The impacts of product market competition on the quantity and quality of voluntary disclosures*

Xi Li†

London Business School

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Abstract

This study examines how firms' voluntary disclosure decisions are influenced by the product market competition. Using separate measures to capture different dimensions of competition, I show that competition from potential entrants increases disclosure quantity while competition from existing rivals decreases disclosure quantity. I also find that competition enhances disclosure quality mainly through reducing the optimism in profit-forecasts and reducing the pessimism in investment-forecasts. Moreover, I find that the above association is less pronounced for industry leaders, consistent with industry leaders facing less competitive pressures than industry followers.

Keywords: Product market competition, Profits, Investments, Management forecasts

JEL classification: D4, D80, L1, M40, M41

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†Tel.: +44 (0)20 7000 8140; Email: xli.phd2005@london.edu

1 Introduction

In the survey by Graham, Harvey, and Rajgopal (2005), 58.8% out of 306 corporate executives agree or strongly agree that the need to avoid giving away "company secrets" or otherwise harming their competitive position is a constraint on more voluntary disclosures. This disincentive for voluntary disclosure is identified as proprietary costs by previous literature. Despite the prevalence of the proprietary cost argument in accounting literature, there is relatively little empirical evidence on the role of product markets in shaping firms' voluntary disclosure decisions. In this study, I address this issue by examining how different dimensions of product market competition affect firms' forward-looking voluntary disclosure. More specifically, this study investigates how two distinct dimensions of competition, competition from potential entrants and competition from existing rivals, influence the quantity and quality of profit- and investment-forecasts issued by a firm.

The motivations for this study are twofold. First, all theoretical studies modeling the relation between competition and voluntary disclosure are based on different assumptions about the nature of the competition, competition from potential entrants (Monopoly game) or competition from existing rivals (Duopoly or Oligopoly games), and the predicted relation is sensitive to the nature of competition (Verrecchia (2001); Healy and Palepu (2001)). For example, Darrough and Stoughton (1990) model competition in the context of an entry game (i.e. a game in which one firm contemplates manufacturing a product already produced by another firm) and find that greater competition encourages more disclosures. Alternatively, Verrecchia (1983) and Clinch and Verrecchia (1997) model competition in the context of a post-entry game (i.e. a game in which both firms are currently producing) and find that greater competition inhibits disclosure. Although these theoretical studies emphasize different dimensions of competition, this difference has been ignored in the empirical literature on competition and disclosure.

Second, existing empirical studies examining the relation between competition and voluntary disclosure face three limitations: (i) these studies exclusively focus on the quantity of disclosure, namely firms' decisions on whether or not to disclose a certain type of information, while other aspects, such as the extent and the accuracy of these disclosures, have not been explored. For example, Scott (1994) examines the disclosure decisions on defined benefit pension plans; Harris (1998) and Botosan and Stanford (2005) examine the disclosure decisions on segment information; Verrecchia and Weber (2006) investigate the decisions to redact proprietary information from the material contract filings; (ii) these studies are often based on a small sample of data limited to a specific industry or a certain type of disclosure. As a result, their findings may not be generalizable to the whole economy. For example, Bhojraj, Blacconiere, and D'Souza (2004) examine the disclosures on firms' strategies to protect the existing customer base and plans to exploit emerging opportunities in electric utilities industry; Guo, Lev, and Zhou (2004) examine the disclosures on product-related information in IPO prospectuses by biotech firms; (iii) these studies typically rely on disclosures provided in SEC filings, while those provided through other channels, such as analyst meetings, conferences and conference calls, have not been investigated (Healy and Palepu (2001)). For example, Clarkson, Kao, and Richardson (1994) examine disclosures in the MD&A section of the annual reports; the information on defined benefit pension plans examined in Scott (1994) and the information on business segments examined in Harris (1998) and Botosan and Stanford (2005) are also disclosed in annual reports. In contrast to existing studies, this paper provides a comprehensive investigation of the importance of competition in shaping firms' disclosure behavior based on a large sample of data and a common type of disclosure.

Prior literature suggests that disclosing more public information reduces a firm's cost of capital (Easley and O'Hara (2004); Lambert, Leuz, and Verrecchia (2007)). However, revealing too much information to existing or potential competitors can harm a firm's product market competitiveness. Moreover, existing theories on competition and disclosure show that the effect of competition on disclosure depends on the nature of the competition. By combining the predictions from existing theories, I initially derive empirically testable predictions for both the quantity and the quality of disclosure. With regard to the quantity, I hypothesize that holding the capital market incentives constant, competition from potential entrants increases disclosure quantity while competition from existing rivals decreases disclosure quantity. With regard to the quality of disclosure, I hypothesize that product market competition enhances the disclosure quality by correcting potential disclosure biases, such as over-reporting profits, which arise for capital market reasons when these disclosures are not immediately verifiable.

I test the trade-offs between capital market incentives and product market concerns by examining firms' voluntary disclosure decisions on future profits and investments. I use management forecasts on future earnings and capital expenditures as proxies for profit- and investment-forecasts, respectively. I focus on forecasts, rather than historical information, as disclosing forward-looking profits and investments reveals information on firms' strategic plans about future operations, which is invaluable to both capital markets and product markets. In addition, since forward-looking disclosures are protected by the "Safe Harbor" Provision, under which false ones are subject to less litigation risk, and the disclosure content is not immediately verifiable, the disclosure quality also reflects a firm's conflicting incentives.

To measure competition from potential entrants and competition from existing rivals separately, I employ two common factors extracted from several industry-level competition variables. I use the industry-pervasiveness of forecasting, measured as the ratio of forecasters to total number of firms in an industry, as the proxy for disclosure quantity and use the industry average forecasting accuracy as the proxy for disclosure quality.

The results support the empirical predictions. First, the industry-pervasiveness of issuing both profit- and investment-forecasts is positively associated with competition from potential entrants and negatively associated with competition from existing rivals. Second, there is a significant positive association between competition and forecasting accuracy, suggesting that competition enhances disclosure quality. In additional analysis, I find intra-industry differences in these results. In particular, the association between disclosure and competition is found to be less pronounced for industry leaders than for industry followers, which is consistent with the argument in prior literature that firms with greater market shares, namely industry leaders, typically face lower competition (Nickell, Wadhwani, and Wall (1992); Nickell (1996)). I also conduct analysis on competition and signed forecast errors and find that competition increases disclosure accuracy mainly through reducing the optimism in profit-forecasts and reducing the pessimism in investment-forecasts. Surprisingly, I find that competition from existing rivals is negatively associated with the accuracy of investment-forecasts for industry followers and further analysis on signed forecast errors suggests that the decreased accuracy arises from the increased pessimism in these investment-forecasts. One potential explanation for this result is that in highly competitive industries, the way for industry followers to survive is to cut their costs and reduce the scales (Wright (1986); Helms and Wright (1997)). Therefore, these firms may use excessive reduction of investments to signal effective cost-cutting.

This paper contributes to existing proprietary cost literature by proposing an alternative method to measure product market competition from various dimensions. I modify Karuna's (2007) method by constructing new variables characterizing the nature of competition. This approach enables me to test multiple theoretical models using a large sample of data covering various industries. Findings in this paper suggest that the association between competition and voluntary disclosure is sensitive to the nature of competition. Therefore, drawing conclusions based on only one dimension of competition might be misleading.

This paper also contributes to management forecast literature by identifying an important economic determinant for forecasting quantity and quality. Previous studies examining management forecasts often ignore industry incentives by including industry fixed-effects in their regressions.[1] Exploring inter-industry differences in forecasting behavior is important, given that firms within the same industry herd in their voluntary disclosure decisions (Dye and Sridhar (1995); Tse and Tucker (Forthcoming)). This paper also provides new evidence on the determinants of management investment-forecasts. Management forecasts other than profits have been largely overlooked in existing accounting research.[2] Examining investment-forecasts in addition to profit-forecasts is important for the following two reasons. First, investments and profits convey information reflecting different aspects of a firm's strategy. Profits, as a comprehensive measure of performance, reflect pricing, marketing, cost managing, and other operating strategies, while investments reflect a firm's strategies on production scheduling and scale. In addition, profit-forecasts and investment-forecasts convey information reflecting different operating horizons. Period-end profits are likely to be determined by current or short-run market demands, while investments are determined by long-run market demands. Therefore, including both types of forecasts in the analysis is a more comprehensive way to measure voluntary disclosure. Second, since actual earnings numbers are influenced by managerial incentives, the disclosure accuracy of management earnings-forecasts is also influenced by biases in actual earnings numbers (e.g.,

[1] The only exception is Rogers and Stocken (2005), who use Herfindahl-Hirschman Index as a proxy for industry concentration. However, as Karuna (2007) points out, industry concentration alone could be a poor proxy for competition due to endogeneity.

[2] To the best of my knowledge, Brown, Gordon, and Wermers (2006) and Jones and Cole (2008) are the only existing papers that study management forecasts on future capital expenditures.

Kasznik (1999)). In contrast, actual investments numbers are less likely to be manipulated by managers, thereby providing a cleaner setting to examine the impacts of product market incentives on the accuracy of management forecasts.

By documenting that product markets may provide disincentives as well as incentives for voluntary disclosure depending on the type of industry competition, this paper aims to emphasize the importance of understanding the multi-dimensional nature of product market competition in determining firms' voluntary disclosure behavior.

The rest of the paper is organized as follows. In Section 2, I review the theories and develop testable predictions. Section 3 describes the sample and data. Section 4 presents empirical models and results. In Section 5, I examine other forecasting behavior and conduct firm-level analysis. In Section 6, I investigate further the robustness of the results. Section 7 summarizes and concludes.

2 Theories and Hypothesis Development

The decision to voluntarily disclose proprietary information is a strategic choice. After new information arrives, the firm needs to decide whether or not to disclose it to the public. Once it has decided to disclose, the firm must also decide on the accuracy of the disclosure. I define the former as the decision on disclosure quantity and the latter as the decision on disclosure quality. These two disclosure decisions are determined by the trade-offs between capital market incentives and product market concerns. The capital market incentive is to reduce the cost of capital or to increase firm valuation and the product market concern is that disclosures in favor of capital markets may adversely affect a firm's competitive position in product markets. Firms generally face two distinctive dimensions of competition in a product market: the threat from potential entrants, whose entry to the market has adverse effects on the incumbent's profits, and the rivalry from firms already producing the same type of goods, whose strategic moves may jeopardize the incumbent's market position. I define the former as potential competition and the latter as existing competition.

For potential entrants, the entry decision depends on the entry costs relative to expected future benefits after entry, while for existing rivals, as entry costs are sunk costs, the production decision mainly depends on the expected future benefits. Therefore, these two dimensions of competition are likely to have different impacts on the incumbent's disclosure decision. In the following subsections, I discuss in detail how potential and existing competition affects firms' voluntary disclosure decisions and provide testable predictions on the association between competition and the quantity and quality of disclosure.

2.1 Competition and Disclosure Quantity

In the realm of financial reporting, all information, both public and private, is disclosed to capital markets in absence of associated costs, as rational investors presume that management has private information about the firm's operation and has incentive to withhold bad news (Grossman and Hart (1980); Grossman (1981); Milgrom (1981)). However, with the existence of proprietary costs associated with disclosing private information, partial-disclosure equilibrium could be achieved, as investors are unsure whether withholding information is due to bad news or due to the costs associated with disclosing good news (Verrecchia (2001)).[3] Such costs come from competitors, whose strategic responses to good news may damage the incumbent's competitive position in product markets. Theories suggest that, in equilibrium, whether competition encourages or discourages disclosure depends on whether the competitive threat comes from potential entrants or from existing rivals.

Competition from Potential Entrants

Theories predict that competition from potential entrants encourages more voluntary disclosures. The intuition underlying this prediction is as follows. When the costs of entry are high and the potential entrant will not enter the product market unless receiving very favorable information (i.e. competition from potential entrants is low), the incumbent could effectively deter entry through withholding information. In this case, although investors have rational expectations, they could not tell the type of the incumbent, as both bad news firms and good news firms have incentives to withhold. One the other hand, when the costs of entry are low and the potential entrant will enter the product market unless receiving very

[3] Dye (1985) and Jung and Kwon (1988) argue that partial-disclosure could also be achieved if investors are unsure about the manager's endowment of private information.

unfavorable information (i.e. competition from potential entrants is high), the incumbent cannot do much to deter entry and all information is disclosed.

The above issue has been addressed in several theoretical studies. For example, Darrough and Stoughton (1990) model a binary entry game consisting of two players, the incumbent and the potential entrant, and two markets, the product market and the capital market. They assume that the incumbent is endowed with private information which is valuable to both capital and product markets. Disclosing favorable information increases the incumbent's valuation in the capital market, but also encourages the potential entrant to enter the product market, which imposes proprietary costs on the incumbent. Both the capital market and the potential entrant have rational expectations about the incumbent's disclosure behavior. Therefore, when the entry costs are low, there exists a full-disclosure equilibrium, in which both bad news and good news are disclosed. Bad news is disclosed to deter entry and good news is also disclosed, because non-disclosure would be interpreted by the entrant as withholding good news. When the entry costs are high, there exists a mixed-strategy partial-disclosure equilibrium, in which good news is withheld and bad news is randomly disclosed and entry is also random. Wagenhofer (1990) models a continuous entry game and finds similar results: there exists a partial-disclosure equilibrium when the entry costs are higher than the expected benefits and full-disclosure is triggered when the entry costs are low.

The first testable prediction in this paper is stated as follows:

H1A: Competition from potential entrants is positively associated with disclosure quantity.

Competition from Existing Rivals

Theories predict that competition from existing rivals discourages voluntary disclosure. The intuition is as follows. Unlike in the case of entry, established properties and equipments are sunk costs to existing rivals, whose production schedules mainly depend on the expected future demands. Disclosing information indicating higher future demands encourages existing rivals to overproduce and thereby adversely affects the incumbent's future profits. Therefore, some favorable information is withheld by the incumbent to avoid such proprietary costs and partial-disclosure is achieved in equilibrium.

