Product market pricing power, industry concentration and analysts' earnings forecasts

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ABSTRACT

This is the first study to establish a link between product market power and analysts' earnings forecast accuracy and bias. Relating two different dimensions of market power to earnings forecastability, we document that (a) a firm's relative pricing power and (b) its industry concentration are strong positive determinants of analysts' earnings forecast accuracy. We find that forecasting earnings of higher market power firms is less complex due to their ability to withstand cost shocks as well as greater informational-efficiency enjoyed by such firms. Further, forecast optimism increases with weakening product market pricing power and with lower industry concentration. The knowledge derived from this study will hopefully improve the accuracy of equity valuation, and thereby engender better buy-side (stock selections) and sell-side recommendations by analysts. Our analysis also suggests that brokerage firms compensating analysts based on forecast accuracy need to adjust for the differential in the information complexity of different industries.

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1. Introduction

The vast body of academic research on analysts' earnings forecasts, both in the accounting and finance literatures, has thus far been silent on the important link between product market power and earnings forecasts. The central question in this study is whether product market competition systematically influences analysts' earnings forecasts. There are two distinct channels of product market competition that can influence earnings forecastability and thereby analysts' earnings forecast accuracy and bias. At the firm (micro) level, earnings forecastability depends on a firm's ability to maintain its profit margin and absorb exogenous cost shocks, which is captured by its pricing power relative to its industry rivals (*intra*-industry or micro-channel). On the other hand, at the industry (macro) level, industry concentration also has an inherent influence on a firm's price-setting ability in that product market (*inter*-industry or macro-channel), where firms in more concentrated industries enjoy greater pricing ability and hence are expected to be associated with better earnings forecastability. Further, the product market structure can have a direct bearing on the strategic decisions made by industry rivals in such a manner that renders the earnings of firms in more concentrated industries less complex.

Another notable feature of the industry-specific nature of analyst forecasts is that analysts specialize by industry in order to improve their efficiency and to formulate better-informed and more reliable forecasts. Analysts thus develop expertise in a specific industry becoming familiar with the operations of all companies within the industry (O'Brien, 1988). We reason that analysts are expected to be more prone to greater error in predicting earnings of companies in industries characterized by a faster rate of change such as in competitive industries. It can also be argued that greater information complexity in competitive industries due to greater innovation activities (Nickell, 1996) renders earnings forecastability more difficult, and hence, earnings forecasts are expected to be less accurate for firms in fragmented industries and vice versa. To date, the accounting and finance literatures have remained silent on whether analysts' forecasts are systematically more prone to error for firms that exhibit less pricing power and firms in less concentrated industries facing greater product market competition.

This study examines the link between (a) product market pricing power and analysts' earnings forecasts and (b) product market structure and analysts' forecasts. Specifically, we seek to focus on the following questions: Is there a link between product pricing power and analyst forecast accuracy? Does pricing power influence analyst earnings forecast bias (i.e. optimism or pessimism)?[1] Does

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[1] The term "bias" in this literature implies systematic deviations, in the positive (optimistic) or negative (pessimistic) direction, of the actual earnings from forecasts.

product market structure, such as industry concentration, influence analysts' earnings forecasts? And if so, how does it affect the accuracy and bias of the forecasts? We believe that shedding light on product market power will substantially enhance our understanding of analysts' earnings forecasts as well as add an important new dimension to this literature by establishing a link to the body of research at the intersection of industrial organization and analysts forecast literatures. To the best of our knowledge, this is the first study to bridge the gap between these two distinct bodies of research.

Understanding the influence of product market power on earnings forecastability is pivotal to investors because of the integral role of earnings in asset pricing. Our findings have implications to investors using analysts' earnings forecasts for company valuation since more accurate forecasts will lead to more precise valuations. Moreover, the results could also assist in deriving the implicit cost of capital estimates by using the residual income valuation approach (see Claus and Thomas, 2001). To the extent that earnings forecasts are value-relevant, our analysis of the role of market power in enhancing accuracy of earnings should provide direct benefits to investors. Recent research supports the notion that analysts with more accurate earnings forecasts better understand the linkage between earnings and stock valuation and effectively translate these forecasts into superior stock recommendations. Loh and Mian (2006) document that analysts who issue more accurate earnings forecasts also issue more profitable stock recommendations, while Ertimur et al.'s (2007) findings suggest that analysts that make more accurate earnings forecasts generate more profitable recommendations. Recent study by Autore et al. (2009) show that stronger shareholder rights are associated with more favorable analysts' recommendations.

Our analysis contributes to the literature in several important ways. Using a large sample of 570,099 firm-month observations for the thirty-year period spanning 1976–2005, we document that product market power is an important determinant of analyst forecast accuracy. Specifically, we report that the mean analyst forecast accuracy is lowest for the quintile of firms exhibiting the least market pricing power, while the analyst forecast accuracy for firms with the highest pricing power quintile is over three times better. The evidence for analyst forecast bias mirrors that obtained for analyst forecast error in that the mean forecast bias for firms in the lowest pricing power quintile is significantly higher (more optimistic) than that for firms in the highest market power quintile. Although the relations between forecast accuracy and bias on the one hand and industry concentration on the other in the univariate analysis are not strictly monotonic, forecast accuracy (bias) is generally increasing (decreasing) in industry concentration.

In multivariate regression analysis, we find compelling evidence that firms' product market power has a significant effect on analysts' earnings forecast accuracy even after controlling for firm earnings' volatility and the usual factors that influence forecast accuracy. In particular, we document a positive and significant link between pricing power and earnings forecast accuracy suggesting that estimating earnings of firms with high pricing power is less complex due to the firm's ability to withstand cost shocks and the greater informational-efficiency enjoyed by such firms. Our findings also reveal that analysts forecast accuracy is significantly greater for firms in concentrated industries. This supports the notion that greater information complexity in competitive industries due to greater innovativeness of these firms (Nickell, 1996) and greater susceptibility to new radical technologies (Nerkar and Shane, 2003) renders earnings forecasts more challenging and prone to greater inaccuracy. Our results for product market structure are also in support of the view that industries characterized by concentration are more likely to cooperate on issues that

could bolster their cash flows and reduce negative fluctuations thus rendering their earnings' forecasts more accurate.

In addition, when we include both measures of product market power, namely relative or intra-industry (micro-channel) pricing power and industry-level (macro-channel) concentration, in the same regression specification, our findings corroborate the view that these two factors have significant incremental explanatory power and capture different dimensions of product market competition. Put differently, our findings document that both intra- and inter-industry channels are relevant to earnings' forecasts accuracy. In an alternative specification to test the robustness of our results, we use firm market share as another metric of product market power and find that it also is significantly positively related to forecast accuracy, indicating that a firm's dominance within its industry enhances its earnings forecastability.

Furthermore, multivariate analysis also indicates that analysts' forecast optimism (i.e. positive forecast bias) increases with weakening product market power. Our empirical findings document that the information content of the firm's product market pricing power and industry structure have significant additional value to investors and analysts beyond just the variability in the firm's earnings. We perform a battery of robustness checks to confirm the validity of our results. Our conclusions are robust to alternative specifications, variable measurements, and estimation procedures. We add another novel dimension to the study by exploiting the one-time events of industry deregulations to ascertain and verify the impact of a change in competition on analysts' forecasts accuracy and bias. The exogenous shock to market power due to industry deregulation provides us with a clean natural experiment and a unique opportunity to study the effect of competition on analysts forecast accuracy. We examine a subset of industries in our sample that have undergone deregulation and find that analysts' forecast accuracy declines significantly in the post-deregulation period, while analyst optimism increases significantly.

Overall, the findings presented in this study advance our knowledge in the areas of analysts' earnings forecast accuracy and analyst forecast bias by identifying product market power as a significant determinant of accuracy and bias. Arguably, adding product market dimensions to this important body of research improves the estimation of cost of capital and accuracy of equity valuation, and thereby is expected to engender better stock selections (buy-side) and recommendations (sell-side) by analysts. This study also has implications for equity analysts' compensation. Our findings suggest that brokerage firms compensating analysts based on forecast accuracy need to adjust for the differential in the information complexity of different industries.

The paper is organized as follows. Section 2 outlines and develops the hypotheses related to the influence of product market structure and pricing power on analysts forecast accuracy and bias. Section 3 details the sample formation process, sample description, and the variables used for forecast accuracy, forecast bias and product market power measures. The empirical findings associated with market power and earnings forecast accuracy and forecast bias are presented in Section 4. Section 5 concludes the paper.

2. Hypotheses development

In this section we discuss the influence of the two channels of product market competition (firm-specific pricing power and industry concentration) on earnings forecastability, and thereby analysts' forecast accuracy and bias. There are a number of potential reasons why pricing power and industry structure are expected to affect the predictability of earnings. We first present the role that pricing power can play on earnings forecast accuracy.

Uniqueness and superiority of product lines or a strong brand name are the hallmarks of strong pricing power and competitive advantage. While industry-wide elasticity of demand is determined by the aggregate demand curve for the industry, we argue that *intra*-industry product differentiation can affect the price elasticity of demand faced by a *specific* firm, regardless of the industry structure in which it operates. Research in this area has identified that the advantages derived from pricing power are multi-faceted, such as the firm's ability to absorb cost shocks, reduced likelihood of exit and increased stock liquidity (Kale and Loon, 2009; Peress, 2010).

Firms with greater pricing power can better maintain their profit margins when they are subject to exogenous productivity shocks because of the uniqueness of their products and/or strong brand name. Greater product differentiation (or lower product substitutability) can lead to more inelastic demand curve for a firm's product, which affords the firm the flexibility to pass on cost shocks to its customers. In other words, product substitutability increases price competition.[2]

Greater product market pricing power makes it easier for investors to learn about the underlying firm profitability, thereby improving earnings forecastability as uncertainty about the firm's future cash flows declines. We expect the complexity in forecasting earnings to be smaller for firms that command pricing power because of their ability to extract a higher price from their customers in the face of an idiosyncratic cost shock, regardless of the market structure. Several studies in the analysts' earnings forecast literature document a positive link between earnings forecastability and analysts' earnings forecast accuracy.[3] Thus, a case can be made that by cushioning firms from cost shocks, pricing power can improve the firm's earnings forecastability.

