HELSINKI SCHOOL OF ECONOMICS (HSE)

Department of Accounting and Finance

PERFORMANCE OF FORWARD-LOOKING VALUE DRIVERS IN STOCK SCREENING

Making automated recommendations based on future forecasts

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Lauri Puro
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Abstract
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PURPOSE OF THE STUDY

The purpose of this study is to analyze different value drivers and their capability of explaining future stock returns. The value drivers are evaluated based on their performance using backward- and forward-looking data. The forward-looking value drivers are tested both with perfect foresight, i.e. actual future fundamentals, and with analyst forecasts. The main objective is to find the best value drivers that can be used to create automatic stock recommendations based on future forecasts. Finally, the performance of these auto-recommendations is compared against the performance of analysts' own consensus stock recommendations.

DATA

In this study, the US stock market data is used as the primary source of data. The data is gathered from Compustat and CRSP databases and it covers years 1975-2007. In total, the sample consists of 98,688 company-year combinations. The average number of stocks in a single year is 2,990. This data is complemented with equity analyst forecasts and recommendations gathered from I/B/E/S database.

RESULTS

The main finding of this study is that the P/E ratio and to some extent the PEG ratio are good forward-looking value drivers that provide significant stock screening potential when applied to earnings forecasts of good quality. However, when applying analyst consensus forecasts these value drivers do no result in significantly better performance than using only backward-looking value drivers with historical financial figures. Despite the relatively low performance in absolute terms the auto-recommendations made with the value driver approach outperform significantly the consensus recommendations of the analysts. As a conclusion, investors and analysts would be better off making recommendations based on systematic value drivers rather than the current ad-hoc methods.

KEYWORDS

Value drivers, stock screening, analyst forecasts, perfect foresight, auto-recommendations

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Lauri Puro

ENNUSTEISIIN PERUSTUVIEN ARVOAJUREIDEN TOIMINTA OSAKEVALINNASSA
Automaattisten osakesuositusten laatiminen tulevaisuuden ennusteista

TUTKIMUKSEN TARKOITUS

Tutkimuksen tarkoitus on vertailla eri arvoajureita (value driver) ja niiden kykyä selittää tulevaisuuden osaketuottoja. Arvoajureita analysoidaan käyttäen sekä toteutuneita tilinpäätöstietoja että tulevaisuuden ennusteisiin liittyvää dataa. Tulevaisuuteen katsovat arvoajurit testataan sekä tulevaisuuden toteutuneilla luvuilla eli ns. täydellisillä ennusteilla että tavanomaisilla analyytikkojen konsensusennusteilla. Tutkimuksen päätavoite on löytää parhaat arvoajurit, joita voidaan käyttää automaattisten osakesuositusten tekemiseen tulevaisuuden ennusteiden pohjalta. Lopuksi näiden automaattisuositusten kannattavuutta verrataan analyytikoiden omien konsensussuositusten kannattavuuteen.

AINEISTO

Pääasiallisena lähteenä tässä tutkimuksessa käytetään tietoja Yhdysvaltojen osakemarkkinoilta. Tiedot on kerätty Compustat ja CRSP tietokannoista vuosilta 1975-2007. Yhteensä tutkimusotoksessa on 98 688 osake-vuosi-yhdistelmää ja keskimäärin otoksessa on 2 990 osaketta kutakin vuotta kohden. Aineistoa täydennetään analyytikkoennusteiden ja –suositusten suhteen IBES tietokannalla.

TULOKSET

Tutkimuksen päätulos on, että P/E –luku ja tietyissä määrin myös PEG –luku ovat hyviä tulevaisuuteen katsovia arvoajureita, ja ne osoittavat selkeää potentiaalia osakevalinnan työkaluksi, jos käytettävissä on korkealaatuisia ennusteita. Kun näihin arvoajureihin sovelletaan analyytikoiden konsensusennusteita, näiden kannattavuus kuitenkin heikkenee merkittävästi eikä ennusteisiin perustuva osakevalintamenetelmä enää johdakaan parempaan lopputulokseen kuin pelkkiin toteutuneisiin lukuihin perustuva menetelmä. Tästä huolimatta arvoajureiden avulla lasketut automaattisuositukset ovat selkeästi parempia kuin analyytikoiden omat konsensussuositukset. Yhteenvetona voidaan todeta, että sijoittajat ja analyytikot voisivat parantaa suositusten kannattavuutta merkittävästi, jos he käyttäisivät systemaattista arvoajureihin perustuvaa lähestymistapaa nykyisten menetelmien sijasta.

AVAINSANAT

Arvoajurit, analyytikkoennusteet, täydelliset ennusteet, automaattisuositukset

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1 INTRODUCTION

Forecasting is always difficult, but still thousands of equity analysts all over the world try to predict the future stock prices every day. There is a wide body of academic literature available on predicting future stock prices using backward-looking financial figures. These studies are focused on finding stock market anomalies, which could be used to gain abnormal profits in the long-run. Moreover, numerous studies have been made on the predicting abilities of equity analysts and the usefulness of their forecasts and recommendations. In these studies the researchers discuss the interesting biases in the analyst forecasts and the conflicts of interests between the analysts and the investors.

From the viewpoint of an investor willing to conduct extensive fundamental analysis based on future forecasts these streams of literature seem to provide somewhat conflicting results. The market anomaly studies provide a nice starting point for the investor in terms of what to forecast and how to interpret the results, but it raises an obvious question: if one can achieve statistically significant abnormal profits by just looking at historical financial figures, how high abnormal profits could one achieve by taking into account forecasts about the future performance of the company? The equity analyst related literature answers this question by simply saying: not much. For many different reasons, the forecasts and recommendations made by the equity analysts are strongly biased and thus the performance of equity analysts is generally not very flattering. However, a self-confident (or over-confident) investor can easily believe that she will be able to outperform the equity analysts because there are no conflicts of interest between her analyses and her investment decisions. This brings us to the key questions of this study: if an investor strongly believes that her forecasts are unbiased estimates on the most likely future scenario, what investment strategy should she follow to get the most out of them? What forward-looking value drivers should the investor use to screen stocks in these circumstances? As an answer, I try to find the best forward-looking value drivers that could be used to make *auto-recommendations* based on the user’s own forecasts.

However, the practical relevance of this study is not confined to over-confident investors who think they can predict the future perfectly. I apply the auto-recommendation model to equity analysts' consensus forecasts and show that the auto-recommendations clearly outperform the consensus recommendations of the equity analysts themselves. This implies that although both the forecasts and the recommendations of the equity analysts are heavily biased, the analysts seem to do a better job in making the forecasts than the recommendations. A possible reason for this phenomenon is that in making the forecasts the analyst can focus only on company specific issues. When making the recommendation, however, the analyst must take into account the current price of the stock and its relative profitability compared to other stocks on the market. The other practical implication of this study is that analysts could use a decision-aid tool, such as the auto-recommendation model suggested in this study, in making the final stock recommendations. Alternatively, investors could themselves improve the quality of the analyst recommendations by feeding the analyst forecasts into the auto-recommendation model.