For example, Clinch and Verrecchia (1997) model a post entry Duopoly game, in which firms competing in the product market are endowed with private information about aggregate future demands. Since high demands stimulate overproduction across firms whereas low demands curtail production, well-informed firms are inclined to withhold evidence of high demands in order to exploit underproduction by their competitors and disclose evidence of low demands to discourage production. However, the uninformed firms have rational expectations and can make correct inferences from nondisclosure. In equilibrium, informed firms always voluntarily disclose some realizations of their signals, but choose to withhold information indicating either very high or very low future demands. In each of these cases, informed firms prefer to hide their knowledge in order to exploit incorrect production decisions made by the uninformed competitors. The model also shows that both the range of the disclosure interval and the *ex ante* disclosure probability of an informed firm decrease as the level of competition increases.

Verrecchia (1983) also models competition among existing rivals and voluntary disclosure. He finds that there exists a unique partial-disclosure equilibrium and the proprietary costs are positively associated with the threshold level of disclosure.[4] He interprets this finding as "the disclose-related costs introduce noise by extending the range of possible interpretations of withheld information to include news which is actually favorable".

The above models generate the following testable prediction:

H1B: Competition from existing rivals is negatively associated with disclosure quantity.

2.2 Competition and Disclosure Quality

Once the decision to disclose proprietary information is made, firms must then decide on the disclosure accuracy. When disclosed information is not immediately verifiable, the disclosure setting becomes a "cheap-talk" game, where the credibility of the incumbent's message arises endogenously from other players' usage of it. Firms may prefer to provide the most favorable information to the capital market and the least favorable information to the product market. Theories show that when the capital market and the product market operate in isolation,

[4]In other words, the news needs to be favorable enough in order to be disclosed.

there is no truthful disclosure (Gigler (1994); Evans and Sridhar (2002)). But when these two markets use the same disclosures, the offsetting demands could potentially enhance the disclosure quality. For example, to raise the valuation, firms may overstate their profitability to the capital market. However, the concern that bright prospects may induce competitors to overproduce prevents firms from disclosing overly optimistic information and increases the disclosure quality (see Evans and Sridhar (2002) for an entry game and Gigler (1994) for a post entry game).

The above argument implies a positive association between both dimensions of competition and disclosure quality. Hence, the formed hypotheses, written separately for each dimension of competition, are as follows:

H2A: Competition from potential entrants is positively associated with disclosure quality.

H2B: Competition from existing rivals is positively associated with disclosure quality.

3 Measures and Data

In this section, I discuss in detail the measures for product market competition and voluntary disclosure, as well as their data sources.

3.1 Measures of Product Market Competition

I construct variables to separately measure competition from potential entrants and competition from existing rivals by conducting Principal Component Analysis on commonly employed proxies of competition. The most widely used proxy for competition is industry concentration, measured as Herfindahl-Hirschman Index (IND-HHI) or four-firm concentration ratio (IND-CON4). Karuna (2007) suggests three determinants of industry competition: industry PP&E, product market size and price-cost margin. Industry PP&E (IND-PPE) is calculated as the weighted average of PP&E for all firms operating in the same industry and measures the minimum investments required to enter the market. Product market size (IND-MKTS) is measured as the natural log of aggregate industry sales. Price-cost margin

(IND-MGN) is calculated as industry aggregate sales divided by industry aggregate operating costs or the negative reciprocal of price-demand elasticity. I also use industry research and development intensity (IND-R&D), calculated as the weighted average of R&D for all firms in an industry, industry capital expenditures (IND-CPX), calculated as the weighted average of capital expenditures for all firms in an industry, total number of firms operating in an industry (IND-NUM), and industry return on assets (IND-ROA), calculated as industry aggregate EBITDA divided by industry aggregate total assets, as additional measures for competition.[5]

Although the above nine proxies for competition are interrelated, they also characterize different factors related to competition. Based on the aspect of competition that they are most closely related to, these proxies could be categorized into the following three groups:

1) *Proxies for competition from potential entrants:* Industry-average size of plants and equipments (IND-PPE) is widely used to measure the setup costs for a new player to enter the product market (see Chapter 4 of Sutton (1991) for a discussion). Since industry-average R&D outlays (IND-R&D) and capital expenditures (IND-CPX) also reflect necessary investments for potential entrants to make in order to compete with existing rivals, they are also likely to be positively related with entry barrier.[6] Product market size (IND-MKTS) is likely to be negatively associated with potential competition. First, large market size is usually associated with high entry barrier, as industries with large sales are usually associated with heavy investments in either PP&E (to increase volume) or technology (to increase price). Second, entry is also less harmful to the incumbent operating in a product market with higher demand. For example, Nakao (1980) find that when the demand growth is sufficiently large, the established firm will choose to raise price above the entry-preventing level, accepting a decrease in its market share caused by entry of a successive finite number of new firms.

2) *Proxies for competition from existing rivals:* The variables related to industry concentration, namely IND-CON4, IND-HHI and IND-NUM, capture competition amongst existing rivals, as highly concentrated industries or industries with fewer existing firms typically face lower existing competition. Product market size (IND-MKTS) is also likely to be positively

[5] Using equally-weighted PP&E, capital expenditures and R&D in the analysis does not change the results.

[6] For example, Sutton (1991) regards R&D outlays as endogenous sunk costs firms incur at stage 1 in order to enhance the demand for their products at stage 2. In contrast, setup costs are regarded as exogenous sunk costs at stage 1.

associated with existing competition. First, aggregate sales are positively associated with the number of firms in the market. Second, large market demand attracts more entrants, which would in turn lead to more firms competing in the same product market (Sutton (1991)).

3) *Industry profitability:* The industry profitability measures, IND-MGN and IND-ROA, are likely to reflect the effects of product differentiation or equivalently, the lack of substitute products. This group of measures complements the above two dimensions of competition, as it may potentially influence firms' responses to competition. For example, Shaked and Sutton (1982) argue that high product differentiation relaxes price competition and Bresnahan (1989) argues that firms respond less to competitive moves by rivals when their products are more distinct. Since profitability reflects the perceived benefits of entering the market, it is also an important factor for potential entrants to consider (Darrough and Stoughton (1990); Newman and Sansing (1993)). Empirical studies also regard profitability as positively associated with proprietary costs, as high profits attract entrants (Scott (1994); Harris (1998)). Therefore, it is necessary to control for the industry profitability when analyzing competition structure. However, the association between industry profitability and competition is ambiguous, as high profitability could indicate either more competition from potential entrants or less competition from existing rivals.

To reduce the number of variables employed in the regressions, but still capture the various effects of competition, I conduct Principal Component Analysis on the above nine variables. After using orthogonal rotation method and requiring eigenvalues to be greater than one, I retain three components. The results of Principal Component Analysis are reported in Table 1. Panel A shows that the first three principal components have eigenvalues greater than one and account for approximately 75% of the total variance. Consistent with the prior that these nine variables are categorized into three groups, the rotated factor pattern reported in Panel B suggests that PC1 is loaded by IND-MKTS, IND-CON4, IND-HHI and IND-NUM, that PC2 is loaded by IND-PPE, IND-R&D, IND-CPX, and IND-MKTS, and that PC3 is loaded by IND-MGN and IND-ROA. Therefore, PC1, PC2 and PC3 measure competition from existing rivals, competition from potential entrants and industry profitability, respectively. The standardized scoring coefficients of each variable are reported in Panel C.[7] In the following analysis, I use the inverse of PC1, denoted as EXIST-COMP, to

[7]Note that to compute the value of principal components, original variables are standardized. Therefore,

measure competition from existing rivals, the inverse of PC2, denoted as POTENT-COMP, to measure competition from potential entrants, and PC3, denoted as IND-PROFIT, to measure industry profitability. Larger values of EXIST-COMP, POTENT-COMP and IND-PROFIT suggest higher competition from existing rivals, higher competition from potential entrants and higher industry profitability, respectively.

Data for Competition Measures

The data used to calculate competition measures are obtained from Segments database and Fundamentals Annual database of Compustat North America. In U.S, *SFAS No. 14* requires multi-industry firms to disclose revenues, operating profits, identifiable assets, depreciation and amortization, research and development and capital expenditures for their significant industry segments. Therefore, using segment-level data to measure competition is a more accurate way than using firm-level data.[8] A detailed description of the methodology is included in Appendix B.

Table 2 reports descriptive statistics for competition variables used in Principal Component Analysis. The sample consists of 27,053 industry-years, spanning the period from 1977 to 2007. Panel A presents summary statistics. The sample shows considerable variance for all variables. Panel B presents correlation matrix. Within each group, variables are highly correlated with each other, while across groups, the correlations are relatively low. The last three rows present correlations between principal components and raw competition variables. Again, the correlation pattern is consistent with categorizing competition proxies into

principal components could have negative values.

[8] Ali, Klasa, and Yeung (2009) argue that Compustat-based industry concentration measures are subject to measurement error problem, as most of the private firms are not covered by Compustat and high Compustat-based concentration ratio is likely to be due to the declining of the industry, which is left with only a few large, public firms relative to private firms. Alternatively, they suggest that researchers should use concentration ratios from US Census data. In this paper, I choose to use Compustat concentration measures for the following reasons. First, the US Census measure of concentration is only available for the year 2002 of my sample period and only available for manufacturing industries. Hence, using US Census data would largely reduce the sample size, thereby contradicting the aim of this paper to provide large sample evidence. Second, using Compustat-based concentration measure in this paper is a conservative approach. Previous literature suggests that firms with poor performance usually provide less voluntary disclosures (Miller (2002); Kothari, Shu, and Wysocki (2009)). Therefore, if the Compustat-based concentration ratio is capturing the declining of the industry, using it will work against me finding the results for **H1B** that existing competition (industry concentration) is negatively (positively) associated disclosure quantity. Nevertheless, I further address the measurement error problem with Compustat-based competition measures in the robustness analysis by using Exploratory Factor Analysis.

three groups based on their relation to competition. Consistent with the findings in Karuna (2007), IND-MKTS is both positively correlated with IND-PPE and negatively correlated with IND-CON4. A potential explanation for the positive association between product market size and industry-average PP&E is that product market size is measured by aggregating sales and large capacity is usually achieved by heavy investments in plants and machineries. The negative association between product market size and industry concentration could be explained as the expansion in product market size attracting entry, which leads to a fall in concentration (e.g., Philips (1976); Sutton (1991)).

3.2 Measures of Disclosure

I use management forecasts on future earnings and capital expenditures as proxies for voluntary disclosures on future profits and investments. Therefore, throughout the paper, these two types of management forecasts are referred to as profit-forecasts and investment-forecasts, respectively. Focusing on management forecasts has the following advantages. First, it enables me to conduct more powerful tests on the extent of voluntary disclosure, as the precise disclosure time is known and the *ex post* accuracy of management forecasts can be measured through the actual realizations of earnings or capital expenditures (Healy and Palepu (2001)). Also, as management forecasts are not verifiable at the time when they are issued and because of Safe Harbor Provision, false forecasts are subject to less litigation risk compared with other types of disclosure, managers may strategically bias their forecasts.[9] Therefore, focusing on management forecasts enables me to test theoretical models that consider the credibility of disclosure (Verrecchia (2001)). Lastly, proprietary costs associated with management forecasts increase with time, as the information is less valuable when the forecasting date approaches the actual announcement date. This attribute is in line with the assumptions made in theoretical models. For example, Verrecchia (1983) argues that proprietary costs can be viewed as a function of time: as time approaches zero, proprietary costs associated with disclosing private information decrease. In this paper, I focus on annual forecasts, as annual forecasts typically allow a longer time horizon for rival firms to respond

[9]Under Safe Harbor, it is more difficult to prove the defendant guilty, because plaintiffs must identify the specific statement or statements that are misleading when they file the lawsuit rather than undertaking a "fishing expedition" for supporting documentation during the discovery process (Johnson, Kasznik, and Nelson (2001)).

strategically.

In order to use management forecasts as the proxy for voluntary disclosure to test the above hypotheses, I make the following assumptions in the empirical tests. First, to test **H1A** and **H1B**, I assume that management forecasts are generally truthful, in the sense that managers do not distort the sign of the news in their forecasts, as "truthful disclosure" is an explicit assumption underlying all the theoretical studies modeling the relation between competition and disclosure quantity. Considering the high litigation risk associated with hiding bade news (Skinner (1994)), assuming that managers are unlikely to lie about the sign of the news is not unreasonable. Second, to test **H2A** and **H2B**, I assume that managers might strategically bias their forecasts, as "cheap-talk" is an assumption underlying the models studying competition and disclosure quality. This assumption is in line with previous studies examining the credibility of management earnings forecasts (e.g., Rogers and Stocken (2005)). Below is an example illustrating how these two assumptions work together in this paper. A manager forecasts next year's earnings per share to be $1 higher, when in fact he knows that the actual earnings per share would be only $0.5 higher. The fact that the manager discloses good news (higher earnings) is captured by the measure of disclosure quantity and the fact that the manager exaggerates the good news by $0.5 is captured by the measure of disclosure quality.

To be consistent with the competition measures, the primary measures for disclosure quantity and quality are also computed at the industry level. I use the industry-pervasiveness of forecasts, defined as the percentage of forecasters in an industry (FORECASTER%), to measure disclosure quantity. A firm is identified as a forecaster if it issues at least one forecast for the subsequent fiscal year-end. Higher percentage of forecasters indicates higher disclosure quantity. I use the *ex post* forecasting accuracy to measure disclosure quality. A firm's forecasting accuracy is defined as:

$$ACCURACY = - \mid \frac{\text{Actual value - Forecasted value}}{\text{Market value of equity}} \mid,$$

where larger value of ACCURACY indicates higher forecasting accuracy. To be consistent with previous literature, the earliest point or range forecast is used for the calculation of forecasting accuracy for each firm-year (Rogers and Stocken (2005); Johnson, Kasznik, and Nelson (2001)). Disclosure quality is measured as the average forecasting accuracy across all firms in an industry. Higher forecasting accuracy indicates higher disclosure quality.

Data for Disclosure Measures

The data for profit-forecasts are obtained from First Call database. The data for investment-forecasts are manually collected from Factiva.[10] Examples of investment-forecasts are illustrated in Appendix C.

3.3 Sample and Descriptive Statistics

I start from the sample with valid competition measures as described in Appendix B and delete industries with less than three member firms.[11] As in Karuna (2007), I delete observations with a zero value for the fourth digit of SIC code to avoid ambiguity in the industry classification. I further restrict the sample to the coverage of First Call database and require sufficient data to compute control variables.[12] Since First Call started systematically expanding its coverage in 1998 (Anilowski, Feng, and Skinner (2007)), 1998 is the starting year for my sample period. Finally, all continuous variables are winsorized at the bottom and top one percentile levels.