By increasing cash flows and dampening volatility, product market pricing power serves to raise the immunity level of the firm in deteriorating economic conditions, while firms with weaker pricing power are more likely to falter. The enhanced cash flow cushion translates into a lower likelihood of distress, and hence, a lower likelihood of exit.

Peress (2010) demonstrates that product market power influences the informativeness of stock prices, which in turn affects allocation of capital. Because investors channel more capital when they are better informed, the more informationally-efficient stock prices are expected to experience greater allocation of capital. Kale and Loon (2009) document that firms with superior pricing power exhibit higher stock liquidity which should bring about a lower cost of capital as well as lower trading costs in the firm's stock. Moreover, such firms are better able to weather discount rate shocks. Again, this benefit from market power gives rise to more precise earnings forecastability by analysts, which is attributed to enhanced liquidity.

Given that strong product market power confers advantages to forecastability of earnings, we propose that the greater complexity associated with earnings prediction for firms with weak product market pricing power will render their earnings forecasts less accurate. In our case, the source of the complexity is low product

pricing power.[4] Based on the combination of factors discussed above that enhance earnings forecastability, we propose:

Hypothesis 1. Analysts make more (less) accurate earnings forecasts for firms with more (less) pricing power.

Another dimension that influences product market competition is product market structure. Besides the obvious effect on the price-setting ability of the firm, industry concentration has a direct influence on the strategic decisions made by product market participants in that industry. Industry structure can therefore be an important determinant of earnings forecastability, and thereby analysts' forecast accuracy. In contrast to pricing power, the theoretical and empirical literatures on industry concentration do not offer a clear directional link between industry concentration and earnings forecast accuracy. We present various arguments from the existing literature some of which support the view that earnings of firms in fragmented industries are more challenging to predict while others do not.

The first potential link between competition and earnings' forecast is related to the degree of disclosure of information in an industry. The release of information by competing firms in the same sector could improve earnings' forecasts. However, theoretical models offer divergent views on information disclosure by competing firms. While Verrecchia (1983) and Clinch and Verrecchia (1997) propose that firms in industries characterized by intense product market competition disclose less information because of the potential harm to a firm's competitive position, Stivers (2004) demonstrates that the unraveling of proprietary information intensifies with competition. He argues that an industry with a greater number of competitors is more likely to have at least one firm with quality high enough to release its information, and therefore begins the process of unraveling the information. This unraveling process ensures full disclosure as the number of firms in an industry increases.

Another plausible reason why firms in more competitive industries may be prompted to reveal proprietary information is the need to reduce informational asymmetry costs which would allow such firms to obtain financing at more favorable conditions. Hoberg and Phillips (2010) postulate that gathering firm-specific information in concentrated (competitive) industries is less (more) costly. They find compelling evidence supporting the notion that market participants in competitive industries do not fully internalize the negative externality of industry competition on cash flows and stock returns. Confirming this notion are Gaspar and Massa's (2006) findings that concentrated industries experience lower dispersion in earnings forecasts. However, a number of empirical papers document that less competitive industrial sectors are less likely to disclose segment information than highly competitive sectors (see Harris, 1998; Hayes and Lundholm, 1996). The opposing predictions of the above studies with regard to information generation in an industry raises an interesting empirical question of whether analysts make more or less accurate earnings forecasts for firms in more concentrated industries.

Another rationale for a link between competition and earnings' forecast is related to the degree of innovation in an industry. Empirical studies point to a positive relation between innovative activities and product market competition (Nickell, 1996). In addition, Hou and Robinson (2006) conclude that firms in more concentrated industries are less risky because they engage in less innovation. This is in contrast to Schumpeter's (1950) prediction that the most likely candidates to engage in creative destruction are firms in less competitive industries. Schumpeter argues that

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[2] For example in the case of Apple Inc., its superior product positioning in the high tech consumer electronics sector exemplifies product market power. The ability of Apple Inc. to differentiate its product offerings through superior design and innovation gives it the ability to set prices for its products at the high end. Hence it is possible for a company with product market power to operate with low market share in a competitive industry and yet have the ability to set higher prices for its products. An example from a low-tech industry would be the restaurant industry. A restaurant with a high quality product and first rate service commanding higher prices will enjoy high product market power while operating in a highly competitive industry.

[3] See for example Brown et al., 1987; Lang and Lundholm, 1996; and Duru and Reeb, 2002.

[4] Brown (1993) concludes that the accuracy of the forecast depends on the complexity associated with making the forecast.

larger firms, with some degree of monopoly power, have an advantage in developing costly innovations because of access to better resources and greater market power.[5] Innovative firms associated with greater technological discontinuities (a term used in the literature to convey sudden and dramatic changes in the use of a certain technology), inject high information complexity rendering the implication of such information on earnings more difficult to assess. The information complexity can arise from a number of sources, one of which stems from difficulty in quantifying potential success of innovations; another stems from the deeply complex task of projecting counter responses of rival firms. Thus, the higher degree of innovation introduces information complexity that negatively impacts earnings' forecast accuracy.

In addition, Nerkar and Shane (2003) show that survival of firms introducing radical innovations is contingent on industry environment. Specifically, they document that new technological ventures are less likely to survive in concentrated industries even when their radical technologies are difficult to imitate. They conclude that industry concentration inhibits the exploitation of new innovations because of the difficulty of creating, marketing and manufacturing assets necessary for survival. This evidence implies that firms in concentrated industries have less to fear from new innovations that can disrupt their operations and their cash flows. On the other hand, the greater susceptibility to new radical technologies in fragmented industries undermines the cash flows of such firms in unpredictable ways. Therefore, based on this argument, analyst forecast accuracy would be higher for concentrated industries than competitive industries.

Third, in a theoretical model, Mao and Zaleski (2001) show that the greater the industry concentration, the more likely that the firms cooperate on group issues such as joint lobbying. They demonstrate that when an industry sector is characterized by a large number of small firms, the marginal benefit of cooperation is very low. A prime recent example of this behavior is the airline industry lobbying Congress for special treatment after the 9/11 incident, whereas fragmented taxi companies, that were also negatively impacted by the event, did not lobby nor get similar favorable treatment. We reason that the ramification of such behavior is that cash flows of firms in concentrated industries will be less prone to negative fluctuations unlike fragmented industries, leading to better forecastability of earnings of firms in concentrated industries.

Collectively, the above discussion unveils an interesting tension in the potential relation between analysts' earnings forecasts accuracy and industry concentration. Hence, this relation is an empirical question. We propose the following competing hypotheses:

Hypothesis 2A. Analysts make more (less) accurate earnings forecasts for firms in more (less) concentrated industries.

Hypothesis 2B. Analysts make less (more) accurate earnings forecasts for firms in more (less) concentrated industries.

For completeness we also examine how market power affects analysts' earnings forecast bias (optimism or pessimism). Past research has established, theoretically and empirically, some of the factors that affect analysts' forecast optimism. A number of studies document that analysts' forecast are optimistically biased (Lin and McNichols, 1998). Lim (2001) develops a model that shows that analysts' optimism is strongest when disagreement among analysts is high, while Diether et al. (2002) and Das et al. (1998) find that as earnings become less predictable, analysts issue more optimistic

forecasts, supposedly to curry favor with managers to maintain access to management's private information. This body of research on analyst forecast (optimism) bias, in conjunction with our argument that high intra-industry product pricing power is positively related to earnings forecastability, leads us to postulate that firm-specific product market pricing power should be an important determinant of analyst forecast bias. In particular, firms with low market power inherently have more complex earnings predictability and will be associated with more optimistic analysts' earnings forecasts. Based on the above arguments, we propose the following:

Hypothesis 3. Analysts make more (less) optimistic earnings forecasts for firms with less (more) market pricing power.

The directional relation between industry concentration and bias in earnings' forecasts is an empirical issue. Empirical evidence by Gaspar and Massa (2006) shows that concentrated industries experience lower dispersion in earnings forecasts which would suggest that earnings' forecasts will be less optimistically biased for concentrated industries. Examining the link between industry-level competition and industry boom and bust cycles, Hoberg and Phillips (2010) conclude that analyst estimates are biased upwards in competitive industries when there is high industry investment and in competitive industries that experience high growth. Given the ambiguity of the impact of competitiveness on forecastability (discussed earlier), it is unclear whether earnings' forecasts are more optimistic for concentrated as compared to competitive industries. We therefore propose two alternative hypotheses as follows:

Hypothesis 4A. Analysts make more (less) optimistic earnings forecasts for firms in less (more) concentrated industries.

Hypothesis 4B. Analysts make less (more) optimistic earnings forecasts for firms in less (more) concentrated industries.

3. The sample

3.1. Sample formation

Our sample selection process starts by including all firms that are at the intersection of the I/B/E/S Summary History file, the Compustat database and CRSP files with the share code 10 and 11 over the 30-year period from 1976 to 2005. The beginning of our sample period is determined by the I/B/E/S Summary data that starts in 1976. We eliminate (1) foreign firms, (2) firms in the utility industry starting with three-digit SIC codes of 481, 491 and 494, and the financial industry (SIC codes of 6000–6999), (3) firms that are missing required financial information necessary for our analyses in the Compustat database, and (4) firms with less than two earnings forecast estimates.[6] To incorporate as much information as possible, we use all available earnings forecasts for the fiscal year from the I/B/E/S summary file. To be consistent in the measurement of earnings forecasts and actual earnings, we obtain actual earnings from I/B/E/S database (instead of Compustat) since I/B/E/S forecasts usually exclude extraordinary items and a few special items (see Philbrick and Ricks, 1991). The forecasted and actual earnings used in the study are both based on continuing operations. Applying the above screens results in a sample of 570,099 firm-month observations for the 30-year period of the study.

