0.27
Margin	0.28	0.28	0.14
Log Shares	3.97	4.00	–0.42
Log Age	2.44	2.43	0.41
Stock Exchange			
NYSE	54.44%	56.06%	–0.64
AMEX	3.06	3.17	–0.15
NASDAQ	42.40	40.77	0.68
	100.00%	100.00%	
Major Industry			
Agriculture	0.08%	0.11%	–0.23
Mining	4.83	5.13	–0.28
Construction	1.40	1.37	0.05
Manufacturing	40.91	40.57	0.14
Transportation/ Comm. / Utilities	8.78	8.47	0.22
Wholesale Trade	3.42	3.06	0.45
Retail Trade	5.27	6.12	–0.73
Finance, Ins. & Real Estate	19.14	18.52	0.32
Services	16.16	16.64	–0.26
	100.00%	100.00%	

TABLE 13 (continued)
Matching Without Replacement

Panel B: IR and Matched Non-IR Control Firm Outcome Variables

(1) Variable	(2) N	(3) IR	(4) Non-IR Control	(5) Diff	(6) T-stat
Analyst Following, Institutional Ownership, and Stock Market Characteristics					
# analysts	3,564	7.32	4.92	2.40	10.55***
Any analyst following	3,564	0.89	0.79	0.10	8.90***
% institutional investors	3,564	0.62	0.44	0.18	17.86***
# institutional investors	3,564	155.35	101.49	53.86	15.95***
Days to earnings announcement	3,453	39.90	49.49	– 9.59	–15.26***
Probability of informed trading	3,422	0.16	0.19	– 0.03	–15.79***
Mean bid-ask spread	3,511	0.62%	0.86%	– 0.24%	– 9.74***
Mean daily share turnover	3,504	0.80%	0.66%	0.14%	5.71***
Differences in Income Objectives					
MBE	3,011	0.69	0.62	0.07	5.17***
MBE ALL YEARS	2,282	0.20	0.13	0.07	3.72***
SUSPECT NI (%)	3,561	1.97	2.95	–0.98	–2.58###
MB LAST YEAR	3,561	0.63	0.65	–0.02	–1.49#
SMOOTHNESS	3,071	1.12	1.11	0.01	0.14

TABLE 13 (continued)
Matching Without Replacement

Panel B (continued): IR and Matched Non-IR Control Firm Outcome Variables

(1) Variable	(2) N	(3) IR	(4) Non-IR Control	(5) Diff	(6) T-stat
Earnings Management to Meet Analyst Expectations					
% relying on accrual management	2,848	50.40%	55.13%	–4.73%	2.26**
% relying on R&D management	2,620	40.85%	45.75%	–4.90%	2.19**
Expectations Management to Meet Analyst Expectations					
Any management earnings forecast	3,564	0.53	0.33	0.20	12.34***
MBE – beginning	3,011	0.50	0.47	0.03	2.05**
MBE	3,011	0.69	0.62	0.07	5.17***
Forecast dispersion – beginning	2,548	0.14	0.14	–0.00	–0.21
Forecast dispersion	2,533	0.05	0.07	–0.02	–4.93***
Forecast accuracy – beginning	2,987	–2.43	– 2.49	0.06	0.43
Forecast accuracy	2,989	– 0.66	– 0.92	0.26	4.18***
Forecast revision volatility	2,938	0.07	0.07	–0.00	–0.36
% relying on exp mgmt	1,510	47.72%	43.22%	4.50%	1.86**
Cases likely affected by exp mgmt	3,134	55.24%	46.39%	8.85%	4.58***
Cases less likely affected by exp mgmt	2,888	17.30%	20.38%	–3.08%	2.11**

