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Determinants of Analyst Forecasting Accuracy

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Abstract

This paper examines recent trends in sell-side analyst forecast accuracy, with a particular focus on the industry of the firm being forecasted. Using median forecast data from 2000-2013 as provided by I/B/E/S, this study provides evidence indicating that forecast accuracy has been steadily decreasing over the sample period and that forecast dispersion has been steadily increasing. In addition, it finds that there are significant differences in forecast accuracy by industry. Finally, this study confirms the findings of prior research. Many of the factors found in prior studies as significant, remain significant even in the face of recent regulatory and economic changes. These factors include the size of the firm, the analyst coverage, the type of earnings and the change in earnings.

Keywords

Analysts' forecasts, Industry, Firm-specific factors, Forecast accuracy, Forecast bias

Disciplines

Business

Determinants of Analyst Forecasting Accuracy

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ABSTRACT

This paper examines recent trends in sell-side analyst forecast accuracy, with a particular focus on the industry of the firm being forecasted. Using median forecast data from 2000-2013 as provided by I/B/E/S, this study provides evidence indicating that forecast accuracy has been steadily decreasing over the sample period and that forecast dispersion has been steadily increasing. In addition, it finds that there are significant differences in forecast accuracy by industry. Finally, this study confirms the findings of prior research. Many of the factors found in prior studies as significant, remain significant even in the face of recent regulatory and economic changes. These factors include the size of the firm, the analyst coverage, the type of earnings and the change in earnings.

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INTRODUCTION

This study examines the impact of the industry of the forecasted firm on analyst forecasts. For three different measures of forecast accuracy, it finds significant differences across industries. In addition, this study replicates past research using more recent data to examine the impact of the forecast horizon, the duration of the interval between when analysts issue their recommendations and the actual firm reporting date. It will also be shown that significant variation in forecasts occur between 2000-2007 and 2008-2013. Consequently, future research using aggregate data would benefit from better scrutiny in their selection of sample data and in their selection of forecast horizon.

Within this study, the term “forecasts” refers to estimates of annual earnings per share (EPS) provided by sell-side analysts. To explore the factors that affect an analyst’s ability to issue accurate forecasts, this paper examines three different properties of analyst forecasts.. Forecast “accuracy,” is defined as the absolute value of the percentage difference between realized EPS and forecasted EPS. “Bias” refers to the percentage difference between realized EPS and forecast EPS, and measures analyst optimism or pessimism. Finally, “dispersion,” or the standard deviation among analysts’ forecasts for a forecast horizon divided by the realized EPS, is a measure of the spread of analyst forecasts.

DETERMINANTS OF FORECAST ACCURACY

The engagement by sell-side analysts to forecast the earnings of publicly traded companies is an important component in efficient capital markets. As pointed out in a number of past studies, such as those by Kothari (2001), Michaely and Womack (2005) and Frankel, Kothari and Weber (2006), the recommendations and forecasts issued by sell-side analysts significantly impact the operations of the markets. These studies suggest that, in an efficient capital market, analyst forecasts perform several key roles. First, almost all financial valuation models are based on earnings forecasts, either directly or indirectly. Thus, forecasts drive significant movements in the level and variability of equity prices and returns and as such play a key role within the economy. Second, policy research by both regulators and academics relies extensively upon the financial statement analyses and recommendations provided by security analysts. Given the importance of these forecasts, these studies claim that systematic, aggregate errors lead to increased corporate agency costs and reduced informational efficiency within financial markets. As a result, a significant body of research has been devoted to identifying those factors that drive systematic errors within forecasts.

Past research has focused on multiple determinants of forecast accuracy. These studies cover factors ranging from firm specific indicators, to the quality and type of analysts covering the firm, to the state of the economy, some of which will be included as control variables within the analysis.

Industry:

The industry and business operations of the firm are well documented causes of variation in forecast accuracy. (See Brown (1997), Dunn & Nathan (1998) and Coën, Desfleurs and L'Her (2009).) The relationship of industry to forecast accuracy revolves around the ability of analysts in certain industries being better able to conduct their analyses. There are multiple potential causes to this. First, there is likely to be variation in the stability of operations among industries. For example, utilities, are likely to be subject to fewer exogenous than are firms operating with the mining sector, whose operations are subject to fluctuations in commodity prices. Second, forecast accuracy is likely to be affected by the innate skill of the analyst. Second, certain industries may have greater aggregate analyst coverage, which can lead to better marginal information gathering and more accurate consensus estimates. Finally, accounting factors can be another link in the relationship between accuracy and industry. DeFond and Hung (2003) note that the accounting choices that firms make and that affect their reported earnings vary by industry. And, they find that cross-sectional differences in accounting choice are systematically correlated with differences in accuracy and bias.

Forecast Horizon:

The forecast horizon, or the time between when an analyst submits an EPS forecast and the announcement by the company of the actual EPS, significantly affects the accuracy of forecasts. Intuitively, the further out one makes an estimate, the greater the probability of error. A number of past studies have shown this to be the case (Richardson, Teoh, & Wysocki, 1999; Burgstahler and Eames, 2003; Eames and Kim, 2012). As expected, this study finds that accuracy decreases as the horizon increases.

Firm Size:

The size of the firm is a well-documented determinant of forecast accuracy, with larger firms generally having more accurate forecasts (Brown 1998). The principle rationale explaining this relationships is that larger firms generally have a large analyst following, which contributes to more extensive coverage and aggregate information gathering. Other potential explanations include greater scrutiny by market participants that pressure the company into better reporting, stable earnings and more comprehensive disclosure by the firm's managements.

Analyst Following:

Significant research has been devoted to identifying measures and indicators of competence and efficacy of sell-side research analysts (Mikhail, Walther, and Willis 1997). For the purposes of this study, the focus will rest primarily on general trends in the analyst following, such as the number of analysts following a firm within the coverage period and the dispersion in their forecasts. Several studies have reported that a larger analyst following is associated with greater forecast accuracy (Alford and Berger 1999). They argue that, at the margin, each additional analyst contributes new information to the consensus estimate.

Earnings Type:

The earnings type (profits vs. losses and year over year increases vs. decreases) has been found to be associated with forecast accuracy (Brown 1998; Ciccone 2005; Dowen 1996). The association has been attributed to the incentive structure of sell-side analysts. Those analysts who issue a negative recommendation risk their relationships with the firm's management and, thus, their access to information (Lim 2001; Das, Levine, and Sivarmakrishnan 1998). In addition, research devoted to the study of cognitive biases in analysts. (Easterwood and Nutt, 1999) has found that analysts have a tendency to overreact to good earnings information and underreact to bad earnings information. In addition, Capstaff et al. (1998) find that forecast errors are much smaller for earnings increases than for decreases.

Earnings Management:

The impact of earnings management and earnings quality on forecast accuracy is well-documented. While a number of different definitions of earnings quality have been proposed in the literature, all focus on the usefulness of the earnings measure for decision making (Dechow, Ge and Schrand 2010). Within the context of this paper, the term “earnings management” refers to actions undertake by management that undermine earnings quality and thus the ability of sell-side analysts to issue accurate forecasts. Some of the proxies for earnings quality examined in prior research include specific financial accounting manipulations, such as discretionary accounts, transaction-timing and reporting incentives (Salerno 2014). A direct examination of the specific mechanism of earnings management is outside of the scope of this paper, however one source of debate has been the observed discontinuity in earnings around zero. Prior studies have noted a statistically significant difference in those firms having slightly negative vs. slightly positive earnings, with a larger than expected number of firms reporting slightly positive earnings. Recent literature using more current data suggests however that this discontinuity has disappeared for realized earnings, although not necessarily for analyst forecasts (Gilliam et al. 2015).

Burgstahler and Eames (2003) find that analysts exhibit significant forecast pessimism, overestimating earnings, for those firms that report zero earnings and significant forecast optimism, underestimating earnings, for those firms associated with zero earnings forecasts. Specifically, they find that analysts have higher than expected forecasting errors around zero. These results have been corroborated by both Eames and Kim (2012) and Gilliam et al. (2015).

