An Empirical Study of Financial Analysts Earnings Forecast Accuracy

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ABSTRACT

Over the past 12 years, financial analysts across the world have been optimistically wrong with their 12-month earnings forecasts by 25.3%. This study may be the first of its kind to assess analyst earnings forecast accuracy at all listed companies across the globe, covering 70 countries.

A review of prior research shows little uniformity in the preparation of the data set, yet differences in how outliers are treated, for example, can create substantially different results. This research lays out six specific steps to prepare the data set before any analysis is done.

Three main conclusions come from this research: First, analyst earnings forecasts globally were 25.3% optimistically wrong, meaning on average, analysts started each year forecasting company profits of US$125, but 12 months later that company reported profits of US$100. Second, analysts had a harder time forecasting earnings for companies in emerging markets, where they were 35% optimistically wrong. Third, that analyst optimism mainly occurred when the companies they forecasted experienced very low levels of actual earnings growth, analysts did not make an equal, but opposite error for fast growth companies.

The uniqueness of this research is most likely the first that it is global—including all analysts, covering all stocks, across all countries. Furthermore, it is not US-centric. Second, it covers the complete population of data, not a sample or an unrealistically small number of companies. Third, it is long term in nature, covering a total of 12 years from 2003 through 2014, a period that spans more than just one portion of the business cycle. Fourth, this research includes China. This is one of the first papers on analyst earnings forecast accuracy to fully incorporate all Chinese companies that are large and liquid. Fifth, this research is based on the mean earnings forecasts of all analysts, or what is commonly referred to as the “consensus” forecasts, not on the performance of individual analysts. Sixth, this research is comparable. Unlike most prior research in this area, this research scales earnings forecast error by actual earnings, rather than by share price, hence it does not distort results by including the highly variable, random share price factor

into the equation. This makes the results of this research comparable across time, geography, sectors, and both developed and emerging markets. Finally, this research is actionable. This study focuses on a 12-month, consensus forecast, rather than a much shorter-term forecast time horizon, something that investors can actually follow and profit from.

After properly preparing the data set, the methodology employed to test the significance of numerous factors was group compare. The factor focused on, which has not previously been tested, was the level of actual earnings that a company reported. This research grouped companies into four groups based upon the actual earnings growth they produced each year: very fast, moderately fast, moderately slow, and very slow. Though a regression was performed to test the association between analyst forecast accuracy and the group that the company fell into, such a test was less reliable since the main measure tested, whether the actual earnings of a company were high or low, was also a component of the dependent variable, scaled forecast error. In addition, this research clearly shows that the distribution is skewed, rather than a normal distribution, making regression less applicable. Instead, of regression this research used a group compare methodology and showed that almost all of the analyst earnings optimism appears at companies which exhibited very slow growth. And that analysts were not equally inaccurate when a company had very fast earnings growth.

From this work, a few areas for further research stand out. This research showed that as the number of analysts increased, earnings forecast accuracy improved. However, at a level of coverage above 30 analysts, accuracy worsened. It would be interesting to ascertain the source of this difference.

Of the Emerging Countries South Korea, China and Brazil are all highly skewed; in fact, the level of skewness in South Korea is above all others and provides for an excellent area of further research.

A further question to answer in future research is whether analysts are more successful during certain periods of market movements or of the earnings cycle.

Lastly, is to consider research on whether a profitable trading strategy could be adopted from this deeper understanding of analyst earnings forecast error.

Keywords: Analyst earnings forecast accuracy, financial analysts, experts, sell-side analysts.

INTRODUCTION

Investors place a significant amount of trust in financial analysts working for investment banks and brokers, hereafter referred to as sell-side financial analysts. These analysts are expected to advise clients on what stocks to buy or sell and when to complete transactions. Media channels regularly call on them to provide opinions about the investment environment and individual stocks. Financial analysts have three main measurable tools at their disposal: recommendations, target prices, and earnings forecasts. This paper is the first of its kind to comprehensively explain the degree of accuracy in earnings forecasts that can be expected from these analysts across the globe. Based on this knowledge, this research has two goals: To help investors better use, as well as question, the advice they receive from these sell-side analysts and to help financial analysts better understand their biases and therefore increase the value that they bring to their clients.

Prior research has clearly demonstrated that financial analysts are biased; they repeatedly produce optimistic earnings forecasts that the companies they cover are unable to hit. The literature on this topic is exhaustive. Based on this prior work, analysts face three major pressures, two external and one internal. First, their actions are meant to attract clients for the companies that employ them and, as a result, increase trade income, or commissions generated on the stock market trades those clients make. Second, a strong analyst at an investment bank can be an attractive feature for a company planning an initial public offering (IPO). Hence, analysts have the pressure of contributing to the generation of underwriting income. The third factor is the analyst's own reputation, an internally motivated factor derived from an analyst's desire to be correct. Besides providing personal satisfaction, being correct also has financial benefits for analysts in the future in the form of higher compensation. So, the first two factors are external and drive an analyst to be overly optimistic and the third is internal and drives the analyst to be accurate. These forces are illustrated in Figure 1. Since analysts are optimistically biased we can conclude that the external forces seem to override the internal.

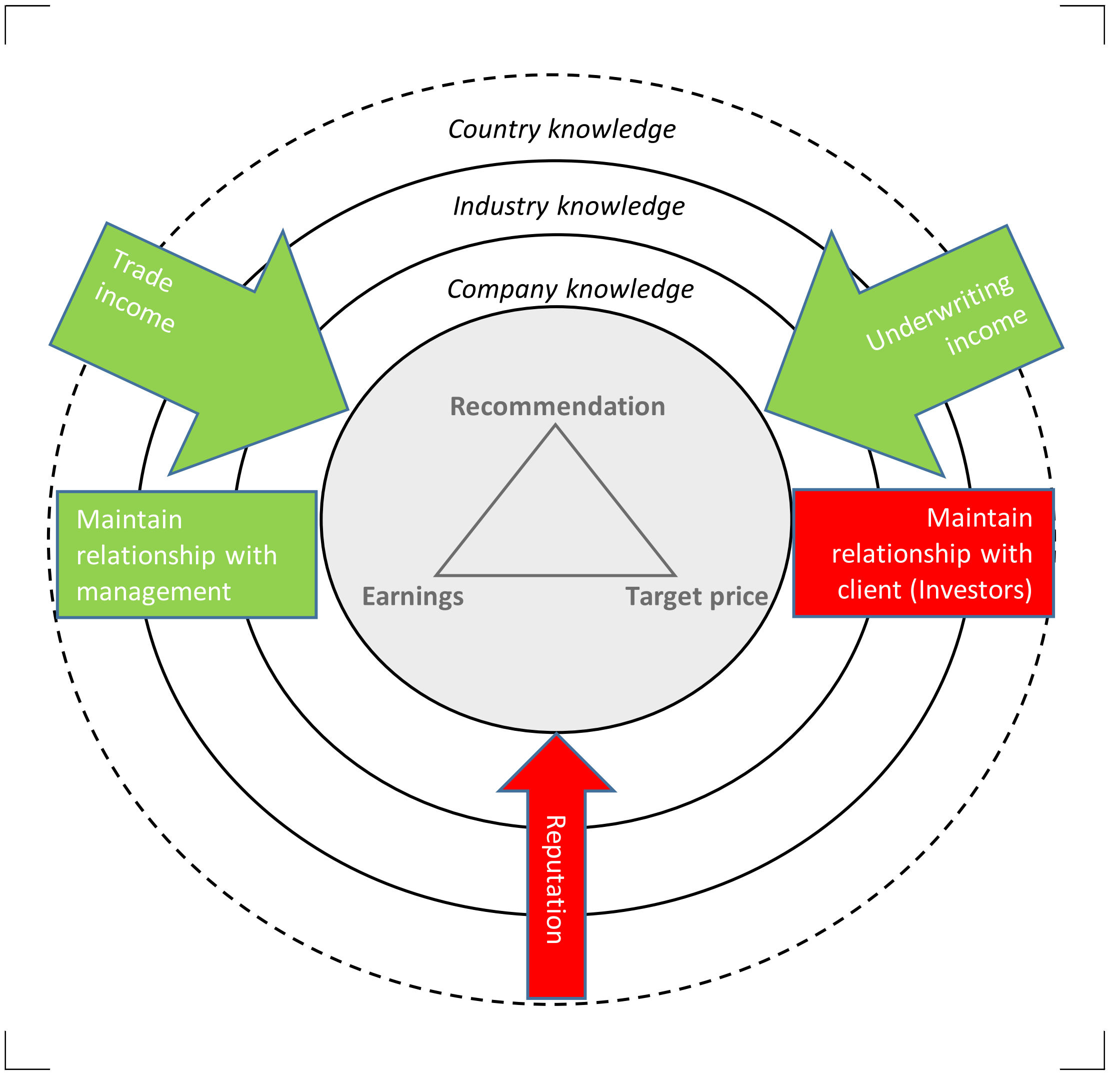

Figure 1. Three major pressures on analysts: Trade income, underwriting income, and reputation. Sell-side analysts are under pressure to give overly optimistic (shown in green) forecasts from two external sources in the investment banking business, to generate trade income in the stocks they cover and to support the company in gathering underwriting income. Meanwhile, two forces cause them to be more realistic (shown in red) with their forecasts: the pressure to build their reputations as an accurate and truthful analyst and the pressure to help their ultimate clients to make money.

In general, financial analysts are optimistically biased, or what the average person would call being "wrong," in their earnings forecasts, yet they continue to maintain their jobs and draw significant salaries. This implies that they perform other valuable functions, such as helping their clients increase their knowledge of the companies or industries that the analysts cover or the country that those stocks are listed in. Another such function is that of fulfilling the desire to know the unknowable (the future), and therefore believe that the unknowable is in fact knowable.

We limit this research to the performance of financial analysts in forecasting the earnings of the companies they cover. The uniqueness of this research is first that it is global—it is the first to include all analysts, covering all stocks, across all countries. Furthermore, it is not US-centric.

Second, this research covers the complete population of data. This paper has the widest data set and is the first to cover all listed stocks in the world. Unlike some other studies, this research is not a sample of data; rather it is as close to the complete data set as possible. Third, this research is long term in nature, covering a total of 12 years from 2003 through 2014, a period that spans more than just one portion of the business cycle.

Fourth, this research includes China. This is one of the few papers to fully incorporate all Chinese companies, not just those listed in Hong Kong S.A.R (usually referred to as China H shares). With more than 3,000 listed companies, China is now the world's second-largest stock market, by the number of companies, surpassed only by the United States of America (USA). In the early years of the data in this research, financial analyst coverage of China was minimal, but that has changed over the past 8 to 10 years. Hence, we argue that to understand financial analyst behavior in modern times it does not work to extend the time horizon beyond about a decade, as there would be no Chinese stocks in the earlier part of that data set.

Fifth, this research is based on the mean announced earnings forecasts of all analysts, or what is commonly referred to as the "consensus" forecasts. Considerable research has been done on the performance of individual analysts, including the factors that could possibly allow someone to predict whether an analyst might be successful in the future period. However, the average investor more much often focuses on consensus earnings rather than following those of an individual analyst. In fact, these forecasts of consensus earnings are an integral part of the financial world as they are used as inputs in cost-of-capital calculations and expected return calculations.

Sixth, this research is comparable. Unlike most prior research in this area, this research scales earnings forecast error by actual earnings, rather than by share price. Unlike many other papers on the subject, this paper avoids introducing the additional, and highly variable, random share price factor into the equation. The results are therefore comparable across time, geography, sectors, and developed and emerging markets.

Finally, this research is actionable. This study focuses on a 12-month consensus forecast, rather than a much shorter-term forecast time horizon, something that investors can actually follow and profit from.

The remainder of this material starts with a literature review, then a discussion of the data set, the methodology, and finally the analysis.

LITERATURE REVIEW

Standardized definitions

Almost every paper in this area of study, new and old, has either the same definition or approximately the same definition of forecast error, but each author or team words it in several ways. To make it more convenient for the reader, in this paper the meanings are standardized.

Forecast Error (FE) is the difference between the Forecast earnings (F) and Actual earnings (A): [FE=F-A].

Scaled Forecast Error (SFE) is the FE relative to something such as Share Price (P) or Actual earnings (A): [SFE=FE/Absolute Value of (A)*100].

The absolute value of A in the denominator assures the correct calculation emerges in cases of A being a negative value. To illustrate, imagine three different companies had the same Actual earnings of -4, and Forecasts of -5, -3, or +5. For the first company, the analysts Forecast was below Actual, the second was slightly above and the third, largely above. However, without taking the absolute value of -4, the SFEs would be 25%, -25% and -225%, all incorrect. By taking the absolute value of -4, the calculation yields the correct SFEs of -25%, 25%, and 225% respectively.

Absolute Forecast Error (AFE) is the absolute value of the difference between Forecast and Actual earnings [AFE=|F-A|].

Scaled Absolute Forecast Error (SAFE) is the AFE relative to something such as share price or actual earnings. [SAFE=[AFE/absolute(A)*100].

These abbreviations are used throughout the rest of the paper.

1972 to 1982: Individual analyst earnings forecasts – superior to statistical models

As early as the 1960s, studies were conducted to assess forecast accuracy in the stock market. Earlier studies focused mainly on how accurate an individual firm was at forecasting its own profits.

A starting point for this review is Brown & Rozeff (1978), who looked across 50 U.S. firms over three years from 1972 to 1975 and stated that prior research methods were wrong. The authors measured Scaled Absolute Forecast Error (SAFE), scaled by actual earnings, and applied four different statistical tests to better understand the performance of financial analysts' forecasts. This research truncated all absolute errors greater than 100% to deal with outliers. Their work did refute prior research, demonstrating that individual analyst earnings forecasts, as represented by *The Value Line Investment Survey* newsletter[1], were superior to time-series models. Because Value Line did not have any brokerage or investment banking business, their analysts were considered less biased, or independent. The authors proposed that it was logical that analysts' forecasts outperformed times-series forecasts as the cost of employing analysts was much higher than the cost of executing a simple time-series model. This was the challenge of man versus machine. In this case, man won

Critchfield et al. (1978) continued the focus on financial analysts' earnings forecast accuracy and concluded that forecast accuracy increased as the earnings reporting date approached. Obviously, analysts making a forecast 12 months prior to the actual announcement of results had considerably less information than if they were making the forecast closer to the announcement date. Clearly, these are incompatible time horizons; a simple solution to this would have been to calculate rolling 12-month accuracy.

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[1] Value Line is an independent financial and investment research and publishing company based in New York and founded in 1931. It is best known for publishing *The Value Line Investment Survey*, a highly regarded and widely used stock analysis newsletter and independent investment research resource, tracking about 1,700 publicly traded stocks in more than 99 industries.

Next, looking not at the accuracy of analyst earnings forecasts, but whether changes in earnings forecasts could be a predictor of future share price performance of that stock, major research in this area was found by Givoly & Lakonishok (1979). To test the information content of analyst forecasts, they ignored cases in which earnings forecast revisions were preceded by company earnings forecast announcements. They used Standard & Poor's Earnings Forecaster data of all analysts covering these stocks and then identified the prior year's most active individual analyst and used that analyst as the "representation of the group of forecasters." From this, they gleaned that abnormal stock price movements across 49 U.S. firms, in three major industries, and over the seven years from 1967 to 1974, were correlated with individual analysts' earnings forecast revisions. Abnormal returns, even after adjusting for estimated transaction costs, were observed up to two months following the months in which the revisions were made. Man wins again?

Next to consider the matter were Fried & Givoly (1982), who used a much larger data set than Brown & Rozeff (1978), covering 23 years from 1951 to 1974 and 425 U.S. companies. They showed that average analyst earnings forecast accuracy was superior to time-series models, but by little. SAFE of 16% compared with 19 to 20% for the models. Man wins again, but the margin for the win was tiny, and could disappear with transaction costs.

SUMMARY OF DEVELOPMENTS DURING THIS PERIOD

These early papers used small data sets compared with modern times, so it is hard to extrapolate almost any meaning from them for today. Crichfield et al. (1978) highlighted that knowing sooner is better, meaning that it is more profitable for an investor to receive accurate earnings forecast long before the actual earnings are announced. The weakness of Givoly & Lakonishok (1979) was that they studied only the most active analysts among all analysts. How would an investor find these analysts at that time? How often would they have to update the numbers necessary to find such analysts? How often would these analysts change over time? It could be a full-time job just designating the most active analysts. Also, is it possible that once these most active analysts' behaviors were averaged across all the other analysts, their results would be offset by the lack of success of the other analysts? So, the answer to whether analysts, collectively, add informational value may not have been completely addressed in this research. Fried & Givoly (1982) solved most of these problems by using the arithmetic mean of all analysts. This arithmetic mean was not widely available in those days but it is now; hence, his result of 16% absolute earnings forecast error carries forward and is relevant today.

Two issues arise regarding research methods: dealing with outliers and addressing incomparable time horizons. Brown & Rozeff (1978) avoided outliers by using a very constrictive ±100% of all errors. Crichfield et al. (1978) appeared to be comparing incompatible time horizons. To claim that analysts were more accurate the closer they got to the actual earnings announcement date, as many papers did was mixing time horizons. It would be like an archer who is shooting from 100 meters out, then steps only 10 meters away from the target, aims, and shoots and then proclaims that his accuracy has improved. Yes, his arrows may be hitting the bull's-eye more often, but if he stepped back to his original 100-meter firing point there would be no change in his accuracy.

1987 to 1988: Investigated where this analyst superiority came from

The next significant paper in this period attempted to attack the problem from all angles by using many different statistical models to test analyst superiority and many ways of handling outliers. Brown et al. (1987a) attempted to explain where individual analyst quarterly earnings forecast outperformance came from and attributed this superiority relative to time-series models to timing and information advantage. The timing advantage meant that analysts did not issue their forecasts until, on average, 39 days after the prior quarterly profits were announced. The time-series model, on the other hand, produced its forecast at the time the latest information hit the market. Information advantage came from analysts using more information than just the past earnings data. The authors used *The Value Line Investment Summary* for their data on individual analyst forecast and considered 233 U.S. companies from 1975 to 1980. They went into more detail on truncation by testing four different methods of truncating error outliers: removing SAFE ≥300%, ≥100%, at three standard deviations, and no truncation. The information advantage they identified lasted even after controlling for the analysts' timing advantage. Brown and his colleagues scaled their error estimates by actual earnings and calculated SAFE for a nine-month forecast at 29%, much higher than Fried & Givoly (1982). However, when the analysts' forecasts were compared with time-series forecasts near the time that such forecasts were released, this advantage became much smaller. In the paper, they discussed the improving accuracy as forecasts were issued closer to the time horizon, again comparing different time horizons.

In the next study led by Brown (1987b), he and his team showed that larger firm size meant consensus analyst forecasts were likely to outperform a time-series model. Prior dispersion of analysts' forecasts and the number of lines of business the company being forecasted was involved in were both negatively correlated with analyst earnings forecast accuracy outperformance relative to a time-series model. This research used *The Value Line Investment Survey* for quarterly individual analyst forecasts and the Institutional Brokers' Estimate System (I/B/E/S) for consensus forecasts focused mainly on annual forecasts. The research covered the largest number of U.S. companies to date, at 702, over the five years from 1977 to 1982.

Most work up to this point had been on individual analyst forecasts, until O'Brien (1988) displayed that when using the arithmetic mean of all forecasts (also referred to as consensus) provided by the I/B/E/S, the most recent forecasts were more accurate than the average of all forecasts. Her research looked at the seven years from 1975 to 1982 and considered 184 U.S. companies. This research was valuable because it showed one major weakness of relying on the average of all analysts. Since most investors end up relying on an average for most the stocks they are considering, this allows them to know the potential weakness of their actions.

Summary of Developments During This Period

During this period, 1987-1988, Brown et al. (1987a) improved and deepened the testing of man versus time series by continuing trials on SAFE over a nine-month time horizon. The key feature they identified was that if the timing advantage was removed, the analyst advantage almost disappeared. Brown et al. (1987b) followed this up by showing that the larger firm size meant more accurate forecasts. They also discovered that if an analyst's prior forecast had been volatile, then future forecasts were likely to be less accurate. They also found that the more complex the business, the less accurate the forecast. O'Brien (1988) studied consensus forecasts and found that the most recent forecast was more valuable than the arithmetic mean of all forecasts. This sparked the idea of quickly trading on the most recent analyst information. However, from a practical perspective this information may be hard to actually execute, as an investor would need to follow all analysts to identify which has the most recent forecast and then the investor would need to quickly buy the stock on that information, which is not always able to happen quickly.

1990 to 1992: Determined that analysts' earnings forecasts were too extreme

Trying to understand analyst bias, De Bondt & Thaler (1990) looked over the eight years from 1976 to 1984 at 623 U.S. companies and uncovered that average analyst overreaction to past earnings changes caused overly optimistic forecasts. The authors considered earnings forecasts over a one- and two-year horizon, using I/B/E/S consensus data and considering an April starting point for the one-year forecasts. They proposed that positive bias came from brokerage analysts' responsibility for encouraging trading and explained that optimistic bias was preferable as all clients could potentially be interested in a "Buy" recommendation, whereas only a few would be interested in a "Sell" recommendation. By this time, research was already showing a bias in recommendations toward "Buys." They also considered value stocks versus growth stocks and found a similar bias.

Schipper's (1991) own literature review showed that too much focus had been aimed at analysts' earnings forecast accuracy, which had failed to consider other functions of the analyst's job, such as issuing recommendations, generating trade income, or maintaining good relationships with management of the companies on which they carried out forecasts. She defined two types of services that analysts provide: First, assimilation and processing of public information and second, acquisition and dissemination of new information. Though she did not break down the portion of an analyst's job spent on each, later work by Altinkiliç (2013) would show that analysts add little to no value through their attempts to acquire new information. She was also the first to mention that investors may make more gains from good earnings forecasts given sooner (e.g. 12 months prior to the results announcement date) rather than later (one month before announcement date).

Stickel (1992) surveyed the four years from 1981 to 1985, across U.S. companies. By comparing the unscaled earnings forecast error (FE) of *Institutional Investor* magazine's "All-American Research Team" analysts to non- "All-American Research Team" analysts, he found that well-known analysts produced more accurate earnings forecasts. This was partly because they issued forecasts more often, giving them a timing advantage. Abnormal returns, compared with less well-known analysts, could be earned over a two-week period after a large upward revision. This differential was non-existent after large downgrades of earnings. However, the statistical and economic significance diminished over longer periods. This was one of the papers to explicitly mention the importance of comparing identical time horizons. The author found the same results when scaling the error by earnings per share (EPS). In his process of scaling he set any denominator EPS below \$0.25 at \$0.25, to avoid "small denominators." As well, he truncated scaled forecast errors at ±200% to "avoid giving undue weight to outliers."

The first major paper covering Asia came from Lui (1992), which looked at the performance of consensus forecasts in Asia and focused on 60 large companies in Hong Kong (later to become Hong Kong S.A.R) over two years, 1988 and 1989. Though the period was short and the number of companies in the study was small, the author observed that consensus forecasts had an upward bias, that they were inaccurate, and that, unlike prior research in the U.S. market, a naïve random walk model was no worse than an analyst's forecast. One-year-ahead analyst SFE was about 14.5% and the mean squared forecast error was about 21%.

SUMMARY OF DEVELOPMENTS DURING THIS PERIOD

By this time in the research anthology, De Bondt & Thaler (1990) had proved that analysts overreacted to past earnings changes, that this optimism was driven by the desire to increase trade income for their brokerage employer. They had also explained the bias toward "Buy" recommendations, being that more clients would potentially be interested in a "Buy" recommendation than a "Sell." Hence from a business and an investor perspective, the skewness toward "Buy" recommendations made sense.

Up to this point, Schipper (1991) had encouraged research to focus on more than just earnings forecast accuracy since analysts must also issue recommendations, generate trade income for their brokerage business, and maintain good relationships with the management of companies for which they carry out forecasts. Financial analysts bring two main benefits to the public: assimilation of public information and acquisition of new information. This followed from Crichfield et al. (1978) arguing that investors make more gains from good earnings forecasts, 12 months prior to the actual earnings announcement, than one month prior. Clearly, if an analyst can give crucial information long before an outcome occurs it would give the investor time to study and then fully act upon this information. Or think of the opposite, an analyst issuing accurate earnings forecast the day before the announcement. Most investors would probably neither know about it, nor be able to act upon it.

During this phase of the research, Stickel (1992) turned the focus to the performance of well-known analysts and showed that they produced more accurate earnings forecasts. This was partly because they issued forecasts more often, giving them a timing advantage. In addition, he showed that investors could earn a profit from these forecasts, but, only within a two-week period and only after a large upward revision. No outperformance could be achieved by following downward revisions or small upward revisions. In addition, the issue of incomparable time horizons started to be discussed, showing that comparing a 12-month forecast to a one-month forecast was without meaning, as they were completely different time horizons. This is a warning to future researchers to make sure to compare identical time horizons. Finally, this paper looked at earnings forecast error three separate ways: AFE, SAFE-scaled by EPS, and SAFE-scaled by price. To deal with distortions of the data, he eliminated outliers of ±200% and to eliminate small denominators distorting percentage calculations he winsorized points below $0.25.

During this period came the first research covering Asia, with Lui (1992) studying a small number of Hong Kong S.A.R firms over a two-year period. As in the U.S.-based research, he detected that consensus forecasts had an upward bias; SFE was 14.5%. But, a key finding was that unlike findings in the U.S., a naïve random walk model for forecasting earnings produced about the same results as analyst earnings forecasts. This was the first and only time in the research that an author used the log of earnings forecast divided by actual earnings announced, which reduced the impact of outliers. In addition, this was one of the first times that research on the topic removed companies that had produced negative earnings.

1993 to 1997: Considered profiting from recommendations and earnings forecasts

Among the first to relate analyst earnings forecasts with analyst recommendations, Francis & Philbrick's (1993) survey considered 306 U.S. companies over two years from 1987 to 1989. They used *The Value Line Investment Survey* data since analysts at Value Line only produced earnings forecasts, not recommendations. Also, Value Line was not a brokerage firm; hence there was no pressure to generate trade income. This meant that the main pressures felt by analysts were to maintain good relations with management. The authors found that analysts' earnings forecasts were more optimistic for companies that had a "Sell" (12% above actual earnings) or "Hold" (9%)

recommendation, rather than companies with a "Buy" (3%). This research stated that accuracy was not the only goal for analysts; they were also driven by their desire to keep on the good side of management, especially when analysts' recommendations were not a "Buy." The authors suggested that future research on analyst earnings accuracy should control for analyst recommendations. This was one of the early papers to present the distribution of Value Line analyst recommendations, which looked like a normal distribution at the time, not skewed toward "Buys" as had been seen in I/B/E/S data over time. Finally, this study calculated unscaled FE and SFE, the latter was scaled by price and by actual earnings.

Lys & Soo (1995) controlled for company-specific forecasting difficulty by using a randomly selected sample of Zacks Investment Research consensus earnings forecasts based on size and ended up with 22 companies in each of the three different sized groupings. The final sample was 62 companies with an adequate number of quarterly forecasts over the period 1980 to 1986. This research was narrowly focused on forecast precision and its expected direct relationship to generating higher fees for the brokerage business. They said that "more precise forecasts are assumed to be more expensive to produce, and therefore costs are likely to increase with the forecast accuracy supplied." They saw that as the number of analysts following a company increases, the analysts can follow each other, thereby reducing analyst research costs. They measured SAFE, scaled by price. Scaling by price, they claimed, allowed for cross-sectional comparisons. They considered one-quarter-ahead, rather than annual, forecasts. Their conclusion: The more analysts cover a stock, and the larger the market capitalization of the stock, the more precise the forecast.

By this time, it was clear that analysts felt two main pressures from the businesses they operated in: first, the pressure to generate trade income and second, the pressure to generate underwriting income. In a more quantified follow-up to De Bondt & Thaler (1990), La Porta (1996) studied the nine years from 1982 to 1991 across 914 large U.S. companies and found that individual analyst earnings forecasts were too extreme. He used I/B/E/S consensus forecast data rather that individual analyst forecast data. Stocks where analysts expected low future long-term earnings growth (what he calls “value stocks,” which we would call stocks where analysts have low expectations or are pessimistic) dramatically outperformed those where analysts were optimistic about future growth (“glamor stocks”). He described this as “error-in-expectations” and showed that analysts sharply revised forecasts as earnings turned. Buying stocks with a low price-to-expected-growth rate and shorting those with the opposite yielded excess return. Lastly, he found no evidence that stocks for which analysts had low expectations were any riskier than others.

Next Mikhail et al. (1997) investigated factors, beyond the timing and information advantage, that caused individual analysts to be better than others. Using Zacks’ database of individual analysts’ quarterly forecasts, they considered 15 years covering 1980 to 1995 and 434 U.S. firms. They required that an analyst had 32 quarters of forecasts for a stock; hence this study was not of the performance of all analysts in the market, but rather the most experienced. The issue with this practice is that if investors generally rely on consensus estimates, these analyst results would be mixed with those of all other analysts covering that company. In this study, he found that individual analysts’ earnings forecast accuracy improved as they received more firm-specific earnings forecasting experience. However, this experience was unrelated to abnormal returns when analyst recommendation revisions were followed. Because this research is scaled by price it is hard to compare the results over a period other than the sample period.

SUMMARY OF DEVELOPMENTS DURING THIS PERIOD

This period of research saw a focus on profiting from earnings forecasts and recommendations. First, Francis & Philbrick (1993) produced one of the first papers to relate analyst earnings forecasts with analyst recommendations. They found that analysts’ earnings forecasts were more optimistic for companies for which they had a “Sell” or “Hold” recommendation, which was driven by analysts' desires to keep on the good side of management. The study continued a trend of scaling by price, as well as by actual earnings.

Then, Lys & Soo (1995) noticed that as the number of analysts following a company grew, analysts could follow each other's forecasts and this reduced the marginal analyst research costs. They also learned that the more analysts covered a stock, and the larger the market capitalization of that stock, the more precise the forecast. They used SAFE, scaled by price.

One unexplored explanation of this improved accuracy could simply be that larger companies have larger investor relations departments which provide more complete and consistent information, thereby assisting analysts in making more accurate forecasts.

Individual analyst earnings forecasts were too extreme, La Porta (1996) ascertained. In fact, investors could take advantage of this by investing in stocks in which analysts had the lowest growth expectations, because these dramatically outperformed those on which analysts were optimistic about future growth. From what I have seen in my own professional investing experience, this anomaly continues today. This strategy can be constructed by buying stocks with a low price-to-expected-growth-rate ratio and shorting those with the opposite. Such a strategy would yield excess returns. What is even more exciting about this research was that he found no evidence that stocks for which analysts had low expectations were any riskier than others.

More work was done by Mikhail et al. (1997) to continue with how to make money from individual analyst forecasts; this extended prior research on an individual analyst's timing and information advantage. They found that individual analyst earnings forecast accuracy improved as analysts gained more firm-specific earnings forecasting experience, but this experience was unrelated to abnormal returns when analyst recommendation revisions were followed. They measured SFE and scaled by price.

1998: Investigate motives of analysts and why they were so optimistic

Lin & McNichols (1998) studied 919 U.S. firms over the five years from 1989 to 1994. The authors used earnings forecasts from Research Holdings, Ltd., a different data set than commonly used for this line of research. They found again that analysts were favorable in their long-term earnings growth forecasts and recommendations when their employer had an underwriter relationship. But, the difference did not seem to be economically significant. Their observation of the distribution of recommendations, unlike Francis & Philbrick (1993) who relied on independent research firm Value Line's *Investment Survey* data, showed a large skew toward "Strong Buys" and "Buys." However, an additional finding was that affiliated analysts were no more favorable in their earnings forecasts. The weakness of this paper is that it only looks at a sample of companies from the U.S. stock market (those related to IPOs), hence companies that issued common stock during the period. The study deflated error by price and calculated a one-year error between 0.07 and 0.09, again a number hard to compare over time.