TABLE 13 (continued)
Matching Without Replacement

Panel C: Stock Market Reaction to Meeting/Missing Analyst Expectations

Variables	CAR [EA_{t-1} + 2, EA_t +1] Coef	T-stat	CAR [EA_t, EA_t + 1] Coef	T-stat
$CAR_t = \alpha + \beta_1 FE_t + \beta_2 MBE_t + \beta_3 IR_t + \beta_4 IR_t * FE_t + \beta_5 IR_t * MBE_t + \varepsilon$				
Forecast error	1.49	5.42***	–0.02	–0.54
MBE	0.05	3.45***	0.02	8.86***
IR	0.04	2.45***	–0.01	–2.96***
IR*Forecast error	0.31	0.76	0.01	0.29
IR*MBE	–0.02	–0.76	0.01	2.41**
Constant	0.07	5.81***	–0.01	–5.51***
N	5,670		5,670	
R^2	0.04		0.06	

F-tests of Significance

	Coef	F-stat	Coef	F-stat
MBE + IR*MBE=0	0.04	4.76**	0.03	115.58***
IR + IR*MBE=0	0.03	5.11**	0.00	0.00

TABLE 13 (continued)
Matching Without Replacement

Table 13:

This table replicates the analyses of Tables 3–8 but match IR and non–IR control firms on a one–to–one basis by propensity score based on a "nearest neighbor" *without replacement* matching algorithm and a 0.01 caliper. The symbols ***, **, * denote statistical significance at the 0.01, 0.05 or 0.10 level respectively based on two-tailed tests. T-statistics are based on heteroskedasticity–consistent standard errors clustered by firm. An IR (non-IR) firm has (does not have) a NIRI member in both 2001 and 2006. **Log MVE** is the log of market value of equity; **Log Assets** is log of total assets; **LOSS** is an indicator variable equal to one if net income before extraordinary items (NIBE) is negative; **ROA** is NIBE divided by total assets; **MB** is market value of equity divided by book value of equity; **Leverage** is (long-term debt + short-term debt) divided by total assets; **Litigation** is an indicator variable equal to one if a firm is in the following industries pharmaceuticals/biotechnology (SIC codes 2833–2836, 8731–8734), computers (3570–3577, 7370–7374), electronics (3600–3674), or retail (5200–5961); **Financing Activity** is an indicator variable equal to one if a firm issued common equity or debt in year t–1, t, or t+1; **M&A Activity** is an indicator variable equal to one if a firm engaged in mergers and acquisitions in year t–1, t, or t+1; **Margin** is (Sales – Cost of Goods Sold) / Sales for the year; **Log Shares** is the log of common shares outstanding; **Log Age** is the log of the number of years the firm has been listed on CRSP; **NYSE (NASDAQ)** are indicator variables equal to one if a firm is listed on NYSE (NASDAQ). **# analysts** is the number of analysts in the median consensus earnings forecast immediately prior to the earnings announcement; **Any analyst following** is an indicator variable equal to one if a firm has one or more analysts; **% (#) institutional investors** are the percentage of shares outstanding held by institutions and number of institutions holding shares as of the 13-f filing report immediately prior to the fiscal year-end date; **Days to earnings announcement** is the number of days after the fiscal year end until the earnings announcement based on COMPUSTAT; **Probability of informed trading (PIN)** is the mean quarterly probability of informed trading measure over the fiscal year; **Mean bid-ask spread** is the mean daily (Closing Ask – Closing Bid) / Price over the fiscal year; **Mean daily share turnover** is the mean daily turnover divided by shares outstanding for the fiscal year. The number of analysts and institutional investor variables are set to zero for years where the firm is publicly traded but there is no analyst data in I/B/E/S or institutional investor data in 13-filings. **MBE** is an indicator variable = 1 if a firm's actual annual earnings are greater than or equal to the median consensus forecast; **MBE ALL YEARS** is an indicator variable = 1 if a firm's actual annual earnings are greater than or equal to the median consensus forecast in each year from 2001 to 2006; **SUSPECT NI** is an indicator variable = 1 if a firm's net income before extraordinary items (NIBE) divided by total assets is greater than or equal to zero and less than 0.005; **MB Last Year** is an indicator variable = 1 if a firm's NIBE is greater than or equal to last year's NIBE; **Smoothness** is the ratio of a firm's standard deviation of annual NIBE divided by beginning total assets, to the standard deviation of CFO divided by beginning total assets calculated over the period 2001 – 2006. **% relying on accrual management** is the proportion of firm-years where MBE=1 but where the earnings per share adjusted for abnormal accruals per share are less than the median consensus forecast. Abnormal accruals are calculated using the Jones (1991) model estimated annually for each 2-digit SIC code. **% relying on R&D management** is the proportion of firm-years with MBE=1 but where the earnings per share adjusted for abnormal R&D per share are less than the median consensus forecast. Abnormal R&D is calculated by estimating the following model annually for each 2-digit SIC code: $\frac{RD_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{RD_{t-1}}{Assets_{t-1}} + \beta_2 \frac{Funds_t}{Assets_{t-1}} + \beta_3 TobinsQ_t + \beta_4 \frac{Capex_t}{Assets_{t-1}} + \varepsilon_t$. **Any management earnings forecast** is an indicator variable equal to one if a firm issued earnings guidance during the year. Meeting expectations, forecast dispersion and accuracy are based on the consensus forecast at two points in time: (1) immediately before the current year's earnings announcement, and (2) the beginning of the annual forecast period starting the month after the prior year's earnings announcement. **Forecast accuracy** is –100 * |Actual EPS – Median Forecast EPS | divided by beginning of year price; **Forecast dispersion** is the standard deviation of mean earnings forecast