From a theoretical viewpoint, this study contributes to the literature in two ways. First, I use the perfect foresight method, which is rarely used in this kind of studies. The value driver literature has mainly focused on backward-looking value drivers or occasionally using analyst forecasts as a proxy for future performance. A possible reason for this is that the practical relevance of such a study is not very clear. In this sense, this study has some links to behavioral finance as well, where investors have been proven to be overconfident when making forecasts and investment decisions. Fully rational investors would probably not spend a lot of resources in trying to make as good forecasts as possible when considering the difficulties and uncertainties involved. Despite the obvious difficulty people still try to make these forecasts and this study suggests a framework for those people to apply when making investment decision based on the forecasts.

Secondly, this study contributes to the equity analyst literature by studying the interconnection between analyst forecasts and recommendations. A few studies related to this matter have been made, but the research field is still very young. On the basis of my findings I suggest a value driver based framework to analyze whether the analyst has got the forecast or the recommendation or both right. The framework could be used to further study the different biases in the analyst forecasts and recommendations.

1.1 Research problem and purpose

The purpose of this study is to develop an auto-recommendation model, which would produce higher than average stock returns based on a set of forward-looking value drivers. The objective is to find the best value drivers that distribute the stocks into portfolios so that the difference in stock returns between the buy and the sell portfolio is as large as possible. In other words, the return of an investment strategy, where the investor has a long position in the buy portfolio and a short position in the sell portfolio, is maximized.

The research question in this study is:

"What forward-looking value drivers provide the best basis for investment strategy given the most accurate, unbiased forecasts available?"

The research problem is complemented with four sub-questions.

- Based on existing literature, which value drivers show the best potential for explaining future stock returns?
- What is the level of value driver performance using only backward-looking value drivers, i.e. what is the minimum level of performance expected from forward-looking value drivers?
- Which value drivers perform the best when perfect foresight is applied, i.e. what is the maximum level of performance that someone can achieve by using the value drivers?
- What is the value driver performance when analyst consensus forecasts are applied in generating the auto-recommendations? How do the value driver generated auto-recommendations compare with analysts' consensus recommendations?

The first sub-question is designed to outline the most influential value drivers on which the following analyses can later be focused. The purpose of the study is not to test every possible value driver, but choose small set of potential drivers that also have a strong theoretical link to the value of the firm. The second sub-question allows us to establish a lower limit of the value driver performance that the following analyses have to exceed. There is no sense in making difficult forecasts if you can accomplish the same level of performance with historical values. The third sub-question is the key to the main research question. Here the value drivers are tested with best forecasts available, namely the actualized future financial figures. This analysis reveals to us the value drivers that work best when estimates are unbiased and perfectly accurate. The analysis also determines the maximum level of performance that one could get ever achieve by using these value drivers. Real forecasts will naturally underperform dramatically, but still this measure could be used as one kind of benchmark as a measure of forecast accuracy. The last sub-question is related to the practical application of the value drivers with real analyst forecasts. Now the performance of the analyst forecasts can be compared to the backward-looking value drivers and the value drivers using perfect foresight. Moreover, the performance of the auto-recommendations derived using the value drivers is compared to the performance of the real consensus recommendations given by the analysts.

1.2 Limitations of the study

The study has a number of limitations that must be taken into account when interpreting the results. First, I focus in this study only on value drivers that consist of items that are considered analyzable. This means that the item used in calculating the value driver must be commonly forecasted by the equity analysts or at least it could be forecasted by the equity analysts. Items such as the volatility or trading volume are excluded, because they can be considered as unpredictable as the stock price itself. Since I am trying to explain stock prices using the value drivers, the future stock price can not be a part of the value driver either. Furthermore, dividends are excluded for the same reason because the item is already calculated in the stock return.

Secondly, the perfect foresight method used in the study does not take into account any common biases that might be related to making forecasts. However, this is rather a characteristic of the method than a limitation, because I explicitly wanted to bypass any biases caused by the analyst data. Anyway, one should keep in mind that when choosing the value drivers using analyst data, the drivers are also ranked according to their capability of handling the biased data. In the domain of perfect foresight, on the other hand, any systematic bias in the forecasts could possibly lead to a much worse outcome that expected.

Thirdly, the data used in the study suffers from database related issues such as selection biases that are common in these kinds of studies. These limitations are discussed in more detail in section 3.2. Finally, the data in this study is restricted to US companies only, but other studies suggest that results derived from the US markets can usually be extended to other markets as discussed in section 3.2.1.

1.3 Structure of the study

The structure of the study is the following. In Chapter 2 the existing literature is reviewed and the potential value drivers are identified for further analyses. Chapter 3 describes the data and methodology used in the study. Chapter 5 begins with examining the backward-looking value drivers and establishing a lower boundary for the portfolio returns in the next analyses. Chapter 5 goes on to study the performance of the forward-looking value drivers using perfect foresight and thus establishing the upper boundary for the portfolio returns. Chapter 6 begins the second phase of the study where the analyst data is applied to the forward-looking value drivers. First, the profitability of the auto-recommendations created by using analyst forecasts is examined separately and then the profitability of auto-recommendations is compared against analyst consensus recommendations. Chapter 7 concludes and makes suggestions for future research.

2 PREVIOUS RESEARCH AND CHOICE OF VALUE DRIVERS

There previous studies related to this study can be categorized in three streams of literature. First of all, a vast amount of literature deals with building screening models for portfolio formation. However, most of these studies use only historical financial figures, and thus concentrate on identifying stock market anomalies, i.e. market inefficiencies that anybody could utilize in gaining abnormal profits. The second stream of literature related to this study focuses on accounting based value drivers. Again researchers try to find value drivers that would explain abnormal stock returns, but this time the focus is on accounting items rather than the classical ratios such as the price-to-earnings (P/E) ratio. Although many of the value drivers tested in this study are taken from the classical anomaly studies, the spirit of this study is closer to the accounting literature. Here, instead of finding market anomalies, the objective is to identify which items drive the value of a company so that the managers could focus their actions on maximizing the right accounting measures. In this study, the same information is used to find profitable investment strategies based on the company's expected ability reach these measures. Finally, the third stream of literature is related to professional equity analysts and the usefulness of their forecasts and recommendations in achieving abnormal profits. Much of this literature is focused on the biases in the analyst forecasts and the conflicts of interests that cause them. However, some of these studies also use the analyst forecasts in deriving forward-looking value drivers, which provide an interesting benchmark for the second phase of this study, where analyst forecasts are used to see how well the value drivers perform under biased equity analyst forecasts.

2.1 Streams of literature related to the study

2.1.1 Anomaly studies

Quickly after the introducing the market efficiency theory in 1960s, researchers started to find evidence that contradicted the efficient market hypothesis. In the 1990s, the burdening amount of evidence on market inefficiencies led to the emergence of behavioral finance in the mainstream of finance literature. These empirical studies searched for any backward-looking value drivers that had explanatory power over the future stock returns. The efficient market hypothesis claimed that all public information is already reflected in the stock prices and thus nobody should be able to find backward-looking value drivers that could explain the stock returns. As mentioned above, however, the researchers found several market anomalies that should have been arbitraged away if the markets would have been efficient in the classical sense. These include, for example, the small market capitalization anomaly, the net stock issue anomaly, the positive price momentum anomaly, and the positive earnings momentum anomaly (see Fama and French (2008) for a recent survey on different anomalies). However, in this study we are interested in value drivers that can be turned into forward-looking by incorporating future forecasts into them. In this particular field, the most well known market anomalies are the price-to-book (P/B) anomaly and the price-to-earnings (P/E) anomaly. These anomalies are commonly known also as the value vs. growth anomaly, because the issue usually boils down to steady value companies outperforming more exotic growth companies. The thoroughly researched value vs. growth anomaly provides this study with a necessary framework for sorting stocks according to the chosen value drivers.