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[5] Schumpeter's earlier work posited that smaller companies are in better position to innovate since they are more nimble, entrepreneurial and flexible than larger companies ensnared and hamstrung in bureaucratic structures.

[6] The number of estimates variable (numest) in IBES summary files closely matches the analysts following for a firm, excluding extreme, non-verifiable estimates. When using IBES summary files, we use the number of estimates as the proxy for analysts following the firms.

3.2. Measuring analyst earnings forecast variables

Following much of the analyst earnings literature, we construct analyst earnings forecast accuracy as the negative of the absolute value of the difference between the firm's consensus forecast annual earnings per share (EPS) and the firm's actual EPS standardized by the closing stock price on the trading day preceding the forecast date. It is conventional in the literature to multiply the absolute value of the difference between the firm's forecast earnings per share (EPS) and the actual EPS by −1 to make the measure increasing in forecast accuracy.

$$Forecast\ Accuracy_{jt} = -1 * \frac{|EPS_{jt}^{Forecast} - EPS_{jt}^{Actual}|}{P_{j,t-1}} \tag{1}$$

We then industry-adjust forecast accuracy for each month by subtracting the industry mean forecast accuracy from the forecast accuracy of each firm. Throughout the paper, we define industry membership for a firm based on the two-digit SIC code using the entire universe of firms in that industry that are available in the Compustat database.

Analyst earnings forecast bias is measured as the firm's consensus forecast EPS less the actual EPS standardized by the closing stock price on the trading day preceding the forecast date.

$$Forecast\ Bias_{jt} = \frac{EPS_{jt}^{Forecast} - EPS_{jt}^{Actual}}{P_{j,t-1}} \tag{2}$$

Like forecast accuracy, we industry-adjust forecast bias each month by subtracting the industry mean forecast bias from the forecast bias for each firm.

3.3. Measuring product market power variables

Following much of the industrial organization literature (see Lindenberg and Ross (1981) among others), we construct our product market pricing power measure based on the price–cost margin (PCM), often referred to as Lerner Index (LI) (Lerner, 1934). It is calculated as follows:

$$PCM = LI = \frac{Sales - COGS - SG\&A}{Sales} \tag{3}$$

where sales is Compustat item #12, cost of goods sold, COGS, is Compustat item #41, and sales, general and administrative expenses, SG&A, is Compustat item #189. The PCM measure excludes depreciation, interest, special items and taxes. We use operating income (item #178) to calculate price–cost margin when there is missing data for the above items.

Although the price–cost margin has been used to capture a firm's product market power, this measure does not, however, isolate the firm-specific factors that influence product market pricing power from industry-wide factors. Because the price–cost margin metric can fluctuate due to industry-specific attributes that are unrelated to a firm's market pricing power, we use an industry-adjusted Lerner Index to capture *firm-specific* product market power by subtracting the sales-weighted price–cost margin of all firms within the industry from the price–cost margin of the firm. We refer to this industry-adjusted measure as the excess price–cost margin (EPCM) or the industry-adjusted Lerner Index (LI$_{adj}$).

$$EPCM_i = LI_{adj} = LI_i - \sum_{i=1}^{N} \omega_i LI_i \tag{4}$$

where LI$_i$ is the Lerner Index for firm i as calculated in (1), ω_i is the proportion of sales of firm i to total industry sales, and N is the total number of firms in the two-digit SIC code industry.

This modified Lerner Index captures purely the intra-industry market power of a firm based on firm-specific factors, therefore, distilling the effects of industry-wide effects common to all firms in a specific industry from firm-specific factors. Further, this adjustment addresses the fact that different industries have structurally different profit margins due to factors unrelated to intra-industry differences in market power of the firms. Gaspar and Massa (2006) and Peress (2010) use measures similar to our EPCM. Since our analysis in the paper is based on the industry-adjusted Lerner Index, for brevity we henceforth refer to this variable as Lerner Index.

The Herfindahl–Hirschman Index (HHI), henceforth Herfindahl Index, measuring industry concentration, is calculated as the sum of the squares of the market shares of the firms' sales within an industry. We compute this measure at the end of each fiscal year. HHI, which contains information of market share of all firms in the industry, is decreasing in the number of competitors and increasing with the variability in firm market share within the industry.

$$Herfindahl\ Index_j = \sum_{i=1}^{n} \left(\frac{Sales_i}{\sum_{i=1}^{n} Sales_i}\right)^2 \tag{5}$$

where Sales$_{ij}$ (Compustat item #12) is the sales market share of firm i in industry j, and n is the number of firms in industry j computed as of the fiscal year end.

3.4. Sample description

Table 1 presents the salient summary statistics for our sample. Panel A of Table 1 presents the mean, median, and standard deviation of firm characteristics for the full sample as well as the mean and median over each of three 10-year sub-periods during our sample period—1976–1985, 1986–1995, and 1996–2005. To reduce the effect of outliers, all the variables are winsorized at the 1 and the 99 percentile breakpoints in our analysis. Our findings are robust to trimming these variables, instead of winsorizing them.

As shown in Panel A, the mean (median) sales-based *Herfindahl Index* is 0.22 (0.23) which is comparable to that reported by Rogers and Stocken (2005). The mean industry-adjusted Lerner Index of −0.087 is similar to that reported by Gaspar and Massa (2006). However, the corresponding median (0.002) is higher because analysts tend to cover more profitable firms. Our sample firms have an average market capitalization of $1.42 billion with a range of $24 million to $38 billion. We measure *Market Capitalization*, based on CRSP data, as the product of the number of shares outstanding and the closing stock price on the trading day preceding the day of the earnings forecast.

The mean earnings *Volatility*, measured as standard deviation of actual earnings per share (as recorded in IBES files) calculated over the preceding three-year period, is 0.83. The mean earnings *Skewness* based on the last three years of actual earnings for our sample is −0.097. *Skewness* is defined as:

$$Skewness_{jt} = \frac{n_j}{(n_j - 1)(n_j - 2)} \sum_t ((EPS_{jt} - \overline{EPS_j})/s_j)^3 \tag{6}$$

where $\overline{EPS_j}$ is the mean of earnings per share for firm j, s_j is the standard deviation of EPS for firm j, and n_j is the number of observations of EPS during the preceding 3 year estimation window. The volatility and skewness measures are similar to those documented by Duru and Reeb (2002).

Forecast dispersion is computed as the standard deviation of all earnings forecasts used to compute consensus mean forecast deflated by the closing stock price on the trading day preceding the forecast date. We extract the value of the standard deviation variable from IBES Historical Summary files. The stock price is taken from CRSP files. We update this measure monthly. This variable captures the extent of analyst disagreement about a firm's future

Table 1

Descriptive statistics. This table reports the summary statistics for some salient characteristics of our sample. The statistics are based on 570,099 firm-month observations drawn from the intersection of the I/B/E/S, COMPUSTAT, and CRSP databases spanning the period 1976–2005. The firms included are US firms exclude utilities and finance firms. Herfindahl Index is the sum of squares of market share of firm's sales within the industry. Lerner Index is the sales-weighted industry-adjusted Lerner Index (price–cost margin). Volatility is the standard deviation of actual earnings per share (EPS) over preceding three-year period. Skewness is for EPS. Dispersion is the standard deviation of analysts' forecasts scaled by the closing stock price on the trading day preceding forecast date. Following is the number of analysts following the firm. Horizon is the number of days the analyst forecast is made prior to the actual earnings release. Forecast Accuracy is the *negative* of the absolute value of the difference between the analysts consensus forecast annual EPS and the firm's actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. Forecast Bias is the firm's consensus annual forecast EPS less the actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. The statistics reported are time-series description of monthly cross-sectional averages.

Variable	Full sample period		1976–1985	1986–1995	1996–2005
	Mean (Median)	Std. Dev.	Mean (Median)	Mean (Median)	Mean (Median)
Panel A: Characteristics related to market power, size, earnings and analysts					
Herfindahl Index	0.22	0.04	0.24	0.24	0.19
	(0.23)		(0.24)	(0.25)	(0.19)
Lerner Index	−0.087	0.116	0.018	−0.042	−0.227
	(0.002)		(0.020)	(−0.002)	(−0.229)
Market Cap (in $ mil)	1421.44	809.63	686.72	1152.71	2424.89
	(1195.39)		(661.76)	(1187.08)	(2474.55)
Volatility	0.83	0.10	0.84	0.83	0.82
	(0.82)		(0.83)	(0.82)	(0.79)
Skewness	−0.097	0.101	−0.014	−0.122	−0.157
	(−0.113)		(−0.033)	(−0.155)	(−0.155)
Dispersion	0.011	0.004	0.010	0.012	0.010
	(0.010)		(0.009)	(0.012)	(0.009)
Forecast Horizon	140.28	51.25	141.43	138.17	141.24
	(141.49)		(137.35)	(141.58)	(146.30)
Analysts Following	8.28	0.75	8.27	8.81	7.75
	(8.28)		(8.30)	(9.05)	(7.69)
Variable	Total Sample		1976–1985	1986–1995	1996–2005
	Mean (Median)		Mean (Median)	Mean (Median)	Mean (Median)
Panel B: Forecast accuracy and bias					
Forecast Accuracy	−0.0352		−0.0351	−0.0387	−0.0319
	(−0.0327)		(−0.0273)	(−0.0390)	(−0.0298)
Forecast Bias	0.0234		0.0228	0.0292	0.0183
	(0.0208)		(0.0150)	(0.0281)	(0.0178)

earnings. It is typically used as a proxy for earnings uncertainty. We find a mean (median) forecast dispersion of 0.011 (0.010) for our sample. Because our earnings forecast metric includes *all* earning forecasts made throughout the year, the forecast dispersion is expected to be smaller than dispersion based only on the first forecast given that more recent forecasts tend to be more accurate (O'Brien, 1988). The mean number of forecast days or forecast period, *Horizon*, is 140.28 days prior to the actual earnings release. *Analysts Following*, measured as the number of analysts following the sample firm, ranges from 2 to 50, with a mean of 8.28. These numbers are consistent with previous studies.