Over the four years from 1989 to 1993, Das et al. (1998) considered a sample of 239 U.S. firms. The authors sought to link "earnings predictability to forecast bias as opposed to forecast accuracy" and used independent research also from *The Value Line Investment Survey* to obtain forecast data. They found that analysts issued more positively biased earnings forecasts for companies that had unpredictable earnings and concluded that analysts did this to strengthen their relationship with management so that they had more access to non-public information and, in turn, enhanced forecast accuracy. Again, the trend to scale the error by price continues, making the results hard to compare over time.

SUMMARY OF DEVELOPMENTS DURING THIS PERIOD

Research during 1998 focused more on individual analyst's motives and pressures than on the behavior of the average of all analysts. Lin & McNichols (1998) focused on one of the pressures on analysts, which was the need to support underwriting income at investment banks. They demonstrated that analysts were favorable in their long-term earnings growth forecasts and recommendations when their employer had an underwriter relationship. But, the difference was not economically significant. So, favorable forecasts were enough to give a positive impression to the company they were underwriting, but seemed to be balanced with the analysts' need to generate trade income from the ongoing brokerage clients they dealt with. Their conclusion was that affiliated analysts, those involved in underwriting, were no more favorable in their earnings forecasts.

Researchers tried to identify the motives of analysts, especially when they found the job of forecasting very difficult. Though it had yet to be fully proven at the time, it made sense that companies with unpredictable or volatile prior earnings were harder to forecast. What Das et al. (1998) found was that analysts issued more positively biased earnings forecasts for companies that had unpredictable earnings to strengthen their relationship with management so they had more access to non-public information and, in turn, enhanced forecast accuracy. Studies during this time still scaled by price, not earnings.

1999 to 2000: Identified specific factors that influenced analyst forecast accuracy

One of the first papers to consider a large sample size of U.S. companies was Clement (1999), who studied such a grouping of firms for the 11 years from 1983 to 1994. He used I/B/E/S Detail History[2] file to obtain individual analyst forecasts. His work compared one analyst's forecast error against the error of other analysts covering the same stock; hence there was no need to scale the error by either price or EPS. He concluded that individual analyst forecast accuracy was positively associated with that analyst's years of experience (ability) and the size of her employer (resources). Accuracy was negatively associated with the number of firms and industries

[2] I/B/E/S Detail History is a database now owned by Thomson Reuters forms a timeline of individual analysts' earnings forecasts (daily records at the analyst level). The U.S. edition starts in 1983, while the international edition starts in 1987.

the analyst followed (complexity). These factors could help to predict an individual analyst's forecast accuracy.

Next came research by Jacob et al. (1999), whose work appears to have refuted the Mikhail et al. (1997) finding about the influence of experience. This study covered a large sample of U.S. firms over the 11 years from 1981 to 1992 and obtained individual quarterly analyst forecasts from Zacks Investment Research database. The authors discovered that, in fact, analysts failed to learn from their forecasting experience. When controlling for an analyst's ability in forecasting earnings of a specific company, there was no considerable influence of experience on forecast accuracy. Unlike others, they found a lack of learning-by-doing. This paper rejected the work of Mikhail et al. (1997) and Clement (1999), but confirmed that of Hong et al. (2000). Jacob's was the first paper in this review to mention the weakness of the commonly used price-deflated-forecast-error calculation and how it could distort analysis by bringing in the impact of the value of the share price. So, to remove these uncontrollable and random price effects, they concluded that forecast error (FE) should be scaled by earnings, not price.

In their second major foray into the topic, Mikhail et al. (1999) studied the 10-year period from 1985 to 1995. For this study, they collected individual analyst quarterly forecasts from Zacks' database focusing on firms covered by at least five analysts. To reach its conclusions on the performance of individual analysts, the research was mainly designed to compare one analyst to another. The research found that analysts with low earnings forecast accuracy, relative to similar analysts, had higher job turnover. They controlled for firm- and time-period effects, forecast horizon, and industry forecasting experience. This study also scaled by price.

Chang et al. (2000) was the first paper to look at analyst forecast error comprehensively across the world, considering 47 countries. Their sample was of the 30 largest companies in each country and the companies excluded financial and utilities industries, using I/B/E/S forecast data. They found that accuracy could mainly be explained by firm size, size of the stock market relative to GDP, the quality of account disclosure, and the country's legal origin. In addition, they looked specifically into emerging market countries (unless otherwise stated, MSCI country classification was followed) and found that it was harder to forecast the earnings of business group companies. Lowest SFEs were in the U.S. (2.3%) and the U.K. (5.3%), like the results I uncovered, though their actual level of SFE was very low relative to mine. Their arithmetic mean across all countries was 25.5%, much more in line with my findings. They tested the prior 24 months' monthly standard deviation of share price and found that less volatile prior share price was directly correlated with better forecast accuracy. They also found that firm size had no significant impact on accuracy, but this could be because all their sample companies were large.

Hong et al. (2000) assessed 13 years of U.S. companies from 1983 to 1996, on average 348 companies per year, and linked analyst earnings forecast herding with career concerns. They extracted individual analyst forecast data from the I/B/E/S Detail Earnings Estimate History file. Their methodology calculated an analyst's AFE on all the stocks covered and then compared this against that of other analysts. The team arrived at the finding that the consequences suffered by junior analysts for inaccurate earnings forecasts and inaccurate bold earnings forecasts were harsher than those felt by more senior analysts. Therefore, younger analysts more often than older analysts tended to follow the other analysts, that is, followed the herd.

SUMMARY OF DEVELOPMENTS DURING THIS PERIOD

During this period, researchers went into deep detail about specific factors that could influence the forecast accuracy of a single analyst. This started with Clement (1999), who showed that accuracy improved with an analyst's experience (ability) and based on the size of the employer (resources), but accuracy fell as the number of firms and industries the analyst followed (complexity) increased.

At the same point, Jacob et al. (1999), proved on another data set that analysts did not learn from their forecasting experience. They were also the first to mention the weakness of price-deflated forecast error and they recommended that forecast error (FE) should be scaled by earnings, not price.

In another study scaled by price, Mikhail et al. (1999) showed that analysts with low earnings forecast accuracy had higher job turnover, revealing the analyst's need to protect his reputation.

In the last study of individual analysts of this period, Hong et al. (2000) found that younger analysts tended to follow the herd, because getting it wrong would be more damaging for a new analyst than for a more experienced analyst.

Chang et al. (2000) published the first paper to look at analyst forecast error at large companies across the world, though they excluded financial and utilities industries. They found that accuracy could mainly be explained by firm size, the size of the stock market relative to GDP, the quality of account disclosure, and the country's legal origin. The SFE of all countries was 25.5%, very close to my findings. They also found that analysts were less accurate with companies that had highly volatile prior share price.

2001 to 2003: Investors fail to learn from individual analyst characteristics

In further solo work by Brown (2001), he considered 12 years of U.S. company data from 1986 to 1998, using Thomson Reuters I/B/E/S U.S. detail data. Since he was measuring individual analyst forecast accuracy, he considered each analyst's forecast error related to other analysts. His research found that a simpler, past accuracy model for predicting analyst earnings accuracy was just as successful as Clement's (1999) analyst characteristics model which focused on: forecast age, general analyst experience, analyst's company-specific experience, company complexity, industry complexity, and brokerage size.

By this time, it was very clear that individual analysts were positively biased. Lim (2001) reviewed 12 years of U.S. company data from 1984 to 1996 seeking to explain how analysts resolved the conflict between producing positively biased forecasts to increase management access (and prevent being shut out by unhappy management) and producing accurate forecasts. He argued that an analyst was trying to create an optimal forecast, which balances these two forces. So, an analyst tries to reduce earnings forecast error, not bias. In his study, he scaled by price to "reduce heteroscedasticity across stocks." His research found that large companies with many analysts covering them had less forecast bias. Companies with more price volatility and those where analysts were more reliant on management access tended to have more forecast bias.

Hong & Kubik (2003) looked at an average of 497 U.S. firms per year over a 17-year period from 1983 to 2000. Their data set was the I/B/E/S Detail Earnings Estimate History file, which provided data on individual analyst forecasts. They scaled the analysts' error by price and compared each analyst's performance across all stocks that he covered to the same measure of other analysts. They measured the accuracy of individual analysts in two ways: 1) SAFE (scaled by the share price at the time of earnings announcements) of all firms covered by the analyst in a year, and 2) relative forecast accuracy to rank the analysts among each other. Relative forecast accuracy of various analysts is outside the scope of this paper but relevant to their conclusions. They found that the pressure to generate underwriting business and trading commission was probably causing brokerage house analysts to be more rewarded for optimism than earnings forecast accuracy. The authors disclosed evidence that brokerage houses rewarded optimism rather than forecast accuracy, especially if the firms being forecasted were underwritten by the brokerage houses that the analyst was employed by. The key takeaway from this paper was that the authors found a relationship between analysts' forecast biases with their career outcomes and a probable conflict of interest arising from employment.

Hong & Kubik (2003) produced a SAFE that was scaled to share price, but I saw flaws in this methodology. To illustrate, imagine standing on a stretch of open road with cars racing toward you; your job is to estimate the speed at which they are traveling. Car A races by and you estimate its speed at 130km/h, but it was traveling at 100km/h, so the error of your estimate is 30. If we scale this 30 to the actual speed, then we can say that your estimate was 30% above the actual speed. Next, Car B flashes by and you estimate that it is traveling at 170km/h, but it was traveling at 131km/h. You are off by 39, and the error of your estimate is also 30% above the actual speed. Based on these scaled errors, we can say that you are equally inaccurate in estimating the speed of both Car A and Car B. Now imagine that you scale your forecast error to the price of the car rather than the actual speed. If Car A has a price of US$1,000 and you divide your forecast error of 30 by the price of the car it would mean your error is 3.0% above the price. And if Car B has a price of US$5,000, and we put the 39 that you were off with Car B in relation to its price we would say that your estimate is above the price by 0.8%. So, when scaled to actual speed, you were equally accurate, but when scaled to the price of the car, there is a dramatic difference in your accuracy. The car price is an unrelated factor. Hence, I did not use stock price in our calculation of accuracy and doubted the usefulness of conclusions from papers that scale to price.

Hope (2003a) considered 445 companies across 22 countries, over the two-year period from 1993 to 1995. He used I/B/E/S U.S. and international summary files, scaled analyst forecast error by price to "facilitate comparisons across firms," winsorized the analyst forecast error at 100%, and found that analyst forecast accuracy improved if annual report disclosure was stronger than other countries in the study, as well as if the accounting standard enforcement was stronger in that country.

After analyzing U.S. firms over the 15 years from 1983 to 1998, Gu & Wu (2003) concluded that since analysts' objective was to minimize the mean AFE, the optimal forecast accuracy measure should be the median, not the mean. This was due to the natural skewness in the distribution, caused by analysts' optimistic bias, using the statistical definition of bias, "systematic deviations of actual realizations from forecasts." Their measure of skewness was the "mean – median difference of the earnings distribution," which they scaled by stock price as well as the skewness coefficient of the distribution. The research showed a positive relationship between earnings skewness and analysts' forecast bias. It also looked at an analyst's actual EPS minus consensus. Their source of analyst forecast data was the I/B/E/S Detail file, and the forecasts they used were within 90 days of the company's actual earnings announcement date; hence they were taking a short-term focus. They considered other time horizons but settled on presenting this one. One problem with this research is that while the average practitioner probably has only enough time to consider whether an analyst was correct in his forecast of a company, they would generally not calculate the "mean absolute forecast error."

Clement & Tse (2003) looked at the four years of U.S. company data from 1994 to 1998. They obtained their forecast data from I/B/E/S, excluded extreme data points at the top and bottom 1% of earnings revisions, and used the data of companies that have at least two analysts covering them. They employed a seven-factor model to try to capture every possible analyst characteristic and its influence on forecast accuracy. Their measure of accuracy compared individual analysts against other individual analysts forecasting the same firm, rather than the consensus, and found that regarding investors' response to analysts' forecast revisions, forecast accuracy was not all that mattered. In fact, they found that investors had failed to use analyst characteristics factors that had been shown to add value in finding accurate forecasters. This paper challenges the finding in Brown (2001) that past performance was a good proxy for analysts' characteristics for predicting future accuracy. What Clement & Tse (2003) found was that forecast frequency was "just as important as past forecast accuracy." One last finding, which appeared in response to Brown (2001), was that broker size was more important than past forecast accuracy. He tested and confirmed Schipper's (1991) comment about analysts preferring earnings forecasts sooner rather than later.

SUMMARY OF DEVELOPMENTS DURING THIS PERIOD

One key discovery by Brown (2001) during this 2001 to 2003 period was that just understanding an analyst's past forecast accuracy was as successful as Clement's (1999) analyst characteristics model. So, there was no need to gather information on the age of the forecast, general analyst experience, an analyst's company-specific experience, company complexity, industry complexity, and brokerage size.

Lim (2001) showed that an analyst tries to reduce earnings forecast error, not positive forecast bias. The large company effect was demonstrated, showing that large companies with many analysts covering them had less forecast bias. Furthermore, companies with more price volatility and those where analysts were more reliant on management access tended to have more forecast bias.

Hong & Kubik (2003) observed that the pressure to generate underwriting business and trading commission was probably causing brokerage house analysts to be more rewarded for optimism than the pressure from clients to issue accurate earnings forecast accuracy. Brokerage houses rewarded optimism rather than forecast accuracy, especially if the firms being forecasted were underwritten by the brokerage houses that the analyst was employed by.

Hope (2003a) winsorized the analyst FE at 100%, a tighter constraint than Stickel's (1992) 200%. I show later in this paper that the difference in the results that a researcher gets based on either 100% or 200% can be quite substantial. Hope (2003a) found that analyst FE improved if annual report disclosure was higher and if accounting standard enforcement was stronger.

During this period, Gu & Wu (2003) unsuccessfully attempted to shift the research direction to use the median analyst FE, rather than the mean. The argument was that the analyst's objective was to minimize the mean absolute forecast error. The argument continued that due to the natural right skewness in the distribution, caused by analysts' optimistic bias median was a more suitable measure. All four of the prior research paper's Scaled Absolute Forecast Error were by price.

Clement & Tse (2003) excluded extreme data points at the top and bottom 1% of earnings revisions and used data of companies that had at least two analysts covering them. They used a massive seven-factor model to try to capture every possibly relevant analyst characteristic and its influence on forecast accuracy. Most importantly they found that investors failed to use analyst characteristic factors that have been shown to add value in finding accurate forecasters. However, one new factor was proven to be valuable in predicting analysts' FE: the size of the broker that they worked for.

2005 to 2008: The dilemma of being accurate and generating reputation or being bold and generating income

Analysts' earnings forecasts were either "herding" or "bold," so the team of Clement & Tse (2005) classified them after reviewing nine years of U.S. company data from 1989 to 1998. Their study first noticed that boldness likelihood increased with the analyst's prior accuracy, brokerage size, and experience and declined with the number of industries the analyst followed, consistent with the theory linking boldness with career concerns and ability. Second, they learned that bold forecasts were more accurate than herding forecasts. Finally, the team asserted that herding forecast revisions were more strongly associated with analysts' earnings forecast errors than were bold forecast revisions. To sum it up, bold forecasts incorporated analysts' non-public information more completely and provided more relevant information to investors than did herding forecasts.

Coën et al. (2005) were the first to consider the accuracy of analysts in the markets of Asia. Rather than looking at the behavior of individual analysts, they instead considered the performance of the arithmetic mean (or consensus) earnings forecast of all analysts covering a company, using those that had at least three analysts making forecasts. For each year, the authors looked at the last annual forecast made prior to the fiscal year end. They defined forecast accuracy the same as Hong & Kubik (2003), that is, SAFE, but they improved on reliability by scaling to actual earnings instead of to share price. The authors also considered whether there were biases in the analysts' forecasts by studying whether the mean value of FE was positive or negative, rather than just the absolute deviation. They concluded that analyst forecasts were overly optimistic. The authors witnessed that for the eight Asian countries (Hong Kong S.A.R, Korea, Indonesia, Malaysia, Philippines, Singapore, Taiwan region, and Thailand) examined, the mean SAFE was significant for the 1990 to 2000 period. They noted that the forecast accuracy was best in Hong Kong S.A.R, with a SAFE of 18%, and the worst, in Korea, at 31%, and that the average SAFE for all eight countries was 22%. By dividing their sample into subsets – before the Asian financial crisis of 1990 to 1996, during the crisis of 1997 to 1998, and post-crisis 1999 to 2000 – the authors concluded that the crisis did not lead to any gains in analyst forecast accuracy.

Asquith et al. (2005) brought the research on earnings forecast accuracy together with recommendations and target prices. They looked at a very limited list of 1,126 *Institutional Investor's* All-America Research Team reports released during 1997, 1998, and 1999. Their data set included only 56 unique analysts and it was discovered that two-thirds of all reports in their sample of reports were reiterations of previous earnings, target prices, and recommendations. They found that, as with other studies when earnings forecasts were considered independently, the market impact of earnings revisions and recommendations downgrades was "significantly larger at small firms and firms with fewer analysts following them." But, the market's reaction to price target changes in general seemed to be most powerful. They found that half of the reports in their sample were issued at the same time as companies announced significant news. Their findings show that the market reacts most strongly to changes in target prices, and that there was no major significance for upgrades. Finally, across their very small data set they found that analyst price targets were achieved or exceeded over a 12-month period about 54% of the time. About 73% of reports included price targets, though analysts had a much lower level of disclosure if the report was a hold reiteration or a hold downgrade.

Jackson (2005) studied Australian companies for 10 years from 1992 to 2002 using the I/B/E/S database of analyst earnings forecasts. He found that optimistic analysts generated more trading commission for their brokerage. Conversely, their earnings forecast inaccuracy could prevent their reputations from rising, reducing their future trade generation ability. So, the analyst's dilemma was between telling the truth, and hence developing a reputation as an accurate analyst, and misleading investors with optimistic forecasts. This research was not easily comparable with others over time as the study had scaled analyst earnings error by price.

Authors Hope & Kang (2005) defined forecast accuracy as the negative of SAFE scaled by the actual share price at the time earnings were reported (the forecast value taken is the median I/B/E/S consensus for a 12-month forecast for period *t* made for a firm at time *t-1*). The rationale behind using the negative value was that more accurate forecasts were represented by a larger number, with zero being perfectly accurate. The sample consisted of 431 distinct firms across 21 countries from 1992 to 2002, cross-listed in the U.S. as American Depositary Receipts (ADRs). So, even though this was a more international universe, it was still a very narrow one, because most companies outside of the U.S. did not have ADRs traded in the U.S. The authors then used a regression model where the forecast accuracy was the dependent variable while several country-level macroeconomic factors, their transformations, and/or their changes were taken as independent variables. They disclosed that increased macroeconomic uncertainty is directly correlated with increased forecast error. This was the first paper with an emphasis on macroeconomic factor uncertainty as a driver of forecast errors by analysts. The importance of this paper is that it shows analysts' forecasts are less reliable in an environment of higher economic uncertainty. However, as noted with some prior papers, I believe that scaling to price may invalidate most of the conclusions.

Cowen et al. (2006) tested six years of U.S. company data from 1996 to 2002 and assessed that analyst's at large investment banks tended to be less optimistic, while those at retail brokerages were more optimistic. Their conclusion was that an analyst's incentive to issue optimistic earnings forecasts was driven more by the desire to generate trading income than by generating underwriting business.

The research with the second-widest geographical reach of any study so far was done by Bae et al. (2008). He and his team covered 32 countries (excluding the U.S.) and a total of 611 firms using the I/B/E/S International Data file. Unfortunately, they looked at only two years of data. They found that local analysts made more accurate forecasts than did foreign analysts. This research was naturally biased toward large companies as that is where most of the work of foreign analysts is focused. Earnings forecast accuracy was scaled by price, which makes comparisons across time difficult.

Coën & Desfleurs (2008) considered 13 countries in Europe over the 16 years from 1990 to 2006 and used I/B/E/S forecast data. Like Chang et al. (2000) they used a cutoff of at least three analysts covering the firm. Similar to Castoff et al. (1998), they removed any absolute forecast error greater than 100%. The major conclusion from this work was that country and industry effects on analysts' forecast accuracy were not the major drivers of forecast accuracy; rather the main drivers were company-specific factors. A conclusion that could be derived from this is that the world has grown more interconnected and that, as a result, investors looked less as what country or industry a company was operating in but rather mainly considered the financial performance of each company on its own.

Ernstberger et al. (2008) investigated German-listed firms from 1998 to 2004, a period during which the accounting standards in Germany were in a transitional phase. They defined accuracy similar to Hope & Kang (2005) as the negative of SAFE using monthly median analyst forecasts and scaled it by share price at the middle of the forecast month. The rationale behind using monthly frequency was that the authors used time as one of many different control variables and hypothesized that the forecast accuracy should be more accurate closer to the announcement date. The authors trimmed the data at ±1% before calculating the error, hence removing these extreme data points. Following a thorough analysis of forecasts on U.S. and German companies, the authors concluded that forecasts based on International Financial Reporting Standards (IFRS) and U.S. Generally Accepted Accounting Principles (U.S. GAAP) were more accurate than those based on German GAAP. Apart from a new direction of analysis that was delving into accounting principles as a driver of forecast errors, the authors had removed outliers and had taken the median of forecast errors to remove the effect of extreme events. The key takeaway from the paper is that the more stringent the accounting principles were, the less forecast error there was. Again, as with some prior papers, we believe that scaling to price may invalidate most of the conclusions.

SUMMARY OF DEVELOPMENTS DURING THIS PERIOD

During the period of 2005 to 2008, research started homing in on the conflicts financial analysts were facing. Clement & Tse (2005) found that the likelihood of an analyst's boldness increased with the analyst's prior accuracy, brokerage size, and experience and declined with the number of industries the analyst followed, consistent with the theory linking boldness with career concerns and ability. They also found that bold forecasts were more accurate than herding forecasts. Bold forecasts incorporated analysts' non-public information more completely and provided more relevant information to investors than herding forecasts.

Coën et al. (2005) was the first in this review to focus on the FE of analysts in Asia, using consensus forecast for companies that had at least three analysts making forecasts and scaling SAFE by both share price and actual earnings. Analysts were optimistically biased and most accurate in Hong Kong S.A.R and worst in Korea (this exceptionally high optimism shows up in our research as well). The arithmetic mean SAFE for all eight countries was 22%. And lastly, they found that analysts did not improve accuracy after the 1997 economic crisis.

Asquith et al. (2005) observed that the market impact of earnings revisions and recommendations downgrades a signal that investors followed. By bringing Target Price estimates into the analyses they found that the market's reaction to price target changes were powerful.

Another finding was that half of the reports in their sample were issued at the same time as companies announced significant news. This would later be called piggybacking by Altinkiliç et al. (n.d.).

The true dilemma that financial analysts faced was demonstrated by Jackson (2005), who found that optimistic analysts generated more trading commission for their brokerage. But, their earnings forecast inaccuracy could prevent their reputations rising, reducing their future trade generation ability. The analyst's dilemma was between telling the truth, and hence developing a reputation as an accurate analyst, and misleading investors with optimistic forecasts. This research, like most past research scaled FE by price.

Like Gu & Wu (2003), Hope & Kang (2005) used median rather than mean of 12-month forecasts to calculate SFE, which they scaled by price. They also found that increased macroeconomic uncertainty increased FE.

Cowen et al. (2006) discussed that trade generation pressure on an analyst may overpower underwriting pressure.

Bae et al. (2008) looked over a global universe and found another factor—whether the analyst was foreign or local—and concluded that local analysts were more accurate. Earnings FE was scaled by price

Coën & Desfleurs (2008) came back with research into countries in Europe, where, as with their prior work, they considered only companies with three or more analyst forecasts and became the second paper to trim SFE at 100%. They found that the main driving factor of FE was company-specific factors, not country or industry effects.

Revisiting the median vs. mean debate, Ernstberger et al. (2008) calculated a SAFE using median analyst FE and scaled it by share price. He trimmed data at ±1% before calculating the error, removing extreme data points. The key finding was that the more stringent the accounting principles were, the less forecast error there was.

2009 to 2015: Challenging what we thought we knew on the subject

Coën et al. (2009) considered 18 developed countries from 1990 to 2004 using I/B/E/S forecast data. Their research was scaled by earnings, which allowed the results to be compared across time. Their objective was to break down the performance of earnings forecasts into three separate parts: country, industry and firm-specific impact. This study considered accuracy when analysts were forecasting earnings one month away up to nine months away from the actual announcement of earnings. Like Chang et al. (2000), they considered only companies that had at least three analysts covering them and removed absolute errors above 100%, which removed 5.6% of all data points. Their absolute error was 27.99% and their SFE at 13.61% was low compared with Chang et al. (2000). Some findings were that analysts made more errors when earnings were decreasing, and that increasing analyst coverage meant more accurate forecasts. A major conclusion was that though country effects were more powerful than industry effects, both paled in comparison to the nearly 80% of variation in earnings forecast errors coming from company-specific effects, such as whether a company was producing loss or profit or whether earnings were increasing or decreasing.

In 2009, a research bombshell was dropped. In their paper, Ljungqvist et al. (2009) documented changes to the historical I/B/E/S analyst stock recommendations database over the period of 2000 to 2007, throwing prior findings from the data set under a shadow of doubt. This prompted an investigation by I/B/E/S, and based on this, the company made some changes to its policies and fixed what they claimed to be a small number of actual errors. Enough information has been provided to conclude that this was a temporary problem that no longer exists in the I/B/E/S data set. This was a notable example of how an academic research finding made the world a better place. The conclusion is that the I/B/E/S data used in my analysis is reliable.

In their paper, Hsu & Chao (2011) define forecast accuracy as SAFE scaled by the actual EPS and look at a quarterly time horizon. Their data set comprised U.S. firms that were represented in both the Center for Research in Security Prices (CRSP) database and the I/B/E/S database between 1984 and 2006. However, they required a minimum of four analyst forecasts for inclusion in their sample; therefore, their main analysis started in 1988, because the earlier sample was insufficient. The reason for this requirement was to avoid distorting the results with forecast errors that may occur when a firm is covered by only one or two analysts. Using a Markov chain analysis, the authors considered the persistence of forecast errors in analyst predictions. The authors studied the explanatory factors behind this persistence and delved into the categorization of this persistence across industry sectors. They concluded that analysts' workload and the size and growth rate of the firms covered were among the long-lasting influencing factors and the strength of each of these factors varied significantly from one industry to another. The authors found two variables that had a statistically significant impact on forecast accuracy. The market capitalization of the covered firm and the growth rate of market capitalization of the firm had a directly proportional impact on forecast accuracy. This offers a new direction in this analysis, which tests whether the forecast errors of analysts are predictable or that they are persistent in their level of accuracy. The paper showed that since forecast error was somewhat predictable and not completely random, a model could possibly be built to account for the forecast errors.

Bradshaw et al. (2012) raise additional concern in this area of research when they considered a large sample of U.S. companies over the 25 years from 1983 to 2008 and found that, contrary to prior findings, analysts were not superior to time-series forecasts for U.S. companies when the time horizon was one to three years ahead. Accuracy of any significance seemed to have occurred during the period of three months prior to the announcement date.

As this research area was recovering from the Bradshaw et al. (2012) findings, another devastating study was produced by Altinkiliç et al. (2013). She and her team considered U.S. companies over the 10 years from 1997 to 2007. Their research repudiated most prior research in this area through their study of short-term price reactions to analyst earnings forecast revisions.

They uncovered that analysts were just quickly responding to significant company news, or what she called “piggybacking” on that news. Once price reaction for a company’s news release was controlled for, she found that analysts neither outperformed, nor added any specific information to the market.

In 2015, Kerl & Ohlert (2015) looked at 1,159 companies across eight developed countries over the five years from 2005 to 2010. In their research, they showed absolute earnings forecast error across the eight developed countries of about 29%, but showed that some analysts were persistent in their forecasting accuracy. Star analyst earnings forecasts outperformed non-star analysts in the year after the award was given.

The most recent paper around analyst forecast accuracy was Huang & Wright (2015), who studied 1,298 Chinese companies over the seven years from 2004 to 2011. This research found that the higher the state ownership in Chinese companies, the more optimistically inaccurate were analysts’ forecasts.

SUMMARY OF DEVELOPMENTS DURING THIS PERIOD

From 2009 to present time there has been considerable challenge to prior research. First, Coën et al. (2009) looked at 18 developed countries, abandoning the scaling of FE by price and replacing it with earnings. In addition, they consider only companies that had at least three analysts covering them and removed absolute forecast errors above 100%, which removed 5.6% of all data points. Their SAFE was 27.99% and SFE was 13.61%, low compared with Chang et al. (2000), which could be attributed to their use of a 100% cut-off point. They added a new element, which was the direction of the earnings that analysts were trying to predict, showing that analysts had made more errors when earnings were decreasing. They also showed, as had been seen previously, that increasing analyst coverage meant more accurate forecasts. As their prior research had showed, though country effects were more powerful than industry effects, both paled compared with nearly all variation in earnings forecast errors coming from company-specific effects, such as whether a company was producing loss or profit or whether earnings were increasing or decreasing.

This period was interrupted when Ljungqvist et al. (2009) questioned the reliability of the I/B/E/S data that nearly all research conclusions in this area were based on. Fortunately, I/B/E/S listened and improved its data (and fixed prior data) so research could continue.

A shift seems to have been made more toward scaling SAFE by price, as was the case for Hsu & Chao (2011); in their research, they tightened their inclusion by requiring a minimum of four analyst forecasts within their sample. They concluded that analysts' workload and the size and growth rate of the firms covered were among the enduring factors influencing FE.

Bradshaw et al. (2012) challenged prior work showing that analysts were not superior to time-series forecasts for U.S. companies when the time horizon was one to three years ahead and that accuracy of any significance seems to have occurred during the period of three months prior to the announcement date.

Altinkiliç et al. (2013) repudiated most prior research. By studying short-term price reactions to analyst earnings forecast revisions, they found that analysts were just quickly responding to significant company news, or what the research team called "piggybacking" on that news. Once price reaction for this company's news release was controlled for, she found that analysts neither outperformed, nor added any specific information to the market.

In 2015, Kerl & Ohlert (2015) calculated a SAFE of 29% (scaling by EPS) across eight developed countries. They found that star analyst earnings forecasts outperformed non-star analysts in the year after the award was given.

This period wraps up with Huang & Wright's (2015) study of 1,298 Chinese companies over the seven years from 2004 to 2011. They found that the higher the state ownership in Chinese companies, the more optimistically inaccurate were analysts' forecasts.

SUMMARY OF CONCLUSIONS FROM LITERATURE REVIEW

A review of literature on the topic of analyst forecast accuracy has shown that, in most cases, the authors agreed that analysts were inaccurate and optimistic. In addition to calculating the degree of forecast error, the authors focused on two issues: 1) explaining this inaccuracy and 2) identifying whether this forecast error had a pattern to it. In some papers, instead of working with individual analyst forecast error, the authors took an average at some level, for example, the average of forecast errors for all analysts following a firm in a year (usually referred to as "consensus forecast"), the average of all analyst forecast errors following firms in a sector for a given year, or the average of all analyst forecast errors when all forecasted companies were subject to a set of accounting treatment.