For profit-forecasts, the disclosure quantity sample consists of 21,033 firm-year observations covering 3,649 industry-years and the disclosure quality sample consists of 5,268 firm-year observations covering 1,987 industry-years over the period 1998 to 2006.

Investment-forecast sample is constructed by following the procedures described above. Since financial firms generally do not have or have few capital expenditures, I eliminate

[10] Management forecasts are mainly issued through conference calls, conferences, analyst meetings, shareholders presentations and press releases. To obtain information about management investment-forecasts, I first use key words to search in Factiva and download all output articles. The search period starts 24 months before the forecasting fiscal year-end. Then, I use Perl to extract relevant information from downloaded articles. Finally, I manually read and code the extracted information.

[11] The purpose of this data requirement is to have meaningful industry-average measures. Nevertheless, the results are not sensitive to this data requirement (unreported).

[12] Two possible reasons may cause the data on management forecasts to be missing: (1) the firm did not issue any forecast; (2) the firm was outside the coverage of First Call database, which primarily covers only firms followed by analysts (Anilowski, Feng, and Skinner (2007)). I, therefore, limit the sample to firms that have data available on analyst estimates. In other words, a firm with missing data on management forecasts is regarded as a non-forecaster only if it has non-missing data on analyst estimates. Firm-years that are not covered by analysts are excluded from the sample.

financial industries in the investment-forecast sample (SIC code from 6000 to 6999). To further facilitate the data collection process, I limit the sample to firms with fiscal year ending in December. I collect data on management forecasts on next year's capital expenditures for the years from 2001 to 2005. For these forecasts, the disclosure quantity sample consists of 6,252 firm-year observations covering 1,105 industry-years and the disclosure quality sample consists of 2,508 firm-year observations covering 811 industry-years.

Table 3 presents the number of sample firms, the number of forecasters, as well as the percentage of forecasters by year for profit-, investment- and profit-&investment-forecast samples, respectively. For profit-forecasts, the percentage of forecasters is increasing monotonically until 2003, probably due to the passage of SEC Regulation Fair Disclosure (Reg FD). On average, firms issue more investment-forecasts than profit-forecasts: the average percentage of forecasters in an industry is 42.30% for the investment-forecast sample, compared with 34.96% for the profit-forecast sample. On average, only 20.69% of firms in an industry issue both profit- and investment-forecasts.

Summary statistics for selected variables used in the regressions are presented in Table 4. Panel A reports the statistics for disclosure quantity sample, which consists of 21,033 firm-years for profit-forecast sample and 6,252 firm-years for investment-forecast sample. Consistent with the findings in Table 3, on average, around 35% of firms in the sample issue profit-forecasts and around 42.3% issue investment-forecasts. Compared with the statistics reported in Table 2, firms in the final sample come from industries with lower competition from potential entrants and higher competition from existing rivals, indicating that First Call analysts tend to follow firms from more established industries. Firm characteristics are generally comparable across the profit-forecast sample and the investment-forecast sample, except that the latter contains slightly larger firms. This panel also presents differences in the means across non-forecaster and forecaster groups, where a firm-year is classified as a forecaster if it issues at least one forecast for the subsequent fiscal year-end. The results also suggest that forecasters are more likely to cluster in industries with higher competition from potential entrants and lower competition from existing rivals, consistent with the predictions of **H1A** and **H1B**. Forecasters are also characterized with larger firm size, lower market-to-book ratio, higher leverage, more analysts following and higher institutional ownership.

Panel B reports the statistics for disclosure quality sample, including 5,268 firm-years for profit-forecast sample and 2,508 firm-years for investment-forecast sample. The average forecasting accuracy (ACCURACY) and forecasting surprise (SURPRS) are comparable to the average forecast error (FE) and forecasting news (FN) reported in Rogers and Stocken (2005).[13] Compared with disclosure quantity sample, disclosure quality sample is characterized with higher competition from potential entrants, lower competition from existing rivals, larger firm size, higher leverage ratio, more analysts following and higher institutional ownership. The earliest profit- and investment-forecasts are issued roughly 300 days before the forecasting period end. Average profit-forecasts convey bad news (SURPRS<0), while average investment-forecasts generally convey good news (SURPRS>0).

Table 5 lists industries and their two-digit SIC codes sorted into deciles by competition measures. Industries, such as railroad transportation (two-digit SIC 40), tobacco products (SIC 21), and general merchandize stores (SIC 53), face the lowest competition from potential entrants, while services industries, such as educational services (SIC 82), social services (SIC 83) and engineering, accounting, research, management, and related services (SIC 87) face the highest competition from potential entrants; mining industries, such as metal mining (SIC 10), coal mining (SIC 12) and mining and quarrying of nonmetallic minerals, except fuels (SIC 14) face lowest competition from existing rivals, while financial industries (SIC 62, 63, 64, and 65) and restaurant industries (SIC 58) face the highest competition from existing rivals. This table also presents the average percentage of forecasters in each competition decile. The relation between POTENT-COMP or EXIST-COMP and the percentage of forecasters is non-monotonic, probably due to the fact that capital market incentives are not controlled in this analysis. Nevertheless, in profit-forecast sample (Panel A), industries in the lowest decile of POTENT-COMP and in the highest decile of EXIST-COMP have the lowest percentages of forecasters. In contrast, in investment-forecast sample (Panel B), industries in the top two deciles of POTENT-COMP and in the bottom two deciles of EXIST-COMP have the lowest percentages of forecasters, probably due to the fact that industries, like forestry (SIC 8) and personal services (SIC 72) have few capital expenditures.

[13]Note that the numbers for ACCURACY and SURPRS in this paper are multiplied by 100.

4 Empirical Results

4.1 Competition and Disclosure Quantity

I use the following OLS regression to examine the impacts of competition on disclosure quantity.

$$\begin{aligned}\text{FORECASTER}_{jt}\% &= \alpha_1\text{POTENT-COMP}_{jt} + \alpha_2\text{EXIST-COMP}_{jt} + \alpha_3\text{IND-PROFIT}_{jt} \\ &+ \text{Capital Market Incentives} + \text{Litigation Risk} + \text{Year Dummies} \quad (1)\end{aligned}$$

This regression is estimated at the industry-year level, where j denotes industry and t denotes year. The dependent variable is the percentage of forecasters in industry j at year t, and the main independent variables of interest are POTENT-COMP_{jt} and EXIST-COMP_{jt}, measuring competition from potential entrants and competition from existing rivals for industry j at year t, respectively. All firm-level control variables are averaged within each industry-year. Since forecasting behavior is likely to be correlated across time, the standard errors are adjusted for Newey-West heteroscedasticity and autocorrelation.[14]

As discussed above, it is necessary to control for industry profitability (IND-PROFIT) when analyzing the impacts of competition on disclosure, because profitability is an important factor affecting firms' responses towards competitive threats.

I also control for a variety of capital market incentives in the regression. Since firms are likely to disclose more information before accessing capital markets in order to reduce their cost of capital (Frankel, McNichols, and Wilson (1995)), I control for the external financing needs by including a dummy variable ISSUE equal to one if the firm issues public equity or debt in a subsequent two-year period. Firm size (SIZE) is generally regarded as positively associated with management forecasts, as the costs of issuing forecasts are lower for big firms (Lev and Penman (1989); Frankel, McNichols, and Wilson (1995); Baginski and Hassell (1997)). I use the natural log of market value of equity at fiscal year-end to measure firm size. Due to the forecasting difficulty, firms with higher growth rate or higher earnings/capital expenditures volatility are less likely to issue management forecasts on future earnings/capital expenditures (see Bamber and Cheon (1998) and Rogers and

[14]The results are qualitatively similar but with lower statistical significance if the standard errors are clustered at industry-level, due to the small degrees of freedom for industry-level regressions.

Stocken (2005) for the former and Waymire (1985) for the latter). Therefore, I use market-to-book ratio (MTB) and standard deviation of earnings/capital expenditures over a five-year period prior to the forecast year (STDEV) to control for growth opportunities and earnings/capital expenditures volatility, respectively.

Dye (1985) and Jung and Kwon (1988) argue that when investors are unsure about managers' information endowment, managers are able to withhold even nonproprietary information. Therefore, including the historical earnings/capital expenditures volatility (STDEV) in the regression also controls for managers' ability to possess forward-looking information, as future profits and investments are more difficult to be predicted for firms operating in more volatile businesses.

Theoretical models of capital structure and product market competition suggest that leverage softens the extent of product market competition (Fudenberg and Tirole (1986); Fudenberg and Tirole (1990)). This argument has also been supported by empirical evidence (Chevalier (1995)). Hence, I control for capital structure by including leverage ratio (LEV) in the regression. In addition, Ajinkya, Bhojraj, and Sengupta (2005) argue that institutional ownership also affects firms' voluntary disclosure decisions and Bhojraj, Blacconiere, and D'Souza (2004) use the percentage of institutional ownership to control for capital market incentive. Lang and Lundholm (1993) find that the level of disclosure is positively associated with the analyst coverage. Ajinkya and Gift (1984) find that managers issue forecasts to avoid large earnings change. Therefore, I also include the percentage of institutional ownership (SHRINST), the number of analysts following (ANALYST), the magnitude of earnings/capital expenditures change (ABSCH) and the sign of earnings/capital expenditures change (DCH) as additional controls in the regressions. Institutional ownership also controls for corporate governance, as institutional investors are generally regarded as active monitors. Cotter, Tuna, and Wysocki (2006) argue that managers may issue earnings forecasts to "walk-down" optimistic analyst estimations. Therefore, I control for the analyst optimism (OPTM) in the profit-forecast regression.

Besides capital market incentives, litigation risk might be also a determinant factor for voluntary disclosure. For example, Skinner (1994), among others, argues that a firm issues earnings forecasts, especially bad news forecasts, to mitigate its litigation risk. Therefore, riskier firms are more likely to issue management forecasts. I control for the litigation risk by including a dummy LIT equal to one if a firm operates in an industry facing high litigation risk. I also include year dummies in the regression to control for year-fixed effects. A detailed description of the above control variables is included in Appendix A.

Regression results for Equation (1) are reported under Column "FORECASTER%" in Table 6. Consistent with the predictions that competition from potential entrants encourages disclosure (**H1A**) and competition from existing rivals discourages disclosure (**H1B**), the coefficient on POTENT-COMP is positive and the coefficient on EXIST-COMP is negative, both significant at the 1% level. The above associations are also economically significant. For example, the coefficient of -0.045 on EXIST-COMP in the profit-forecast regression indicates that when competition from existing rivals increases by one standard deviation (1.252), the percentage of profit-forecasters in an industry decreases by 5.6% in absolute value or 16.1% relative to the sample mean; the coefficient of 0.033 on POTENT-COMP in the investment-forecast regression indicates that when competition from potential entrants increases by one standard deviation (2.322), the percentage of investment-forecasters in an industry decreases by 7.7% in absolute value or 18.1% relative to the sample mean.

The coefficients on control variables are generally consistent with prior studies. For example, industries with larger size, higher leverage ratios, larger numbers of analysts following, higher institutional ownership and higher litigation risk have larger percentages of firms issuing forecasts. The negative and significant coefficients on STDEV and ABSCH in the profit-forecast regression are consistent with the forecasting difficulty argument that firms operating in volatile businesses are less likely to issue forecasts on future profits. Similarly, the negative coefficient on MTB in the investment-forecast regression also indicates that growth firms are less likely to issue forecasts on future investments. In contrast, the coefficient on ABSCH in investment-forecast regression is positive, indicating that larger changes in capital expenditures encourage firms to issue more investment-forecasts, probably to avoid surprises in the change of investment plans.

4.2 Competition and Disclosure Quality

Next, I use the following OLS regression to examine the impacts of competition on disclosure quality.

$$\begin{aligned}\text{ACCURACY}_{jt} &= \alpha_1\text{POTENT-COMP}_{jt} + \alpha_2\text{EXIST-COMP}_{jt} + \alpha_3\text{IND-PROFIT}_{jt} \\ &+ \text{Capital Market Incentives} + \text{Litigation Risk} + \text{Year Dummies} \qquad (2)\end{aligned}$$

This regression is estimated at industry-year level, where j denotes industry and t denotes year. The dependent variable is the average forecasting accuracy for industry j at year t, and the main independent variables of interest are POTENT-COMP$_{jt}$ and EXIST-COMP$_{jt}$, measuring competition from potential entrants and competition from existing rivals for industry j at year t, respectively. All firm-level control variables are averaged within each industry-year. Since forecasting behavior is likely to be correlated across time, the standard errors are adjusted for Newey-West heteroscedasticity and autocorrelation.[15]

Similar to the disclosure quantity analysis, I control for industry profitability (IND-PROFIT), capital market incentives, litigation risk and year fixed-effects in the regression. Previous studies identify external financing, firm size, growth opportunities, number of analysts following and institutional ownership as capital market incentives that influence disclosure quality (e.g., Johnson, Kasznik, and Nelson (2001); Rogers and Stocken (2005)). In addition, historical volatility (STDEV), forecasting horizon (HORIZ) and forecasting news (SURPRS) are also likely to influence forecasting accuracy (e.g., Anilowski, Feng, and Skinner (2007); McNichols (1989)). Therefore, the above variables are included as additional controls in the regression.

Furthermore, investors' ability to assess the truthfulness of forecasts and earnings management may also influence the accuracy of earnings forecasts (see Rogers and Stocken (2005) for the former and Kasznik (1999) for the latter). Therefore, I include the standard deviation of analyst estimations prior to the management forecast (DIFFI), stock return volatility (STDRET) and discretionary accruals (DACCR) as additional controls in the profit-forecast regression. DIFFI and STDRET are expected to be negatively related to investors' ability to assess the credibility of forecasts and DACCR is expected to be positively associated with

[15]The results are qualitatively similar but with lower statistical significance if the standard errors are clustered at industry-level, due to the small degrees of freedom for industry-level regressions.

earnings management. A detailed description of the above variables is included in Appendix A.