As early as 1977, Basu proved empirically that stocks with low P/E ratio generated higher average returns compared to stocks with high P/E ratios. Later the same result has been repeated in dozens of other studies (see e.g. Chan et al., 1991, Fama and French, 1992, and Lakonishok et al., 1994). The results were not in line with Capital Asset Pricing Model (CAPM) developed a decade earlier (Sharpe, 1964 and Lintner, 1965), because the stocks with low P/E ratios did not appear any riskier at least when examined with traditional risk measures. Thus, a lot of academic interest was attached to this matter. In 1984, Rosenberg et al. showed that also price-to-book (P/B) ratio seemed to explain stock market returns. Again, other researchers quickly confirmed the results, and the abnormal returns gained by the P/B ratio seemed to be even higher than the returns achieved by using the P/E ratio (see e.g. Chan et. al, 1991, Fama and French, 1992, and Lakonishok et al., 1994). Actually, Fama and French (1992) started a stream of literature where the anomalies were studied thoroughly with cross-section regressions. In this method the regression model is used to predict future stock returns, for example, over the next year. The independent variables in the model were backward-looking value drivers such as the P/B or the P/E ratio. As a result of the regression, they got the best value drivers that explained the future stock returns. These studies irrefutably showed that value stocks outperformed growth stocks and the best driver to dissect value stocks seemed to be the P/B ratio. As mentioned earlier, under growing evidence the market efficiency defenders finally had to admit that value stocks generate higher profits than growth stocks. However, the next logical argument was that the value stocks are just riskier and the higher return is a result of higher risk. The discussion goes on still today, but so far nobody has been able to develop a risk measure that could properly explain the difference in the returns (Chan and Lakonishok, 2004).

There is another important anomaly that is related to the value vs. growth anomaly and the approach used in this study. Banz (1981) was the first to report that stocks with low market capitalization, i.e. small companies, produce higher stock returns than large companies. Although the market capitalization is surely not among the good forward-looking value drivers, it has relevance over this study as well. The high returns of small companies tend to disturb the results if small companies dominate some portfolios. Therefore, many of the value vs. growth studies report the results separately for small, medium and large companies. In this study, the companies are analyzed together in order to maximize the number of companies in the sample but the effect of size anomaly is closely monitored and, whenever needed, the size effect is documented using additional analyses.

This study takes advantage of the anomaly literature in two important ways. First, the existing literature is used to screen suitable value drivers that have been proved to work with historical financial statement data. Any anomaly already present in the value driver creates a good starting point for adding information about future financial figures. Combinations that utilize the historical market anomaly and add future expectations on top of that are particularly interesting in the context of this study, because there is evidence that equity analysts generally take advantage of these anomalies only to a certain extent in making their recommendations (Stickel, 2007). The most relevant value drivers studied in this field of literature are presented in section 2.2.

The methods used in this study follow quite closely the methods developed in the anomaly literature. The cross-section regression in the spirit of Fama and MacBeth (1973) has been the prevalent study method in this field of literature after it was first applied by Fama and French (1992). However, the functional form of the regression is not very useful in practical applications. Thus, most of the studies include also a sorting model, which is used in this study as well. The sorting method allows creating simple ranking rules that are easy to apply in practice. Fama and French (2008) report that the cross-section regression method and the sorting method lead generally in similar results. The chosen method of this study is described in detail section 3.1.

A vast majority of the anomaly literature has limited the value drivers to historical fundamentals only. Some studies use analyst forecasts as proxies for future expectations. However, the perfect foresight approach used in this study has been very rarely applied in these kinds of studies. Grauer (2008) uses the future actualized returns in determining optimal asset allocation strategies between stocks and Treasury bills. Moreover, Arnott et al. (2008) use actualized future cash distributions in determining ex post realized value of individual stocks and compare these to the original stock price. However, in my knowledge there are no studies that would use the perfect foresight method in acquiring future financial statement data and test the performance forward-looking value drivers based on these figures.

2.1.2 Accounting literature

The accounting literature related to this study is quite close to the anomaly studies presented above. The study by Ou and Penman (1989) can be considered as the seminal work in this field of literature. Other key studies are, for example, Lev and Thiagarajan (1993) and Haugen and Baker (1996). The differences between the anomaly and the accounting literature arise from the motivation of the researchers and the scope of value drivers that are tested. The primary motive of these studies is not to prove market efficiency theory right or wrong but to find the best managerial measures that drive the value of the company. In other words, researchers examine what financial characteristics unite successful companies in terms of stock returns. The practical implication of these studies is a suggestion that managers should focus on maximizing these value drivers in order to create shareholder value. The scope of value drivers included in these studies is much wider than in the anomaly studies. Basically, any income statement, balance sheet or cash flow statement item is a potential value driver in this stream of literature. When a typical market anomaly study concentrates around a few key figures, the accounting studies include up to 50 different value drivers.

In this study, the accounting literature is utilized to establish a large value drive base from which the final value drivers to be tested in the study are selected. The wide range of possible value drivers enables us to choose value drivers that have a strong link to the valuation theory and that have been proven to explain stock returns in the previous studies. However, the negative side of many accounting based value drivers is that they have been derived from very detailed financial items, and thus they could be extremely difficult to forecast. Moreover, some of the value drivers found significant in these studies make little sense in terms of financial theory. Indeed, these kinds of studies have been accused of data snooping bias, where one is bound to find some correlation with stock returns when enough value drivers are tested. The most relevant value drivers found in this stream of literature are presented in section 2.2.

2.1.3 Analyst forecasts literature

The third stream of literature related to this study is focused on equity analysts. The purpose of the equity analysts is to outsource demanding analysis work of the investors and provide the investors with good investment advice. From very early on researchers have been interested in the profitability of the analyst recommendations. Quickly, however, it was clear that the analyst recommendations do not result in significant abnormal profits (Cowles, 1933), and the earnings forecasts of equity analysts seemed to be systematically biased upwards (Fried and Givoly, 1982, O’Brian, 1988). Much of the literature has therefore been devoted to understanding why analysts perform so badly in making their forecasts. The researchers have identified many conflicts of interest between the analysts and the investors that cause these biases. Comprehensive articles surveying the literature on conflicts of interests between analysts and investors have been written by Brown (1993) and Ramnath (2008). Because of the commonly known poor quality of the analyst forecasts, the value drivers are tested in this study also using the perfect foresight method.