In the distant past, studies using small samples and short time periods showed that analysts appeared to have been superior relative to statistical models. In the more recent past though, this has not seemed to be as conclusive. Analysts appeared to be less successful over longer time periods. Below I have summarized the key findings from my literature review.

Analyst characteristics (for example, years of experience, years forecasting on that company, or the firm they work for) may help an investor identify an analyst who might produce earnings forecasts that outperform in the future. However, since even professional investors rarely read academic research, it appears that investors seem unaware of this, or if they are aware, they neglect using this information.

Analysts have more success when the companies they are forecasting are large and provide good disclosure of their financial and business information.

Analysts are too extreme in their forecasts, and usually extremely positive. This optimism seems to come from their desire to maintain good relationships with the management of the companies they cover.

The less information revealed about a company, the more likely it is that an analyst will be positive in his earnings forecasts, which appears to be a tool to, over time, tease out more information from management.

Internationally, analyst optimism continues its prevalence. Analysts for a country appear to be better at forecasting about local companies than foreign analysts covering the same companies.

Almost all studies scale the error by price. Most studies looked at individual analyst behavior, rather than consensus of all analysts. When scaled by earnings, the average error ranged between 15% and 30%.

In 2009, it was found that the database provided by I/B/E/S, upon which almost all analysis was done, may have been compromised prior to 2007. The company subsequently cleaned up that data and improved its collection policies so this problem appears to have disappeared.

It turns out that analysts are not as good at forecasting as has been previously thought, and that instead, they mainly issue revisions to their forecasts shortly after material company news events. Hence, they never really anticipated earnings, but rather were fast reporters of it.

DILEMMAS THAT REMAIN

Scaling error by price, rather than earnings. Most studies scale by price, which brings a very random and volatile impact of price into the studies and makes them difficult to interpret and act upon. In addition, scaling by price makes the results less comparable over time, region, and industry, as error measurements are significantly impacted by the price level of the market during the period studied.

Shifting definition of forecast time horizon. Some studies look at earnings forecasting over very short periods. Additionally, some studies treat forecast accuracy over different periods as comparable.

Execution time frame. Many studies are unrealistic about trading time frames. Very few fund managers can “Buy” or “Sell” a stock based on an analyst changing his forecast or recommendation. In most cases, the fund manager would need to perform due diligence on a particular investment, meaning that it could take weeks or even months before being ready to act on the analyst’s forecast. But, by this time, most studies show that any gain would be gone. This means that most research is for the pleasure of understanding, rather than for actually applying the learning in the real world.

Overly focused on explaining individual analyst forecasts. Most research has focused on understanding individual analyst behavior and success factors. Yet, most institutional investors have neither the time nor ability to track the large number of analysts as they become more and less reliable. In addition, there is little proof of persistent forecast accuracy beyond about one year. Hence, the research may be identifying random variation that they believe is persistence—or “false discoveries” as it is referenced in the research of Barras et al. (2010) on the performance of fund manager persistence.

Analysts as reporters, not originators. Recent research has shown that analysts may no longer outperform times-series models. In addition, it appears that analysts are simply quickly reporting news that the companies are announcing, meaning they are just “piggybacking” on this news. This recent line of research could mean that, thanks to the wide and fast dissemination of company news these days, research analysts are not as accurate or successful as was thought.

Expected return. A major task of market participants is to determine expected return for a stock as well as for the overall market. Research on consensus estimates could help practitioners solve this dilemma.

Underutilized research. Research in this area has even shown that investors do not apply the findings of the research in this area! Specifically, the findings on the impact of analysts’ characteristics on future accuracy are underutilized. In fact, much of the research is unable to be applied in real life or the advantage gained would not exceed the effort, fees, and costs involved in executing on them. This falls short of invalidating the prior research but it does guide us to try to keep our research applicable.

Cost—benefit. At best the research finds small areas where an investor could achieve an advantage from the findings. Consider La Porta (1996), who showed that an investor could profit from buying stocks where analysts' earnings estimates were most pessimistic. However, what must be considered is the billions of dollars spent on research analysts. Very rarely would any trading strategy based upon their earnings forecasts be able to offset their massive cost.

DATA

Since this paper spans all the stocks of all the listed companies in the world, across all markets, across 12 years, the data set is very large. The first step in handling this data is to remove small companies, as they rarely have analyst coverage and are also very hard for most investors to invest in. This left me with Universe #1. Of course, the lack of analyst coverage of small companies and the fact that they are often overlooked provide an investment opportunity for those who dare to venture into that space. But, for my purposes, they rarely would have many analysts covering them and hence I excluded them. Next, I removed stocks that had no analyst coverage, to arrive at Universe #2. Finally, to make sure that the remaining companies were comprehensively covered by financial analysts, I required that they all have at least one financial analyst earnings forecast, one target price, and one recommendation, which brings us to Universe #3. Some characteristics of the stocks that remained were highlighted.

Data set description

Based on World Bank data as of 2012, there were 109 stock markets in the world, with a total of 46,724 listed companies and a total market capitalization of US$52 trillion[3]. To build my data set, I gathered monthly data on stock-exchange-listed companies across the globe that were trading in the stock market at any point during the 12-year period from January 2003 until December 2014. I sourced consensus estimate data from Thomson Reuters I/B/E/S Estimates, using their Summary History data, which contains records on over 45,000 companies across 70 markets.

Universe #1 Remove small companies

To avoid being overloaded with data, I required that to be included in this study a company had to have a size of at least US$50m market cap as of December 2014. To ensure there was no

[3] http://data.worldbank.org/indicator/CM.MKT.LCAP.CD/countries?display=map

survivorship bias, I applied the same rule to any stock on its last day of trading for those stocks that delisted during those years. I called this Universe #1. At the beginning of the period, this data set had 6,337 companies globally, 4,395 (69.4%) listed in developed markets, and 1,942 listed in emerging markets. By December 2014, Universe #1 had nearly doubled to 12,711 companies, at which time 63.4% of these came from developed markets. The boom in emerging stock market initial public offerings was evidenced by the 140% increase of emerging market companies in Universe #1.

Table 1. Universe #1. All stocks in the world with ≥US$50m market capitalization

This study started with a data set of 6,337 companies worldwide, 69.4% of which were in developed market countries and ended with 12,711 companies in 2014, 63.4% of which were in developed countries.

	2003	2005	2010	2014
Developed market companies	4,395	7,191	7,566	8,054
Emerging companies	1,942	3,025	3,365	4,657
Total companies	6,337	10,216	10,931	12,711
% of total				
Developed market companies	*69.4*	*70.4*	*69.2*	*63.4*
Emerging companies	*30.6*	*29.6*	*30.8*	*36.6*

Universe #2 Remove companies with no analysts covering them

My objective was to study the performance of analysts, so I next needed to remove from this data set companies that did not have any analysts covering them. The first step in this process was to remove all companies without minimal analyst coverage, which I defined as having at least one analyst earnings forecast. If, for any given month, this criterion was not met, I removed the company from that period only. By applying this step to Universe #1, I arrived at Universe #2. Applying this additional filter in 2003 led to a 34.9% decrease in the data set to 4,127 companies from 6,337 companies. In December 2014, it fell only 13.0% to 11,061 companies from 12,711 companies. The 34.9% drop at the beginning of this data set shows that years ago, there was much less financial analyst coverage of companies across the globe. The lower 13.0% drop in the 2014 number shows that a much higher number of large listed companies had at least minimal financial analyst coverage.

Table 2. Universe #2. All stocks in the world ≥US$50m market capitalization, ≥1 EPS forecast

Reduced the data set by requiring that a company have at least one analyst covering them. This reduces the universe significantly in earlier years since during that time there was considerably less analyst coverage. The study considers Universe #2 as the starting point as it excludes companies that do not have at least a minimal amount of analyst coverage.

	2003	2005	2010	2014
Developed market companies	3,296	5,498	6,655	6,824
Emerging companies	831	1,281	2,859	4,237
Total companies	4,127	6,779	9,514	11,061
% of total				
Developed market companies	*79.9*	*81.1*	*69.9*	*61.7*
Emerging companies	*20.1*	*18.9*	*30.1*	*38.3*
% reduction from universe #1	*(34.9)*	*(33.6)*	*(13.0)*	*(13.0)*

Universe #3 Remove stocks with less than one earnings forecast, target price, and recommendation

The next objective was to make sure that each company under study had complete analyst coverage. To do this, any companies were excluded that had just earnings forecasts but did not have at least one target price and at least one recommendation. In 2003, this additional filter caused Universe #3 to be 20.5% smaller than Universe #2. By 2014 these reductions had gotten much smaller as more companies across the globe were receiving more complete analyst coverage. The result of this process was to end up with a data set of companies with analyst coverage that was as wide as possible. Given its breadth, I claim that this data set covers the entire world, making it the first in the literature on the topic of analyst forecast accuracy to do so.

Table 3. Universe #3. All stocks in the world ≥US$50m market capitalization, ≥1 EPS forecast, ≥1 target price, ≥1 recommendation

Universe #3 adds on the condition that, in addition to having an earnings forecast, the stock must have at least one target price and one recommendation. The result is that the companies that remain in the universe are truly "covered" by analysts.

	2003	2005	2010	2014
Developed market companies	2,609	4,757	6,358	6,677
Emerging companies	670	1,106	2,528	4,055
Total companies	3,279	5,863	8,886	10,732
% of total				
Developed market companies	*79.6*	*81.1*	*71.6*	*62.2*
Emerging companies	*20.4*	*18.9*	*28.4*	*37.8*
% reduction from universe #2	*(20.5)*	*(13.5)*	*(6.6)*	*(3.0)*

Highlight of the largest companies in this data set

The company that had the highest number of analysts covering it in 2014 was Apple with 55 analysts. In fact, during the whole period of the study only four different companies at any time had the highest number of analysts (Nokia, Cisco, Infosys, and Apple). In 2009, there was the inclusion of the first company from an emerging market, Infosys from India, which either had the highest number of analysts or was tied for the highest number in 2009 and again in 2011 to 2013. Throughout the whole period of the study, we see from Table 4 that the company with the highest number of analysts covering it each year was in the telecom and information technology sector.

Table 4. Companies with the greatest amount of analyst coverage

Over the whole period the companies with the highest number of analysts covering them were all companies in the telecom sector. In 2009, emerging markets started to be represented by Infosys from India.

		Company w/ max # of analysts			Tied for first		
Year	Max # of analysts	Name	Country	Market	Name	Country	Market
2003	53	Nokia	Finland	Dev			
2004	47	Nokia	Finland	Dev			
2005	42	Cisco	USA	Dev			
2006	47	Nokia	Finland	Dev			
2007	47	Nokia	Finland	Dev			
2008	42	Nokia	Finland	Dev			
2009	45	Nokia	Finland	Dev	Infosys	India	Emer
2010	50	Nokia	Finland	Dev			
2011	59	Infosys	India	Emer			
2012	53	Apple	USA	Dev	Infosys	India	Emer
2013	56	Apple	USA	Dev	Infosys	India	Emer
2014	55	Apple	USA	Dev			

METHODOLOGY

In this research, I focused on analyst earnings forecast error, calculating both absolute and scaled forecast error, though my focus was mainly on the latter. The study started by considering each company in the world, and as described in the data section, small companies and those not completely covered by financial analysts were filtered out.

In this section, I explain my methodology and then apply it to the removal of any remaining data outliers. Once that was done, it brought me to the last step of preparing the data, which was to determine the most representative minimum number of analysts covering a company.

Once this has been done, I prepared a summary of the data set. First considered was the global data, covering all stocks in the world. Second, I aggregated the companies by stage of development: developed versus emerging markets. Third, I aggregated the companies by regions across the world. Finally, I aggregated the companies into sectors.

Calculation of 12-month analyst forecast accuracy

Nearly every paper on analyst earnings forecast accuracy uses March, April, or May as the starting date to calculate 12-month earnings forecasts. In doing this, they assume that by this date the company will have announced its full-year earnings. In this paper, I took a more exact approach by identifying the date that a company announced its actual earnings and then stepped back 12 months from that date to construct an exact 12-month forecast horizon. One of the major weaknesses of prior papers is the constantly changing time horizons that make comparisons nearly useless. To claim that analysts are more accurate the closer they get to the actual earnings announcements, as many papers do, is mixing time horizons unless actual announcement dates are considered. As stated before, it would be like an archer stepping closer and closer to his target and proclaiming that the closer he gets the more accurate he is. By maintaining a 12-month horizon, I produce a result that is comparable across companies, across countries, and over the years.

I define Forecast Error (FE) as the difference between the forecast earnings (F) on the forecast date 12 months before the actual earnings (A) were reported.

$$FE_t = F_{t-12\,months} - A_t$$

Scaled Forecast Error (SFE) is the FE relative to the absolute value of actual earnings (A).

$$SFE_t = \frac{F_{t-12\,months} - A_t}{|A_t|}$$

The Scaled Absolute Forecast Error (SAFE) is given by the absolute value of SFE:

$$SAFE_t = |SFE_t|$$

Outliers – Remove outliers that distort results

UNIVERSE #4 REMOVE SMALL NUMBERS THAT COULD DISTORT RESULTS

Removing outliers is a critical next step, because leaving extreme values in the data set would massively twist results. In this and prior research, we can see that such numbers come from either error in data or from very small numbers. Regardless of the source, they massively distort the results.

My first step in removing outliers was to remove data points that could distort the results due to having tiny numbers in the denominator. Consider if an analyst had earnings forecast of one dollar and the company ended up making only one cent; the analyst would be off by 9,900%. That massive error would have a very strong impact on the average error of the universe, yet I argue that this impact is not as meaningful as it appears. Of all the prior research in this area, the only work to explicitly state how this was dealt with was Stickel (1992), who removed any data points that were smaller than US$0.25. The purpose of excluding tiny numbers was to remove excessively high percentages that could be caused by the denominator being tiny. To decide at what point to remove tiny numbers, I considered various levels of exclusion from data points with absolute value below 0.12 down to 0.04 (I do not consider currency in this case, just the actual value of EPS). However, I excluded only those tiny data points that had a Scaled Absolute Forecast Error (SAFE) above 200%. This increased the precision of the removal of only tiny numbers that were distorting results.

Table 5 shows that removing tiny numbers of less than absolute value of 0.12, with a SAFE over 200%, from Universe #3 causes SFE to drop from 104.5% to 56.5%. However, that would remove more than 4% of the total data set and my objective was to remove as little as necessary form the data set. Therefore, I selected 0.04 as the tiny-number cutoff point as it substantially reduced SFE and yet cut off only 2.1% of the universe.

Table 5. Deciding what level of tiny numbers to exclude from the data set

I considered various levels of tiny numbers which also have SAFE over 200%. Using a high number such as 0.12 removes a very large 4.3% of the universe. I choose 0.04 since it significantly reduces SFE from 104.5% to 67.1%, but only removes 2.1% of the universe.

	Companies	% excluded	SFE (%)
Universe #3	10,732	-	104.5
Excluded EPS that was less than 0.12	10,275	4.3	56.5
Excluded EPS that was less than 0.10	10,314	3.9	57.9
Excluded EPS that was less than 0.08	10,372	3.4	60.1
Excluded EPS that was less than 0.06	10,433	2.8	62.9
Excluded EPS that was less than 0.04	10,510	2.1	67.1

Table 6 shows Universe #4 after excluding tiny data points, which causes the data set to fall to 10,510 in 2014, a 2.1% reduction.

Table 6. Universe #4. All stocks in the world ≥US$50m market capitalization, ≥1 EPS forecast, ≥1 target price, ≥1 recommendation, removing tiny numbers (0.04) and with SAFE above 200%

In Universe #4 I removed small stocks, those with no analyst coverage and those that have tiny numbers which give percentage errors over 200%. This reduces the number of companies in the data set by about 2.1%, but is considerably more precise than just the data at some low percentage cutoff point.

	2003	2005	2010	2014
Developed market companies	2,544	4,677	6,242	6,546
Emerging companies	661	1,081	2,465	3,964
Total companies	3,205	5,758	8,707	10,510
% of total				
Developed market companies	*79.4*	*81.2*	*71.7*	*62.3*
Emerging companies	*20.6*	*18.8*	*28.3*	*37.7*
% reduction from universe #3	*(2.3)*	*(1.8)*	*(2.0)*	*(2.1)*

UNIVERSE #5 DECIDE WHERE TO TRUNCATE RESULTS

My next step in removing outliers was to apply the error methodology to decide where to truncate outlier data points.

To solve this problem, I started by testing Universe #4 by setting a maximum and minimum allowable error at ±10,000%, which eliminated a tiny 66 data points from the data set, 0.07% of the total data points. At ±5,000%, this became 0.13%, at ±1,000%, it was 0.94%, at ±500% it cut out 2.35% of the data points. When I moved this filter to ±200%, it eliminated a very large 7.52% of the data set. The level at ±100% shows the removal of 16.48% of the data set, causing the scaled forecast error to fall to nearly zero at 4.4%. Clearly, neither 101.7% nor 4.4% is a realistic number.

Capstaff et al. (1998) and Coën et al. (2009) both used ±100% as the cutoff point, which in their research removes more than 10% of the total data points. Stickel (1992) used ±200%. Using such a low cutoff point for SFE in our data set would remove too many data points so that the universe I am using would not represent the total market universe. I have produced the first research that cuts off the data set at ±500%, which I believe balances the constraints.

Table 7. Deciding where to truncate remaining data
I removed outlier scaled forecast errors (SFE) for the whole data set that were above or below 500%.
At ±500%, this removed 2.35% of all data points in the data set.

	Scaled forecast error (%)	Data points included	Data points excluded	Data points excluded (%)
All data	101.7	93,482		
Eliminate ±10,000%	52.6	93,416	66	0.07
Eliminate ±5,000%	49.2	93,360	122	0.13
Eliminate ±1,000%	36.8	92,603	879	0.94
Eliminate ±500%	28.7	91,282	2,200	2.35
Eliminate ±200%	15.5	86,448	7,034	7.52
Eliminate ±100%	4.4	78,073	15,409	16.48

Once I removed small companies and those with minimal analyst coverage and applied filters of various levels of outlier exclusion, I could get the first glimpse of the results of my study. In Figure 2, I plotted the scaled forecast error (SFE) for the various levels of outlier exclusion.

From this, it could be seen that an exclusion of SFE of more than ±10,000% (though only excluding 66 data points or 0.07% of the universe, with at least one analyst coverage), still showed a very high 52.6% SFE. As I removed more outliers from the data set of all SFEs for the case of one analyst covering a company there was a dramatic fall to 36.8% at ±1,000%. Figure 2 on the next page shows that all SFEs began to stabilize as I increased analyst numbers. Ultimately at this point, I needed to decide on one line that best represented the reality of an analyst's average forecast.

I believe that a line that was flatter shows a better representation. Consider the line at ±10,000%, which showed the SFE at one analyst to be 2.3x higher than that of a company covered by 10 analysts. Though I expected some reduction in error as more analysts covered a company, this level of reduction told me that results with a very wide filter of ±10,000% still included extreme outliers. At ±5,000%, the curve flattened with the ratio of the first point on the curve compared with the last coming down to 1.6x. The rest of the lines were almost equally flat, showing that the first data point was only 1.3x the level of the last data point—a much more reasonable outcome. Prior research provided no definitive guide, with some removing any absolute SFE greater than 100%, while others truncate the data at 1%. I chose ±500% as it produced a stable result and already removed a smaller 4.9% of data points. In fact, this analysis caused me to question the outcomes of research that used a low cutoff, such as 100%. At that cutoff, it is very possible that the research understates the real analyst earnings forecast error.

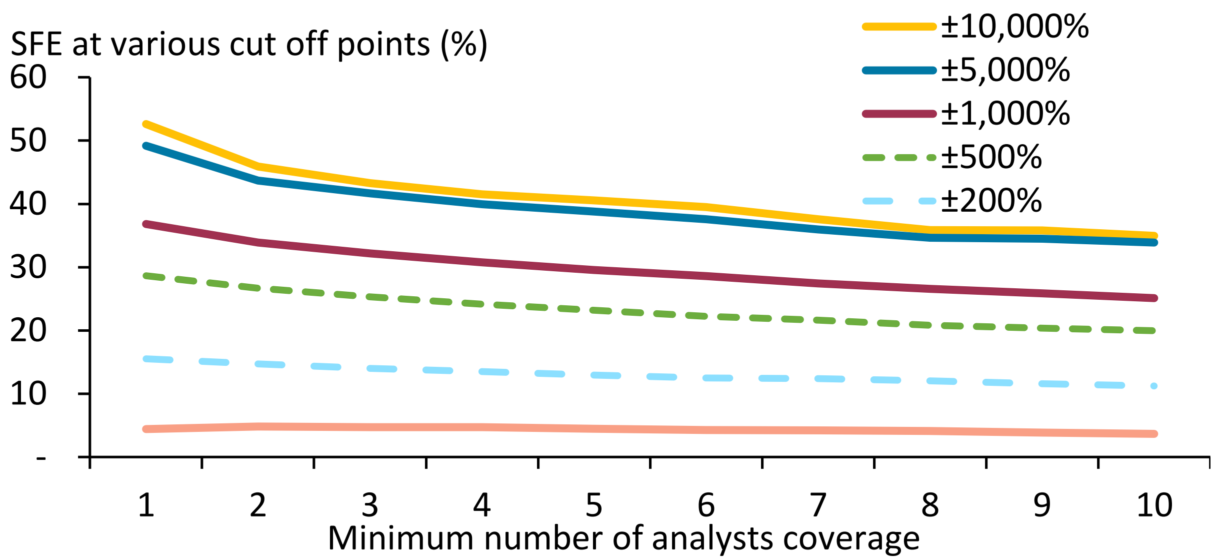

Figure 2. ***Scaled Forecast Errors (SFE) at different outlier removal levels and a different number of analysts.*** *We chart the various SFE at various levels of outlier exclusion and at various minimum number of covering analysts.*

After choosing my ±500% cutoff point, it caused the universe in 2014 to fall 2.2% to 10,279, which is now a complete and clean data set.

Table 8. Universe #5. All stocks in the world ≥US$50m market capitalization, ≥1 EPS forecast, ≥1 target price, ≥1 recommendation, removing tiny numbers (0.04) and with SAFE above 200%, remove SAFE outliers ±500%

In Universe #5, I have removed small stocks, those with no analyst coverage and those that have tiny numbers which SAFE over 200%. After this I removed any remaining outlier which lie outside ±500%. This reduces the number of companies in the data set by about 2.2% from Universe #4.

	2003	2005	2010	2014
Developed market companies	2,518	4,614	6,138	6,463
Emerging companies	631	1,048	2,423	3,816
Total companies	3,149	5,662	8,561	10,279
% of total				
Developed market companies	*80.0*	*81.5*	*71.7*	*62.9*
Emerging companies	*20.0*	*18.5*	*28.3*	*37.1*
% reduction from universe #4	*(1.8)*	*(1.7)*	*(1.7)*	*(2.2)*

Deciding minimum number of coverage analysts to include

After concluding that I would use a data set that excluded SFE ±500%, my next step was to determine whether to include all stocks with one or more analyst coverage or to exclude all except those that have two or more or three and so on. Or should I go to another extreme and consider only those stocks that had a large number, such as 10, of analysts covering them.

In prior research, Clement & Tse (2003), included data of companies that had at least two analysts covering the company. What was more common in the prior research was the use, such as in Coën, et al., (2005), of consensus forecast for companies that had at least three analysts, which he repeated in Coën & Desfleurs (2008). I consider this as a guideline, though what follows is my full justification of the choices I made.

My first step in this process was to remove stocks that had only one analyst covering them as clearly this was not an average analyst forecast. Since my goal was to assess the performance of the average analyst forecast (also referred to as consensus forecasts), I excluded stocks from the data set if there was only one analyst covering them.

This left my starting point at two analysts. Moving to three, four or 10 analysts brought up three opposing constraints. Increasing the minimum number of analysts increased the stability of the SFE, which was good; but it had the opposing impact of changing the data set to include fewer small companies and emerging market companies, both outcomes that I considered undesirable and hence to be minimized.

After removing the case of coverage by only one analyst, my starting point now was to include all companies that had two or more analysts covering them. At this point, the standard deviation of all SFEs was 80.9%, while the arithmetic mean SFE was 26.7%. Meanwhile, 74.6% of the data would be from within developed countries, hence 25.4% would be from within emerging countries. In addition, the average size of companies in the data set at that point was US$5,163m. At this starting point, there were 6,291 companies in the data set.

To go to the other extreme, if I required a minimum of 10 analysts, then the standard deviation of SFE came down to 69.4% and the average SFE was 20.0%. Meanwhile, a high 81.1% of the companies would have come from developed countries, hence reducing the representation of emerging countries to only 19%. In addition, the average size of companies in the data set would increase 126% to US$11,652m, while the number of companies in the data set would fall 66% to 2,157 from 6,291 at two analysts covering the companies. This demonstrates the opposing constraints and shows why I attempted to keep the minimum number of analysts as close to two as possible, so as not to cause the analysis to represent mainly large companies, and mainly companies in developed markets. As the one-step move from two analysts to three covering the company had negligible impact on all the opposing items, I saw no need to move further. Hence, I chose a cutoff point at a minimum of three analysts. The addition to the prior literature is that I show a clearer justification for this selection of three or more analysts.

Table 9. Final choice is a minimum of three-analyst coverage

I included all companies that had a minimum of three analysts covering them. This gave a 25.3% SFE and most fully represents emerging markets as well as small companies.

Min # of analyst covering-->	2	3	4	5	6	7	8	9	10
Average SFE (%)	26.7	25.3	24.2	23.2	22.2	21.6	20.8	20.4	20.0
Standard deviation of SFE	80.9	78.8	76.8	75.6	74.1	72.6	70.9	70.3	69.4
% developed countries	74.6	76.1	77.2	78.1	78.8	79.3	79.8	80.3	81.1
Average size (US$m)	5,163	5,861	6,551	7,328	8,118	8,945	9,780	10,715	11,652
Companies included	6,291	5,390	4,687	4,079	3,577	3,139	2,772	2,445	2,157

Universe #6 Final data set

Excluding outliers beyond plus or minus 500% and excluding companies that were covered by only one or two analysts, left a data set in 2014 of 7,434 companies, of which 66.9% were from Developed countries, the remainder from Emerging countries.

Table 10. Universe #6. All stocks in the world ≥US$50m market capitalization, ≥3 EPS forecast, ≥1 target price, ≥1 recommendation, removing tiny numbers (0.04) with SAFE above 200%, remove SAFE outliers ±500%

In Universe #6 I have removed small stocks, those with less than three analysts covering them as well as at least one analyst with a target price and one analyst with a recommendation. As well I have removed those that have tiny numbers, which give percentage errors over 200%. Finally, I remove any SAFE outliers ±500%. This reduces the number of companies in the data set by about 3% from Universe #5.

	2003	2005	2010	2014
Developed market companies	2,024	3,344	4,466	4,977
Emerging companies	447	542	1,366	2,457
Total companies	2,471	3,886	5,832	7,434
% of total				
Developed market companies	*81.9*	*86.1*	*76.6*	*66.9*
Emerging companies	*18.1*	*13.9*	*23.4*	*33.1*
% reduction from universe #5	*(21.5)*	*(31.4)*	*(31.9)*	*(27.7)*

MORE DETAIL ON THE FINAL DATA SET

Table 11. Companies by stage of market development

The final data set had 66.9% of companies from developed markets compared with 62.2% in the universe #3; I attempted to minimize this tilt toward developed markets by requiring only three or more analysts to cover the company.

As of 2014	Universe #3		Final data set	
Region	Companies	% of total	Companies	% of total
Developed	6,677	62.2	4,977	66.9
Emerging	4,055	37.8	2,457	33.1
Total	10,732	100.0	7,434	100.0

The average market capitalization of my final universe in 2014 was US$6,655m, 33.1% larger than the equivalent 2003 data set, and this size increased 54.1% over the period from 2003 to 2014.

Table 12. Average market capitalization of US$6,597m

The average market capitalization in 2014 was US$6,597m, a 54.4% increase from 2003; market capitalization then jumps 36% for the final universe as we exclude companies with less than three analysts covering them.

Average market capitalization (US$m)	2003	2014	% change
Universe #3 ≥1 EPS Forecast	3,353	4,851	44.7
Final universe ≥3 EPS forecasts & maximum 500%	4,272	6,597	54.4
% increase in size	27.4	36.0	

In my final data set, there were a total of 70 countries represented, with the top-10 Developed countries accounting for 66.9% of data points in 2014. In 2014, the US had accounted for 1,978 companies in the final data set, China 698, and Japan 597. These countries accounted for 44% of all data points in the study. Regarding companies in the study, the biggest addition to the company count came from China, which went from zero companies in the data set to 698 companies. The slowest growth in companies coming into the data set was Japan, which due to decades of poor stock market performance, saw only 13% growth over the period.

Table 13. Data points in study by country – Developed markets

Every major country is represented in this research, with data points from the top-10 Developed market countries accounting for 65.7% of all companies

Developed-Top 10	Country	Data points	% of All
1	USA	18,172	28.09
2	Japan	6,476	10.01
3	United Kingdom	4,012	6.20
4	Canada	3,346	5.17
5	Hong Kong SAR	2,700	4.17
6	Australia	2,028	3.14
7	France	2,001	3.09
8	Germany	1,673	2.59
9	Switzerland	1,063	1.64
10	Italy	1,004	1.55
	Total	42,475	65.67
	Global	65,340	

Developed-Others	Country	Data points	% of All
1	Sweden	960	1.48
2	Singapore	831	1.28
3	Spain	723	1.12
4	Norway	709	1.10
5	Finland	637	0.98
6	Netherlands	604	0.93
7	Belgium	474	0.73
8	Denmark	410	0.63
9	New Zealand	383	0.59
10	Greece	321	0.50
11	Austria	283	0.44
12	Portugal	201	0.31
13	Ireland	173	0.27
14	Luxembourg	7	0.01
	Total	6,716	10.38
	Global	65,340	

Table 14. Companies by country – Emerging markets

Every major country is represented in this research, with data points from the top-10 Emerging market countries accounting for 19.97% of all companies

Emerging-Top 10 Country	Data points	% of All	Emerging-Others Country	Data points	% of All	Emerging-Other Country	Data points	% of All	Emerging-Other Country	Data points	% of All
1 China	3,927	6.07	1 Poland	402	0.62	13 Qatar	54	0.08	25 Ukraine	13	0.02
2 India	2,206	3.41	2 Mexico	375	0.58	14 Czech Rep.	52	0.08	26 Croatia	13	0.02
3 Malaysia	1,211	1.87	3 Philippines	302	0.47	15 Oman	37	0.06	27 Slovenia	12	0.02
4 Taiwan region	1,243	1.92	4 Saudi Arabia	218	0.34	16 Kuwait	33	0.05	28 Lebanon	9	0.01
5 Thailand	1,061	1.64	5 Russia	156	0.24	17 Vietnam	31	0.05	29 Estonia	4	0.01
6 South Korea	939	1.45	6 UAE	127	0.20	18 Romania	29	0.04	30 Jordan	5	0.01
7 South Africa	717	1.11	7 Chile	126	0.19	19 Kenya	28	0.04	31 Bahrain	3	0.00
8 Indonesia	618	0.96	8 Egypt	113	0.17	20 Argentina	25	0.04	32 Bulgaria	2	0.00
9 Brazil	531	0.82	9 Israel	114	0.18	21 Colombia	24	0.04	33 Kazakhstan	2	0.00
10 Turkey	467	0.72	10 Pakistan	86	0.13	22 Morocco	23	0.04	34 Uganda	2	0.00
Total	12,920	19.97	11 Hungary	61	0.09	23 Sri Lanka	19	0.03	35 Ivory Coast	1	0.00
Global	65,340		12 Nigeria	54	0.08	24 Peru	15	0.02	36 Lithuania	1	0.00

I classified the 70 countries in my final data set into six groups based on the number of companies from the country that appear in our data set. Table 15 shows there were 14 countries, such as Romania, which had between one and five companies in our final data set. There were five countries, such as Germany, which had 151 to 300 companies in the final data set. The final group of countries, such as India and USA, had more than 300 companies in the final data set.