Regression results are reported under Column "ACCURACY" in Table 6. For both profit- and investment-forecasts, the coefficients on POTENT-COMP are positive and significant at the 1% level, consistent with the hypothesis that competition from potential entrants increases disclosure quality (**H2A**). For profit-forecasts, the positive coefficient on EXIST-COMP is consistent with the prediction in **H2B** that competition from existing rivals increases disclosure quality. However, for investment-forecasts, the coefficient on EXIST-COMP is not different from zero, suggesting that competition from existing rivals has no impact on the accuracy of investment-forecasts for the *average* firm in an industry. I leave the interpretation of this result to the next section, where I further explore the intra-industry differences in competition and conduct the regression analysis at firm level.

The coefficients on control variables suggest that firms in industries with larger size, higher growth opportunities and lower leverage ratios issue more accurate forecasts and forecasts issued with longer horizons are less accurate. Consistent with findings in Rogers and Stocken (2005) and Kasznik (1999), investors' ability to assess the truthfulness of forecasts and earnings management increase the *ex post* accuracy of profit-forecasts. In addition, I also find that historical volatility of capital expenditures and industry profitability significantly reduce the accuracy of investment-forecasts.

5 Additional Analysis

5.1 Other Forecasting Behavior

In this section, I conduct additional analysis to further explore the impacts of product market competition on management forecasting behavior, including forecasting frequency, forecasting type and forecasting horizon.

Forecasting Frequency

In Equation (1), a firm is treated as a forecaster if it issues at least one forecast for the subsequent fiscal year-end and disclosure quantity is measured as the percentage of forecasters in an industry. In this way, firms issuing multiple forecasts per year are treated in the same way as those issuing only one. However, it is likely that firms reveal more information by frequently updating their forecasts. Therefore, to take into account the extra information contained in updated forecasts, I use forecasting frequency, defined as the total number of forecasts issued by a firm-year, as an alternative measure for disclosure quantity. The distributional statistics of forecasting frequency are reported in Panel A of Table 7. For both profit- and investment-forecasts, the majority of forecasters issue multiple forecasts per year. Although a firm is more likely to issue at least one investment-forecast in a certain year, it updates profit-forecasts more frequently, consistent with the finding in Table 4 that the mean value of NUM-FOR is higher for the profit-forecast sample.

The regression results of competition on forecasting frequency are reported in Table 8 under Column "Frequency". The dependant variable is forecasting frequency averaged across firms within each industry-year. The results are similar to those reported in Table 6, suggesting that competition from potential entrants encourages firms to issue forecasts more frequently while competition from existing rivals reduces forecasting frequency.

Forecasting Type

In Equation (1), I treat point, range and qualitative forecasts alike. However, forecasters may also strategically choose their forecasting type. For example, Verrecchia (2001) argues that "the manager may vaguely claim that the firm is expected to have earnings of at least $1 per share when in fact she expects earnings to be exactly $1 per share." To take into account the extra information contained in more precise forecasts, I assign a numeric score to each type of forecast, i.e. 4 for point forecasts, 3 for close range forecasts, 2 for open-end forecasts, 1 for qualitative forecasts and 0 for non-forecasters. A higher score suggests that more precise information is disclosed. If a firm issues multiple forecasts per year, the score of the earliest one is used. The distributional statistics of forecasting type are reported in Panel B of Table 7. For both profit- and investment-forecasts, the majority are issued in the format of close range or point. Compared with profit-forecasts, investment-forecasts are more likely to be point ones, probably because managers are more certain about future investments than future profits.

The regression results of competition on forecasting type are reported in Table 8 under Column "Type". The dependent variable is forecasting type averaged across firms within each industry-year. The results are similar to those reported in Table 6, suggesting that competition from potential entrants encourages more precise forecasts while competition from existing rivals reduces forecast precision.

Forecasting Horizon

As the information contained in management forecasts is more valuable if disclosed earlier, forecasting horizon may also reflect a firm's strategic choice. In this section, I examine how competition affects firms' forecasting horizon. Forecasting horizon is defined as the difference between the forecasting date and the forecasting fiscal year-end divided by 100. If a firm issues multiple forecasts per year, the date of the earliest one is used. For non-forecasters, forecasting horizon is set to be 0, as the information on profits and investments is revealed once financial statements become public. Panel C of Table 7 presents the distributional statistics for forecasting horizon. For both profit- and investment-forecasts, most firms issue their forecasts approximately one year in advance.

The regression results of competition on forecasting horizon are reported in Table 8 under Column "Horizon". The dependant variable is forecasting horizon averaged across firms within each industry-year. The results are similar to those reported in Table 6, suggesting that competition from potential entrants encourages firms to forecast early while competition from existing rivals delays forecasts.

The above analyses suggest that product market competition not only affects a firm's decision on whether or not to disclose, but also affects the decisions on how often, what and when to disclose. Results suggest that, consistent with the hypotheses on disclosure quantity, competition from potential entrants encourages firms to forecast more frequently, more precisely and earlier, while competition from existing rivals reduces forecasting frequency, precision and horizon.

5.2 Firm-level Competition and Disclosure

So far, the analyses only explore the inter-industry differences of disclosure behavior, as competition is measured at industry level and all firms within the same industry are assumed to face the same level of competition. However, firms within the same industry are also likely to face different levels of competition depending on their market position. Nickell, Wadhwani, and Wall (1992) and Nickell (1996) suggest that firms with greater market shares in an industry typically face lower competition, as higher market share indicates greater market power. Therefore, I further divide firms within the same industry into subgroups according to their market shares. Their arguments imply that, compared with industry followers, industry leaders face less competitive pressures. Therefore, I expect the association between competition and disclosure to be less pronounced for industry leaders.

Firms within the same industry are sorted into quartiles according to their market shares and those in the top quartile are identified as industry leaders. In the following two subsections, I discuss the empirical results of competition and disclosure quantity and quality at firm level.

Firm-level Competition and Disclosure Quantity

I use the total number of forecasts issued by a firm in a certain year to measure the firm-level disclosure quantity, and use the following regression to examine the impacts of competition on disclosure quantity.

$$\begin{aligned} NegBin(\text{NUM-FOR}_{ijt}) &= F(\alpha_1 \text{POTENT-COMP}_{jt} + \alpha_2 \text{EXIST-COMP}_{jt} + \alpha_3 \text{IND-PROFIT}_{jt} \\ &+ \text{Capital Market Incentives} + \text{Litigation Risk} + \text{Year Dummies}) \quad (3) \end{aligned}$$

This is a Negative Binomial regression model estimated at firm-year level, where i denotes firm, j denotes industry and t denotes year. The dependant variable NUM-FOR$_{jit}$ is the total number of forecasts issued by firm i at year t. Similar to the industry-level analysis, I control for capital market incentives, litigation risk and year fixed-effects in the regression. The standard errors are clustered by industry.[16]

[16]The results are similar if the standard errors are clustered by both industry and calendar year.

The regression analysis is conducted on the full sample, as well as separately on the industry followers and leaders sub-samples. The results are reported in Table 9. The coefficients on POTENT-COMP and EXIST-COMP are similar to those reported in Table 6, indicating that competition from potential entrants increases disclosure quantity and competition from existing rivals decreases disclosure quantity. Consistent with the argument that industry leaders face less competitive pressures, the above association is less pronounced for industry leaders. Although coefficients on both POTENT-COMP and EXIST-COMP have the correct sign in the industry leader regression, neither of them is significant. The results by comparing the coefficients across sub-samples suggest that the impacts of competition on disclosure are smaller for industry leaders, probably because product market competition is less of a concern for them. The negative and significant coefficient on EXIST-COMP for industry followers is also in line with the findings in Verrecchia and Weber (2006) that small firms in competitive industries elect to redact proprietary information from their material contracts as they are willing to trade off the benefits from avoiding disseminating proprietary information in product markets against the costs associated with the increased adverse selection in capital markets.

Coefficients on control variables show some interesting patterns. For example, external financing needs (ISSUE) encourage more profit-forecasts while discourages investment-forecasts; historical volatility and absolute change of earnings discourage profit-forecasts while historical volatility and absolute change of capital expenditures encourage investment-forecasts, suggesting that for investment-forecasts, forecasting needs outweigh forecasting difficulty. Therefore, unlike forecasts on future earnings, which have been documented as serving multiple capital market purposes (e.g., reducing analyst optimism, reducing litigation risk, and reducing information asymmetry between insiders and investors), the major capital market incentive for issuing investment-forecasts is to provide additional information on future investment plans in order to reduce uncertainty.

Firm-level Competition and Disclosure Quality

Next, I use the firm-level forecasting accuracy to measure disclosure quality and use the following OLS regression to examine the impacts of competition on disclosure quality.

$$\begin{aligned} \text{ACCURACY}_{ijt} &= \alpha_1\text{POTENT-COMP}_{jt} + \alpha_2\text{EXIST-COMP}_{jt} + \alpha_3\text{IND-PROFIT}_{jt} \\ &+ \text{Capital Market Incentives} + \text{Litigation Risk} + \text{Year Dummies} \qquad (4) \end{aligned}$$

This regression is estimated at firm-year level, where i denotes firm, j denotes industry and t denotes year. Similar to the industry-level analysis, I also control for capital market incentives, litigation risk and year fixed-effects in the regression.

The regression analysis is conducted on the full sample, as well as separately on the industry followers and leaders sub-samples. The results are reported in Table 10. For both profit- and investment-forecasts, consistent with **H2A**, the coefficients on POTENT-COMP are positive and significant across all samples, suggesting that competition from potential entrants increases disclosure quality. For profit-forecasts, consistent with **H2B**, the coefficients on EXIST-COMP are positive and significant for the full sample and industry followers sub-sample. For investment-forecasts, the coefficients on EXIST-COMP are negative and statistically significant for the industry follower sub-sample, indicating that existing competition decreases the forecasting accuracy of investment forecasts, in contrary to **H2B**.

To further investigate the mechanism through which competition influences disclosure quality, I examine the impacts of competition on the signed forecast error, which is defined as follows:

$$ERROR = \frac{\text{Actual value - Forecasted value}}{\text{Market value of equity}}.$$

A positive ERROR suggests a pessimistic forecast compared with the actual value and a negative ERROR suggests a optimistic one. I implement this analysis by replacing ACCURACY in Equation (4) with ERROR. The regression results are reported in Table 11. Panel A reports the results for the full sample, while in Panels B and C, I split the sample based on the sign of ERROR.

For profit-forecasts, in Panel A, both the means and medians of the dependent variable ERROR are negative, suggesting that profit-forecasts are optimistic on average. The coefficients on POTENT-COMP and EXIST-COMP are positive, suggesting that competition reduces optimism in profit-forecasts. The means and medians of ERROR in Panel C are much larger than those in Panel B, suggesting that forecast errors are mainly attributable to optimistic forecasts. Therefore, competition improves the accuracy of profit-forecasts mainly through reducing forecast optimism.

For investment-forecasts, in Panel A, the means of the dependant variable ERROR are positive, suggesting that forecast errors mainly come from pessimistic investment-forecasts.[17] The coefficient on POTENT-COMP is negative, suggesting that potential competition reduces pessimism in investment-forecasts. This finding is consistent with the argument in Spence (1977) and Fudenberg and Tirole (1983) that firms could deter entry by committing to overproduction and threatening would-be entrants with lower profits in the post-entry equilibrium. As a result, firms facing high potential competition are less likely to be pessimistic about their investment plans. The above association is more pronounced in Panel B, suggesting that competition from potential entrants improves the accuracy of investment-forecasts mainly through reducing forecast pessimism. Interestingly, the coefficient on EXIST-COMP is positive and significant, especially for industry followers, suggesting that industry followers facing high competition from existing rivals issue more pessimistic investment-forecasts. One potential explanation for this result is that in highly competitive industries, industry followers cannot sustain by imitating industry leaders and one way for industry followers to survive is to cut costs and reduce their scales (Wright (1986); Helms and Wright (1997)). Therefore, industry followers may use investment-reduction to signal effective cost-cutting.

Compared with the results on forecasting accuracy, those on forecast error have less power. However, this finding is not surprising, as forecasting accuracy is better able to capture the offsetting informational demands from capital markets and product markets. Theories argue that the offsetting informational demands from capital markets and product markets enhance disclosure quality. However, the directional demand from one market is uncertain. For example, theories argue that if capital market incentives lead to optimistic

[17]Although the medians are negative, but the magnitudes are much smaller, indicating a long right tail. The reason why investment-forecasts are pessimistic on average is unclear and outside the scope of this paper. The empirical evidence on the market reaction to investment-announcements is mixed. For example, McConnell and Muscarella (1985) find that announcements of increases in capital expenditures lead to significant positive stock returns for industrial firms, but such association does not exist for public utility firms. Chung, Wright, and Charoenwong (1998) find that share price reaction to a firm's capital expenditure decisions depends critically on the capital market's assessment of the quality of its investment opportunities.

disclosure on future profits, the concern that overly optimistic prospects attract potential entrants or encourage existing rivals to produce more will enhance the disclosure credibility by reducing disclosure optimism. However, in practice, it is unlikely that all firms want to overstate their future profits. For example, in order to create positive earnings surprises, some firms may intentionally issue pessimistic earnings forecasts (e.g., Matsumoto (2002)). On the other hand, some firms in competitive industries may prefer to overstate future profits in order to pre-empt competitors. In this case, offsetting informational demands from capital markets and product markets have positive impacts on forecasting accuracy, but the opposite impacts on forecast error will wash out the results.

6 Robustness Analysis

6.1 Issues with Competition Measures

In Equations (1) and (2), competition measures are constructed by using Principal Components Analysis on original competition measures. As discussed in Section 3.1, due the the coverage of Compustat, it is likely that the original competition variables are measured with error. The advantage of Principal Component Analysis is to obtain maximum variance from original variables. However, if the variables are measured with error, Exploratory Factor Analysis (EFA) should be a better method. The advantage of EFA is to identify the latent variables or common factors underlying a group of raw variables and keep only variance of these common factors. Applying EFA in the analysis may result in some loss of information, but could mitigate the measurement error problem by throwing away uncommon variances existing in the data. Similar to Principal Component Analysis, three common factors EF1, EF2, and EF3 are retained from EFA by requiring eigenvalues larger than one. EF1 is loaded by IND-MKTS, IND-CON4, IND-HHI and IND-NUM, EF2 is loaded by IND-PPE, IND-R&D, IND-CPX, and IND-MKTS, and EF3 is loaded by IND-MGN and IND-ROA. Therefore, EF1, EF2 and EF3 measure competition from existing rivals, competition from potential entrants and industry profitability, respectively. I use the inverse of EF1, denoted as EXIST-COMP$_{EFA}$, to measure competition from existing rivals, the inverse of EF2, denoted as POTENT-COMP$_{EFA}$, to measure competition from potential entrants, and EF3, denoted as IND-PROFIT$_{EFA}$, to measure industry profitability in the robustness analysis.

