Do voluntary disclosures of product and business expansion plans impact analyst coverage and forecasts?

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Abstract: We investigate whether voluntary disclosures of product and business expansion plans affect analyst coverage and forecasts. We find that the level of analyst coverage is positively associated with the incidence of disclosures of product and business expansion plans. We also find that product and business expansion disclosures increase the informativeness of analyst earnings forecasts. We find no evidence that product and business expansion disclosures increase analyst forecast errors. Overall, our study contributes to understanding the role of product and business expansion disclosures in analyst forecast behaviour.

Key words: nonfinancial disclosures; analyst coverage; forecast informativeness; forecast errors

***JEL Classification*:** G12; G14; G24; M41

1 Introduction

Financial analysts play an important role in the financial marketplace; they provide earnings forecasts and stock recommendations to investors. In fulfilling this role, analysts rely on a variety of information involving both financial and nonfinancial disclosures made by firms (Dhaliwal et al. 2012). The importance of financial information in equity valuation is well established (e.g., Holthausen and Watts 2001). Nonetheless, such information might become less value-relevant compared with nonfinancial information (Amir and Lev 1996, Francis and Schipper 1999, Rajgopal et al. 2003, Dontoh et al. 2004). The reasons include globalisation, technological revolution, transition to knowledge economies, financial crises, and/or the rapid growth in socially responsible investments (Orens and Lybaert 2013), all of which raise the potential value relevance of corporate nonfinancial information disclosures.

Various nonfinancial information disclosures are potentially value-relevant. Most such disclosures are made on a voluntary basis, covering issues such as corporate social responsibility (e.g., Dhaliwal et al. 2011, Dhaliwal et al. 2012, Cormier and Magnan 2014), corporate environmental policies (e.g., Beets and Souther 1999, Aerts et al. 2008), customer relationship (e.g., Luo et al. 2010, Ngobo et al. 2012), intellectual capital (e.g., Hsu and Chang 2011), research and development expenditures (e.g., Barron et al. 2002, Jones 2007, Xu et al. 2007), and product and business expansion plans (e.g., Nichols 2010, He 2018). Evidence suggests that corporate nonfinancial disclosures can affect analyst forecast decisions (e.g., Lang and Lundholm 1996, Aerts et al. 2008, Simpson 2010). Product and business expansion plan disclosures appear particularly pertinent. The reasons are two-fold. First, firms typically have product and business expansion plans, with the announcement of such plans occurring often in practice. Second, product and business expansion plans are key input information in strategy analysis that is crucial for forecasts and valuations (Wahlen et al. 2014, Peek et al. 2016). Thus, these plans should have an impact on analyst research. Despite this, little research attention has been paid to understanding the impact of product and business expansion (hereafters, PBE) disclosures on analyst research activities. We seek to fill this void in the literature. We investigate whether and how nonfinancial disclosures of PBE plans affect analyst coverage and forecasts.

Nonfinancial disclosures of PBE plans are increasingly used by firms to convey information to market participants. Nichols (2010) documents that PBE disclosures have implications to market participants for long-term streams of future earnings and are thus value-relevant.[1] To the extent that PBE disclosures enrich the information available to analysts and resolve the perceived uncertainty associated with PBE activities, analysts should be able to generate accurate and consensus forecasts at lower information acquisition and/or processing costs. Further, on account of the important role of forecast accuracy in determining analysts' compensation and career developments, analysts should have a stronger incentive to follow firms with more PBE disclosures so as to secure forecast accuracy. Prior studies show that analysts in general are more efficient in processing nonfinancial information compared to investors. To the extent that analysts do a better job than investors in extrapolating the implications of PBE disclosures for future earnings, additional PBE disclosures should increase investor demand for analyst services, thereby attracting more analyst coverage. Therefore, we

[1] The PBE disclosure itself facilitates outsiders' learning over a firm's fundamentals and performance, and thereby helps outsiders infer future earnings and make better forecasts and valuations. Put differently, though a disclosure per se has no impact on a firm's future earnings, but it could have an impact on the way outsiders interpret a firm's performance and form expectation about a firm's future earnings.

predict a positive association between PBE disclosures and analyst coverage.

Our empirical tests cover the period of 2002-2012.[2] To control for potential sample selection bias, we use a propensity-score-matching approach to construct a sample of control observations that do not have PBE disclosures. These observations are matched with the treatment observations that have PBE disclosures. The sample used for the main analysis consists of both the treatment and control samples, which total 3,812 firm-year observations. Consistent with our predictions, we find that analyst coverage is positively associated with nonfinancial disclosures of product and business expansion plans.

Voluntary disclosures and analyst coverage might be endogenously determined (Lang and Lundholm 1996), and this concern also applies to our research context. Regulation Fair Disclosure (Reg. FD), introduced in 2000, prohibits firms from selectively releasing private information to financial analysts. Because our sample period falls within the post Reg. FD period, the concern that PBE disclosures and analyst coverage are endogenously determined by private information is reduced. To further address potential endogeneity issues, we also undertake the following. First, we measure analyst coverage in a period lagged by PBE disclosures, and we include an extensive list of control variables that are likely related to both analyst coverage and PBE disclosures. Second, we apply a firm-fixed-effects regression model. Third, we use a two-stage-instrumental-variables specification in which three proxies for proprietary costs of disclosures as per Karuna (2007) are used as instrumental variables. Proprietary costs are expected to be positively correlated with the incidence of PBE disclosures

[2] We end our sample period in year 2012 because of the data availability on PBE disclosures.

but have little direct impact on analyst coverage, thus satisfying the condition of being a valid instrument. Our results are robust to using all three approaches to address endogeneity concerns.

We also examine whether PBE disclosures impact the informativeness of analyst earnings forecasts. Following Frankel et al. (2006), we measure analyst forecast informativeness by the three-day cumulative abnormal stock returns surrounding analyst forecast dates. PBE disclosures could add value to analyst reports and make analyst forecasts more informative on condition that: (i) the information disclosed is value-relevant; and (ii) analysts are perceived by investors to be more efficient in processing PBE information and in inferring its implications for future earnings, thereby rendering analyst forecasts more informative to investors. If both conditions hold, we expect to find a positive association between PBE disclosures and analyst forecast informativeness. Our results support this prediction, which is consistent with and complements two strands of literature which shows that (i) PBE disclosures are value-relevant (Nichols 2010; He 2018) and that (ii) analysts are more sophisticated than investors in processing information (e.g., Chandra et al. 1999, Rajgopal et al. 2003). We do not find evidence that additional disclosures of PBE information increase or decrease analyst forecast errors. We interpret this as suggesting that absent a PBE disclosure, analysts are inclined to expend more efforts and costs in acquiring and processing information that is necessary for securing forecast accuracy, and that disclosure of PBE plans helps analysts save on such efforts and costs. Finally, our additional tests reveal that our main results for the effect of PBE disclosures on analyst coverage and forecasts are amenable to (i) using a coarsened-exact-matching technique to form our sample for the hypothesis tests and (ii) clustering the standard errors of the coefficients by industry when estimating the regressions.

Our study contributes to the literature in several respects. First, notwithstanding that PBE disclosures are value-relevant and occur frequently in practice as a vehicle for firms to convey information to market participants, few papers consider whether and how such disclosures influence analyst decisions. Our study fills this gap by being the first to provide evidence on the impact of PBE disclosures on analyst coverage. We argue for a positive link between PBE disclosures and analyst coverage from the perspectives of both the supply of and demand for analyst services, and our empirical results confirm our conjectures.

Second, our study is the first to link nonfinancial disclosures, particularly PBE disclosures, with analyst forecast informativeness, the latter of which is measured by stock market reaction to analyst earnings forecasts. Our finding that PBE disclosures increase market reaction to analyst forecasts suggests that analysts are perceived by investors as being better able to comprehend the implications of PBE disclosures for future earnings. As such, our study complements the extant view (e.g., Chandra et al. 1999, Rajgopal et al. 2003) that analysts are generally more efficient in processing information than investors, and that analyst are serving an active role in promoting informational efficiency in financial markets.[3]

Third, the impact of voluntary disclosures on analyst forecast accuracy has been examined, with evidence (e.g., Waymire 1986, Hassell et al. 1988, Lang and Lundholm 1996, Williams 1996) suggesting that value-relevant voluntary disclosures increase forecast accuracy. The presumption underlying this research is that the absence of additional value-relevant disclosures would not prompt analysts to engage more in their valuation research to mitigate the adverse impact of fewer value-relevant disclosures on analyst forecast accuracy. However,

[3] Analysts' role in contributing to stock price efficiency is still a debatable issue in the literature. See Frankel et al. (2006), for example, for the detailed review over this literature.

this presumption is not necessarily true for some disclosures that are crucial to forecasting by analysts. Unlike prior literature, we examine PBE disclosures that have strong implications for future earnings. We find no evidence that such disclosures significantly improve forecast accuracy. This is consistent with the notion that without PBE disclosures made by firms, analysts tend to incur more efforts and costs in their research to maintain forecast accuracy. Our study hence offers insight that additional value-relevant disclosures and analyst efforts in information acquisition/processing may act as substitutes in contributing to the accuracy of analyst forecasts.

Last but not least, extant research (e.g., Barth et al. 2001, Vanstraelen et al. 2003, Simpson 2010) on the association of analyst coverage and forecasts with nonfinancial disclosures examines disclosures regarding intangible assets, customer acquisition costs, web traffic growth, etc, of firms in a relatively narrow scope of industries, typically, high-tech industries. By contrast, our study examines the disclosure as to product and business expansion which prevail among firms in a range of industries. Moreover, PBE activities play an important role in firm business development and have substantive impact on firm performance, thus analysis of PBE disclosures is crucial in the valuation process. As such, it is worthy of an investigation as to whether PBE disclosures influence analyst coverage and forecasts.

The paper proceeds as follows. Section 2 reviews the literature and develops our hypotheses. Section 3 describes the data source and sample. Section 4 explains the research design. Section 5 presents and discusses the empirical results. Section 6 presents the additional analysis. Section 7 concludes.

2 Literature review and hypothesis development

In this section, we first illuminate the value relevance of voluntary PBE disclosures. We then develop our main hypothesis regarding the relationship between analyst coverage and voluntary PBE disclosures. Following this, we develop supplemental hypotheses as to whether voluntary PBE disclosures are related to the informativeness of, and errors in, analyst earnings forecasts.

2.1 Value relevance of voluntary PBE disclosures

Product-related plans relate to the disclosures of information pertaining to the introduction, change, modification, and/or discontinuation of a company's products or services. Business expansion plans concern a proposed increase in current operations through internal growth. Business expansion plans may involve, for instance, entering into new markets with existing products, opening a new branch, establishing a new division, increasing production capacity, and/or investing additional capital in the current business; such plans are exclusive of growth by merger and acquisition.[4] Appendix III gives examples of firms' product and business expansion plans. Voluntary disclosures of such business plans tend to occur via press releases or news outlets. PBE plans have strong implications to outsiders for a firm's long-term stream of future earnings and cash flow and are thus value-relevant. Consistent with this view, Nichols (2010) finds that disclosures of PBE plans generate significant positive stock market reactions of 30-60 basis points on average. Prior studies (e.g., Brown et al. 1987, Hong and Kubik 2003, Leone and Wu 2007) find that analysts have incentives to gather as much value-relevant

[4] The definitions of the product and business expansion plan disclosures follow Capital IQ's definitions. Capital IQ is a division of Standard and Poor's.

information as possible for their forecasts and valuations. Therefore, a PBE disclosure, given its value-relevance nature, should have an impact upon analysts' decision-making.

