ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
MSc Economics & Business
Master Specialisation Financial Economics

The effect of initial public offering experience on the forecasting accuracy of financial analysts on individual level

Author:	L. H. de Ridder
Student number:	360595
Thesis supervisor:	Drs. H.T. Haanappel
Finish date:	10 May 2017

ABSTRACT

A vast amount of research has been conducted on trying to determine factors that have a significant influence on earnings forecasting errors of individual financial analysts. Forecasting experience is assumed to be a factor that increases forecasting accuracy, but the definition of forecasting experience is broad and several kinds of experience exist. This study examines the effect of general and initial public offerings (IPO) experience on the earnings per share forecasting accuracy of analysts in the year that a company went public. General experience is defined as the amount of time an analyst is producing forecasts in general, while IPO-experience reflects the amount of IPO's an analyst has covered over the past years. The effect is tested by performing ordinary least squares regressions with the relative forecasting error of individual analysts as dependent variable. The results of this study indicate that general forecasting experience increases forecasting accuracy significantly, whereas specific IPO-experience has no significant effect on the forecasting error. These findings have implications for investors, since they base their investment decision to a great extent on earnings forecasts. Moreover, valuation models rely heavily on this metric.

Keywords: Earnings forecasts, financial analysts, initial public offerings, forecasting accuracy, experience

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 Introduction

One of the most important and widely used metrics produced by financial analysts is their forecast on future earnings of a company. Investors use these forecasted earnings in their investment decision, whereas stock valuation models commonly rely on it as the most important parameter. As a matter of fact, Brown, Foster & Noreen (1985) found evidence that security analysts have substantial influence on the stock market and L. Brown (1993) supports this outcome by arguing that earnings numbers are an essential piece of information in the process of assessing the value of equity securities.

Furthermore, Givoly and Lakonishok (1984) state that the value of forecasts is not solely limited to the predicted earnings numbers for the future, but that the dispersion between the forecast numbers of different analysts is a valid indicator of the riskiness (hence return) of an investment.

Because of the evident relevance of earnings forecasts, it is not surprising that there is much interest in finding the most accurate and precise forecasts. A vast amount of research is dedicated to the question on how to gather the best and most accurate forecasts; this area of research is still developing nevertheless. Since the end of the past century, academics agree on the fact that there are significant systematic differences in the forecast accuracy between individual analysts; evidence is documented in articles from Stickel (1992) or Sinha, Brown and Das (1997) for instance.

Since then, much research has been done on identifying factors or characteristics of individual analysts that have a significant impact on the accuracy of their forecasts[1]. One of the most straightforward factors one would think of is experience and, indeed, this factor is covered extensively in the literature. However, there is no unambiguous outcome which kind of experience is most important. General (Clement 1999) and firm-specific (Mikhail et al., 1997) experience are documented as possible factors that increase forecast accuracy among individual analysts.

Clement, Koonce and Lopez (2007), however, suggest that it is not general or firm specific experience that is most relevant, but that analysts learn from experience around particular corporate actions, the so-called 'task-specific' experience. The task their study focuses on is downsizing restructurings, which simply means that a company exits a part of their activities. The authors find evidence for increasing forecasting accuracy around a restructuring when an analyst has covered restructurings before.

This study builds on this finding and will try to find further evidence for task-specific experience, which in this case is defined as experience of an analyst with producing earnings forecasts around certain corporate finance events. By looking at initial public offerings (IPO's) this thesis will question whether analysts become better at forecasting earnings of a company that recently went public when they have covered more IPO's in their career. Forecasting accuracy around IPO's suits this research well, as it gives those analysts with IPO-experience the opportunity to demonstrate their

[1] See section 2.3 for information on the factors and characteristics that might influence forecasting accuracy

ability to produce more accurate forecasts than those who are inexperienced. The main reason for this is that IPO's are often a thorough change for a company and are followed by a relatively unsecure period regarding earnings and thus make it challenging to produce precise forecast earnings. The main research question of the study will be:

Does individual forecast accuracy around initial public offerings increase when an analyst has prior experience with covering companies that went public?

By using data from the International Brokers' Estimates System (IBES) database and performing ordinary least square regressions with the average individual forecast error as dependent variable, this study will test whether IPO-experience has a significant positive influence on the forecasting accuracy of an individual analyst. Obviously, some important control-variables have to be included in the regressions to make this research reliable and relevant[2].

The results of this study show that general forecasting experience statistically significant decreases the forecasting error of an analyst. General experience is defined in this paper as the number of years an analyst is producing earnings forecasts in general. There is no evidence found, however, that IPO-experience significantly influences the forecasting accuracy. The definition of IPO-experience in this study is the number of IPO's an analyst has covered over the past five years. These findings have implications for both investors and security analysts, since it could be profitable to put more weight on the forecasts of experienced analysts when analysing a firm that just went public. When looking at the other variables used in the regressions, it is notable that the level of industry specialization of an analyst is the factor that reduces the forecasting error most significantly. The fact that the forecasting error decreases when an analyst follows more firms or industries could be an interesting subject of future research, since prior literature draws a contrary conclusion on this matter.

This study adds to the existing literature by looking deeper into the phenomenon of task-specific experience of financial analysts. Whereas several factors have been identified over the past years that significantly improve forecasting accuracy, this specific field is relatively undiscovered and allows for further research. IPO-experience is just a part of this particular kind of experience and many other 'tasks' are suitable to be investigated in the future.

The remainder of this study is build up as follows. The next section gives a comprehensive overview of the theoretical background and most important literature regarding forecast accuracy. The third section explains how the data is gathered, followed by a section that explains which methodology is used in order to answer the research question. The fifth section discusses the empirical results, while the last section contains a summary and the conclusion of this study.

---

[2] Further information on the control variables can be found in section 3.4

2 Theoretical Background

Because of the relevance and importance of forecasting accuracy, it is not surprising that there is already a vast amount of research regarding this subject available. This section will give a comprehensive overview of theoretical background and relevant publications over the past fifty years in the area of earnings forecasting and the effect of experience on the accuracy of those forecasts.

2.1 Analysts' forecasts versus time-series models

At the end of the 1970s, research on earnings forecasting seemed to be at a dead end since most academics shared the opinion that there is no correlation between future and past growth in earnings. Little (1962) was the first one who drew the conclusion that it is useless to try to predict future earnings and based his findings on a sample from the United Kingdom. He argues that a prolonged period of steady success is most attributable to luck and that the forces of competition prevent firms from being successful over an extensive period. Ball and Watts (1972) documented that annual earnings follow a random walk process as well and did so by investigating a sample from the United States.

In the case that earnings actually follow a random walk, the role of analysts' forecasts would be limited since it would not be possible to make meaningful predictions. If this were true, the area of earnings forecasting research would become rather redundant. There are two arguments, which cannot be seen on their own, why forecasting literature flourished nevertheless in the late 1980s (Brown, 1993).

First, in 1976 the International Brokers' Estimates System[3] (IBES) database was developed. By using this database, it became possible to determine whether forecasts of analysts were accurate on a large scale. It was from that moment that academics started paying more attention to this area of research and began exploring the possibilities to analyse the data that was becoming available.

Second, a publication of Foster (1977) stated that capital market literature requires a proxy for the expectations of earnings by the market and that this proxy could be found by looking at the overall consensus of forecasts of analysts, since useful data was becoming increasingly available. The fact that earnings forecasting became much more linked to capital market research in the late 1980s, meant a major change in the way of thinking of academics (Brown, 1993).

Fried and Givoly (1982) and Brown et al. (1987) did research on the difference in performance between univariate time-series models and analysts' forecast consensus. Both publications conclude that analysts' forecasts perform better and should be used in favour of time-series model forecasts when a proxy for the expectation of the market is needed. From this moment on, academics began using analysts' forecasts instead of time-series model forecasts on a large scale (Bradshaw, 2011)

[3] For further information on the International Brokers' Estimates System, see section 4.1

2.2 Systematic differences in forecasting performance on individual level

Building on the research that compared analysts' forecast consensus relative to time-series models, academics started investigating whether more refined and extended research designs could identify factors that are correlated with increased forecasting accuracy. Brown (1991) provides evidence that the accuracy of the consensus forecast gets more accurate if older forecasts are dropped for instance.

It has not always been undisputed whether there are systematic differences in forecast accuracy between analysts on individual level. O'Brien (1990) investigates whether financial analysts with superior earnings forecasting ability can be distinguished on the basis of their prior forecast accuracy. The outcome of his paper is that there are no systematic differences in forecast accuracy across individuals. Publications of Richards (1976), Coggin and Hunter (1989) and Butler and Lang (1991) are in line with this research and share the same conclusion on this subject.

When research got more advanced and data more detailed, this finding was invalidated however. Stickel (1992) tests whether members of the *Institutional Investor (II) All-American Research Team* (an exclusive annual ranking of the leading analysts of the United States, based on institutional election through voting) supply more accurate earnings forecasts than others. One of the main conclusions of Stickel is that team members of the All-Americans forecast more accurately indeed. The mean absolute forecast error of the members of the team is 95 cents, whereas non-members have a mean absolute forecast error of 98 cents. No least squares regressions were performed though and hence the publication has limited statistical significance.

Sinha, Brown and Das (1997) find further evidence that there are certainly systematic differences between individual analysts. They test whether analysts who performed better in the past produce more accurate forecasts by looking at their annual earnings per share (EPS) forecasts. The authors argue that previous publications have failed to find differences in individual forecasting accuracy because they do not control for the differences in recency of forecasts issued by the analysts. By using both an estimated generalized least squares estimation procedure and a matched-pair design, the authors find evidence that differential forecast accuracy amongst analysts exists. The authors validate their findings by testing whether these differences in forecast accuracy persist in a holdout period (out of sample) and this is convincingly the case.

2.3 Factors that influence forecasting accuracy

It was at the end of the past century that the vast majority of the academics agreed on the thought that systematic and time persistent differences in forecast accuracy between individual analysts did exist. The question that naturally followed was whether it would be possible to investigate why these differences exist and if it would be possible to determine which factors have a significant influence on forecasting accuracy.

One of the first researches that tries to relate certain factors to forecasting accuracy is the publication of Brown, Richardson and Swager (1987). The three factors they take into account are firm size, prior dispersion of analysts' forecasts (as an ex ante proxy for earnings uncertainty) and the number of lines of businesses the covered company has (as a proxy for the correlation among the information variables). Whereas the correlation between forecasting accuracy and both firm size (positive) and prior dispersion (negative) is significant, there is no significant relation found for the lines of businesses.

The publication of Clement (1999) builds on the same question and investigates analysts' characteristics that are potentially associated with forecast accuracy. He argues that prior research on forecast accuracy lacks relevance since they do not control for differences that contribute to forecast variation. The author investigates the effects of experience (further information on the effect of experience on forecasting accuracy in section 2.4), number of firms and industries followed by the analyst, and employer size. He also controls for firm-year variation in both the dependent and independent variables since it can be more difficult to make precise forecasts of a firm's earnings in certain years relative to others.

The conclusion of the publication of Clement is that forecasting accuracy is positively associated with general and firm-specific experience and employer size. The finding that employer size positively contributes to more accurate forecasts is attributable to the fact that they have access to superior resources. The correlation between the number of firms and industries that an analyst is following and forecast accuracy is negative according to the article; this finding could be explained by the fact that it is more difficult to follow a larger set of firms and industries.