In the context of this study, the analyst literature is important for two reasons. First, it is a good source of studies testing forward-looking value drivers. The value drivers in these studies are calculated using equity analyst forecasts as the best approximate for future financial figures. The most commonly used item is earnings-per-share (EPS) forecasts. In the second phase of this study, the value drivers identified with perfect foresight method are tested with actual analyst forecasts. These results can be compared against other studies in this field of literature. Moreover, the results provide a lower limit of returns that any investor making unbiased forecasts herself should be able to gain, if the she devotes enough time and resources to the task. In addition, using the value drivers to create auto-recommendations from analyst forecasts enables us to study the interconnection between analyst forecasts and recommendations. The connection has not yet been very thoroughly studied in the existing literature (Bradshaw, 2002).

2.2 Value drivers in the existing literature

One of the main purposes of the literature review is to provide a list of potential value drivers to be tested in this study. In this section the most significant value drivers studied in the existing literature are presented and the ones to be tested in the study are chosen. The criteria for a good value driver to be tested are the following:

- The value driver is empirically proven to have significance in explaining future stock returns.
- The value driver must have a logical connection to the value of the company.
- The future fundamentals needed to calculate the value driver must be analyzable in terms that they are commonly analyzed by the equity analysts, or at least they could be analyzed by the equity analysts.

The meaning of the first criterion is to take advantage of the existing literature in restricting the number of possible value drivers only to the most significant ones. The second criterion ensures that the chosen value driver makes sense to other people as well. This is important for any practical applications that could be developed on the basis of this study. The requirement of logical connection also reduces the risk of data snooping bias, where some arbitrary value driver could accidentally correlate to stock returns in this particular data set. Finally, the future looking value drivers must be based on items that can be forecasted. Items like stock issues and positive price momentum are excluded because predicting them is considered to be impossible. For any practical applications, it would be advantageous if the item would be commonly analyzed by equity analysts. This does not, however, mean that in the second phase of this study the future fundamentals should be restricted to those available in the analyst data. Today equity analysts forecast a much wider selection of fundamentals than for which long time-series are available. However, it is important to test at least some forward-looking value drivers that can be calculated from the analyst data in order to conduct the second phase of this study.

Table 1 contains a list of studies which test the explanatory power of different value drivers on stock prices. The list is not all-inclusive, but the most significant studies of the different streams of literature presented above should be included. The value drivers presented in the table are not as straightforward as would seem. The different studies use slightly different compositions of the value drivers, but in this table they are all gathered under the same primary value drivers. For example, price-to-earnings ratio and earnings-to-price ratio are both reported under price-to-earnings, which is the selected composition in this study. Finally, the value drivers that have been shown to result in statistically significant abnormal returns are marked with “S” in the table. However, no direct conclusions can be made because the studies vary considerably in terms of their sample, statistical methods and significance levels. Since the list is not all-inclusive and some other rough approximations have been done in preparing the table, one should not make too far reaching conclusions about the capabilities of the different value drivers on the basis of Table 1. However, the most important value drivers still clearly stand out in terms of their frequency and statistical significance.

Table 1 Articles studying different value drivers and their explanatory power over stock returns

Some of the most important articles testing different value drivers are listed in this table. The articles are in alphabetical and order and the value drivers tested in the article are specified in the table. The value drivers tested in the study are marked with "x". If the driver is statistically tested and found statistically significant, the marker is changed to "S". The list is not comprehensive and not all value drivers tested in articles are necessarily listed.

Studied Fundamental Variables x = Studied S= Found Significant

		Price-adjusted								**Growth**						**Profitability**						**Accounting**													**Stock Market**						**Other**				
Writer	**Year**	P/E	PEG	P/B	P/B & ROE	P/Div	P/CF	P/EBITDA	P/Sales	Earnings growth	Sales growth	Long-term earnings growth	Forecasted Earnigns Y1	Forecasted Earnigns Y2	Earnings surprises	Profit Margin	ROA	ROE	CFO	Capital Turnover	RIM	Accruals	CAPEX	R&D	S&A	Depreciatio	Inventory	Working Capital / Assets	Accounts Receivable	Current ratio	Quick Ratio	Interest coverage	Tax	Losses	Beta	Volatility	Earnings risk	D/E	Price Momentum	Long-tern	Size	Number of analysts	Labour	Orders	Age
Abarbanell & Bushee	1997															S							S		S		S		S				S										S		
Ahmed & Nanda	2001	S		S						S																																			
Barber & Lyon	1997			S																																					S				
Basu	1997	S																																											
Beneish, Lee & Tarpley	2001			S		x			x						S	S						S	S	x										S		x			S		S	x			x
Bradshaw	2004		S																		S																								
Chan, Hamao & Lakonishik	1991	S		S			S																												S						S				
Chan, Jegadeesh & Lakonishok	1995			S																																									
Chan & Lakonishok	2004	S		S		S	S		S																																				
Daniel & Titman	1997			S																																									
Easton	2004		S																																										
Easton & Monahan	2005	x	x										x								x																								
Fama & French	1992	S		S			x				x																												x	x					
Fama & French	1996	S		S			S				x																																		
Fama & French	2008	S		S												S						S	S																S						
Ferson & Harvey	1999	S		S		x	x																													x			S	x					
Frankel & Lee	1998			S																	S																								
Haugen & Baker	1996	S	x	S		x	S		x	x						x	x	S		x												x			x	S	x	x	S						
Lamont	1998	S				S																																			S				
LaPorta	1996	x		x			x					S																																	
LaPorta, Lakoshnik, Shleifer & Vishny	1997														S																														
Leledakis & Davidson	2001								S																													S							
Lev & Thiagarajan	1993															S							S	S	S		S		S				S										S	S	
Liu, Nissim & Thomas	2002	S		S			S	x	x				S	S				S	S																										
Miles & Timmermann	1996	S		x		x																								x								x			x				
Ou & Penman	1989															S	S	S								S	S		S	S	S	S						S							
Piotroski	2000			S												S	S		S	S		S								S								S							
Setiono & Strong	1998															S		S	S								S	S	S	S								S							

As we can see in Table 1, the most commonly studied drivers are the P/E and the P/B ratio by far. The use of these value drivers follows the academic interest in value vs. growth anomaly. The P/E ratio can be made forward-looking quite easily by either using future earnings in calculating the ratio or adding the growth factor in the ratio, i.e. using the PEG ratio. The PEG ratio is much less well studied than the plain P/E ratio, but the results are quite promising (see e.g. Bradshaw, 2002 and Easton, 2004). The P/B ratio is backward-looking and using the analyst forecasts in it is more difficult. However, as mentioned in section 2.1.1, the P/B ratio outperforms the P/E ratio as a measure for the value vs. growth anomaly.

Beyond these two intensively studied value drivers, the rest are somewhat less commonly studied. The cash flow-to-price measure is also quite frequently studied and it has been shown to explain stock prices. However, the link between regular earnings and cash flow measure is usually quite strong and the advantage of the figure is usually associated in dissecting good accounting measures from bad ones. In the right part of the table there are many accounting items mentioned of which most have been found to have some correlation with the stock prices. Although, for example, high R&D costs might unite good companies, this can hardly be considered as a good forward-looking value driver. It is difficult to imagine that by devoting a lot of time into forecasting the company's R&D costs for the following year, one could gain insights that are not already present in the backward-looking value drivers. Therefore, most of the accounting based value drivers are discarded because of lacking analytical value and missing link to valuation theory. However, the different profitability figures stand out as one important group that has emerged from the accounting literature. Profit margin, ROA and ROE are found significant in many other studies as well. From these value drivers ROE offers the best theoretical link to the value of the company.