2.2 The impact of PBE disclosures on analyst coverage

The number of analysts that follow a given firm is driven by the demand for and supply of analyst services. This model as to the determinants of analyst coverage was initially proposed by Bhushan (1989) and has been used in empirical studies (see, e.g., Lang and Lundholm 1996, Frankel et al. 2006). We establish a theoretical link between PBE disclosures and analyst coverage by discussing the role PBE disclosures play in the demand- and supply-curve for analyst services.

From the supply-curve perspective, to the extent that the cost of analysts receiving information from firms is lower than the cost of acquiring information independently from other sources, increased disclosures should increase the supply of analyst services (Lang and Lundholm 1996). When more relevant information is available, analysts should depend less on individual research and be more likely to make more accurate and consistent forecasts at lower information acquisition and/or processing costs. Prior research (e.g., Ho et al. 1995, Lang et al. 2003, Vanstraelen et al. 2003, Dhaliwal et al. 2012) suggests that the more value-relevant information used by analysts, the more accurate their forecasts. Since analysts' forecast accuracy is a crucial determinant of career prospects and rewards (e.g., Stickel 1992, Mikhail et al. 1999, Hong et al. 2000, Hong and Kubik 2003, Clarke and Subramanian 2006, Leone and Wu 2007, Wu and Zang 2009), analysts should rely more on value-relevant disclosures, such as PBE disclosures, to maintain high forecast accuracy.

Due to the availability of PBE data, our sample period starts from year 2002, which is after the implementation of Reg. FD. Post Reg. FD, firms are restricted from selectively disclosing material non-public information to analysts. Consequently, it becomes less likely that analysts would bias their forecasts to please management for access to private information.[5] Given this, analysts should care about their forecast accuracy, as this would determine their compensation and career prospects. In such a scenario, it is expected that analysts are likely to rely on PBE disclosures to help secure forecast accuracy; thus, PBE disclosures should attract more analyst coverage.

The success of new products and business expansion is uncertain. This uncertainty adds complexity to the existing business model and potentially increases business risk. In essence, PBE activities introduce uncertainty and complexity to a firm's business. This calls for and highlights the potential importance of firms' voluntary PBE disclosures, which may reduce outsiders' perceptions about the increased uncertainty and complexity arising from the PBE activities. Whether PBE disclosures turn out to also reduce analysts' perceptions about the uncertainty and complexity depends on how uncertain analysts were before PBE announcements and how informative these announcements are to analysts. PBE plans, before being released to the public, pertain to private information held by insiders, but analysts are restricted from accessing such private information in the post Reg. FD era (in which our sample period for PBE disclosure data falls). In this scenario, absent PBE disclosures, it would be even more difficult for analysts to resolve the perceived uncertainty and complexity associated with

[5] It is worth noting that the communications of private information between analysts and firm management are not fully prevented by Reg. FD (e.g., Soltes, 2014; Brown et al., 2015). That said, it is plausible to suggest that given potential reputational and/or legal penalties for non-compliance with Reg. FD, the private information communications between analysts and insiders, albeit not eliminated completely, are limited, as suggested in a large body of the Reg. FD literature (e.g., Koch et al., 2013).

PBE activities, than otherwise in the presence of such disclosures.[6] In essence, our supply-curve argument is that voluntary disclosures of PBE reduce analyst effort and costs in acquiring and/or processing information, and in resolving the perceived uncertainty and complexity associated with PBE, for purpose of maintaining forecast accuracy; this in turn attracts more analyst following.

From the demand-curve perspective, we argue that the effect of voluntary disclosures on investor demand for analyst services depends on analyst efficiency, relative to that of outside investors, in processing such disclosures. If analysts are perceived by investors to be more sophisticated in processing voluntary disclosures, then additional voluntary disclosures should increase investor demand for analyst services and make analyst reports more valuable to investors. By contrast, if analysts are perceived to be less efficient than investors in processing voluntary disclosures, additional disclosures should reduce investor demand for analyst services and thereby crowd-out the information search by analysts. Applying this rationale to our research context, if analysts are perceived to be more (less) able than investors to extrapolate the implications of PBE disclosures for future earnings, then investors would have greater (lower) demand for analyst services, and accordingly, analyst coverage should increase (decrease) in response to additional PBE disclosures.

Extant literature (e.g., Ball and Brown 1968, Bernard and Thomas 1989, Ball and Bartov 1996, Kausar et al. 2009) provides evidence of various stock market anomalies, suggesting that markets do not always process new, publicly available information promptly and fully. This is

[6] It is plausible that PBE disclosures do not reduce some unsophisticated investors' perceived uncertainty about corporate PBE activities. However, we focus on examining analysts' (rather than investors') responses to PBE disclosures, and analysts are supposed to be more sophisticated in information processing than general investors (Chandra et al. 1999; Rajgopal et al. 2003). As such, we posit that PBE disclosures are likely to reduce analysts' perceptions about uncertainty arising from PBE activities.

more so for investors in their processing of nonfinancial disclosures. There is no uniform format for the presentation of nonfinancial disclosures, resulting in a lack of comparability of such disclosures across firms (Maines et al. 2002, Simpson 2010). This raises the complexity to investors of analysing nonfinancial disclosures. Moreover, unlike management earnings forecasts which provide direct news about future earnings, nonfinancial disclosures are relatively hard to interpret with regards to implications for future earnings. Prior research documents that investors in general fail to appreciate the valuation implications of nonfinancial disclosures. For instance, Hirshleifer and Teoh (2003) and Bloomfield (2002) show that most investors are unable to process and trade on nonfinancial disclosures. Maines and McDaniel (2000) find that investors experience difficulties in understanding the value and earnings effects of nonfinancial disclosures.

In contrast, prior studies demonstrate analysts' efficient processing of nonfinancial information. For example, Chandra et al. (1999) find that analysts manage to distinguish permanent from transitory sales trends by using forward-looking industry-wide disclosures of new orders and shipments. Rajgopal et al. (2003) find evidence that the market misprices disclosures of order backlog, whereas financial analysts appear to recognise the implications of such disclosures for future revenues. Additionally, prior evidence (e.g., Barron et al. 1999, Hope 2003, Jones 2007, Dhaliwal et al. 2012) that nonfinancial disclosures lead to fewer analyst forecast errors and smaller forecast dispersion also supports the view that analysts are sophisticated in processing nonfinancial information.

Because of potential risks associated with changes in products and with business expansions, it is difficult for outside investors to analyse the implications of PBE disclosures for firms' future prospects. Given investors' limited information processing ability relative to that of analysts, additional PBE disclosures should spur the demand for analyst services. In addition to analyst forecast accuracy, investor demand for analyst services is yet another key determinant of analyst payoffs (e.g., Frankel et al. 2006, Beyer et al. 2010). So, if investor demand for analyst forecasts increases as a result of additional PBE disclosures, analyst coverage should concomitantly increase. In essence, to the extent that investors perceive themselves less capable than analysts to process a PBE disclosure promptly and to infer its implications for future earnings (to be empirically demonstrated further in the test of H2 covered in Section 2.3), investors would be more reliant on analyst reports, thereby inducing more analyst following. Based on the above discussion from the perspectives of both supply of and demand for analyst services, we present our main hypothesis:

H1: *Voluntary disclosures of product and business expansion plans increase analyst coverage.*

When firms have high information opacity, the extent to which PBE disclosures enrich the relevant information available to analysts and resolve the perceived uncertainty associated with PBE activities would likely be greater, thus potentially saving analysts' effort and costs to a higher degree in the information acquisitions/processing. Furthermore, when corporate information is more opaque, it is more likely that investors perceive themselves as less capable than analysts to process PBE disclosures and thus have even higher demand for analyst services. Accordingly, we have the following hypothesis to buttress H1:

H1a: *Voluntary disclosures of product and business expansion plans increase analyst coverage to a larger extent for firms that have higher information opacity.*

2.3 The association between PBE disclosures and the informativeness of analyst earnings forecasts

Given the hypothesized, positive influence of PBE disclosures on analyst coverage, we consider whether such disclosures are correlated with the informativeness of analyst forecasts. Following Frankel et al. (2006), we define analyst forecast informativeness according to the magnitude of stock market reaction to analyst forecasts. In developing H1, we argued that analysts are perceived by investors as being more sophisticated in processing PBE disclosures, and thus that investor demand for analyst forecasts will increase with an increase in PBE disclosures. If these arguments hold true as we expect, the stock market should react more strongly to analyst forecasts in response to a PBE disclosure, resulting in a positive association between analyst forecast informativeness and PBE disclosures. If, however, investors believe themselves to be more able than analysts to process PBE disclosures, they will override analyst forecasts, leaving little room for analysts to promote the price formation process. In such a case, PBE disclosures do not render analyst forecasts more informative. The above discussion leads to our second supplemental hypothesis, stated in a null form as follows:

H2: *The informativeness of analyst earnings forecasts is unrelated to voluntary disclosures of product and business expansion plans.*

2.4 The association between PBE disclosures and analyst forecast errors

Given the positive effect of PBE disclosures on analyst coverage, we explore whether such disclosures impact analyst forecast errors. We posit that, under two conditions, PBE disclosures are positively related to analyst forecast accuracy. The first condition is that PBE disclosures do not exhibit systematic bias across firms. Such an assumption is likely to be tenable, because unlike short-term management earnings forecasts, PBE disclosures are much less likely to be generally used by managers to guide analyst short-term earnings expectations. Second, in the absence of PBE disclosures, analysts would not incur additional information acquisition and/or processing costs as a substitute to maintain their forecast accuracy. This assumption, however, does not necessarily hold. PBE information implies for long-term streams of a firm's future revenues and should be the key input information for analyst forecasts and valuations. So, it is more likely that analysts would exert additional costs/efforts to seek substitutes for the absence of PBE disclosures. In such a case, we would not expect that PBE disclosures have significant influences on analyst forecast accuracy. Therefore, we have our third hypothesis stated in a null form as follows.

H3: *The errors in analyst earnings forecasts are unrelated to voluntary disclosures of product and business expansion plans.*

3 Data source and sample

We obtain PBE disclosure data from Capital IQ. Capital IQ provides data on a variety of corporate developments, such as corporate guidance, product announcements, and business expansion announcements, all of which are voluntarily disclosed by publicly traded U.S. firms via press releases and news outlets. The announcements of PBE plans pertain to stand-alone disclosures which, in content, are exclusive of any other type of corporate reporting and disclosures; this helps make our empirical analysis relatively clean and not systematically subject to the confounding effects of other concurrent information disclosures. We restrict our focus to press releases to ensure that PBE plan announcements were initiated by firms. Analyst forecast data are collected from I/B/E/S. Data on institutional holdings are taken from Factset. Other data are gathered from CRSP and Compustat. We require that firms have necessary data from CRSP, Compustat, I/B/E/S, and Factset to construct the variables of interest for our empirical tests.