TABLE 13 (continued)
Matching Without Replacement

Table 13 (continued):

divided by the absolute value of the mean earnings forecast; **Forecast revision volatility** is the standard deviation of month-to-month changes in the median forecast from the month after the prior year's earnings announcement to before the earnings announcement. **% relying on exp mgmt** is the proportion of firms with MBE=1 but where the earnings per share were less than the expected earnings forecast where the expected forecast is estimated using a variation of the Matsumoto (2002) model. Cases likely to be affected by expectations management are cases where **MBE**=1 and **MBE – beginning** =0 scaled by **MBE – beginning** =0. Cases less likely to be affected by expectations management are cases where **MBE**=0 and **MBE – beginning** =1 scaled by **MBE**=1. CAR[Ea_{t-1}+2, EA_t+1] is the market adjusted stock return beginning two trading days after the prior year's earnings announcement and ending one trading day after the current year's earnings announcement. CAR[EA_t, EA_t+1] is the market adjusted stock return from the day of and one trading day after the current year's earnings announcement. The market adjusted return is calculated by subtracting the CRSP value-weighted market index including distributions. **Forecast error** is earnings per share in year t minus the median consensus forecast at the beginning of the period starting in the month after the earnings announcement in year t-1 deflated by share price at the beginning of the year.

APPENDIX A
Propensity Score Matching

I follow the notation of Heckman et al. (1998) and Morgan and Winship (2007) in developing the counterfactual framework.[19] My measure of IR is binary – let IR be an indicator variable equal to one if a firm has IR, and 0 otherwise. I define Y_1 as the potential outcome for a firm with IR and Y_0 as the potential outcome for the *same* firm if it *did not* have IR. More generally, IR can be thought as a treatment a firm undergoes. The treatment effect for the firm is the difference between the firm's outcome with IR and the outcome without IR:

$$\delta = Y_1 - Y_0 \tag{A.1}$$

The problem is that although my ideal goal is to measure the firm's outcome with and without IR, I can only observe one of these states for the same firm at the same time and it is impossible to estimate δ directly. Instead the solution is to estimate the average effect of IR on firms with IR – known as the "average treatment effect on the treated" or ATT.

$$\delta_{ATT} = E(\delta \mid IR=1) = E[Y_1 \mid IR=1] - E[Y_0 \mid IR=1] \tag{A.2}$$

$E[Y_1 \mid IR=1]$ is the observed outcome for the IR firms. However, the counterfactual mean, $E[Y_0 \mid IR=1]$ (ie. the outcome for firms with IR if they did not have IR) is not observable and I need a suitable proxy. One such proxy is the mean of the firms without IR, $E[Y_0 \mid IR=0]$. The difference between the observed outcomes for IR firms and the observed outcomes for non–IR firms is:

$$E\,[Y_1 \mid IR=1] - E[Y_0 \mid IR=0] = \delta_{ATT} + E[Y_0 \mid IR=1] - E[Y_0 \mid IR=0] \tag{A.3}$$

[19] For a more complete discussion please see Caliendo and Kopeinig (2008); Rosenbaum and Rubin (1983); Morgan and Winship (2007); Caliendo (2006).