The strongest link to the finance theory of all the value drivers is probably included in the residual income. The studies often use complicated discounting structures, which make it difficult to apply in practice. A more straightforward method of just replacing earnings in the P/E ratio with residual income that incorporates the cost of capital could be interesting also in the context of this study.

Finally, there are a number of other value drivers in the list that might show potential, but they are omitted because of the method applied in this study. First, the dividend return shows clear potential as a value driver, but making it forward-looking under perfect foresight creates an auto-correlation issue. The future dividends may explain the stock returns, but they are also part of the variable explained. Other omitted value drivers include unpredictable items such as volatility, stock issues and price momentum as mentioned in section 2.1.1.

2.3 Choosing the value drivers for testing

In Table 2, the most significant value drivers identified in the previous section are gathered together and compared numerically. For each value driver some of the most important studies testing the performance of the driver are listed in Table 2. In all of these studies the stocks are sorted according to the value driver and the portfolio performance is reported. In Table 2 I have calculated the performance of an investment strategy where the investor would have a long position in the highest ranking portfolio and a short position in the lowest ranking portfolio. The returns are annualized to one year. The actual buy-and-hold periods in the studies change from daily rebalancing to 36 months. Therefore, in interpreting the results one must remain very precautious. The studies have used different methods in calculating the returns in other areas as well. For example, the sources of data, geographical focus, sample periods and many other important issues differ between the studies. Finally, some studies have not reported the buy vs. short return difference and therefore I have calculated that myself. In studies with more complicated portfolio structures the calculation method is not entirely straightforward and some differences might arise due to my calculations as well. Nevertheless, these results provide some indication which value drivers could provide the best potential according to the previous studies.

Table 2 Performance of value drivers in the existing literature

The table summarizes the performance of different value drivers in the existing literature. The difference between buy and sell portfolio returns (hedge return) is reported for each study. When the data is not directly available, similar figure has been manually calculated. Returns in studies using longer or shorter buy-and-hold periods than one year have been annualized. Studies differ in many ways from each other (data, number of portfolios, methods etc.) and thus comparing the studies with each other should be done with caution. The value drivers studied in the same study are more comparable.

Value Driver	Study	Data	Hedge Return
P/B			
	based on historical figures		
	Fama & French 1992	US (1962-89)	21.27%
	Frankel & Lee 1998	US (1975-1993)	4.90%
	Leledakis & Davidson 2001	UK (1980-1996)	18.84%
	Miles & Timmermann 1996	UK (1975-1990)	9.90%
	Lakonishok, Schleifer & Vishny 1994	US (1963-90)	7.30%
	Chan, Hamao and Lakonishok 1991	JP (1971-88)	14.03%
P/E			
	based on historical figures		
	Fama & French 1992	US(1962-89)	9.90%
	Basu 1977	US 1957-71	6.96%
	Lakonishok, Schleifer & Vishny 1994	US (1963-90)	3.90%
	Miles & Timmermann 1996	UK (1975-1990)	3.17%
	Chan, Hamao and Lakonishok 1991	JP (1971-88)	4.91%
	based on analyst forecasts		
	Frankel & Lee 1998	US (1975-1993)	3.01%
Size			
	based on historical figures		
	Fama & French 1992	US (1962-89)	9.51%
	Frankel & Lee 1998	US (1975-1993)	-0.01%
	Leledakis & Davidson 2001	UK (1980-1996)	21.60%
	Miles & Timmermann 1996	UK (1975-1990)	1.94%
P/B and Size			
	based on historical figures		
	Fama & French 1992	US (1962-89)	12.55%
	Daniel & Titman 1997	US (1963-93)	9.51%
PE & Growth			
	based on historical figures		
	Ahmed & Nanda 2001	US (1982-97)	11.10%
Growth			
	based on analyst forecasts		
	La Porta 1996	US (1982-91)	-20.90%
ROE			
	based on historical figures		
	Fama & French 2008	US (1963-2005)	2.30%
Sales growth			
	based on historical figures		
	Frankel & Lee 1998	US (1975-1993)	-7.80%

(Table 2 continues)

(Table 2 continues)

Value Driver	Study	Data	Hedge Return
P/S			
	based on historical figures		
	Leledakis & Davidson 2001	UK (1980-1996)	18.60%
Long-term growth			
	based on analyst forecasts		
	Frankel & Lee 1998	US (1975-1993)	6.50%
D/E ratio			
	based on historical figures		
	Leledakis & Davidson 2001	UK (1980-1996)	15.24%
	Miles & Timmermann 1996	UK (1975-1990)	3.41%
P/CF			
	based on historical figures		
	Lakonishok, Schleifer & Vishny 1994	US (1963-90)	9.90%
	Chan, Hamao and Lakonishok 1991	Japan (1971-88)	10.03%
P/Div			
	based on historical figures		
	Miles & Timmermann 1996	UK (1975-1990)	-1.90%

2.3.1 Price-to-book ratio and return on equity

As we can see from Table 2, the P/B ratio leads to highest return in almost any study. The companies with low P/B ratios outperform the high P/B companies by a wide margin. It is very natural to include this value driver in this study. However, P/B ratio offers only little room for forward-looking components. The book value next year can be used, but the effect of one year profit performance is very low on P/B ratio. It can be expected that the effect of adding perfect foresight to this value driver will not increase the performance of the value driver significantly. Thus, in the context of this study it would be interesting to add some forward-looking fundamental to this value driver. The best option for this seems to be return on equity (ROE). ROE reflects the company’s current or future profitability. ROE has been shown to explain stock returns in many accounting studies (Ou and Penman, 1989 and Haugen and Barker, 1996, and Liu et al., 2002).

A combination of P/B ratio and ROE is quite interesting for this study. Such a linkage has been suggested by, for example, Clubb and Naffi (2007). The logical link between P/B ratio and ROE is that P/B can be interpreted as a measure of profitability expectations. When P/B ratio is below 1 the company is expected to destroy shareholder value. When the ratio is higher than 1, the company is expected to create shareholder value in the future. ROE, on the other hand, is a measure of profitability. If the next year's ROE is higher than the cost of equity (expected by shareholders), the company creates value and vice versa. In other words, the combination of P/B and ROE creates a framework where a company is allowed to have a high P/B ratio (implying high profitability expectations) and still be included in the "buy" portfolio, if the subsequent ROE forecasts are high as well. Companies with high P/B ratio can be also good investments if they actually meet or exceed the high expectations already present in the stock price. Alternatively, companies with low P/B ratios are not necessarily good investments if the forecasted ROE is also significantly below the cost of capital. From the viewpoint of this study the combination of P/B ratio and ROE is interesting, because it includes the best performing value driver identified in the value vs. growth literature and also a forward-looking component ROE, which can be clearly linked to the original value driver. However, the mathematic formula used to link these two figures is very problematic. Since both figures use the book value of the company as their denominators, there is risk of turning the figure into normal price-to-earnings related value driver. The issue is discussed further in section 4.2.1.