Brown (2001) performed an interesting research by comparing the conclusions of the articles of Sinha et al. (1997) and Clement (1999). Sinha et al. claim that past accuracy of an individual analyst is significantly positively correlated with future performance on the preciseness of forecasts, while Clement documents five characteristics (as mentioned in the paragraph above) that significantly contribute to the forecasting accuracy of an analyst. By using least squares regressions, Brown concludes that there is no significant difference between the methods of looking at past performance or the five defined characteristics of individual analysts.

Jacob, Lys and Neal (1999) have written another article that tries to relate certain factors to the accuracy of forecasts. Aptitude (innate ability), experience, several environmental factors (size and industry-specialization of the brokerage house, turnover of analysts in the brokerage firm) and analyst-company alignment (how well the skills of an analyst fit with the company they are covering) are factors the authors look at in their research. They do so by performing both cross-sectional comparisons, similar to the method of Clement (1999), and time-series comparisons. The authors document that aptitude and the before mentioned firm characteristics are positively correlated with forecasting accuracy, while experience solely does have a significant effect if they do not control for analyst-company alignment.

One of the main findings of the research of Alford and Berger (1999) is that forecasting accuracy increases when more analysts are following a particular company. The reason for this conclusion is that more analysts following a firm lead to an increase of expenditures on information acquisition and thus a higher amount of information gets uncovered. This would logically lead to a decrease in forecasting errors among analysts. The empirical results of the research show that a ten per cent increase in number of analysts that follow a company leads to an improvement of the forecasting accuracy of 5.4 per cent. Both ordinary least square regressions as two-stage least square regressions are performed in the research.

2.4 The effect of experience on forecasting accuracy

Section 2.3 considers several factors that are linked to forecasting accuracy in the literature. The most important factor for this study, however, has not yet been discussed. When thinking of the most straightforward aspect that influences anyone's ability regarding a difficult task, a vast majority will come up with the amount of experience someone has in that particular area of expertise. This is no different for the area of forecasting accuracy by analysts and it follows that there are some interesting publications on the subject of the relation between forecasting performance and individual analysts' experience, this section will discuss the most relevant articles and theories.

The research of Mikhail, Walter and Wallis (1997) is one of the first publications with the effect of experience on forecasting accuracy as main subject. The authors define experience as the number of quarters an analyst has produced quarterly forecast earnings for a particular firm, the so-called firm-specific experience. This is in contrast with prior literature, where simply the number of years that an analyst has produced forecast earnings in general is used as proxy for experience. The main reason for this decision is that Mikhail et al. believe that the general measure for experience does not adequately capture the repetition necessary to develop the skill needed to produce precise forecasts, their more explicit measure of experience provides a better proxy for the experience of an individual analyst in their eyes.

Besides looking at the effect of firm-specific experience, the research also tests whether industry focus of an analyst leads to more precise earnings forecasts. The authors do so by looking at the industry concentration of the portfolio of the analysts and the experience the analyst has in the specific industry (again by looking at the number of quarters the analyst has produced forecasts in a certain industry).

By performing least squares regressions with the mean absolute percentage error as dependent variable, the authors try to find a relation between firm-specific experience and forecasting accuracy. Other variables that are referred to as important in prior research are included in the regression as well. These variables are the number of other analysts following a firm and a dummy that takes one if the analyst issues a forecast within the first month after changing the brokerage house he works for. The reason to include the latter variable is that accuracy of an analyst may temporarily be affected by the transmission to a new employer.

Finally, the control variables included in the regression are the number of days between the forecast release and the forecast announcement (it is documented that forecast accuracy increases when the forecast is made closer to the earnings announcement date) and a dummy that takes one if the forecast is for the fourth quarter of the fiscal year (fourth quarter earnings are influenced by large write-offs and this could increase the forecast error, while the large amount of information available at the end of a fiscal year could decrease this error).

The results of the regression show that firm-specific experience reduces the forecast error significantly, this finding is in line with the expectations of the authors. Furthermore, little significant evidence is found for the relation between industry specialization and an increase in forecasting accuracy. As more information about a firm becomes available, the forecasting error of an analyst decreases substantially according to this research.

As mentioned in section 2.3, the publications of Clement (1999) and Jacob et al. (1999) incorporate the effect of experience in their research as well. Interestingly, the answer on the question whether forecast accuracy improves with experience is contrasting between the two researches. Clement finds evidence for the positive correlation between experience and forecasting accuracy (in line with the publication of Mikhail et al.), while Jacob et al. argue that experience has no significant effect on forecasting accuracy after controlling for innate ability. The reason for these contradictory conclusions is according to Clement attributable to the differences in research design. Clement controls for firm-year effects, whereas Jacob et al. do not. On the other hand, Jacob et al. include variables in their regression that Clement leaves out of his research, forecast frequency for example. Altogether, these interesting publications with no unambiguous conclusion lead to the first hypothesis of this study:

H1: General forecasting experience of an analyst increases his individual forecasting accuracy

The main reference for this study is the article of Clement, Koonce and Lopez (2007), which was published in the Journal of Accounting and Economics. It follows from the previous paragraph that there is not one unambiguous conclusion on the effect of experience on forecasting performance. Clement et al. endorse this and look at analysts' experience in a different manner than prior literature; they investigate whether so-called 'task-specific' experience exists. Furthermore, they look at the effect of innate ability on forecasting ability on its own and in combination with task-specific experience.

According to the authors of the article, the definition of task-specific experience is 'the analyst's experience in forecasting around a particular kind of situation or event'. Clement et al. state that it is not likely that analysts with the same amount of general or firm-specific experience have gained equal experience in a particular task situation. Task-specific experience has in the eyes of the authors a much larger impact on forecasting accuracy than general or firm specific experience.

Downsizing restructurings are referred to as the task in this research. Examples of downsizing restructurings are a closing of a plant, termination of employees or a cancellation of a lease. The decision to focus on downsizing restructurings was made because of several different reasons. First of all it is likely that an analyst experiences several restructurings in his career, secondly restructurings are a relatively homogeneous phenomenon and finally it is an opportunity for experienced analysts to show their ability to make more accurate forecasts than others because of the difficulty of forecasting earnings after a restructuring.

The conceptual model of the research looks as follows:

$$\text{analyst forecast accuracy} = f\ (\text{innate ability, task-specific experience, control variables}). \tag{1}$$

In this formula the dependent variable, analyst forecast accuracy, is measured by taking the proportional mean absolute forecast error (PMAFE). The PMAFE is calculated by dividing the difference between the absolute forecast error (AFE) of an individual analyst and the mean absolute forecast error (MAFE) by the MAFE. This procedure makes sure the variable is mean-adjusted, all the variables in the model are mean-adjusted since this controls for firm-year effects[4].

The most important independent variable is the interaction term between the dummy that takes one if it is a restructuring year (RC_YR) and the mean-adjusted number of restructurings an analyst has encountered in the prior five years (DREXP). These variables are expected to be statistically insignificant on their own, because task-specific experience should only increase the forecast accuracy in a year with a restructuring.

In order to test the effect of innate ability the authors refer to the publication of Jacob et al. (1999), where aptitude is defined as analyst-firm alignment. An analyst-firm dummy is added (not reported in their regression) that takes one for all forecasts made by a given analyst for a specific firm and null otherwise.

Furthermore controls that are identified as relevant in prior literature are incorporated in the regression (expected sign in parentheses behind the abbreviation). Both general (DGEXP, -) and firm-specific (DFEXP, -) experience are included in the regression, even as the number of days from the forecast date to 30 days prior to the fiscal year end (DAGE, +). A dummy whether an analyst works for a top-ten broker in terms of number of employees (DTOP10, -) is included as well. The number of firms (DNCOS, +) and industries (DNSIC2, +) followed by a particular analyst are also incorporated as control variables. How often a forecast revision was provided (DFREQ, -), the forecasting

[4] For further information on the mean-adjustment procedure, see section 3.3

performance of last year (LPMAFE, +) and the percentage of firms followed in the same industry by an analyst (DIEXP, -) are the last three controls that are included.

To summarize, the regression of the research of Clement, Koonce and Lopez looks as follows:

$$\begin{aligned} PMAFE_{ijt+1} &= \alpha_1 DGEXP_{ijt} + \alpha_2 DFEXP_{ijt} + \alpha_3 DAGE_{ijt+1} + \alpha_4 DTOP10_{ijt} \\ &+ \alpha_5 DNCOS_{ijt} + \alpha_6 DNSIC2_{ijt} + \alpha_7 DFREQ_{ijt} + \alpha_8 LPMAFE_{ijt} + \alpha_9 DIEXP_{ijt} \\ &+ \alpha_{10} RC\_YR_{jt} + \alpha_{11} DREXP_{ijt} + \alpha_{12} DREXP_{ijt} \times RC\_YR_{jt} + \varepsilon_{ijt}, \end{aligned} \tag{2}$$

The authors perform four different regressions in which they vary between including task-specific experience and the dummy for innate ability, as described in table 1.

Table 1: Results of the publication by Clement, Koonce and Lopez (2007)

	Column 1 Eq. (2) excluding the task-specific experience variables and excluding dummy variables capturing analysts' innate ability	Column 2 Eq. (2) excluding the task-specific experience variables but including dummy variables capturing analysts' innate ability	Column 3 Eq. (2) excluding the dummy variables capturing analysts' innate ability	Column 4 Eq. (2) including the dummy variables capturing analysts' innate ability
DGEXP	−0.0064**	0.0005	−0.0063**	0.0005
DFEXP	−0.0052**	−0.0012	−0.0057**	−0.0012
DAGE	0.0043**	0.0039**	0.0043**	0.0039**
DTOP10	−0.0825**	−0.0071	−0.0819**	−0.0071
DNCOS	0.0018*	0.0040**	0.0019*	0.0040**
DNSIC2	0.0040*	0.0018	0.0040*	0.0018
DFREQ	−0.0621**	−0.0587**	−0.0626**	−0.0588**
LPMAFE	0.0504**	0.0067**	0.0531**	0.0067**
DIEXP	−0.0968**	−0.1269**	−0.0962**	−0.1268**
RC_YR			0.0017	0.0099
DREXP			0.0007	0.0039
DREXP × *RC_YR*			−0.1101**	−0.0845**
$Adj\text{-}R^2$	0.1883	0.2997	0.1885	0.3002

In the first two columns the effect of task-specific experience is excluded from the regression, innate ability is only included in the second column. The results are in line with prior research; the effect of general or firm-specific experience diminishes when innate ability is taken into account, this is the same conclusion as Jacob et al. (1999) has drawn in his research.

When looking at the third column, the evidence that task-specific contributes to forecast accuracy is provided. The significantly negative coefficient of the interaction term DREEXP*RC_YR says that task-specific experience causes the PMAFE to be lower in a restructuring year than in a non-restructuring year, this is in line with the predictions of the authors of the research. From column 3 follows that for every year of restructuring experience, the PMAFE decreases with approximately 11 percent.

Column 4 shows that the coefficient of the interaction term remains significantly negative when task-specific experience and innate ability are included in the regression. The interpretation of this finding is that task-specific experience still has a statistically significant influence on the PMAFE if innate ability is considered as well. Again, these findings are as the authors of the article expected beforehand.