From the above equation, the self–selection bias is $E[Y_0 \mid IR=1] - E[Y_0 \mid IR=0]$: the difference in the potential "no IR" outcomes for firms with IR and without IR. The ATT will be identified if $E[Y_0 \mid IR=1] - E[Y_0 \mid IR=0] = 0$. In experimental studies, this is accomplished through random assignment to treatment conditions and thus potential outcomes are independent of treatment status. In my setting, randomly assigning IR to firms is not possible. The solution is to construct a matching group of firms who are similar to the IR firms in all relevant firm characteristics.

The development of an adequately matched sample requires the "conditional independence assumption" which states that conditional on a set of observable characteristics, X, potential outcomes are independent of treatment assignment: $Y_0,Y_1 \perp IR|X$. Estimating ATT requires a weaker assumption that $E(Y_0) \perp IR|X$ (Heckman et al., 1997). This implies that $E[Y_0 \mid IR=1,X] = E[Y_0 \mid IR=0,X]$. The bias is eliminated and the ATT becomes:

$$\begin{aligned} \delta_{ATT} &= E(\delta \mid IR=1,X) = E[Y_1 \mid IR=1,X] - E[Y_0 \mid IR=1,X] \\ &= E[Y_1 \mid IR=1,X] - E[Y_0 \mid IR=0,X] \end{aligned} \quad \text{(A.4)}$$

Let X be a vector of observable firm and/or industry characteristics related to the firm's decision to establish IR and the outcome variables. Matching on a subset of characteristics dimension by dimension (e.g. size, growth, industry) quickly becomes problematic to feasibly implement and find acceptable, if any, matches. This is known as the 'curse of dimensionality'. Rosenbaum and Rubin (1983) show that if an outcome is independent conditional on X, it is also independent of treatment conditional on a balancing score: $(Y_0, Y_1) \perp IR \mid X$ then $(Y_0, Y_1) \perp IR \mid b(X)$. The propensity score, $P(IR=1 \mid X) = P(X)$, is one such balancing score.

One further requirement is the existence of a common support, or overlap, condition: $0 < P(IR=1|X) < 1$. Its purpose is to rule out perfect predictability of having IR given X.[20] Without some randomness, it would be impossible to find matches (Caliendo and Kopeinig, 2008; Heckman, Ichimura, and Todd, 1998). Given the conditional independence assumption and existence of common support, the propensity score matching estimator for ATT eliminates selection bias and can be written in general as:

$$\delta_{ATT}(PSM) = E_{P(X)\,|\,IR=1}\;\{\, E[Y_1 \mid IR=1, P(X)] - E[Y_0 \mid IR=0, P(X)] \,\} \qquad \text{(A.5)}$$

The effect of engaging in IR is calculated as the difference between the observed mean outcome of the portfolio of IR firms and the observed mean outcome of the portfolio of matched control firms without IR. Heckman et al. (1997) identify four features of the data related to reducing the potential bias: (1) IR and matched non-IR control firms have the same distributions of unobservable attributes; (2) IR and matched non-IR control firms have the same distributions of observable attributes; (3) outcomes and firm characteristics are measured in the same way for both groups; and (4) IR and matched non-IR control firms are from a common economic environment. I eliminate the bias from (3) and (4) through sample and data selection – IR and non-IR firms are publicly traded firms and matched within the same year; outcome and firm characteristics are defined the same for both firms using the same databases. Item (2) is controlled for through propensity score matching that creates two portfolios of firms, IR and non-IR, with matched observable distributions.