Naturally, the ROE is tested also separately as it has shown explanatory power in the previous studies. The negative aspect of ROE as such is that the valuation level of the stocks is not reflected in the driver through the current price. Therefore, the value driver does not take into account whether the level profitability is already reflected in the price or not. Final value driver related to the P/B ratio and profitability is the debt-to-equity ratio (D/E). Researchers have found that companies with high leverage tend to outperform companies with low leverage. However, similarly to the P/B ratio the problem with D/E ratio is its lacking capability of capturing much forward-looking information in it.

2.3.2 Price-to-earnings ratio and growth

The next interesting value driver is the P/E ratio. Although the value driver has been shown to result in abnormal profits, it seems to underperform the P/B ratio in almost every study where both value drivers are tested. The effect is still clear; the companies with low P/E ratios significantly outperform the high P/E companies. Despite the smaller abnormal returns, the P/E ratio has some significant advantages compared to the P/B ratio especially from the viewpoint of this study. The P/E ratio is one of the easiest value drivers for incorporating future forecasts. Forward-looking P/E ratio is calculated simply by replacing the forecasted next year's earnings in the denominator. There are other options as well. Incorporating P/E ratio with growth (PEG ratio) creates a similar framework as the P/B ratio and ROE. The P/E ratio is generally considered to be a proxy for the growth expectations of the stock. In this context, the framework is usually called *Growth at Reasonable Price (GARP).* GARP enables investing in companies with high P/E ratio (high growth expectations) if the forecasted growth is also high. On the other hand, companies with low P/E ratio are not automatically good investments if their forecasted growth is very low.

The negative aspect of P/E and PEG ratios is that they create very strict requirements for the analyzed companies. P/E ratio works properly for only companies with positive earnings and thus, any companies with negative earnings must be omitted from the sample. Calculating the growth also creates extra requirements. Both actualized earnings in year t=0 and forecasted earnings in year t=1 should have the same sign. Moreover, the growth rate should be positive, because in calculating the PEG ratio the P/E ratio is divided by the growth rate. These requirements decrease the data sample significantly. The problem is further discussed in section 4.2.1.

Also growth as such is tested in the study, but is suffers from the same drawback as ROE, i.e. no direct link to the current valuation level of the company. Even if companies with high earnings growth would result in higher stock returns, this is not the case if the future growth is already overemphasized in the stock price.

2.3.3 Residual income

The third value driver type to be tested in this study is the residual income (RI) or economic value added (EVA). Theoretically speaking this value driver has the strongest link to financial theory. RI takes into account also the cost of equity and thus, really reveals if the company is creating value for its shareholders or not. From the theoretical point of view, the RI should really drive the value of the company and at least by using perfect foresight screening companies according to their RI should result in abnormal profits. However, the setback of this value driver is that the cost of equity is extremely hard to estimate accurately even with perfect foresight. Previous studies in this field include Frankel and Lee (1998) and Ali et al. (2003), both of whom have found that their relatively complicated RI models using analyst forecasts results resulted in abnormal profits. In this study, a simplified version of a RI is used to calculate a P/RI ratio. The simplification is discussed more in depth in section 5.1.1.

2.3.4 Other value drivers

There are still many value drivers left in Table 2 that could be tested in this study. However, the value drivers mentioned above show the best potential in terms of buy vs. sell returns reported in previous studies and in terms of linkage between the value driver and financial theory. For future research, at least the P/CF ratio, the P/S ratio, and long-term growth provide excellent sources of new value drivers to be tested.

3 METHODS AND DATA

3.1 Methods used in the study

The method used to test the different value drivers in this study is the classical sorting method. A widely used alternative method would be the cross-section regression in the spirit of Fama and MacBeth (1973). The sorting method was chosen mainly because the result of the method is a simplistic sorting rule, which can be easily used in practical applications. This section starts with discussing the choice of the research method and then the chosen sorting method is described in detail.

3.1.1 Sorting vs. cross-section regression

The sorting method is very straightforward. The stocks are simply sorted by the value driver into portfolios and the return of each portfolio is then reported. The negative side is that only one or in some cases two value drivers can be studied at the same time. Moreover, the sorting method does not reveal much about the functional form of the relation between the value driver and the stock return. The interaction between different value drivers is also left in the dark. The advantage of the method is that it is very transparent. The method can also be easily implemented in any practical applications. Just by reporting the sorting criteria anybody can take advantage of the findings of this study. The sorting method is also more flexible in many ways. The calculation method of portfolio returns can be easily altered. For example, the portfolio returns can be calculated as average or median depending on the situation.

In the cross-section regression the dependent variable, the future stock returns, are explained by the independent variables, the different value drivers. The advantage of this approach is that it can be simultaneously run on multiple value drivers and the interaction between different drivers can be examined more easily. Secondly, the method gives a functional form of the relation between the value driver and the stock returns. The functional form can be utilized further and, for example, the marginal effects can be measured. However, the functional form is also a shortcoming. The chosen functional form might turn out to be incorrect, which creates biased results. Therefore, it must be heavily tested for reliability. Moreover, there is a risk of emphasizing small stocks in the regression, because each company has to be equally weighted in the regression. Finally, also extreme values have direct effect on the regression coefficients and considerable effort must be put to omit outliers from the data. Fama and French (2008) thoroughly discuss the different characteristics of both methods. They also conclude that both the cross-section regression and the sorting method seem to produce similar results when applied to the same data set. This further strengthens the case that the study method can be chosen in a way that enables easy practical applications.

3.1.2 Description of the sorting method used in the study

The sorting method is used to calculate buy-and-hold period returns of one year for each of the stocks in the study. Each year in the study starts with financial statements that are dated at the end of the fiscal year of the company. The latest such date is the last day of each year (December 31st), which is also the most common fiscal-year end-date. However, the financial statements are not made publicly available on that date. Instead, it takes usually a few months for the company to prepare and publish the financial statements. To avoid having undisclosed information incorporated in the value drivers, the buy-and-hold period starts on April 1st the next year. In other words, it is assumed that the financial statements are published at the latest on March 31st. The same timeline is used in several other studies (see e.g. Lakonishok et al., 1994). However, in some studies focused on market anomalies the quarantine period is even more conservative starting from July 1st (e.g. Fama and French, 1992). In the context of this study the three month period is considered to be long enough. The disadvantage of having a longer period is that the stock price in July reflects already everything that has happened in the first half of the year including the first quarter for most companies. The long quarantine period means very strong handicap for any sorting models still using reported fundamentals from the last year.

The price used in calculating value drivers is taken from March 31st, which is the last day before the start of the buy-and-hold period. In practice this means that up-to-date stock prices are available in creating the portfolios on April 1st. Also the number of outstanding shares is taken from March 31st. Any companies delisting during the holding period are included in the sample in order to avoid the survivorship bias. The stock prices of these companies are followed as far as they are available including the delisting return (e.g. -100% for bankrupted companies). The stock returns on the following months after delisting are tied to S&P 500 index in order to cause minimal disturbance on the results.