Financial Crisis:

As noted by Espahbodi, Espahbodi and Espahbodi (2015), the accuracy and dispersion of forecast errors have changed over time, shifting from pessimistic to optimistic. They find that, within their sample from 1993-2013, both the magnitude and the dispersion of forecast errors, have been steadily increasing. Several studies have pointed to significant changes in regulation and the economy, with mention to the Great Recession in the United States, as the primary catalysts for these changes. Chronologically within the data set examined, the major exogenous financial shocks or regulatory changes encountered include the Regulation Fair Disclosure (Reg FD), implemented by the Security and Exchange Commission in the US in October 2000, the early 2000's recession, Sarbanes-Oxley in 2002, the Global Settlement in 2003, the Great Recession in 2007-2008 and the passage of Dodd-Frank in July 2010. The stated intentions of the early 2000 reforms have been to reduce sell-side analyst incentives to issue biased recommendations (e.g. the Global Settlement), to improve accounting practices within financial reporting and finally to level the playing field for access to information, reducing incentives for companies to report selective information to certain analysts. Following these regulations, studies have found that analysts have had a lower propensity to report optimistic forecasts and recommendations (Herrmann, Hope and Thomas 2008; Hovakimian and Saenyasiri 2010). Hovakimian and Saenyasiri (2010), in particular, found that the median forecast bias essentially disappeared following the Global Settlement.

DATA

Actual and forecasted annual earnings per share for the years 2000-2013 were obtained from the Institutional Brokers Estimate System (I/B/E/S) for all U.S. firms that are included in the database. Forecasts are submitted to I/B/E/S by each analyst following a firm. Each analyst forecast was classified based on the forecast horizon: 1-90, 91-180, 181-270 and 271-360 days prior to the actual announcement day. For each forecast horizon, the median forecast was obtained. While analysts may update their forecasts year within a forecast horizon interval, only the most current forecast within each interval has been included in this study. The median forecast, as opposed to individual forecasts, is used to simplify the comparison with forecast dispersion and to mimic the use of the consensus estimate among market practitioners. Past research also indicates little difference between the use of the median forecast versus the average in the calculation of the composite forecast (Coën et al. 2009). In addition, this study excludes those firms with fewer than three analysts, or forecasts, for a forecast horizon (Chang et al. 2000; Coën et al. 2009). This allows for a more precise calculation of forecast dispersion.

The data was adjusted to exclude outliers, defined as forecasts which are in excess of 100% of the absolute value of realized earnings (Capstaff, Paudyal and Rees 1998). These outliers can be caused by data errors or other transitory factors, such as M&A activity or similar atypical events. In addition, to limit the effect of small divisors, such as those used in the calculation of forecast errors and dispersion, any divisors smaller than 0.02 are set to 0.02 within those calculations (Ciconne 2005). Finally, forecasts that have incomplete data, which are either missing or incorrect industry identifiers or missing year over year changes in earnings, such as for the first year a company reports earnings, are removed.

Additional information on individual factors is included within the methodology section. Tables 1-4 provide descriptive statistics for the sample, including descriptive statistics concerning the outlier removal procedure discussed above.

METHODOLOGY

There are three different measures of forecast accuracy that this study examines. The first is forecast error (FE), which is calculated as the difference between the realized earnings (RE) and median forecast for the period (F), divided by the realized earnings.

$$FE = \frac{RE - F}{|RE|}$$

The second is the absolute forecast error (AFE), which is the absolute value of the forecast error.

$$AFE = |FE|$$

The third measure is forecast dispersion (FD), which is calculated as the standard deviation (σ_F) of the forecasts divided by the actual earnings.

$$FD = \frac{\sigma_F}{|RE|}$$

Within this paper, the forecast error is interpreted as a measure of the bias of analysts. When the error is negative, their forecasts are greater than the reported earnings and are referred to as "optimistic". Conversely, when the error is positive, the forecast is smaller than the realized earnings and so they can be considered pessimistic. The absolute forecast error is interpreted as a measure of the accuracy of analysts in their forecasts: the larger the absolute error, the further away the forecast is from the realized earnings.

This analysis also includes an examination of the forecast dispersion. Although the consensus estimate is generally the primary statistic employed by market participants within their analyses, the consensus estimate loses significant information about the distribution of the forecasts. For example, dispersion is sometimes interpreted as an indicator of herding behavior among analysts (Hong, H., Kubik, J., and Solomon, A. 2000). Within this paper, however, low dispersion is seen as desirable for two reasons. First, Ciccone (2001) claims that those firms which are potential candidates to hide bad information have been associated with higher dispersion in forecasts. Second, table 4 suggests there exists a correlation between higher forecast errors and higher analyst dispersion. Consequently, this paper also analyzes whether the same factors that are believed to affect forecast accuracy and bias are also significant in impacting the dispersion of analyst errors.

To identify what, if any effects the discussed factors have on the earnings forecasts, the following ordinary least squared regression is run:

$$FP = \alpha + \sum_{i=1}^{n}(\beta_{1,i} * I) + \sum_{i=1}^{m}(\beta_{2,i} * INT) + \beta_3 * ANL + \beta_4 * \ln MCAP + \beta_5 * CHNG + e$$

Where:

- FP: The forecast property being tested, FE, AFE, or FD, as defined above.
- I: Categorical variables representing the firm's industry classification, as defined by the Standard Industrial Classification (SIC) system. These variables are coded as 1 if the forecast is for a firm within an industry or 0 otherwise. This paper uses eight industry groups, as defined by the SIC system, with the ranges of numbers included below:
  - I1 (0100-1799): Agriculture, Forestry and Fishing, Mining and Construction. Three different divisions are combined to form I1 due to small sample size for the Agriculture and Forestry and Fishing divisions.
  - I2 (4000-4999): Transportation, Communications, Electric, Gas and Sanitary service
  - I3 (5000-5199): Wholesale Trade

  - I4 (5200-5999): Retail Trade
  - I5 (6000-6799): Finance, Insurance and Real Estate
  - I6 (7000-8999): Services
  - I7: Other, or all other companies not tied to a predefined industry group.
  - I8 (2000-3999): Manufacturing. This industry is used as the reference, or baseline, against which all other industries are compared to in all the regressions.
- INT: Categorical variables representing intervals of realized earnings. Variables are coded as 1 if the realized earnings for the associated forecast falls within the interval:
  - INT1: All negative realized earnings to small losses ($-\infty$, -0.1).
  - INT2: Small losses (-0.1, 0).
  - INT3: Small profits (0, 0.1).
  - INT4: All remaining positive realized earnings (0.1, ∞). The variable representing this interval is used as the baseline in all regressions.
- MCAP: the log of the market cap, taken as the share price multiplied by the shares outstanding at the beginning of the year.
- ANL: The number of analysts reporting forecasts for the firm. Those firms with less than three forecasts and thus three different analysts within the forecast period have been excluded.
- CHNG: A categorical variable representing whether realized earnings increased or decreased from the last announcement date. The value is coded as 1 if the realized earnings declined. The baseline in the regression is an increase in realized earnings.

To conduct the analysis, regressions were performed for each of the forecast horizons: 1-90, 91-180, 181-270 and 271-360 days prior to the actual announcement day. It is expected that as forecasts approach the announcement date, both the magnitude and the dispersion of the forecast errors will decrease because, as the report date draws closer, analyst are likely to have more information about events that have occurred and that have an effect on the earnings for the year, and because the remaining forecast horizon . The reason for this is because, on the one hand analysts have access to additional quarterly reports and management guidance that would improve their accuracy and on the other hand fewer outside events are likely to happen in a shorter forecast horizon. What is less clear and what this study will attempt to discern is what effects the forecast horizon has on the significance of the factors that affect forecast accuracy.