To examine the stability of firm characteristics over time, we partition our sample period into three 10-year sub-periods (1976–1985, 1986–1995, 1996–2005) and recalculate the statistics presented in column 2 of Panel A. As expected, firm capitalization increases progressively over the three periods. The Lerner Index for our sample declines over time, which may be evidence of deregulation and increased global competition confirming evidence reported by Gaspar and Massa (2006). The *Herfindahl Index* figures support this conjecture as the mean for the first and second 10-year sub-periods declines from 0.24 to 0.19 in the third sub-period. The remaining variables are essentially stable during our study period.

Panel B of the table documents the mean and median statistics for our two earnings forecast metrics, forecast accuracy and forecast bias for the total sample period and three (10-year) sub-periods. The mean (median) earnings forecast accuracy for the whole sample period is −0.0352 (−0.0327), which is highly significant ($p < 0.0001$). An examination of the mean accuracy over the three sub-periods indicates that forecast accuracy is stable over time. Our findings reveal that the mean (median) forecast bias for the whole sample period is 0.0234 (0.0208) which is also highly

significant. These statistics indicate that annual earnings forecasts for our study period are on average optimistic, consistent with findings of Abarbanell and Lehavy (2003), among others.

A comparison of mean and median earnings forecast bias over the three sub-periods reveals no specific pattern. For example the mean increases from 0.0228 in the first sub-period to 0.0292 in the second sub-period but then it declines to 0.0183 in the third sub-period. Thus the optimistic bias that we observe is not period-specific. Although, Brown (2001) reports a decline in the median forecast errors, their findings indicate a *pessimistic* bias over 1984–1999 time interval.

3.5. Correlation matrix

In Table 2 we present the Pearson correlation coefficients between the independent variables used in this study. We first note that the actual magnitudes of the correlation coefficients are rather small (with a few exceptions) indicating that the variables are not highly correlated.

It is noteworthy that the significant negative correlation between *Lerner Index* and *Loss* supports the notion that firms with greater market power are able to pass on cost shocks to consumers as per the premise of this study, and hence, experience significantly lower losses than firms with lower market power. *Loss* is a binary variable that takes a value of 1 if the *forecasted* current earnings are negative, and 0 otherwise.

The correlation coefficient between *Lerner Index* and *Volatility* is very small at -0.04. This result indicates that the informational overlap between product market pricing power and volatility is negligible, and that pricing power has implications to the firm beyond just volatility of earnings. We also observe a negative correlation between pricing power and dispersion of analyst forecast.

Table 2

Pearson correlations between independent variables. This table presents the time-series average of monthly Pearson correlation coefficients between all the independent variables used in the analysis. Herfindahl Index is the sum of squares of market share of firm's sales within the industry. Lerner Index is the sales-weighted industry-adjusted Lerner Index (price–cost margin). Firm size is market capitalization. Volatility is the standard deviation of actual earnings per share (EPS) over preceding three-year period. Skewness is for EPS. Dispersion is the standard deviation of analysts' forecasts scaled by the closing stock price on the trading day preceding forecast date. Analysts following is the number of analysts following the firm. Horizon is the number of days the analyst forecast is made prior to the actual earnings release. Loss is a binary variable that takes a value of 1 if the *forecasted* current earnings are negative, and 0 otherwise. Correlations significant at 1% level or better are in bold. The significance levels are based on two-tailed *t*-tests.

Variables	Lerner Index	Herfindahl Index	Firm Size	Volatility	Analyst Following	Horizon	Loss	Skewness	Dispersion
Lerner Index	1.00	**0.04**	**0.16**	−0.04	**0.12**	**0.02**	**−0.36**	0.03	**−0.17**
Herfindahl Index		1.00	**−0.07**	−0.05	−0.06	−0.01	−0.02	0.01	−0.01
Firm Size			1.00	**0.13**	**0.79**	**0.06**	**−0.23**	−0.03	**−0.22**
Volatility				1.00	**0.09**	0.00	**0.09**	−0.07	**0.09**
Analysts Following					1.00	**0.05**	**−0.15**	0.02	**−0.14**
Forecast Horizon						1.00	**−0.10**	−0.00	−0.01
Loss							1.00	−0.03	**0.41**
Skewness								1.00	−0.02
Dispersion									1.00

Because the forecast dispersion signals the extent of disagreement among analyst, the negative correlation signifies that the earnings of low product market power firms are more complex to predict which is exhibited by less consensus among the analysts. Diether et al.'s (2002) finding that greater disagreement among analysts leads to more optimistic forecasts combined with the negative correlation between analyst dispersion and pricing power gives credence to our prediction that earnings forecast bias will be greater for firms with weak product pricing power.

The significant negative correlation between *Size* and *Loss* suggests that larger firms tend to report lower losses. *Size* is calculated as the natural logarithmic transformation of market capitalization. We also find that firms with greater pricing power tend to be larger in size, with greater analyst following and exhibit higher *Skewness*, while experiencing lower *Volatility* and *Dispersion* in analyst earnings forecasts. Furthermore, the results in the table suggest that the industry concentration is very weakly related to all of the variables as the correlation coefficients are small ranging from -0.07 to 0.01. Although our finding of positive correlation of 0.04 between *Lerner Index* and the *Herfindahl–Hirschman Index* indicates that higher industry concentration is associated with greater pricing power, the association between these two variables is weak suggesting that these two dimensions, namely the micro-channel and the macro-channel respectively, are capturing two different aspects of competition and pricing power in product markets.

4. Does market power influence analyst forecast accuracy and forecast bias?

4.1. Univariate analysis

This section presents evidence on the association between the two proxies for product market power and the quality of analysts' earnings forecasts (i.e. forecast accuracy and bias). In Panel A of Table 3, we sort firm-month observations each month of our sample period into product market pricing power quintiles in ascending order based on the industry-adjusted *Lerner Index*, while Panel B sorts firm-month observations each month into industry concentration quintiles in ascending order based on the *Herfindahl Index*. For each product market power quintile, we then calculate analyst forecast accuracy and forecast bias as the time-series average of cross-sectional means. We use the same procedure for the other variables.

The findings in Panel A document the relationship between pricing power (*Lerner Index)* and forecast accuracy in the second column of the table and the link between pricing power and forecast bias in the third column. In support of our first hypothesis,

these univariate results clearly show that analyst forecast accuracy significantly improves with increase in the firm's pricing power. Both means and medians of analysts' forecast accuracy are monotonically increasing in product market power. Specifically, the mean (median) analyst forecast accuracy of −0.068 (−0.066) is the smallest for the lowest product market pricing power group (quintile 1), while the analyst forecast accuracy of firms with the highest pricing power (quintile 5) is approximately three times larger with a mean (median) of −0.022 (−0.020). The difference between the mean forecast accuracy for the first and fifth quintiles is highly statistically significant at better than 0.001 level. These results are consistent with the notion that for low pricing power firms, it is a relatively more complex undertaking to predict their earnings given their lower ability to absorb firm-specific cost shocks and greater vulnerability to pricing pressure. Our results corroborate Brown (1993) who concludes that the accuracy of forecasts depends on the complexity associated with making the forecasts. In our case, the source of the complexity is low product market pricing power.

The evidence in the third column of the table with regard to analyst forecast bias mirrors that obtained for analyst forecast error. For instance, the mean (median) forecast bias for the lowest pricing power quintile is 0.044 (0.040) as compared to 0.015 (0.012) for firms in the highest quintile. Again, the difference between the means for the top and bottom quintiles is highly statistically significant. These findings support our Hypothesis 3 that more optimistic analyst earnings forecast are associated with firms with low product market pricing power. This result is consistent with the notion put forth by Das et al. (1998) and Lim (2001) that analysts' optimism is strongest when disagreement among analysts is highest.

The remaining columns tabulate the mean and median values for the variables used in the analysis for each market power quintile. The results indicate that low market power firms are smaller in size with higher earnings volatility and negative skewness. We observe that firm size and skewness of earnings are both monotonically increasing with market power, while volatility is decreasing with product market power. Additionally, firms in the first quintile have the smallest number of analysts following (mean of 6.14 vs. 9.34 for fifth quintile firms) with the highest earnings forecast dispersion (mean of 0.023 vs. 0.006 for fifth quintile firms).

We also conduct the analysis in Panel A using a normalized Lerner Index averaged over the preceding three years instead of one year in an attempt to circumvent any temporary factors that may affect the Lerner Index. The results are indistinguishable from those obtained in Table 3 reflecting the stability of the Lerner Index. The univariate results are also robust to the use of equally-weighted Lerner Index (as opposed to the

Table 3

The effect of market power on analysts earnings forecast accuracy and forecast bias. Summary statistics (mean and median) of analyst forecast accuracy and forecast bias partitioned in quintiles in Panel A by our measure pricing power, the sales-weighted industry-adjusted Lerner Index and in Panel B by sales-based Herfindahl Index. The first (last) quintile represents firms with the least (most) market power. The statistics are based on 570,099 firm-months observation drawn from the intersection of the I/B/E/S, COMPUSTAT, and CRSP. Herfindahl Index is the sum of squares of market share of firm's sales Lerner Index is the sales-weighted industry-adjusted Lerner Index (price–cost margin). Forecast Accuracy is the *negative* of the absolute value of the difference between the analysts consensus forecast annual EPS and the firm's actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. Forecast Bias is the firm's consensus annual forecast EPS less the actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. Volatility is the standard deviation of actual earnings per share (EPS) over preceding three-year period. Firm size is market capitalization in millions. Skewness is skeweness for EPS. Dispersion is the standard deviation of analysts' forecasts scaled by the closing stock price on the trading day preceding forecast date. Loss is a binary variable that takes a value of 1 if the *forecasted* current earnings are negative, and 0 otherwise. Analysts following is the number of analysts following the firm. Forecast Horizon is the number of days the analyst forecast is made prior to the actual earnings release. The statistics reported are time-series means of monthly cross-sectional averages.