This study builds on the results of Clement et al. by investigating a different form of task-specific experience, namely experience with initial public offerings. By further looking into different kinds of specific experiences, it is possible to determine more specifically which factors play a major role in producing accurate forecasts. This leads to the second hypothesis:

H2: The individual forecasting accuracy of an analyst around an initial public offering increases when he has covered more initial public offerings before

Table 2: An overview of prior literature on the subject of forecasting accuracy on individual level

Author(s), year	**Journal of**	**Main findings**	**Methodology**
Brown, Richardson and Swager, 1987	Accounting Research	Firm size (positively) and prior dispersion (negatively) are significantly related to forecast accuracy. Number of business lines is not significantly related	Least squares regression analysis
O'Brien, 1990	Accounting Research	There are no systematic differences in forecast accuracy across individuals	Fixed effects regression model
Stickel, 1992	Finance	Members of the All-American team produce more accurate forecasts than non-members	Comparing forecasted EPS with the actual EPS
Sinha, Brown and Das, 1997	Contemporary Accounting Research	Differential forecast accuracy amongst analysts exists	Generalized least squares estimation and a matched-pair design
Mikhail, Walther and Willis, 1997	Accounting Research	Forecast accuracy increases significantly with firm-specific experience, while little evidence is found that industry-specialization decreases the forecast error	Least squares regression analysis
Alford and Berger, 1999	Accounting, Auditing and Finance	The number of analysts that follow a certain company is positively correlated with the forecast accuracy of that firm	Ordinary least squares and two-stage least squares regressions
Clement, 1999	Accounting and Economics	General and firm specific experience and employer size are positively correlated with forecast accuracy, while number of firms and industries followed is negatively correlated	Cross-sectional regression analysis
Jacob, Lys and Neal, 1999	Accounting and Economics	Forecasting accuracy is positively related to aptitude, analyst/company alignment, brokerage size and industry specialization, and not by experience.	Both cross-sectional and time-series correlations
Brown, 2001	Financial Analysts Journal	There is no significant difference in forecasting performance between the methods used by Sinha et al. (1997) or Stickel (1999)	Least squares regression analysis
Clement, Koonce and Lopez, 2007	Accounting and Economics	Task-specific experience (restructurings) leads to more accurate earnings forecasts, this effect holds when innate ability is considered as a relevant factor	Least squares regression analysis

2.5 Incentives to produce or refrain from making accurate forecasts

Whether analysts intend to produce forecasts that are as accurate as possible or not, is an on-going discussion in the literature. On the one hand, there is a vast amount of publications that argue that analysts are stimulated to maximize forecast accuracy, while on the other hand there could be reasons for analysts to purposely refrain from this.

A striking example of an analyst who consciously produced investment reports that where false, is the case of telecom specialist Jack Grubman at the beginning of this century.[5] At that time, Grubman was the best-paid analyst on Wall Street, with annual earnings of 20 million dollars. During the heydays of the telecom sector, Grubman was known for his straight-shooting analysis in this industry: 'If Jack said it was good, it had to be good'. Things changed when the telecom bubble burst in 2001 and investors were loosing money on large scale, meanwhile Grubman was refusing to downgrade his overly bullish investment advice. When it came out that he was advising telecom firms and generating investment-banking business at the same time, the conflict of interest was inevitable. In 2003 Grubman had to pay a 15 million dollar fine and was banned from the financial industry.

It is most likely that there is no unambiguous conclusion on the matter whether analysts are trying to produce accurate forecasts or not in general, this section will shed light on both sides of the discussion.

The article of Stickel (1992) is one of the earliest and most cited publications in favour of the thought that analysts are incentivized to produce accurate forecasts. An important result of the study is that members of the *Institutional Investors All-American Research Team* provide forecasts that are more precise than other analysts (as mentioned in section 2.2). Although analysts are not directly selected for the All-American team by looking at their past forecasting accuracy, this plays an evident role in the process. Every year about 2000 money managers are asked to assess analysts on their performance and forecasting accuracy is an important factor in this process. It is documented that once an analyst is in the All-American analyst team, his remuneration will increase significantly (Groysberg, Healy, Maber, 2011).

Stickel (1992) refers to an article in the Wall Street Journal[6], which states that the wage of an analysts at most firms is not directly determined by past forecasting accuracy. Although it is not an explicit factor according to the article, it is subsumed in other factors that determine wages, such as receiving offers from competitors or the trading volume of stocks the analyst recommends. An analyst is quoted: "If your estimates aren't accurate, nobody's going to buy your stock".

Another solid argument for analysts to produce accurate forecasts is that it can have significant influence on their career. Hong, Kubik and Solomun (2000) provide evidence that analysts who

[5] Source: CNN Money, '*Is Jack Grubman the worst analyst ever?*', 25 April 2002

[6] Stickel does not explicitly mention which article of the Wall Street Journal he refers to

produce inaccurate forecasts are more likely to lose their job. Publication of Groysberg et al. (2011) and Mikhail et al. (1999) draw the same conclusion on this subject. When looking at the positive side of producing precise forecasts, Hong and Kubik (2003) document that analysts who produce accurate forecasts are more likely to move to bigger brokerages and assumedly better jobs.

As mentioned, there are arguments that contradict the thought that analysts always intend to minimize their forecast errors. Over optimism is regarded as the most important phenomenon that leads to less precise forecasts. The following paragraphs will elaborate on the reasoning behind it.

The most prevalent cause for analysts to be overoptimistic in their forecasts is that their employer often has, besides equity research, investment banking activities in their portfolio (Bradshaw, 2011). The fruitful underwriting fees of an investment banking department form a substantial part of the total incoming cashflow and thus it is crucial for a firm to keep on receiving these fees. Positive coverage by analysts is essential in the process of bringing in investment banking business and it follows that banks face a conflict of interest between their investment banking division and their research department. Bradshaw even states that sell-side research departments are compensated by the investment banking department if they provide positive earnings forecasts for firms on affiliated deals.

Groysberg et al. (2011) test whether investment bank analysts provide less accurate forecasts than non-investment bank analysts, which you would expect according to the theory, and find that this is not the case. Analysts who are employed by an investment bank provide forecasts with lower forecast errors (and thus less biased results) than those who are not working for an investment bank, this contradicts the argument that related analysts are incentivized to produce over optimistic forecasts for the investment banking department of their employer.

In addition, Paleari and Vismara (2007) find that affiliated analysts are not producing more overoptimistic forecasts than analysts that are not affiliated at all. This finding contradicts the thought that analysts working for a firm with investment banking activities as well produce favourable research reports on purpose.

A second often heard argument is that analysts are afraid to produce negative earnings forecasts since they fear that managers of the particular firm will punish them (Das et al., 1998). One of the most highly regarded sources of information on which forecasts are based is the information issued by managers of the firm itself, since these managers can provide analysts extremely valuable insights. Obviously, it is not favourable for a manager if an analyst produces disappointing forecasts on his firm and one way to avoid this is to exclude that particular analyst from certain information if he does so.

Clearly, analysts are not always producing too optimistic forecasts. Sometimes they are too pessimistic about the future earnings of a firm. The difference with them being overoptimistic on purpose is that they are not aware of being too pessimistic most likely. The main reason that analysts underestimate earnings is the fact that a firm is managing its earnings and by doing so they can set an artificially low benchmark. Obviously it is in the favour of a firm to beat the forecast consensus and announce positive surprises (Burgstahler and Eames, 2003).

The Global Analyst Research Settlement

In April 2003, the Securities and Exchange Commission (SEC) announced enforcement actions against almost all of the large investment banks[7]. The reason for these enforcement actions, led by New York Attorney General Eliot Spitzer, was the fact that most investment banks were facing a conflict of interest between their investment banking division and their research department, as mentioned in section 2.5. Analysts were publishing research reports that were unreasonably optimistic, especially around IPO's, in order to do a favour to the investment-banking department of their firm. This is often regarded as one of the main causes for the Dotcom bubble at the beginning of the century.

In order to avoid such businesses in the future, the SEC announced the Global Analyst Research Settlement. Besides some substantial fines, several laws were introduced. The main purpose of these laws was to strengthen the so-called 'Chinese Wall' between the research department and the investment banking division within a firm. Furthermore the 'quiet periods'[8] were extended and several other measures were taken against purposely producing overoptimistic research reports.

To conclude, the outcomes of the researches by Groysberg et al. (analysts working for an investment bank produce more accurate forecasts than those who are not employed by an investment bank) and Paleari et al. (affiliated analysts are not more overoptimistic than unaffiliated analysts) provide sufficient evidence to assume that the vast majority of analysts is not producing inaccurate forecasts on purpose. Moreover, the Global Analyst Research Settlement was introduced in 2003 in order to enforce this by law and firms will be punished if the SEC finds out that analysts do consciously produce inaccurate forecasts.

2.6 Summary

To summarize, this chapter provides an extensive overview of the literature and theoretical background on earnings forecasting over the past fifty years. When earnings forecasts of analysts where linked to capital markets research, the importance of them became clear. It followed that the overall consensus of analysts on forecasts is more accurate as a proxy for market expectations than time-series models. Since then many studies have been conducted to determine factors that have significant influence on the forecasting accuracy of an analyst. It has been documented that several different kinds of experience (general, firm-specific, industry-specific, task-specific) have significant

[7] Source: Press release of the SEC, 'Ten of Nation's Top Investment Firms Settle Enforcement Actions Involving Conflicts of Interest Between Research and Investment Banking', April 28, 2003

[8] A period in which an analyst is not allowed to write about a company while their bank is underwriting its IPO

influence on forecasting accuracy; this thesis builds on the so-called task-specific experience. The last part of this chapter discusses the question whether analysts are incentivized to produce accurate forecasts or refrain from this on purpose. Evidence was found to conclude that the vast majority of analysts tries to be as accurate as possible, especially since the Global Analyst Research Settlement was enforced in 2003.

CHAPTER 3 Methodology

This chapter discusses the methodology used in order to answer the main research question and to test whether the hypotheses hold. First the research setup will be explained and then both the dependent and independent variables will be discussed.

3.1 Research setup

Similar to most prior academic research on the subject of earnings forecasting, a cross-sectional regression will be used to test the effect of IPO-experience on individual forecasting accuracy. Earnings per share (EPS) of a company is used as parameter for forecasting performance because of the large amount of data that is available for this metric. Besides that, the vast majority of prior literature uses this metric as well in their studies, which makes it possible to compare and possibly validate the findings of this research. The conceptual model looks as follows:

$$Individual\ Forecasting\ Accuracy = \\ f(IPO\ experience, general\ experience, control\ variables) \quad (3)$$

First the effect of general experience on individual forecasting accuracy will be investigated. General experience is regarded as the experience an analyst has in producing forecasts in general, without looking at more specific kinds of experience. By doing so, the first hypothesis will be tested:

H1: General forecasting experience of an analyst increases his individual forecasting accuracy

After investigating general experience, this study will try to provide evidence for the thought that more specific experience, IPO-experience, has a significant influence on forecasting accuracy of individual analysts. The second hypothesis will be tested:

H2: The individual forecasting accuracy of an analyst around an initial public offering increases when he has covered more initial public offerings before

3.2 Dependent variable

The dependent variable in the regression represents the individual forecasting accuracy of an analyst. This is measured by looking at the proportional mean absolute forecast error (PMAFE). This method is equal to prior literature (Clement, 1999; Jacob et al. 1999; Clement et al., 2007) and compares the forecast error of an individual analyst with the average of all other analysts that produce forecasts on the same company over the same period. Since the subject of this study is the effect of experience on future forecasting accuracy, the research setup is designed to look at the forecast accuracy of one year in the future (T+1). In order to retrieve the PMAFE, several steps have to be taken.

First the absolute forecast error (AFE) of an analyst has to be determined by calculating the absolute difference between the forecast of an analyst and the actual figures.

$$AFE_{ijt+1} = ABS\ (Forecast_{ijt+1} - Actual_{jt+1}) \tag{4}$$

AFE_{ijt} represents the absolute forecast error of analyst *i* for company *j* in year *t+1* while $Forecast_{ijt+1}$ and $Actual_{ijt+1}$ stand for the forecasted and actual earning numbers respectively.