The second constraint is that separate regressions are run across the sample years. In the course of collecting and assembling the data, it became apparent that there were noticeable differences in the three forecast measures across time. Specifically, large differences were noticed between the 2000-2007 and 2008-2013 intervals. Thus, in addition to regressions run for the three forecast measures across the entire sample dates, separate regressions are also run for the two intervals mentioned.

RESULTS AND ANALYSIS

Analysis of Data:

Figures A. – C. show the evolution of forecast error, absolute forecast error and forecast dispersion from 2000 to 2013. In all three figures, the forecasts measures are broken up by forecast horizon.

Figure A. displays average FE over time, which can be interpreted as a measure of analyst bias. In the 0-90 day forecast period, which is the best approximations for the last estimate provided by analysts before the announcement date, the average error is low and slightly positive, or pessimistic. The average error remains relatively stable at slightly above 0% for all years except 2008 and 2009, where the average error is negative, or slightly optimistic, at -0.8% and -0.3% respectively. Bias within the 91-180 forecast period is more variable, ranging from -2.9% in 2001 to 1.9% in 2010, with significant periods of optimism during 2008 and 2009. Bias for the 181-270 and 271-360 horizons is more pronounced. In this case, the forecast errors are substantially larger and negative during periods associated with the recessions in 2002 and 2007-2009. Figure B. represents the time series of AFE. As noted by Espahbodi et al. (2015), this measure of forecast accuracy can be observed to have increased modestly over the sample period. Across all four forecast horizons, the absolute value of errors increased over time. For the 0-90 day forecast horizon, they increased from 6.1% in 2002 to 7.2% in 2013 and for the 271-360 horizon from 8.7% to 8.9%. As one would expect, the absolute forecast errors are substantially larger during the recessionary periods for 2000-2001 and 2009-2010.

Figure C reports the time series of the dispersion among analyst forecasts. The results of this study are consistent with those of Espahbodi et al. (2015). The dispersion among forecasts are increasing over time. In contrast to the time series for FE and for AFE, there does not appear to be a substantial difference across forecast horizons. The average dispersion across forecast horizons has increased from roughly 0.1 in 2001 to over 0.3 in 2010, before falling back to 0.16 in 2013.

Figure D reports the time series of FE by industry. There is no evidence of a substantial difference in the time series across industries. Again, the evidence suggests that the forecast errors for all of the industries were more pronounced during the recessionary periods 2000-2001 and 2009-2010. With the exception of those intervals, the forecast errors for all industries vary around zero.

Figure E reports the time series of AFE by industry. Two observations are noteworthy. First, there is evidence of differences in the magnitude of the average absolute forecast errors across industries. The evidence suggests that the time series pattern and magnitude of the average absolute forecast errors for Manufacturing, Services, Transportation, Communications, Electric, Gas and Sanitary Service (T/C/E/G/S) and Retail Trade, are similar. However, the magnitude of the absolute errors for Agriculture, Mining and Construction, Wholesale Trade, and Finance, Insurance and Real Estate appear to be significantly larger. For example, for the period 2001-2013, the average forecast error for Agriculture, Mining and Construction was 17.4%. In contrast, for the same period the average absolute forecast error for Retail Trade was 11.5%.

Second, the evidence indicates a significant change in forecast accuracy after 2008. In particular, prior to 2008, the average absolute forecast error for the Finance, Insurance and Real Estate industry was 7.1%. Following 2008, the average was, 15.2%. In addition, the time series pattern for all industries appears to have changed following 2008. Figure F reports the dispersion of analyst forecasts over time. Prior to 2010, there is little evidence of across industry differences in the magnitude of the dispersion or in the time series pattern of the dispersion. There is a noticeable spike in the dispersion for all industries around 2010. The change is most pronounced for Finance, Insurance and Real Estate and for Agriculture, Mining and Construction.

Regression Analysis:

Tables 5a – 7c report the results from the regressions for each of the three measures of forecast error. Based on the evidence from Figures A-C, regarding the changes following 2008, separate regressions were performed for 2000-2007 and for 2008-2013. This is done in an attempt at removing some of the effects of large residuals from the 2008-2013 period, which would otherwise alter results.

Forecast Error:

Tables 5a – 5c report the results of the regressions with FE as the dependent variable. As expected, the coefficients for ANL, MCAP and CHNG are significant for each regression. Although the coefficient is small, the number of analysts is positively associated with pessimism in forecasts bias, whereas the market cap and yearly changed in EPS are much more strongly associated with optimism. The estimated parameters for the realized earnings interval (loss, small loss, small profit, profit) are less obvious. While it is apparent in all periods that losses are associated with optimism in forecasts, the significance of small losses and small profits varies. The evidence suggests that there is significant variation in forecast error compared to the baseline, which is represented by differences to positive earnings within the regressions, when the reported earnings are small. The coefficients associated with bias for small losses depend on the sample period. The predicted coefficients for the 1-90 and 181-270 day forecast horizons are pessimistic and significant for the 2000-2007 period, but optimistic and not significant for the other two horizons. In the 2008-2013 sample date, the coefficients are positive and thus pessimistic in the 1-90 and 91-180 day horizons, but negative and thus optimistic in the 181-270 and 271-360 day horizons – the estimated coefficient for the 91-180 day horizon is not significant, however. The results for forecasts of firms with small reported earnings is similar.

All predicted coefficients in the 2000-2007 period are positive and thus pessimistic, although the 91-180 day horizon is not significant. In the 2008-2013 sample dates, none of the coefficients are significant, thus there is little difference between companies with small profits and regular profits.

The significance of the estimated industry coefficients, which are measures of the difference between forecasts of one industry as compared to the reference industry, Manufacturing, vary by forecast horizon and sample dates. Using the entire sample data, or 2000-2013, four industries, Agriculture, Mining and Construction, T/C/E/G/S, Retail Trade and Finance, Insurance and Real Estate, have estimated parameters that are significant in all four forecast horizons. All of the estimated parameters reveal that analysts overestimate errors for firms in these industries, as compared to the Manufacturing industry baseline. Coefficients for Wholesale Trade are only significant in the 91-180 and 181-270 forecast horizons, but are also negative. Coefficients for Services and Other are not significant, revealing no variation to the baseline.

Using only forecasts from the 2000-2007 period the coefficients for Retail Trade are significant across all four forecast horizons and reveal that analysts overestimate forecasts for this period. Estimated coefficients for the Services industry are significant in the 91-180, 181-270 and 271-360 horizons and reveal that analysts underestimate earnings for this industry, compared to manufacturing. For the Agriculture, Mining and Construction and Finance, Insurance and Real Estate industries, only coefficients for two forecast horizons are found to be significant, both in the 1-90 and 91-180 day periods and both showing that analysts overestimate forecasts for these two industries. Regressions results for the remaining industries, T/C/E/G/S, Wholesale Trade and Other reveal significance in none or only one forecast horizon.

From 2008-2013, similar observations to those found using the entire sample are noted. Agriculture, Mining and Construction, T/C/E/G/S and Finance, Insurance and Real Estate continue to remain significant in all four forecast horizons, with the same predicted signs. Retail Trade is no longer significant in the 1-90 day horizon, but remains significant in the other three horizons with the same predicted signs. Predicted coefficients for Wholesale Trade and Services are significant in only two of the four forecast horizons, although all are positive, revealing that analysts overestimate forecasts for these two industries. Coefficients for Other continue to remain insignificant.

Absolute Forecast Error:

Tables 6a – 6c report the results of the regressions with AFE as the dependent variable. The three firm specific factors, ANL, MCAP and CHNG are significant across all three sample dates (2000-20013, 2000-2007 and 2008-2013) and across the four forecast horizons. The number of analysts, although significant, has little effect on the accuracy. Both the market cap and change in realized earnings, however, have large coefficients associated with more accurate forecasts, or in the case of decreases in earnings, less accurate forecasts. For the earnings interval, negative earnings contribute to poorer accuracy. Of note, although a small loss which would normally fall into the negative earnings bucket is associated with larger errors, the coefficient for it and for small profits is significantly larger. That is, the results suggest that analysts are meaningfully less accurate in their predictions of companies with earnings near zero. One potential explanation for this is in the methodology used for measuring forecast errors, which is usually as a percentage of difference from the realized earnings. The raw difference between the realized earnings and forecasts for near zero earnings is very small and as such these small numbers magnify into larger percentage differences.