Lener Index quartiles	Forecast Accuracy	Forecast Bias	Firm Size	Volatility	Analysts Following	Forecast Horizon	Loss	Skewness	Dispersion
Panel A: Quintiles are based on industry-adjusted Lerner Index									
First quintile	−0.068	0.044	534.18	0.93	6.14	137.06	0.31	−0.20	0.023
	(−0.066)	(0.040)	(457.73)	(0.91)	(6.19)	(139.3)	(0.24)	(−0.24)	(0.03)
Second quintile	−0.037	0.024	10,266	0.92	7.74	140.46	0.07	−0.15	0.011
	(−0.032)	(0.023)	(971.72)	(0.89)	(7.51)	(142.93)	(0.05)	(−0.18)	(0.01)
Third quintile	−0.025	0.017	1648.5	0.80	8.85	141.12	0.03	−0.08	0.007
	(−0.024)	(0.015)	(1409)	(0.80)	(8.64)	(140.91)	(0.03)	(−0.09)	(.007)
Fourth quintile	−0.022	0.016	1877.5	0.78	9.33	142.28	0.03	−0.06	0.0006
	(−0.020)	(0.014)	(1567)	(0.78)	(9.28)	(142.44)	(0.03)	(−0.06)	(.006)
Fifth quintile	−0.022	0.015	2022.6	0.69	9.34	140.47	0.04	−0.01	0.006
	(−0.020)	(0.012)	(1528)	(0.69)	(9.45)	(143.90)	(0.03)	(−0.02)	(.006)

Herfindahl Index quintile	Forecast Accuracy	Forecast Bias	Firm Size	Volatility	Analysts Following	Forecast Horizon	Loss	Skewness	Dispersion
Panel B: Quintiles are based sales-based Herfindahl Index									
First quintile	−0.030	0.018	1931.9	0.98	9.70	142.99	0.14	−0.11	0.010
	(−.029)	(0.017)	(2021.4)	(0.96)	(9.92)	(150.00)	(0.12)	(−0.12)	(0.011)
Second quintile	−0.037	0.025	1636.47	0.92	8.84	141.43	0.10	−0.11	0.012
	(−.034)	(0.021)	(1469.5)	(0.93)	(8.50)	(144.21)	(0.08)	(−0.15)	(0.011)
Third quintile	−0.039	0.025	1196.77	0.85	8.16	140.02	0.09	−0.11	0.011
	(−.034)	(0.023)	(937.67)	(0.79)	(8.26)	(138.11)	(0.08)	(−0.11)	(0.010)
Fourth quintile	−0.036	0.026	1058.26	0.70	7.33	139.66	0.07	−0.09	0.010
	(−.033)	(0.023)	(748.98)	(0.70)	(7.41)	(137.77)	(0.07)	(−0.11)	(0.009)
Fifth quintile	−0.031	0.021	1300.70	0.69	7.39	137.18	0.07	−0.06	0.009
	(−.029)	(0.019)	(797.99)	(0.69)	(7.47)	(134.17)	(0.07)	(−0.08)	(0.008)

sales-weighted Lerner Index) to calculate the industry adjustment for this variable. In this study, we focus on the sales-weighted measure because it more appropriately captures the size of the firms when we make the industry adjustment for the price–cost margin. Overall, the univariate results presented in Panel A of Table 3 suggest a strong positive relation between product market pricing power and analyst forecast accuracy and a significant negative relation between market power and analyst earnings optimism.

Except for the first two quintiles, Panel B of Table 3 shows that the median forecast accuracy is increasing in industry concentration (Herfindahl Index). For the first quintile, contrary to expectation, the forecast accuracy is highest and the forecast bias is the lowest. Although the forecast bias is not strictly monotonically decreasing in industry concentration, the third column reveals that mean forecast bias is constant in the middle three quintiles (quintile 2–4) at around 0.25 and decreases to 0.21 for the highest quintile. Univariate evidence for industry concentration is not clear cut, most likely because forecast accuracy and bias are influenced by other variables.[7] The multivariate analysis should provide a more reliable and clearer picture of the relation between market structure and earnings forecast metrics. Notable observations from the remaining figures in the panel are that as we move from lowest to highest quintile of industry concentration, earnings' volatility declines, analyst forecast dispersion becomes lower and the frequency of firms with losses is smaller. These results are consistent with our expectation.

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[7] It is worth noting that when using the more rigorous Fama and MacBeth (1973) univariate regression in subsequent section, we find that industry concentration and analyst forecast accuracy are strongly and significantly related.

4.2. Multivariate analysis

4.2.1. Does market power determine analysts' earnings forecast accuracy?
4.2.1.1. The model.
In this section we utilize a multivariate framework to examine the link between product market power variables and analysts' earnings forecast accuracy and bias, while controlling for the salient determinants of analysts' forecast metrics that have been previously identified in the literature. To test our first two hypotheses, we estimate different specifications of the following model:

$$
\begin{aligned}
Forecast\ Accuracy_{jt} = \ & \beta_0 + \beta_1 Lerner\ Index_{jt} + \beta_2 Herfindahl\ Index \\
& + \beta_3 Size_{jt} + \beta_4 Loss_{jt} + \beta_5 Volatility_{jt} \\
& + \beta_6 Dispersion_{jt} + \beta_7 Following_{jt} \\
& + \beta_8 Horizon_{jt} + \varepsilon_{jt}
\end{aligned}
\tag{7}
$$

For Tables 4–7, we utilize Fama and MacBeth (1973) regressions to circumvent the problem of cross-sectional dependence inherent in pooled cross-section time-series data. We first estimate monthly cross-sectional regressions for each month during our 30-year sample period, 1976–2005, and then report time-series averages of the heteroskedasticity-adjusted monthly cross-sectional coefficient estimates pertaining to forecast accuracy in Table 4. Dependent and independent variables are industry-adjusted in these regression specifications. Because we use mean monthly forecasts in monthly regressions and to the extent that some analysts do not change their forecast every month, standard errors of coefficients are understated. To adjust for this embedded autocorrelation we employ the Newey and West (1987) adjustment technique with 12 lags.

Table 4
Fama–MacBeth regressions explaining the role of market power on analyst forecast accuracy. This table reports the results of Fama–MacBeth regressions explaining the role of product market power on analyst forecast accuracy. The sample consists of firms with at least two analysts following in the I/B/E/S database and with financial information in the CRSP and Compustat databases during the period 1976–2005. The dependent variable is Forecast Accuracy defined as the *negative* of the absolute value of the difference between the analysts consensus forecast annual EPS and the firm's actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. Herfindahl Index is the sum of squares of market share of firm's sales Lerner Index is the sales-weighted industry-adjusted Lerner Index (price–cost margin). Volatility is the standard deviation of actual earnings per share (EPS) over preceding three-year period. Firm size is natural logarithm of market capitalization. Dispersion is the standard deviation of analysts' forecasts scaled by the closing stock price on the trading day preceding forecast date. Loss is a binary variable that takes a value of 1 if the *forecasted* current earnings are negative, and 0 otherwise. Following is the natural logarithm of number of analysts following the firm. Horizon is the number of days the analyst forecast is made prior to the actual earnings release. The table reports time-series average of heteroskedasticity-adjusted coefficients obtained from monthly Fama and MacBeth (1973) cross-sectional regressions. All variables are industry-adjusted. *p*-Values are reported in parentheses below the coefficient estimates and adjusted for autocorrelation using the Newey–West technique.

$$Forecast\ Accuracy_{jt} = \beta_0 + \beta_1 Herfindahl\ Index_{jt} + \beta_2 Lerner\ Index_{jt} + \beta_3 Size_{jt} + \beta_4 Loss_{jt} + \beta_5 Volatility_{jt} + \beta_6 Dispersion_{jt} + \beta_7 Following_{jt} + \beta_8 Horizon_{jt} + \varepsilon_{it}$$

Independent variables	Predicted sign	Model 1	Model 2	Model 3	Model 4	Model 5
Herfindahl Index * 100	+/−			0.312	0.215	0.252
				(0.045)	(0.036)	(0.018)
Lerner Index * 100	+	8.464	0.712			0.691
		(<.0001)	(0.020)			(0.023)
Size * 100	+		0.595		0.606	0.596
			(<.0001)		(<.0001)	(<.0001)
Loss * 100	−		−0.024		0.002	−0.026
			(0.419)		(0.491)	(0.464)
Volatility * 100	−		−0.140		−0.146	−0.14
			(<.0001)		(<.0001)	(<.0001)
Dispersion	−		−2.285		−2.283	−2.284
			(<.0001)		(<.0001)	(<.0001)
Analysts Following * 100	?		0.003		−0.005	0.003
			(0.478)		(0.473)	(0.475)
Forecast Horizon * 100	−		−0.005		−0.004	−0.005
			(<.0001)		(<.0001)	(<.0001)
N		570,079	518,247	570,079	518,247	518,247

In our regression model the focus explanatory variable, *Lerner Index*, captures firm-specific product market pricing power while the *Herfindahl Index* captures the industry-level dimension of product market power. *Size* is included as a proxy for greater availability of public information that should lead to more accurate forecasts. Hwang et al. (1996) show that analysts' forecasts of losses are generally less accurate than their profit forecasts. Further, Brown (2001) finds that analysts issue more optimistic earnings forecasts during loss periods. Therefore, we expect loss-generating firms to be associated with less forecast accuracy and more optimistic forecasts. We use an ex ante *Loss* dummy as a control variable, which assumes a value of one if the forecasted earnings are negative and zero otherwise, because using actual losses to calculate forecast accuracy as an explanatory variable is subject to a mechanical relationship.

Based on research by Kross et al. (1990) and Lim (2001), we include the volatility of actual earning, *Volatility,* as a control variable because it has been shown to be associated with less forecast accuracy and typically more optimistic forecast. To the extent that pricing power leads to more stable earnings, and hence lower volatility, the effect of our pricing power proxy on earnings accuracy will be dampened.