Each year the sample is divided into five portfolios according to the value driver under investigation. The number of portfolios is fixed to five, because of the analogy to analyst recommendations. Thus, having five portfolios makes practical applications easier when the recommendations are already on a familiar scale. A larger number of portfolios could provide more detailed results about the portfolio returns, but five portfolios are considered to be sufficient to study whether the buy vs. sell portfolio returns differ statistically significantly. The results are also easier to apply later in smaller markets such as in Finland, where the sample will certainly not be high enough for more than five portfolios. The portfolios in this study are formed so that each portfolio has the same amount of stocks in it. Finally the buy-and-hold returns of each portfolio are calculated using average or median and reported as the portfolio return for the year when the buy-and-hold period started in April.

3.1.3 Diagnostics and statistical tests

As mentioned before, the main result of the sorting method is the average or median return of each portfolio in a given year. The yearly returns can be combined in many ways. The easiest way is to give each year an equal weight and just report the average portfolio returns over the whole time period. This method is used as the primary method in this study. There is a certain risk involved in it however. First, each year is given an equal weight, which means that years with extreme market conditions can have a dominant effect on the results. In addition, some information gets lost when the yearly portfolios are averaged and then the years are averaged again.

Therefore, an alternative method is used to study the portfolio returns as well. Here the average return of all stocks is calculated for every year separately. Before sorting the stocks into portfolios, an abnormal return is calculated for each stock for each year. The abnormal return is the difference between the stock return and the average return of all stocks in that year. Then the stocks are sorted into portfolios according to the value driver and instead of calculating a yearly average, now all the abnormal returns from all years can be combined together, because they are adjusted against yearly changes already. The average return of each portfolio can be calculated as single average or median over all the stock-year combinations in the sample. This approach is used to conduct a t-test between the buy and sell portfolios in order to test whether the average abnormal returns in these portfolios differ from each other and whether the difference is statistically significant. The testing is performed using standard t-test assuming different variances. The null hypothesis in the t-test is that there is no difference in the stock returns of the buy and sell portfolio. The null hypothesis is rejected if the absolute value of the t-stat is higher than the t-stat of the required confidence level.

The objective of a good value driver is to separate stocks into different portfolios according to their future stock returns. More specifically, the aim is to create a maximally wide gap between the highest ranking buy portfolio and the lowest ranking sell portfolio. Therefore, the difference in average or median returns between the buy and the hold portfolio is used as the most important criterion in this study. Later, this gap between the buy and sell portfolio returns is called *the buy vs. sell return* or more specifically *the hedge return*, as it would be the return of an investment strategy where the investor would have a long position in the buy portfolio and a short position in the sell portfolio.

Another measure of the value driver performance, particularly in the domain of perfect foresight, is the proportion of maximum hedge return that the value driver is able to dissect. The maximum hedge return is calculated by sorting the stocks according to their actualized future stock returns. This is the maximum return that any value driver could ever achieve by separating the stocks perfectly in to different portfolios based on their stock returns. Naturally, this is impossible even under the perfect foresight method as none of the value drivers can correlate with stock return perfectly. The difference of the theoretical maximum return of buy and sell portfolios is calculated similarly to the value driver hedge return. This analysis enables us to see how large proportion of the maximum gap the current value driver is able to generate. This measure is particularly useful in this study, because the number of stocks included in each value driver test is different. All value drivers have their own data requirements as we will see in Chapter 4. In this study, the largest possible set of stocks is always used to study the performance of each value driver. The proportion of theoretical maximum return allows us to compare the different value drivers even if the data sample is not entirely the same for all value drivers.

3.2 Data

3.2.1 Geographical focus

The sorting method requires a large data sample to provide reliable results. In addition, the data must be comprised of long time-series, which extend over many economical cycles, because the performance of different value drivers might vary between upturns and downturns. Because of the requirement for a vast amount of data, the study is geographically focused on stock markets in the United States. The US stock market data provides the highest number of publicly traded companies and the longest observation periods in the available databases. Moreover, the different databases used in this study have the best coverage over US companies. The stock exchanges included in this study are New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and National Association for Securities Dealers Automated Quotations (NASDAQ). These are the three most important stock exchanges in the US consisting the most relevant US companies.

A great majority of other studies with similar research methods have been conducted with the US data as well. However, there are also studies where similar tests run on US companies have been repeated with data from other markets. In general, the results show that the same principles work in the other markets as well. See e.g. Chan et al. (1991), Haugen and Baker (1996) and Miles and Timmermann (1996) for international evidence. Naturally all markets have their own characteristics, but on a general level the results of this study can be extended to other markets as well.

3.2.2 Selected databases

The data for this study is gathered from three different databases. First, the historical financial statement items are extracted from Compustat database run by Standard and Poor's. The Compustat database includes all the basic items of the income statement, the balance sheet, and the cash-flow statement. The data is detailed enough for the purposes of this study.

The stock market data is taken from the Center of Research in Security Prices (CRSP) database, which includes a comprehensive collection of stock market data. The most important data items taken from CRSP are the monthly stock returns, stock prices, number of outstanding shares, and possible delisting returns.

Finally, the analyst forecasts and recommendations used in the second phase of this study are collected from the Institutional Broker's Estimate System (IBES) database run by ThomsonReuters. The absolutely best coverage of all the estimate items available on the IBES database is in the estimated earnings-per-share (EPS) item. All the other items are significantly less well reported in the database. Therefore, the second phase of this study relies heavily on the EPS-related value drivers and analyst recommendations. The EPS estimates used in the study are consensus figures calculated by IBES. The consensus is calculated using the average of individual analysts' forecasts. Later in the study also consensus recommendations are used in addition to the consensus forecasts. The consensus recommendations are calculated from the IBES database by extracting the number of recommendations in each of the 5 possible categories: strong buy, buy, hold, underperform, and sell. The recommendations are transformed into numerical form by assigning number 1 to sell portfolio and number 5 to buy portfolio and calculating the respective average of individual analyst's recommendations.

3.2.3 Length of the observation period

As mentioned above, the observation period has to be long in studies using the sort method. The most important reason for this is that over a long period of time single upturns or downturns do not dominate the results. By choosing a long observation period it can be ensured that the value drivers work in all kinds of market situations as expected. The observation period in other studies using similar methods has been around 30 years. For example, Fama and French (1992) used an observation period of 27 years. As the geographical focus of this study is the US, there are three particularly interesting major exchanges: NYSE, AMEX and NASDAQ. Since the NASDAQ is the youngest of these three exchanges, the observation period was selected according to it. The NASDAQ started its operations in early 1970s, and therefore the observation period in this study has been selected to be 1975-2007. The sample ends in year 2007, which means that the stock returns are calculated up to March 2008, which represents the latest data available in the databases.

When using the analyst data, the observation period is shorter due to data availability. The EPS forecasts are available starting from year 1984. Thus, when analyzing the value driver performance with analyst forecasts the observation period is 23 years (1984-2007). The analyst recommendations are available in the IBES database from year 1994 on. This means that the observation period, when analyzing the performance of auto-recommendation compared to analyst recommendations, is only 13 years (1994-2007).

3.2.4 Selecting the stocks

There are many issues that should be considered when selecting the stocks that can be used in the study. There should be no selection biases allowed in the selection, but still all companies do not qualify for the analysis. Certain industries are typically excluded from the data sample, because of their industry specific characteristics. In this study, banks and insurance companies are omitted because of their special reporting principles. The omission is based on Standard Industrial Classification (SIC), where companies with codes 6000-6999 were omitted.