The results of the regression corroborate the observations noted above in Figure E. Namely, analysts in certain industries have significant differences in their forecast accuracy. Here, in particular, the importance of running regressions for two different sets of dates is noted. When using data on all available dates, only Agriculture, Mining and Construction is significant across all four forecast horizons, with positive predicted coefficients that indicate higher absolute forecast errors. Coefficients for Retail Trade and Finance, Insurance and Real Estate are significant in three of the four horizons. The magnitude of these coefficients is small, however, and their sign varies by horizon, indicating that even though the differences are statistically significant, they are small and depend upon the choice of forecast horizon. The remaining industries are significant in only one or two of the forecast horizons. From 2000-2007, Agriculture, Mining and Construction remains significant in all forecast horizons, with positive predicted parameters. T/C/E/G/S and Finance, Insurance and Real Estate have significant coefficients in three of four horizons, Retail Trade and Services in two and Wholesale Trade and Other in only one interval. As noted previously, the predicted signs vary inconsistently between forecast horizons, although the magnitude of the predicted parameters appear to be increasing with further out forecast horizons. From 2008-2013, Agriculture, Mining and Construction and Finance, Insurance and Real Estate are significant in all horizons, with positive predicted parameters. Retail Trade has significant coefficients in three of four horizons, T/C/E/G/S in two, and Services in one interval. No coefficients for Wholesale Trade or Other are significant. As before, the size and sign of the predicted parameters varies by forecast horizon, but with little discernible pattern.

The explanation for the noted differences in forecast accuracy likely follow the discussions in the introduction: differences in earnings stability, accounting practices and susceptibility to outside shocks, such as commodity prices and regulations. Although there exist systematic differences in forecast accuracy between certain industries of errors, the magnitude of the errors vary by forecast horizon. Because Manufacturing is used as the standard against which all other industries are measured, it is unclear what is causing the underlying differences in the results for the different forecast horizons. Across all sample dates and forecast horizons, however, Agriculture, Mining and Construction is always associated with fairly large, positive predicted coefficients and thus lower accuracy. In addition, in the 2008-2013 sample date, the Finance, Insurance and Real Estate industry is similar associated with larger, positive predicted coefficients. These results corroborate the findings noted above in regards to Fig B.

Forecast Dispersion:

Tables 7a – 7c report the results of the regressions run with FD as the dependent variable. The results suggest that there are few factors that are significant in explaining variations in the forecast dispersion. Among the three sample dates, four factors are uniformly significant in all four forecast horizons. These are the three earnings intervals and the change in YoY earnings. In terms of realized earnings change, those firms which report a decrease in EPS have significantly higher dispersion in analyst forecasts. In addition, those firms which report negative earnings have higher dispersion than profit firms. Similar to the results reported on forecast accuracy, firms with earnings near zero, both slightly negative and slightly positive, also report higher than average dispersion. Whether this is because of the effects discussed before or due to other causes is unclear.

Finally, as noticed in Fig. F, the industry of the forecasted firm is generally not significant as a predictor of dispersion, at least compared to the baseline. In the entire sample date, only Agriculture, Mining and Construction, which is significant in three of four horizons, T/C/E/G/S, which is significant in two of four horizons and Finance, Insurance and Real Estate, which is significant in all four horizons have predicted parameters that reveal significantly larger dispersions. From 2000-2007, however, Finance, Insurance and Real Estate is no longer significant in all horizons, but rather only in the 91-180 day horizon. Agriculture, Mining and Construction continues to remain significant in three horizons, whereas T/C/E/G/S and Services are significant in only one horizon. All predicted coefficients that are significant, apart from the one for Services, are positive, indicating greater forecast dispersion than the mean. From 2008-2013, Finance, Insurance and Real Estate is significant within all four forecast horizons. Agriculture, Mining and Construction is significant in two horizons, 181-270 and 271-360 and T/C/E/G/S and Services are significant in one interval each. As before, all predicted coefficients are positive. Based on the results of these regressions, only certain industries result in significant variability in forecast dispersion.

CONCLUSION

The purpose of this study was to identify what effects the industry has on forecast accuracy and dispersion and what recent trends in measures of analyst forecast accuracy have been. This paper found that there exist significant and often times consistent differences in forecast accuracy among certain industries. In addition, it also found that analyst forecast accuracy has decreased over the past 13 years, but that most of the variability in accuracy can be attributed to forecasts made after 2008. The choice of forecast horizon also has a significant impact on the conclusions reached – when looking at just the latest forecast (0-90 day period), analysts have been mostly pessimistic in their projections, which has been closely associated with the phenomenon of target beating. Longer forecast horizons, however, are optimistic, particularly during years associated with poor economic performance. Measures of forecast dispersion have also gradually increased over the sample dates, which significant increases after 2008 and a gradual stabilization after 2011. The data suggests that dispersion within two specific industries, “Agriculture, Mining and Construction” and “Finance, Insurance and Real Estate” explains much of this increase. Finally, this study shows that common factors associated with variability in forecast accuracy measures are significant across the sample dates and horizons. Taken together, the results from this study provide better clarity on the evolution of forecast accuracy, bias and dispersion from 2000-2013. They also provide a better understanding of the variation in these measures attributable to industry effects.

APPENDIX:

Table 1. Sample Statistics: Outlier Removal

	Number of Observations	Mean FE	Median FE	Standard Deviation
Original Data Set	107,428	-14.8%	0.53%	1.86
With Errors Removed	84,839	-11.73%	1.00%	1.57
With Outliers Removed	79,009	-1.66%	0.75%	0.22
Difference to original	*5,830*	*-13%*	*-0.23%*	*1.6*

Table 2. Sample Distribution by Industry for 1–90 Day Forecast Horizon

Industry	Number of Forecasts	Number of Forecasts
Agriculture, Mining and Construction	1,216	9.9%
Manufacturing	4,219	34.2%
Transportation, Communications, Electric, Gas and	1,530	12.4%
Wholesale Trade	259	2.1%
Retail Trade	1,095	8.9%
Finance, Insurance and Real Estate	2,168	17.6%
Services	1,766	14.3%
Other	66	0.5%
Total	12,319	100%

Table 3. Sample Sizes by Forecast Horizon

Forecast Horizons	Number of Forecasts
1–90 Days	12,319
91–180 Days	23,355
181–270 Days	22,228
271–360 Days	21,107
Total	79,009

Table 4. Pairwise Correlations

	FE	*AFE*	*FD*	INT1	INT2	INT3	ANL	MCAP	CHNG	I1	I2	I3	I4	I5	I6	I7	I8
FE																	
AFE	-0.335																
FD	-0.035	0.237															
INT1	-0.169	0.247	0.097														
INT2	-0.008	0.149	0.084	-0.032													
INT3	0.015	0.153	0.066	-0.038	-0.009												
ANL	0.036	-0.081	-0.017	-0.102	-0.029	-0.028											
MCAP	0.045	-0.234	-0.052	-0.299	-0.077	-0.082	0.570										
CHNG	0.180	-0.301	-0.088	-0.171	-0.095	-0.101	0.049	0.188									
I1	-0.031	0.072	0.025	-0.015	0.008	0.021	0.123	0.031	-0.036								
I2	-0.020	-0.001	0.009	0.018	-0.010	-0.023	-0.022	0.053	-0.014	-0.100							
I3	0.003	-0.027	-0.015	-0.048	-0.007	-0.009	-0.045	-0.019	0.021	-0.048	-0.060						
I4	-0.015	-0.019	-0.019	-0.049	-0.009	-0.011	0.076	-0.010	0.041	-0.081	-0.100	-0.049					
I5	-0.014	-0.028	0.010	-0.077	-0.029	-0.037	-0.049	0.045	0.000	-0.122	-0.150	-0.073	-0.122				
I6	0.032	-0.008	-0.004	0.016	0.027	0.051	-0.001	-0.121	0.035	-0.133	-0.164	-0.079	-0.133	-0.200			
I7	0.007	0.009	-0.003	0.042	-0.007	-0.001	-0.028	-0.066	-0.004	-0.026	-0.032	-0.016	-0.026	-0.040	-0.043		
I8	0.021	0.007	-0.008	0.077	0.012	0.000	-0.036	0.035	-0.027	-0.218	-0.269	-0.130	-0.218	-0.328	-0.357	-0.071	

Notes: This table reports pairwise Pearson correlations between all the tested variables. Definitions for the variables are listed in the Methodology section.