The availability of PBE disclosures data from Capital IQ narrows our sample period to 2002-2012. Reg. FD, implemented in 2000, prohibits companies from disclosing material non-public information to analysts. Hence, our sample period falling in the post Reg. FD period largely reduces the concern that both PBE disclosures and analyst research activities are endogenously driven by private corporate information. Panels A (B) of Table 1 presents the distribution of the incidence of PBE disclosures by year (industry). Firms in the industry of business equipment, telecommunication, and health have the highest incidence of PBE disclosures.

There might exist systematic differences in firm characteristics between firms that make PBE disclosures and those that do not. This suggests potential endogeneity/selectivity issues associated with the decision to voluntarily disclose PBE information. To address this, we employ a caliper propensity-score-matching approach to obtain a sample that consists of the treatment observations (i.e., firm-years that have PBE disclosures) and the matched controlled observations (i.e., firm-years without a PBE disclosure). Each treatment observation is matched, without replacement, with a control observation using the closest propensity score.[7] The

[7] We change the matching ratio from one-to-one to one-to-two/one-to-three in our caliper propensity score matching, and obtain similar results and insights from all the related empirical tests. Nor our results change qualitatively if we employ a nearest-neighbourhood propensity-score-matching approach to balance the treatment sample and control sample groups.

propensity score is estimated from a logit regression, in which the incidence of PBE disclosures is modelled as the function of a vector of covariates. The covariates include capital expenditures (*capex*), intangible assets (*intangible*), firm size (*size*), book-to-market ratio (*btm*), sales growth (*salesgrowth*), abnormal stock returns (*qtrret*), abnormal trading volume (*abtradvol*), financial leverage (*debt*), litigation risk (*litigation*), earnings volatility (*stdearnings*), and finally proprietary costs of disclosures (proxied by *mktsize*, *substitution*, and *entrycost*, respectively). All are expected to be correlated with the incidence of PBE disclosures and are defined in Appendix I. The results of the logit regression are reported in Panel A of Appendix II. To ensure close matches, we set the caliper (i.e., the difference in propensity scores between the treatment and matched firm-years) to be 1%. Our final sample after the propensity score matching comprises 2,784 firm-year observations for 1,824 unique firms.

4 Research design

4.1 Test of the main hypothesis (H1 & H1a)

It is possible that both PBE disclosures and analyst coverage are simultaneously determined by some omitted variable(s). It is also possible that insiders' anticipation of future analyst coverage drives their current PBE disclosure decisions, thereby raising the possibility of reverse causality. However, because our sample period falls in the post Reg. FD period in which private-information communications between insiders and analysts are restricted, insiders' ability to anticipate future analyst coverage is, arguably, also restricted; this helps mitigate the reverse causality possibility. To further alleviate endogeneity concerns, in our multivariate analysis, we measure analyst coverage in a way such that its measurement period is preceded by that of PBE disclosures. We also include an extensive list of control variables that are likely related to both analyst coverage and PBE disclosures. We use firm-fixed-effects regression and two-stage-instrumental-variables regression technique, respectively, to check the robustness of our results.

The following regression model is specified to test the impact of PBE disclosures on analyst coverage:

$$\begin{aligned} lanacov &= \alpha_0 + \alpha_1 inci + \alpha_2 stdearnings + \alpha_3 tradingvol + \alpha_4 salesgrowth + \alpha_5 beta + \alpha_6 intangible \\ &+ \alpha_7 retvol + \alpha_8 price + \alpha_9 regulated + \alpha_{10} size + \alpha_{11} btm + \alpha_{12} insti + \alpha_{13} capex + \alpha_{14} qtrret + \varepsilon \end{aligned} \quad (1)$$

The dependent variable is *lanacov*, which equals the natural logarithm of 1 plus the number of analysts that make at least one earnings-per-share (hereafters, EPS) forecast for a firm for a fiscal year following the beginning of the third fiscal quarter.[8] *lanacov* equals 0 if there is no analyst forecasting the EPS for a firm over the last two fiscal quarters of a fiscal year. The treatment variable is *inci*, which is equal to 1 if a firm makes a product or business expansion plan disclosure over the first two fiscal quarters, and 0 otherwise.[9] Based on H1, the coefficient for *inci* should be positive and statistically significant at conventional levels.

We control for a broad set of variables to mitigate potential correlated-omitted-variables bias. Bhushan (1989) argues that investor demand for analyst services is greater for firms with greater uncertainty and thus analyst coverage for such firms should be higher. We use firm beta (*beta*) to control for firm-specific uncertainty, and expect it to be positively associated with

[8] We measure analyst coverage and forecasts based on the window starting from the beginning of the third fiscal quarter, because analysts are reluctant to issue/revise their annual earnings forecasts in the first two fiscal quarters (e.g., Stickel 1989). Accordingly, our PBE disclosure variable is measured based on the window of the first two fiscal quarters. All our results remain qualitatively the same if we alternatively use the third (fourth) fiscal quarter as the measurement window for PBE disclosures (for analyst coverage and forecasts).

[9] Our results remain qualitatively the same if the frequency of PBE disclosures over the first two fiscal quarters is used as the treatment variable for the multivariate tests.

analyst coverage. Bhushan (1989) also contends that analyst coverage is positively correlated with institutional ownership, to the extent that institutional investors are the main clients of analyst services and account for the majority of transaction business in analyst brokerage houses. Thus, we control for institutional ownership (*insti*) and expect that *insti* has a positive relation with analyst coverage. We include firm size (*size*) as analysts tend to follow larger firms to generate more transaction business for their brokerage houses (Bhushan 1989). Investor gain from trading on firm-specific information is higher for firms with high return variability, which increases investor demand for analyst services and attracts more analyst coverage (Bhushan 1989). Therefore, we control for return volatility (*retvol*) which we expect to be positively related to analyst coverage.

Brennan and Hughes (1991) show that share price is an inverse measure of the brokerage commission rate, and that analysts have incentives to follow firms with lower share prices. Brennan and Hughes (1991) also find a negative correlation between analyst coverage and stock returns. The reasons for this may be twofold. First, for firms that have experienced a large stock price appreciation, the major sources of value have already been exploited and analysts thus perceive the probability of discovering new sources of value to be relatively low. Second, analysts believe that firms with high abnormal returns are likely to be overvalued and be associated with lower future returns. Since analysts are reluctant to issue unfavourable opinions for firms that would underperform (McNichols and O'Brien 1997, Das et al. 2006), it follows that analysts are less likely to provide coverage for firms that have high abnormal stock returns. Therefore, we control for stock price (*price*) and stock returns (*return*) and expect them to be negatively related to analyst coverage.

Information asymmetry (put differently, the richness of corporate information environments) also affects analyst coverage. If analysts act as information intermediaries which process information from firms and relay it to investors, then richer information environments would likely attract more analyst following (Lang and Lundholm 1996, Chang et al. 2006). However, if financial analysts act as information providers that compete with other information disclosures, analyst coverage would decrease with the richness of firms' information environments (Lang and Lundholm 1996). We control for the effect of information asymmetry by including intangible assets (*intangible*), capital expenditures (*capex*), sales growth (*salesgrowth*), and book-to-market ratio (*btm*), which extant literature (Aboody and Lev 2000, Barth et al. 2001, Huddart and Ke 2007) uses as proxies for information asymmetry. Ambiguity in accounting treatments of intangible assets and of capital expenditures (inclusive typically of research and development expenditures) is high, and hence high capital expenditures and large intangible assets are associated with high financial opacity and high information asymmetry. High growth firms, charaterized by the low book-to-market ratio, high capital expenditures, or high sales growth, tend to have greater information asymmetry, because managers of growth firms have superior knowledge about their firms' investment opportunity set as well as future cash flow realizations (Smith and Watts 1992, Barth and Kasznik 1999, Huddart and Ke 2007).

High earnings volatility increases information processing costs for analysts and makes it more difficult for them to forecast earnings accruately. As such, analysts are less inclined to follow firms that have high earnings variability (Lang and Lundholm 1996). We therefore control for earnings volatility (*stdearnings*) in our regression model. We control for the effect of industrial regulatory status (*regulated*), since prior research (e.g., O'Brien and Bhushan 1990, Groysberg et al. 2011) shows that analysts prefer to follow firms that operate within regulated industries. We include trading volume (*tradingvol*) in our regression. Because commission fees paid to financial analysts are based on trading volume which reflects outside investor demand for analyst services, analysts tend towards covering firms with high trading volume (Hayes 1998, Frankel et al. 2006). Finally, we include industry- and year-fixed effects in our regression.

As a robustness test for H1, we use firm-fixed-effects model to control for unobserved firm characteristics and cross-sectional heterogeneity. An effective firm-fixed-effects model requires that independent variables display sufficient within-firm variation over time. So, in applying firm-fixed-effects regression to model (1), we remove *regulated* (*stdearnings*) which has no (little) time-series variation. We also employ a two-stage-treatment-effect model to address potential endogeneity. Firms that are subject to high proprietary costs of disclosures should be less likely to disclose PBE plans to the public. But proprietary costs are unlikely to have direct impact on analyst coverage, making it a valid instrument for the two-stage treatment-effect regression.[10] Following Karuna (2007), we use three dimensions of product market competition, product substitutability (*substitution*), market size (*mktsize*), and entry costs (*entrycost*), as the proxies for proprietary costs of disclosures. Public disclosures of PBE plans increase a firm's risk of leaking its proprietary information to its competitors. A firm that has low product substitutability (*substitution*), low entry costs (*entrycost*), or large market size of competing products (*mktsize*) faces fierce product market competition and is thus subject to

[10] The fundamental determinants of the firm-level analyst coverage are the expected costs and benefits to analysts of covering a firm (Bhushan 1989; Lang and Lundholm 1996; Frankel et al. 2006). Analysts can obtain the benefit of enhanced industry knowledge only when they cover a considerable amount of firms in the same industry. It is plausible that industrial product market competition drives the industry-level analyst coverage. But our study of the association between PBE disclosures and analyst coverage pertains to a firm-level analysis. Thus, we expect that industrial market competition would not have a direct impact on the firm-level analyst coverage.

high proprietary costs of disclosures. Except the three instrumental variables, the control variables used in the first-step estimate of the two-stage regression are the same as those included in model (1) (Wooldridge 2000).

H1a concerns whether the association between the incidence of PBE disclosures and analyst coverage is higher for firms with high information opacity. We use earnings volatility (*stdearnings*) to capture information opacity. The more volatile firm earnings, the more difficult is for analysts to synthesize earnings forecasts based on PBE disclosures, and the greater demand investors tend to have for analyst forecasts. Thus, earnings volatility is appropriate for use as a proxy for information opacity. In line with Ayers et al. (2011), we use the top (bottom) quintile point of the sample distribution of *stdearnings* as the cut-off point to define high (low) earnings volatility for the moderating effect analysis. In particular, earnings volatility is regarded as high (low) for an observation if it has the value of *stdearnings* higher (lower) than the top (bottom) quintile point. To test H1a, we split our sample into the high-earnings-volatility subsample and the low-earnings-volatility subsample, and run model (1) separately for these two subsamples. H1a predicts that the coefficient on *inci* is more positive for the high-earnings-volatility subsample than for the low-earnings-volatility subsample.