Table 15. Companies by country

Every major country is represented in this research, with companies from the top-10 countries accounting for 73% of all companies.

Range of companies in final data set

1 to 5	6 to 20	21 to 60	61 to 150	151 to 300	301 to 2,400
Romania	Portugal	Finland	Malaysia	Taiwan	USA
Morocco	UAE	Turkey	Thailand	South Korea	China
Czech Republic	Greece	Netherlands	Sweden	Australia	Japan
Hungary	Nigeria	Mexico	Switzerland	Germany	United Kingdom
Peru	Egypt	Saudi Arabia	Brazil	France	Canada
Argentina	Ireland	New Zealand	Italy		Hong Kong
Croatia	Vietnam	Philippines	Indonesia		India
Lebanon	Israel	Russia	Singapore		
Estonia	Oman	Belgium	Norway		
Jordan	Qatar	Denmark	Spain		
Kazakhstan	Colombia	Pakistan	Poland		
Luxembourg	Sri Lanka	Austria	South Africa		
Slovenia	Kenya	Chile			
Uganda	Kuwait				

All 10 of the MSCI & Standard and Poor's Global Industry Classification Standard (GICS) were represented; the top-three industries were Industrial, Consumer Discretionary and Financial. These three sectors accounted for about half of all companies. The biggest growth came in the Materials industry, which went from having 191 companies or 7.5% of the total, to 748 companies or 10.2% of the total. The slowest growing industry was Telecommunication services which, given its highly-regulated environment, had few new entrants.

Table 16. Companies by sector
All 10 GICS sectors were represented with most companies in the top three.

	Number of companies		% of companies		Growth
Sector	2003	2014	2003	2014	(%)
Industrials	380	1,304	15.4	17.5	243.2
Cons Disc	457	1,209	18.5	16.3	164.6
Financials	427	1,182	17.3	15.9	176.8
Info Tech	342	949	13.8	12.8	177.5
Materials	179	745	7.2	10.0	316.2
Health Care	200	678	8.1	9.1	239.0
Cons Staples	191	491	7.7	6.6	157.1
Energy	128	471	5.2	6.3	268.0
Utilities	98	263	4.0	3.5	168.4
Telcoms	69	142	2.8	1.9	105.8
Total	**2,471**	**7,434**	**100.0**	**100.0**	**200.8**

Methodology related to source of analyst forecast error

In this research, I hypothesize that most the SFE is coming from the case of analysts failing to predict low earnings growth, not from analysts being across the board optimistic. This second section of the methodology focuses on research related to the source of analyst error. Some of the methodologies which may be used in this type of research are regression analysis, cluster analysis, and SUEST (Seemingly unrelated estimations) however, in this research a group compare methodology appears to have produced good evidence to allow for a relatively reliable conclusion. For future research, regression could be applied after overcoming two issues which appear to make it a less suitable methodology. The first is that the distribution of the data is clearly skewed, rather than normal. The second is that the independent variable in my hypothesis, actual EPS growth, is also used to calculate SFE which is the dependent variable. So, in this research I used group compare to identify if analyst were equally able to forecast the earnings of fast growth companies as well as slow growth companies.

To do this I calculated the arithmetic mean of actual earnings growth of all companies in the data set for each year. Then divided each year’s actual earnings growth in two halves, above average growth companies I called fast growth and below slow growth. After applying this for each year I then calculated the average SFE for each group and compared that against the average for the overall data set in that year.

To add another level of clarity, I separated the data into quartiles defining them as fast growth, moderately fast growth, moderately slow growth and slow growth and repeated the above process.

ANALYSIS

Analysts across the world were optimistically wrong by 25%

The first major finding of this research is that analysts around the world, over the 12-year period from 2003 to 2014, were optimistically wrong in their earnings forecasts by 25.3%. Figure 3 shows this arithmetic mean and a range from 53.1% in 2008 to 7.4% in 2004. Of the studies covered in the literature review, there were only a small number that had reviewed a wide universe of countries and that also calculated SFE scaled by EPS. Of those Coën's et al. (2009) shows the lowest SFE of 13.6% in 18 developed countries. Lu (1992) calculated a SFE of 14.5% in Asia, the next highest SFE was Coën et al. (2005) who came up with a SFE of 22% across eight countries in Asia. Finally, the highest SFE of 25.5% came from Chang et al. (2000) who also looked across Asia.

The strength of this research is that it considers the entire world of analyst forecasts and provides the most precise step-by-step process for handling the universe of data. Hence the claim of 25.3% analyst forecast accuracy could be considered most complete, hence most valid.

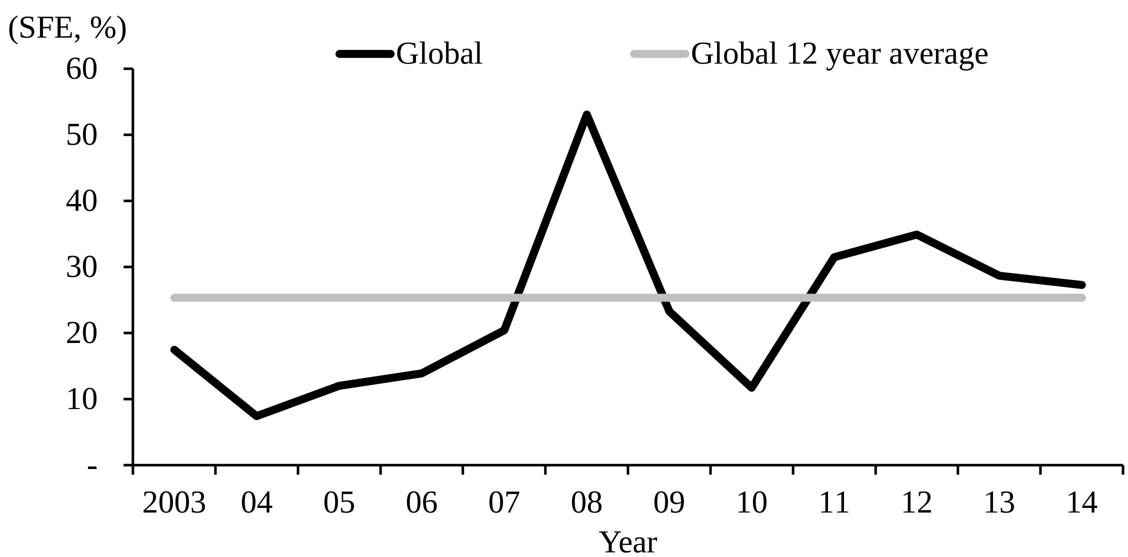

Figure 3. 25% wrong over the past 12 years. Across the globe analysts were 25% optimistically wrong in their earnings forecasts.

Figure 4 shows the frequency distribution of SFE across all stocks in the world. For ease of viewing, data points ±100% are captured in the respective tails of the figure. As prior research has shown, the distribution is right-skewed, demonstrating analyst optimism. The fact that the largest group of data points is >100% shows the high number of extremely positive outcomes. A calculation of the Pearson skewness coefficient showed 0.28%, which, if perfectly normally distributed, would be zero, implying an optimistic bias in SFE.

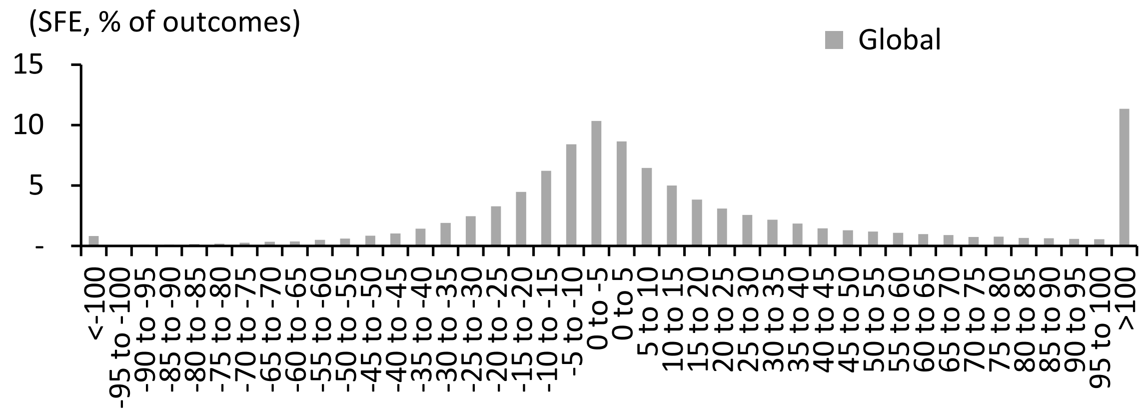

Figure 4. Optimistically skewed. The figure shows the frequency distribution of all 62,919 data points. Only 0.16% of points fell between -100% to -100.

Table 17 shows more detail of the output of the analysis. The average number of earnings estimates per company was about 10, the data show in recent times analysts are more likely to publish an earnings estimate, a recommendation, and a target price. One significant finding of this research is that over the year’s analysts have begun producing target prices about as often as they issue earnings estimates and recommendations. The SFE mean of 25.3% over the period versus the median of 3.3% is a straightforward way of visualizing the level of skewness of the distribution.

Table 17. Analyst earnings forecast accuracy of all countries globally

This table shows the details of the outcome of my analysis, key findings are that SFE was 25.3% over the period and SAFE was 43.9%.

Global countries	2003	2005	2010	2014	All years
Number of companies	2,471	3,886	5,832	7,434	5,390
Maximum number of earnings forecasts	43	42	50	55	59
Maximum number of recommendations	49	47	57	55	57
Maximum number of target prices	32	37	48	55	58
Average number of earnings estimates	10.2	9.1	9.9	10.4	9.9
Average number of recommendations	11.5	10.9	10.9	11.3	10.9
Average number of target prices	6.2	6.7	9.2	9.7	8.4
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	4,272	5,926	5,562	6,597	5,861
Median market cap (US$m)	868	1,369	1,367	1,625	1,367
Maximum market cap (US$m)	267,867	447,261	344,275	470,011	726,886
Mean SFE (%)	17.5	12.0	11.7	27.3	25.3
Median SFE (%)	0.3	(2.8)	(2.2)	5.8	3.3
Maximum SFE (%)	499.3	494.4	491.7	498.5	499.3
Minimum SFE (%)	(490.3)	(349.4)	(493.5)	(451.0)	(497.7)
Standard deviation of SFE (%)	74.9	66.3	74.2	75.3	78.8
Mean SAFE (%)	39.9	34.2	40.2	42.0	43.9
Median SAFE (%)	16.5	15.3	18.8	16.7	17.8
Maximum SAFE (%)	499.3	494.4	493.5	498.5	499.3
Minimum SAFE (%)	0.0	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	65.8	58.1	63.5	68.2	70.2

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error

Analysts forecast error for countries in Emerging market was a much higher 35%

The global nature of the data set allows the break out and comparison of SFE of Emerging markets versus the world. Both Figures 5 and 6 show that analysts in Emerging markets were less accurate, showing a SFE of 35%. As well, their earnings forecast was slightly more volatile.

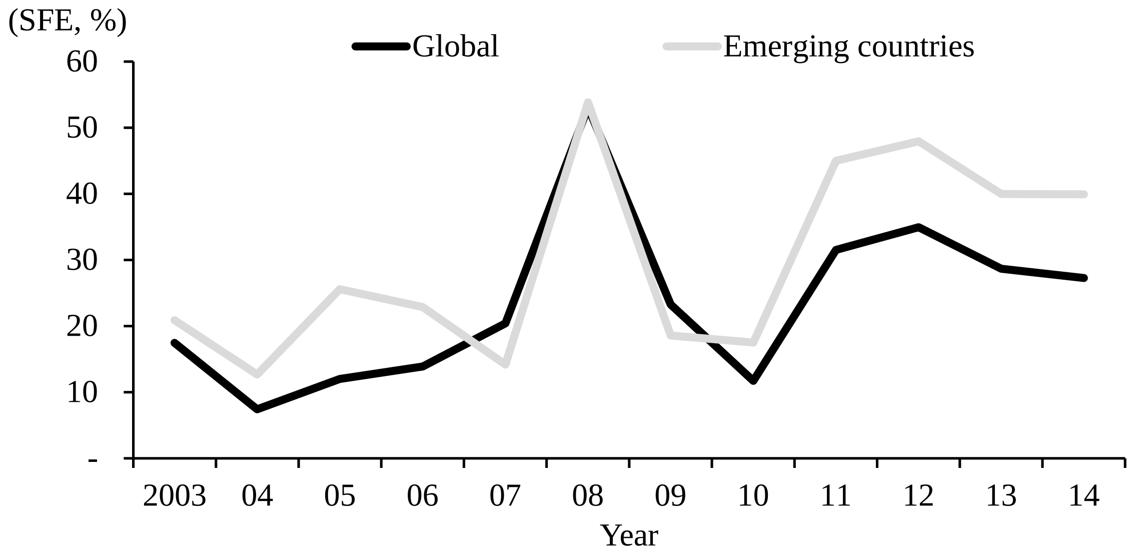

Figure 5. More analyst forecast error in Emerging markets. Analysts were less accurate, SFE was optimistically wrong at 35%, and SFE was more volatile in Emerging markets.

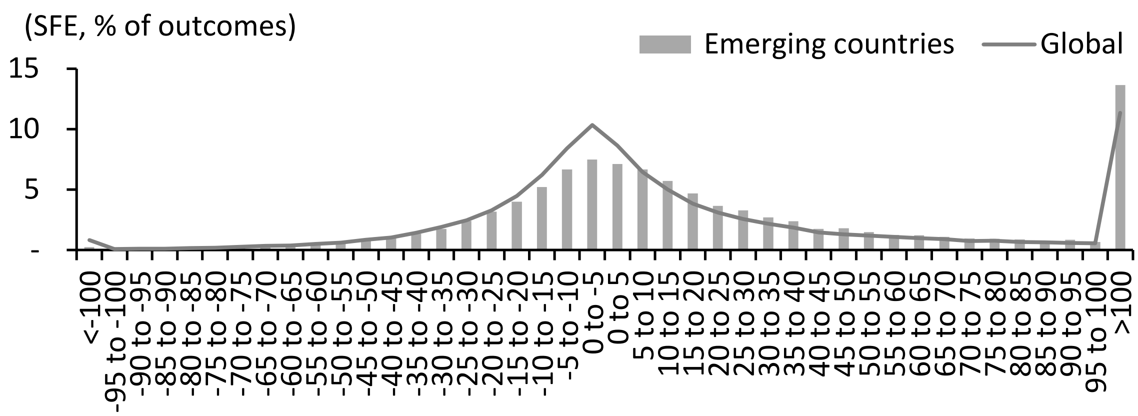

Figure 6. Greater analyst bias in EM. Analysts showed more positive bias in Emerging markets.

Table 18 shows more detail broken down by a country's level of economic development. As expected, Emerging market companies are considerably smaller than Developed market companies. Though it is not a focus of this research, it is clear from prior research that company size is positively correlated with forecast accuracy and that result shows itself in this research. Analyst earnings forecasts in Emerging markets are considerably less accurate, at 35%.

Table 18. Analyst earnings forecast accuracy across world by level of economic development
This table shows the details of the outcome of this analysis. Key findings are that SFE in Emerging countries at 35.0% was considerably higher than in developed countries at 22.3%.

Detail of output	Global countries	Developed countries	Emerging countries	Dev'd countries ex US countries
Number of companies	5,390	4,099	1,291	2,585
Maximum number of earnings forecasts	59	56	59	50
Maximum number of recommendations	57	57	55	57
Maximum number of target prices	58	49	58	46
Average number of earnings estimates	9.9	10.3	8.8	10.1
Average number of recommendations	10.9	11.0	10.7	11.0
Average number of target prices	8.4	8.2	8.9	8.2
Minimum number of earnings estimates	3	3	3	3
Minimum number of recommendations	1	1	1	1
Minimum number of target prices	1	1	1	1
Mean market capitalization (US$m)	5,861	6,378	4,219	5,849
Median market cap (US$m)	1,367	1,394	1,311	1,378
Maximum market cap (US$m)	726,886	726,886	449,435	726,886
Mean SFE (%)	25.3	22.3	35.0	25.6
Median SFE (%)	3.3	1.8	9.8	3.2
Maximum SFE (%)	499.3	499.3	498.6	499.3
Minimum SFE (%)	(497.7)	(497.7)	(477.4)	(497.7)
Standard deviation of SFE (%)	78.8	77.5	82.1	79.5
Mean SAFE (%)	43.9	42.2	49.5	44.9
Median SAFE (%)	17.8	16.7	21.7	18.5
Maximum SAFE (%)	499.3	499.3	498.6	499.3
Minimum SAFE (%)	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	70.2	68.7	74.3	70.4

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error

Analysts forecast error was higher for cyclical industries

Globally, analysts were least accurate in forecasting earnings of companies that were in cyclical sectors such as Materials and Energy. They were much more accurate in the non-cyclical sectors such as Health Care, Telecoms, and Utilities. In fact, cyclical company forecast error was at least double that of non-cyclical.

Table 19. Test of correlation of prior EPS volatility and earnings forecast volatility – By sector
SFE in the cyclical sectors Materials sector was three times as inaccurate as the non-cyclical Health Care sector.

Sector	Mean SFE (%)
Materials	41.7
Energy	36.5
Info Tech	30.3
Industrial	26.6
Cons Disc	24.9
Cons Staples	20.6
Financial	18.1
Utilities	16.8
Telecom	16.3
Health Care	13.1
Global	25.3

More analysts make for more accurate forecasts, to a point

This research shows that as the number of analysts increased, earnings forecast accuracy improved. Moving from 3-5 analysts to 6-10 analyst caused accuracy to improve by almost five percentage points, and this continued to 11-20 analysts and finally to 20-30 analysts. An interesting finding shows in Figure 7 which is that above 30 analysts, accuracy actually worsened. An area of further study would be to ascertain the source of this difference.

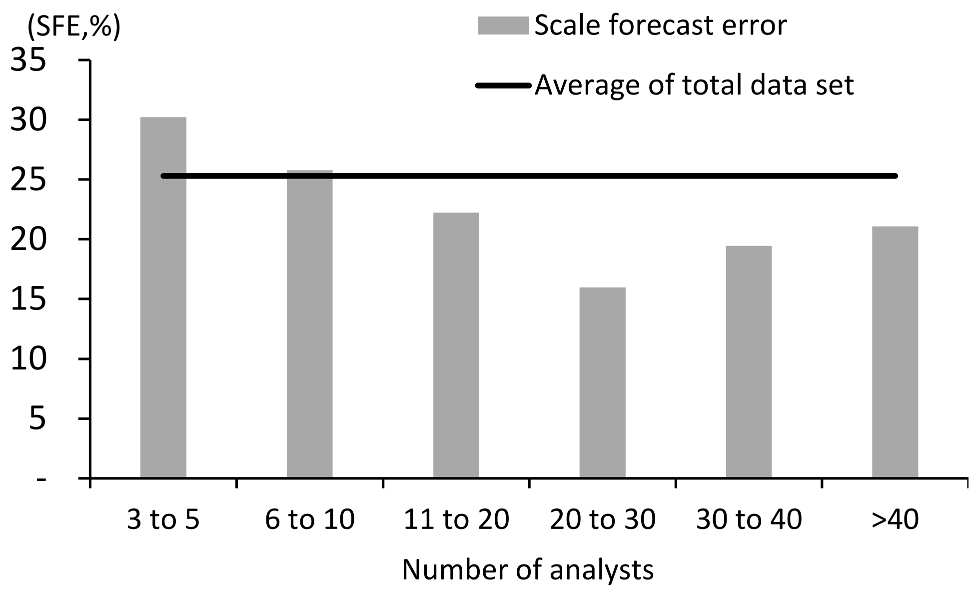

Figure 7. More analysts, more accurate forecasts, to a point. As the number of analysts forecasting a company rises, the average accuracy of those analysts improves. But this does not seem to apply for cases of more than 30 analysts covering a company, which at that point earnings forecast accuracy falls.

Degree of skewness varied, generally Developed market forecast were less skewed

As had been revealed in prior research analyst forecasts were optimistically biased, to find a better understanding of the degree of that bias this research measures the level of skewness of the data. Table 20 shows that for the total universe mean SFE was 25.3%, median was 3.3%, while standard deviation of SFE was 78.8%. I used the Pearson skewness coefficient to measure the degree of skewness. A perfectly normal distribution gave a Pearson coefficient of zero as the mean was no different than the median, a positive coefficient illustrated a positive skew.

Table 20. Degree of skewness - By stage of development and region

Analysts are positively biased and this shows in the level of Skewness. Testing with the Pearson Skewness Coefficient shows that Emerging markets and Asia ex-Japan were most skewed, while the Developed world, especially North America, was least skewed

	Mean SFE (%)	Median SFE (%)	Standard deviation of SFE (%)	Pearson skewness coefficient
Global	25.3	3.3	78.8	0.28
Stage of development:				
Developed	22.3	1.8	77.5	0.26
Developed ex US	25.6	3.2	79.5	0.28
Emerging	35.0	9.8	82.1	0.31
By regions:				
Asia ex Japan	34.1	9.4	81.0	0.31
Latin America	22.1	3.4	70.0	0.29
Europe	37.3	12.7	83.7	0.27
ASEAN	19.5	0.7	77.1	0.27
North America	22.7	2.0	75.6	0.24

The degree of skewness by sector shows a breakdown that is related to cyclical vs non-cyclical companies. Companies within cyclical sectors such as Materials and Industrial sectors tend to be harder to forecast and are more positively skewed compared with non-cyclical companies such as Health Care and Telecoms.

Table 21. Degree of skewness – By sector

Analysts are positively biased and this shows in the level of Skewness. Testing with the Pearson Skewness Coefficient shows that the Materials sector was most skewed, while sectors with less volatile earnings such as Health Care and Telecoms were much less skewed

	Mean SFE (%)	Median SFE (%)	Standard deviation of SFE (%)	Pearson skewness coefficient
Materials	41.7	10.9	95.8	0.32
Industrials	26.6	3.5	78.8	0.29
Info Tech	30.3	4.7	88.3	0.29
Energy	36.5	8.7	94.7	0.29
Cons Disc	24.9	4.0	75.3	0.28
Cons Staples	20.6	3.3	62.6	0.28
Financials	18.1	0.2	69.5	0.26
Utilities	16.8	0.1	64.1	0.26
Telecom	16.3	3.9	67.7	0.18
Health Care	13.1	1.6	68.1	0.17
Global	25.3	3.3	78.8	0.28

Of the Developed Countries Italy, Canada and Japan all are highly positively skewed, which appears to be driven mainly by their elevated level of SFE. Countries such as UK and US are least skewed, due mainly to lower SFE.

Table 22. Degree of skewness – By top-10 Developed countries

Analysts are positively biased and this shows in the level of Skewness. Testing with the Pearson Skewness Coefficient shows that countries such as Italy and Canada are most skewed, while more established and developed markets in countries like the UK and US were much less skewed

	Mean SFE (%)	Median SFE (%)	Standard deviation of SFE (%)	Pearson skewness coefficient
Japan	30.9	3.2	91.6	0.30
Italy	36.1	8.7	84.7	0.32
Canada	35.5	7.6	92.3	0.30
Germany	29.1	4.6	83.8	0.29
Australia	22.1	4.5	63.4	0.28
Hong Kong SAR	24.6	4.4	71.9	0.28
France	24.4	4.0	77.7	0.26
Switzerland	20.2	2.9	68.9	0.25
USA	16.6	0.0	73.5	0.23
United Kingdom	10.3	(1.4)	55.8	0.21
Global	25.3	3.3	78.8	0.28

Of the Emerging Countries South Korea, China and Brazil are all highly skewed, in fact, the level of skewness in South Korea is above all others and provides for an excellent area of further research. For this study, we have used MSCI country classifications and they continue to classify South Korea as emerging due to the limited convertibility of the currency and prohibition of in-kind transfers of securities. Based upon my experience I believe that the pressures on analysts to maintain a positive relationship with the management of the companies they forecast is causing this extreme degree of optimism in their forecast. However, more work needs to be done to test the validity of this belief.

Table 23. Degree of skewness – By top-10 Emerging countries

South Korea and China are global stand outs which both experience the highest level of skewness. Malaysia has had the lowest level of skewness.

	Mean SFE (%)	Median SFE (%)	Standard deviation of SFE (%)	Pearson skewness coefficient
South Korea	65.4	30.1	106.0	0.33
China	45.9	18.1	83.5	0.33
Brazil	46.4	17.1	90.5	0.32
India	32.6	7.0	82.7	0.31
Indonesia	30.1	6.4	79.7	0.30
South Africa	24.1	4.7	66.6	0.29
Turkey	23.3	(0.0)	78.7	0.30
Thailand	26.2	4.9	76.6	0.28
Taiwan region	34.7	10.1	88.2	0.28
Malaysia	19.9	3.0	65.2	0.26
Global	25.3	3.3	78.8	0.28

Almost all analyst earnings forecast error comes when earnings are falling

The prior literature on this subject, as well as our findings shows that clearly analysts have a positive bias. To investigate the source of this, I apply the group compare methodology outlined in the above methodology section. Figure 8, shows the ups and downs of earnings of all companies in the study with an average annual earnings growth during this period of 17.7%.

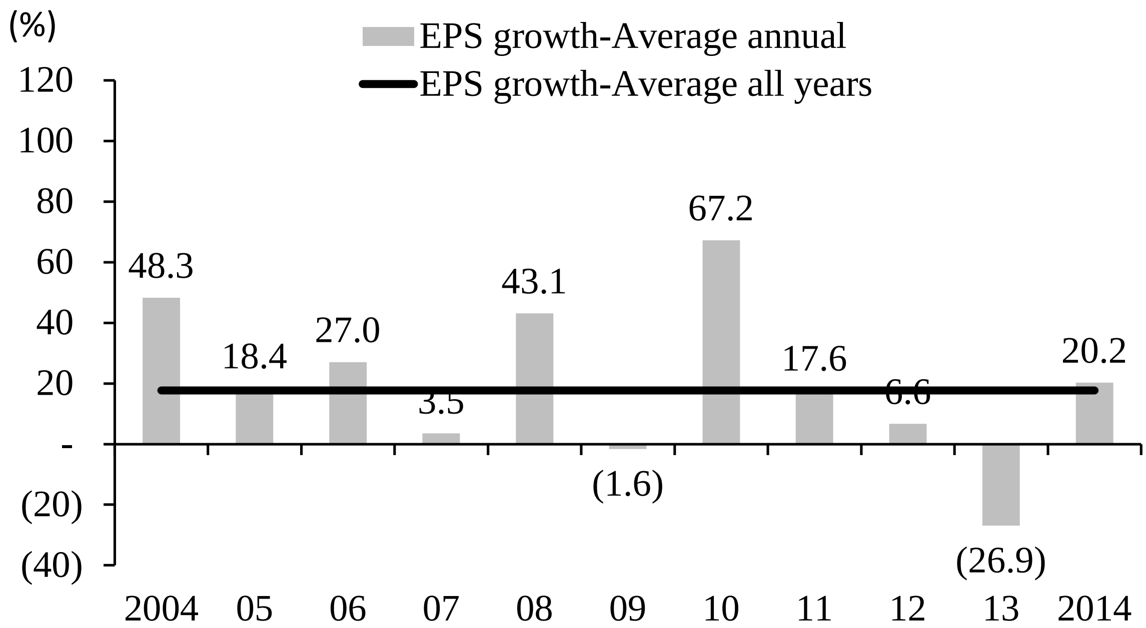

Figure 8. Yearly average earnings growth. This chart shows that actual earnings per share (EPS) growth of all companies in the data set were up as high as 67.2% in 2010 and as low as 26.9% in 2013 and had an average growth rate of 17.7%.

The next step was to split the universe into halves, each year with the half above that year's average actual EPS growth being considered fast growth companies and those in the bottom half as slow growth companies. I then took the arithmetic mean SFE for each group. Figure 9 shows that for fast growth companies, unlike my finding of optimism of 25.3% of the whole universe, analysts were pessimistic, with actual earnings beating analysts' forecasts by 4.6%. For slow growth companies, analyst estimates were 54.9% above the actual earnings. This shows that that analyst optimism was almost completely coming from slow growth companies.

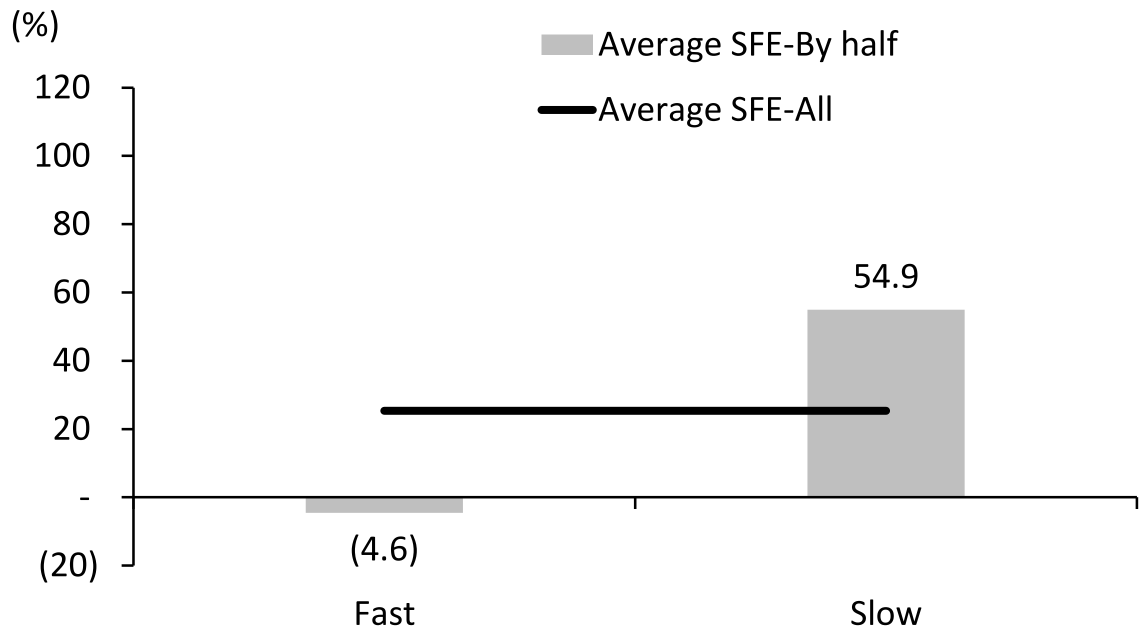

Figure 9. Forecast error for fast and slow growth companies. When we separate, the data set into companies that produced above average or below average earnings growth in each year we find that almost all the optimism is related to slow growth companies. Analyst SFE was optimistic by 54.9% for slow companies vs. analyst pessimism of 4.6% in fast growth companies.