Previous work has also identified that forecast dispersion captures uncertainty and divergence of analysts' opinion about future earnings of the firm (Bamber et al., 1997). Lang and Lundholm (1996) document that forecast dispersion is associated with less accurate earnings forecast. Güntay and Hackbarth (2010) document that forecast dispersion seems to proxy future cash flow uncertainty in the corporate bond markets and higher dispersions are associated with significantly higher credit spreads. Hence, we include *Dispersion* as a control variable in our model. Further, Gu and Wu's (2003) study suggests that forecast dispersion is associated with less positively biased (optimistic) forecasts.

Prior research indicates that analyst following is related to forecast accuracy and bias. Lys and Soo (1995) document that forecast accuracy improves with analyst following, while Das et al. (1998)

conclude that less optimistic forecasts are issued for more heavily followed firms. However, some studies argue that since larger firms attract greater analyst following, the relationship between *Forecast Bias* and *Following* is unclear. We include *Following,* measured as the natural logarithm of the number of analysts following the firm as reported in the I/B/E/S database, as a control variable. Forecast horizon has been documented by previous studies to be a significant determinant of forecast accuracy. Longer forecast horizons are associated with less accurate earnings forecasts (see e.g. Brown et al., 1987), while Das et al. (1998) find weak support that longer horizon forecasts are more optimistic (i.e. more positive forecast bias). We include *Horizon*, defined as the number of days the analyst forecast is made prior to the actual earnings release, to control for the forecast horizon.

4.2.1.2. Empirical findings. Table 4 presents Fama–MacBeth regressions explaining the role of product market power on analyst forecast accuracy. In the first regression, we regress *Forecast Accuracy* against *Lerner Index*, measured as the sales-weighted industry-adjusted Lerner Index, while the full model (Model 2 in column 3) incorporates all the control variables. In support of our first hypothesis, the coefficients for *Lerner Index* are positive and highly significant in both models indicating increased analyst forecast accuracy for firms with greater pricing power. Gauging the economic importance of this variable, we find that when market pricing power declines by one-standard deviation from its mean value, the *Forecast Accuracy* worsens 2.33 times. The coefficient of the *Volatility* variable in Model 2 takes on the predicted negative sign consistent with prior research (Kross et al., 1990; Lim, 2001). Examination of the economic role of *Volatility* reveals that a one-standard deviation increase in *Volatility* from the mean barely affects *Forecast Accuracy* (13.7%). Thus, our findings demonstrate that not only product market pricing power plays a significant role in analyst forecasts, even after controlling for *Volatility*, but that its influence on forecast accuracy is much more pronounced than that of volatility. These results support our prediction that pricing

Table 5

Robustness checks: Fama–MacBeth regressions explaining analysts' forecast accuracy. This table reports the results of Fama–MacBeth regressions explaining the role of product market power on analyst forecast accuracy. The sample consists of firms with at two analysts following in the I/B/E/S database and with financial information in the CRSP and Compustat databases during the period 1976–2005. The dependent variable, Forecast Accuracy, is the *negative* of the absolute value of the difference between the analysts consensus forecast annual EPS and the firm's actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. Herfindahl Index is the sum of squares of market share of firm's *assets* within the industry. Market Share is the fraction of firm's sales within its industry. Lerner Index is the sales-weighted industry-adjusted Lerner Index (price–cost margin). Volatility is the standard deviation of actual earnings per share (EPS) over preceding three-year period. Firm size is natural logarithm of market capitalization. Dispersion is the standard deviation of analysts' forecasts scaled by the closing stock price on trading day preceding forecast date. Loss is a binary variable that takes a value of 1 if the *forecasted* current earnings are negative, and 0 otherwise. Analysts Following is the natural logarithm of number of analysts following the firm. Forecast Horizon is the number of days the analyst forecast is made prior to the actual earnings release.The table reports the time-series average of heteroskedasticity-adjusted coefficients obtained from monthly Fama and MacBeth (1973) cross-sectional regressions. All variables are industry-adjusted. *p*-Values are given in parentheses below coefficients and adjusted for autocorrelation using the Newey–West technique.

$$Forecast\ Accuracy_{jt} = \beta_0 + \beta_1 Herfindahl\ Index_{jt} + \beta_2 Lerner\ Index_{jt} + \beta_3 MarketShare + \beta_4 Size_{jt} + \beta_5 Loss_{jt} + \beta_6 Volatility_{jt} + \beta_7 Dispersion_{jt} + \beta_8 Following_{jt} + \beta_9 Horizon_{jt} + \varepsilon_{it}$$

Independent variables	Predicted sign	Model 1	Model 2	Model 3	Model 4	Model 5
Asset-based Herfindahl Index * 100	+/−	0.174 (0.065)			0.222 (0.028)	
Market Share * 100	+		0.975 (<.0001)	0.168 (0.047)		0.193 (0.026)
Lerner Index * 100	+				0.687 (0.024)	0.956 (0.007)
Size * 100	+	0.604 (<.0001)			0.595 (<.0001)	
Loss * 100	−	0.004 (0.494)		−0.217 (0.460)	−0.025 (0.467)	−0.212 (0.476)
Volatility * 100	−	−0.146 (<.0001)		−0.079 (0.005)	−0.140 (<.0001)	−0.073 (0.009)
Dispersion	−	−2.283 (<.0001)		−2.314 (<.0001)	−2.285 (<.0001)	−2.314 (<.0001)
Analysts Following * 100	?	−0.003 (0.480)		0.878 (<.0001)	0.005 (0.470)	0.868 (<.0001)
Forecast Horizon * 100	−	−0.005 (<.0001)		−0.005 (<.0001)	−0.005 (<.0001)	−0.005 (<.0001)
N		518,246	570,079	518,246	518,246	518,246

Table 6

Fama–MacBeth regressions explaining the role of market power on analysts' forecast bias. This table reports the results of Fama–MacBeth regressions explaining the role of product market power on analysts' forecast bias. The sample consists of firms with at two analysts following in the I/B/E/S database and with financial information in the CRSP and Compustat databases during the period 1976–2005. The dependent variable, Forecast Bias, is the firm's consensus annual forecast EPS less the actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. Herfindahl Index is the sum of squares of market share of firm's sales within the industry. Lerner Index is the sales-weighted industry-adjusted Lerner Index (price–cost margin). Volatility is the standard deviation of actual earnings per share (EPS) over preceding three-year period. Skewness is skeweness of EPS. Dispersion is the standard deviation of analysts' forecasts scaled by the closing stock price on trading day preceding forecast date. Analysts Following is the number of analysts following the firm. Forecast Horizon is the number of days the analyst forecast is made prior to the actual earnings release. Size is the natural logarithmic transformation of market capitalization. Loss is a binary variable that takes a value of 1 if the *forecasted* current earnings are negative, and 0 otherwise. The table reports the time-series average of heteroskedicity-adjusted coefficients obtained from monthly Fama and MacBeth (1973) cross-sectional regressions. All variables are industry-adjusted. *p*-Values are in parentheses and adjusted for autocorrelation using the Newey–West technique.

$$Forecast\ Bias_{jt} = \beta_0 + \beta_1 Herfindahl\ Index_{jt} + \beta_2 Lerner\ Index_{jt} + \beta_3 Size_{jt} + \beta_4 Loss_{jt} + \beta_5 Volatility_{jt} + \beta_6 Dispersion_{jt} + \beta_7 Following_{jt} + \beta_8 Horizon_{jt} + \beta_9 Skewness_{jt} + \varepsilon_{it}$$

Independent variables	Predicted sign	Model 1	Model 2	Model 3	Model 4	Model 5
Herfindahl Index * 100	+/−			−0.248 (0.032)	−0.312 (0.003)	−0.388 (0.000)
Lerner Index * 100	−	−5.948 (<.0001)	−0.507 (0.085)			−0.494 (0.0931)
Size * 100	−		−0.551 (<.0001)		−0.559 (<.0001)	−0.555 (<.0001)
Loss * 100	+		−0.482 (0.035)		−0.618 (0.028)	−0.479 (0.072)
Volatility * 100	+		0.163 (.0066)		0.169 (0.059)	0.161 (0.069)
Dispersion	+		1.445 (<.0001)		1.441 (<.0001)	1.444 (<.0001)
Analyst Following * 100	?		0.130 (0.0674)		0.141 (0.050)	0.131 (.0033)
Forecast Horizon * 100	+		0.004 (<.0001)		0.004 (<.0001)	0.004 (<.0001)
Skewness * 100	−		−0.009 (0.337)		−0.011 (0.314)	−0.008 (0.353)
N		570,079	518,247	570,079	518,247	518,247

power's multi-dimensional benefits provide analysts with greater informational content, hence enhancing analysts' ability to more accurately forecast earnings.