4.2 Tests of the supplemental hypotheses (H2 & H3)

To conduct the supplemental test of whether the informativeness of analyst earnings forecasts is related to voluntary PBE disclosures, we use the following regression model:

$$\begin{aligned} car &= \alpha_0 + \alpha_1 inci + \alpha_2 stdearnings + \alpha_3 tradingvol + \alpha_4 salesgrowth + \alpha_5 beta + \alpha_6 retvol + \\ &\alpha_7 intangible + \alpha_8 price + \alpha_9 regulated + \alpha_{10} size + \alpha_{11} btm + \alpha_{12} insti + \alpha_{13} capex + \alpha_{14} qtrret + \varepsilon \end{aligned} \tag{2}$$

The dependent variable, *car*, equals the three-day [-1, 1] cumulative unsigned abnormal stock returns around an analyst's last EPS forecast issued for the current fiscal year following the beginning of the third fiscal quarter.[11] The abnormal stocks returns are calculated using a market model with an estimation period of [-181, -2] relative to the forecast date. If there are multiple analysts who make the EPS forecasts for the same firm, *car* is taken as the average of the abnormal returns associated with these forecasts. As reported in Panel A of Table 2, the mean value of *car* is 0.089, indicating that, on average, the market reacts positively to analyst earnings forecasts made in the last two fiscal quarters. We control for trading volume (*tradingvol*), firm beta (*beta*), return volatility (*retvol*), stock price (*price*), firm size (*size*), analyst forecast revision (*revision*), book-to-market ratio (*btm*), institutional ownership (*insti*), capital expenditures (*capex*), sales growth (*salesgrowth*), earnings volatility (*stdearnings*), industrial regulatory status (*regulated*), intangible assets (*intangible*), abnormal stock returns (*qtrret*), and industry- and year-fixed effects. All of the above are documented by prior research (e.g., Frankel et al. 2006, Arand et al. 2015) to be related to the informativeness of analyst forecasts. If PBE disclosures increase the informativeness of analyst forecasts, *inci* should have a positive coefficient that is statistically significant at conventional levels.

We use the following regression model for the supplemental test of whether analyst forecast errors are associated with voluntary PBE disclosures:

$$\begin{aligned} error &= \alpha_0 + \alpha_1 inci + \alpha_2 retvol + \alpha_3 size + \alpha_4 btm + \alpha_5 horizon + \alpha_6 price + \alpha_7 intangible \\ &+ \alpha_8 capex + \alpha_9 salesgrowth + \alpha_{10} abtradvol + \alpha_{11} dedi + \alpha_{12} qtrret + \alpha_{13} changeeps + \varepsilon \end{aligned} \tag{3}$$

[11] We use the last forecast of EPS for a fiscal year for three reasons. First, it reflects analysts' ability to aggregate complex information (inclusive critically of PBE information therein) and to translate it into an output in a form that is more informative to and more demanded by investors. Second, it represents analysts' most updated expectations about a firm's future earnings and hence might be valued the most by outsiders. Third, it facilitates a relatively clear-cut lead-lag setting to establish a causal relation between PBE disclosures and analyst forecast informativeness. We obtain qualitatively the same results if the first forecast of EPS after the beginning of the third fiscal quarter is used alternatively to define *car*.

error is equal to the absolute difference between actual EPS and a given analyst's last forecast of EPS for a given firm for a fiscal year following the beginning of the third fiscal quarter, divided by the firm's stock price.[12] If there are multiple analysts who make the EPS forecasts for the firm, the average is taken of these analysts' last forecasts of EPS. Based on prior literature (e.g., Huberts and Fuller 1995, Lang and Lundholm 1996, Das et al. 1998, Lim 2001, Ali et al. 2007, Dhaliwal et al. 2011), we control for abnormal trading volume (*abtradvol*), forecast horizon (*horizon*), return volatility (*retvol*), stock price (*price*), firm size (*size*), the book-to-market ratio (*btm*), dedicated institutional ownership (*dedi*), sales growth (*salesgrowth*), capital expenditures (*capex*), intangible assets (*intangible*), abnormal stock returns (*qtrret*), change in annual EPS (*changeeps*), and industry- and year-fixed effects. If PBE disclosures reduce analyst forecast errors, the coefficient for *inci* should be negative and statistically significant at conventional levels.

5 Empirical results

5.1 Covariate balance check after propensity score matching

In applying propensity score matching, it is advisable to check whether the distributions of covariates are balanced between treatment and control samples (Caliendo and Kopeinig 2008). We attempt this by using two-sample t-tests and standardised bias. The formula for calculating the standardised bias is as follows (Rosenbaum and Rubin 1985):

$$Standardised\ \ Bias = \frac{\bar{x}_{treatment} - \bar{x}_{control}}{\sqrt{\frac{s^2_{treatment} + s^2_{control}}{2}}} \tag{4}$$

[12] For the same reasons as mentioned in footnote 11, we use the last forecast of EPS for a fiscal year to define *error*. Our results remain qualitatively the same if the first forecast of EPS after the beginning of the third fiscal quarter is used to define *error*.

$\bar{x}$ represents the mean value of a covariate; s^2 represents the standard deviation of a covariate to the power of two. As mentioned in Section 3, the vector of covariates pertains to the determinants of the incidence of PBE disclosures. Panel B of Appendix II reports the results for the covariate balance check. From the results of two-sample tests of mean, we can see that the covariates are, in general, statistically indistinguishable between treatment and control groups. Nearly all the mean differences in the covariates are statistically insignificant, with the standardised bias of less than 10% for most covariates. This indicates that our matching procedure approaches a covariate balance and thus has substantively reduced observable differences across the PBE disclosure sample and non-PBE disclosure sample. In ensuring that the treatment and control samples differ insignificantly along most of the observable firm-specific covariates, we increase the chance that they might also differ insignificantly along unobservable firm-specific covariates, and as a result, potential endogeneity bias is reduced (Roberts and Whited 2012).

5.2 Univariate results

Panel A of Table 2 provides descriptive statistics of the variables involved in the multivariate tests. *lanacov*, the natural logarithm of 1 plus analyst coverage, has a mean value of 2.603, suggesting that our sample firms, on average, are followed by 15 analysts over the last two fiscal quarters of a year. The mean value of *freq* is 2.051, implying that a firm, on average, makes two PBE announcements over the first two fiscal quarters of a year. The mean of *car*, which represents the average abnormal stock returns to PBE disclosures, amounts to 0.089; this suggests that PBE disclosures are value-relevant. Panel B of Table 2 reports the results for the two-sample tests of mean and median values. *lanacov* averages 3.1494 for the treatment group and 2.6030 for the control group. The mean difference amounts to 0.5464 and is statistically significant at the 1% level (t-stat.=11.802). The treatment sample has a median value of *lanacov* up to 3.2581, which is higher than the median of *lanacov* for the control sample. The median difference is 0.2624, which is statistically significant at the 1% level (Chi^2=8.247). These results lend initial support to our prediction that PBE disclosures induce more analyst coverage. Table 3 shows the results for the Spearman correlation among the variables used in model (1). *lanacov* is positively correlated with *inci*. The magnitude of the correlation amounts to 15.63% and is statistically significant at the 1% level. This correlation result is consistent with H1: that analyst coverage is higher for firms which have PBE disclosures compared to firms that do not.

5.3 Multivariate regression results

Table 4 presents the OLS regression results for the test of H1. The coefficient on *inci* is positive and statistically significant at the 1% level. This supports H1: that PBE disclosures increase analyst coverage. A one-unit change in *inci* leads to an increase in *lanacov* by 0.409, which is equivalent to 14.22% of the mean value of *lanacov* for our overall sample and is economically significant. The coefficients for the majority of the control variables are statistically significant in the expected direction. Column (1) of Table 5 reports the firm-fixed-effects regression results for our hypothesis test. The coefficient for *inci* is positive and highly significant at the 1% level, again consistent with H1.

Column (2) of Table 5 reports the two-stage treatment-effect regression results. In the first-step probit estimate, *mktsize* (*entrycost*) has a negative (positive), statistically significant coefficient. This is in line with the notion that high proprietary costs of disclosures, as proxied by high *mktsize* and low *entrycost*, dis-incentivize managers to voluntarily disclose PBE plans to the public. The significant coefficients for *mktsize* and *entrycost* support their validity for use as instruments in our two-stage treatment-effect model (Lennox et al. 2012). For the second-stage regression result, the coefficient for *inci* is significantly positive at the 1% level, suggesting that our results reported in Table 4 are robust to correcting for endogeneity.

Table 6 reports the results for the test of H1a. The coefficient for *inci* is incrementally more positive in the high-*stdearnings* subsample than in the low-*stdearnings* subsample; the difference in the coefficient for *inci* is statistically significant (λ^2=3.85; p=0.0498). These results suggest that when firms have high information opacity, PBE disclosures would increase analyst coverage to a larger extent. This is consistent with H1a.

Table 7 reports the regression results for the test of the supplemental hypothesis, H2. *inci* has a positive, statistically significant coefficient, supporting the argument that PBE disclosures increase the informativeness of analyst earnings forecasts. The coefficient for *inci* in Column (1) ((2)) suggests that a one-unit increase in *inci* leads to an increase in *car* by 0.0073 (0.00461), which accounts for 8.20% (5.18%) of the overall sample mean of *car* and is economically significant. Reg. FD prohibits insiders from releasing private information to analysts without simultaneously disclosing it to general investors. As a consequence, the information gap between analysts and investors is reduced. Analysts and investors have equivalent exposures to publicly available PBE information. A natural follow-up question to ask is whether given the same access to PBE information as analysts do, investors are still reliant on analysts for their trading decisions. Our analysis, which is carried out based on a sample period enclosed in the post Reg. FD period, sheds light on this issue. Specifically, our results for H2 indicate that investor demand for analyst earnings forecasts increases in response to a given PBE disclosure, therein reinforcing the view that analysts are regarded by investors as more efficient information processors on PBE disclosures. This result supports the importance of analysts' role in enhancing informational efficiency of capital markets, and is also consistent with our presumption made in support of H1.

Table 8 report the results for the test of the supplemental hypothesis, H3. It is shown that the coefficient on *inci*, albeit negative, is not statistically significant. There is no evidence suggesting that analyst forecast errors are negatively related to the incidence of PBE disclosures. This suggests that in maintaining forecast accuracy, analysts tend to incur additional information acquisition and/or processing costs to make up for the absence of a PBE disclosure from a firm.[13] The insignificant result, however, does not contradict with our earlier argument that PBE disclosures help analysts increase forecast accuracy at lower information acquisition and/or processing costs.