To understand the data better we extend the grouping analysis to cover not only the actual earnings growth but also the size of the company as well as the number of analysts covering the company. I compare each group and find that actual earnings growth for the fast growth group of companies was 106.2% while for the slow growth group it was negative 70.8%. The average number of analysts covering the companies was about equal at 10 analysts and the average market capitalization was nearly equal at about US$6bn. My conclusion from this group compare analysis is that the most significant factor determining SFE was whether the company had fast or slow earnings growth.

Table 24. SFE based on the direction of EPS growth

Companies with slow EPS growth relative to the average growth of all companies per year is where the analyst optimism resides.

	Fast	Slow	All companies
Average number of companies	2,659	2,660	5,318
Average actual EPS growth (%)	106.2	(70.8)	17.7
Average SFE (%)	(4.6)	54.9	25.2
Average number of analyst covering	10.0	10.1	10.1
Average market capitalization (US$m)	6,078.0	6,057.2	6,067.6

To get more precise at identifying the source of analyst optimism in Figure 10 I group the universe into quartiles, rather than halves. This seems to show that analysts were unable to be equally accurate in their earnings forecast for fast and slow growth companies. Analysts were 96.2% optimistic in their forecasts for this slowest growth group of companies, the other three quartiles averaged out to slightly above zero.

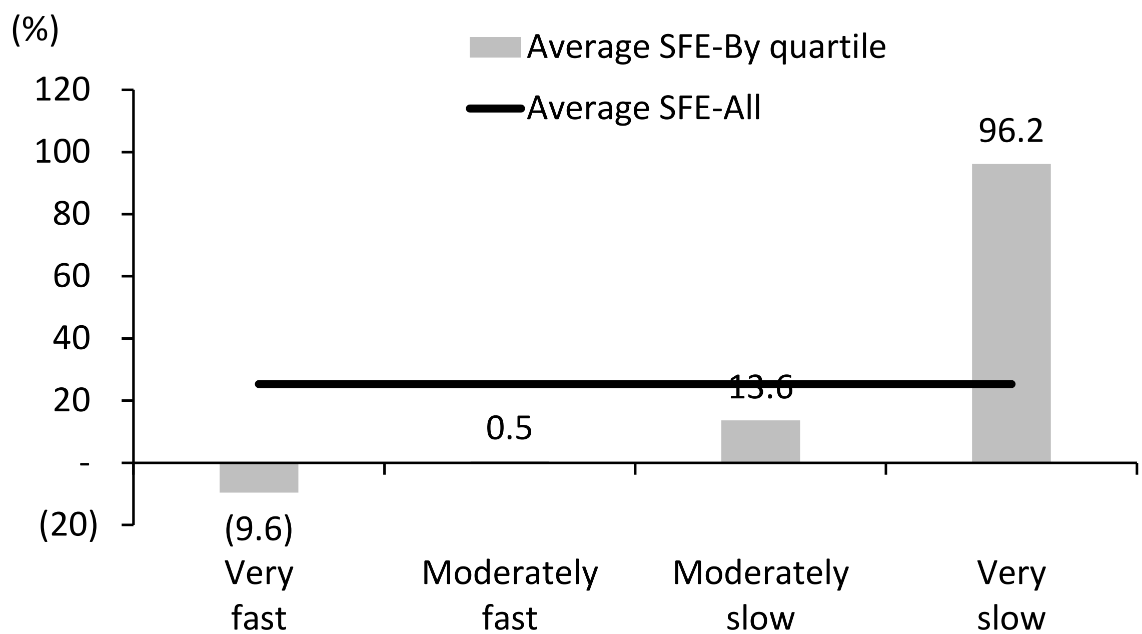

Figure 10. Forecast error for very fast, moderately fast, moderately slow, and very slow growth companies. When the data is separated into four groups of companies based upon each year's actual earnings growth almost all the optimism is related to very slow growth companies. Analyst SFE was optimistic by 96.2% for very slow growth companies vs. analyst pessimism of 9.6% in very fast growth companies.

Table 25 provides more detail of the group compare analysis which shows again that actual earnings growth was very strongly positive for very fast growth companies at 192% vs negative 140% for very slow growth companies. The difference from the prior grouping is that quartile grouping allows us to segregate and consider more extreme cases. The average number of analysts covering companies that ended up in the most extreme quartiles was about 9 compared with 11 for the two moderate quartiles, while average market capitalization at moderate quartiles of about US$8bn, was nearly two times those of the most extreme.

Table 25. SFE based on more extreme direction of EPS growth

To add more precision to the analysis the table shows companies broken into quartiles based upon their level of actual EPS growth. The conclusion is that very fast and very slow growth companies are about equally likely to be smaller companies and companies with slightly less analyst coverage. However, SFE tends to be most optimistic at very slow growth companies.

	Very fast	Moderately fast	Moderately slow	Very slow	All companies
Average number of companies	1,329	1,330	1,329	1,330	5,318
Average actual EPS growth (%)	192	20.1	(1.3)	(140)	18
Average SFE (%)	(9.6)	0.5	13.6	96.2	25.2
Average number of analyst covering	9.2	10.8	10.8	9.3	10.1
Average market capitalization (US$m)	4,394	7,761	7,999	4,118	6,068

This grouping study leads us to conclude that the number of analysts and size of companies follows a somewhat normal distribution across the four quadrants and that such a distribution is not the case for average SFE.

Grouping and investigating the relationship between EPS growth volatility and the average SFE reveals:

1) Almost all analyst optimism appears to be coming from the slowest growth companies, in fact, the most extremely slow growth companies.
2) Companies with extremely fast or slow actual earnings growth are equally likely to be smaller companies and companies with slightly less than an average number of analysts covering them.

CONCLUSION

Over the past 12 years, financial analysts across the world have been optimistically wrong with their 12-month earnings forecasts by 25%. This study is the first of its kind to assess analyst earnings forecast accuracy at all listed companies across the globe, covering 70 countries.

Prior research shows little uniformity in the preparation of the data set, yet differences in how outliers are treated, for example, can create substantially different results.

The first uniqueness of this research is its clear description of steps to take to prepare the data related to analyst forecast accuracy. That process was first to remove small companies, second to remove companies which did not have at least one analyst covering them, third to require that there was at least one target price and recommendation, fourth was to remove tiny numbers which can distort the results, fifth was to eliminate outliers that exceed ±500%, and finally to focus the study on companies which had three or more analysts and at least one target price and at least one recommendation.

Main conclusions from this analysis were that analyst earnings forecasts globally were 25.3% optimistically wrong. That analysts had a harder time forecasting earnings for companies in emerging markets where they are 33.7% optimistically wrong. That analysts found it harder to forecast companies where earnings growth was extremely slow.

From this work, a few areas for further research stand out. This research showed that as the number of analysts increased, earnings forecast accuracy improved. However, at a level of coverage above 30 analysts, accuracy worsened. It would be interesting to ascertain the source of this difference.

Of the Emerging Countries South Korea, China and Brazil are all highly skewed, in fact, the level of skewness in South Korea is above all others and provides for an excellent area of further research.

A further question to answer in future research is whether analysts are more successful during certain periods of market movements or of the earnings cycle.

Lastly, is to consider research on whether a profitable trading strategy could be adopted from this deeper understanding of analyst earnings forecast error.

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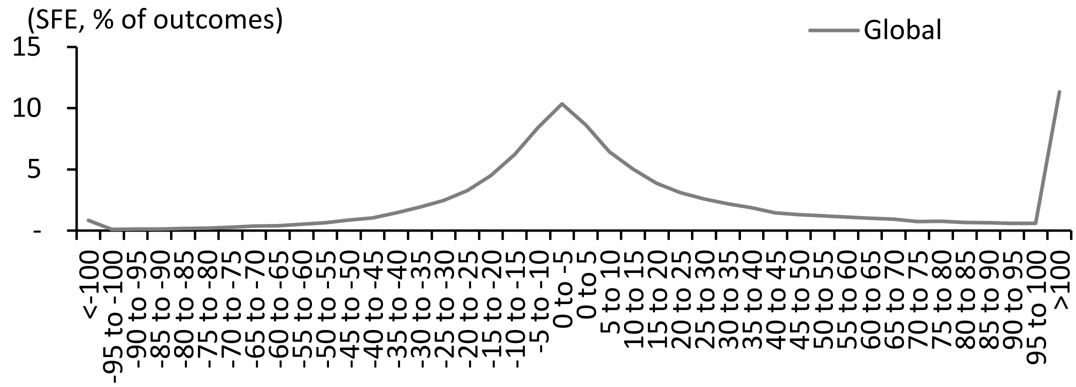
APPENDIX

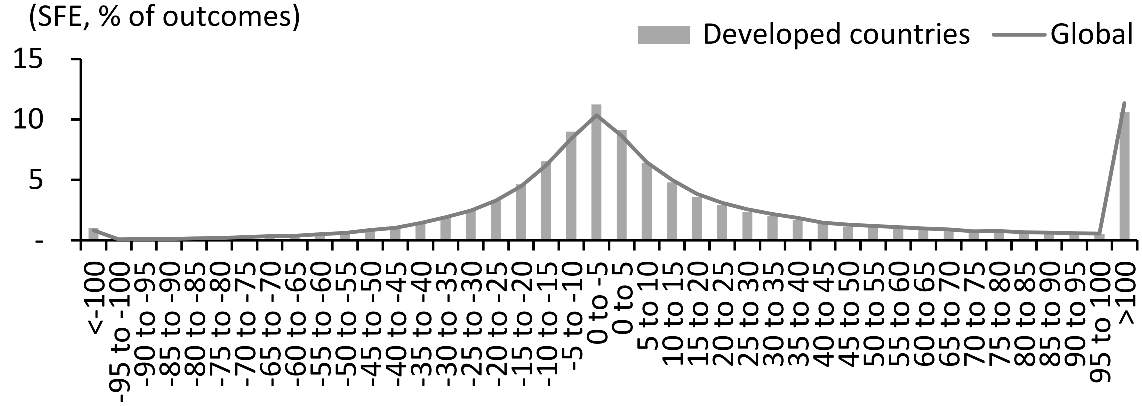
Appendix 1: Frequency distribution of SFE and statistic – Global



Global	2003	2005	2010	2014	All years
Number of companies	2,471	3,886	5,832	7,434	5,390
Maximum number of earnings forecasts	43	42	50	55	59
Maximum number of recommendations	49	47	57	55	57
Maximum number of target prices	32	37	48	55	58
Average number of earnings estimates	10.2	9.1	9.9	10.4	9.9
Average number of recommendations	11.5	10.9	10.9	11.3	10.9
Average number of target prices	6.2	6.7	9.2	9.7	8.4
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	4,272	5,926	5,562	6,597	5,861
Median market cap (US$m)	868	1,369	1,367	1,625	1,367
Maximum market cap (US$m)	267,867	447,261	344,275	470,011	726,886
Mean SFE (%)	17.5	12.0	11.7	27.3	25.3
Median SFE (%)	0.3	(2.8)	(2.2)	5.8	3.3
Maximum SFE (%)	499.3	494.4	491.7	498.5	499.3
Minimum SFE (%)	(490.3)	(349.4)	(493.5)	(451.0)	(497.7)
Standard deviation of SFE (%)	74.9	66.3	74.2	75.3	78.8
Mean SAFE (%)	39.9	34.2	40.2	42.0	43.9
Median SAFE (%)	16.5	15.3	18.8	16.7	17.8
Maximum SAFE (%)	499.3	494.4	493.5	498.5	499.3
Minimum SAFE (%)	0.0	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	65.8	58.1	63.5	68.2	70.2

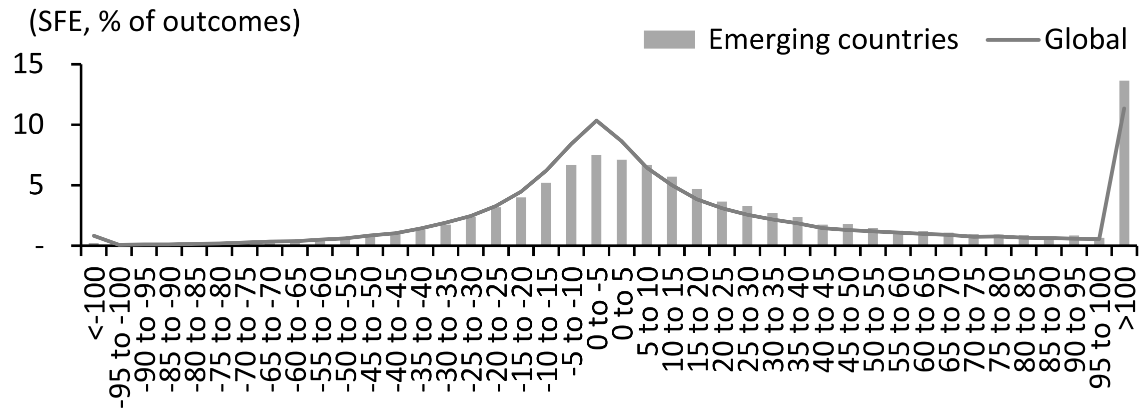
Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error

Appendix 1: Frequency distribution of SFE and statistics – Stage of development



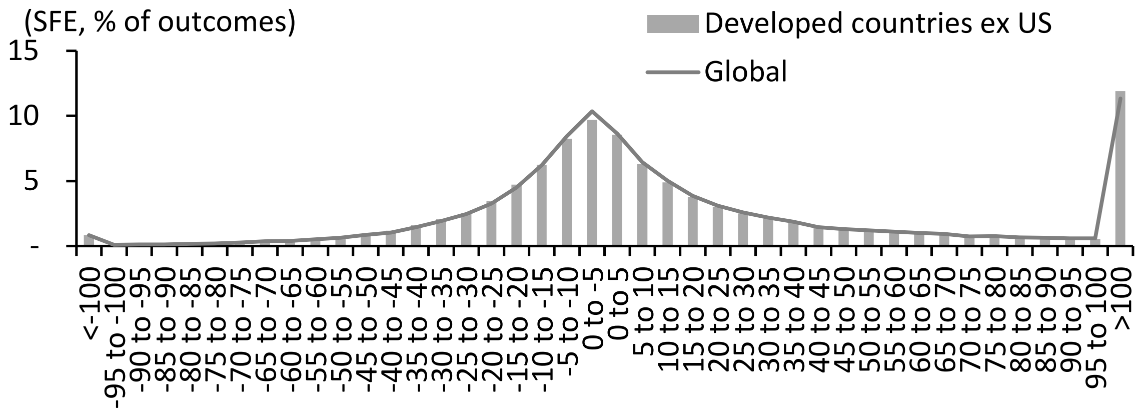
Developed countries	2003	2005	2010	2014	All years
Number of companies	2,024	3,344	4,466	4,977	4,099
Maximum number of earnings forecasts	43	42	50	55	56
Maximum number of recommendations	49	47	57	55	57
Maximum number of target prices	32	30	46	49	49
Average number of earnings estimates	10.3	9.4	10.4	10.9	10.3
Average number of recommendations	11.4	11.0	11.1	11.4	11.0
Average number of target prices	6.1	6.5	9.1	10.1	8.2
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	4,906	6,507	5,700	7,814	6,378
Median market cap (US$m)	947	1,465	1,295	1,797	1,394
Maximum market cap (US$m)	267,867	447,261	209,516	470,011	726,886
Mean SFE (%)	16.7	9.8	9.9	21.0	22.3
Median SFE (%)	0.2	(3.6)	(3.4)	2.9	1.8
Maximum SFE (%)	499.3	494.4	489.7	496.9	499.3
Minimum SFE (%)	(490.3)	(349.4)	(493.5)	(451.0)	(497.7)
Standard deviation of SFE (%)	73.3	63.7	76.5	70.1	77.5
Mean SAFE (%)	38.0	32.9	41.2	37.5	42.2
Median SAFE (%)	14.4	14.9	18.8	14.5	16.7
Maximum SAFE (%)	499.3	494.4	493.5	496.9	499.3
Minimum SAFE (%)	0.0	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	64.9	55.4	65.3	62.8	68.7

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



Emerging countries	2003	2005	2010	2014	All years
Number of companies	447	542	1,366	2,457	1,291
Maximum number of earnings forecasts	28	28	46	50	59
Maximum number of recommendations	30	41	45	54	55
Maximum number of target prices	23	37	48	55	58
Average number of earnings estimates	9.7	7.5	8.1	9.3	8.8
Average number of recommendations	12.0	10.3	10.3	10.9	10.7
Average number of target prices	6.9	7.9	9.6	9.0	8.9
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	2	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	1,405	2,343	5,110	4,133	4,219
Median market cap (US$m)	514	887	1,591	1,358	1,311
Maximum market cap (US$m)	32,576	65,732	344,275	223,728	449,435
Mean SFE (%)	20.9	25.6	17.5	39.9	35.0
Median SFE (%)	1.7	2.9	1.8	14.0	9.8
Maximum SFE (%)	488.3	492.8	491.7	498.5	498.6
Minimum SFE (%)	(467.5)	(85.4)	(477.4)	(391.1)	(477.4)
Standard deviation of SFE (%)	81.7	79.1	65.7	83.5	82.1
Mean SAFE (%)	48.5	42.1	36.9	51.1	49.5
Median SAFE (%)	25.9	17.8	18.5	21.4	21.7
Maximum SAFE (%)	488.3	492.8	491.7	498.5	498.6
Minimum SAFE (%)	0.0	0.1	0.0	0.0	0.0
Standard deviation of SAFE (%)	69.0	71.7	57.2	77.1	74.3

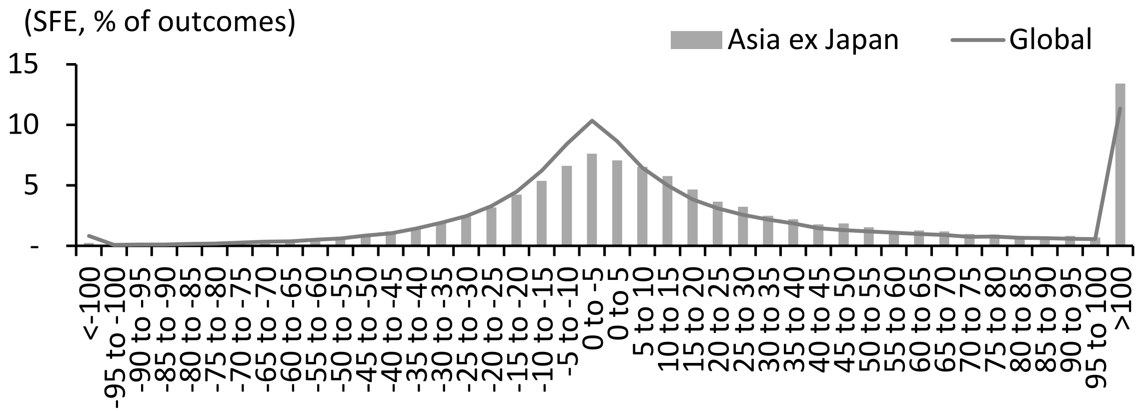
Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



Dev'd countries ex US	2003	2005	2010	2014	All years
Number of companies	969	2,077	2,921	2,999	2,585
Maximum number of earnings forecasts	43	35	50	40	50
Maximum number of recommendations	49	47	57	44	57
Maximum number of target prices	25	24	46	37	46
Average number of earnings estimates	11.1	8.7	10.3	10.6	10.1
Average number of recommendations	13.0	11.1	11.1	11.2	11.0
Average number of target prices	4.8	6.1	9.4	10.3	8.2
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	3,679	5,873	5,377	7,099	5,849
Median market cap (US$m)	813	1,428	1,336	1,755	1,378
Maximum market cap (US$m)	267,867	447,261	193,000	241,363	726,886
Mean SFE (%)	19.2	9.4	14.6	23.9	25.6
Median SFE (%)	1.9	(4.9)	(1.9)	4.8	3.2
Maximum SFE (%)	499.3	494.4	480.6	496.5	499.3
Minimum SFE (%)	(490.3)	(248.4)	(389.4)	(316.3)	(497.7)
Standard deviation of SFE (%)	74.9	64.7	76.2	69.6	79.5
Mean SAFE (%)	41.8	35.2	42.1	39.2	44.9
Median SAFE (%)	17.7	17.3	19.1	16.5	18.5
Maximum SAFE (%)	499.3	494.4	480.6	496.5	499.3
Minimum SAFE (%)	0.0	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	65.0	55.1	65.2	62.2	70.4

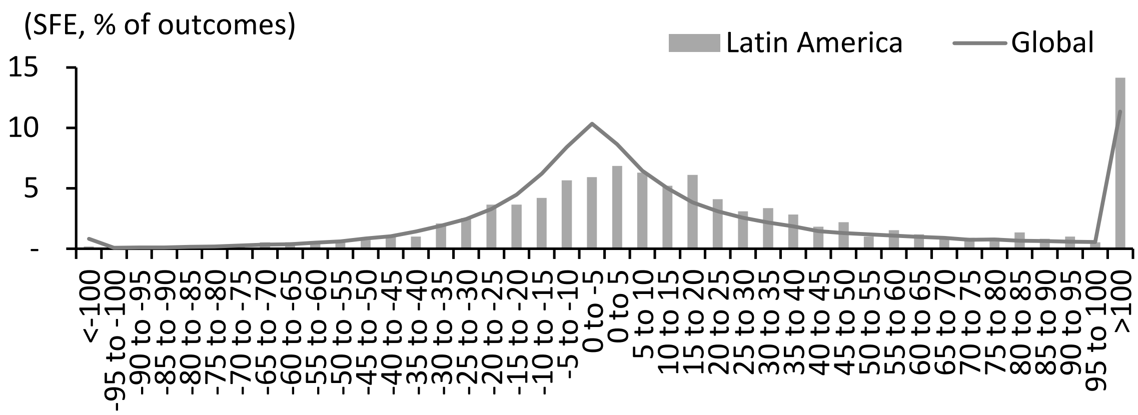
Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error

Appendix 1: Frequency distribution of SFE and statistics – Regions



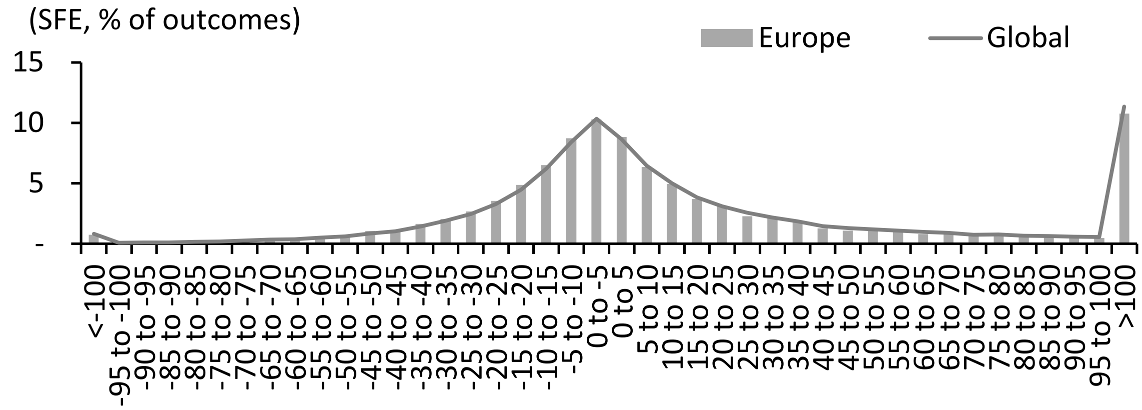
Asia ex Japan	2003	2005	2010	2014	All years
Number of companies	555	651	1,285	2,225	1,253
Maximum number of earnings forecasts	31	28	46	50	59
Maximum number of recommendations	31	41	45	54	55
Maximum number of target prices	25	37	48	55	58
Average number of earnings estimates	11.0	8.7	8.9	10.3	9.7
Average number of recommendations	13.3	11.1	11.0	11.6	11.5
Average number of target prices	8.3	8.8	9.9	9.5	9.4
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	2	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	1,522	2,232	5,112	4,133	4,114
Median market cap (US$m)	491	669	1,599	1,340	1,229
Maximum market cap (US$m)	38,968	64,411	344,275	223,728	449,435
Mean SFE (%)	18.5	24.2	15.4	41.5	34.1
Median SFE (%)	2.5	2.9	0.1	15.6	9.4
Maximum SFE (%)	488.3	492.8	491.7	498.5	498.6
Minimum SFE (%)	(467.5)	(95.1)	(477.4)	(391.1)	(477.4)
Standard deviation of SFE (%)	73.5	77.5	64.7	83.4	81.0
Mean SAFE (%)	43.5	41.8	35.4	51.8	48.7
Median SAFE (%)	23.3	18.0	17.4	21.9	21.4
Maximum SAFE (%)	488.3	492.8	491.7	498.5	498.6
Minimum SAFE (%)	0.0	0.1	0.0	0.0	0.0
Standard deviation of SAFE (%)	62.0	69.5	56.3	77.5	73.1

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



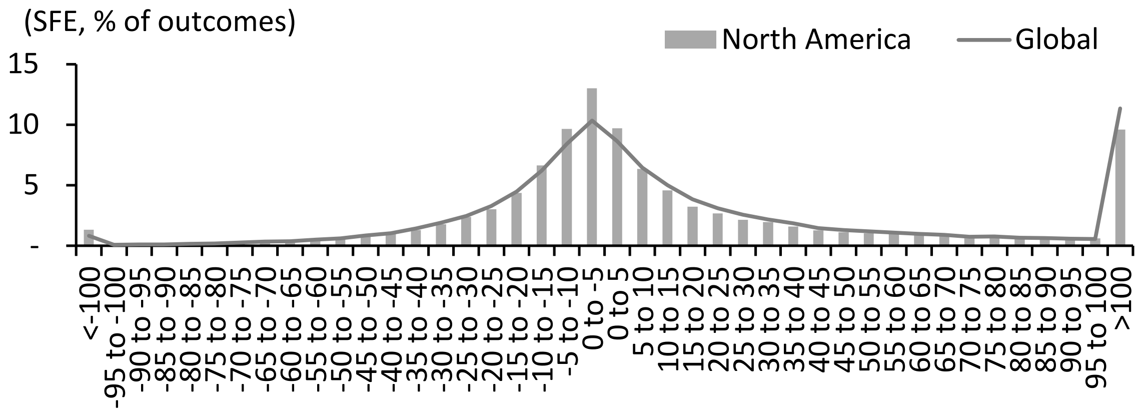
Latin America	2003	2005	2010	2014	All years
Number of companies	57	33	98	179	91
Maximum number of earnings forecasts	19	12	13	17	19
Maximum number of recommendations	19	16	22	20	23
Maximum number of target prices	10	14	23	20	23
Average number of earnings estimates	8.8	5.2	6.5	7.8	7.2
Average number of recommendations	8.6	8.2	9.6	10.0	9.6
Average number of target prices	4.7	7.3	9.7	9.9	9.3
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	3	2	3	2
Minimum number of target prices	1	2	3	2	1
Mean market capitalization (US$m)	1,977	5,925	7,668	6,990	6,891
Median market cap (US$m)	702	2,347	2,760	2,652	2,539
Maximum market cap (US$m)	17,254	65,732	133,257	153,300	200,078
Mean SFE (%)	49.1	3.2	12.8	45.8	37.3
Median SFE (%)	20.0	(3.1)	1.3	15.2	12.7
Maximum SFE (%)	370.1	313.5	186.8	450.7	471.4
Minimum SFE (%)	(131.4)	(85.4)	(50.8)	(99.0)	(131.4)
Standard deviation of SFE (%)	101.0	63.2	48.2	86.6	83.7
Mean SAFE (%)	74.0	31.7	32.0	56.5	52.0
Median SAFE (%)	44.2	19.8	21.0	22.0	24.0
Maximum SAFE (%)	370.1	313.5	186.8	450.7	471.4
Minimum SAFE (%)	1.6	0.6	0.2	0.1	0.1
Standard deviation of SAFE (%)	84.2	54.5	38.1	79.9	75.5

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



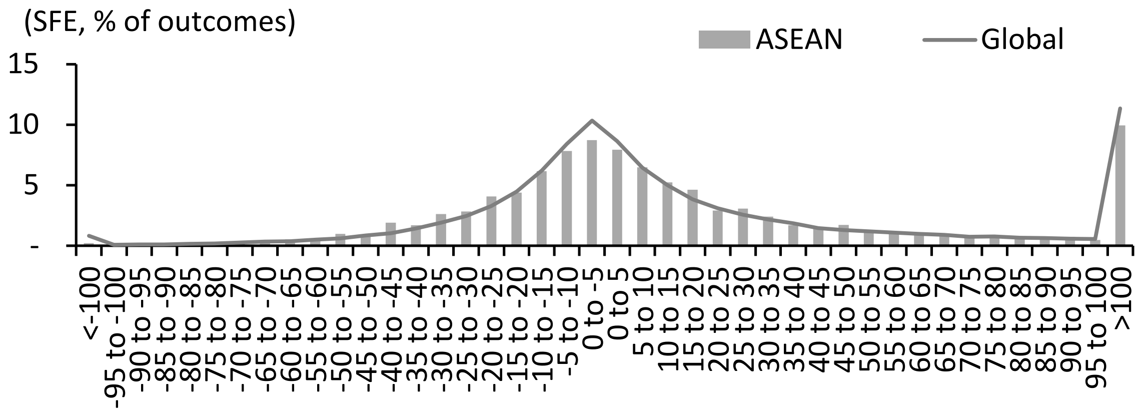
Europe	2003	2005	2010	2014	All years
Number of companies	427	1,019	1,592	1,524	1,359
Maximum number of earnings forecasts	43	35	50	40	50
Maximum number of recommendations	49	47	57	44	57
Maximum number of target prices	7	24	46	35	46
Average number of earnings estimates	12.7	9.3	11.7	11.7	11.3
Average number of recommendations	16.3	13.6	12.7	12.6	12.6
Average number of target prices	2.6	6.7	11.0	11.5	9.2
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	5,633	7,898	5,838	8,460	6,770
Median market cap (US$m)	1,385	1,656	1,123	1,981	1,355
Maximum market cap (US$m)	267,867	447,261	176,576	241,363	726,886
Mean SFE (%)	18.5	5.8	10.5	21.8	22.7
Median SFE (%)	1.5	(8.0)	(4.1)	5.0	2.0
Maximum SFE (%)	499.3	494.4	472.9	470.8	499.3
Minimum SFE (%)	(340.7)	(248.4)	(389.4)	(316.3)	(497.7)
Standard deviation of SFE (%)	78.5	66.6	72.7	66.2	75.6
Mean SAFE (%)	42.6	36.1	40.0	37.1	41.9
Median SAFE (%)	16.9	18.9	19.0	15.3	17.3
Maximum SAFE (%)	499.3	494.4	472.9	470.8	499.3
Minimum SAFE (%)	0.0	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	68.5	56.3	61.6	59.0	67.0

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



North America	2003	2005	2010	2014	All years
Number of companies	1,202	1,477	1,876	2,334	1,793
Maximum number of earnings forecasts	39	42	45	55	56
Maximum number of recommendations	38	42	43	55	56
Maximum number of target prices	32	30	39	49	49
Average number of earnings estimates	9.5	10.0	10.1	10.9	10.2
Average number of recommendations	9.7	10.5	10.7	11.5	10.7
Average number of target prices	7.3	7.2	8.6	9.7	8.2
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	5,575	6,967	5,878	8,251	6,777
Median market cap (US$m)	1,029	1,443	1,178	1,689	1,309
Maximum market cap (US$m)	257,125	382,485	209,516	470,011	559,129
Mean SFE (%)	15.3	13.2	6.3	19.8	19.5
Median SFE (%)	(0.5)	(1.6)	(4.5)	1.8	0.7
Maximum SFE (%)	468.9	487.2	489.7	496.9	497.6
Minimum SFE (%)	(490.3)	(349.4)	(493.5)	(451.0)	(493.5)
Standard deviation of SFE (%)	74.7	65.9	80.9	73.8	77.1
Mean SAFE (%)	36.0	32.1	42.5	38.2	40.6
Median SAFE (%)	12.1	12.2	18.5	12.8	15.0
Maximum SAFE (%)	490.3	487.2	493.5	496.9	497.6
Minimum SAFE (%)	0.1	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	67.3	59.1	69.1	66.2	68.4