By definition, (1) cannot be controlled for in a non-experimental analysis but there are reasons to believe this potential bias has been mitigated in this setting. By

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[20] In my analysis, I impose a restriction that the non-IR firm must be within 0.01 propensity score of the IR firm, which enforces the common support condition.

estimating the average treatment effect on the treated, I am using a weaker assumption than the conditional independence assumption; specifically, $E(Y_0) \perp IR \mid P(X)$. Also, the use of a rich data set can mitigate potential bias as it is likely any important unobserved variables are correlated with the vector of firm and industry characteristics used in the first stage. For example, growth opportunities or financing constraints are likely to be strongly correlated with equity and debt issuance, market-to-book, size, M&A activity, and profitability. In addition, Dehejia and Wahba (1999) show that treatment effect estimates from propensity score matching were closer to experimental benchmark estimates than traditional econometric methods and Heckman et al. (1997) note that potential bias due to (1) is only a relatively small part of the bias in their experimental study.

APPENDIX B
Variable Definitions

Control Variables Used in the Propensity Score Estimation

MVE: The market value of equity measured as of the beginning of the fiscal year.

Assets: Total Assets.

ROA:* Net Income Before Extraordinary Items / Total Assets.

Loss: Indicator variable = 1 if Net Income Before Extraordinary Items is negative, and 0 otherwise.

MB:* Market value of equity / Book value of equity

Leverage: (Long–term Debt + Short–term Debt)/ Total Assets.

Litigation: Indicator variable = 1 if the firm is in the following industries: pharmaceuticals/biotechnology (SIC codes 2833–2836, 8731–8734), computers (3570–3577, 7370–7374), electronics (3600–3674), or retail (5200–5961), and 0 otherwise.

Financing activity: Indicator variable = 1 if the firm issued common equity, convertible equity, or debt (syndicated loans or non–convertible bonds) in year t–1, t, or t+1 as reported on SDC, and 0 otherwise.

M&A Activity: Indicator variable = 1 if the firm engaged in mergers and/or acquisitions in year t–1, t, or t+1 as reported on SDC, and 0 otherwise.

Margin:* (Sales – Cost of Goods Sold) / Sales.

Shares: Number of common shares outstanding.

Age: Number of years the firm has been listed on CRSP.

Industry dummies: Based on 2–digit SIC codes.

Exchange dummies: Dummy variables representing NYSE, AMEX, and NASDAQ.

APPENDIX B (continued)
Variable Definitions

Other Variables

MBE: Indicator variable = 1 if Actual – Median Consensus Forecast >= 0, and 0 otherwise.

MBE ALL YEARS: Indicator variable = 1 if a firm's Actual – Median Consensus Forecast >= 0 in each year from 2001 – 2006, and 0 otherwise.

SUSPECT NI: Indicator variable = 1 if a firm's Net Income Before Extraordinary Items divided by Total Assets is greater than or equal to 0 and less than 0.005, and 0 otherwise.

MB Last Year: Indicator variable = 1 if a firm's Net Income Before Extraordinary Items is greater than or equal to last year's Net Income Before Extraordinary Items, and 0 otherwise.

Smoothness:* (Std Dev of $NIBE_t$ / Total $Assets_{t-1}$) / (Std Dev of CFO_t / Total $Assets_{t-1}$) estimated over 2001 – 2006 where NIBE is Net Income Before Extraordinary Items and CFO is Cash Flow from Operations. Larger values indicate less smooth earnings.

 # analysts: Number of analysts in the most recent consensus earnings forecast prior to the earnings announcement.

Any analyst following: Indicator variable = 1 if the number of analysts >= 1, and 0 otherwise.

APPENDIX B (continued)
Variable Definitions

% institutional investors: The percentage of outstanding shares held by institutional investors as of the most recent report date on or prior to the fiscal year end.

 # institutional investors: The number of institutional investors holding the stock as of the most recent report date on or prior to the fiscal year end.

Any management earnings forecast: Indicator = 1 if the company issued earnings guidelines during the fiscal year as reported in First Call's Company Issued Guidelines, and 0 otherwise.

Days to earnings announcement:* The number of days after the fiscal year end until the earnings announcement.

Mean bid-ask spread:* The mean daily $\frac{Closing\ Ask_t - Closing\ Bid_t}{Price_t}$ measured over the fiscal year.