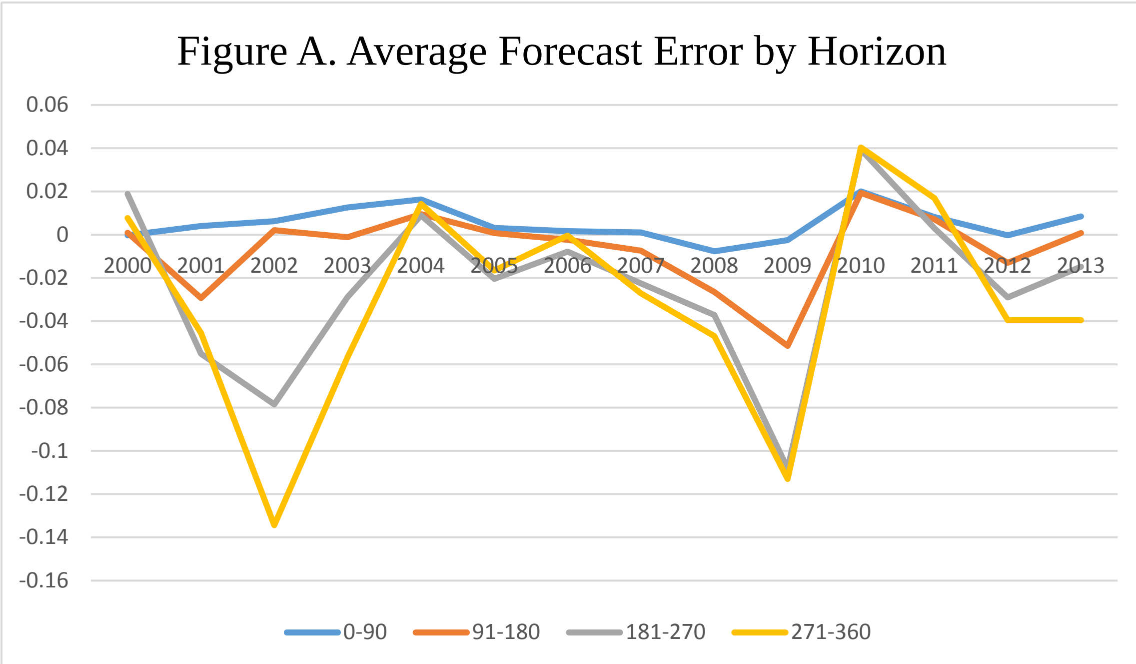
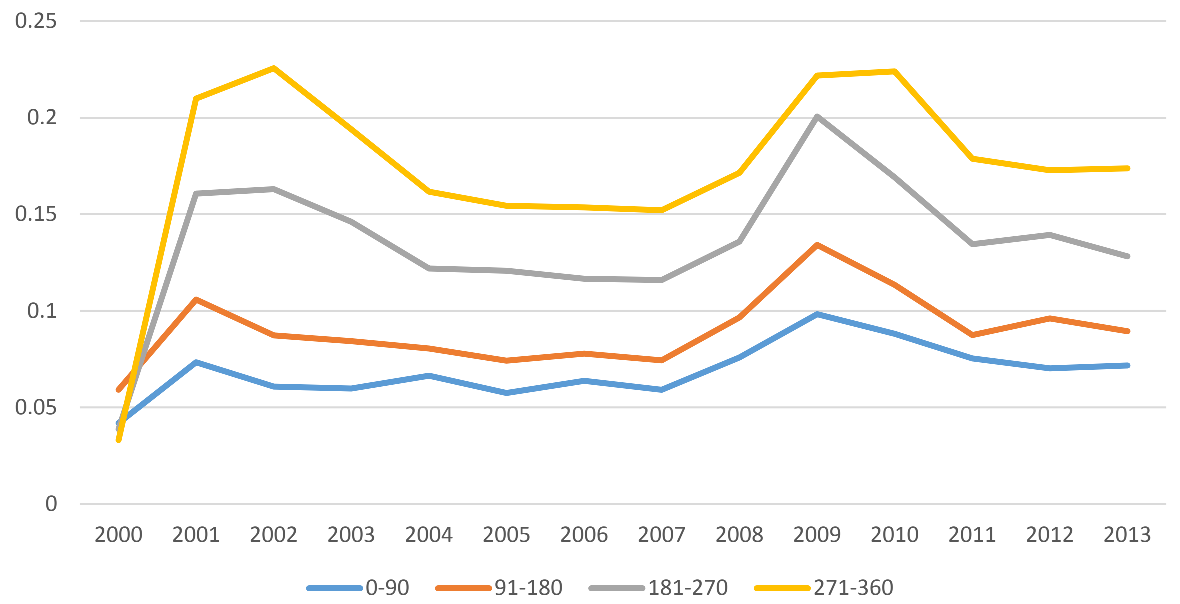


Figure A. Average Forecast Error by Horizon
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
-0.16
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
0-90
91-180
181-270
271-360

Figure B. Average Absolute Forecast Error by Horizon



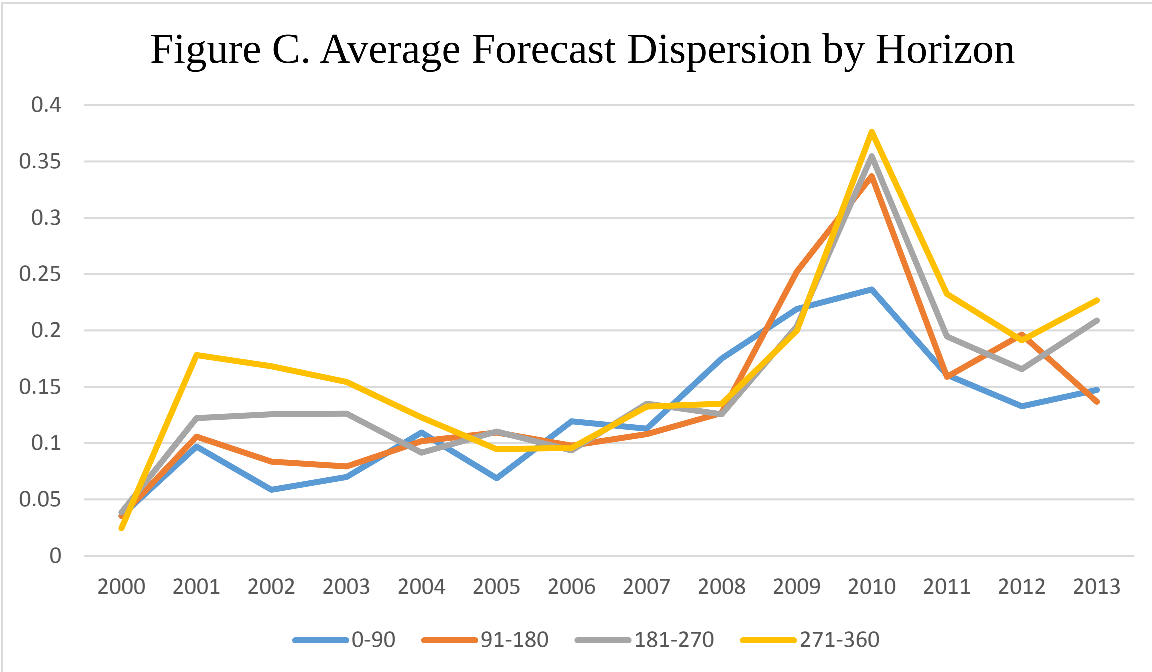


Figure C. Average Forecast Dispersion by Horizon
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
0-90
91-180
181-270
271-360