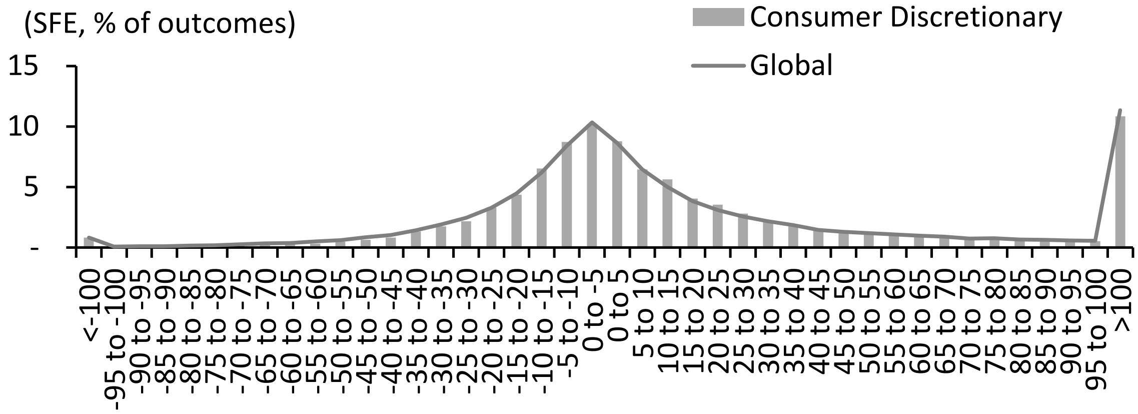
Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



ASEAN	2003	2005	2010	2014	All years
Number of companies	236	302	339	439	338
Maximum number of earnings forecasts	28	24	25	27	28
Maximum number of recommendations	30	27	26	28	30
Maximum number of target prices	19	21	25	28	30
Average number of earnings estimates	11.9	8.7	9.7	10.2	9.9
Average number of recommendations	12.8	10.1	10.4	10.9	10.8
Average number of target prices	7.7	8.0	10.2	11.1	9.8
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	2	2	1	1
Minimum number of target prices	1	1	2	2	1
Mean market capitalization (US$m)	888	1,340	2,772	3,674	2,574
Median market cap (US$m)	333	458	963	1,382	867
Maximum market cap (US$m)	14,040	25,839	33,024	49,584	49,584
Mean SFE (%)	14.2	25.1	6.3	32.7	22.1
Median SFE (%)	0.1	3.5	(3.4)	12.9	3.4
Maximum SFE (%)	266.9	492.8	325.6	460.9	492.8
Minimum SFE (%)	(171.1)	(72.6)	(122.1)	(81.6)	(339.3)
Standard deviation of SFE (%)	59.9	80.1	50.5	70.4	70.0
Mean SAFE (%)	39.8	42.3	30.2	42.6	40.3
Median SAFE (%)	24.8	17.7	17.7	19.6	19.2
Maximum SAFE (%)	266.9	492.8	325.6	460.9	492.8
Minimum SAFE (%)	0.1	0.1	0.0	0.1	0.0
Standard deviation of SAFE (%)	46.9	72.4	40.9	64.9	61.4

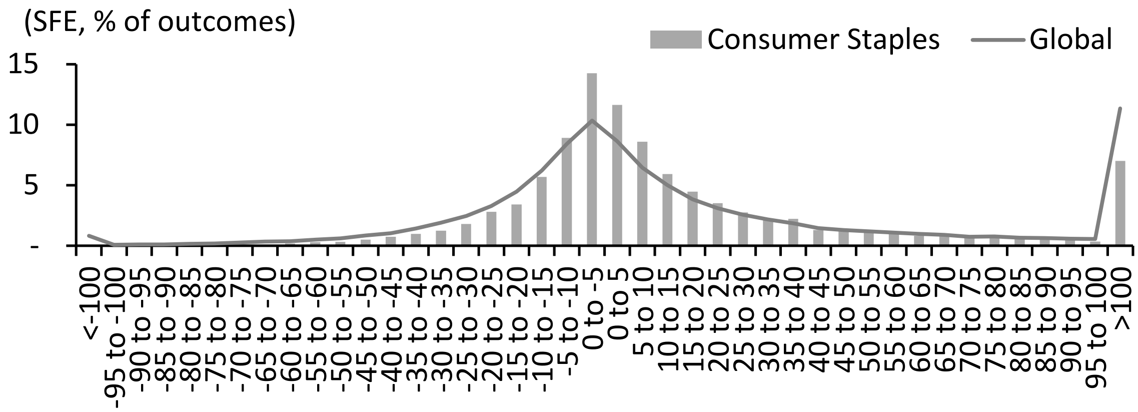
Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error

Appendix 2: Frequency distribution of SFE and statistics – Sectors



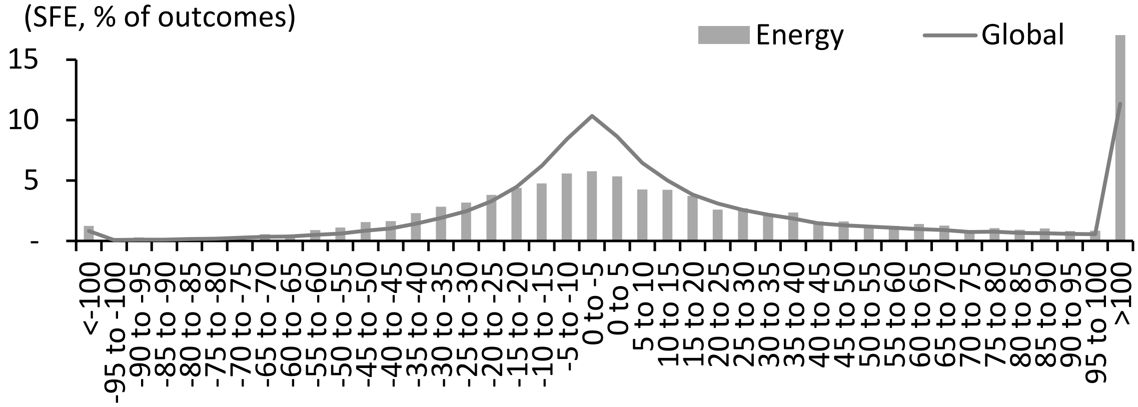
Consumer Discretionary	2003	2005	2010	2014	All years
Number of companies	457	719	923	1,209	912
Maximum number of earnings forecasts	43	33	36	50	53
Maximum number of recommendations	47	40	40	54	55
Maximum number of target prices	24	37	47	55	55
Average number of earnings estimates	10.2	9.4	10.1	10.8	10.2
Average number of recommendations	11.6	11.3	11.0	11.4	11.1
Average number of target prices	6.2	6.7	9.0	9.7	8.1
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	2,496	3,958	3,426	5,243	3,903
Median market cap (US$m)	822	1,241	1,199	1,428	1,167
Maximum market cap (US$m)	53,771	116,239	112,730	179,408	191,776
Mean SFE (%)	18.4	16.0	1.4	30.8	24.9
Median SFE (%)	0.1	(0.6)	(7.0)	9.6	4.0
Maximum SFE (%)	452.3	461.3	443.1	496.9	498.6
Minimum SFE (%)	(340.7)	(111.0)	(350.3)	(191.7)	(481.4)
Standard deviation of SFE (%)	70.3	63.4	62.2	71.0	75.3
Mean SAFE (%)	35.1	32.4	35.1	40.7	41.9
Median SAFE (%)	13.5	13.3	18.4	17.3	17.0
Maximum SAFE (%)	452.3	461.3	443.1	496.9	498.6
Minimum SAFE (%)	0.0	0.1	0.1	0.0	0.0
Standard deviation of SAFE (%)	63.7	56.8	51.3	65.8	67.3

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



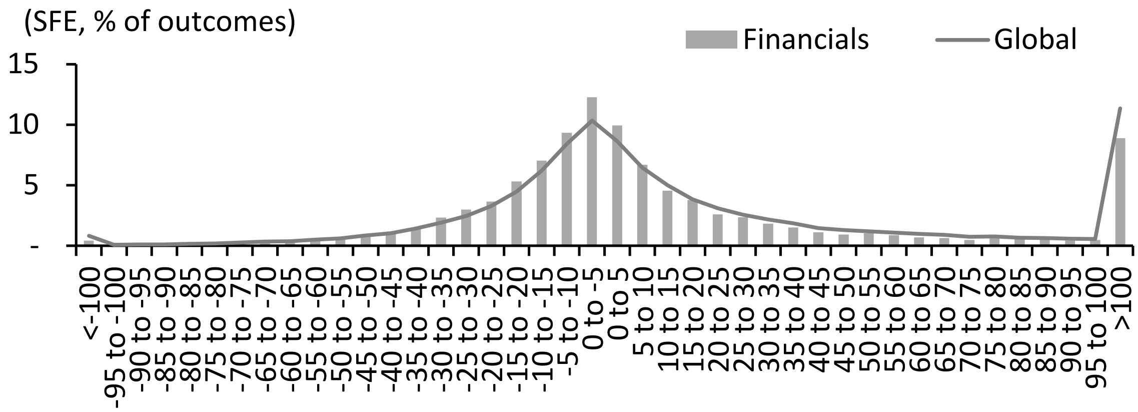
Consumer Staples	2003	2005	2010	2014	All years
Number of companies	191	264	396	491	367
Maximum number of earnings forecasts	34	33	42	39	44
Maximum number of recommendations	44	45	43	43	47
Maximum number of target prices	18	22	37	43	43
Average number of earnings estimates	10.5	8.5	9.7	10.6	9.8
Average number of recommendations	11.8	10.6	10.6	11.5	10.8
Average number of target prices	5.6	6.1	9.1	9.9	8.2
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	2	1	2	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	7,425	7,826	7,689	9,616	8,122
Median market cap (US$m)	1,246	1,633	1,535	2,081	1,667
Maximum market cap (US$m)	211,224	218,517	204,709	241,505	256,763
Mean SFE (%)	12.6	9.9	10.6	34.2	20.6
Median SFE (%)	2.5	0.3	(0.5)	9.7	3.3
Maximum SFE (%)	306.9	492.8	435.8	496.5	498.3
Minimum SFE (%)	(64.1)	(157.5)	(64.8)	(85.2)	(323.3)
Standard deviation of SFE (%)	44.4	53.2	50.9	72.4	62.6
Mean SAFE (%)	23.4	23.7	24.5	40.8	31.9
Median SAFE (%)	9.7	10.1	11.6	14.7	12.6
Maximum SAFE (%)	306.9	492.8	435.8	496.5	498.3
Minimum SAFE (%)	0.1	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	39.8	48.6	45.8	68.9	57.7

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



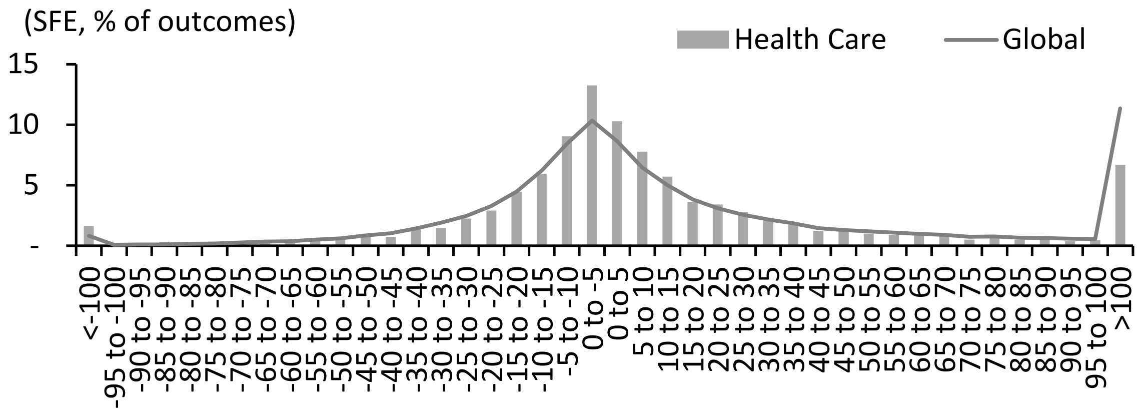
Energy	2003	2005	2010	2014	All years
Number of companies	128	213	364	471	327
Maximum number of earnings forecasts	30	36	41	45	47
Maximum number of recommendations	30	43	43	45	54
Maximum number of target prices	24	28	38	47	51
Average number of earnings estimates	10.9	10.0	11.0	12.5	11.3
Average number of recommendations	11.5	11.6	12.2	13.9	12.4
Average number of target prices	7.8	8.1	10.8	12.5	10.3
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	2	2	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	2,806	7,894	8,854	8,940	8,747
Median market cap (US$m)	909	1,465	1,623	1,761	1,569
Maximum market cap (US$m)	68,788	232,564	344,275	223,728	449,435
Mean SFE (%)	16.8	(6.5)	43.5	45.2	36.5
Median SFE (%)	(9.7)	(22.1)	13.3	18.4	8.7
Maximum SFE (%)	420.5	315.5	480.6	494.7	496.5
Minimum SFE (%)	(78.2)	(133.3)	(275.8)	(451.0)	(451.0)
Standard deviation of SFE (%)	85.3	59.2	96.8	100.0	94.7
Mean SAFE (%)	47.9	39.4	63.1	68.4	60.7
Median SAFE (%)	27.3	28.7	29.3	37.6	29.6
Maximum SAFE (%)	420.5	315.5	480.6	494.7	496.5
Minimum SAFE (%)	1.3	0.6	0.1	0.0	0.0
Standard deviation of SAFE (%)	72.5	44.7	85.3	85.7	81.3

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



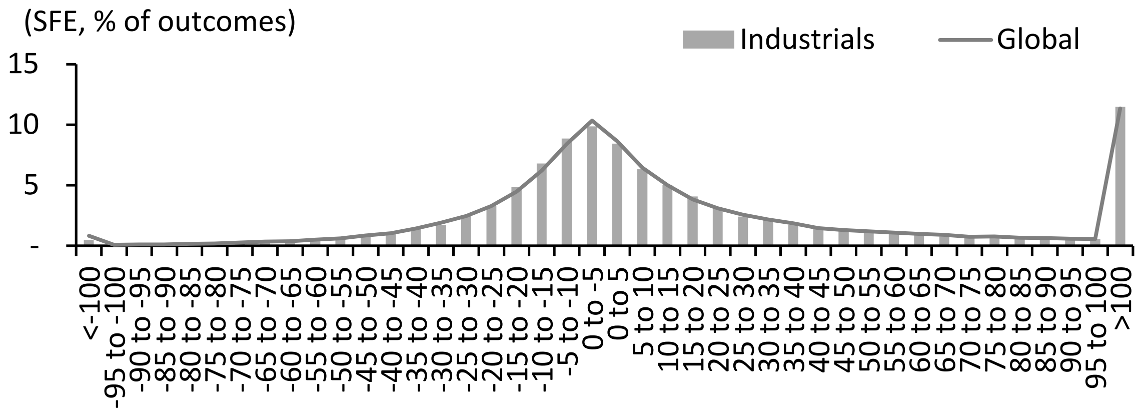
Financials	2003	2005	2010	2014	All years
Number of companies	427	637	934	1,182	854
Maximum number of earnings forecasts	41	35	41	49	50
Maximum number of recommendations	44	47	44	51	53
Maximum number of target prices	24	23	44	51	51
Average number of earnings estimates	11.2	9.4	10.2	10.7	10.4
Average number of recommendations	12.2	11.6	11.5	12.0	11.7
Average number of target prices	6.8	7.5	10.2	10.8	9.3
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	6,618	9,036	7,990	9,286	8,503
Median market cap (US$m)	1,581	2,357	2,187	2,611	2,226
Maximum market cap (US$m)	267,867	447,261	222,271	308,730	726,886
Mean SFE (%)	10.9	4.2	11.5	11.2	18.1
Median SFE (%)	(1.9)	(3.4)	(1.8)	(0.4)	0.2
Maximum SFE (%)	499.3	308.7	472.9	473.5	499.3
Minimum SFE (%)	(145.6)	(95.1)	(451.3)	(333.3)	(451.3)
Standard deviation of SFE (%)	57.3	47.8	74.7	54.2	69.5
Mean SAFE (%)	29.7	25.3	38.5	27.0	36.5
Median SAFE (%)	12.8	11.5	17.7	11.9	15.1
Maximum SAFE (%)	499.3	308.7	472.9	473.5	499.3
Minimum SAFE (%)	0.1	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	50.2	40.7	65.0	48.3	61.9

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



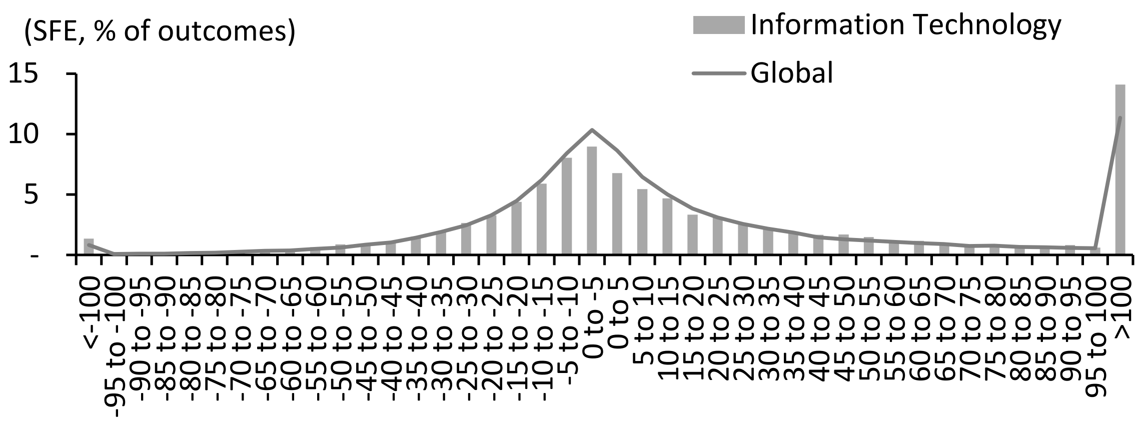
Health Care	2003	2005	2010	2014	All years
Number of companies	200	308	472	678	445
Maximum number of earnings forecasts	37	34	38	43	43
Maximum number of recommendations	41	46	38	46	46
Maximum number of target prices	24	24	35	47	47
Average number of earnings estimates	9.5	8.7	9.8	9.0	9.4
Average number of recommendations	10.2	9.8	10.4	9.5	10.0
Average number of target prices	6.0	6.0	8.3	8.0	7.4
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	2	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	4,999	6,448	4,962	6,138	5,461
Median market cap (US$m)	522	821	978	1,152	922
Maximum market cap (US$m)	187,078	192,028	173,137	249,541	279,450
Mean SFE (%)	10.0	10.2	7.9	12.1	13.1
Median SFE (%)	(0.5)	(2.4)	0.6	3.7	1.6
Maximum SFE (%)	410.0	410.2	433.3	498.5	498.5
Minimum SFE (%)	(240.0)	(145.8)	(493.5)	(354.4)	(493.5)
Standard deviation of SFE (%)	59.8	57.2	78.9	62.0	68.1
Mean SAFE (%)	31.0	30.2	37.6	34.0	34.8
Median SAFE (%)	13.4	15.4	12.8	14.6	14.1
Maximum SAFE (%)	410.0	410.2	493.5	498.5	498.5
Minimum SAFE (%)	0.0	0.0	0.1	0.1	0.0
Standard deviation of SAFE (%)	52.1	49.6	69.8	53.3	59.9

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



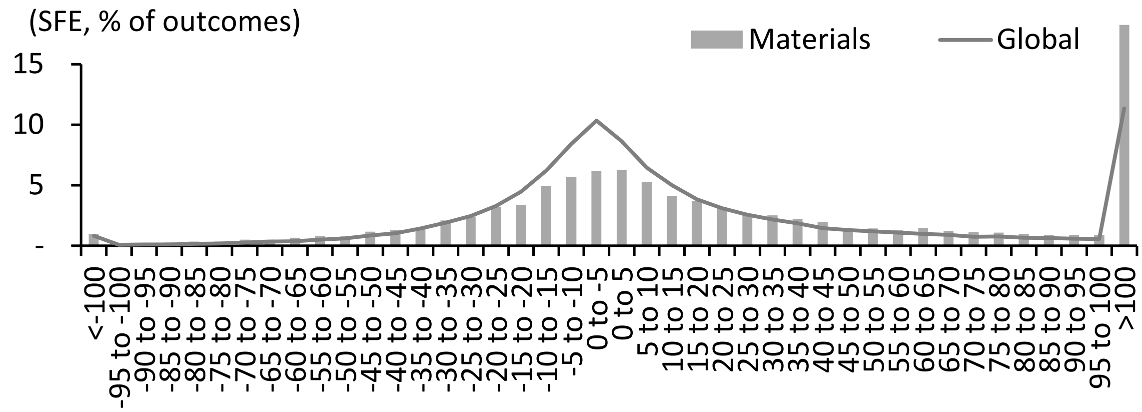
Industrials	2003	2005	2010	2014	All years
Number of companies	380	672	1,097	1,304	980
Maximum number of earnings forecasts	38	33	36	39	44
Maximum number of recommendations	44	46	37	46	49
Maximum number of target prices	21	22	45	46	47
Average number of earnings estimates	8.8	7.8	9.1	9.7	9.0
Average number of recommendations	10.3	9.6	9.9	10.4	9.8
Average number of target prices	5.1	5.5	8.2	8.8	7.3
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	2,857	4,011	3,422	4,494	3,764
Median market cap (US$m)	682	1,182	1,115	1,540	1,180
Maximum market cap (US$m)	230,703	382,485	171,462	252,830	382,485
Mean SFE (%)	24.6	8.6	6.1	33.2	26.6
Median SFE (%)	3.3	(5.8)	(5.2)	7.4	3.5
Maximum SFE (%)	468.9	487.2	491.7	479.7	497.9
Minimum SFE (%)	(200.0)	(85.4)	(373.2)	(391.1)	(475.6)
Standard deviation of SFE (%)	69.0	66.8	64.8	80.2	78.8
Mean SAFE (%)	39.9	32.1	37.0	44.5	43.6
Median SAFE (%)	15.8	14.9	19.7	15.5	17.5
Maximum SAFE (%)	468.9	487.2	491.7	479.7	497.9
Minimum SAFE (%)	0.1	0.1	0.0	0.0	0.0
Standard deviation of SAFE (%)	61.4	59.2	53.5	74.5	70.8

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



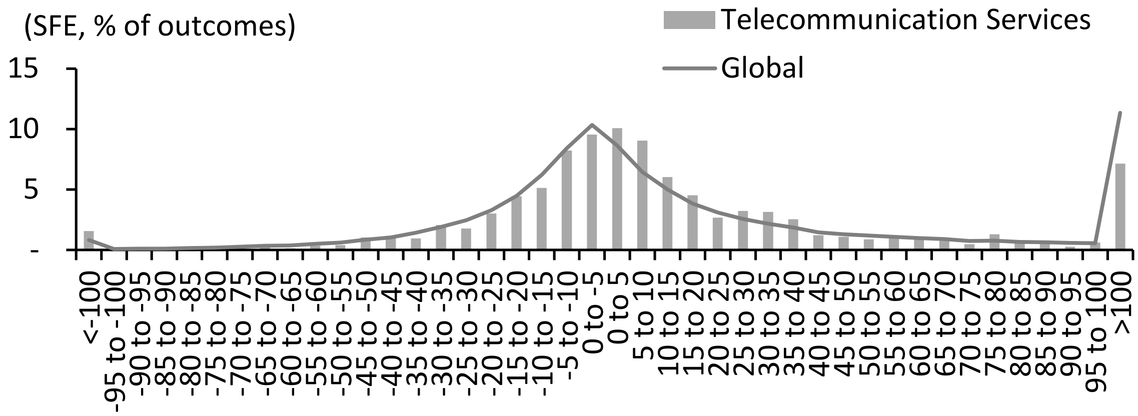
Information Technology	2003	2005	2010	2014	All years
Number of companies	342	523	711	949	690
Maximum number of earnings forecasts	39	42	50	55	59
Maximum number of recommendations	38	45	57	55	57
Maximum number of target prices	32	30	48	55	58
Average number of earnings estimates	10.6	10.3	9.9	10.3	10.0
Average number of recommendations	12.0	11.6	11.0	10.9	11.0
Average number of target prices	7.3	7.0	8.8	8.9	8.1
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	3,943	4,752	4,548	5,632	4,804
Median market cap (US$m)	583	878	832	1,103	823
Maximum market cap (US$m)	257,125	309,458	209,516	470,011	559,129
Mean SFE (%)	23.6	23.7	12.3	23.8	30.3
Median SFE (%)	0.3	0.3	(5.3)	3.2	4.7
Maximum SFE (%)	488.3	494.4	466.7	492.3	496.9
Minimum SFE (%)	(467.5)	(349.4)	(364.0)	(350.0)	(471.0)
Standard deviation of SFE (%)	107.5	88.4	81.9	78.3	88.3
Mean SAFE (%)	63.2	49.6	46.2	43.5	52.0
Median SAFE (%)	27.1	21.0	22.6	17.6	21.9
Maximum SAFE (%)	488.3	494.4	466.7	492.3	496.9
Minimum SAFE (%)	0.0	0.0	0.1	0.0	0.0
Standard deviation of SAFE (%)	90.1	76.8	68.8	69.3	77.5

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



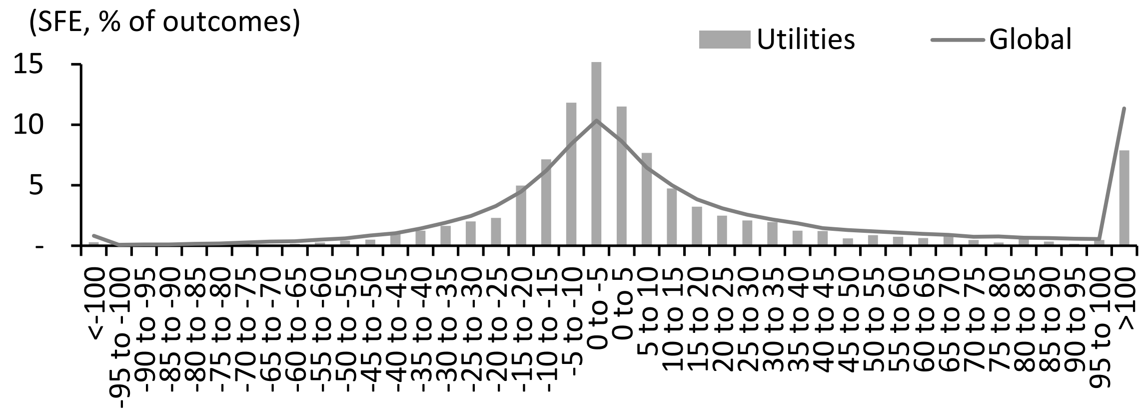
Materials	2003	2005	2010	2014	All years
Number of companies	179	319	574	745	502
Maximum number of earnings forecasts	35	29	37	41	44
Maximum number of recommendations	40	36	39	45	49
Maximum number of target prices	19	20	43	46	48
Average number of earnings estimates	8.6	7.8	9.0	9.5	9.0
Average number of recommendations	10.1	9.5	10.2	10.5	10.1
Average number of target prices	4.5	5.6	8.8	9.2	7.8
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	2,251	4,194	5,068	4,626	4,877
Median market cap (US$m)	723	1,783	1,688	1,445	1,596
Maximum market cap (US$m)	27,095	110,032	156,667	153,428	205,089
Mean SFE (%)	37.8	27.7	20.2	42.5	41.7
Median SFE (%)	8.9	(2.3)	(0.9)	12.4	10.9
Maximum SFE (%)	438.3	439.3	489.7	464.7	496.8
Minimum SFE (%)	(97.8)	(128.0)	(328.6)	(133.4)	(497.7)
Standard deviation of SFE (%)	91.2	88.1	89.8	90.4	95.8
Mean SAFE (%)	56.2	52.4	53.4	56.8	62.2
Median SAFE (%)	23.1	22.7	26.0	23.3	28.9
Maximum SAFE (%)	438.3	439.3	489.7	464.7	497.7
Minimum SAFE (%)	0.0	0.2	0.1	0.0	0.0
Standard deviation of SAFE (%)	81.0	76.0	75.0	82.1	84.0

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



Telecommunication Services	2003	2005	2010	2014	All years
Number of companies	69	91	143	142	122
Maximum number of earnings forecasts	36	38	41	40	46
Maximum number of recommendations	49	42	44	42	49
Maximum number of target prices	25	34	44	42	46
Average number of earnings estimates	14.0	12.7	13.4	14.9	14.0
Average number of recommendations	16.4	16.9	15.4	16.5	16.0
Average number of target prices	8.7	11.0	13.7	15.2	12.8
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	3	3	1	2	1
Minimum number of target prices	1	1	1	2	1
Mean market capitalization (US$m)	9,231	14,275	12,564	15,903	14,409
Median market cap (US$m)	1,993	4,500	3,552	5,087	3,807
Maximum market cap (US$m)	94,193	88,335	193,000	184,005	298,058
Mean SFE (%)	(15.1)	13.1	11.8	25.8	16.3
Median SFE (%)	(8.9)	(0.8)	4.7	7.4	3.9
Maximum SFE (%)	159.7	234.6	199.8	364.1	490.6
Minimum SFE (%)	(490.3)	(138.0)	(477.4)	(76.9)	(490.3)
Standard deviation of SFE (%)	89.3	57.1	65.6	62.7	67.7
Mean SAFE (%)	53.3	34.1	35.5	38.2	36.3
Median SAFE (%)	31.7	16.2	15.3	17.2	16.2
Maximum SAFE (%)	490.3	234.6	477.4	364.1	490.6
Minimum SAFE (%)	0.4	0.2	0.2	0.3	0.0
Standard deviation of SAFE (%)	73.0	47.5	56.3	55.9	59.3

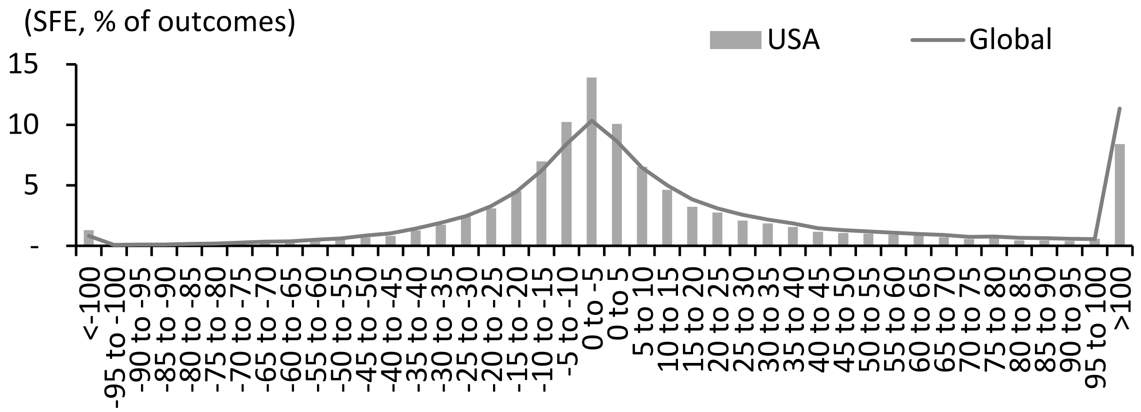
Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