Mean daily share turnover:* The mean daily $\frac{Volume_t}{Shares\ Outstanding_t}$ measured over the fiscal year.

Probability of informed trading (PIN):* the mean quarterly Probability of Informed Trade measure over the fiscal year from the website of Professor Stephen Brown (Brown et al. 2004), who calculated PIN according to the Easley et al. (1997) model.

Forecast accuracy:* $-100*|Actual_t - Median\ Forecast_t|/Price_{t-1}$ based on the most recent Median Consensus Forecast prior to the earnings announcement. Larger values indicate more accurate forecasts.

APPENDIX B (continued)
Variable Definitions

*Forecast accuracy – beginning******: Defined as Accuracy but based on the first Median Consensus Forecast available after the prior year's earnings announcement. Larger values indicate more accurate forecasts.

Forecast dispersion:* Std Dev(Forecasts$_t$) / |Mean Forecast$_t$| based on the most recent consensus forecasts prior to the earnings announcement. Larger values indicate greater forecast dispersion.

Forecast dispersion – beginning:* Defined as Forecast dispersion but based on the first consensus forecasts available after the prior year's earnings announcement. Larger values indicate greater forecast dispersion.

Forecast revision volatility:* the standard deviation of month–to–month changes in the Median Consensus Forecast from the first Median Consensus Forecast after the prior year's earnings announcement to immediately before the earnings announcement. Larger values indicate greater forecast volatility.

CAR *: the cumulative abnormal market-adjusted (value-weighted) returns over two periods: (1) from two days after the prior year's earnings announcement until one day after the current year's earnings announcement [EA_{t-1}+2, EA_t+1]; and (2) the day of and day after the current earnings announcement: [EA_t, EA_t+1].

Forecast error:* $\frac{Actual_{\,t} - Median\ \ Consens\ us\ Forecast_{\,t}}{Price_{\,t-1}}$ where the consensus forecast is from the beginning of the year starting the month after the prior year's earnings announcement.

APPENDIX B (continued)
Variable Definitions

Abnormal accruals (Ab AA):* The regression residuals from the Jones (1992) model estimated cross–sectionally for each sample year and two–digit SIC code with an least 10 observations: $\frac{Accruals_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{1}{Assets_{t-1}} + \beta_2 \frac{\Delta Sales_t}{Assets_{t-1}} + \beta_3 \frac{PPE_t}{Assets_{t-1}} + \varepsilon.$

POSAA: Indicator variable = 1 if abnormal accruals >= 0, and 0 otherwise.

Abnormal R&D (Ab RD)*: The regression residuals from the following model estimated cross-sectionally for each sample year and two-digit SIC code with at least 10 observations $\frac{RD_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{RD_{t-1}}{Assets_{t-1}} + \beta_2 \frac{Funds_t}{Assets_{t-1}} + \beta_3 TobinsQ_t + \beta_4 \frac{Capex_t}{Assets_{t-1}} + \varepsilon_t$ where Funds is Net Income Before Extraordinary Items plus R&D and Depreciation Expense; TobinsQ is (MVE+Book Value of Preferred Stock + Long-term Debt + Short-term Debt) / Total Assets; and Capex is Capital Expenditures.

NEGRD: Indicator variable = 1 if abnormal R&D is negative, and 0 otherwise.

*Abnormal CAPX** (Ab CAPX): The regression residuals from the following model estimated cross-sectionally for each sample year and two-digit SIC code with at least 10 observations. $\frac{CAPX_t}{Assets_{t-1}} = \alpha + \beta_1 \frac{CAPX_{t-1}}{Assets_{t-1}} + \beta_2 \frac{Funds_t}{Assets_{t-1}} + \beta_3 TobinsQ_t + \beta_4 \frac{PPE_t}{Assets_{t-1}} + \varepsilon_t$ where Capex is Capital Expenditures; Funds is Net Income Before Extraordinary Items plus R&D and Depreciation Expense; and TobinsQ is (MVE+Book Value of Preferred Stock + Long-term Debt + Short-term Debt) / Total Assets.