In the third and fourth models, we test the influence of product market structure on forecast accuracy. In Model 3, we simply fit *Forecast Accuracy* against *Herfindahl Index* (in column 4). The full

Table 7

Robustness checks: Fama–MacBeth regressions explaining analysts' forecast bias. This table reports the results of Fama–MacBeth regressions explaining the role of product market power on analyst forecast bias. The sample consists of firms with at least two analysts following in the I/B/E/S database and with financial information in the CRSP and Compustat databases during the period 1976–2005. The dependent variable, Forecast Bias, is the firm's consensus annual forecast EPS less the actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. Herfindahl Index is the sum of squares of market share of firm's *assets* within the industry. Market Share is the fraction of firm's sales within its industry. Lerner Index is the sales-weighted industry-adjusted Lerner Index (price–cost margin). Volatility is the standard deviation of actual earnings per share (EPS) over preceding three-year period. Skewness is skeweness of EPS. Dispersion is the standard deviation of analysts' forecasts scaled by the closing stock price on trading day preceding forecast date. Analysts Following is the number of analysts following the firm. Forecast Horizon is the number of days the analyst forecast is made prior to the actual earnings release. Size is the natural logarithmic transformation of market capitalization. The table reports the time-series average of heteroskedasticity-adjusted coefficients obtained from monthly Fama and MacBeth (1973) cross-sectional regressions. All variables are industry-adjusted. *p*-Values are given in parentheses and adjusted for autocorrelation using the Newey–West technique.

$$Forecast\ Bias_{jt} = \beta_0 + \beta_1 Herfindahl\ Index_{jt} + \beta_2 Lerner\ Index_{jt} + \beta_3 MarketShare_{jt} + \beta_4 Size_{jt} + \beta_5 Loss_{jt} + \beta_6 Volatility_{jt} + \beta_7 Dispersion_{jt} + \beta_8 Following_{jt} + \beta_9 Horizon_{jt}$$
$$+ \beta_{10} Skewness_{jt} + \varepsilon_{it}$$

Independent variables	Predicted sign	Model 1	Model 2	Model 3	Model 4	Model 5
Asset-based Herfindahl Index * 100	+/−	−0.290			−0.380	
		(0.004)			(0.000)	
Market Share * 100	−		−0.849	−0.328		−0.375
			(<.0001)	(0.000)		(0.000)
Lerner Index * 100	−				−0.502	−0.839
					(0.09)	(0.023)
Size * 100	−	−0.558			−0.554	
		(<.0001)			(<.0001)	
Loss * 100	+	−0.619		−0.401	−0.481	−0.297
		(0.027)		(0.167)	(0.071)	(0.277)
Volatility * 100	+	0.170		0.0486	0.161	0.039
		(0.055)		(0.216)	(0.065)	(0.264)
Dispersion	+	1.441		1.472	1.444	1.475
		(<.0001)		(<.0001)	(<.0001)	(<.0001)
Analysts Following * 100	?	0.140		−0.716	0.129	−0.715
		(0.026)		(<.0001)	(0.035)	(<.0001)
Forecast Horizon * 100	+	0.004		0.0040	0.004	0.004
		(<.0001)		(<.0001)	(<.0001)	(<.0001)
Skewness * 100	−	−0.011		−0.022	−0.009	−0.018
		(0.313)		(0.173)	(0.35)	(0.211)
N		491,836	570,079	491,836	491,836	491,836

model (in column 5) includes the *Herfindahl Index* variable and all of the control variables. The evidence in Models 3 and 4 depicting positive and highly statistically significant coefficients for the *Herfindahl Index* indicate that industry concentration plays an important role in enhancing forecast accuracy. More specifically, our findings, net of the two opposing hypotheses (2A and 2B), indicate that the earnings of less concentrated industries are more challenging to forecast lending support to the notion that gathering information for less concentrated sectors is more costly due to less disclosure and that higher innovation in these industries injects information complexity that negatively influences earnings forecastability and hence accuracy. Our results provide supporting evidence to Nerkar and Shane's (2003) findings documenting that industry concentration inhibits introduction of new technological ventures. Hence, firms in fragmented industries display greater susceptibility to new radical technologies and their cash flows are less predictable. Another source of complexity for fragmented industries stems from lower likelihood of cooperation of firms with each other in these industries. Our results for product market structure are in support of the view that industries characterized by concentration are more likely to cooperate on issues that could bolster their cash flows and reduce negative fluctuations thus rendering their earnings' forecasts less prone to error.

Of the control variables, as expected, *Dispersion* is found to be associated with significantly less accurate earnings forecast which confirms results obtained by Lang and Lundholm (1996) and Brown et al. (1987). Similarly, *Horizon* is significantly negatively associated with earnings accuracy. As expected, the coefficient for the size variable is significantly positive indicating that larger firms have more accurate forecasts. The coefficients for the remaining two control variables have the predicted signs, however, none is statistically significant.

In Model 5 of Table 4, we examine whether the two proxies for product market power, relative pricing power and industry structure, capture similar or different aspects of product market power. By testing the importance of *Herfindahl Index* and *Lerner Index* in separate regressions, it is not clear whether these two variables are alternative measures of the same aspect of market power or whether they gauge different aspects of market power. By including both variables in one regression in Model 5, it is possible to test the incremental effect that each factor contributes to forecast accuracy. The low correlation between these two variables (0.041) points to that possibility (see Table 2). The empirical results from this specification provide another piece of evidence toward that conclusion. Our findings reveal that the coefficients for both product market power proxies remain highly significant with the expected signs. Furthermore, the size of each of these two coefficients is similar in magnitude to that obtained in Models 2 and 4 which include only one of these variables at a time. These findings imply that these product market factors are gauging different dimensions of market power and hence affect earnings forecast accuracy through different channels.

4.2.2. Robustness checks – multivariate analysis

We perform a battery of robustness checks to validate our results presented in the preceding section. In Table 5, we perform robustness checks by re-estimating the regressions using alternative market power variables. In Model 1, we replace the sales-based measure of *Herfindahl Index* with the asset-based version. Asset-based *Herfindahl Index* is calculated as the sum of squares of firms' asset share in the same industry. With a positive and significant coefficient for this alternative *Herfindahl Index*, our main finding remains unchanged. In Models 2 and 3, we use firm market share of sales (firm sales as a percent of industry sales) as another

metric for product market power. Dominant position through higher market share endows the firm with greater customer recognition and has the potential to enhance cash flows at the expense of competitors.

Similar to our predictions with the other product market power proxies, we expect better forecast accuracy for firms with greater market share. The coefficients in both models are of the predicted sign and are highly significant suggesting that earning forecasts of firms that are dominant in their industry (due to higher market share) are less prone to error. We remove firm size from Model 3 that includes *Market Share* because these two variables are highly correlated. The results in Model 4, which includes asset-based *Herfindahl Index* and *Lerner Index*, indicate that both these variables significantly contribute to forecast accuracy. Finally in Model 5, we include *Market Share* and *Lerner Index* in the same regression. The empirical findings reveal that each of these proxies of market power has incremental effect on analysts' forecast accuracy.[8]

In unreported regressions, we also verify that our empirical results are not influenced by data errors or instability in the industry-adjusted Lerner Index by normalizing the variable over the most recent three-year period. All our findings remain unchanged when we use this alternate measure. We also conduct the regression analysis using PCM (price–cost margin without industry adjustment) as a proxy for product market power. The PCM coefficients also emerge as positive and highly significant. In addition, our findings are robust to the calculation of earnings volatility based on the preceding five-year's actual yearly earnings, instead of earnings from the preceding 3 years. We focus on calculations using earnings data for the preceding 3 years, instead of 5 years to maximize our sample size.

We also estimate different model specifications using various combinations of the control variables along with our focus variables. Our findings with regard to the importance of the two proxies of product market power as determinants of analysts' forecast accuracy remain unchanged. When we re-estimate Table 4 regressions excluding the volatility variable, we find that the coefficients for all of our focus variables are almost identical to those previously reported but these variables are even more significant. Finally, our main results are robust to estimating the regression models using the fixed effects technique with clustered standard errors at the firm level to control for cross-sectional and time-series correlations as described in Petersen (2009).

4.3. Does product market power determine analysts earnings forecast bias?

Based on our third and fourth hypotheses, we expect that analyst forecast bias to be negatively related to product market power. In other words, analyst optimism about future earnings should increase as the product market pricing power of firms decrease and/or industry concentration declines. We test these hypotheses in a multivariate framework by estimating various specifications of the following model:

$$
\begin{aligned}
Forecast\ Accuracy_{jt} = {} & \beta_0 + \beta_1 Lerner\ Index_{jt} + \beta_2 Herfindahl\ Index \\
& + \beta_3 Size_{jt} + \beta_4 Loss_{jt} + \beta_5 Volatility_{jt} \\
& + \beta_6 Dispersion_{jt} + \beta_7 Following_{jt} \\
& + \beta_8 Horizon_{jt} + \beta_9 Skewness_{jt} + \varepsilon_{jt}
\end{aligned} \tag{8}
$$

Again, all dependent and independent variables are industry-adjusted in the above regression specification. All the control variables used in Table 4 explaining the relation between market

power and forecast accuracy are included, except that here we add *Skewness* because it has been shown that earnings skewness is associated with more optimistically biased forecast. We expect the sign for *Skewness* to be negative. Our discussion of the control variables in the preceding section rationalizes the inclusion of each of the control variables in Table 6.

Supporting our Hypothesis 3, regression estimates presented in Table 6 document a strong negative relation between product market pricing power and *Forecast Bias*. We present coefficient estimates for the simple model that includes only the focus variable *Lerner Index* and for the complete model that incorporates all the control variables. The coefficients of the pricing power variable are significantly negative in both regression models (Models 1 and 2) indicating that firms with lower product market power are associated with more optimistic analysts' earnings forecast (i.e., positive forecast bias). This finding is maintained even when controlling for earnings' volatility. Our evidence also supports the notion posited in Lim's (2001) model that analysts issue more favorable forecasts for firms with more complex and less predictable earnings in order not to jeopardize their access to private information from firm managers. In terms of relative economic importance of this variable based on the size of the coefficient, we conclude that an increase of pricing power by one-standard deviation from the mean decreases forecast bias by 33%.[9]

The regression estimates presented in columns 3, 4 and 5 test the importance of the sales-based *Herfindahl Index,* our proxy for product market structure, on forecast bias. The net results support Hypothesis 4A (as opposed to Hypothesis 4B) and echo the findings of Models 1 and 2 as coefficients for product market structure are negative and statistically significant in support of the view that analysts earnings forecast are more optimistic for firms in less concentrated industries. These results complement Hoberg and Phillips' (2010) findings that competitive industries experiencing high growth draw more upwardly biased forecasts. The above findings are also consistent with previous research that document that analyst optimism increases with increasing difficulty in predicting earnings.

All our control variables included in the regression models, except *Loss,* have the predicted signs. The sign for the *Loss* variable may be affected by the high correlation between *Loss* and *Dispersion.*[10] The variables *Size, Dispersion, Following* and *Horizon* are all statistically significant. The control variable *Following* has a positive sign supporting the argument that greater competition among analysts (higher number of analysts following) will result in more optimistic forecasts to gain favor from the management. Even though *Skewness* emerges with the correct negative sign, it is not statistically significant.