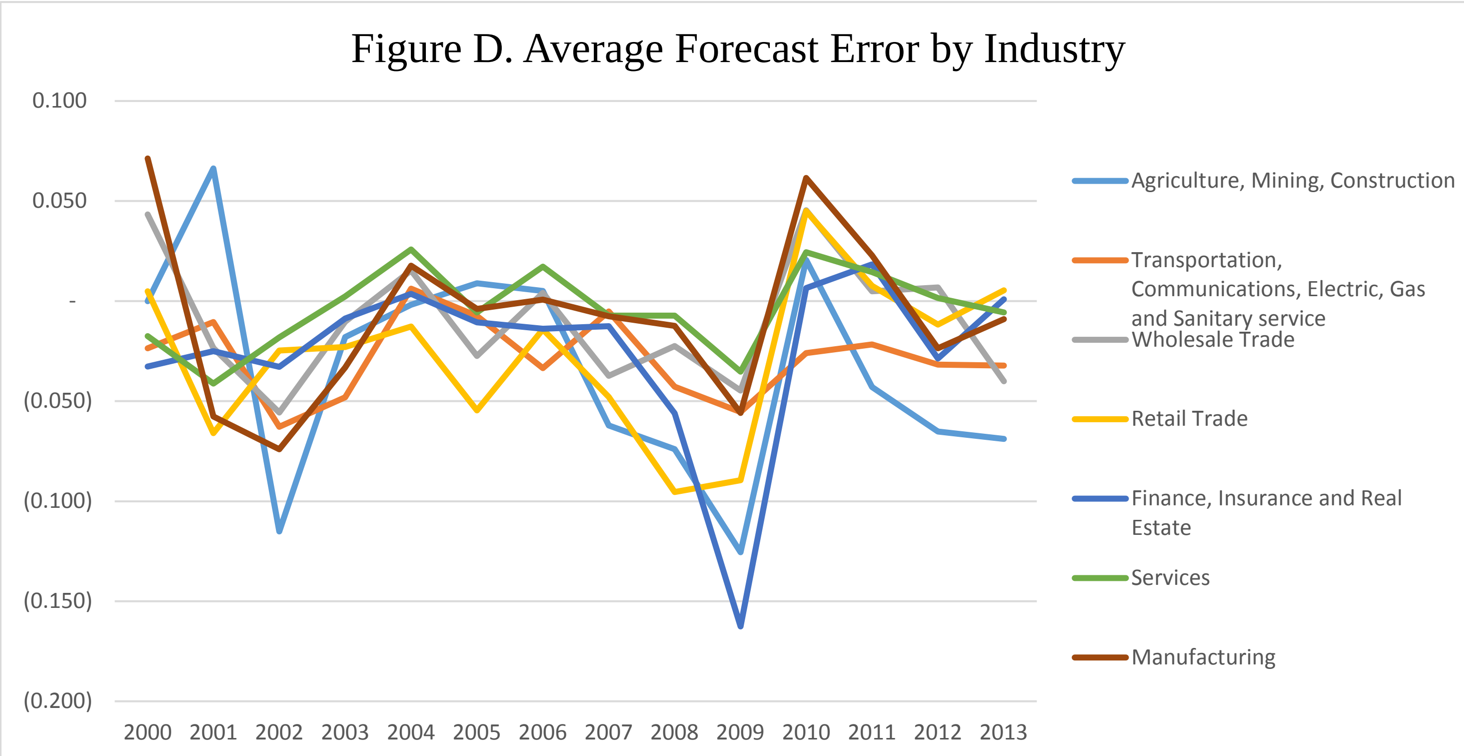


Figure D. Average Forecast Error by Industry
0.100
0.050
-
(0.050)
(0.100)
(0.150)
(0.200)
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013
Agriculture, Mining, Construction
Transportation, Communications, Electric, Gas and Sanitary service
Wholesale Trade
Retail Trade
Finance, Insurance and Real Estate
Services
Manufacturing

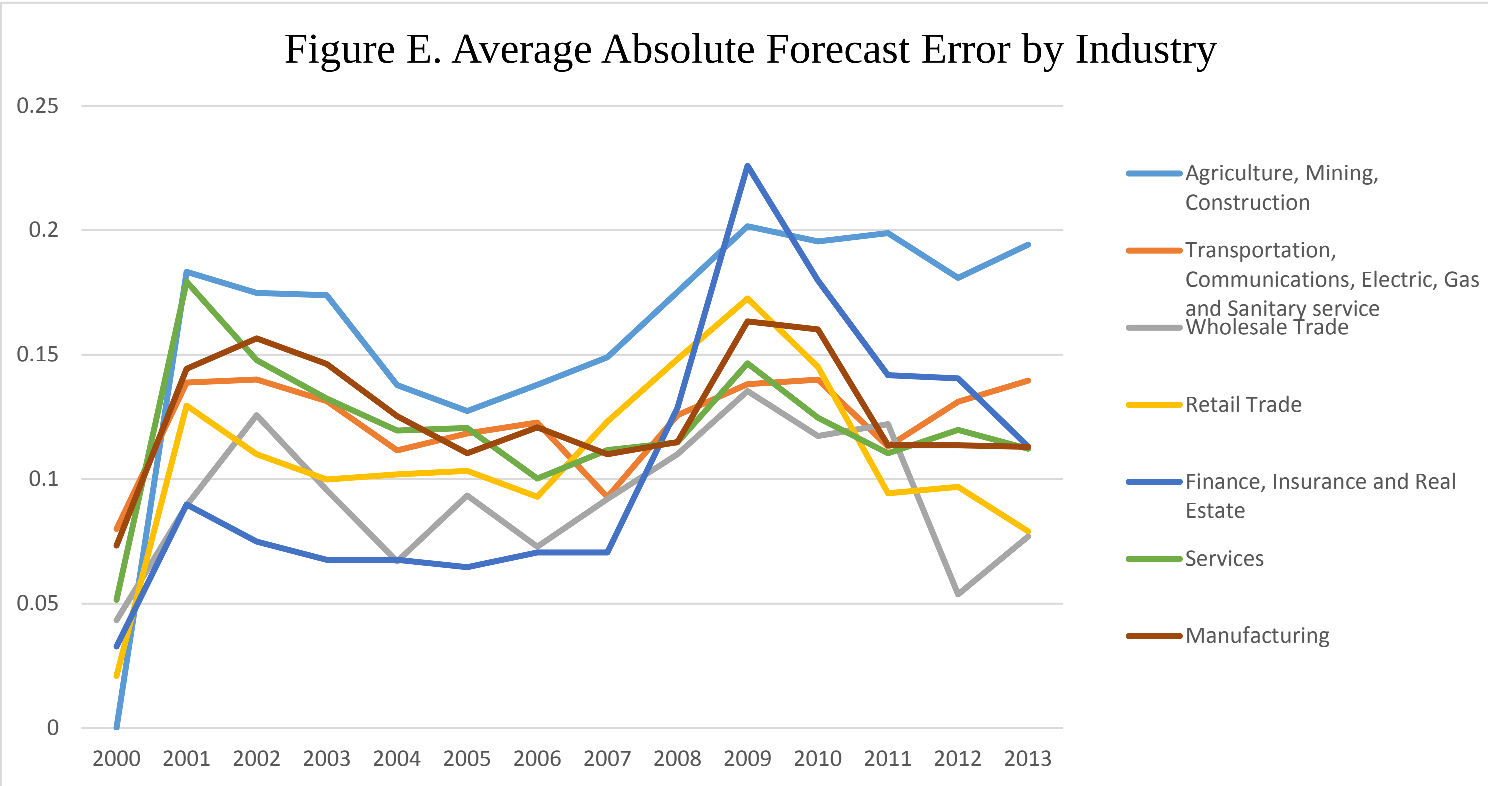


Figure E. Average Absolute Forecast Error by Industry
0.25
0.2
0.15
0.1
0.05
0
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
Agriculture, Mining, Construction
Transportation, Communications, Electric, Gas and Sanitary service
Wholesale Trade
Retail Trade
Finance, Insurance and Real Estate
Services
Manufacturing