APPENDIX B (continued)
Variable Definitions

NEGCAPX: Indicator variable = 1 if abnormal CAPX is negative, and 0 otherwise.

Expected forecast: An annual variation of Koh et al. (2008) that estimates the following model cross-sectionally for each sample year and four-digit SIC code with at least 10 observations: $\frac{(Actual_{\,t} - Actual_{\,t-1})}{Price_{\,t-1}} = \alpha + \beta_1 \frac{(Actual_{\,t-1} - Actual_{\,t-2})}{Price_{\,t-1}} + \varepsilon$ where Actual is the earnings per share reported in I/B/E/S and Price is split-adjusted. Using the coefficient estimates from the previous year, the firm's expected annual forecast is: $E(Actual_t) = Actual_{t-1} + \left[\hat{\alpha} + \widehat{\beta_1}\left(\frac{Actaul_{\,t-1} - Actual_{\,t-2}}{Price_{\,t-1}}\right)\right] * Price_{t-1}$.

Abnormal production (Ab Prod)*: The regression residuals from the following model estimated cross-sectionally for each sample year and two-digit SIC code with at least 10 observations: $\frac{Prod_{\,t}}{Assets_{\,t-1}} = \alpha + \beta_1 \frac{1}{Assets_{\,t-1}} + \beta_2 \frac{Sales_{\,t}}{Assets_{\,t-1}} + \beta_3 \frac{\Delta Sales_{\,t}}{Assets_{\,t-1}} + \beta_4 \frac{\Delta Sales_{\,t-1}}{Assets_{\,t-1}} + \varepsilon_t$ where Prod is Cost of Goods Sold plus ΔInventory.

POSPROD: Indicator variable = 1 if abnormal production >=0, and 0 otherwise.

Abnormal cash flow (AB CFO):* The regression residuals from the following model estimated cross-sectionally for each sample year and two-digit SIC code with at least 10 observations: $\frac{CFO_t}{Assets_{\,t-1}} = \alpha + \beta_1 \frac{1}{Assets_{\,t-1}} + \beta_2 \frac{Sales_{\,t}}{Assets_{\,t-1}} + \beta_3 \frac{\Delta Sales_{\,t}}{Assets_{\,t-1}} + \varepsilon_t$ where CFO is Cash Flow from Operations.

NEGCF: Indicator variable = 1 if abnormal cash flow is negative, and 0 otherwise.

MBE ACC: Indicator variable = 1 if a firm's EPS adjusted for abnormal accruals per share >= Median Consensus Forecast, and 0 otherwise.

APPENDIX B (continued)
Variable Definitions

MBE RD: Indicator variable = 1 if a firm's EPS adjusted for abnormal R&D per share >= Median Consensus Forecast, and 0 otherwise.

MBE DOWN: Indicator variable = 1 if EPS – Expected Forecast >=0, and 0 otherwise.

Length of operating cycle: Log (Days Receivable + Days in Inventory) where Days Receivable = [365 / (Sales/average Accounts Receivable)] and Days in Inventory = [365 / (Cost of Goods Sold / average Inventory)].

Altman's Z-score: = 1.2(Net Working Capital / Total Assets) + 1.4(Retained Earnings / Total Assets) + 3.3(EBIT / Total Assets) + 0.6(MVE / Total Liabilities) + 1.0(Sales / Total Assets) based on Altman, 1968.

Net working capital: Current Assets – current Liabilities.

Herfindahl index: $\sum_i$ $(Sales_i/Industry\ Sales)^2$ for all i in the 2–digit SIC industry.

SD_ret: Standard deviation of daily returns over the fiscal year.

Net operating activities: (Shareholders $Equity_t$ – Cash and Marketable $Securities_t$ + Short-term $Debt_t$ + Long-term $Debt_t$) / $Sales_{t-1}$

Effective tax rate: Federal Income Taxes / (Net Income Before Extraordinary Items + Federal Income Taxes + Minority Interest – Extraordinary Items and Discontinued Operations – Equity in Earnings of Unconsolidated Subsidiaries)

* denotes variables that were truncated at the 1^{st} and 99^{th} percentiles.