We perform the same series of robustness checks discussed in Section 4.2.2 and find that the key results presented in this section are not sensitive to alternative estimation techniques and variable measurements. Specifically, Table 7 reports regression estimates using various alternative measures of our focus variables. The results confirm that the use of asset-based *Herfindahl Index* produces similar conclusions to those obtained when using sales-based measure in Table 6. Models 2 and 3 validate that *Market Share* has a significant influence on forecast bias such that earnings of firms with lower market share are associated with more optimistic earnings forecasts. Model 4 combines the asset-based *Herfindahl Index* with the *Lerner Index* while Model 5 combines *Market Share* with the *Lerner Index*. Both models indicate that the product market power variables have significant incremental explanatory power.

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[8] To avoid introducing noise with inconsistent forecast horizons, we repeat the analysis using the analyst forecast that is closest to one year from the firm's fiscal year-end date. Our main findings are robust to the use of the longest forecasts.

[9] De Jong and Apilado (2009) document that earnings forecasts are biased for both value and growth stocks but the bias is ameliorated by Reg FD.

[10] We would like to note that the Pearson correlation coefficient between *Loss* and *Bias* has the expected positive sign.

Table 8
Effect of deregulation on forecast accuracy, forecast bias, forecast dispersion and analyst following. This table presents data on the magnitude of analysts' earnings forecast accuracy and bias, forecast dispersion and number of analyst following for selected industries before and after deregulation. Forecast Accuracy is the *negative* of the absolute value of the difference between the analysts consensus forecast annual EPS and the firm's actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. Forecast Bias is the firm's consensus annual forecast EPS less the actual annual EPS standardized by the closing stock price on the trading day preceding forecast date. Dispersion is the standard deviation of analysts' forecasts scaled by the closing stock price on the trading day preceding forecast date. Analyst Following is the number of analysts following the firm. Horizon is the number of days the analyst forecast is made prior to the actual earnings release.

Industry	Variables	Before regulation			After deregulation			Difference of means
		N	Mean	Median	N	Mean	Median	
Airline	Accuracy	186	−0.0384	−0.0350	6290	−0.1274	−0.0676	−0.089***
	Bias		−0.0047	−0.0046		0.0931	0.0455	0.098***
	Dispersion		0.0286	0.0281		0.0437	0.0277	0.015***
	Analyst Following		7.7734	7.7301		10.3223	10.3440	2.549***
Entertainment	Accuracy	483	−0.0291	−0.0214	2927	−0.4031	−0.0726	−0.374***
	Bias		0.0165	0.0103		0.3977	0.0615	0.381***
	Dispersion		0.0111	0.0079		0.1307	0.0118	0.120***
	Analyst Following		7.2355	7.0833		8.1469	8.0000	0.911***
Natural Gas	Accuracy	422	−0.0106	−0.0082	20,862	−0.9890	−0.1625	−0.978***
	Bias		0.0040	0.0027		0.8557	0.0804	0.852***
	Dispersion		0.0063	0.0045		0.1897	0.0474	0.183***
	Analyst Following		7.8014	7.7144		11.0472	10.7465	3.246***
Trucking	Accuracy	173	−0.0401	−0.0486)	5698	−0.0425	−0.0295	−0.002
	Bias		0.0348	0.0435)		0.0376	0.0230	0.003
	Dispersion		0.0045	0.0036)		0.0117	0.0075	0.007***
	Analyst Following		5.5004	5.4500)		7.6639	7.5000	2.164***
Telecommunication	Accuracy	4035	−0.0192	−0.0118	4397	−0.0667	−0.0389	−0.048***
	Bias		0.0125	0.0066		0.0353	0.0217	0.023***
	Dispersion		0.0066	0.0052		0.0362	0.0246	0.030***
	Analyst Following		10.4135	10.1250		8.4419	8.1976	−1.972***

*** Significance of the difference in means at the 1% level.

In summary, our analysis documents compelling empirical evidence indicating that product market power of the firm is an important determinant of both analysts' earnings forecast accuracy and forecast bias. We find that industry structure, pricing power and product market dominance are all effective in enhancing earnings accuracy.

4.4. Evidence from deregulated industries

In this section we explore product market power from a different angle. In this additional robustness check we aim to ascertain the impact of industry competitiveness on analysts forecasts by analyzing a set of industries that were deregulated during our study period. Since deregulation removes barriers to entry, thus enabling more competition, recent deregulation episodes in certain sectors make for a natural experiment to evaluate the change in analysts' forecast accuracy and bias. By examining analysts' forecast accuracy, forecast bias, forecast dispersion and analysts following before and after deregulation of these industries we can examine whether analyst forecast accuracy declines and whether positive bias increases after the deregulatory episodes.

We use the set of deregulated industrial industries examined by Irvine and Pontiff (2009) because these industries experience a sole deregulatory event: airlines (1978), natural gas (1978), trucking (1980), entertainment (1984) and telecommunications (1996). Our method of forming industry group classifications follows that of Andrade et al. (2001) and Irvine and Pontiff (2009). The airline industry is formed of firms with SIC codes 4500 and 4599, natural gas industry includes firms with SIC codes between 1310 and 1389; entertainment industry consists of firms in SIC codes between 7800 and 7841.

In Table 8, we provide summary statistics for the pre- and post-deregulation periods and the differences in these statistics between the two periods. The table includes the mean and median for analysts' forecast accuracy, forecast bias, analysts' forecast dispersion and the number of analysts following. For each deregulated industry, we consider 1976 (first year in our original sample) until year prior to deregulation as the pre-deregulation period, while the year following deregulation year until 2005 (the last year of our sample period) defines the post-deregulation period.

The analysis reveals a number of remarkable findings. First, for all of the industry sectors except one, the analysts' forecast accuracy declines significantly after deregulation. The most extreme example is the natural gas industry for which the mean forecast accuracy declines by more than 90 times from −0.011 to −0.989. Similar results are obtained for analysts' forecast (optimistic) bias as four of the five industries exhibit a significant increase in forecast bias in the post-deregulation period. Moreover, the percent changes in mean forecast bias from pre- to post-deregulation eras are much larger than the corresponding increases in mean forecast accuracy. In combination, the above findings affirm our previous results of the relevance and importance of product market power (in this case, from change in competition due to deregulation) to earnings' forecasts. We also observe that analysts forecast dispersion increases significantly after deregulation, which may be indicative of greater difficulty in interpreting firm information when a larger number of firms populate an industry sector. In addition, in all cases except one, the number of analyst following rises significantly after deregulation. For instance, the average number of analyst following for the Airline industry during the pre-deregulation period is 7.8 but rises to 10.3 in the post-deregulation era. This empirical evidence could be interpreted to mean that industries with larger population of firms, and hence relatively more complex industries to analyze, draw a greater number of analysts. This result contradicts the conjecture that more accurate analysts choose to follow firms with more market power because they are easier to forecast.

5. Conclusions

This is the first study to document a link between product market power and analyst earnings forecasts. Our analysis yields

several interesting findings. Specifically, we document that our proposed two dimensions of market power, namely relative pricing power and industry concentration, are significant determinants of analyst forecast accuracy and forecast (optimism) bias. Our analysis extends our knowledge in both the industrial organization literature and the analysts' forecast literature.

Using a comprehensive sample spanning three decades, we document that there is a significant positive relation between product market pricing power and analyst forecast accuracy. The observed higher forecast accuracy for firms with superior pricing power can be attributed to the ability of such firms to pass on cost shocks to consumers and the greater informational-efficiency attributed to these firms. We also document that industry product market structure is a key determinant of forecast accuracy. Our empirical results show that earnings for firms in less concentrated industries are more difficult to forecast. This finding supports the notion that in competitive industries gathering information is more costly and information complexity is greater, likely due to greater innovation activities and greater susceptibility to new entrants with radical technologies rendering earnings forecasting more onerous. Our results for product market structure also support the notion that firms in concentrated industries are more likely to cooperate on issues that could bolster their cash flows and reduce negative fluctuations thus rendering their earnings' forecasts less prone to error. Further, we show that a firm's dominant position in its industry, proxied by market share, can also improve accuracy of earning forecasts.

The second important insight from this study is that product market power is negatively associated with analysts' forecast bias. Particularly, our findings reveal that forecast optimism is higher for firms in lower concentrated industries, firms with lower pricing power, and firms with less industry dominance (market share). These finding are consistent with previous research that documents that analyst optimism increases with increasing difficulty of predicting earnings. Our results are highly robust to a series of robustness checks, such as alternate computations of product market power proxies and different multivariate model specifications. Thus our key findings that product market power is positively related to the earnings forecast accuracy and negatively associated with earnings forecast bias and not sensitive to the various issues identified above.

We add another novel dimension to the study by exploiting the one-time events of industry deregulations to ascertain and verify the impact of a change in competition on analysts' forecasts accuracy and bias. The exogenous shock to market power due to industry deregulation provides us with a clean natural experiment and a unique opportunity to study the effect of competition on analysts forecast accuracy. We examine a subset of industries in our sample that experienced deregulation and find that analysts' forecast accuracy declines significantly in the post-deregulation period, while positive bias rises significantly. These results reaffirm our earlier findings. Moreover, we find that earnings forecast dispersion increases significantly after deregulation and that these sectors begin to attract a greater number of analysts' following.

Overall, by linking analyst forecast research to the industrial organization (market power) literature, we present findings that advance our knowledge in the important area of analyst earnings forecast. The knowledge derived from this study will hopefully improve estimation of cost of capital and the accuracy of equity valuation, and thereby engender better stock selections (buy-side) and recommendations (sell-side) by analysts. Our findings also suggest that brokerage firms compensating analysts based on forecast accuracy need to adjust for the differential in the information complexity of different industries when designing analysts' compensation packages.

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