The regression results are reported in Panel A of Table 12. The coefficients on competition measures are qualitatively similar to those in Table 6.

One shortcoming of factor analysis is the difficulty in interpreting the results. Therefore, in this section, instead of using common factors to measure competition, I use the original competition variables. Since competition variables within the same category are highly correlated with each other (Table 2), to avoid multicollinearity, I use only one competition variable from each category in the regression. In the first set of competition variables, IND-PPE, the minimum investments that a firm needs to incur in order to enter the market, is used as an inverse measure for competition from potential entrants; IND-CON4, the industry concentration ratio, is used as an inverse measure for competition from existing rivals; IND-MGN is used as the control for industry profitability. In the second set of competition variables, I use IND-CPX, the capital intensity of an industry, as an inverse measure for competition from potential entrants, IND-NUM, the number of firms operating in the same industry, as a measure for competition from existing rivals, and IND-ROA as the control for industry profitability. The regression results, as reported in Panel B, are similar to those in Table 6. As IND-MKTS is highly correlated with both variables in potential competition category and those in existing competition category, it is excluded from the analysis. However, after including IND-MKTS in the regression, results are qualitatively unchanged (unreported).[18]

Existing literature argues that market structure is endogenous and that concentration indices alone are poor measures of competition (Raith (2003)). Although I include multiple competition variables in the same regressions, there are still concerns regarding whether high industry concentration (or low EXIST-COMP) indicates low competition. Panzar and Rosse (1987) develop an index (H-statistic) from a reduced form revenue equation to measure the competitiveness of an industry.[19] H-statistic is equal to the sum of the factor price elasticity, with less than 0 being monopolists, between 0 and 1 being monopolistic competition and 1 being perfect competition. Although Panzar and Rosse (1987) argue that H-statistic could

[18]Note that competition measures based on common factors, such as POTENT-COMP, EXIST-COMP, POTENT-COMP$_{EFA}$ and EXIST-COMP$_{EFA}$, have been multiplied by -1, so that higher value indicates higher competition level. Therefore, the coefficients on some of the original variables, such as IND-PPE, IND-R&D, IND-CPX, IND-CON4, and IND-HHI, in this table have the opposite signs as those on POTENT-COMP and EXIST-COMP in Table 6.

[19]I thank the referee for pointing out this issue and suggesting the H-statistic.

be interpreted as a measure for the degree of competition under certain assumptions (e.g., long-run equilibrium, demand with constant elasticity and a Cobb-Douglas technology), this methodology is rarely used in empirical studies.[20] The main difficulty in applying this measure to large sample studies is to identify common input factors in the production function and the corresponding prices of these factors for a variety of industries. To obtain consistent H-statistics across a number of industries, I estimate the following reduced-form revenue equation on a pooled sample for each industry (four-digit SIC).

$$\begin{aligned}\ln(\mathrm{SALE}_{ijt}) &= \alpha_{1,j} + \beta_{1,j}\ln(\mathrm{COGS}_{ijt}) + \beta_{2,j}\ln(\mathrm{DEP}_{ijt}) + \beta_{3,j}\ln(\mathrm{SG\&A}_{ijt}) \\ &+ \gamma_{1,j}\ln(\mathrm{ASSETS}_{ijt}) + \gamma_{2,j}\ln(\mathrm{CAPEX}_{ijt}) + \gamma_{1,j}\ln(\mathrm{EQUITY}_{ijt}) \\ &+ \text{Year Dummies,} \qquad (5)\end{aligned}$$

This regression is estimated at firm-year level, where i denotes firm, j denotes industry and t denotes year. SALE_{ijt} is the ratio of sales to total assets, a proxy for output price. COGS_{ijt} is the ratio of cost of goods sold to total assets, a proxy for input price of raw materials. DEP_{ijt} is the ratio of depreciation to total assets, a proxy for input price of equipment and fixed capital. $\mathrm{SG\&A}_{ijt}$ is the ratio of selling, general and administrative expenses to total assets, a proxy for input price of labor. I also control for firm characteristics, including total assets (ASSETS_{ijt}) to control for firm size, the ratio of capital expenditures to total assets (CAPEX_{ijt}) to control for fixed investments and the ratio of equity to total assets (EQUITY_{ijt}) to control for leverage. The above model shares a similar logic to the one in Claessens and Laeven (2004), which estimates H-statistics for banking industries.

As H-statistic is derived from individual firm's revenue function, which depends on the decisions of its actual and potential rivals, it is a comprehensive measure for industry competitiveness, combining both existing competition and potential competition (Panzar and Rosse (1987); Claessens and Laeven (2004)). Since the focus of this paper is to examine the impacts of different dimensions of competition on disclosure, H-statistic is not an alternative measure for either competition from potential entrants or competition from existing rivals. Therefore, I only use H-statistic to assess the validity of the competition measures used in this paper. In unreported analysis, I find that H-statistic is positively correlated with EXIST-COMP, suggesting that EXIST-COMP is a valid measure for competition. Further-

[20]So far, this measure has only been empirically applied in banking industries.

more, after adding H-statistic as a separate independent variable in Regressions (1) and (2), I obtain results that are qualitatively unchanged.

6.2 Endogeneity Between Competition and Disclosure

An alternative explanation for the negative association between competition from existing rivals and disclosure is that voluntary disclosure facilitates mergers and acquisitions among firms, thereby leading to more concentrated industry structure. To address this endogeneity concern, I examine the endogenous link between competition and disclosure quantity by using Granger causality test as follows.

$$\begin{aligned}
\text{Forecasters}_{j,t}\% &= \alpha_1\text{Forecasters}_{j,t-1}\% + \alpha_2\text{Forecasters}_{j,t-2}\% \\
&+ \alpha_3\text{POTENT-COMP}_{j,t-1} + \alpha_4\text{POTENT-COMP}_{j,t-2} + \alpha_5\text{EXIST-COMP}_{j,t-1} \\
&+ \alpha_6\text{EXIST-COMP}_{j,t-2} + \alpha_7\text{IND-PROFIT}_{j,t-1} + \alpha_8\text{IND-PROFIT}_{j,t-2} \\
&+ \text{Capital Market Incentives} + \text{Litigation Risk} + \text{Year Dummies} \qquad (6)
\end{aligned}$$

This regression is estimated at industry-year level, where $\text{FORECASTER}_{j,t-i}\%$, $\text{POTENT-COMP}_{j,t-i}$, $\text{EXIST-COMP}_{j,t-i}$, and $\text{IND-PROFIT}_{j,t-i}$ denote the percentage of forecasters, competition from potential entrants, competition from existing rivals and industry profitability for industry j at year $t-i$, respectively. Results are reported in Table 13. The coefficients on $\text{FORECASTER}_{j,t-1}\%$ and $\text{FORECASTER}_{j,t-2}\%$ are positive and significant, suggesting that management forecasting behavior is highly auto-correlated. F-test results suggest that the sum of coefficients on $\text{POTENT-COMP}_{j,t-1}$ and $\text{POTENT-COMP}_{j,t-2}$ is positive and significant, indicating that competition from potential entrants increases disclosure quantity in a Granger sense. Similarly, the sum of coefficients on $\text{EXIST-COMP}_{j,t-1}$ and $\text{EXIST-COMP}_{j,t-2}$ is negative and significant, indicating that competition from existing rivals decreases disclosure quantity in a Granger sense.

6.3 Forecasts Issued in MD&A

So far, the analyses are based on management forecasts collected from First Call and Factiva, which only cover information disclosed in press releases, conference calls, conferences, analyst meetings and shareholder presentations. In other words, management forecasts issued in the

MD&A section of SEC filings (10-Ks and 10-Qs) are not studied. Although one could argue that ignoring disclosures in the MD&A limits the disclosure sample used in this study, it is worth noting that the disclosures in the SEC filings are often required by an auditor, which makes these disclosures less voluntary. Moreover, forward-looking disclosures in MD&A could be preceded by disclosures through other channels, such as conference calls, which makes the MD&A disclosures stale. Nonetheless, to check the robustness of the results and to investigate whether competition affects the information disclosed in SEC filings in a similar way to that disclosed outside the filings, I repeat the earlier analysis for a sample of management forecasts on capital expenditures collected from the MD&A section of SEC filings. I collect the MD&A disclosures by searching the 10-K and 10-Q filings of all sample firms in the years 2003 and 2004.

In Panel A of Table 14, the results from analyzing MD&A disclosures are reported under Column "MD&A". I also combine the data from SEC filings with those collected from Factiva and regression results are reported under Column "All". The coefficients are similar to those reported in Table 6, suggesting that the main findings of this paper are robust to the disclosure media and in particular, are robust to disclosures both inside and outside SEC filings.

6.4 Other Robustness Analyses

In above analyses, firms are assigned to industry groups according to their primary SIC code. This approach assumes that a firm's product market concern is only attributable to the competition in its primary industry, even if the firm operates in multiple industries. To check whether the results are sensitive to this assumption, I conduct analysis based on firms with a single segment. The regression results as reported in Panel B of Table 14 are similar to before.

One shortcoming of the measure for potential competition in this paper is that intangible entry barrier is not captured. For example, firms operating in regulated industries face extremely high entry barrier, and such barrier is not reflected in physical investments. Although regulated industries are typically regarded as facing high litigation risk and are captured by LIT dummy, to further test the robustness of the results, in Panel C, I conduct analysis after excluding regulated industries, namely industries with SIC 4812-4813, 4833, 4841, 4899 (communications), 4911, 4922-4924, 4931, 4941 (utilities) from the sample. The results are still unchanged.

In Panel D, I conduct cross-sectional analysis where all the regression variables are averaged across time and results are qualitatively similar to before.

So far, I use *ex post* forecasting accuracy to measure disclosure quality, which is likely to be influenced by managers' ability to forecast, managers' incentives to meet the forecasts and the difficulty of forecasting. Although in the regressions, I control for these factors by including proxies for the volatility of firms' operating environment, growth opportunities, earnings management, etc., the above concern still cannot be fully eliminated. Therefore, as an alternative, in the robustness analysis (unreported), I use an *ex ante* proxy to measure disclosure quality. In particular, I use previous year's forecasting accuracy ($t-1$) as the *ex ante* measure for disclosure quality and the results are qualitatively unchanged (Hutton and Stocken (2009)).[21]

7 Summary and Conclusions

Product market competition is an important determinant of corporate decisions, and in particular on decisions about a firm's disclosure strategy. In this paper, I investigate the effects of product market competition on firms' voluntary disclosure decisions. Using separate variables to measure different dimensions of competition and using management profit- and investment-forecasts as proxies for voluntary disclosure, I show that competition from potential entrants increases disclosure quantity while competition from existing rivals reduces disclosure quantity. This finding potentially explains the controversial evidence on competition and disclosure in existing studies. I also find that given a certain level of capital market incentive, competition generally increases disclosure quality. Further analysis suggests that competition increases disclosure quality mainly by reducing forecasting optimism in profit-forecasts and by reducing forecasting pessimism in investment-forecasts.

Overall, this paper provides large sample evidence supporting the proprietary cost ar-

[21] I thank the referee for pointing this out and suggesting the alternative measure. The results are qualitatively similar if I use the average forecasting accuracy from years $t-3$, $t-2$ and $t-1$.

gument that product market competition shapes corporate voluntary disclosure behavior. Findings in this paper contribute to the management forecast literature by providing rationale underlying the inter-industry differences in management forecasting behavior. This paper also contributes to the literature by providing some initial evidence on the determinants of management investment-forecasts, which have been largely ignored in extant accounting research.

APPENDICES

Appendix A: Variable Definition

IND-PPE The weighted average of property, plant and equipment of all firms in an industry. A firm's market share, calculated as the ratio of its segment sales to industry aggregate sales, is used as its weight. A firm's segment PP&E is allocated according to the ratio of the segment sales to the firm's total sales.

IND-R&D The weighted average of research and development of all firms in an industry. A firm's market share, calculated as the ratio of its segment sales to industry aggregate sales, is used as its weight. If a firm's segment R&D is missing, it is replaced by the firm's total R&D multiplied with the ratio of the segment sales to the firm's total sales.

IND-CPX The weighted average of capital expenditures of all firms in an industry. A firm's market share, calculated as the ratio of its segment sales to industry aggregate sales, is used as its weight. If a firm's segment capital expenditures are missing, they are replaced by the firm's total capital expenditures multiplied with the ratio of the segment sales to the firm's total sales.

IND-MKTS Product market size, measured as the natural log of industry aggregate sales.

IND-CON4 Four-firm concentration ratio, measured as the sum of market shares of the four largest firms in an industry.

IND-HHI Herfindahl-Hirschman Index, measured as the sum of squared market shares of all firms in an industry.

IND-NUM Total number of firms in the industry.

IND-MGN Price-cost margin, measured as industry aggregate sales divided by industry aggregate operating costs. If a firm's segment operating cost is missing, it is replaced by the segment sales divided by the firm's price-cost margin.

IND-ROA Return on assets, measured as industry aggregate operating profit before depreciation divided by industry aggregate total assets. If a firm's segment operating profit before depreciation is missing, it is replaced by the segment assets multiplied with the firm's ROA. If a firm's segment total assets are missing, they are replace by segment operating profit before depreciation divided by the firm's ROA. If both segment operating profit before depreciation and segment total assets are missing, they are replaced by the firm's total operating profit before depreciation multiplied with the ratio of the segment sales to the firm's total sales and the firm's total assets multiplied with the ratio of the segment sales to the firm's total sales, respectively.

POTENT-COMP The inverse of PC2 from Principal Component Analysis of nine competition variables. It measures competition from potential entrants.

EXIST-COMP The inverse of PC1 from Principal Component Analysis of nine competition variables. It measures competition from existing rivals.

IND-PROFIT PC3 from Principal Component Analysis of nine competition variables. It measures industry profitability.

FORECASTER% The ratio of forecasters to the total number of firms in an industry. A firm-year is identified as a forecaster if it issues at least one forecast for the subsequent fiscal year-end.

NUM-FOR Total number of forecasts issued by a firm in a certain year.