Next the mean absolute forecast error (MAFE) must be determined; this is possible by looking at the absolute difference between the overall forecast consensus of all analysts and the actual figures.

$$MAFE_{jt+1} = ABS\ (Consensus_{jt+1} - \ Actual_{jt+1}) \tag{5}$$

$MAFE_{jt+1}$ represents the mean absolute forecast error of firm j in year *t+1* while $Consensus_{jt+1}$ and $Actual_{jt+1}$ are the mean forecast and actual number of the earnings of company *j* in year *t+1*.

Now that the AFE and MAFE are determined, it is possible to calculate the proportional mean absolute forecast error (PMAFE). The difference between the AFE and the MAFE is divided by the MAFE to arrive at the PMAFE.

$$PMAFE_{ijt+1} = \frac{AFE_{ijt+1} - MAFE_{jt+1}}{MAFE_{jt+1}} \tag{6}$$

As the PMAFE gets higher, the relative forecasting accuracy of an analyst decreases. A positive PMAFE says that the analyst has produced a worse forecast than the average analyst on that particular company.

3.3 Mean-adjustment procedure

The procedure of subtracting the firm-specific mean in a certain year from the actual forecasted value is referred to in the literature as the mean-adjustment procedure. The reason to scale the difference is that it controls for firm-year effects (Clement, 1999). This important procedure ensures that factors that make it easier or more difficult to predict earnings relatively between certain years for a particular company are filtered out. There are years with events that make it harder or easier to make a forecast of the earnings of a company, a year with a merger or an acquisition for instance. By using the mean-adjustment procedure, a measure is taken to control for these differences in difficulty since all analysts (and thus the mean forecast error) have to cope with them. Using the mean-adjustment procedure filters out both time and firm effects, this is the reason that there is no need to include time-specific control variables, such as a dummy for the financial crisis for instance. The mean-adjustment procedure applies to all variables in this study. It is not possible to adjust for a firm effect in the variable that represents the number of analyst that are following the firm (NRAN) in a certain year, so the model solely corrects for the time-effect in this variable.

3.4 Independent variables

This section will discuss the variables used in the regression as independent variables. Obviously the most important one is the variable that represents the IPO-experience, but clearly it is important to address other factors that influence forecasting accuracy as well.

IPO-experience

As mentioned, the main independent variable of this study will be the one that describes the level of experience an analyst has with IPO's. The more IPO-experience an analyst has, the lower the PMAFE around a public offering is expected to be. IPO-experience is measured as the number of IPO's an analyst has covered over the prior 5 years. The definition of IPO coverage is that the analyst has to have produced at least one EPS forecast in the year after the IPO of the company. The expected sign of this variable is negative, since IPO-experience should decrease the forecasting error.

General Experience

The effect of general forecasting experience is widely documented in the literature and it is important to take this factor into account in this study. Clement (1999) finds evidence for the fact that analysts' forecast error reduces as they gain more experience with generating earnings forecasts. General forecasting experience will be measured as the number of years an analyst has produced at least one forecast prior to year *t.* The expected sign of the coefficient is negative, as general experience is assumed to be a factor that reduces forecasting error.

Industry Specialization

Besides general experience, the amount of industry specialization is assumed to be a factor that has significant influence on forecasting accuracy. Similar to Clement et al. (2007), industry specialization is determined by looking at the percentage of firms covered by the analyst in year *t* with the same first digit SIG code. It is expected that the coefficient of this variable is negative, since specialization leads to more in depth knowledge of the industry and thus a better ability to maximize forecast accuracy.

Number of days to end of fiscal period

It is documented that the forecast error reduces when the forecast is produced closer to the fiscal year end (Mikhail et al., 1997). The rationale behind this finding is that more information becomes available during the fiscal year, due to disclosures of the management of a firm and research done by other analysts, which makes it relatively easier to produce accurate forecasts when the end of a fiscal year is coming closer. It is expected that the sign of the coefficient of this variable is positive, because this means that the forecast error increases when there are more days left until the end of the fiscal year.

Portfolio complexity

Two variables will be included in the regression, to measure the effect of the complexity of the analyst in year *t*. Both the number of firms and the number of industries an analyst is covering in year *t* will be included in the regression, equal to Clement et al. (2007). The coefficient is expected to be positive for both the variables, since more firm or industry coverage leads to a more complex portfolio and thus a higher PMAFE.

Number of analysts that cover the firm

Alford and Berger (1999) argue in their publication that it becomes easier to produce accurate forecasts when more analysts are covering the same company, since each additional analyst contributes new information to the consensus estimate. A variable is included that measures the number of analysts that cover the company in its first year after the IPO, the coefficient is expected to be negative since a higher coverage should lead to a lower forecast error.

Employer size

Prior literature (Clement, 1999) has identified the phenomenon that analysts produce significantly more accurate forecasts when working for a larger employer, where size of the employer is determined by looking at the number of employees working for the firm. Unfortunately it was not possible to retrieve information about the employer per analyst from the IBES database. This information was necessary in order to determine the size of the employer per analyst when he produced his forecast.

3.5 Final regression

To conclude this chapter, the final regression looks as follows. The D in front of the variables stands for differenced, since the variables are firm-year mean adjusted. This is also the reason that there is no intercept included in regression, the means are subtracted from the variables. Furthermore the expected sign of the coefficients before the variables is denoted between parentheses in the description.

$$PMAFE_{ijt+1} = \alpha 1\ DIPOX_{it} + \alpha 2\ DGEXP_{it} + \alpha 3\ DSPEC_{ijt} + \alpha 4\ DDAYS_{ijt+1} + \alpha 6\ DNRFI_{it} + \alpha 7\ DNRIN_{it} + \alpha 8\ DNRAN_{jt} + \varepsilon_{ijt} \quad (7)$$

$PMAFE_{ijt+1}$	Analyst *i*'s proportional mean absolute forecast error of firm *j*'s earnings for *t*+1 (one year after the IPO)
$DIPOX_{it}$ (-)	The IPO-experience of analyst *i* at *t* (the moment of the IPO) measured as the number of IPO's analyst *i* has covered in the five years prior to *t*
$DGEXP_{it}$ (-)	The general experience of analyst *i* at *t* measured as the number of years analyst *i* has produced at least one forecast prior to *t*, with a maximum of ten years.
$DSPEC_{ijt}$ (-)	The industry specialization of analyst *i* at *t* measured as the percentage of firms followed by analyst *i* in the same first digit SIG code as firm *j*
$DDAYS_{ijt+1}$ (+)	The number of days from the date of analyst *i*'s forecast of company *j* until the fiscal year end date in year *t*+1
$DNRFI_{it}$ (+)	The number of firms analyst *i* follows at *t*, measured by the number of firms analyst *i* has produced at least one forecast for in the year before *t*
$DNRIN_{it}$ (+)	The number of industries analyst *i* follows at *t*, measured by the number industries with different first digit SIG codes analyst *i* has produced at least one forecast for in the year before *t*
$DNRAN_{jt}$ (-)	The number of analysts that follow firm *j* at *t*, measured as the number of analysts that have produced a forecast of the earnings of firm *j* in the year after *t*

After developing the model and determining the design of the final regression, it is possible to summarize the methodology in order to test the hypotheses as mentioned in section 3.1. As table 3 shows, the first hypothesis will be tested by looking at the coefficient in front of the variable that represents the general experience (DGEXP) of an analyst. The variable that represents IPO-experience (DIPOX) is added when the second hypothesis is tested. Interpreting the coefficient in front of DIPOX will test the second hypothesis.

Table 3. Hypotheses and their related variables

This table summarizes the two hypotheses developed in order to answer the main research question of this study. By interpreting the coefficients of their related variables, it is possible to draw a conclusion whether the hypotheses hold or not. As observable, theory suggests that both the coefficients of the variables are negative, which would mean that general and IPO-experience reduce the relative forecast error of an analyst.

	Variable	Expected sign
H1: General forecasting experience of an analyst increases his individual forecasting accuracy	DGEXP	-
H2: The individual forecasting accuracy of an analyst around an initial public offering increases when he has covered more initial public offerings before	DIPOX	-

CHAPTER 4 Data

This chapter discusses the data that is used in order to perform this study. Most data is retrieved from the International Brokers' Estimate System, as will be discussed in section 4.1. A list of IPO's in the United States (company name, ticker and first trading day) is retrieved from the Field-Ritter dataset of company founding dates[9], as used in Field & Karpoff (2002) and Loughran & Ritter (2004)[10]. Furthermore, several adjustments have been made to the dataset with the purpose of increasing the reliability of the results in the end.

4.1 International Brokers' Estimate System

The International Brokers' Estimate System (I/B/E/S) is a database that is currently owned by Thomson Reuters. It contains historical forecasts of analysts on individual level, dating back to 1976. In combination with the actual realized figures of the covered companies, it is possible to determine the forecast accuracy of analysts over an extensive amount of time, both on individual and on overall consensus level. After retrieving individual forecasts of analysts, it is possible to calculate metrics such as the experience of analyst or the number of industries a particular analyst is covering in a certain year. It is not possible to directly retrieve these variables by using the IBES database; this should be calculated by using software programs such as Office Excel.

4.2 Sample period

The data of this study covers the period from 2003 until 2015. There are two main reasons to take 2003 as a starting point.

First of all, as discussed in section 2.5, New York State Attorney General Elliot Spitzer announced enforcement actions against the majority of the largest investment banks on Wall Street in 2003. The purpose of the Global Analyst Research Settlement was to strengthen the 'Chinese Wall' between the research department and the investment banking division, in order to avoid research reports that are purposely overly optimistic. It is assumable that analysts were much less able to produce non-accurate forecasts on purpose from this point on, which obviously is favourable for this study.

Secondly, at the end of the past century technological firms that were highly overrated went public on a large scale and the fact that these companies were highly overvalued lead to the burst of the Dotcom Bubble in 1999. This collapse was followed by a severe recession in the United States, which lasted until 2003. In order to create a dataset that is not biased by this Dotcom Bubble and the subsequent crisis, 2003 is a logical beginning point of this study.

---

[9] Source: https://site.warrington.ufl.edu/ritter/files/2016/09/FoundingDates.pdf

[10] A figure with the number of IPO's per year can be found in Appendix A

4.3 Adjustments to the dataset

Some adjustments are made in order to make the dataset more reliable; these adjustments are based on prior studies (Clement, 1999; Clement et al., 2007). First of all, companies that are covered by less then three analysts during their first year after the IPO are not taken into account, since this would make the mean-adjustment procedure impossible. Three forecasts of different analysts are needed at least to determine a precise mean for each variable. Although this measure could possibly create a minor bias in the sample, the advantages of generating an accurate mean for the variables are considered to outweigh this.

Furthermore, forecasts that were made more than 365 days before the end of the fiscal year were deleted with the purpose of removing inactive analysts from the sample. Finally, forecasts that were made 30 days or less before the end of the fiscal period were not taken into account. The possibility that these forecasts are influenced by forecasts of other analysts is considerable and this would have the consequence that these forecasts do not represent the forecasting ability of the analyst himself. After applying these adjustment procedures, the most recent (closest to the fiscal year end) forecast per analyst is used in the dataset. Due to these adjustments the final dataset for the years 2003 until 2015 was reduced from 16.998 to 13.269 observations[11].