6. Additional analysis

To examine the robustness of our results, we conduct two additional analyses. First, we

[13] The insignificant association between analyst forecast errors and the incidence of PBE disclosures could imply that analysts assign the same weight to the disclosures in forecasting as the weight attributable to this PBE information in the earnings generating process. This possibility, however, is less likely to systematically exist, not least as prior research documents that (i) there exists significant heterogeneity in the value-relevant information sets that are held and processed by different analysts (e.g., Lang and Lundholm 1996); (ii) the forecasting models used by different analysts differ substantively (e.g., Lang and Lundholm 1996; Ramnath et al. 2008); (iii) the sophistication in, and capability of, processing value-relevant information vary considerably across different analysts (e.g., Clement et al. 2007; Ramnath et al. 2008).

use an automated coarsening *k*-to-*k* coarsened exact matching to form our sample for the tests of H1-H3. For this, we match the treatment firms with the control firms based on the same covariates as we use for the propensity score matching, and then run models (1)-(3) based on the coarsened-exact-matched sample. The coarsening bounds used for covariates are chosen *ex ante* in an automatic manner, obviating the need to check *ex post* the covariate balance. Instead of doing the covariate balance check, L1 statistics could be used to check the quality of the matching (e.g., Blackwell et al., 2010; Iacus et al., 2012). If L1 statistics are significantly reduced post-matching, the quality of matching can be assured. As reported in Panel A of Table 9, the post-matched L1 statistics are significantly lower than the pre-matched ones for the majority of the covariates. Panel B reports the regression results for the re-tests of H1-H3 which are done based on the coarsened-exact-matched sample; we see that the results are qualitatively identical to those reported in Tables 4, 7, and 8.

Second, the effect of PBE disclosures on analyst coverage and forecasts may vary systematically across different industries, causing the residuals of our estimated regressions to be correlated within industries. To address this concern, we repeat our regression analysis for H1-H3 by clustering the standard errors of the regression coefficients by industry. The results (available upon request) remain qualitatively the same, thus supporting H1-H3.

7 Conclusion

In this paper, we examine the impact of voluntary disclosures of PBE plans on analyst coverage and forecasts. We argue for a positive link between PBE disclosures and analyst coverage from both the supply- and demand-curve perspectives. First, given that PBE disclosures have strong implications for the long-term stream of a firm's future revenues, PBE disclosures should increase the amount of value-relevant information available to analysts, helping them reach more accurate and consensus conclusions at lower information gathering and/or processing costs. Second, analysts are arguably more able than investors to decipher the implications of PBE disclosures for future earnings. It follows from this that PBE disclosures would increase investor demand for analyst forecasts and thereby attract more analyst following. Both arguments lead to the same prediction, namely, that analyst coverage is positively associated with the incidence of PBE disclosures. After controlling for potential endogeneity, we find results consistent with this prediction.

We also find that the incidence of PBE disclosures is positively related to the market reaction to analyst earnings forecasts, which suggests that investors perceive analysts to be more capable of inferring the implications of PBE disclosures for future earnings and that investor demand for analyst forecasts increases in response to a PBE disclosure. This finding supports analysts' role in promoting the informational efficiency of capital markets, but is in contrast with some prior studies (e.g., Lin and McNichols 1998, Michaely and Womack 1999). Finally, we find no evidence that the incidence of PBE disclosures is negatively associated with analyst forecast errors, implying that absent a PBE disclosure, analysts have an intent to take more efforts and costs to acquire and process information that is necessary for securing forecast accuracy, and that disclosures of PBE plans save analysts such efforts and costs.[14]

Overall, our study holds implications for academics and practitioners in their

[14] Analyst efforts are unobservable and are difficult to measure and test empirically in an acceptable manner in an archival study. Any empirical proxy for analyst efforts inevitably involve nontrivial measurement errors, which are thus likely to yield spurious results and inferences in any empirical analysis. We therefore leave this issue as an avenue for future research in an experimental setting.

understanding of the role that PBE disclosures may play in financial analysts' decisions. Specifically, PBE activities play a key role in business development and value creation for firms. As such, the analysis of PBE disclosures is crucial in the valuation process. However, investors might lack analytical skills to evaluate the implications of PBE disclosures for firms' future prospects. Financial analysts may assist investors in this aspect, that is, in helping them better understand and trade on firm PBE disclosures. Indeed, we find evidence to suggest that investors are more inclined to resort to analyst forecasts in the presence of PBE disclosures. It thus becomes important that analysts, as information intermediaries, do a good job in incorporating the PBE-related information into their forecasts. Given our evidence that PBE disclosures not only attract greater analyst coverage but also increase investor demand for analyst forecasts, we may deduce that voluntary disclosures of PBE plans are conducive to promoting the capital market efficiencies via the channel of financial analysts. Thus, PBE disclosures should be encouraged by both firms and regulators, though such disclosures might, in some sense/cases, be difficult for investors to understand in terms of the implications for firms' future prospects.

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Table 1 Distribution of the incidence of PBE disclosures

Panel A: ***The average incidence of PBE disclosures across years***

Year	Mean *inci*	Number of observations
2002	0.4483	29
2003	0.4242	33
2004	0.4857	70
2005	0.4854	103
2006	0.5047	107
2007	0.5676	111
2008	0.5313	367
2009	0.5280	500
2010	0.4955	553
2011	0.4651	688
2012	0.4978	223

Panel B: ***The average incidence of PBE disclosures across the Fama-French 12 industries***

Industry (SIC) distribution	Mean *inci*	Number of observations
Consumer nondurables --- food, tobacco, textiles, apparel, leather, toys	0.5079	126
Consumer durables --- cars, TVs, furniture, household appliances	0.4677	62
Manufacturing --- machinery, trucks, planes, paper, computer printing	0.4644	267
Energy --- oil, gas, and coal extraction and products	0.3727	110
Chemistry --- chemicals and allied products	0.4634	423
Business Equipment --- computers, software, and electronic equipment	0.6223	887
Telecommunication --- telephone and television transmission	0.5694	72
Utilities	0.5000	36
Shops --- wholesale, retail, and some services such as laundries, repair shops	0.3581	296
Health --- healthcare, medical equipment, and drugs	0.6115	157
Money --- finance	0.3462	52
Others -- mines, construction, transportations, hotels, bus services, entertainment	0.3615	296

Notes: Panel A reports the incidence of PBE disclosures by year. Panel B presents the incidence of PBE disclosures based on the Fama-French 12 industry classification. The observations are at the firm-year level for the sample period of 2002-2012.

Table 2 Univarate statistics

Panel A: ***Summary statistics of variables***

Variables	No. of firm-years	No. of unique firms	Mean	25%	Median	75%	Std. Dev.
lanacov	2784	1824	2.8762	2.3026	3.1355	3.7612	1.2513
car	2300	1472	0.0890	0.0481	0.0757	0.1126	0.0568
error	2273	1447	0.0379	0.0018	0.0055	0.0169	0.1377
inci	2784	1824	0.5000	0.0000	0.5000	1.0000	0.5001
freq	2784	1824	2.0510	0.0000	0.5000	2.0000	4.6558
stdearnings	2784	1824	2.4391	0.1827	0.5117	1.5374	12.4122
tradingvol	2784	1824	53.7607	1.8259	9.2867	40.6420	145.0918
intangible	2784	1824	0.0215	0.0000	0.0000	0.0000	0.0891
beta	2784	1824	1.1499	0.8234	1.1231	1.4529	0.4846
retvol	2784	1824	0.1375	0.0868	0.1195	0.1661	0.0923
price	2784	1824	26.3156	7.7200	18.7750	35.2950	34.4513
regulated	2784	1824	0.0374	0.0000	0.0000	0.0000	0.1897
size	2784	1824	6.8502	5.5923	6.8205	8.0602	1.8780
btm	2784	1824	0.5703	0.2565	0.4385	0.7323	0.5277
insti	2784	1824	0.6338	0.4012	0.7195	0.8915	0.3316
capex	2784	1824	0.0424	0.0000	0.0000	0.0000	0.7603
salesgrowth	2784	1824	0.2859	-0.0538	0.0715	0.2124	3.6755
qtrret	2784	1824	0.0331	-0.1607	0.0014	0.1637	0.3439
debt	2784	1824	0.0810	0.0000	0.0000	0.1277	0.1374
litigation	2784	1824	0.3671	0.0000	0.0000	1.0000	0.4821
substitution	2784	1824	1.1539	1.0840	1.1298	1.2367	0.1766
mktsize	2784	1824	0.3339	0.0306	0.1616	0.3963	0.4542
entrycost	2784	1824	0.0129	0.0018	0.0084	0.0130	0.0229

Panel B: ***Univariate analysis***

Variables	Mean *inci*=0	Mean *inci*=1	Mean differences (t-stat.)	Median *inci*=0	Median *inci*=1	Median differences (Chi^2)
lanacov	2.6030	3.1494	-0.5464	2.9957	3.2581	-0.2624
			(-11.802)***			(-8.247)***
stdearnings	3.0698	1.8083	1.2615	0.4900	0.5309	-0.0409
			(2.6842)***			(-1.181)
tradingvol	46.1461	61.3753	-15.2292	7.8798	10.4501	-2.5703
			(-2.772)***			(-4.287)***
intangible	0.0220	0.0210	0.0011	0	0	0
			(0.315)			(-0.540)
beta	1.1149	1.1849	-0.0699	1.0969	1.1470	-0.0501
			(-3.816)***			(-3.526)***
retvol	0.1376	0.1373	0.0003	0.1167	0.1229	-0.0062
			(0.079)			(-2.214) **

price	26.3552	26.2760	0.0792	20.2850	17.6900	2.5950
			(0.061)			(1.419)
regulated	0.0460	0.0287	0.0172	0	0	0
			(2.400)**			(2.398) **
size	6.7899	6.9105	-0.1206	6.8366	6.8187	0.0179
			(-1.695)*			(-1.021)
btm	0.5548	0.5859	-0.0311	0.4329	0.4410	-0.0081
			(-1.556)			(-0.299)
insti	0.5974	0.6701	-0.0727	0.6901	0.7416	-0.0515
			(-5.818)***			(-4.816)***
capex	0.0630	0.0217	0.0413	0	0	0
			(1.433)			(-0.716)
salesgrowth	0.3843	0.1875	0.1967	0.0631	0.0772	-0.0141
			(1.412)			(-2.411) **
qtrret	0.0313	0.0349	-0.0036	0.0011	0.0016	-0.0005
			(-0.277)			(-0.507)

Notes: Panel A tabulates descriptive statistics of the variables used for the hypothesis tests. The sample period ranges from 2002 to 2012. All the variables are defined in Appendix I. Panel B reports the univariate results for the two-sample tests of mean and median for the main hypothesis. The sample period ranges from 2002 to 2012. *inci* equals 1 if a firm discloses a product or business expansion plan over the first two fiscal quarters; and 0 otherwise. There are 1,392 firm-year observations in the disclosure (*inci*=1) and non-disclosure (*inci*=0) samples, respectively. *lanacov* equals the natural logarithm of 1 plus the number of analysts that make at least one EPS forecast for a firm for a fiscal year following the beginning of the third fiscal quarter. All the other variables are defined in Appendix I. ***, **, * denote statistical significance at 1%, 5%, and 10% levels (two-tailed), respectively.