Utilities	2003	2005	2010	2014	All years
Number of companies	98	140	218	263	191
Maximum number of earnings forecasts	42	31	33	35	42
Maximum number of recommendations	42	40	36	43	48
Maximum number of target prices	17	24	38	44	46
Average number of earnings estimates	10.4	9.1	9.8	10.4	10.1
Average number of recommendations	11.7	11.6	11.4	11.5	11.5
Average number of target prices	5.8	7.0	9.9	10.4	9.1
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	3	2	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	3,465	6,266	6,923	6,551	6,768
Median market cap (US$m)	1,411	2,678	2,925	3,003	2,873
Maximum market cap (US$m)	33,695	56,771	92,738	73,907	173,478
Mean SFE (%)	3.7	(0.1)	17.3	17.9	16.8
Median SFE (%)	(1.6)	(3.9)	0.1	(1.1)	0.1
Maximum SFE (%)	232.2	202.5	447.7	361.9	490.8
Minimum SFE (%)	(163.9)	(46.9)	(48.6)	(87.0)	(397.1)
Standard deviation of SFE (%)	45.4	28.9	61.9	61.6	64.1
Mean SAFE (%)	25.0	16.3	29.5	34.1	31.5
Median SAFE (%)	13.5	10.5	11.7	14.0	11.3
Maximum SAFE (%)	232.2	202.5	447.7	361.9	490.8
Minimum SAFE (%)	0.0	0.3	0.0	0.1	0.0
Standard deviation of SAFE (%)	38.0	23.9	57.0	54.3	58.3

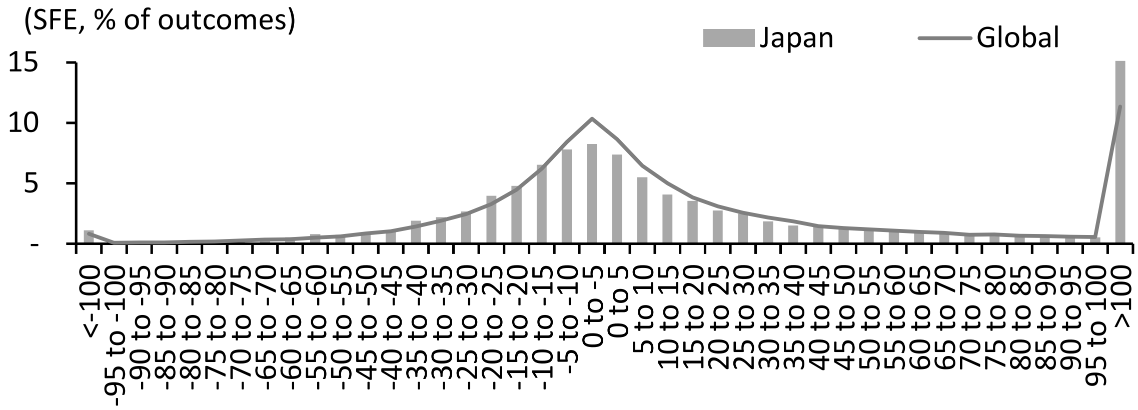
Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error

Appendix 3: Frequency distribution of SFE and statistics – Top 10 developed countries



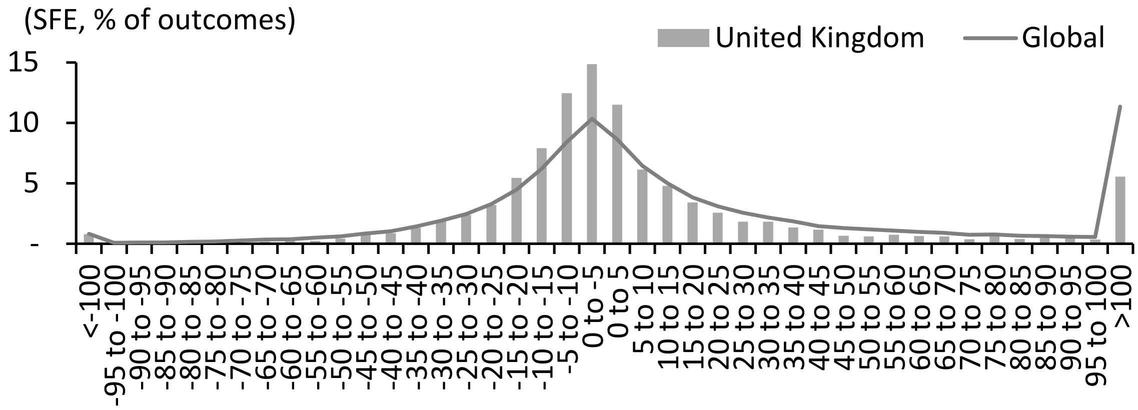
USA	2003	2005	2010	2014	All years
Number of companies	1,055	1,267	1,545	1,978	1,514
Maximum number of earnings forecasts	39	42	45	55	56
Maximum number of recommendations	38	42	43	55	56
Maximum number of target prices	32	30	39	49	49
Average number of earnings estimates	9.6	10.4	10.6	11.4	10.6
Average number of recommendations	9.9	10.9	11.1	11.8	11.0
Average number of target prices	7.3	7.0	8.6	9.8	8.1
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	6,032	7,547	6,311	8,896	7,283
Median market cap (US$m)	1,129	1,555	1,240	1,855	1,419
Maximum market cap (US$m)	257,125	382,485	209,516	470,011	559,129
Mean SFE (%)	14.4	10.5	1.2	16.7	16.6
Median SFE (%)	(0.6)	(2.1)	(5.4)	1.0	0.0
Maximum SFE (%)	465.5	487.2	489.7	496.9	497.6
Minimum SFE (%)	(445.5)	(349.4)	(493.5)	(451.0)	(493.5)
Standard deviation of SFE (%)	71.8	62.1	76.4	70.6	73.5
Mean SAFE (%)	34.4	29.3	39.5	35.0	37.4
Median SAFE (%)	11.7	11.4	18.0	11.6	13.8
Maximum SAFE (%)	465.5	487.2	493.5	496.9	497.6
Minimum SAFE (%)	0.1	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	64.7	55.8	65.4	63.6	65.4

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



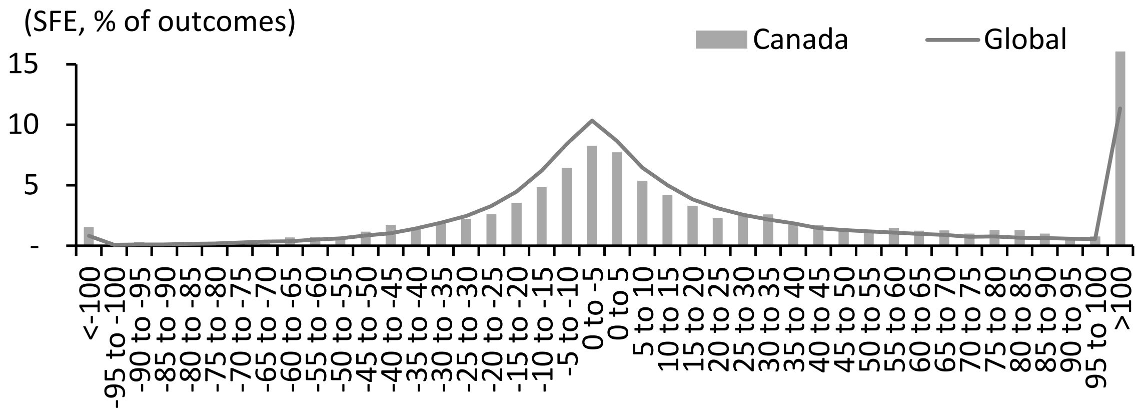
Japan	2003	2005	2010	2014	All years
Number of companies	86	521	585	597	540
Maximum number of earnings forecasts	19	20	23	26	26
Maximum number of recommendations	19	21	23	24	26
Maximum number of target prices	9	13	18	21	21
Average number of earnings estimates	7.8	7.5	8.5	8.7	8.3
Average number of recommendations	7.7	8.2	8.8	8.6	8.4
Average number of target prices	2.5	3.6	6.0	7.1	5.4
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	1	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	2,258	4,663	4,825	5,735	5,191
Median market cap (US$m)	814	1,926	1,888	2,243	1,907
Maximum market cap (US$m)	27,712	116,239	112,730	179,408	191,776
Mean SFE (%)	2.7	7.0	19.9	17.3	30.9
Median SFE (%)	(5.3)	(4.9)	0.6	(2.1)	3.2
Maximum SFE (%)	300.6	389.9	464.1	496.5	496.5
Minimum SFE (%)	(84.9)	(138.0)	(319.9)	(108.0)	(471.0)
Standard deviation of SFE (%)	55.8	53.1	86.0	71.2	91.6
Mean SAFE (%)	33.6	30.0	49.9	37.4	53.4
Median SAFE (%)	16.5	16.8	23.4	16.4	21.4
Maximum SAFE (%)	300.6	389.9	464.1	496.5	496.5
Minimum SAFE (%)	0.1	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	44.4	44.3	72.8	63.0	80.5

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



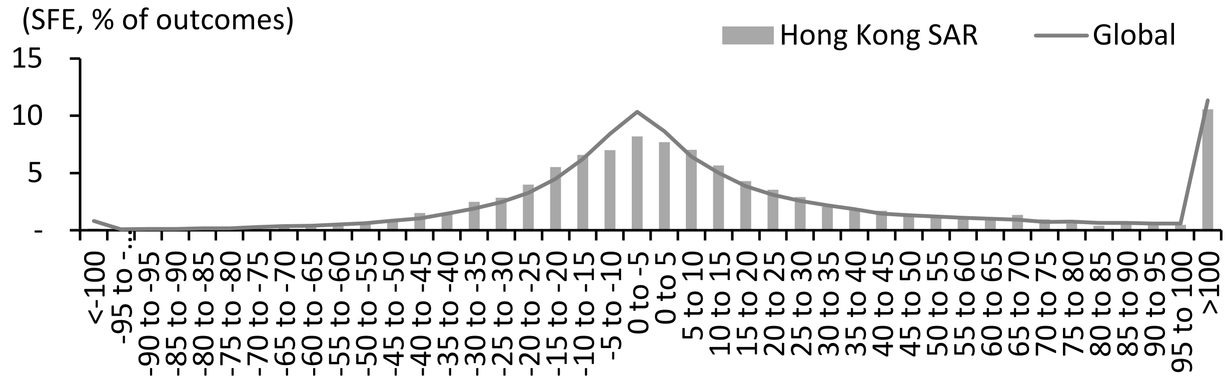
United Kingdom	2003	2005	2010	2014	All years
Number of companies	132	231	422	390	334
Maximum number of earnings forecasts	26	32	38	31	39
Maximum number of recommendations	36	44	38	35	44
Maximum number of target prices	6	20	33	29	33
Average number of earnings estimates	7.6	8.4	11.1	11.7	10.8
Average number of recommendations	12.8	13.3	12.0	12.3	12.1
Average number of target prices	2.6	6.5	10.1	11.1	9.0
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	3	2	1	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	5,413	9,433	5,767	8,856	7,350
Median market cap (US$m)	1,519	1,890	898	1,854	1,322
Maximum market cap (US$m)	100,930	232,564	176,576	198,556	232,564
Mean SFE (%)	0.7	2.3	0.5	9.5	10.3
Median SFE (%)	(3.4)	(5.7)	(5.4)	1.8	(1.4)
Maximum SFE (%)	266.5	425.1	264.0	372.1	496.5
Minimum SFE (%)	(340.7)	(111.0)	(389.4)	(316.3)	(389.4)
Standard deviation of SFE (%)	55.2	52.0	49.1	47.8	55.8
Mean SAFE (%)	29.0	26.8	26.5	23.2	28.1
Median SAFE (%)	13.7	14.5	14.0	10.1	11.5
Maximum SAFE (%)	340.7	425.1	389.4	372.1	496.5
Minimum SAFE (%)	0.0	0.0	0.0	0.0	0.0
Standard deviation of SAFE (%)	46.9	44.6	41.3	42.8	49.3

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



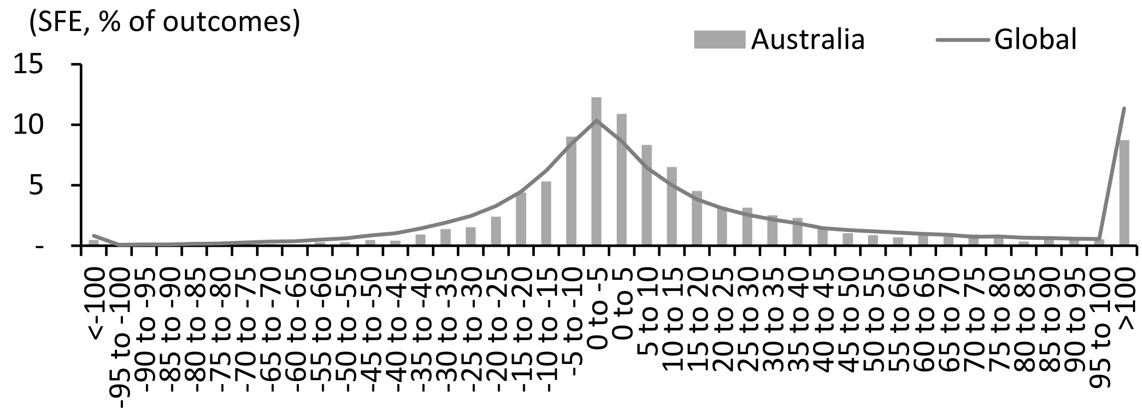
Canada	2003	2005	2010	2014	All years
Number of companies	147	210	331	356	279
Maximum number of earnings forecasts	26	23	23	28	28
Maximum number of recommendations	25	25	23	29	29
Maximum number of target prices	22	23	23	26	27
Average number of earnings estimates	8.2	7.8	7.7	8.1	7.8
Average number of recommendations	8.5	8.6	8.7	9.5	8.8
Average number of target prices	7.6	8.2	8.7	9.4	8.6
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	3	1	2	1
Minimum number of target prices	2	2	2	1	1
Mean market capitalization (US$m)	2,296	3,467	3,853	4,667	4,029
Median market cap (US$m)	595	878	878	947	853
Maximum market cap (US$m)	25,218	37,250	75,887	96,826	96,826
Mean SFE (%)	21.8	29.8	29.9	37.2	35.5
Median SFE (%)	2.0	1.6	5.4	11.4	7.6
Maximum SFE (%)	468.9	433.3	480.6	483.1	488.6
Minimum SFE (%)	(490.3)	(145.8)	(328.6)	(133.4)	(490.3)
Standard deviation of SFE (%)	93.0	83.7	96.1	87.6	92.3
Mean SAFE (%)	47.2	49.1	56.4	56.0	57.6
Median SAFE (%)	18.9	19.0	21.5	28.4	26.5
Maximum SAFE (%)	490.3	433.3	480.6	483.1	490.3
Minimum SAFE (%)	0.3	0.3	0.1	0.1	0.0
Standard deviation of SAFE (%)	83.0	74.0	83.3	76.9	80.5

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



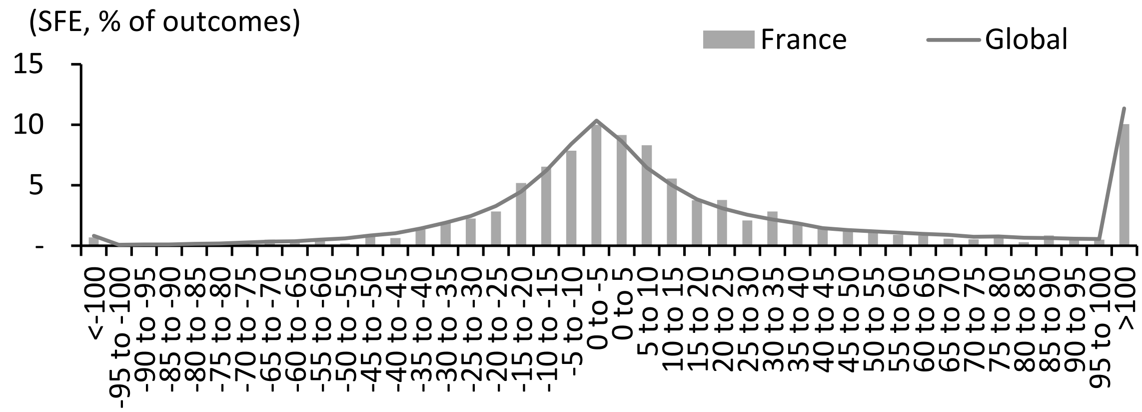
Hong Kong SAR	2003	2005	2010	2014	All years
Number of companies	130	159	234	305	225
Maximum number of earnings forecasts	31	28	29	36	36
Maximum number of recommendations	31	28	31	37	37
Maximum number of target prices	25	22	27	37	37
Average number of earnings estimates	13.5	10.7	9.9	12.5	11.2
Average number of recommendations	14.8	12.0	11.2	13.3	12.3
Average number of target prices	10.2	9.3	10.2	13.3	10.8
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	2	2	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	2,181	3,087	5,721	6,394	4,964
Median market cap (US$m)	499	770	2,287	2,087	1,621
Maximum market cap (US$m)	38,968	64,411	193,000	184,005	298,058
Mean SFE (%)	25.2	20.5	7.1	38.4	24.6
Median SFE (%)	8.5	1.5	(2.8)	14.7	4.4
Maximum SFE (%)	337.5	492.4	291.3	444.7	492.4
Minimum SFE (%)	(72.0)	(95.1)	(78.1)	(83.5)	(116.9)
Standard deviation of SFE (%)	63.9	72.3	53.7	77.8	71.9
Mean SAFE (%)	40.7	41.1	29.9	48.7	41.3
Median SAFE (%)	21.8	18.4	16.0	21.3	18.9
Maximum SAFE (%)	337.5	492.4	291.3	444.7	492.4
Minimum SAFE (%)	0.0	0.3	0.1	0.2	0.0
Standard deviation of SAFE (%)	55.2	62.9	45.1	71.8	63.8

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



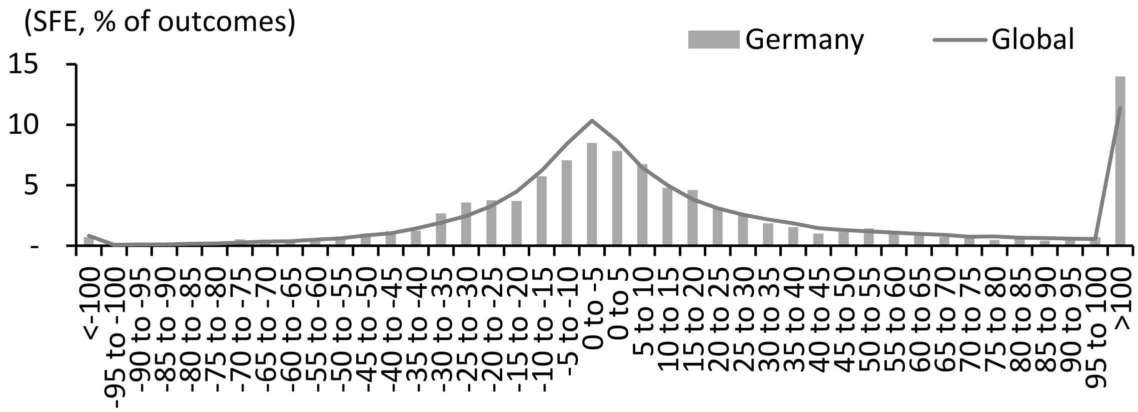
Australia	2003	2005	2010	2014	All years
Number of companies	102	111	193	225	169
Maximum number of earnings forecasts	17	14	17	21	21
Maximum number of recommendations	17	15	18	20	20
Maximum number of target prices	6	8	15	20	21
Average number of earnings estimates	8.6	7.8	9.0	10.4	8.8
Average number of recommendations	9.1	8.0	9.4	10.1	9.2
Average number of target prices	3.5	4.0	7.6	10.2	7.4
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	3	2	3	2	2
Minimum number of target prices	1	1	1	2	1
Mean market capitalization (US$m)	2,514	4,047	5,167	5,513	4,951
Median market cap (US$m)	497	1,006	876	847	900
Maximum market cap (US$m)	34,446	49,885	156,667	153,428	205,089
Mean SFE (%)	18.9	7.1	15.4	18.1	22.1
Median SFE (%)	2.1	(1.9)	(0.4)	4.4	4.5
Maximum SFE (%)	231.5	247.1	452.8	287.9	489.4
Minimum SFE (%)	(163.9)	(55.7)	(100.2)	(115.6)	(303.3)
Standard deviation of SFE (%)	57.7	46.7	61.2	49.5	63.4
Mean SAFE (%)	33.7	24.0	31.7	29.1	34.6
Median SAFE (%)	15.2	12.3	14.0	12.5	13.8
Maximum SAFE (%)	231.5	247.1	452.8	287.9	489.4
Minimum SAFE (%)	0.0	0.2	0.2	0.1	0.0
Standard deviation of SAFE (%)	50.4	40.6	54.5	43.9	57.6

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



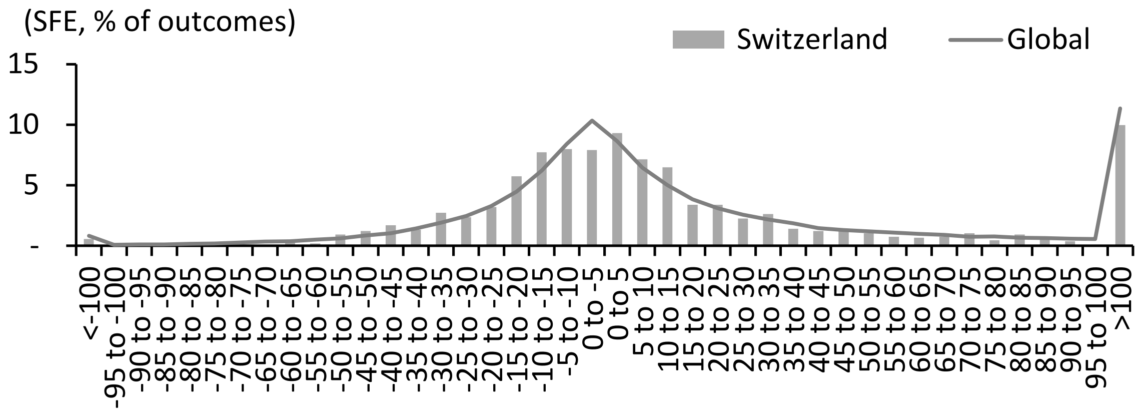
France	2003	2005	2010	2014	All years
Number of companies	77	139	185	146	167
Maximum number of earnings forecasts	35	24	35	31	40
Maximum number of recommendations	41	42	37	34	42
Maximum number of target prices	6	23	31	29	34
Average number of earnings estimates	16.7	10.2	12.5	13.6	12.4
Average number of recommendations	21.0	14.8	13.5	14.4	13.9
Average number of target prices	2.7	7.7	11.4	12.4	9.4
Minimum number of earnings estimates	4	3	3	3	3
Minimum number of recommendations	4	3	2	2	2
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	5,068	8,695	8,297	13,542	8,748
Median market cap (US$m)	2,095	1,306	1,392	4,017	1,602
Maximum market cap (US$m)	43,730	152,052	124,695	147,253	173,478
Mean SFE (%)	36.6	(4.3)	5.4	31.2	24.4
Median SFE (%)	10.2	(10.6)	(5.2)	9.6	4.0
Maximum SFE (%)	333.0	238.9	443.1	465.3	494.7
Minimum SFE (%)	(107.9)	(248.4)	(122.7)	(191.3)	(404.8)
Standard deviation of SFE (%)	73.7	53.3	69.4	75.9	77.7
Mean SAFE (%)	49.6	32.5	35.9	41.4	41.2
Median SAFE (%)	17.9	19.8	18.3	15.4	16.1
Maximum SAFE (%)	333.0	248.4	443.1	465.3	494.7
Minimum SAFE (%)	0.1	0.1	0.1	0.5	0.0
Standard deviation of SAFE (%)	65.5	42.3	59.5	70.8	70.2

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



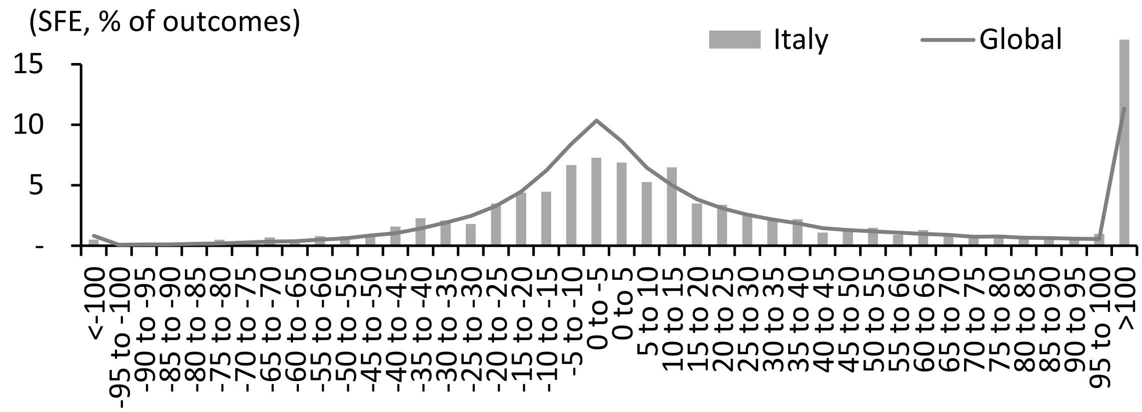
Germany	2003	2005	2010	2014	All years
Number of companies	37	99	173	180	139
Maximum number of earnings forecasts	43	35	42	40	43
Maximum number of recommendations	49	44	44	44	49
Maximum number of target prices	6	22	38	34	39
Average number of earnings estimates	23.3	14.0	13.8	13.6	14.2
Average number of recommendations	26.0	17.9	15.1	14.7	15.7
Average number of target prices	3.1	9.1	12.3	13.7	10.9
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	3	2	1	2	1
Minimum number of target prices	1	1	1	2	1
Mean market capitalization (US$m)	7,124	8,409	5,755	9,115	7,294
Median market cap (US$m)	2,017	1,459	762	1,673	1,166
Maximum market cap (US$m)	56,205	83,743	77,202	117,450	134,478
Mean SFE (%)	45.4	17.7	3.0	31.6	29.1
Median SFE (%)	7.7	(4.6)	(8.6)	8.5	4.6
Maximum SFE (%)	499.3	417.1	442.9	470.8	499.3
Minimum SFE (%)	(234.7)	(104.8)	(292.1)	(285.9)	(292.1)
Standard deviation of SFE (%)	128.7	76.3	76.9	83.5	83.8
Mean SAFE (%)	77.7	41.6	45.1	49.1	49.0
Median SAFE (%)	17.3	18.3	26.7	20.2	20.8
Maximum SAFE (%)	499.3	417.1	442.9	470.8	499.3
Minimum SAFE (%)	0.9	0.2	0.1	0.2	0.0
Standard deviation of SAFE (%)	111.7	66.2	62.3	74.5	73.9

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



Switzerland	2003	2005	2010	2014	All years
Number of companies	40	62	106	96	89
Maximum number of earnings forecasts	28	34	36	37	41
Maximum number of recommendations	34	46	39	37	46
Maximum number of target prices	5	24	34	30	37
Average number of earnings estimates	11.5	9.5	11.2	11.1	10.6
Average number of recommendations	13.4	14.2	11.9	11.7	11.7
Average number of target prices	1.9	7.6	9.9	10.1	8.1
Minimum number of earnings estimates	4	3	3	3	3
Minimum number of recommendations	6	3	2	2	2
Minimum number of target prices	1	1	2	2	1
Mean market capitalization (US$m)	4,150	9,605	7,600	12,542	8,422
Median market cap (US$m)	661	1,907	1,433	2,461	1,505
Maximum market cap (US$m)	78,068	116,335	172,848	241,363	241,363
Mean SFE (%)	20.7	13.6	3.7	14.7	20.2
Median SFE (%)	(2.0)	(4.6)	(1.4)	4.5	2.9
Maximum SFE (%)	354.7	320.9	349.6	345.1	443.8
Minimum SFE (%)	(89.9)	(47.5)	(358.4)	(150.5)	(358.4)
Standard deviation of SFE (%)	86.4	64.1	82.5	54.9	68.9
Mean SAFE (%)	48.0	31.0	47.5	28.5	38.7
Median SAFE (%)	20.2	13.4	25.8	13.9	17.0
Maximum SAFE (%)	354.7	320.9	358.4	345.1	443.8
Minimum SAFE (%)	0.8	0.2	0.1	0.0	0.0
Standard deviation of SAFE (%)	74.4	57.7	67.5	49.1	60.5

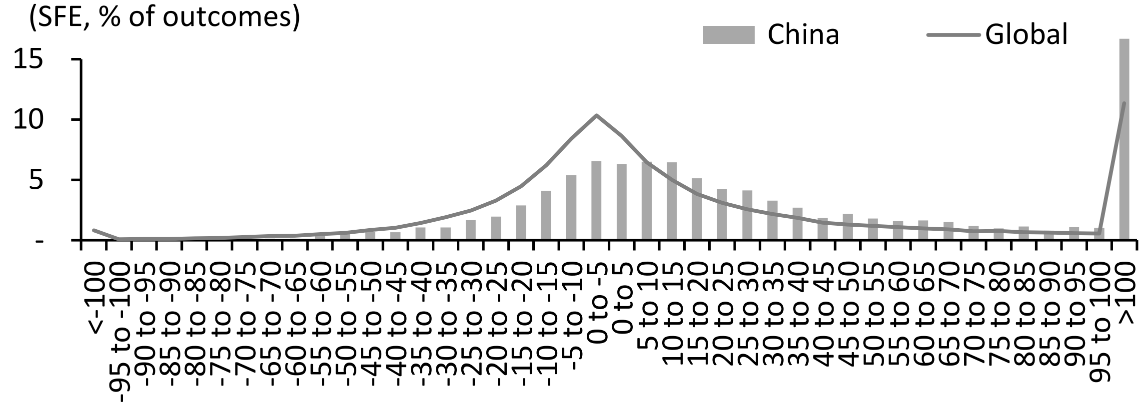
Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