4.4 Descriptive statistics

Table 4 and 5 show the descriptive statistics of the final dataset, after applying the adjustments described above. The median values are mentioned, because the mean-adjustment procedure forces all means to be 0. Table 4 contains the distribution of the regression variables without mean adjusting them. Most of the values are in line with prior literature. The median value for the number of firms (NRFI = 17) or industries (NRIN = 3) and industry specialization (SPEC = 0,36) are highly comparable to the foundlings of Clement et al. (2007) for instance. After performing a T-test on the forecast error (FE) variable, it is possible to conclude that this variable is statistically significant different from zero (P-value = 0,0000)[12]. The fact that the median value of the forecasting error is - 0,02 means that analysts in general underestimate the earnings per share of a company within this sample.

The absolute forecasting error (AFE) of 0,17 is relatively high compared to previous studies. This finding is most likely due to the fact that IPO's are followed by a relatively unsecure period, in which it could be difficult to procedure accurate forecasts. Furthermore it is noticeable that the median of the IPO-experience has the value on 1, this implies that a lot of forecasts in the sample were produced without any IPO-experience at all. Section 5.4 will further elaborate on this subject. Finally it is noteworthy that median level is specialization is 36%, which is almost perfectly in line with the finding that the median number of firms and industries an analyst follows are 17 and 3 respectively.

---

[11] Appendix B contains information on the number of IPO's and related forecasts per year

[12] Appendix C contains specific information on the one sample T-test on the forecast error (FE)

Table 5 shows the distribution of the mean-adjusted variables used in the regression. The fact that the median values of PMAFE, DIPOX, SPEC and DNRIN are negative, means that the right tail of the dataset is larger. In other words, the positive entries for these variables lie further away from the median than the negative ones. This makes sense when looking at the IPO experience variable for instance, with a median value of 1 as we can see in table 3. Since it is not possible to obtain negative IPO experience, it is logical that this variable is skewed to the right. The opposite holds for the general experience with a median of 6 years, since this variable is limited to a maximum of 10 years. Again, the signs of these median values are in line with prior research.

Table 4. Distribution of variables used in regression (7) without mean adjusting (N=13.269)

	FE	*AFE*	*IPOX*	*GEXP*	*SPEC*	*DAYS*	*NRFI*	*NRIN*	*NRAN*
Q1	-0,16	0,06	0	2	0,08	61	11	2	7
Median	-0,02	0,17	1	6	0,36	139	17	3	10
Q3	0,18	0,47	2	9	0,75	222	22	4	15

Variable definitions for table 4:
FE_{ijt+1} = Analyst *i*'s forecast error of firm *j*'s earnings for *t*+1 (one year after the IPO) measured as the EPS forecast of analyst *i* minus the actual EPS. AFE_{ijt+1} = Analyst *i*'s absolute forecast error of firm *j*'s earnings for *t*+1 (one year after the IPO). $IPOX_{it}$ = The IPO-experience of analyst *i* at *t* (the moment of the IPO) measured as number of IPO's analyst *i* has covered in the five years prior to *t*. $GEXP_{it}$ = The general experience of analyst *i* at *t* measured as the number of years analyst *i* has covered prior to *t*, with a maximum of ten years. $SPEC_{ijt}$ = The industry specialization of analyst *i* at *t* measured as the percentage of firms followed by analyst *i* in the same first digit SIG code as firm *j*. $DAYS_{ijt+1}$ = The number of days from the date of analyst *i*'s forecast of company *j* until the fiscal year end date in year *t*+1. $NRFI_{it}$ = The number of firms analyst *i* follows at *t*, measured by the number of firms analyst *I* covers in the year before *t*. $NRIN_{it}$ = The number of industries analyst *i* follows at *t*, measured by the number industries with different first digit SIG codes analyst *i* covers in the year before *t*. $NRAN_{jt}$ = The number of analysts that follow firm *j* at *t*, measured as the number of analysts that cover firm *j* in the year after *t*.

Table 5. Distribution of mean-adjusted variables used in regression (7) (N=13.269)

	PMAFE	*DIPOX*	*DGEXP*	*DSPEC*	*DDAYS*	*DNRFI*	*DNRIN*	*DNRAN*
Q1	-0,52	-1,00	-2,63	-0,12	-42,28	-5,27	-0,64	-5,01
Median	-0,09	-0,33	0,20	-0,02	0,00	0,00	-0,04	-1,50
Q3	0,30	0,70	2,67	0,07	44,00	4,81	0,60	2,70

Variable definitions for table 5:

$PMAFE_{ijt+1}$ = (AFE_{ijt+1} - $MAFE_{jt+1}$) / $MAFE_{jt+1}$. AFE_{ijt+1} = Analyst *i*'s absolute forecast error of firm *j*'s earnings for *t*+1 (one year after the IPO). $MAFE_{jt+1}$ = Mean absolute forecast error of analysts that follow firm *j* for year *t+1*. $DIPOX_{it}$ = The IPO-experience of analyst *i* at *t* (the moment of the IPO) measured as number of IPO's analyst *i* has covered in the five years prior to *t* minus the average IPO experience of analyst that cover the same company in *t*. $DGEXP_{it}$ = The general experience of analyst *i* at *t* measured as the number of years analyst *i* has produced at least one forecast prior to *t*, with a maximum of ten years, minus the average general experience of analysts that cover the same company in *t*. $DSPEC_{ijt}$ = The industry specialization of analyst *i* at *t* measured as the percentage of firms followed by analyst *i* in the same first digit SIG code as firm *j* minus the average percentage of industry specialization of analysts that cover the same company in *t*. $DDAYS_{ijt+1}$ = The number of days from the date of analyst *i*'s forecast of company *j* until the fiscal year end date in year *t*+1 minus the average number of days of all forecasts for the same company in *t*. $DNRFI_{it}$ = The number of firms analyst *i* follows at *t*, measured by the number of firms analyst *I* covers in the year before *t* minus the average of the number of firms that analysts who cover the same company follow in *t*. $DNRIN_{it}$ = The number of industries analyst *i* follows at *t*, measured by the number industries with different first number SIG codes analyst *i* covers in the year before *t* minus the average number of industries that analysts who cover the same company follow in *t*. $DNRAN_{jt}$ = The number of analysts that follow firm *j* at *t*, measured as the number of analysts that cover firm *j* in the year after *t* minus the average number of analysts following a company in year *t*. *Note*: The average values are not mentioned since the mean-adjustment procedure forces the mean to be zero.

4.5 Development of forecasting errors over time

Figure 1 and 2 show the development of the forecasting error (FE) and the absolute forecasting error (AFE) over the period 2003-2015, respectively. As observable from figure 1, it seems that the forecasting error is relatively stable and fluctuates around the value of -0,02, which is the median of the entire sample as well. This finding implies that analysts generally underestimate the earnings per share of a company during the length of nearly the entire sample.

Figure 1. Median forecasting error (FE) over time

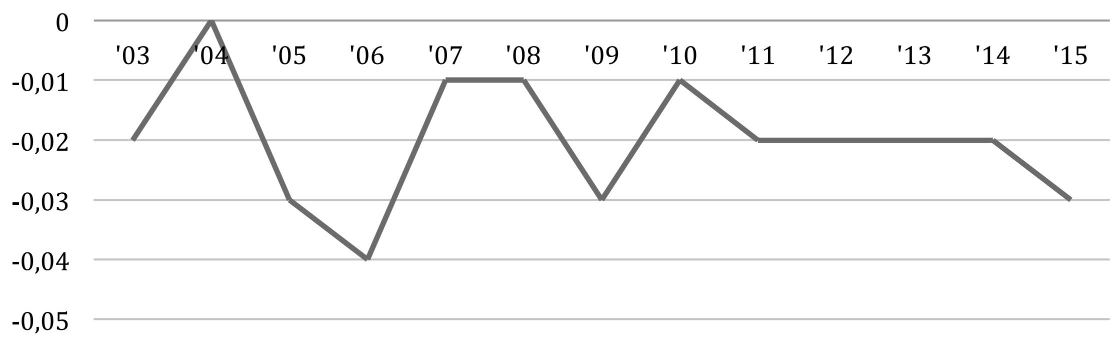
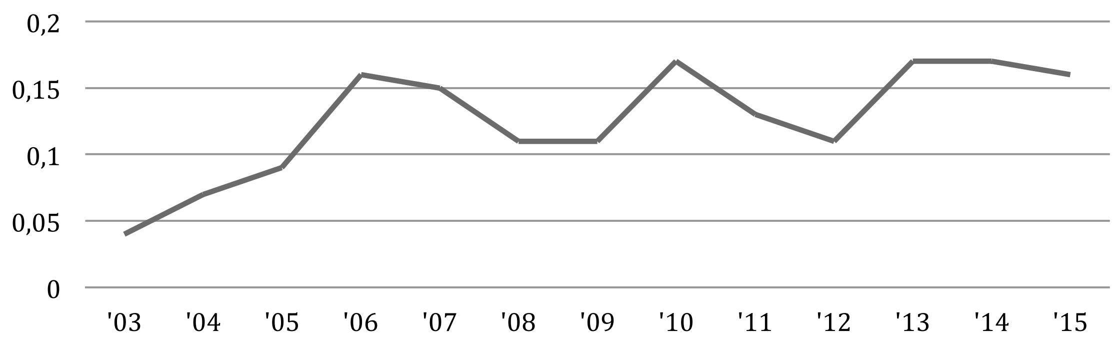


Figure 2 clearly shows an upward trend for the median absolute forecasting error over time, this trend indicates that analysts are becoming less accurate over the period 2003-2015. This finding could sound counterintuitive, since technology and information sources are improving obviously. A possible explanation for this phenomenon could be the fact that analysts are becoming more confident in their own ability to produce precise forecasts and thus are willing to produce more risky, less conservative forecasts. The development of forecasting accuracy over time could be an interesting topic for further research.

Figure 2. Median absolute forecasting error (AFE) over time



CHAPTER 5 Empirical results

This chapter discusses the results that stem from the regressions as mentioned in chapter 3. First, the effect of general experience on forecasting accuracy after an IPO will be examined and afterwards the effect of IPO-experience will be discussed. Furthermore several robustness checks will be performed in order to validate the findings of this study.

5.1 Pearson correlation table

Table 5 shows an overview of the Pearson correlation coefficients of the variables used in the regression and their significance levels. The negative correlation between the proportional mean absolute forecast error (PMAFE) and the general experience (DGEXP), IPO-experience (DIPOX) and specialization (DSPEC) are as expected since these are all factors that are assumed to lower the forecast error. The positive correlation between PMAFE and the days until fiscal year end (DDAYS) is not surprising either, as it makes sense that forecasts become less accurate when they are made further in advance of the fiscal year end. The negative signs in front of the correlation coefficients between the PMAFE and the number of firms following (DNRFI) and the number of industries following (DNRIN) are not as expected. This correlation says that the forecasting error reduces when an analyst follows more firms or industries at that moment, this is counterintuitive. Obviously it is necessary to find out whether the relations found in table 6 are statistically significant by performing ordinary least squares regressions on them.

Table 6. Pearson correlation coefficients of the variables used in regression (7)

	PMAFE	DGEXP	DIPOX	DDAYS	DNRFI	DNRIN	DSPEC	DNRAN
PMAFE	1,0000							
DGEXP	-0,0281*	1,0000						
DIPOX	-0,0193*	0,4363*	1,0000					
DDAYS	0,1880*	-0,0118	0,0010	1,0000				
DNRFI	-0,0182*	0,4939*	0,4237*	-0,0451*	1,0000			
DNRIN	-0,0135	0,2600*	0,1898*	-0,0053	0,4963*	1,0000		
DSPEC	-0,0245*	-0,2313*	-0,1341*	0,0241*	-0,3794*	-0,3913*	1,0000	
DNRAN	-0,0006	-0,0026	-0,0020	0,0302*	-0,0040	-0,0001	0,0043	1,0000

* Statistically significant at the p<0,05 level, two-tailed test

5.2 The effect of general experience on forecasting accuracy around IPO's

In order to test the first hypothesis, which states that the PMAFE decreases significantly when the general forecasting experience of an analyst increases, regression (7) is performed without including the IPO-experience variable.