ACCURACY Forecasting accuracy, defined as the inverse of the absolute difference between actual earnings per share and management earnings forecast deflated by stock price two trading days before management forecast date. For investment-forecasts, it is defined as the inverse of the absolute difference between actual capital expenditures and management capital expenditures forecast deflated by market value of equity at fiscal year-end.

ERROR Forecast error, defined as the difference between actual earnings per share and management earnings forecast deflated by stock price two trading days before management forecast date. For investment-forecasts, it is defined as the difference between actual capital expenditures and management capital expenditures forecast deflated by market value of equity at fiscal year-end.

SIZE Firm size, measured as natural log of a firm's market value of equity (Item prcc_f*csho) at fiscal year-end.

MTB Market-to-book ratio, measured as market value of equity plus book value of liability (Item lt) divided by book value of total assets (Item at).

LEV Leverage ratio, measured as total liability (Item lt) minus deferred taxes (Item txdb) divided by total assets (Item at).

STDEV Earnings or capital expenditures volatility, measured as the standard deviation of earnings before extraordinary items or the standard deviation of capital expenditures scaled by total assets over the past five years. At least three years' observations are required.

ANALYST The number of analysts following. Data are obtained from I/B/E/S database.

SHRINST The percentages of shares owned by institutional investors. Data are obtained from Thomson-Reuters Institutional Holdings (13F) Database.

ABSCH Absolute value of actual earnings change scaled by market value of equity; absolute value of actual capital expenditures change scaled by total assets.

DCH Dummy variable indicating that the actual earnings/capital expenditures during forecasting period are higher than the previous year.

OPTM Analyst optimism, measured as the difference between analyst consensus estimation at the beginning of the fiscal year and the actual earnings per share, scaled by the absolute value of actual earnings per share.

SURPRS Management forecasting surprise, defined as the difference between management earnings forecast and the latest consensus analyst estimation deflated by stock price two trading days before management forecast date. For investment-forecasts, previous year's actual capital expenditures are used as the proxy for market expectation and the market value of equity at fiscal year-end is used as the scalar.

DIFFI Forecasting difficulty, measured as the standard deviation of analyst estimates prior to the corresponding management forecast.

HORIZ Forecasting horizon, measured as the number of days between forecast release date and forecasting fiscal year-end divided by 100.

ISSUE A dummy variable equal to one if the firm issues either public equity or public debt in a subsequent two-year period, and zero otherwise. Data are extracted from Thomson Deal (SDC) database.

LIT Proxy for litigation risk, measured as a dummy variable equal to one if the firm operates in an industry facing high litigation risk, namely industries with primary four-digit SIC code 2833-2836, 8731-8734 (bio-tech), 3570-3577 (computer hardware), 3600-3674 (electronics), 7371-7379 (computer software), 5200-5961 (retailing), 4812-4813, 4833, 4841, 4899 (communications), or 4911, 4922-4924, 4931, 4941 (utilities).

STDRET Standard deviation of stock returns over a 120-day period prior to the forecast release date.

DACCR Discretionary accruals, estimated using the cross-sectional modified Jones model.

ACCURACY, ERROR, SURPRISE, STDRET and DIFFI are multiplied by 100 in descriptive statistics and regressions for expositional purpose.

Appendix B: Measuring Product Market Competition

The data for computing product market competition variables are extracted from Compustat Segments and Fundamentals Annual databases for the period from 1977 to 2007.[22] The data and sample selection process are described as follows:

1. I delete firms incorporated outside the U.S, as those firms are likely to face a different product market.

2. Data on net sales (Item sale), operating profit (Item ops), operating income before depreciation (Item oibd), research and development (Item rd), capital expenditures

[22] *SFAS No. 14* became effective in 1976. Therefore, 1977 is the first calendar year when segment data were available for all firms.

(Item capx) and identifiable total assets (Item at) are obtained from Compustat Segments. Only business segments with valid primary four-digit SIC code (Item ssic1) are retained. Segments with identical SIC codes under the same firm are merged into one and all financial items are aggregated.

3. Merge segment data with Compustat Fundamentals Annual data. Firms without segment information are treated as having a single segment.

4. Calculate industry-wide variables: IND-PPE, IND-R&D, IND-CPX, IND-MKTS, IND-CON4, IND-HHI, IND-NUM, IND-MGN and IND-ROA.

5. I require non-missing values for all competition variables to conduct Principal Component Analysis and Exploratory Factor Analysis. The final sample consists of 27,053 industry-years over the period from 1977 to 2007.

6. Classify firms into different industries according to their primary segment SIC code. If a firm has multiple business segments, the segment with the same four-digit SIC code as the firm is identified as the primary segment. If none of the segments have the same SIC code as the firm, the segment with the largest sales is treated as the primary segment.[23]

Appendix C: Examples for Investment-forecasts

Management investment-forecasts data used in this paper are hand-collected from Factiva Search Engine. I use management forecasts on future capital expenditures as the proxy for investment-forecasts. Examples for investment-forecasts are illustrated below:

Q4 2003 ALLTEL Corp. Earnings Conference Call, Jan. 23, 2004:
"Turning to 2004, as Scott mentioned, we are making organizational changes to improve service delivery to our customers. These organizational changes which include a reduction of approximately 400 to 600 employees will result in a one-time charge of roughly $15 million in the first quarter, an operating expense savings of approximately $20 million this year. For

[23] This is consistent with the methodology that SIC uses to assign primary SIC code to each firm.

the year, we expect total revenue growth of 2% to 5%, **capital expenditures** of \$1.2 billion to \$1.3 billion, and earnings per share from current businesses of \$3.10 to \$3.30."

Q4 2003 AMETEK Inc. Earnings Conference Call, Jan. 28, 2004:
"For 2004 we expect the **capital expenditures** will total approximately \$23 million, while depreciation and amortization should be about \$35 million. Operating cash flow for 2004 is expected to be up low to mid single digit percentage from the exceptional 2003 level, driven by higher income and less positive changes in the balance sheet."

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Table 1: Principal component analysis results

Panel A: Eigenvalues of The Correlation Matrix					
Principal Components	**Eigenvalue**	**Difference in Eigenvalue**		**Variance Explained**	**Cumulative Variance**
PC1	3.479	1.679		38.65%	38.64%
PC2	1.800	0.301		20.00%	58.65%
PC3	1.499	0.848		16.65%	75.30%
PC4	0.651	0.060		7.23%	82.54%
PC5	0.591	0.187		6.57%	89.10%
PC6	0.404	0.100		4.49%	93.59%
PC7	0.304	0.154		3.38%	96.97%
PC8	0.150	0.028		1.67%	98.64%
PC9	0.122			1.36%	100%

Raw Variables	*Panel B: Rotated Factor Pattern* **PC1**	**PC2**	**PC3**	*Panel C: Standardized Scoring Coefficients* **PC1**	**PC2**	**PC3**
IND-PPE	-10%	93%	3%	0.079	0.405	-0.030
IND-R&D	-12%	70%	2%	0.042	0.301	-0.027
IND-CPX	-9%	91%	3%	0.081	0.396	-0.025
IND-MKTS	-63%	48%	20%	-0.184	0.127	0.086
IND-CON4	93%	-5%	1%	0.369	0.097	0.048
IND-HHI	86%	-1%	-5%	0.343	0.107	-0.0005
IND-NUM	-85%	22%	1%	-0.314	-0.009	-0.049
IND-MGN	-11%	6%	85%	-0.002	-0.029	0.552
IND-ROA	3%	2%	88%	0.050	-0.030	0.580

This table presents the Principal Component Analysis of competition measures based on data obtained from Compustat Segments and Fundamentals Annual databases over the period from 1977 to 2007. The sample consists of 27,053 industry-year observations. Four-digit SIC code is used to identify industry. PC1-PC9 are principal components extracted from the analysis by using orthogonal rotation method. IND-PPE, IND-R&D, IND-CPX, IND-MKTS, IND-CON4, IND-HHI, IND-NUM, IND-MGN and IND-ROA are raw competition variables used for the analysis. The definition of each variable is included in Appendix A.

Table 2: Descriptive statistics for competition variables

	N	Mean	Min	Q1	Median	Q3	Max	Stdev
Panel A: Summary Statistics								
IND-PPE	27,053	819.42	0.088	31.38	139.89	569.64	14536.86	2084.16
IND-R&D	27,053	18.80	0	0	0.141	5.056	512.18	68.40
IND-CPX	27,053	84.83	0.003	3.000	13.56	53.37	1806.78	241.03
IND-MKTS	27,053	6.574	-0.449	5.176	6.782	8.191	11.74	2.414
IND-CON4	27,053	0.906	0.353	0.870	1.000	1.000	1.000	0.158
IND-HHI	27,053	0.538	0.0528	0.263	0.486	0.875	1.000	0.318
IND-NUM	27,053	10.549	1	2	4.000	10	103	17.14
IND-MGN	27,053	1.108	0.508	1.043	1.090	1.147	2.026	0.171
IND-ROA	27,053	0.148	-0.349	0.091	0.147	0.205	0.580	0.121
POTENT-COMP	27,053	0	-8.113	0.052	0.274	0.405	1.117	1
EXIST-COMP	27,053	0	-2.003	-0.765	-0.231	0.452	3.979	1
IND-PROFIT	27,053	0	-4.499	-0.391	-0.005	0.411	5.141	1

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Table 2: Descriptive statistics for competition variables – Continued

Panel B: Correlation Matrix									
	IND-PPE	IND-R&D	IND-CPX	IND-MKTS	IND-CON4	IND-HHI	IND-NUM	IND-MGN	IND-ROA
IND-PPE		0.510	0.867	0.491	-0.161	-0.114	0.266	0.097	0.030
IND-R&D			0.457	0.351	-0.126	-0.103	0.303	0.049	0.059
IND-CPX				0.441	-0.152	-0.111	0.269	0.113	0.028
IND-MKTS					-0.502	-0.577	0.505	0.183	0.175
IND-CON4						0.695	-0.815	-0.107	0.027
IND-HHI							-0.562	-0.095	-0.034
IND-NUM								0.139	-0.028
IND-MGN									0.523
POTENT-COMP	-0.930	-0.704	-0.908	-0.480	0.046	0.010	-0.218	-0.056	-0.017
EXIST-COMP	0.101	0.119	0.090	0.628	-0.927	-0.859	0.847	0.106	-0.031
IND-PROFIT	0.027	0.017	0.033	0.204	0.014	-0.052	-0.008	0.852	0.884

Table 3: Number of observations by calendar year

Year	Profit			Investment			Profit&Investment		
	#Forecasters	#Firms	%Forecasters	#Forecasters	#Firms	%Forecasters	#Forecasters	#Firms	%Forecasters
1998	480	2,349	20.43%						
1999	504	2,178	23.14%						
2000	801	2,261	35.43%						
2001	856	2,246	38.11%	427	1,289	33.13%	223	1,226	18.19%
2002	922	2,269	40.63%	616	1,305	47.20%	292	1,246	23.43%
2003	985	2,266	43.47%	497	1,185	41.94%	235	1,111	21.15%
2004	926	2,421	38.25%	526	1,237	42.52%	222	1,185	18.73%
2005	967	2,521	38.36%	577	1,236	46.68%	262	1,193	21.96%
2006	929	2,522	36.84%						
Average	819	2,337	34.96%	529	1,250	42.30%	247	1,192	20.69%
Total	7,370	21,033		2,643	6,252		1,234	5,961	

This table presents the average number of forecasters, the average number of sample firms and the average percentage of forecasters in an industry by calendar year for profit-, investment- and profit-&investment-forecasts, respectively.

Table 4: Descriptive statistics

	Profit					Investment				
	N	Mean	Median	Stdev	Diff(Non-For)	N	Mean	Median	Stdev	Diff(Non-For)
Panel A: Disclosure Quantity Sample										
FORECASTER	21,033	0.350	0	0.477		6,252	0.423	0	0.494	
NUM-FOR	21,033	1.151	0	1.963		6,252	1.025	0	1.495	
POTENT-COMP	21,033	-1.552	-0.642	2.180	$-0.310^{\S}$	6,252	-2.141	-1.709	2.322	$-0.295^{\S}$
EXIST-COMP	21,033	1.698	1.879	1.252	$0.191^{\S}$	6,252	1.768	2.095	1.133	$0.348^{\S}$
IND-PROFIT	21,033	-0.094	-0.107	0.742	$-0.080^{\S}$	6,252	-0.229	-0.184	0.675	$-0.039^{\ddagger}$
SIZE	21,033	6.346	6.252	1.754	$-1.018^{\S}$	6,252	6.417	6.302	1.678	$-1.185^{\S}$
MTB	21,033	2.222	1.569	1.844	$0.049^{\ddagger}$	6,252	2.220	1.670	01.556	$0.629^{\S}$
LEV	21,033	0.467	0.466	0.244	$-0.038^{\S}$	6,252	0.452	0.437	0.247	$-0.106^{\S}$
ANALYST	21,033	9.077	7	7.697	$-3.293^{\S}$	6,252	10.16	8	8.217	$-4.367^{\S}$
SHRINST	21,033	0.537	0.559	0.276	$-0.131^{\S}$	6,252	0.554	0.581	0.271	$-0.176^{\S}$
STDEV	21,033	0.105	0.040	0.184	$0.058^{\S}$	6,252	0.031	0.019	0.035	$0.002^{\S}$
ABSCH	21,033	0.085	0.085	0.187	$0.050^{\S}$	6,252	0.028	0.011	0.046	0.002
Panel B: Disclosure Quality Sample										
ACCURACY	5,268	-1.728	-0.675	2.106		2,508	-2.417	-0.802	5.062	
POTENT-COMP	5,268	-1.510	-0.687	2.018		2,508	-1.959	-1.223	2.266	
EXIST-COMP	5,268	1.507	1.567	1.254		2,508	1.561	1.600	1.163	
IND-PROFIT	5,268	-0.058	-0.073	0.641		2,508	-0.198	-0.156	0.644	
SIZE	5,268	7.213	7.037	1.582		2,508	7.123	6.988	1.485	
MTB	5,268	2.321	1.766	1.676		2,508	1.858	1.499	1.134	
LEV	5,268	0.478	0.485	0.213		2,508	0.513	0.508	0.225	
ANALYST	5,268	12.51	11	7.855		2,508	12.74	11	8.346	
SHRINST	5,268	0.652	0.689	0.241		2,508	0.657	0.699	0.237	
STDEV	5,268	0.066	0.028	0.124		2,508	0.030	0.018	0.034	

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Table 4: Descriptive statistics – Continued

	Profit				Investment			
	N	Mean	Median	Stdev	N	Mean	Median	Stdev
HORIZ	5,268	3.155	3.280	1.190	2,508	3.001	3.180	1.150
SURPRS	5,268	-0.223	-0.035	1.054	2,508	0.022	0.320	6.157

This table presents summary statistics for disclosure quantity and quality samples. In Panel A, Column "Diff(Non-For)" compares sample means of the non-forecaster group with the forecaster group. A firm-year is classified as a forecaster if it issues at least one forecast for the subsequent fiscal year-end. §, ‡ and † indicate significance at 1%, 5%, and 10% levels, respectively.