Italy	2003	2005	2010	2014	All years
Number of companies	20	80	93	78	84
Maximum number of earnings forecasts	36	32	35	32	42
Maximum number of recommendations	40	41	38	33	42
Maximum number of target prices	6	22	36	29	36
Average number of earnings estimates	18.4	8.6	12.0	11.9	11.4
Average number of recommendations	22.0	13.0	12.7	12.1	12.7
Average number of target prices	3.4	6.8	11.4	11.1	9.1
Minimum number of earnings estimates	5	3	3	3	3
Minimum number of recommendations	6	3	2	2	1
Minimum number of target prices	1	1	1	2	1
Mean market capitalization (US$m)	9,822	7,670	5,859	8,102	6,677
Median market cap (US$m)	4,418	2,196	1,484	2,904	1,622
Maximum market cap (US$m)	33,695	96,383	81,791	87,406	127,239
Mean SFE (%)	(6.0)	0.9	44.0	28.4	36.1
Median SFE (%)	(6.5)	(16.9)	10.3	8.9	8.7
Maximum SFE (%)	108.0	271.2	419.3	338.9	493.2
Minimum SFE (%)	(77.4)	(107.9)	(164.2)	(33.3)	(203.3)
Standard deviation of SFE (%)	41.2	64.2	98.9	54.8	84.7
Mean SAFE (%)	30.0	41.2	60.2	34.0	53.6
Median SAFE (%)	22.2	30.8	23.1	13.4	23.0
Maximum SAFE (%)	108.0	271.2	419.3	338.9	493.2
Minimum SAFE (%)	1.2	0.4	0.1	0.3	0.0
Standard deviation of SAFE (%)	28.1	49.0	89.8	51.4	74.8

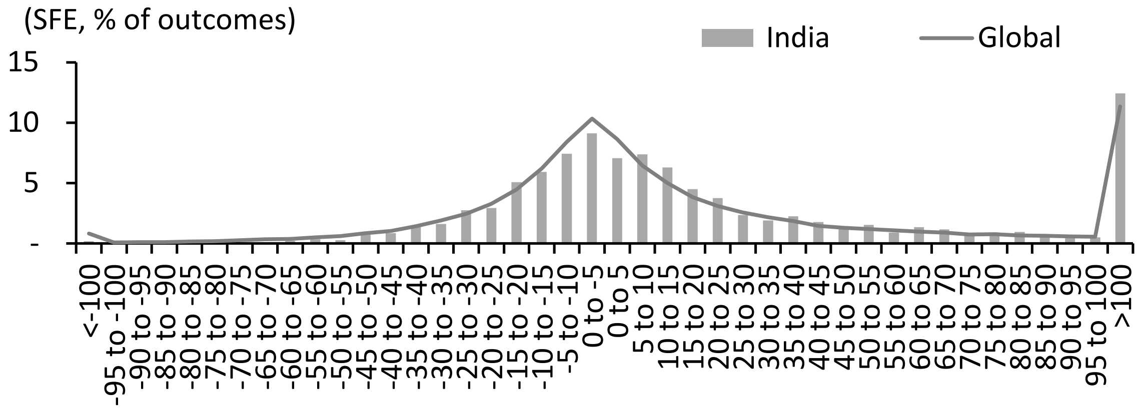
Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error

Appendix 3: Frequency distribution of SFE and statistics – Top 10 emerging countries



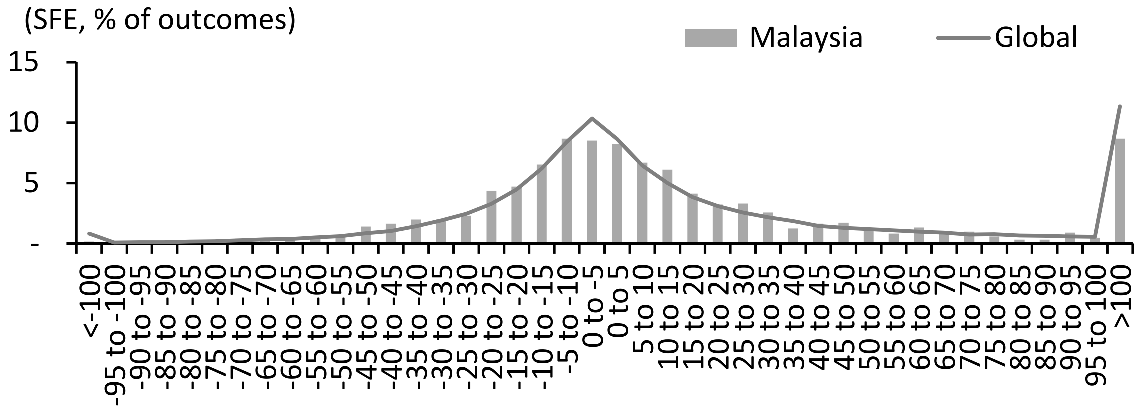
China	2003	2005	2010	2014	All years
Number of companies	-	45	371	698	327
Maximum number of earnings forecasts	-	11	20	22	27
Maximum number of recommendations	-	13	23	23	27
Maximum number of target prices	-	9	15	15	20
Average number of earnings estimates	na	5.0	5.7	6.3	6.5
Average number of recommendations	na	4.8	6.9	7.0	7.1
Average number of target prices	na	2.9	3.1	2.8	3.0
Minimum number of earnings estimates	-	3	3	3	3
Minimum number of recommendations	-	2	1	1	1
Minimum number of target prices	-	1	1	1	1
Mean market capitalization (US$m)	na	2,166	7,488	4,310	5,504
Median market cap (US$m)	na	1,194	1,748	1,413	1,366
Maximum market cap (US$m)	-	10,297	344,275	223,728	449,435
Mean SFE (%)	na	10.0	20.1	45.4	45.9
Median SFE (%)	na	1.0	4.6	19.2	18.1
Maximum SFE (%)	-	173.2	424.3	498.5	498.5
Minimum SFE (%)	-	(53.7)	(78.1)	(72.0)	(125.6)
Standard deviation of SFE (%)	na	47.4	62.6	80.4	83.5
Mean SAFE (%)	na	29.9	36.7	52.6	55.4
Median SAFE (%)	na	18.6	19.2	23.9	25.4
Maximum SAFE (%)	-	173.2	424.3	498.5	498.5
Minimum SAFE (%)	-	0.2	0.2	0.0	0.0
Standard deviation of SAFE (%)	na	37.9	54.5	75.9	77.5

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



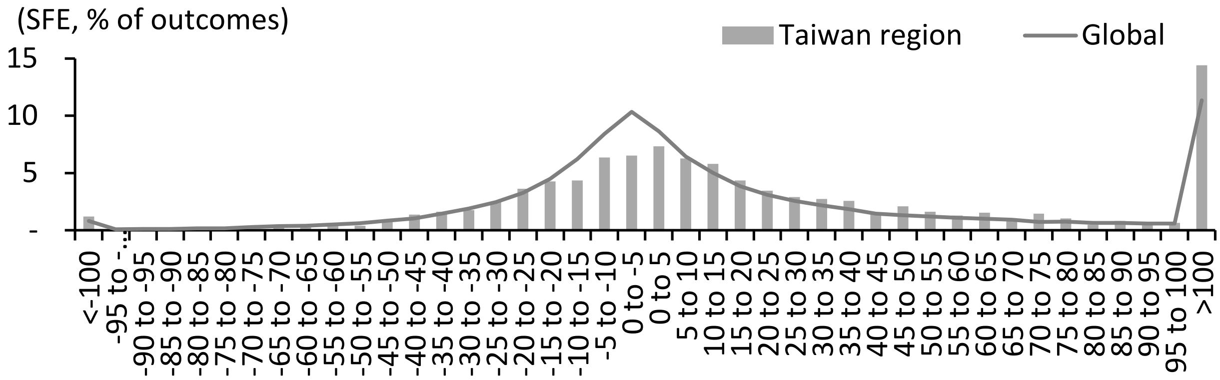
India	2003	2005	2010	2014	All years
Number of companies	56	59	218	308	184
Maximum number of earnings forecasts	17	19	46	50	59
Maximum number of recommendations	20	22	39	54	55
Maximum number of target prices	12	19	48	55	58
Average number of earnings estimates	10.9	8.2	12.1	14.9	12.5
Average number of recommendations	13.1	12.6	16.2	18.8	16.1
Average number of target prices	6.3	10.1	20.0	19.2	16.9
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	4	2	1	2	1
Minimum number of target prices	1	1	3	2	1
Mean market capitalization (US$m)	1,659	3,359	4,652	3,717	3,738
Median market cap (US$m)	743	1,477	1,586	1,084	1,163
Maximum market cap (US$m)	14,855	30,807	69,522	71,059	93,934
Mean SFE (%)	(3.3)	26.6	23.7	33.5	32.6
Median SFE (%)	(12.3)	2.0	3.2	11.5	7.0
Maximum SFE (%)	292.7	461.8	450.3	460.4	498.6
Minimum SFE (%)	(87.6)	(33.5)	(477.4)	(194.5)	(477.4)
Standard deviation of SFE (%)	50.0	87.8	77.1	75.7	82.7
Mean SAFE (%)	29.2	37.9	39.7	44.4	46.3
Median SAFE (%)	18.9	12.6	16.4	18.2	18.5
Maximum SAFE (%)	292.7	461.8	477.4	460.4	498.6
Minimum SAFE (%)	0.7	0.4	0.1	0.1	0.0
Standard deviation of SAFE (%)	40.5	83.5	70.2	69.9	75.9

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



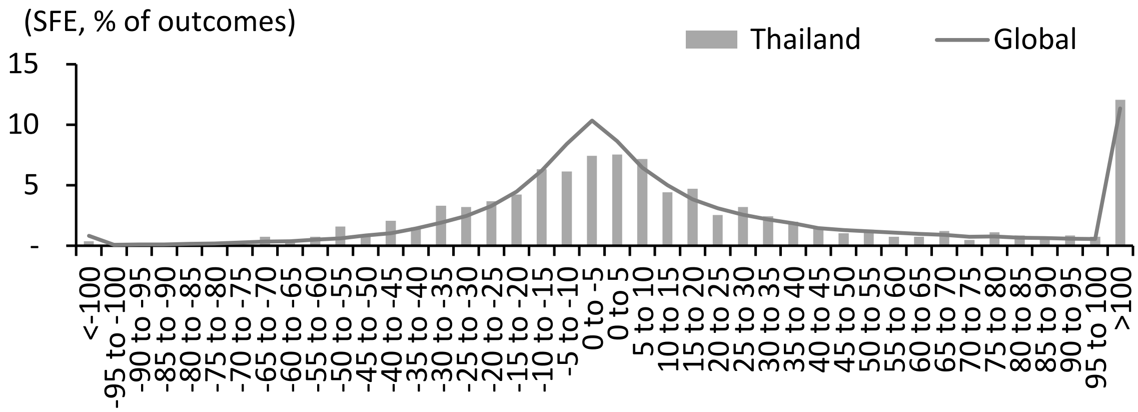
Malaysia	2003	2005	2010	2014	All years
Number of companies	73	84	118	112	101
Maximum number of earnings forecasts	28	24	25	27	28
Maximum number of recommendations	30	27	26	28	30
Maximum number of target prices	19	20	25	28	30
Average number of earnings estimates	13.3	9.7	9.3	10.5	10.1
Average number of recommendations	14.2	11.9	9.7	11.0	10.9
Average number of target prices	7.5	8.5	9.7	11.0	9.8
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	1	2	2	3	1
Minimum number of target prices	1	1	2	3	1
Mean market capitalization (US$m)	945	1,104	1,872	3,588	2,003
Median market cap (US$m)	425	381	567	1,352	636
Maximum market cap (US$m)	8,175	9,824	14,079	26,444	26,444
Mean SFE (%)	10.4	24.6	7.6	31.0	19.9
Median SFE (%)	(0.1)	6.2	(4.7)	15.5	3.0
Maximum SFE (%)	226.8	439.3	231.2	386.2	488.9
Minimum SFE (%)	(171.1)	(72.6)	(122.1)	(81.6)	(171.1)
Standard deviation of SFE (%)	55.2	75.1	51.2	61.7	65.2
Mean SAFE (%)	36.0	39.8	31.0	41.2	37.2
Median SAFE (%)	21.8	17.8	15.9	22.5	18.0
Maximum SAFE (%)	226.8	439.3	231.2	386.2	488.9
Minimum SAFE (%)	0.1	0.8	0.1	0.2	0.1
Standard deviation of SAFE (%)	42.9	68.2	41.3	55.3	57.1

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



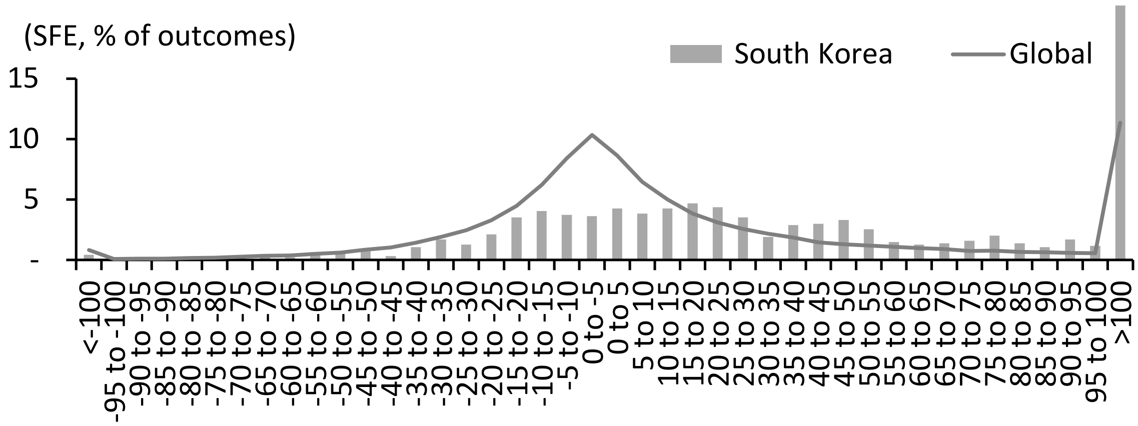
Taiwan region	2003	2005	2010	2014	All years
Number of companies	76	50	84	253	104
Maximum number of earnings forecasts	19	17	23	32	32
Maximum number of recommendations	23	22	25	34	37
Maximum number of target prices	19	20	22	29	33
Average number of earnings estimates	8.1	6.2	7.9	8.7	8.4
Average number of recommendations	10.7	11.1	12.1	9.6	11.6
Average number of target prices	7.9	9.8	10.2	6.9	9.4
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	3	2	1	1
Minimum number of target prices	1	2	1	1	1
Mean market capitalization (US$m)	2,008	3,497	3,830	2,435	3,249
Median market cap (US$m)	1,020	1,754	1,205	716	1,100
Maximum market cap (US$m)	22,764	15,911	47,404	89,748	89,748
Mean SFE (%)	26.3	16.5	21.7	20.5	34.7
Median SFE (%)	(2.3)	1.9	6.8	4.8	10.1
Maximum SFE (%)	488.3	235.6	464.3	457.5	488.3
Minimum SFE (%)	(467.5)	(55.8)	(123.4)	(343.1)	(467.5)
Standard deviation of SFE (%)	124.5	58.9	83.9	74.4	88.2
Mean SAFE (%)	65.7	35.6	46.0	39.5	53.1
Median SAFE (%)	23.2	20.7	21.6	17.6	23.1
Maximum SAFE (%)	488.3	235.6	464.3	457.5	488.3
Minimum SAFE (%)	0.0	0.1	0.6	0.2	0.0
Standard deviation of SAFE (%)	108.8	49.6	73.4	66.3	78.5

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



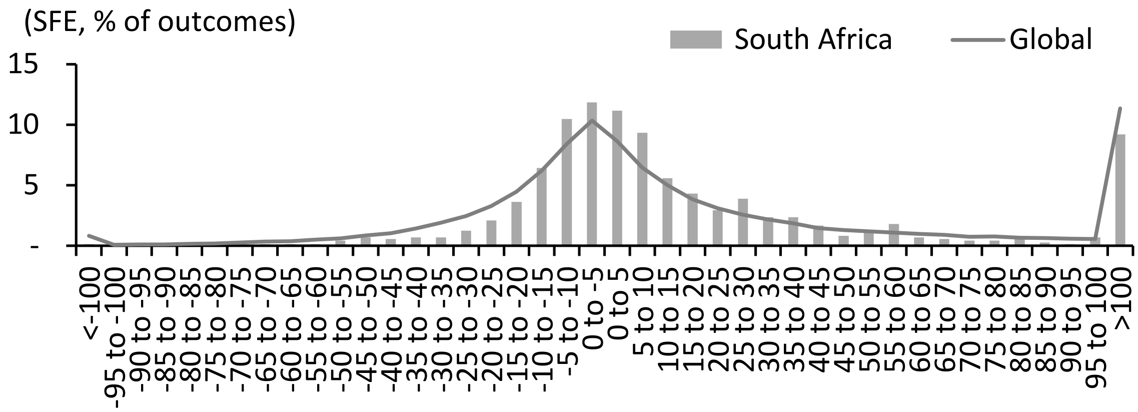
Thailand	2003	2005	2010	2014	All years
Number of companies	61	96	80	112	88
Maximum number of earnings forecasts	24	22	22	27	28
Maximum number of recommendations	25	22	21	27	30
Maximum number of target prices	18	21	22	28	30
Average number of earnings estimates	12.4	8.8	11.2	11.3	10.7
Average number of recommendations	13.0	9.9	12.1	12.0	11.8
Average number of target prices	9.1	8.8	12.4	12.9	11.1
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	2	3	2	2
Minimum number of target prices	1	2	3	3	1
Mean market capitalization (US$m)	467	942	1,753	2,603	1,771
Median market cap (US$m)	201	253	600	812	537
Maximum market cap (US$m)	2,971	13,800	19,889	25,731	34,045
Mean SFE (%)	3.2	33.5	9.6	38.4	26.2
Median SFE (%)	(6.3)	4.6	(1.9)	13.1	4.9
Maximum SFE (%)	185.0	430.8	225.1	423.1	470.4
Minimum SFE (%)	(68.7)	(58.0)	(55.0)	(47.1)	(339.3)
Standard deviation of SFE (%)	51.6	88.2	56.0	78.1	76.6
Mean SAFE (%)	36.0	49.8	34.9	46.7	45.5
Median SAFE (%)	28.7	19.9	19.2	23.7	21.2
Maximum SAFE (%)	185.0	430.8	225.1	423.1	470.4
Minimum SAFE (%)	0.3	0.6	0.7	0.1	0.0
Standard deviation of SAFE (%)	36.8	80.0	44.7	73.4	67.0

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



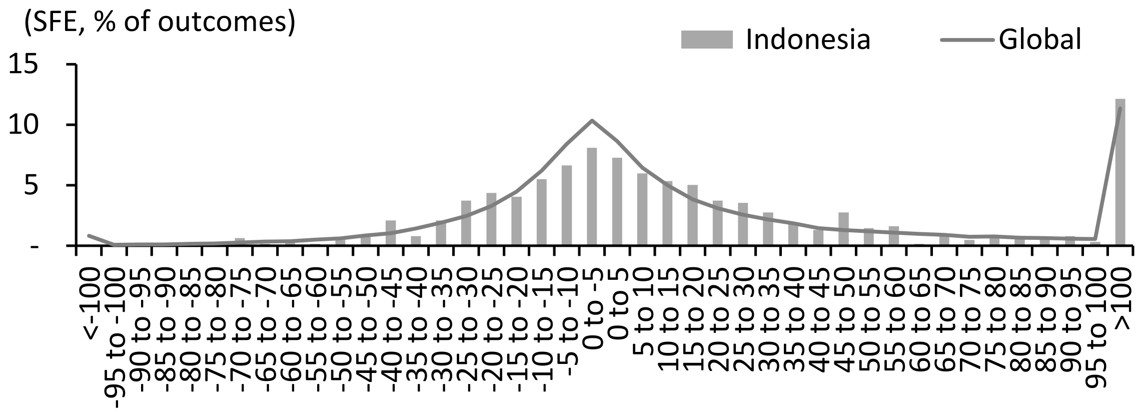
South Korea	2003	2005	2010	2014	All years
Number of companies	57	36	39	234	78
Maximum number of earnings forecasts	17	28	35	49	49
Maximum number of recommendations	29	41	45	54	54
Maximum number of target prices	23	37	27	40	40
Average number of earnings estimates	6.0	9.4	10.6	14.8	13.0
Average number of recommendations	15.5	20.3	22.9	17.3	20.0
Average number of target prices	9.0	16.8	13.8	11.5	12.8
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	5	3	3	1	1
Minimum number of target prices	1	1	1	1	1
Mean market capitalization (US$m)	1,861	2,415	4,515	3,758	4,430
Median market cap (US$m)	447	604	1,356	1,111	1,382
Maximum market cap (US$m)	32,576	16,153	34,985	154,971	173,488
Mean SFE (%)	32.3	57.4	40.6	82.0	65.4
Median SFE (%)	9.2	21.8	10.3	40.4	30.1
Maximum SFE (%)	228.6	439.8	491.7	492.3	492.3
Minimum SFE (%)	(70.4)	(76.5)	(44.4)	(391.1)	(391.1)
Standard deviation of SFE (%)	69.2	103.3	104.8	118.6	106.0
Mean SAFE (%)	50.3	70.8	53.0	92.3	77.8
Median SAFE (%)	30.1	30.4	17.9	47.9	38.3
Maximum SAFE (%)	228.6	439.8	491.7	492.3	492.3
Minimum SAFE (%)	0.1	0.4	0.1	0.2	0.1
Standard deviation of SAFE (%)	57.3	94.3	98.9	110.8	97.3

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



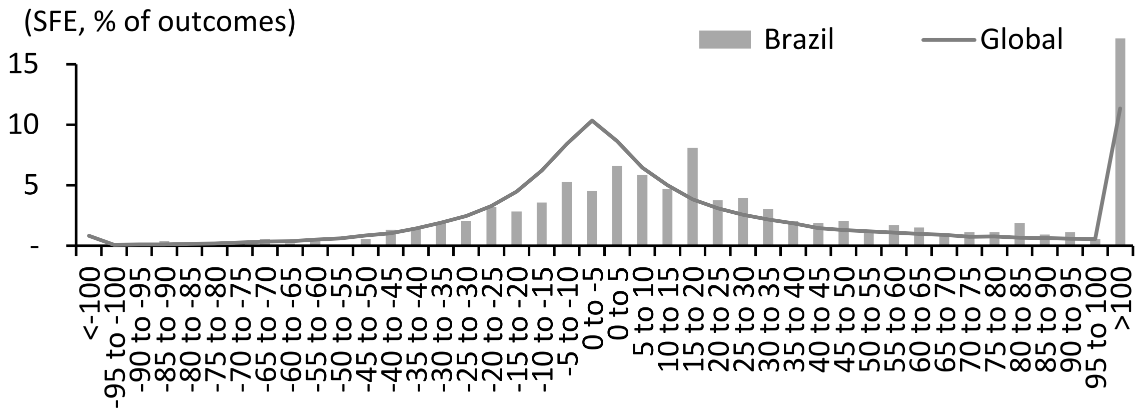
South Africa	2003	2005	2010	2014	All years
Number of companies	20	39	80	61	60
Maximum number of earnings forecasts	14	12	16	14	17
Maximum number of recommendations	12	13	17	18	18
Maximum number of target prices	3	5	16	17	17
Average number of earnings estimates	7.3	6.2	7.2	8.4	7.1
Average number of recommendations	7.9	7.7	7.8	9.2	7.7
Average number of target prices	1.5	1.9	7.3	8.0	5.5
Minimum number of earnings estimates	4	3	3	3	3
Minimum number of recommendations	3	3	2	2	2
Minimum number of target prices	1	1	2	2	1
Mean market capitalization (US$m)	1,612	3,110	3,916	5,763	4,235
Median market cap (US$m)	1,050	2,212	1,667	3,237	2,008
Maximum market cap (US$m)	4,552	12,141	28,292	37,052	38,004
Mean SFE (%)	55.8	25.2	11.2	28.5	24.1
Median SFE (%)	34.1	1.7	4.4	6.7	4.7
Maximum SFE (%)	345.1	320.2	156.4	436.8	444.1
Minimum SFE (%)	(39.5)	(54.1)	(196.9)	(38.8)	(196.9)
Standard deviation of SFE (%)	94.0	74.7	40.9	91.2	66.6
Mean SAFE (%)	67.9	39.1	25.5	36.1	34.7
Median SAFE (%)	39.7	9.6	15.1	11.4	12.8
Maximum SAFE (%)	345.1	320.2	196.9	436.8	444.1
Minimum SAFE (%)	1.9	1.3	0.1	0.2	0.0
Standard deviation of SAFE (%)	85.2	68.3	33.8	88.4	61.8

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



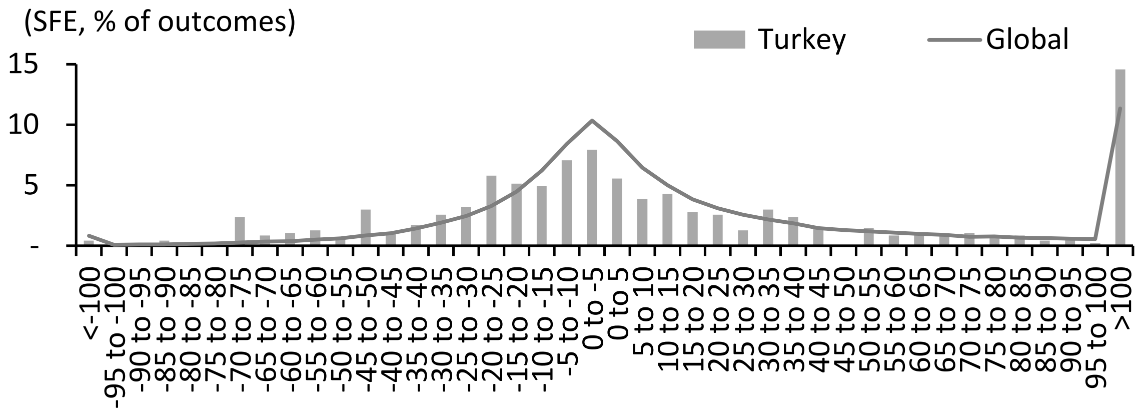
Indonesia	2003	2005	2010	2014	All years
Number of companies	26	44	45	81	52
Maximum number of earnings forecasts	13	16	21	22	26
Maximum number of recommendations	14	21	21	26	28
Maximum number of target prices	10	18	20	25	28
Average number of earnings estimates	8.4	7.6	9.6	9.6	9.7
Average number of recommendations	9.0	8.9	10.4	10.7	10.7
Average number of target prices	5.0	7.6	10.4	11.1	10.1
Minimum number of earnings estimates	3	3	3	3	3
Minimum number of recommendations	2	3	3	3	2
Minimum number of target prices	1	2	2	3	1
Mean market capitalization (US$m)	648	1,085	4,345	3,474	3,099
Median market cap (US$m)	367	511	2,780	1,484	1,349
Maximum market cap (US$m)	3,743	4,786	18,661	24,236	33,305
Mean SFE (%)	23.0	47.5	11.7	41.2	30.1
Median SFE (%)	10.0	10.1	(2.2)	15.0	6.4
Maximum SFE (%)	172.5	492.8	325.6	367.0	492.8
Minimum SFE (%)	(63.1)	(45.6)	(45.6)	(48.5)	(100.0)
Standard deviation of SFE (%)	59.4	95.4	59.7	81.1	79.7
Mean SAFE (%)	44.2	55.4	30.6	51.4	46.1
Median SAFE (%)	31.7	20.7	17.8	22.3	21.4
Maximum SAFE (%)	172.5	492.8	325.6	367.0	492.8
Minimum SAFE (%)	0.7	0.1	0.1	1.6	0.1
Standard deviation of SAFE (%)	45.2	90.9	52.4	74.9	71.6

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



Brazil	2003	2005	2010	2014	All years
Number of companies	7	10	57	88	44
Maximum number of earnings forecasts	10	12	13	16	19
Maximum number of recommendations	17	16	22	20	23
Maximum number of target prices	10	14	23	20	23
Average number of earnings estimates	7.1	5.8	7.2	8.7	8.0
Average number of recommendations	10.6	9.0	11.5	11.4	11.5
Average number of target prices	6.3	8.5	11.5	11.3	11.3
Minimum number of earnings estimates	4	3	3	3	3
Minimum number of recommendations	6	4	4	3	2
Minimum number of target prices	2	4	4	2	2
Mean market capitalization (US$m)	892	9,666	7,013	4,805	4,722
Median market cap (US$m)	834	2,707	2,360	1,685	2,049
Maximum market cap (US$m)	1,707	65,732	133,257	113,067	133,257
Mean SFE (%)	(1.1)	(3.2)	17.0	53.8	46.4
Median SFE (%)	(20.7)	(4.0)	3.3	16.1	17.1
Maximum SFE (%)	95.9	47.2	186.8	450.7	471.4
Minimum SFE (%)	(55.6)	(85.4)	(39.4)	(59.5)	(88.2)
Standard deviation of SFE (%)	51.4	43.9	50.8	91.1	90.5
Mean SAFE (%)	39.7	35.1	35.0	62.1	58.7
Median SAFE (%)	25.2	33.5	23.6	23.4	26.2
Maximum SAFE (%)	95.9	85.4	186.8	450.7	471.4
Minimum SAFE (%)	19.6	3.1	0.2	0.2	0.2
Standard deviation of SAFE (%)	28.2	23.8	40.3	85.7	83.0

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error



Turkey	2003	2005	2010	2014	All years
Number of companies	1	10	49	59	39
Maximum number of earnings forecasts	6	6	20	21	25
Maximum number of recommendations	10	13	21	28	30
Maximum number of target prices	1	7	23	28	32
Average number of earnings estimates	6.0	3.7	9.2	9.9	8.8
Average number of recommendations	10.0	11.8	10.6	14.5	12.5
Average number of target prices	1.0	5.1	12.7	14.9	12.4
Minimum number of earnings estimates	6	3	3	3	3
Minimum number of recommendations	10	9	3	4	2
Minimum number of target prices	1	4	4	4	1
Mean market capitalization (US$m)	434	4,034	3,686	2,830	3,264
Median market cap (US$m)	434	2,801	1,335	1,179	1,309
Maximum market cap (US$m)	434	11,649	19,629	11,520	21,811
Mean SFE (%)	53.9	0.1	18.2	22.7	23.3
Median SFE (%)	53.9	(4.2)	(5.5)	4.4	(0.0)
Maximum SFE (%)	53.9	109.6	343.7	273.1	423.6
Minimum SFE (%)	53.9	(45.2)	(70.7)	(85.2)	(137.8)
Standard deviation of SFE (%)	na	41.3	79.3	73.4	78.7
Mean SAFE (%)	53.9	23.5	45.9	46.8	49.7
Median SAFE (%)	53.9	11.6	19.3	20.5	25.3
Maximum SAFE (%)	53.9	109.6	343.7	273.1	423.6
Minimum SAFE (%)	53.9	1.8	1.1	1.2	0.0
Standard deviation of SAFE (%)	na	33.1	66.9	60.7	65.3

Notes: SFE: Scaled Forecast Error, SAFE: Scaled Absolute Forecast Error

Appendix 4: Publication and research work done during 2013-2016

Since starting at USTC, the author has produced more than 4,000 pages of professional, stock selection research written, translated and published 2 books, gotten two papers published and one preliminary submitted.

1. Ten stocks are enough in Asia. The Journal of Business and Finance Research, Spring/Summer 2015, pp. 18-40. ISSN 19419392
2. Eight stocks are enough in China. Accounting Practice and Research, Vol. 1, Issue I 2014 pp. Spring/Summer 2015, pp. 27-63 ISSN: 24081159.
3. You Won't Get Rich in the Stock Market Until You Change the Way You Think About It. May 21, 2015, Amazon Digital Services LLC. ASIN: B00Y25765G.
4. Transform Your Business with Dr. Deming's 14 Points Paperback. September 4, 2015, Amazon Digital Services LLC. ISBN: 978-1511579575.
5. Financial Analysts Were Only Wrong by 25%， proposed to and received feedback from editor of Financial Analysts Journal, ISSN:0015-198X, OCLC:4889170