One important assumption when performing an ordinary least squares regression is that the variance of the residuals should not be heteroskedastic. A Breusch-Pagan test detects if there are signs of heteroskedasticity and the results of this test are shown in Appendix D. It is possible to conclude that there are signs of heteroskedasticity and thus the model is adjusted by using heteroskedasticity robust White-standard errors (White, 1980) to solve this issue[13]. Furthermore it is important that there is no sign of multicollinearity in the model and this is tested by looking at the variance inflation factor (VIF). The results of this test, denoted in Appendix E, reflect that there are no signs of multicollinearity in the model. Finally the distribution of each variable is visually tested, in order to check whether they are roughly normally distributed or not. Due to the mean-adjustment procedure most variables are indeed approximately normally distributed, the density curves of the variables are shown in Appendix F. The decision to test the distributions graphically is based on the fact that statistical normality tests, such as a Shapiro-Wilk test, become rather unreliable when the data sample is relatively large.

When looking at the results of the first regression in table 7 it is possible to conclude that the first hypothesis holds. The significantly negative coefficient in front of DGEXP reflects the fact that general experience indeed reduces the PMAFE. Over the full sample of 2003-2015, an increase of 1 in the mean-adjusted general experience of an analyst, leads to a decrease of 0.007 (0.7%) in the proportional mean absolute forecast error. The P-value of 0.002 indicates that this relation is significant at a 1% significance level. When looking at the years in the sample individually, it turns out that seven of the thirteen years confirm this relation at a significance level of at least 10%. The finding that relatively few years show a significant relation between the PMAFE and DGEXP could be attributed to the fact that individual years obviously have less observations than the full sample and, thus, less statistical power.

Furthermore it is clear that the number of days until the fiscal year end (DDAYS) has a significantly positive relation with the PMAFE, which is in line with prior literature. Both the number of industries an analyst is following (DNRIN) and his industry specialization (DSPEC) have a significantly negative relation with the PMAFE. Especially the amount of industry specialization seems to diminish the forecast error, as can be retrieved from the coefficient of -0.161. Whereas the negative relation was expected for DSPEC, the sign in front of the DNRIN was expected to be positive. This finding is surprising since it makes sense that it is harder to produce accurate forecasts when the portfolio of an analyst exists of more distinct industries. The study of Clement et al. (2007)

[13] Source: https://www.princeton.edu/~otorres/Regression101.pdf

finds a positive relation between these variables as well in their dataset however. This could be an interesting phenomenon to examine in further research, especially since the study of Clement (1999) contradicts this result.

Table 7. Results of regression (7) testing the first hypothesis

This table represents the results of the regression that tests whether general experience has a significant influence on the forecasting accuracy around IPO's. The dependent variable is the proportional mean absolute forecast error (PMAFE). The independent variables are the general forecasting experience (DGEXP), days until the fiscal year end (DDAYS), the number of firms an analyst is following (DNRFI), the number of industries an analyst is following (DNRIN), the industry specialization (DSPEC) and the number of analyst that cover the IPO (DNRAN). The D in front of most variables reflects the fact that these variables are mean-adjusted. The number of observations of the total sample is 13.269 with an adjusted R-squared of 0.0377. Reported in parentheses are p-values. *, ** and *** indicate the 10%, 5% and 1% significance levels respectively.

Dependent variable: PMAFE

	DGEXP	DDAYS	DNRFI	DNRIN	DSPEC	DNRAN	N	Adj. R²
2003	-.016** (0.029)	.007*** (0.000)	.012 (0.308)	-.049 (0.371)	-.175 (0.490)	-0.025 (0.260)	349	0.0848
2004	.005 (0.555)	.003*** (0.000)	-.009** (0.040)	-.050*** (0.005)	-.291*** (0.002)	-0.002 (0.174)	1.950	0.0683
2005	-.008** (0.036)	.002*** (0.000)	.002 (0.566)	-.053** (0.024)	-.316*** (0.001)	0.002 (0.312)	1.336	0.0402
2006	-.001* (0.085)	.003*** (0.000)	-.002 (0.460)	.026 (0.201)	-.197* (0.093)	-.006* (0.063)	1.158	0.0827
2007	.003 (0.686)	.002*** (0.000)	.003 (0.416)	-.014 (0.554)	-.051 (0.657)	.006* (0.066)	1.365	0.0450
2008	-.004 (0.654)	.002*** (0.000)	-.005 (0.184)	.033 (0.198)	-.050 (0.748)	0.003 (0.419)	201	0.0645
2009	-.003 (0.669)	.002*** (0.000)	.002 (0.580)	.015 (0.460)	.008 (0.935)	-.001 (0.890)	449	0.0118
2010	-.021** (0.013)	.002*** (0.000)	.007 (0.115)	-.010 (0.711)	-.014 (0.909)	.005 (0.175)	834	0.0482
2011	.008 (0.310)	.002*** (0.000)	-.004 (0.297)	.003 (0.929)	-.009 (0.947)	.000 (0.912)	891	0.0256
2012	-.017** (0.032)	.002*** (0.000)	0.002 (0.515)	-.030 (0.312)	-.251** (0.033)	-.006** (0.011)	899	0.0725
2013	-.025*** (0.009)	.002*** (0.000)	.003 (0.510)	.010 (0.773)	-.142 (0.364)	.008 (0.195)	1.435	0.0286
2014	-.000 (0.992)	.002*** (0.000)	-.001 (0.662)	-.008 (0.738)	-.163 (0.179)	-.001 (0.726)	1.787	0.0243
2015	-.019*** (0.008)	.001*** (0.000)	.000 (0.942)	-.000 (0.998)	.048 (0.711)	-.002 (0.699)	615	0.0188
Full sample	**-.007*** (0.002)**	**.002*** (0.000)**	**-.000 (0.916)**	**-.015** (0.042)**	**-.161*** (0.000)**	**-.001 (0.492)**	**13.269**	**0.0377**

5.3 The effect of IPO-experience on forecasting accuracy around IPO's

Table 8 represents the results of the regression that tests whether the second hypothesis holds. This hypothesis states that the individual forecast error after a public offering decreases when the analyst has experience with covering IPO's in the past.

The model was tested for heteroskedasticity, multicollinearity and normally distributed variables just like the model mentioned in section 5.2, the results of these tests can be found in Appendix G and H. It is possible to conclude that there are signals of heteroskedasticity, so robust standard errors are used once more. Furthermore there were no signs of multicollinearity, as can be derived from the scores of the variance influence test.

When looking at the results it is clear that there is no statistically significant relation found between the PMAFE and the IPO-experience (DIPOX) of an analyst and hence the second hypothesis is rejected. The conclusion that DIPOX has no significant relation with PMAFE in the years 2003-2015 is drawn by observing the P-value of 0.277, which is not even significant at a 10 per cent level. The most obvious reason for not finding a significant relation between these two variables is most likely that each IPO has a very different character. It seems that the experience an analyst has gained from covering IPO's in the past is not transferrable into IPO's in the future.

This conclusion could very well be explained by the reasoning that each IPO is followed by a period of chance and uncertainty, which makes it fairly hard to forecast the future earnings accurately. The aspect that it is not likely that there is much historical financial information about the company available before the IPO strengthens this effect. Moreover, it is not unusual that a company releases information about themselves that is overly optimistic in order to raise more money from the public offering, obviously this makes it harder for analysts to produce accurate forecasts during an IPO.

The coefficients of the other variables in the regression are comparable to the ones denoted in table 6. It is possible to conclude that general experience (DGEXP) statistically significant reduces the PMAFE, which is in line with the findings of the regression without a variable that represents IPO-experience. The coefficient reduces just marginally (from -0.007 to -0.006), which indicates that adding the DIPOX variable has influence on DGEXP, this influence is very marginal however. The coefficients of the remaining variables in the regression are almost identical to the ones in table 6, which says that adding the IPO-experience variable has not influenced them notably.

All in all it is possible to give a comprehensive answer to the main research question of this study, which states:

Does individual forecast accuracy around initial public offerings increase when an analyst has prior experience with covering companies that went public?

Whereas general forecasting experience does increase the forecasting accuracy of an analyst, IPO-experience has no significant influence and just slightly diminishes the effect of general experience when added to the model. As discussed, the main explanation for this finding is most likely the fact that each IPO is followed by a period of uncertainty, which makes it relatively difficult to transfer knowledge from previous IPO's into the future. Furthermore the lack of financial information of the company prior to the IPO might play a major role in the difficulty of producing accurate forecasts and the fact that there is not relation found between IPO-experience and forecasting accuracy after a public offering.

Table 8. Results of regression (7) testing the second hypothesis

This table represents the results of the regression that tests whether IPO-experience has a significant influence on the forecasting accuracy around IPO's. The dependent variable is the proportional mean absolute forecast error (PMAFE). The independent variables are the IPO-experience (DIPOX), general forecasting experience (DGEXP), days until the fiscal year end (DDAYS), the number of firms an analyst is following (DNRFI), the number of industries an analyst is following (DNRIN), the industry specialization (DSPEC) and the number of analyst that cover the IPO (DNRAN). The D in front of most variables reflects the fact that these variables are mean-adjusted. The number of observations of the total sample is 13.269 with an adjusted R-squared of 0.0378. Reported in parentheses are p-values. *, ** and *** indicate the 10%, 5% and 1% significance levels respectively.

Dependent variable: PMAFE

	DIPOX	**DGEXP**	**DDAYS**	**DNRFI**	**DNRIN**	**DSPEC**	**DNRAN**	**N**	**Adj. R^2**
2003	-.030 (0.104)	-.009** (0.056)	.007*** (0.000)	.016 (0.195)	-.049 (0.374)	-.130 (0.612)	-.025 (0.264)	349	0.0989
2004	-.011 (0.228)	.008 (0.426)	.003*** (0.000)	-.009** (0.046)	-.045** (0.015)	-.282*** (0.002)	-.002 (0.166)	1.950	0.0690
2005	-.007 (0.399)	-.006* (0.050)	.002*** (0.000)	.003 (0.460)	-.053** (0.024)	-.313*** (0.002)	.002 (0.311)	1.336	0.0405
2006	.016 (0.189)	-.005** (0.047)	.003*** (0.000)	-.003 (0.307)	.026 (0.196)	-.206* (0.081)	-.006* (0.068)	1.158	0.0838
2007	.009 (0.607)	.001 (0.876)	.002*** (0.000)	.002 (0.477)	-.014 (0.557)	-.056 (0.630)	.006* (0.067)	1.365	0.0451
2008	.007 (0.757)	-.005 (0.603)	.002*** (0.000)	-.005 (0.185)	.033 (0.198)	-.053 (0.735)	-.003 (0.417)	201	0.0646
2009	.014 (0.423)	-.005 (0.482)	.002*** (0.000)	.001 (0.672)	.016 (0.444)	.004 (0.970)	-.001 (0.883)	449	0.0150
2010	-.015 (0.564)	-.019** (0.024)	.002*** (0.000)	.007 (0.112)	-.009 (0.712)	-.013 (0.917)	.005 (0.176)	834	0.0485
2011	.017 (0.586)	0.007 (0.448)	0.002*** (0.000)	-.004 (0.275)	-.003 (0.927)	-.008 (0.953)	0.000 (0.916)	891	0.0259
2012	.016 (0.390)	-.018** (0.023)	.002*** (0.000)	.001 (0.719)	-.030 (0.319)	-.258** (0.029)	-.006** (0.011)	899	0.0731
2013	-.028 (0.104)	-.021** (0.044)	.002*** (0.000)	.004 (0.279)	.008 (0.815)	-.145 (0.355)	.008 (0.204)	1.435	0.0311
2014	-.008 (0.400)	.002 (0.800)	.002*** (0.000)	-.000 (0.951)	-.011 (0.648)	-.167 (0.169)	-.001 (0.731)	1.787	0.0247
2015	.010 (0.323)	-.021*** (0.004)	.001*** (0.001)	-.001 (0.713)	.002 (0.952)	.043 (0.738)	-.002 (0.704)	615	0.0198
Full sample	**-.004 (0.277)**	**-.006*** (0.009)**	**.002*** (0.000)**	**.000 (0.863)**	**-.015** (0.040)**	**-.159*** (0.000)**	**-.001 (0.491)**	**13.269**	**0.0378**

5.4 Robustness tests

As already mentioned in section 5.2, several measures were taken to make sure that the results of this study are as reliable as possible. First of all a Breusch-Pagan test was performed to test for heteroskedasticity. When signs of heteroskedasticity were detected, this problem was resolved by using White standard errors. Furthermore there was no multicollinearity found in the model, so no measures had to be taken to correct for it. Finally the distribution of the variables was graphically tested and due to the mean-adjustment procedure they were approximately normally distributed.