Table 3 Correlation matrix

Variables	*lanacov*	*inci*	*stdearnings*	*tradingvol*	*intangible*	*beta*	*retvol*	*price*	*regulated*	*size*	*btm*	*insti*	*capex*	*qtrret*	*salesgrowth*
lanacov	1														
inci	0.1563	1													
	(0.0000)														
stdearnings	0.4163	0.0224	1												
	(0.0000)	(0.2380)													
tradingvol	0.8140	0.0813	0.5425	1											
	(0.0000)	(0.0000)	(0.0000)												
intangible	0.0969	0.0102	0.1151	0.1499	1										
	(0.0000)	(0.5890)	(0.0000)	(0.0000)											
beta	0.1441	0.0668	0.0456	0.1248	0.00270	1									
	(0.0000)	(0.0004)	(0.0160)	(0.0000)	(0.8850)										
retvol	-0.2255	0.0420	-0.1561	-0.3145	-0.1248	0.3019	1								
	(0.0000)	(0.0268)	(0.0000)	(0.0000)	(0.0000)	(0.0000)									
price	0.5101	-0.0269	0.2689	0.6777	0.1335	-0.0405	-0.5136	1							
	(0.0000)	(0.1560)	(0.0000)	(0.0000)	(0.0000)	(0.0328)	(0.0000)								
regulated	-0.0568	-0.0455	-0.0246	-0.0171	0.00360	-0.0963	-0.1246	0.0550	1						
	(0.0027)	(0.0164)	(0.1950)	(0.3670)	(0.8510)	(0.0000)	(0.0000)	(0.0037)							
size	0.7296	0.0193	0.5491	0.8993	0.1901	0.0458	-0.4845	0.7473	0.0335	1					
	(0.0000)	(0.3080)	(0.0000)	(0.0000)	(0.0000)	(0.0157)	(0.0000)	(0.0000)	(0.0776)						
btm	-0.1394	0.00570	-0.0791	-0.1982	0.0186	0.0332	0.0996	-0.2423	0.0184	-0.2780	1				
	(0.0000)	(0.7650)	(0.0000)	(0.0000)	(0.3260)	(0.0797)	(0.0000)	(0.0000)	(0.3310)	(0.0000)					
insti	0.4323	0.0913	0.1290	0.4454	-0.0305	0.1185	-0.2175	0.4186	-0.0628	0.3676	-0.0341	1			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1070)	(0.0000)	(0.0000)	(0.0000)	(0.0009)	(0.0000)	(0.0720)				
capex	0.1235	0.0136	0.1055	0.1588	0.5337	-0.0308	-0.1718	0.1689	-0.0145	0.1900	-0.0615	0.0424	1		
	(0.0000)	(0.4740)	(0.0000)	(0.0000)	(0.0000)	(0.1040)	(0.0000)	(0.0000)	(0.4450)	(0.0000)	(0.0012)	(0.0253)			
qtrret	0.1021	0.00960	0.0266	0.1278	-0.0097	0.0251	-0.0826	0.2759	-0.0201	0.2145	-0.2166	0.0953	0.0402	1	
	(0.0000)	(0.6120)	(0.1600)	(0.0000)	(0.6080)	(0.1860)	(0.0000)	(0.0000)	(0.2890)	(0.0000)	(0.0000)	(0.0000)	(0.0338)		
salesgrowth	0.0997	0.0457	0.0229	0.1281	0.0423	0.0688	-0.0485	0.2220	-0.0029	0.1480	-0.2247	0.0275	0.0798	0.2015	1
	(0.0000)	(0.0159)	(0.2270)	(0.0000)	(0.0256)	(0.0003)	(0.0105)	(0.0000)	(0.8800)	(0.0000)	(0.0000)	(0.1470)	(0.0000)	(0.0000)	

Notes: Table 3 presents the results for the Spearman correlations in the lower triangle. The correlation matrix involves the variables used for the main hypothesis tests. The sample comprises 2,784 firm-years that cover the period 2002-2012. All the variables are defined in Appendix I. *p*-values for the correlation matrix are provided in parentheses.

Table 4 Test of H1: an OLS regression of analyst coverage on PBE disclosures

Variables	Predicted sign	*lanacov*
inci	+	**0.409**
		(11.73) ***
stdearnings	+	-0.00928
		(-3.57) ***
tradingvol	+	0.000194
		(1.09)
beta	+	0.341
		(8.43) ***
retvol	+	0.383
		(1.20)
price	-	-0.000990
		(-1.44)
intangible	-	-0.294
		(-1.67) *
regulated	+	0.281
		(1.64)
size	+	0.420
		(26.43) ***
btm	+	0.0457
		(1.13)
insti	+	0.755
		(10.29) ***
salesgrowth	-	0.00201
		(0.83)
capex	-	-0.0117
		(-0.51)
qtrret	-	-0.150
		(-3.08) ***
constant	?	-1.353
		(-8.33) ***
Observations		2784
Adj. R-square		0.58

Notes: Table 5 reports the OLS regression results for the tests of the impact of the incidence of PBE disclosures on analyst coverage. The sample period is 2002-2012. The dependent variable, *lanacov*, equals the natural logarithm of 1 plus the number of analysts that make at least one EPS forecast for a firm for a fiscal year following the beginning of the third fiscal quarter. The treatment variable, *inci,* equals 1 if a firm discloses a product or business expansion plan over the first two fiscal quarters; and 0 otherwise. All the other variables are defined in Appendix I. Year and industry dummies are included in the regressions but not reported for simplicity. The industry dummies are constructed based on the Fama-French 12 industry classification. *p*-values in parentheses are based on robust standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 5 Tests of H1: Controlling for endogeneity

Variables	Firm-fixed-effects model	Two-stage-treatment-effect model	
	(1) *lanacov*	(2a) First-stage (*inci*)	(2b) Second-stage (*lanacov*)
inci	**0.165**		**0.761**
	(4.83) ***		**(6.31) *****
substitution		0.0463	
		(0.21)	
mktsize		-0.331	
		(-2.16) **	
entrycost		7.045	
		(2.16) **	
stdearnings		-0.0361	-0.00836
		(-4.10) ***	(-3.98) ***
tradingvol	0.000308	0.00112	0.000110
	(1.58)	(3.37) ***	(0.64)
beta	0.112	0.226	0.309
	(2.51) **	(3.49) ***	(7.43) ***
retvol	-0.271	-0.152	0.402
	(-1.52)	(-0.53)	(1.32)
price	0.00109	-0.000303	-0.00102
	(1.24)	(-0.24)	(-1.35)
intangible	0.306	-0.197	-0.273
	(1.33)	(-0.55)	(-1.47)
regulated		-0.0159	0.312
		(-0.04)	(2.09) **
size	0.259	0.0205	0.420
	(6.86) ***	(0.76)	(26.30) ***
btm	0.232	0.150	0.0288
	(4.16) ***	(2.54) **	(0.72)
insti	0.545	0.356	0.705
	(5.16) ***	(3.24) ***	(9.43) ***
salesgrowth	-0.00129	-0.0115	0.00311
	(-1.30)	(-1.43)	(1.21)
capex	0.000691	-0.0459	-0.00675
	(0.08)	(-1.35)	(-0.30)
qtrret	-0.111	0.0297	-0.156
	(-3.38) ***	(0.41)	(-3.19) ***
constant	0.388	-1.230	-0.00836
	(1.29)	(-3.79) ***	(-3.98) ***
Observations	2784	2784	2784
R-square/Wald Chi^2	0.229	0.0658	3564.41

Notes: Table 6 reports the regression results for the tests of H1 which control for potential endogeneity. The sample period is 2002-2012. Column (1) reports the firm-fixed-effects regression results. Because the firm-fixed-effects regression automatically omits explanatory variables that have no/little within-firm variance in the explanatory variables, *regulated* and *stdearnings* are omitted by the firm-fixed-effects regression estimates. Year and industry dummies are included in the fixed-effect regression but not reported for simplicity. Columns (2) report the results for the two-stage treatment effect regression. The first-step probit estimate shows the determinants of the incidence of PBE disclosures (*inci*). The instruments, *substitution, mktsize,* and *entrycost*, are the three proprietary costs proxies developed by Karuna (2007) and are defined in Appendix I. Year and industry dummies are included in both the 1st and 2nd stage regressions but not reported for brevity. The industry dummies are constructed based on the Fama-French 12 industry classification. *p*-values in parentheses are based on the standard errors clustered by firm. All variables are defined in Appendix I. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 6 Tests of H1a: The moderating effect of information opacity

Variables	*Lanacov*	
	High *stdearnings*	Low *stearnings*
Intercept	-2.6383	-2.6451
	(-4.44) ***	(-4.57) ***
inci	**0.5288**	**0.3315**
	(6.48) ***	**(4.19) *****
stdearnings	-0.0088	-0.1342
	(-3.82) ***	(-0.11)
tradingvol	0.00003	0.0027
	(0.14)	(2.03) **
beta	0.4653	0.2721
	(3.77) ***	(2.95) ***
retvol	0.6280	1.0836
	(0.76)	(1.57)
price	-0.0018	-0.0025
	(-1.16)	(-0.84)
intangible	-0.2464	-0.1910
	(-0.60)	(-0.45)
regulated	0.3288	1.0487
	(2.36) **	(5.63) ***
size	0.4750	0.3937
	(11.49) ***	(6.58) ***
btm	0.0307	-0.0111
	(0.27)	(-0.15)
insti	0.5440	1.1301
	(2.97) ***	(4.87) ***
salesgrowth	-0.0420	0.0163
	(-0.90)	(1.19)
capex	-0.1081	0.0276
	(-2.49) **	(0.34)
qtrret	-0.3011	-0.1086
	(-1.98) **	(-1.06)
Observations	556	556
R-square	0.5032	0.6547

Notes: Table 7 reports the OLS regression results for the tests of H1a as to whether the impact of the incidence of PBE disclosures on analyst coverage is moderated by information opacity. The sample period is 2002-2012. The dependent variable, *lanacov*, equals the natural logarithm of 1 plus the number of analysts that make at least one EPS forecast for a firm for a fiscal year following the beginning of the third fiscal quarter. The treatment variable, *inci*, equals 1 if a firm discloses a product or business expansion plan over the first two fiscal quarters; and 0 otherwise. The moderator variable is *stdearnings*, measured by the standard deviation of income before extraordinary items for the previous five fiscal years. Our sample is split into the high-*stdearnings* subsample and low-*stdearnings* subsample, which contain observations with *stdearnings* higher than the top sample quintile point, and those with *stdearnings* lower than the bottom sample quintile point, respectively. All the other variables are defined in Appendix I. Year and industry dummies are included in the regressions but not reported for simplicity. The industry dummies are constructed based on the Fama-French 12 industry classification. *p*-values in parentheses are based on robust standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 7 Test of the supplemental hypothesis (H2): The association between the informativeness of analyst forecasts and PBE disclosures

Variables	*car*	
inci	**0.0073**	**0.00461**
	(2.86) ***	**(2.09)** **
stdearnings		-0.00000180
		(-0.92)
tradingvol		0.0000219
		(2.78) ***
beta		0.00456
		(1.52)
retvol		0.227
		(7.37) ***
price		-0.0000190
		(-0.67)
intangible		-0.00266
		(-0.24)
regulated		-0.0130
		(-1.24)
size		-0.00803
		(-7.42) ***
btm		0.00240
		(0.60)
insti		0.00379
		(0.87)
salesgrowth		0.0000808
		(0.49)
capex		-0.000983
		(-0.86)
qtrret		0.00270
		(0.55)
constant	0.0299	0.111
	(5.46) ***	(8.15) ***
Observations	2300	2300
Adjusted R-square	0.0908	0.276