Table 5: List of industries ranked by competition measures

Panel A: Profit-forecasts

Rank	POTENT-COMP		EXIST-COMP	
	SIC	FORECASTER%	SIC	FORECASTER%
Lowest	40,21,53,61,48,45	28.34%	21,14,52,75,10,31	48.05%
2	49,75,29,58,52,37,28	55.67%	20,29,53,41,32,12,72	48.34%
3	13,12,26,54,38,70,35	45.46%	23,1,22,54,25,33,34	38.12%
4	30,20,79,73,10,36	34.12%	82,26,37,8,44,51	31.68%
5	25,14,78,33,46,24,42	37.16%	79,35,76,46,17,50,24	48.93%
6	51,62,57,47,80,16,59	41.74%	39,55,40,57,30,61,16	40.45%
7	63,44,22,55,56,39	33.96%	78,47,36,27,80,45	37.98%
8	32,34,1,60,27,23,41	34.94%	56,59,83,15,28,42,73	38.17%
9	64,72,50,15,31,82,17	40.81%	65,38,49,13,87,48,70	32.75%
Highest	83,65,87,76,67,8	37.45%	62,67,63,60,64,58	26.69%

Panel B: Investment-forecasts

Rank	POTENT-COMP		EXIST-COMP	
	SIC	FORECASTER%	SIC	FORECASTER%
Lowest	21,29,52,40,53	44.67%	21,10,52,14,31	33.33%
2	45,48,49,54,37,58	56.44%	20,12,8,72,25,1	26.55%
3	10,28,35,20,13	52.56%	29,53,22,34,32	62.01%
4	12,38,73,30,70,79	50.46%	37,82,44,24,26,35	53.13%
5	25,33,78,26,36	64.51%	40,54,33,79,16	71.00%
6	14,51,39,32,22,80	43.37%	30,57,79,50,45,39	46.20%
7	57,59,24,55,34,16	62.29%	47,17,83,46,27,36	34.18%
8	27,42,44,1,56	41.17%	51,80,55,59,38	50.77%
9	72,46,50,82,31,8	27.02%	73,28,49,13,48,70	53.88%
Highest	17,83,47,87,15	27.73%	56,87,15,42,58	41.31%

In this table, industries (two-digit SIC) are sorted into deciles according to competition measures POTENT-COMP and EXIST-COMP. Competition variables and percentages of forecasters are averaged across time within each industry.

Table 6: Industry-level competition and disclosure

	FORECASTER%				*ACCURACY*			
	Profit		**Investment**		**Profit**		**Investment**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
POTENT-COMP	**0.015**§	**(3.35)**	**0.033**§	**(5.61)**	**0.129**§	**(3.00)**	**0.220**§	**(2.81)**
EXIST-COMP	**-0.045**§	**(-6.97)**	**-0.032**§	**(-2.78)**	**0.100**‡	**(1.85)**	**0.022**	**(0.15)**
IND-PROFIT	0.010	(0.90)	-0.020	(-1.12)	-0.090	(-0.98)	-0.367‡	(-2.06)
ISSUE	0.017	(0.72)	-0.041	(-1.06)	0.169	(1.09)	0.087	(0.28)
SIZE	0.031§	(3.22)	0.093§	(6.14)	0.726§	(8.69)	0.324‡	(2.01)
MTB	-0.005	(-0.71)	-0.064§	(-4.47)	0.089‡	(2.03)	0.699§	(6.25)
LEV	0.130§	(2.78)	0.247§	(3.19)	-2.115§	(-4.08)	-2.732§	(-3.15)
ANALYST	0.010§	(3.88)	0.005	(1.33)	-0.023‡	(-1.96)	-0.005	(-0.28)
SHRINST	0.054	(1.22)	0.454§	(5.96)	0.355	(1.07)	0.913	(1.13)
STDEV	-0.289§	(-3.20)	-0.169	(-0.32)	0.205	(0.20)	-58.41§	(-4.79)
DCH	0.028	(1.41)	-0.022	(-0.70)				
ABSCH	-0.275§	(-4.71)	1.520§	(3.00)				
OPTIM	-0.006	(-1.28)						
HORIZ					-0.607§	(-8.37)	-0.247§	(-2.45)
SURPRS					0.128	(1.05)	0.080	(0.79)
DIFFI					-0.088§	(-4.64)		
STDRET					-0.292§	(-3.64)		
DACCR					2.296§	(2.42)		
LIT	0.066§	(3.76)	0.058‡	(2.14)	-0.173	(-1.14)	-0.018	(-0.07)
N	3,649		1,105		1,987		811	
Adj-R^2	15.55%		30.49%		26.74%		25.68%	

This table presents regression coefficients and t-statistics for Equations (1) and (2). Standard errors are adjusted for Newey-West heteroscedasticity and autocorrelation. §, ‡ and † indicate significance at 1%, 5%, and 10% levels, respectively.

Table 7: Forecasting frequency, type and horizon

Panel A: Forecasting Frequency

	Profit		Investment	
Frequency	#Obs	Obs%	#Obs	Obs%
0	13,663	64.96%	3,609	57.73%
1	1,952	9.28%	915	14.64%
2	1,123	5.34%	612	9.79%
3	1,046	4.97%	467	7.47%
4	1,322	6.29%	444	7.10%
5	8,42	4.00%	138	2.21%
>5	1,085	5.16%	67	1.07%
Total	21,033	100%	6,252	100%

Panel B: Forecasting Type

	Profit		Investment	
Type (Score)	#Obs	Obs%	#Obs	Obs%
Unidentifiable or no forecast (0)	13,687	65.07%	3,609	57.73%
Qualitative (1)	350	1.66%	228	3.65%
Open Range (2)	461	2.19%	84	1.34%
Close Range (3)	5,209	24.77%	983	15.72%
Point (4)	1,326	6.30%	1,348	21.56%
Total	21,033	100%	6,252	100%

Panel C: Forecasting Horizon

	Profit		Investment	
Horizon	#Obs	Obs%	#Obs	Obs%
0 day or no forecast	13,664	64.96%	3,609	57.73%
1-100 days	534	2.54%	157	2.51%
101-200 days	652	3.10%	310	4.96%
201-300 days	1,142	5.43%	476	7.61%
301-400 days	3,499	16.64%	1,157	18.51%
401-500 days	1,063	4.00%	369	5.90%
>500 days	479	5.16%	174	2.78%
Total	21,033	100%	6,252	100%

Table 8: Industry-level competition and forecasting frequency, type and horizon

	Profit						Investment					
	Frequency		Type		Horizon		Frequency		Type		Horizon	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
POTENT-COMP	**0.043**§	**(2.22)**	**0.046**§	**(3.34)**	**0.028**‡	**(1.85)**	**0.092**§	**(4.55)**	**0.112**§	**(5.16)**	**0.092**§	**(4.46)**
EXIST-COMP	**-0.163**§	**(-5.86)**	**-0.139**§	**(-6.86)**	**-0.110**§	**(-4.85)**	**-0.105**§	**(-2.73)**	**-0.085**‡	**(-2.02)**	**-0.096**§	**(-2.48)**
IND-PROFIT	0.025	(0.62)	0.042	(1.30)	0.035	(1.01)	-0.048	(-0.73)	-0.028	(-0.44)	-0.069	(-1.14)
ISSUE	0.190‡	(1.77)	0.067	(0.90)	0.080	(0.96)	-0.215†	(-1.73)	-0.128	(-0.98)	-0.185	(-1.47)
SIZE	0.178§	(4.47)	0.077§	(2.49)	0.125§	(3.77)	0.277§	(5.68)	0.361§	(6.73)	0.313§	(6.29)
MTB	-0.018	(-0.57)	-0.013	(-0.55)	-0.019	(-0.75)	-0.191§	(-4.33)	-0.240§	(-5.09)	-0.210§	(-4.55)
LEV	0.546§	(3.05)	0.476§	(3.22)	0.443§	(2.92)	0.769§	(3.43)	0.693§	(2.69)	0.863§	(3.57)
ANALYST	0.033§	(3.23)	0.033§	(4.18)	0.033§	(3.93)	0.026‡	(1.97)	0.005	(0.39)	0.021‡	(1.69)
SHRINST	-0.081	(-0.44)	0.164	(1.18)	0.201	(1.36)	1.274§	(5.51)	1.314§	(4.93)	1.555§	(6.38)
STDEV	-1.462§	(-4.50)	-0.943§	(-3.34)	-1.046§	(-3.91)	1.150	(0.71)	-0.548	(-0.30)	1.291	(0.72)
DCH	0.239§	(3.19)	0.081	(1.30)	0.088	(1.35)	0.011	(0.11)	-0.019	(-0.16)	-0.050	(-0.48)
ABSCH	-0.894§	(-4.50)	-0.793§	(-3.94)	-0.593§	(-3.00)	2.639‡	(1.86)	6.790§	(3.67)	3.529§	(2.24)
OPTIM	-0.022	(-1.41)	-0.015	(-1.03)	-0.003	(-0.21)						
LIT	0.302§	(3.91)	0.216§	(3.82)	0.210§	(3.42)	0.169†	(1.60)	0.259§	(2.57)	0.172‡	(1.84)
N	3,649		3,649		3,649		1,105		1,105		1,105	
Pseudo(Adj)-R^2	22.61%		15.24%		16.61%		31.78%		26.48%		36.06%	

This table presents regression coefficients and t-statistics for industry-level OLS regressions with year dummies. Dependent variables are forecasting frequency, type and horizon, respectively. Standard errors are adjusted for Newey-West heteroscedasticity and autocorrelation. §, ‡ and † indicate significance at 1%, 5%, and 10% levels, respectively.

Table 9: Firm-level competition and disclosure quantity

	Profit						Investment					
	All		Followers		Leaders		All		Followers		Leaders	
	dy/dx	z-stat	dy/dx	z-stat	dy/dx	z-stat	dy/dx	z-stat	dy/dx	z-stat	dy/dx	z-stat
POTENT-COMP	**0.083§**	**(2.66)**	**0.071§**	**(2.88)**	**0.059**	**(1.00)**	**0.047‡**	**(1.97)**	**0.038‡**	**(1.92)**	**0.033**	**(0.73)**
EXIST-COMP	**-0.076‡**	**(-2.08)**	**-0.066§**	**(-2.45)**	**-0.060**	**(-0.86)**	**-0.086§**	**(-2.72)**	**-0.088§**	**(-3.32)**	**-0.054**	**(-0.86)**
IND-PROFIT	-0.019	(-0.33)	0.0002	(0.00)	-0.005	(-0.04)	-0.053	(-0.96)	-0.032	(-0.69)	-0.069	(-0.67)
ISSUE	0.083†	(1.51)	0.032	(0.63)	0.246§	(2.66)	-0.155§	(-3.23)	-0.140§	(-2.84)	-0.134†	(-1.64)
SIZE	0.186§	(5.70)	0.127§	(4.13)	0.220§	(3.47)	0.204§	(6.97)	0.191§	(7.63)	0.203§	(3.10)
MTB	-0.017	(-1.14)	-0.022†	(-1.62)	0.034	(0.93)	-0.170§	(-5.39)	-0.127§	(-3.80)	-0.236§	(-4.06)
LEV	0.343§	(2.78)	0.176†	(1.67)	0.844§	(3.27)	0.706§	(7.49)	0.509§	(5.64)	0.859§	(4.29)
ANALYST	0.004	(0.75)	0.010‡	(1.90)	-0.005	(-0.49)	0.004	(1.08)	0.007†	(1.52)	0.006	(0.80)
SHRINST	0.511§	(6.09)	0.348§	(4.83)	0.697§	(3.74)	0.782§	(6.95)	0.553§	(6.42)	0.676§	(2.67)
STDEV	-0.745§	(-3.50)	-0.461§	(-3.75)	-1.918‡	(-2.16)	3.200§	(3.98)	2.831§	(4.32)	3.486	(1.44)
DCH	0.072‡	(2.40)	0.080§	(2.47)	0.016	(0.33)	0.033	(1.06)	0.044†	(1.59)	-0.017	(-0.25)
ABSCH	-0.753§	(-6.24)	-0.492§	(-4.70)	-1.738§	(-4.99)	0.950†	(1.44)	0.553	(1.10)	2.696‡	(1.92)
OPTIM	-0.018§	(-2.57)	-0.009	(-1.42)	-0.053§	(-3.16)						
LIT	0.291§	(2.39)	0.221‡	(2.15)	0.434§	(2.26)	0.033	(0.34)	0.117†	(1.51)	-0.129	(-1.53)
					Difference (Followers - Leaders)							
POTENT-COMP			**0.012§**	**(2.52)**					**0.005**	**(1.17)**		
EXIST-COMP			**-0.006‡**	**(-1.96)**					**-0.034§**	**(-2.38)**		
N	21,033		13,774		7,259		6,252		4,061		2,191	
Pseudo-R^2	5.99%		5.55%		4.09%		9.12%		10.99%		3.58%	

This table presents regression marginal effects (at means) and z-statistics for Equation (3). Firms are divided into sub-groups according to their market shares. A firm-year is classified as industry leader if its market share ranks in the top quartile. Standard errors are clustered by industry. All variables are defined in Appendix A. §, ‡ and † indicate significance at 1%, 5%, and 10% levels, respectively.