Besides the statistical tests, qualitative robustness tests will be performed as well. First of all section 3.3 explains that the variables are mean-adjusted in order to control for firm- and year-effects. This procedure assumes that there should be no significant difference in the forecasting errors between years or certain periods. The assumption that year-effects have no significant influence on the forecasting error after mean-adjustment is tested by adding a year-dummy variable (0=2003, 12=2015). The results of regression (2) in table 9 show that the year-dummy variable does not have a significant relation with the forecasting error of an analyst. Moreover, the year dummy does not influence the other variables and, thus, the assumption that the time effect is already captured in the mean-adjustment procedure holds. An interaction term was also added to the regression in order to test whether this would affect the outcomes of the model. Regression (3) in table 9 shows that this interaction term with a p-value of 0.972 has no significant effect on the forecasting accuracy of an analyst. The other variables in the regression are not affected either.

Furthermore a crisis-dummy is added to the regression. By doing so the assumption that the effect of the financial crisis has no effect on the forecasting error is tested, since this effect should be already incorporated in the variables by mean-adjusting them. This dummy takes 1 in the years 2008 and 2009 and 0 otherwise. Although regression (4) in table 9 shows that the coefficient of the crisis-dummy is positive (the forecasting error becomes larger during a crisis), it does not show a significant relation when looking at the P-value of 0.199. Furthermore, the other variables are not affected by adding the crisis-dummy, so again it is possible to conclude that the crisis-effect was already incorporated in the model by using the mean-adjustment procedure.

Finally the large number of analysts that have not covered a public offering before could influence the results of this study. Out of the 13.269 observations of the total sample, 6.285 observations were made by analysts who had not covered an IPO before. By removing these first time IPO-forecasts from the sample, slightly more than half of the observations are left. When performing the same regression as on the full sample, it becomes clear that leaving out this large group of inexperienced analysts does not alter the results of the study. The results of this regression are tabulated in appendix I.

Table 9. Results of robustness tests

This table represents the results of the main regression (1), the regression used in order to test the year-effect (2), the regression in order to test the interaction-effect between the year dummy and the IPO-experience (3) and the regression in order to test the effect of the crisis (4). All variables are mean-adjusted, except the year-dummy and the crisis-dummy. As observable, adding the year- and crisis-dummy does not affect the other variables in the regression significantly. Reported in parentheses are p-values. *, ** and *** indicate the 10%, 5% and 1% significance levels respectively.

Dependent variable: Proportional mean absolute forecast error, N= 13.269,

	(1)	**(2)**	**(3)**	**(4)**
IPO-experience	-.004 (0.278)	-.004 (0.278)	-.004 (0.494)	-.004 (0.277)
General experience	-.006*** (0.009)	-.006*** (0.009)	-.006*** (0.009)	-.006*** (0.009)
Days until fiscal year end	.002*** (0.000)	.002*** (0.002)	.002*** (0.000)	.002*** (0.002)
Number of firms following	.000 (0.862)	.000 (0.865)	.000 (0.862)	.000 (0.849)
Number of industries following	-.015** (0.040)	-.015** (0.040)	-0.15** (0.041)	-.015** (0.041)
Industry specialization	-.160*** (0.000)	-.160*** (0.000)	-.160*** (0.000)	-.160*** (0.000)
Number of analyst covering the company	-.001 (0.491)	-.001 (0.931)	-.001 (0.491)	.000 (0.989)
Year dummy (2003-2015)		-.001 (0.606)		
Year dummy*IPO-experience			-.000 (0.972)	
Crisis dummy				.033 (0.199)
Adjusted R-squared	0.0378	0.0378	0.0378	0.0379

CHAPTER 6 Conclusion

This study examines whether the earnings per share forecasts after an IPO become more accurate when an analyst has more general or IPO-experience in producing forecasts. The sample used in order to test this relation consists of 13.269 forecasts made in the years 2003 until 2015. After conducting an extensive literature study of related publications, ordinary least squares regressions are performed in order to test the hypothesis that either general or IPO-experience influence forecasting performance of an analyst after an IPO.

A statistically significant positive relation is found between general forecasting experience of an analyst and his forecasting accuracy after public offerings. This finding is in accordance with prior literature and could have implications for investors, since their investment decision is largely based on forecasted earnings of a company. Furthermore stock valuation models use forecasted earnings as an important parameter and hence it is valuable to know whether certain analysts produce significantly more reliable forecasts than others. The conclusion of this study is that forecasts in the year after an IPO are more precise when analysts with general experience produce them.

Secondly, this study tests the relation between specific IPO-forecasting experience and forecasting accuracy after an IPO. It is possible to conclude that IPO-experience has no statistically significant influence on the forecasting error of an analyst within the sample of this study. This finding implies that the skill or knowledge that an analyst gains when covering an IPO, is not transferrable into future forecasts after a public offering. The main reason for this conclusion is probably the fact that each IPO stands on it own and is followed by a period of change and uncertainty. Moreover it is usual that there is not much financial information available about a company when it is still privately owned before the IPO. Finally it occurs often that that the management of a company releases overly optimistic information prior to a public offering in order to raise more money from the IPO.

This study adds to the existing literature by looking deeper into the phenomenon of task-specific experience of financial analysts. Whereas several factors have been identified over the past years that significantly improve forecasting accuracy, this specific field is relatively undiscovered and allows for further research. IPO-experience is just a part of this particular kind of experience and many other 'tasks' are suitable to be investigated in the future, with the goal of determining certain factors that increase forecasting accuracy of analysts.

6.1 Limitations

As almost every research does, this study also has its limitations and shortcomings. First of all it was not possible to retrieve specific details about the employer of the analysts from the IBES database. As prior research has found evidence for the fact that employer size has a significant influence on forecasting accuracy, including this variable into the regressions could possibly improve the model.

Secondly the dataset could contain a minor bias, since IPO's covered by less than three different analysts are left out of the sample. The reason for taking this measure is that the calculated mean values are more reliable. Finally, the study is limited to a US database due to data availability. It could be interesting to test whether the same conclusions are valid for other parts of the world, such as Europe.

6.2 Recommendations for further research

This study focuses on a particular part of task-specific experience, namely IPO's, but obviously there are much more corporate finance activities that could be examined within the category of task-specific experience. Clement et al. (2007) find that restructuring experience has significant influence on the forecasting accuracy for instance. Other fields of task-specific experiences that could be examined are seasoned equity offerings, change of management or mergers and acquisitions.

Furthermore this study is focussed on the forecasting accuracy of analysts regarding their earnings per share forecasts. It would be interesting to see if the same conclusions hold when other metrics, such as the EBIT (DA) forecasts, are examined. Not much research is available on this subject yet and it would be an interesting extension to the current literature.

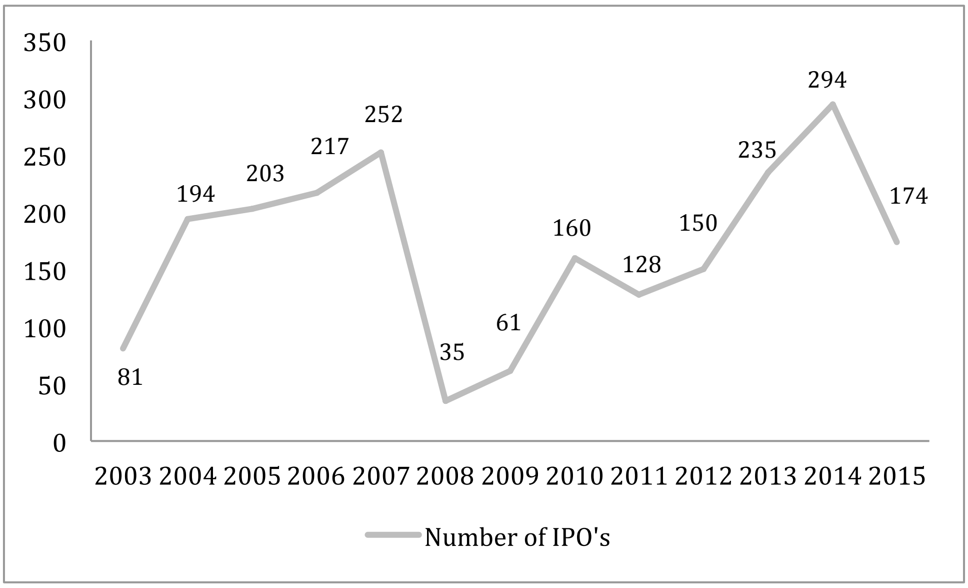
As mentioned in chapter 5, it is remarkable that the variable that represents the number of industries followed by the analyst has a positive relation with the forecasting accuracy of an analyst. Prior literature has found evidence for a negative relation, so it could be interesting to investigate the effect of this variable as main subject with a recent data sample.

Finally, the conclusion of section 4.5 is that the absolute forecasting error increases over the years 2003 until 2015. This finding could be counterintuitive due the increasing amount of data and more advanced technology nowadays, these factors should help analysts in producing more accurate forecasts. The development of forecasts errors over time could be an interesting subject for further research.

APPENDIX

A.

The number of IPO’s in the United States per year according to the Field-Ritter dataset of company founding dates.



B.

The number of IPO’s in the United States and their related forecasts per year. Only the most recent forecast of every analyst per IPO is taken into account.

Year	Number of IPO’s	Number of forecasts
2003	81	349
2004	194	1.950
2005	203	1.336
2006	217	1.158
2007	252	1.365
2008	35	201
2009	61	449
2010	160	834
2011	128	891
2012	150	899
2013	235	1.435
2014	294	1.787
2015	174	615
Total	2184	13.269

C.

Descriptive statistics of the one sample T-test on the forecast error variable

Variable	Obs.	Mean	Std. err.	Std. dev.	(95% Conf. Interval)	
FE	13.269	0,056	0,008	0,928	0,040	0,072

Ho: Mean = 0

Ha: Mean ≠ 0

T= 6,9548

P = 0,0000

D.