Notes: Table 8 shows the OLS regression result for the test of the supplemental hypothesis as to the association between analyst earnings forecast informativeness and the incidence of PBE disclosures. The sample period is 2002-2012. The dependent variable, *car*, equals the three-day [-1, 1] cumulative unsigned abnormal stock returns surrounding an analyst's last forecast of EPS for a given fiscal year after the beginning of the third fiscal quarter. The abnormal stock returns are calculated using market model with an estimation period of [-181, -2] relative to the forecast date. If there are multiple analysts who make the EPS forecasts for the same firm, *car* is taken as the average of the abnormal stock returns associated with these forecasts. *inci* equals 1 if a firm discloses a product or business expansion plan over the first two fiscal quarters; and 0 otherwise. All the other variables are defined in Appendix I. Year and industry dummies are included in the regressions but not reported for simplicity. The industry dummies are constructed based on the Fama-French 12 industry classification. *p*-values in parentheses are based on robust standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 8 Test of the supplemental hypothesis (H3): The association between analyst forecast errors and PBE disclosures

Variables	*error*
inci	**-0.00547**
	(-1.06)
retvol	0.254
	(4.36) ***
size	-0.00757
	(-3.57) ***
btm	0.0571
	(3.09) ***
horizon	0.0000576
	(0.52)
price	0.0000305
	(0.59)
intangible	0.0295
	(0.83)
capex	0.000693
	(0.46)
salesgrowth	-0.000345
	(-1.79) *
abtradvol	-0.00000146
	(-0.05)
dedi	-0.0103
	(-0.32)
qtrret	-0.0143
	(-1.75) *
changeeps	-0.0147
	(-1.41)
constant	0.0157
	(0.59)
Observations	1906
Adjusted R-square	0.151

Notes: Table 9 shows the OLS regression result for the test of the supplemental hypothesis as to the association between analyst earnings forecast errors and the incidence of PBE disclosures. The sample period is 2002-2012. The dependent variable, *error*, equals the absolute difference between actual EPS and an analyst's last forecast of EPS for a given firm for a fiscal year following the beginning of the third fiscal quarter, divided by the firm's stock price. If there are multiple analysts that make the EPS forecast for the firm, the average is taken of the analysts' last forecasts of EPS. *inci* equals 1 if a firm disclose a product or business expansion plan over the first two fiscal quarters; and 0 otherwise. All the other variables are defined in Appendix I. Year and industry dummies are included in the regressions but not reported for simplicity. The industry dummies are constructed based on the Fama-French 12 industry classification. *p*-values in parentheses are based on robust standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 9 Additional test: Use the coarsened exact matching method for the tests of H1-H3

Panel A: ***Diagnostic check of the quality of coarsened exact matching***

Variables	Pre-matched L1 statistics	Post-matched L1 statistics
capex	0.02131	0.01748
salesgrowth	0.00307	0.00599
abtradvol	0.21259	0.09016
qtrret	0.066	0.0512
intangible	0.03628	0.02248
size	0.18979	0.03347
btm	0.13284	0.00799
debt	0.16573	0.09041
stdearnings	0.1009	0.0547
litigation	0.19598	0
substitution	0.15915	0.08591
mktsize	0.15249	0.03272
entrycost	0.16473	0.07393

Panel B: ***Regression results for the tests of H1-H3*** **for the sample formed by coarsened exact matching**

Variables	*lanacov*	*car*	*error*
inci	**0.2576**	**0.00664**	**0.0134**
	(7.10) ***	**(2.90)** ***	**(0.93)**
stdearnings	-0.0113	-6.62e-07	
	(-1.80) *	(-0.18)	
tradingvol	0.0000502	2.24e-11	
	(0.18)	(2.11) **	
beta	0.3739	0.00476	
	(9.40) ***	(1.45)	
retvol	0.1358	0.2816	0.427
	(0.43)	(6.15) ***	(2.11) **
price	-0.00138	-0.0000192	0.000302
	(-7.65) ***	(-0.53)	(1.53)
intangible	-0.2877	0.00501	-0.0189
	(-1.12)	(0.41)	(-0.63)
regulated	0.2833	-0.00522	
	(1.40)	(-0.37)	
size	0.4456	-0.00738	-0.0169
	(23.77) ***	(-5.79) ***	(-2.93) ***
btm	0.0285	0.000339	0.0612
	(0.78)	(0.12)	(2.17) **
insti	0.413	0.001136	
	(2.83) ***	(0.26)	
salesgrowth	0.000652	0.000104	-0.000035
	(0.88)	(3.18) ***	(-0.50)
capex	-0.0371	-0.000267	0.000598
	(-1.54)	(-0.25)	(0.54)
qtrret	-0.137	-0.00260	-0.0566
	(-3.01) ***	(-0.49)	(-2.15) **
horizon			0.000499
			(1.32)

abtradvol			0.0000257
			(0.25)
dedi			0.0800
			(1.14)
changeeps			-0.0498
			(-2.00) **
constant	-1.616	0.0984	-0.0258
	(-5.59) ***	(4.92) ***	(-0.33)
Observations	2885	2753	2314
R-square	0.5873	0.2479	0.0830

Notes: Panel A of Table 10 reports the L1 statistics of the covariates used in the regression that is run for coarsened exact matching. Panel B reports the regression results for the tests of H1-H3 that are done based on the coarsened-exact-matched sample. The sample period is 2002-2012. All the variables are defined in Appendix I. Year and industry dummies are included in the regressions but not reported for simplicity. The industry dummies are constructed based on the Fama-French 12 industry classification. *p*-values in parentheses are based on robust standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Appendix I Summary of variable definitions

Variables	Definitions
lanacov	The natural logarithm of 1 plus the number of analysts that make at least one EPS forecast for a given firm for a fiscal year following the beginning of the third fiscal quarter.
inci	1 if a firm makes a product or business expansion disclosure over the first two fiscal quarters of a fiscal year; and 0 otherwise.
car	The three-day [-1,1] cumulative unsigned abnormal stock returns surrounding an analyst's last forecast of EPS for a given firm for a fiscal year following the beginning of the third fiscal quarter. The abnormal stocks returns are calculated using a market model with an estimation period of [-181,-2] relative to the forecast date. If there are multiple analysts who make the EPS forecasts for the same firm, *car* is taken as the average of the abnormal returns associated with these forecasts.
error	The absolute difference between actual EPS and an analyst's last forecast of EPS for a given firm for a fiscal year following the beginning of the third fiscal quarter, divided by the firm's stock price. If there are multiple analysts making the EPS forecasts for the firm for a fiscal year following the beginning of the third fiscal quarter, the average is taken of the analysts' last forecasts of EPS.
retvol	The standard deviation of daily market excess return over a 12-month period ending at the end of the second fiscal quarter of a given fiscal year.
qtrret	Buy-and-hold abnormal stock returns of a given firm for the first two fiscal quarters for a given fiscal year.
horizon	The natural log of the number of days between analyst earnings forecast date and a firm's earnings announcement date.
tradingvol	Dollar trading volume for a given firm for the first two fiscal quarters of a given fiscal year.
abtravol	Abnormal trading volume for a given firm for the first two fiscal quarters of a fiscal year, which is defined as dollar trading volume over the first two fiscal quarters in the current year minus dollar trading volume over the last two fiscal quarters in the prior year.
btm	The book value of firm equity divided by the market value of firm equity for a given firm at the beginning of a given fiscal year.
price	Stock price of a given firm at the end of the second fiscal quarter of a given fiscal year.
size	The natural logarithm of market value of a firm's equity at the beginning of a given fiscal year.
capex	The sum of research and development expenses and advertisement expenses, divided by income before extraordinary items, for a given fiscal year.
salesgrowth	The difference between the sales for the current fiscal year and the sales for the previous year, divided by the sales for the previous year.
insti	Institutional investors' stock ownership as a percentage of the total outstanding shares for a given firm at the beginning of the second fiscal quarter of a given fiscal year.
beta	Equity beta for a given firm for a given fiscal year.
intangible	Intangible assets divided by total assets for a firm at the end of a fiscal year.
regulated	1 if a firm belongs to a regulated industry (SIC 4900-4999, 6000-6411, or 6500-6999) and 0 otherwise.
dedi	Dedicated institutional investors' stock ownership as a percentage of the total outstanding shares for a firm at the beginning of the second fiscal quarter of a given fiscal year.
stdearnings	The standard deviation of income before extraordinary items for the previous five fiscal years.
changeeps	Annual EPS of a firm for the current fiscal year minus that for the previous year, divided by the firm's stock price at the end of the fiscal year.

debt	Long-term debt divided by total assets at the end of a given fiscal year.
litigation	1 if a firm is in the biotechnology (2833-2836 and 8731-8734), computers (3570-3577 and 7370-7374), electronics (3600-3674), and retail (5200-5961) industries; and 0 otherwise.
entrycost	A proxy for proprietary costs of disclosures, which equals the average gross PPE for all firms in a 2-digit SIC industry for a fiscal year, weighted by each firm's sales in the same industry (in millions of U.S. dollars).
mktsize	A proxy for proprietary costs of disclosures, which equals the sum of sales of all firms in a 2-digit SIC industry for a fiscal year (in millions of U.S. dollars).
substitution	A proxy for proprietary costs of disclosures, which equals the sum of operating costs of each firm in a 2-digit SIC industry for a fiscal year, divided by the sum of the sales of all firms in the same industry.

Appendix II Results for propensity-score-matching specification

Panel A: ***Determinants of the incidence of PBE disclosures for propensity score matching***

Variables	*inci*
capex	0.0265
	(0.82)
salesgrowth	0.00404
	(1.92) *
abtradvol	0.000406
	(1.39)
qtrret	-0.1708
	(-2.34) **
intangible	1.0361
	(2.22)**
size	0.2373
	(8.18) ***
btm	-0.2439
	(-2.76) ***
debt	-1.6115
	(-4.82) ***
stdearnings	-0.0165
	(-2.12) **
litigation	0.8352
	(7.53) ***
substitution	-0.1587
	(-1.32)
mktsize	0.2398
	(1.55)
entrycost	-5.7650
	(-1.73)*
Intercept	-2.8073
	(-10.23)***
Observations	15538
Waldχ^2	23.47

Notes: Panel A reports the logistic regression result for the determinants of the incidence of PBE disclosures. The sample period is 2002-2012. The regression is run for the propensity score matching and involves the full sample of listed firm-years. The dependent variable, *inci,* equals 1 if a firm discloses a product or business expansion plan over the first two fiscal quarters; and 0 otherwise. All the other variables pertain to the determinants of the incidence of PBE disclosures and are defined in Appendix I. Year dummies are included in regressions but not reported for simplicity. *p*-values in parentheses are based on robust standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Panel B: ***Descriptive statistics of PBE disclosure sample and non-PBE disclosure sample formed by propensity score matching***

Variables	Mean *inci*=0 (N=1392)	Mean *inci*=1 (N=1392)	Mean difference (t-stat)	Standardized bias (%)
capex	0.0630	0.0217	0.0413 (1.4325)	-5.43
salesgrowth	0.3843	0.1875	0.1967 (1.4124)	-5.33
abtradvol	2.4052	1.3040	1.1012 (0.7268)	-2.75
qtrret	0.0313	0.0349	-0.0036 (-0.2765)	1.05
intangible	0.0220	0.0210	0.0011 (0.3152)	-1.12
size	6.7899	6.9105	-0.1206 (-1.6946) *	6.39
btm	0.5548	0.5859	-0.0311 (-1.5561)	5.88
debt	0.0787	0.0834	-0.0047 (-0.9077)	3.42
stdearnings	3.0698	1.8083	1.2615 (2.6842) ***	-10.18
litigation	0.3707	0.3635	0.0072 (0.3931)	-1.45
substitution	1.1586	1.1493	0.0093 (1.3962)	-5.67
mktsize	0.3454	0.3224	0.0229 (1.3313)	-5.06
entrycost	0.0129	0.0128	0.0000 (0.0030)	-0.44

Note: Panel B reports descriptive statistics of the covariates in the PBE disclosure sample (*inci*=1) and non-PBE disclosure sample (*inci*=0) that are formed based on the propensity score matching. Specifically, the results for the two-sample tests of mean and standardized bias are provided. All the variables are defined in Appendix I. ***, **, * denote the statistical significance at the 1%, 5%, and 10% levels (two-tailed tests), respectively.