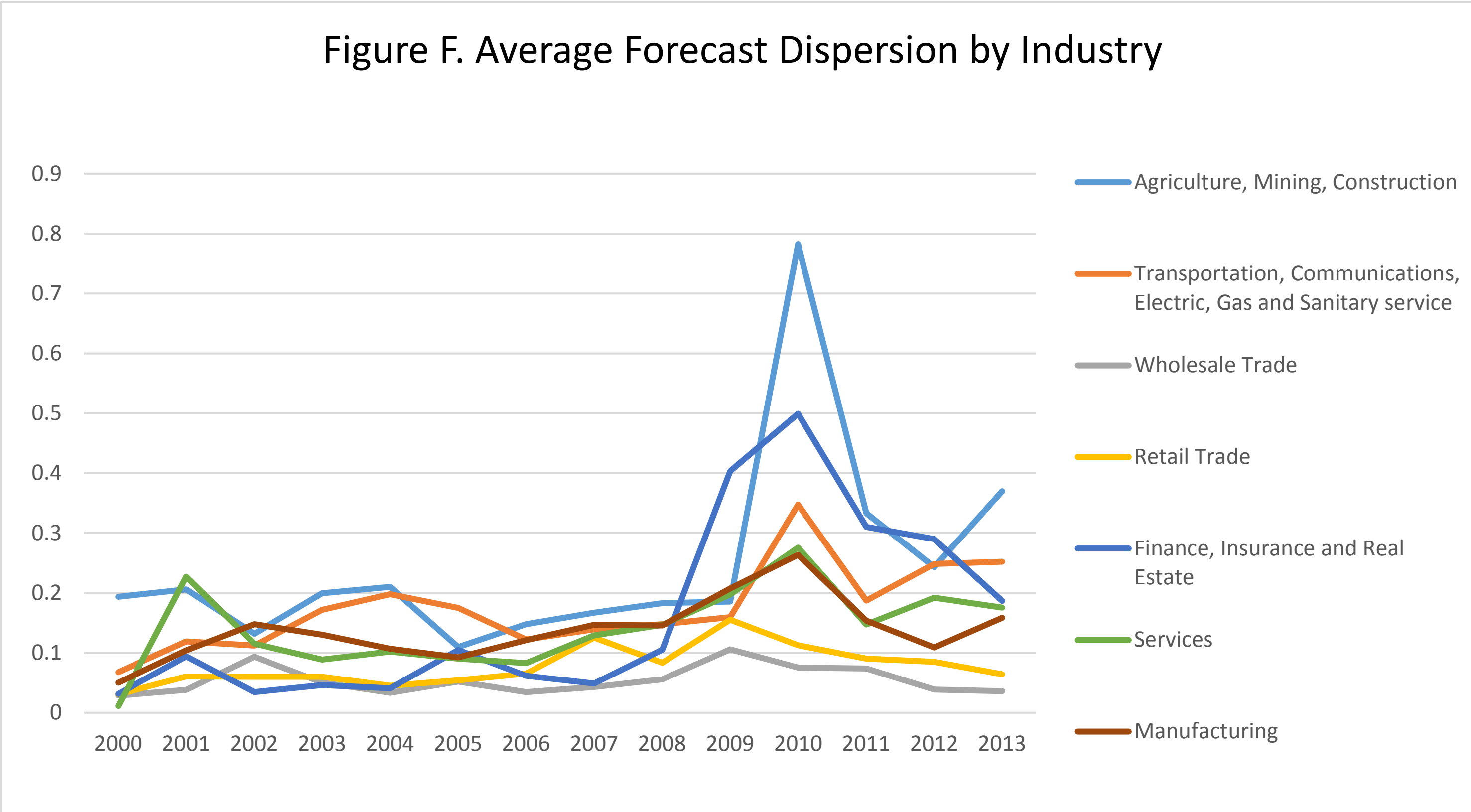


Figure F. Average Forecast Dispersion by Industry
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
Agriculture, Mining, Construction
Transportation, Communications, Electric, Gas and Sanitary service
Wholesale Trade
Retail Trade
Finance, Insurance and Real Estate
Services
Manufacturing

Table 5a. Forecast Error Regression (All Years)

Coefficients	Estimated Parameters			
Forecast Horizon	1-90	91-180	181-270	271-360
Intercept	0.110***	0.087***	0.145***	0.247***
I1	-0.034***	-0.034***	-0.049***	-0.042***
I2	-0.017***	-0.018***	-0.022***	-0.017***
I3	-0.013	-0.021***	-0.028***	-0.018*
I4	-0.020***	-0.026***	-0.053***	-0.058***
I5	-0.023***	-0.029***	-0.023***	-0.016***
I6	-0.006	0.000	0.002	-0.009*
I7	-0.000	0.012	0.016	0.031
INT1	-0.084***	-0.084***	-0.115***	-0.157***
INT2	0.020	0.022*	-0.073***	-0.053*
INT3	0.025**	0.017*	0.078***	0.026
ANL	0.000***	0.001***	0.002***	0.003***
MCAP	-0.005***	-0.005***	-0.009***	-0.015***
CHNG	-0.015***	-0.033***	-0.087***	-0.148***
Adjusted R square	0.034	0.039	0.069	0.104

Notes: This table reports the results of OLS regressions with forecast error (FE) as the dependent variable using forecast data from all available years. Independent variables are sequentially defined within the methodology section.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level

Table 5b. Forecast Error Regression (2000-2007)

Coefficients	Estimated Parameters			
Forecast Horizon	1-90	91-180	181-270	271-360
Intercept	0.076***	0.067***	0.076***	0.149***
I1	-0.038***	-0.023***	-0.015*	0.001
I2	-0.015**	-0.005	0.001	0.009
I3	-0.019	-0.015*	-0.022*	-0.011
I4	-0.025***	-0.025***	-0.047***	-0.043***
I5	-0.024***	-0.015***	-0.010	-0.003
I6	-0.005	0.009**	0.017***	0.014**
I7	-	-0.265**	0.030	-
INT1	-0.064***	-0.059***	-0.079***	-0.105***
INT2	-0.067***	0.022	-0.065***	0.042
INT3	0.022*	0.037***	0.115***	0.018
ANL	0.000*	0.001***	0.002***	0.003***
MCAP	-0.003***	-0.004***	-0.005***	-0.010***
CHNG	-0.008**	-0.028***	-0.101***	-0.171***
Adjusted R square	0.034	0.039	0.069	0.104

Notes: This table reports the results of OLS regressions with forecast error (FE) as the dependent variable using forecast data from 2000-2007. Independent variables are sequentially defined within the methodology section.