The Breusch-Pagan / Cook-Weisberg test for heteroskedasticity for the first regression

Ho: Constant variance	
Chi ^2	154,26
Prob > chi^2	0,0000

E.

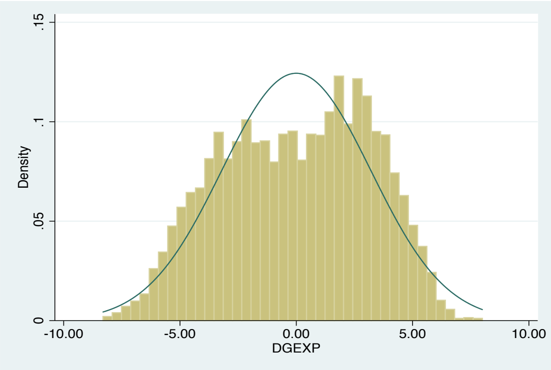
The variance influence factor (VIF) of the variables used in the first regression. A VIF higher than 10 reflects signs of multicollinearity.

	VIF	1/VIF
DNRFI	1,70	0,59
DNRIN	1,42	0,71
DGEXP	1,33	0,75
DSPEC	1,25	0,80
DDAYS	1,00	1,00
NRAN	1,00	1,00
Mean VIF	**1,28**	

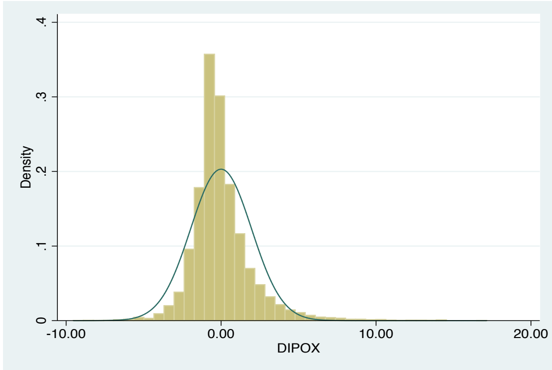
F.

The density curves of the regression variables with the normal distribution line.

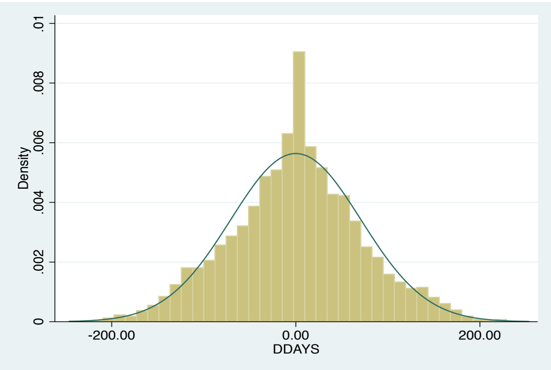
DGEXP



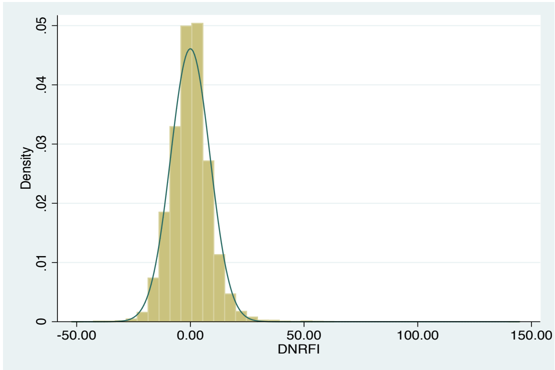
DIPOX



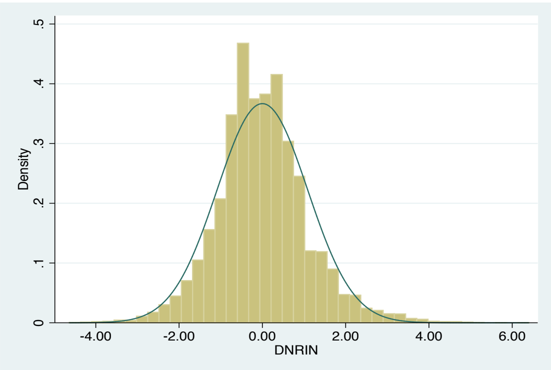
DDAYS



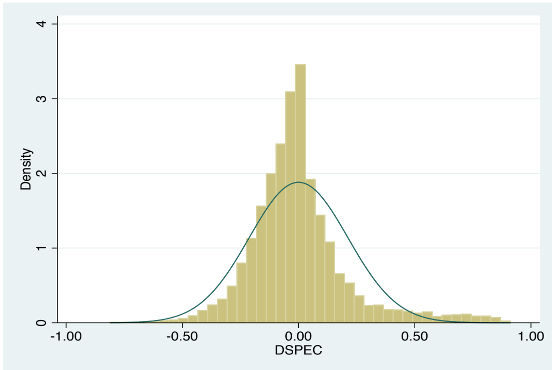
DNRFI



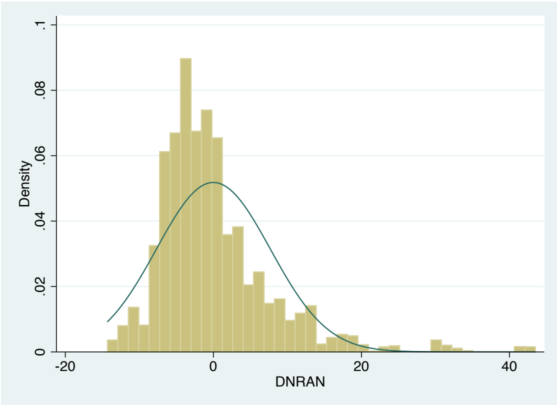
DNRIN



DSPEC



DNRAN



G.

The Breusch-Pagan / Cook-Weisberg test for heteroskedasticity for the second regression

Ho: Constant variance	
Chi ^2	156,95
Prob > chi^2	0,0000

H.

The variance influence factor (VIF) of the variables used in the second regression. A VIF higher than 10 reflects signs of multicollinearity.

	VIF	1/VIF
DNRFI	1,82	0,55
DGEXP	1,45	0,69
DNRIN	1,42	0,70
DIPOX	1,33	0,75
DSPEC	1,25	0,80
DDAYS	1,00	1,00
NRAN	1,00	1,00
Mean VIF	**1,33**	

I.

The results of the regression leaving out the forecasts of analysts without any prior experience with producing forecasts after an IPO. No different conclusions can be drawn from the results of this regression compared to the results of table 7.

Dependent variable: PMAFE, N= 6.984, Adjusted R-squared: 0.0283

	DIPOX	DGEXP	DDAYS	DNRFI	DNRIN	DSPEC	DNRAN
Sample minus 0 experience	-.004 (0.352)	-.006*** (0.060)	.002*** (0.000)	.001 (0.505)	-.029** (0.002)	-.266*** (0.000)	-.022 (0.210)

REFERENCES

Alford, A. W., & Berger, P. G., 1999. A simultaneous equations analysis of forecast accuracy, analyst following, and trading volume. *Journal of Accounting, Auditing & Finance*, 14(3), 219-240.

Ball, R., & Watts, R., 1972. Some time series properties of accounting income. *The Journal of Finance*, 27(3), 663-681.

Bradshaw, M. T., 2011. Analysts' forecasts: what do we know after decades of work? Unpublished working title. Boston College.

Brown, P., Foster, G., & Noreen, E., 1985. Security analysts' multi-year earnings forecasts and the capital market. *Studies in accounting research American Accounting Association,* 21.

Brown, L. D., Richardson, G. D., & Schwager, S. J., 1987. An information interpretation of financial analyst superiority in forecasting earnings. *Journal of Accounting Research*, 49-67.

Brown, L. D., 1993. Earnings forecasting research: Its implications for capital markets research. *International journal of forecasting*, *9*(3), 295-320.

Brown, L. D., 2001. How important is past analyst forecast accuracy?. *Financial Analysts Journal*, 44-49.

Burgstahler, D. C., & Eames, M. J., 2003. Earnings management to avoid losses and earnings decreases: are analysts fooled?. *Contemporary Accounting Research*, 20(2), 253

Butler, K. C., & Lang, L. H., 1991. The forecast accuracy of individual analysts: Evidence of systematic optimism and pessimism. *Journal of Accounting Research*, 150-156.

Clement, M. B., 1999. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?. *Journal of Accounting and Economics*, *27*(3), 285-303.

Clement, M. B., Koonce, L., & Lopez, T. J., 2007. The roles of task-specific forecasting experience and innate ability in understanding analyst forecasting performance. *Journal of Accounting and Economics*, *44*(3), 378-398.

Coggin, D., & Hunter, J., 1989. Analysts forecast of EPS growth decomposition of error, relative accuracy and relation to return. Unpublished working paper. Michigan State University.

Das, S., Levine, C. B., & Sivaramakrishnan, K., 1998. Earnings predictability and in analysts' earnings forecasts. *Accounting Review*, 277-294.

Field, L., & Karpoff, J., 2002. Takeover Defenses of IPO Firms. *Journal of Finance*, 57(5), 1857-1889

Foster, G., 1977. Quarterly accounting data: Time-series properties and predictive-ability results. *Accounting Review*, 1-21.

Fried, D., & Givoly, D., 1982. Financial analysts' forecasts of earnings: A better surrogate for market expectations. *Journal of Accounting and Economics*, 4(2), 85-107.

Givoly, D., & Lakonishok, J., 1984. The quality of analysts' forecasts of earnings. *Financial Analysts Journal*, 40-47.

Groysberg, B., Healy, P. M., & Maber, D. A., 2011. What Drives Sell‐Side Analyst Compensation at High‐Status Investment Banks?. *Journal of Accounting Research*, 49(4), 969-1000.

Hong, H., Kubik, J. D., & Solomon, A., 2000. Security analysts' career concerns and herding of earnings forecasts. *The Rand journal of economics*, 121-144.

Hong, H., & Kubik, J. D., 2003. Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance*, 58(1), 313-351.

Jacob, J., Lys, T. Z., & Neale, M. A., 1999. Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics*, *28*(1), 51-82.

Little, I. M., 1962. Higgledy piggledy growth. *Oxford Bulletin of Economics and Statistics*, 24(4), 387-412.

Loughran, T., & Ritter, J., 2004. Why Has IPO Underpricing Changed Over Time?, *Financial Managemen*t , 33(3), 5-37

Mikhail, M. B., Walther, B. R., & Willis, R. H., 1997. Do security analysts improve their performance with experience?. *Journal of Accounting Research*, 35, 131-157.

Mikhail, M. B., Walther, B. R., & Willis, R. H., 1999. Does forecast accuracy matter to security analysts?. *The Accounting Review*, 74(2), 185-200.

O'Brien, P. C., 1990. Forecast accuracy of individual analysts in nine industries. *Journal of Accounting Research*, 286-304.

Paleari, S., & Vismara, S., 2007. Over-optimism when pricing IPOs. *Managerial Finance*, 33(6), 352-367.

Rajan, R., & Servaes, H., 1997. Analyst following of initial public offerings. *The Journal of Finance*, 52(2), 507-529.

Richards, R. M., 1976. Analysts' performance and the accuracy of corporate earnings forecasts. *The Journal of Business*, 4*9*(3), 350-357.

Sinha, P., Brown, L. D., & Das, S., 1997. A Re‐Examination of Financial Analysts' Differential Earnings Forecast Accuracy. *Contemporary Accounting Research*, *14*(1), 1-42

Stickel, S. E., 1992. Reputation and performance among security analysts. *The Journal of Finance*, 47(5), 1811-1836.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society*, 817-838.