Table 10: Firm-level competition and disclosure quality

	Profit						Investment					
	All		Followers		Leaders		All		Followers		Leaders	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
POTENT-COMP	**0.095**§	**(2.92)**	**0.115**§	**(2.48)**	**0.060**†	**(1.53)**	**0.265**§	**(3.29)**	**0.183**§	**(2.45)**	**0.314**§	**(2.66)**
EXIST-COMP	**0.097**‡	**(2.08)**	**0.146**‡	**(2.09)**	**0.013**	**(0.23)**	**-0.208**	**(-1.55)**	**-0.406**§	**(-3.00)**	**-0.031**	**(-0.17)**
IND-PROFIT	-0.110	(-1.44)	-0.057	(-0.52)	-0.190†	(-1.78)	-0.347	(-1.05)	-0.675	(-1.39)	0.003	(0.01)
ISSUE	0.295§	(3.20)	0.343§	(2.88)	0.178	(1.48)	-0.038	(-0.17)	0.236	(0.61)	-0.159	(-0.62)
SIZE	0.560§	(9.33)	0.799§	(8.34)	0.423§	(6.05)	0.469§	(3.41)	0.552§	(3.03)	0.530§	(2.86)
MTB	0.188§	(6.41)	0.228§	(5.59)	0.136§	(4.65)	0.621§	(7.95)	0.773§	(7.11)	0.398§	(4.37)
LEV	-1.790§	(-5.37)	-2.256§	(-4.79)	-1.446§	(-4.19)	-2.653§	(-4.61)	-3.075§	(-4.23)	-2.504§	(-3.31)
ANALYST	-0.028§	(-3.49)	-0.022	(-1.63)	-0.015†	(-1.90)	-0.030†	(-1.68)	-0.021	(-0.74)	-0.044†	(-1.86)
SHRINST	0.767§	(3.65)	0.674§	(2.40)	0.669§	(2.45)	1.343§	(2.60)	1.701§	(2.37)	0.601	(0.94)
STDEV	-0.176	(-0.37)	-0.223	(-0.38)	-0.065	(-0.10)	-42.97§	(-5.89)	-46.84§	(-6.01)	-28.66§	(-3.33)
HORIZ	-0.509§	(-10.25)	-0.629§	(-8.01)	-0.402§	(-7.81)	-0.316§	(-3.25)	-0.435§	(-3.00)	-0.227‡	(-1.96)
SURPRS	0.030	(0.35)	-0.107	(-1.02)	0.240‡	(2.0)	0.088	(1.35)	-0.006	(-0.08)	0.219‡	(2.16)
DIFFI	-0.081§	(-5.53)	-0.085§	(-4.89)	-0.082§	(-4.78)						
STDRET	-0.387§	(-7.23)	-0.398§	(-5.84)	-0.340§	(-4.74)						
DACCR	2.907§	(4.58)	2.438§	(3.36)	3.322§	(3.40)						
LIT	0.046	(0.37)	0.092	(0.48)	-0.166	(-1.26)	1.100§	(2.93)	1.412§	(3.03)	0.911‡	(2.03)
N	5,268		2,546		2,722		2,508		1,269		1,239	
Adj-R^2	24.05%		25.97%		22.76%		21.61%		22.18%		24.48%	

This table presents regression coefficients and t-statistics for Equation (4). Firms are divided into sub-groups according to their market shares. A firm-year is classified as industry leader if its market share ranks in the top quartile. Standard errors are clustered by industry. All variables are defined in Appendix A. §, ‡ and † indicate significance at 1%, 5%, and 10% levels, respectively.

Table 11: Firm-level competition and forecast error

	Profit						Investment					
	All		Followers		Leaders		All		Followers		Leaders	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Panel A: All Forecasts												
POTENT-COMP	**0.017**	**(0.57)**	**0.017**	**(0.39)**	**0.016**	**(0.42)**	**-0.124**†	**(-1.73)**	**-0.117**†	**(-1.49)**	**-0.102**	**(-1.19)**
EXIST-COMP	**0.105**‡	**(1.97)**	**0.138**‡	**(1.77)**	**0.048**	**(0.77)**	**0.253**	**(1.36)**	**0.345**†	**(1.89)**	**0.167**	**(0.92)**
Mean(Median) ERROR	-0.907	(-0.051)	-1.020	(-0.088)	-0.801	(-0.028)	0.358	(-0.076)	0.574	(-0.047)	0.136	(-0.113)
N	5,268		2,546		2,722		2,508		1,269		1,239	
Adj-R^2	13.22%		13.40%		14.31%		16.33%		16.79%		16.14%	
Panel B: Pessimistic Forecasts (ERROR>0)												
POTENT-COMP	**-0.048**§	**(-2.73)**	**-0.060**†	**(-1.82)**	**-0.032**†	**(-1.79)**	**-0.271**§	**(-2.55)**	**-0.257**§	**(-2.26)**	**-0.239**†	**(-1.84)**
EXIST-COMP	**0.042**	**(1.47)**	**0.024**	**(0.58)**	**0.058**†	**(1.89)**	**0.402**†	**(1.60)**	**0.532**§	**(2.27)**	**0.281**	**(1.05)**
Mean(Median) ERROR	0.844	(0.428)	0.998	(0.476)	0.705	(0.373)	2.800	(0.974)	3.353	(1.264)	2.169	(0.765)
N	2,415		1,147		1,268		1,152		614		538	
Pseudo-R^2	2.03%		1.93%		3.06%		6.00%		6.03%		6.48%	
Panel C: Optimistic Forecasts (ERROR<0)												
POTENT-COMP	**0.035**	**(0.73)**	**0.030**	**(0.47)**	**0.021**	**(0.37)**	**0.030**	**(0.51)**	**-0.013**	**(-0.16)**	**0.074**	**(1.36)**
EXIST-COMP	**0.202**§	**(2.65)**	**0.254**§	**(2.39)**	**0.137**	**(1.54)**	**0.095**	**(0.73)**	**0.084**	**(0.51)**	**0.113**	**(1.00)**
Mean(Median) ERROR	-2.471	(-1.216)	-2.747	(-1.340)	-2.202	(-1.036)	-1.721	(-0.702)	-2.030	(-0.732)	-1.430	(-0.650)
N	2,758		1,362		1,396		1,353		655		698	
Pseudo-R^2	4.92%		4.93%		5.39%		3.31%		3.63%		3.74%	

This table presents regression coefficients and t-statistics for firm-level regressions with year dummies. The dependent variable is forecast error. Firms are divided into sub-groups according to their market shares. A firm-year is classified as industry leader if its market share ranks in the top quartile. The dependent variables is left-censored at 0 in Panel B and is right-censored at 0 in Panel C. Tobit model is used for the regressions in Panels B and C. Standard errors are clustered by industry. All variables are defined in Appendix A. §, ‡ and † indicate significance at 1%, 5%, and 10% levels, respectively.

Table 12: Robustness analysis: using alternative competition measures

	FORECASTER%				*ACCURACY*			
	Profit		**Investment**		**Profit**		**Investment**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Panel A: Factors from Exploratory Factor Analysis								
POTENT-COMP$_{EFA}$	**0.017§**	**(3.94)**	**0.026§**	**(4.24)**	**0.108§**	**(2.53)**	**0.238§**	**(3.06)**
EXIST-COMP$_{EFA}$	**-0.039§**	**(-6.52)**	**-0.029§**	**(-2.79)**	**0.075†**	**(1.48)**	**-0.005**	**(-0.04)**
IND-PROFIT$_{EFA}$	0.050§	(4.07)	0.06	(0.32)	-0.111	(-1.17)	-0.370‡	(-1.96)
N	3,649		1,105		1,987		811	
Adj-R^2	16.35%		29.98%		26.49%		25.91%	
Panel B: Original Competition Variables								
IND-PPE	**-0.007§**	**(-3.42)**	**-0.009§**	**(-3.17)**	**-0.046‡**	**(-2.40)**	**-0.098§**	**(-2.83)**
IND-CON4	**0.245§**	**(6.62)**	**0.153§**	**(2.50)**	**-0.499†**	**(-1.54)**	**0.095**	**(0.12)**
IND-MGN	-0.087‡	(-1.93)	-0.289§	(-2.91)	-0.200	(-0.44)	-1.172	(-1.28)
N	3,649		1,105		1,987		811	
Adj-R^2	15.81%		30.32%		26.33%		25.57%	
IND-CPX	**-0.034‡**	**(-1.86)**	**-0.075§**	**(-2.84)**	**-0.616§**	**(-3.16)**	**-1.113§**	**(-3.24)**
IND-NUM	**-0.001§**	**(-5.34)**	**-0.001§**	**(-2.72)**	**0.006§**	**(2.73)**	**0.007†**	**(1.42)**
IND-ROA	0.444§	(4.56)	0.104	(0.71)	-0.670	(-0.89)	-2.562†	(-1.72)
N	3,649		1,105		1,987		811	
Adj-R^2	15.88%		29.65%		26.79%		26.27%	

This table presents regression coefficients and t-statistics for industry-level OLS regressions with year dummies. In Panel A, POTENT-COMP$_{EFA}$, EXIST-COMP$_{EFA}$ and IND-PROFIT$_{EFA}$ are proxies for competition from potential entrants, competition from existing rivals and industry profitability. They are constructed from three common factors retained from Exploratory Factor Analysis (EFA) of the nine industry-level competition variables as described in Table 2. EXIST-COMP$_{EFA}$ is the inverse of the first common factor, with larger EXIST-COMP$_{EFA}$ indicating higher competition from existing rivals; POTENT-COMP$_{EFA}$ is the inverse of the second common factor, with larger POTENT-COMP$_{EFA}$ indicating higher competition from potential entrants; IND-PROFIT$_{EFA}$ is the third common factor, with larger IND-PROFIT$_{EFA}$ indicating higher industry profitability. In Panel B, the coefficients on IND-PPE and IND-CPX are multiplied by 1000 for expository purpose. Standard errors are adjusted for Newey-West heteroscedasticity and autocorrelation. Coefficients on control variables are omitted. §, ‡ and † indicate significance at 1%, 5%, and 10% levels, respectively.

Table 13: Robustness analysis: Granger causality test

	FORECASTER$_t$%			
	Profit		**Investment**	
	Coef.	**t-stat**	**Coef.**	**t-stat**
FORECASTER$_{t-1}$%	0.457§	(19.07)	0.349§	(6.14)
FORECASTER$_{t-2}$%	0.175§	(7.22)	0.208§	(4.02)
POTENT-COMP$_{t-1}$	0.030‡	(2.00)	-0.038	(-0.96)
POTENT-COMP$_{t-2}$	-0.018	(-1.19)	0.053	(1.35)
EXIST-COMP$_{t-1}$	-0.027	(-0.79)	-0.026	(-0.33)
EXIST-COMP$_{t-2}$	0.010	(0.29)	0.008	(0.10)
IND-PROFIT$_{t-1}$	-0.002	(-0.15)	-0.019	(-0.62)
IND-PROFIT$_{t-2}$	-0.003	(-0.19)	-0.005	(-0.15)
	F-test			
	Coef.	**F-stat**	**Coef.**	**F-stat**
POTENT-COMP$_{t-1}$+POTENT-COMP$_{t-2}$	0.012§	(11.48)	0.014‡	(4.33)
EXIST-COMP$_{t-1}$+EXIST-COMP$_{t-2}$	-0.017§	(8.65)	-0.018†	(2.06)
IND-PROFIT$_{t-1}$+IND-PROFIT$_{t-2}$	-0.005	(0.22)	-0.023	(1.15)
N	2,600		509	
Adj-R^2	40.16%		48.54%	

This table presents regression coefficients and t-statistics for Equation (6). Standard errors are adjusted for Newey-West heteroscedasticity and autocorrelation. Coefficients on control variables are omitted. §, ‡ and † indicate significance at 1%, 5%, and 10% levels, respectively.

Table 14: Other robustness analyses

	FORECASTER%				*ACCURACY*			
Panel A: Industry-level analysis on investment-forecasts disclosed in MD&A								
	MD&A		**All**		**MD&A**		**All**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
POTENT-COMP	**0.023**§	**(2.24)**	**0.028**§	**(3.51)**	**0.202**†	**(1.38)**	**0.369**§	**(2.29)**
EXIST-COMP	**-0.038**‡	**(-1.99)**	**-0.040**§	**(-2.30)**	**-0.127**	**(-0.42)**	**0.029**	**(0.10)**
N	364		364		288		325	
Adj-R^2	15.40%		30.32%		14.45%		20.13%	
Panel B: Industry-level analysis based on firms with a single segment								
	Profit		**Investment**		**Profit**		**Investment**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
POTENT-COMP	**0.019**§	**(3.60)**	**0.026**§	**(3.65)**	**0.097**‡	**(1.68)**	**0.274**§	**(2.83)**
EXIST-COMP	**-0.041**§	**(-5.64)**	**-0.025**‡	**(-1.96)**	**0.100**†	**(1.33)**	**0.068**	**(0.35)**
N	2,989		904		1,384		610	
Adj-R^2	15.27%		29.03%		25.27%		20.13%	
Panel C: Industry-level analysis after deleting regulated industries								
	Profit		**Investment**		**Profit**		**Investment**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
POTENT-COMP	**0.011**§	**(2.40)**	**0.037**§	**(5.99)**	**0.135**§	**(2.97)**	**0.250**§	**(3.00)**
EXIST-COMP	**-0.034**§	**(-4.50)**	**-0.032**§	**(-2.59)**	**0.100**†	**(1.45)**	**0.061**	**(0.42)**
N	3,303		1,050		1,913		758	
Adj-R^2	16.47%		30.76%		27.22%		23.90%	
Panel D: Cross-sectional firm-level analysis								
	Profit		**Investment**		**Profit**		**Investment**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
POTENT-COMP	**0.103**§	**(3.93)**	**0.027**†	**(1.26)**	**0.122**§	**(2.19)**	**0.201**§	**(2.32)**
EXIST-COMP	**-0.074**§	**(-2.28)**	**-0.120**§	**(-3.30)**	**0.191**§	**(2.68)**	**-0.150**	**(-0.90)**
N	4,553		1,900		1,669		1004	
Adj-R^2	18.79%		28.81%		32.39%		25.21%	

In Panel A, "MD&A" indicates that management forecasts are collected from the MD&A section of SEC filings, and "All" indicates that forecasts are collected from both MD&A and Factiva. Standard errors are adjusted for Newey-West heteroscedasticity and autocorrelation for industry-level analysis (Panels A, B and C) and are clustered by industry for firm-level analysis (Panel D). §, ‡ and † indicate significance at 1%, 5%, and 10% levels, respectively.