Therewere no observationsfor I7 for the 1-90 and 271-360 forecast horizions.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level

Table 5c. Forecast Error Regression (2008-2013)

Coefficients	Estimated Parameters			
Forecast Horizon	1-90	91-180	181-270	271-360
Intercept	0.141***	0.111***	0.203***	0.325***
I1	-0.029***	-0.040***	-0.074***	-0.075***
I2	-0.020***	-0.029***	-0.045***	-0.043***
I3	-0.009	-0.025**	-0.035***	-0.027*
I4	-0.014*	-0.026***	-0.057***	-0.068***
I5	-0.021***	-0.040***	-0.036***	-0.030***
I6	-0.007	-0.008*	-0.012**	-0.032***
I7	0.001	0.015	0.004	0.014
INT1	-0.102***	-0.106***	-0.146***	-0.200***
INT2	0.116***	0.020	-0.077***	-0.164***
INT3	0.034	-0.010	0.031	0.048
ANL	0.001***	0.001***	0.002***	0.003***
MCAP	-0.008***	-0.006***	-0.012***	-0.020***
CHNG	-0.021***	-0.036***	-0.076***	-0.132***
Adjusted R square	0.034	0.039	0.069	0.104

Notes: This table reports the results of OLS regressions with forecast error (FE) as the dependent variable using forecast data from 2008-2013. Independent variables are sequentially defined within the methodology section.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level

Table 6a. Absolute Forecast Error Regression (All Years)

Coefficients	Estimated Parameters			
Forecast Horizon	1-90	91-180	181-270	271-360
Intercept	0.136***	0.167***	0.298***	0.444***
I1	0.032***	0.039***	0.057***	0.065***
I2	0.007**	0.015***	0.002	-0.003
I3	-0.006	-0.001	-0.007	-0.028***
I4	-0.011***	0.018***	0.013***	-0.004
I5	0.012***	0.016***	0.002	-0.009**
I6	0.000	-0.003	-0.011***	-0.020***
I7	-0.013	0.000	-0.018	-0.020
INT1	0.094***	0.091***	0.112***	0.126***
INT2	0.297***	0.284***	0.296***	0.245***
INT3	0.244***	0.264***	0.239***	0.184***
ANL	-0.000***	-0.000**	0.000**	0.001***
MCAP	-0.006***	-0.008***	-0.015***	-0.023***
CHNG	0.046***	0.063***	0.099***	0.126***
Adjusted R square	0.034	0.039	0.069	0.104

Notes: This table reports the results of OLS regressions with absolute forecast error (AFE) as the dependent variable using forecast data from all years. Independent variables are sequentially defined within the methodology section.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level

Table 6b. Absolute Forecast Error Regression (2000-2007)

Coefficients	Estimated Parameters			
Forecast Horizon	1-90	91-180	181-270	271-360
Intercept	0.109***	0.155***	0.277***	0.439***
I1	0.024***	0.020***	0.036***	0.047***
I2	0.009*	0.011***	-0.013**	-0.018***
I3	-0.007	-0.007	-0.012	-0.040***
I4	-0.008	0.018***	0.007	-0.023***
I5	-0.005	-0.009**	-0.027***	-0.049***
I6	-0.000	-0.006*	-0.013***	-0.024***
I7	-	0.220**	-0.040	-
INT1	0.080***	0.072***	0.098***	0.105***
INT2	0.359***	0.269***	0.287***	0.231***
INT3	0.230***	0.225***	0.209***	0.187***
ANL	-0.000*	-0.000	0.000**	0.001***
MCAP	-0.004***	-0.007***	-0.014***	-0.022***
CHNG	0.035***	0.059***	0.108***	0.139***
Adjusted R square	0.034	0.039	0.069	0.104

Notes: This table reports the results of OLS regressions with absolute forecast error (AFE) as the dependent variable using forecast data from 2000-2007. Independent variables are sequentially defined within the methodology section. There are no observations associated with I7 within the 1-90 and 271-360 period.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level

Table 6c. Absolute Forecast Error Regression (2008-2013)

Coefficients	Estimated Parameters			
Forecast Horizon	1-90	91-180	181-270	271-360
Intercept	0.166***	0.170***	0.314***	0.443***
I1	0.038***	0.052***	0.075***	0.080***
I2	0.006	0.019***	0.016***	0.010*
I3	-0.006	0.002	-0.003	-0.017
I4	-0.013**	0.018***	0.018***	0.012*
I5	0.025***	0.036***	0.028***	0.024***
I6	0.003	0.001	-0.008*	-0.016***
I7	-0.023	-0.007	-0.019	-0.015
INT1	0.105***	0.106***	0.123***	0.142***
INT2	0.233***	0.302***	0.303***	0.256***
INT3	0.310***	0.325***	0.281***	0.176***
ANL	-0.000***	-0.000***	0.000	0.000**
MCAP	-0.008***	-0.008***	-0.016***	-0.023***
CHNG	0.050***	0.061***	0.087***	0.112***
Adjusted R square	0.034	0.039	0.069	0.104

Notes: This table reports the results of OLS regressions with absolute forecast error (AFE) as the dependent variable using forecast data from 2008-2013. Independent variables are sequentially defined within the methodology section.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level

Table 7a. Forecast Dispersion Regression (All Years)

Coefficients	Estimated Parameters			
Forecast Horizon	1-90	91-180	181-270	271-360
Intercept	0.069	0.043	-0.056	0.250***
I1	0.029	0.093**	0.183***	0.176***
I2	0.019	0.072**	0.057*	0.072***
I3	-0.052	-0.016	-0.024	-0.020
I4	-0.058*	0.007	-0.003	-0.019
I5	0.051**	0.127***	0.071***	0.099***
I6	-0.037	0.041	-0.005	-0.009
I7	-0.069	-0.018	-0.083	-0.070
INT1	0.229***	0.269***	0.404***	0.470***
INT2	1.383***	1.083***	0.984***	1.323***
INT3	0.701***	0.708***	0.814***	0.821***
ANL	-0.002	0.000	-0.001	0.002*
MCAP	-0.000	-0.003	0.006	-0.016***
CHNG	0.109***	0.148***	0.148***	0.148***
Adjusted R square	0.034	0.039	0.069	0.104

Notes: This table reports the results of OLS regressions with forecast dispersion (FD) as the dependent variable using forecast data from all years. Independent variables are sequentially defined within the methodology section.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level

Table 7b. Forecast Dispersion Regression (2000-2007)

Coefficients	Estimated Parameters			
Forecast Horizon	1-90	91-180	181-270	271-360
Intercept	0.115*	-0.074	0.072	0.244***
I1	0.057**	0.081***	0.047*	0.050**
I2	0.057***	0.039	0.038*	-0.003
I3	-0.025	-0.007	-0.033	-0.040
I4	-0.023	0.021	-0.013	-0.042*
I5	-0.015	0.044**	-0.019	-0.033*
I6	-0.020	-0.002	-0.030*	-0.039**
I7	-	0.020	-0.003	-
INT1	0.165***	0.186***	0.249***	0.353***
INT2	0.879***	0.629***	0.844***	1.178***
INT3	0.480***	0.489***	0.470***	0.657***
ANL	-0.000	-0.001	0.001	0.002**
MCAP	-0.005	0.006	-0.002	-0.014***
CHNG	0.055***	0.098***	0.089***	0.093***
Adjusted R square	0.034	0.039	0.069	0.104

Notes: This table reports the results of OLS regressions with forecast dispersion (FD) as the dependent variable using forecast data from 2000-2007. Independent variables are sequentially defined within the methodology section. There are no observations associated with I7 within the 1-90 and 271-360 period.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level

Table 7c. Forecast Dispersion Regression (2008-2013)

Coefficients	Estimated Parameters			
Forecast Horizon	1-90	91-180	181-270	271-360
Intercept	0.009	0.080	-0.203	0.202
I1	-0.005	0.093	0.272***	0.271***
I2	-0.017	0.097*	0.079	0.139***
I3	-0.093	-0.028	-0.020	-0.006
I4	-0.096	-0.010	0.001	-0.001
I5	0.094**	0.176***	0.130***	0.196***
I6	-0.051	0.096**	0.032	0.028
I7	-0.120	-0.058	-0.114	-0.083
INT1	0.282***	0.347***	0.536***	0.570***
INT2	1.971***	1.601***	1.177***	1.545***
INT3	1.384***	1.049***	1.333***	1.138***
ANL	-0.003	0.000	-0.004	0.000
MCAP	0.006	-0.006	0.017	-0.013
CHNG	0.134***	0.176***	0.177***	0.169***
Adjusted R square	0.034	0.039	0.069	0.104

Notes: This table reports the results of OLS regressions with forecast dispersion (FD) as the dependent variable using forecast data from 2008-2013. Independent variables are sequentially defined within the methodology section.

* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level

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