Appendix III Examples of product and business expansion plan disclosures

1. An example of product information plan --- *American Express Introduces New Online and Mobile Payment Security Services*

"*New York, November 3, 2014: American Express today announced the launch of its American Express Token Service, a suite of solutions designed to enable its card-issuing partners, processors, acquirers and merchants to create a safer online and mobile payments environment for consumers.*

With American Express Token Service, traditional card account numbers are replaced with unique "tokens," which can then be used to complete payment transactions online, in a mobile app or in-store with a mobile Near Field Communication (NFC)-enabled device. By using tokens, merchants and digital wallet operators will no longer need to store consumers' sensitive payment account information in their systems. In addition, tokens can be assigned for use with a specific merchant, transaction type or payment device to provide further protection against fraud.

Based on EMVCo's Payment Tokenization Specification and Technical Framework published earlier this year, American Express Token Service offers the following features: (i) a token vault to store and map tokens to card account numbers; (ii) the ability to issue tokens; (iii) lifecycle management services to create, suspend, resume or delete tokens; (iv) additional fraud and risk management services, such as authorization and payment data validation capabilities, for card-issuing financial institutions.

American Express Token Service is available in the U.S., and international rollout is expected to begin in 2015.

"*We believe our payments network is a tremendous asset to American Express – one that will allow us to offer our customers new features and technologies to meet their evolving spending needs," said Paul Fabara, President, Global Banking and Global Network Business, American Express. "As we move ahead, we are excited to bring these new capabilities to our customers and look forward to continuing to serve them."*

American Express also announced that it has developed network specifications for Host Card Emulation (HCE). American Express' HCE specifications provide its card-issuing partners with additional security options and solutions for payments made with mobile NFC-enabled devices that support Android iOS KitKat. With HCE, card issuers use a secure cloud server to store their customers' card account details, which can be transmitted from the cloud server to an NFC-enabled mobile device and then to a Point-of-Sale terminal in a fast, secure manner. American Express' HCE specifications are available today globally."

(Source: Press release from American Express, available at http://about.americanexpress.com/news/pr/2014/amex-intros-online-mobile-payment-security.aspx)

2. An example of business expansion plan --- *Apple Invests €1.7 Billion in New European Data Centres*

"*CORK, Ireland --- February 23, 2015: Apple today announced a €1.7 billion plan to build and operate two data centres in Europe, each powered by 100 percent renewable energy. The facilities, located in County Galway, Ireland, and Denmark's central Jutland, will power Apple's online services including the iTunes Store, App Store, iMessage, Maps and Siri for customers across Europe.*

"*We are grateful for Apple's continued success in Europe and proud that our investment supports communities across the continent," said Tim Cook, Apple's CEO. "This significant new investment represents Apple's biggest project in Europe to date. We're thrilled to be expanding our operations, creating hundreds of local jobs and introducing some of our most advanced green building designs yet."*

Apple supports nearly 672,000 European jobs, including 530,000 jobs directly related to the development of iOS apps. Since the App Store's debut in 2008, developers across Europe have earned more than €6.6 billion through the worldwide sale of apps.

Apple now directly employs 18,300 people across 19 European countries and has added over 2,000 jobs in the last 12 months alone. Last year, Apple spent more than €7.8 billion with European companies *and suppliers helping build Apple products and support operations around the world.*

Like all Apple data centres, the new facilities will run entirely on clean, renewable energy sources from day one. Apple will also work with local partners to develop additional renewable energy projects from wind or other sources to provide power in the future. These facilities will have the lowest environmental impact yet for an Apple data centre.

"*We believe that innovation is about leaving the world better than we found it, and that the time for tackling climate change is now," said Lisa Jackson, Apple's vice president of Environmental Initiatives. "We're excited to spur green industry growth in Ireland and Denmark and develop energy systems that take advantage of their strong wind resources. Our commitment to environmental responsibility is good for the planet, good for our business and good for the European economy."*

The two data centres, each measuring 166,000 square metres, are expected to begin operations in 2017 and include designs with additional benefits for their communities. For the project in Athenry, Ireland, Apple will recover land previously used for growing and harvesting non-native trees and restore native trees to Derrydonnell Forest. The project will also provide an outdoor education space for local schools, as well as a walking trail for the community.

In Viborg, Denmark, Apple will eliminate the need for additional generators by locating the data centre adjacent to one of Denmark's largest electrical substations. The facility is also designed to capture excess heat from equipment inside the facility and conduct it into the district heating system to help warm homes in the neighbouring community.

Apple designs Macs, the best personal computers in the world, along with OS X, iLife, iWork and professional software. Apple leads the digital music revolution with its iPods and iTunes online store. Apple has reinvented the mobile phone with its revolutionary iPhone and App Store, and is defining the future of mobile media and computing devices with iPad."

(Source: Press release from Apple, available at http://www.apple.com/pr/library/2015/02/23Apple-to-Invest-1-7-Billion-in-New-European-Data-Centres.html)

3. An example of a product information plan --- Model X Wins the Golden Steering Wheel

"The Tesla Team --- November 8, 2016: Today, we are truly honored to announce that Model X has been awarded the Golden Steering Wheel (Das Goldene Lenkrad), one of the most prestigious automotive awards in the world. Candidates for this award are nominated by hundreds of thousands across Europe for excellence across six categories. The Golden Steering Wheel jury, composed of professional race car drivers, accomplished technicians, editors, designers, and digital and connectivity experts, then spent three days judging Model X.

This excellence did not come without its share of challenges early on. Model X is a complex vehicle to build, and its advanced feature set introduced some obstacles as we ramped production in early 2016. In the months since, we have introduced significant updates to make Model X an even better car. Most of these refinements have rolled out as over-the-air software updates, which enhance each vehicle regardless of when it was built. For the small number of improvements that are hardware-related, changes have rolled out to our early owners via priority Tesla Service. We have implemented those same changes in our factory immediately, because we do not believe in waiting for the next model year to introduce improvements to our cars.

As a result of this continuous improvement, Model X owners have seen a 92% reduction in reliability concerns over the past year. Nearly 20,000 owners are now experiencing the quickest, smartest, and safest SUV ever, with more than 90% of owners saying they would buy Model X again.

Here are some of the ways Model X has become better over time:

Falcon Wing Doors: (i)2x improvement in door sensor object detection; (ii) 25% improvement in opening/closing speed; (iii) Dynamic profile adjustment to indoor mode when roof sensor detects a low ceiling; (iv) 83% reduction in customer-reported issues with door opening/closing

Powered front doors and remote keyless entry: (i) Refined keyfob detection for smart automatic front door behavior as you approach, enter, or leave the car; (ii) 8x improvement in keyfob battery life; automated alert from the car if the battery gets low; (iii) Several improvements to power front door movement and latching system, leading to 51% reduction in door issues and improved performance on *hills; (iv) Wind noise customer-reported issues reduced by 22% with a combination of hardware modifications and fit/finish improvements*

Interior Temperature Management: (i) Introduced Cabin Overheat Protection by managing the maximum interior temperature of Model X through software; (ii) Improved HVAC performance by increasing maximum fan speed with an over-the-air software update

Second row seats: (i) Multiple over-the-air updates have enhanced seat motion, obstacle detection, pitch calibration, and usability; (ii) Software enhancements have added intelligent behaviors between seats, adjusting spacing differently, for example, depending on which rows are occupied

Infotainment System: (i) Touchscreen and Bluetooth connectivity improvements via over-the-air software update; (ii) Largest user interface overhaul since the launch of Model S in over-the-air Software 8.0 rollout

Our commitment is to be best-in-class in safety, performance, comfort, and reliability in all of our vehicles. Model X is no exception. As we continue to accelerate the advent of sustainable energy, we invite you to visit one of our showrooms or request a stop from a Tesla mobile Design Studio near you."

(Source: Press release from Tesla, available at: https://www.tesla.com/en_GB/blog/model-x-wins-golden-steering-wheel)

4 An example of a business expansion plan --- Battery Cell Production Begins at the Gigafactory

"*The Tesla Team --- January 4, 2017:Tesla's mission is to accelerate the world's transition to sustainable energy through increasingly affordable electric vehicles in addition to renewable energy generation and storage. At the heart of these products are batteries. Today at the Gigafactory, Tesla and Panasonic begin mass production of lithium-ion battery cells, which will be used in Tesla's energy storage products and Model 3.*

The high performance cylindrical "2170 cell" was jointly designed and engineered by Tesla and Panasonic to offer the best performance at the lowest production cost in an optimal form factor for both electric vehicles and energy products.

Production of 2170 cells for qualification started in December and today, production begins on cells that will be used in Tesla's Powerwall 2 and Powerpack 2 energy products. Model 3 cell production will follow in Q2 and by 2018, the Gigafactory will produce 35 GWh/year of lithium-ion battery cells, nearly as much as the rest of the entire world's battery production combined.

The Gigafactory is being built in phases so that Tesla, Panasonic, and other partners can begin manufacturing immediately inside the finished sections and continue to expand thereafter. Our phased approach also allows us to learn and continuously improve our construction and operational techniques as we continue to drive down the cost of energy storage. Already, the current structure has a footprint of 1.9 million square feet, which houses 4.9 million square feet of operational space across several floors. And we are still less than 30 percent done. Once complete, we expect the Gigafactory to be the biggest building in the world.

With the Gigafactory online and ramping up production, our cost of battery cells will significantly decline due to increasing automation and process design to enhance yield, lowered capital investment per unit of production, the simple optimization of locating most manufacturing processes under one roof, and economies of scale. By bringing down the cost of batteries, we can make our products available to more and more people, allowing us to make the biggest possible impact on transitioning the world to sustainable energy.

Finally, bringing cell production to the U.S. allows us to create thousands of American jobs. In 2017 alone, Tesla and Panasonic will hire several thousand local employees and at peak production, the Gigafactory will directly employ 6,500 people and indirectly create between 20,000 to 30,000 additional jobs in the surrounding regions."

(Source: Press release from Tesla, available at: https://www.tesla.com/en_GB/blog/battery-cell-production-begins-gigafactory)