A natural restriction in choosing the companies is the availability of the data. The issue is particularly problematic when different databases are combined. There is always a possibility of introducing a bias in the data sample, when some companies are omitted due to lack of data. For example, the Compustat and the CRSP databases have some differences in their company identification procedures. The identification method used in this study is the CUSIP identification code. This is the most often used identification method when combining different databases. However, it is not completely flawless either. Luckily, the identification issues are relatively well studied among US companies. For example, Chan et al. (1995) report that there would not seem to be significant selection biases related to matching data with CUSIP identification code between the two databases. Every linking method always carries a risk of some errors, but the effect of these errors can be considered minimal in this study due to the large sample size and long observation period.

In the second phase of this study, the two previous databases (Compustat and CRSP) are linked to the third database, IBES. The CUSIP identification code is used in this linkage as well. Every time a new database is linked to the previous ones, some companies are left out of the sample because of mismatch in CUSIP codes. However, the analysts themselves create a much more significant bias in this particular linkage. Naturally, large established companies are followed by the analysts more often than smaller ones. This inevitable bias is much stronger than any bias related to the differences in the identification codes. Thus, in analyzing the results in this phase, we must stay alert for possibly biased sample in terms of company size.

3.2.5 Length of the buy-and-hold period and forecast horizon

In this study the buy-and-hold period is chosen to be one year. The forecast horizon, i.e. the length of perfect foresight or analyst forecasts is chosen to match the buy-and-hold period. If the foresight period would differ from the buy-and-hold period, it would create awkward situations especially when considering perfect foresight. For example, consider a two year perfect foresight period and a one year buy-and-hold period. If the actualized earnings in two years would be significantly lower than reflected in the stock price at the moment the holding period starts, there are no guarantees that the mispricing will be revealed when one year has passed and the value driver performance is evaluated. Instead, the mispricing could become even higher before the actualized earnings are published the next year. In this case the performance of the value driver incorporating the actualized earnings in two years could be very low even though the value driver would have got the recommendation right when considering the full forecast horizon. Thus, the forecast and the holding period should match in order to get reliable results.

The buy-and-hold period is set to one year, because yearly returns are widely used in practice as well. Moreover, increasing the length of the forecast period also decreases the accuracy of the analyst forecasts used in the second phase of this study. In addition, the data amount available in the IBES database decreases as the forecast period increases. Therefore, a holding period of one year also fits the available data well. Shorter holding periods than one year are also problematic. First of all, there is little sense in using monthly level data as the minimum publication frequency of the fundamental data is one quarter. In the perfect foresight method the fundamental value drivers would remain the same and the portfolios would just be shuffled according to the changes in the stock prices. This would merely add noise in the data, and if implemented in practice, it would also make transaction fees significantly higher. Also the quarterly holding period is problematic, because the four month publication quarantines related to the quarterly financial statements would heavily overlap with the next quarter. In addition, the different fiscal-years of companies would have to be calculated separately which would decrease the sample size dramatically. Consequently, the one year buy-and-hold period associated with one year forecasting period is clearly the best option for this study.

3.3 Descriptive statistics

In this section the data sample is introduced and the basic statistical characteristics are presented. First, the possible selection biases caused by technicalities related to database issues are considered together with average stock returns. Secondly, the distribution of the market capitalization in the sample is carefully examined so that the size-effect can be separated in the following phases of this study.

3.3.1 Average returns and number of stocks in the sample

The average returns and the number of companies in the sample are listed on a yearly basis in Table 3. The respective return of Standard & Poor's (S&P) 500 index is also reported for the same years. The different database combinations are reported separately as the data sample is affected by the availability of the analyst data. In the first set, the number of companies is reported for the Compustat and CRSP combination, which is used for calculating the backward-looking value drivers and forward-looking value drivers using perfect foresight. As we can see, the average returns are significantly higher than the respective returns on S&P 500 index. This phenomenon is due to the dominance of small stocks in the sample. In calculating the average each stock is equally weighted and as we saw in section 2.1.1, the small stocks tend to provide higher returns than large stocks. This matter is further discussed in the next section.

The second set describes the number of stocks that have one year EPS forecast available in IBES database. As mentioned earlier, this data is available only from 1984 onwards. We can see that the number of companies in the sample decreases significantly, but the main reason is that there are no EPS estimates available for the smallest companies. This effect is also discussed in more detail in the next section. Finally, the last set documents the number of stocks that have stock recommendations available in the IBES database. The availability of this data starts from year 1994. As we can see, the availability of recommendations increases over time and in the last couple of years almost all companies having EPS forecast have also recommendations.

Table 3 Number of companies and average stock returns in the sample

The table includes the number of stocks and average returns in the sample with different database combinations.The first column states the basic sample of this study where the Compustat fundamentals database is linked to the CRSP stock price database. The next column describes the situation after combining the IBES 1 year consensus EPS forecasts with the previous databases. The third column describes the last database combination where the consensus analyst recommendations are included as well. As we can see, the EPS data on IBES database is available from 1984 and the recommendations from 1994. All the columns include also average stock return of these samples for a buy-and-hold period starting from April 1st and ending on March 31st the next year. Finally the last column includes the S&P 500 composite return for the same buy-and-hold period.

	Compustat & CRSP		**IBES EPS forecast**		**IBES recommendations**		**S&P 500 index return**
Year	No of stocks	Average return	No of stocks	Average return	No of stocks	Average return	S&P 500 index return
1975	2002	52.6%					23.3%
1976	1951	15.4%					-4.2%
1977	2096	23.7%					-9.4%
1978	2075	31.6%					13.9%
1979	2052	9.4%					0.5%
1980	2004	69.1%					33.2%
1981	2029	-8.0%					-17.7%
1982	2081	74.3%					36.6%
1983	2149	10.6%					4.1%
1984	2325	15.2%	1510	15.2%			13.5%
1985	2375	32.4%	1564	33.2%			32.2%
1986	2408	20.7%	1569	19.3%			22.1%
1987	2533	-7.6%	1696	-8.3%			-11.2%
1988	2619	16.8%	1703	15.2%			13.9%
1989	2602	12.3%	1761	11.6%			15.3%
1990	2583	15.2%	1771	14.1%			10.4%
1991	2678	30.8%	1817	22.2%			7.6%
1992	2896	15.9%	1973	13.7%			11.9%
1993	3121	16.4%	2198	10.8%			-1.3%
1994	3455	11.4%	2463	10.0%	1893	10.5%	12.3%
1995	3606	37.0%	2633	34.8%	2121	35.1%	28.9%
1996	3819	12.2%	2859	9.0%	2385	8.3%	17.3%
1997	4125	44.2%	3181	44.4%	2755	43.9%	45.5%
1998	4181	-7.7%	3254	-7.9%	2919	-7.9%	16.8%
1999	4002	87.8%	3109	77.8%	2824	81.4%	16.5%
2000	4009	-11.4%	3081	-10.6%	2812	-10.7%	-22.6%
2001	3942	30.3%	2917	26.7%	2693	26.7%	-1.1%
2002	3818	-20.4%	2690	-24.5%	2498	-24.9%	-26.1%
2003	3776	112.1%	2675	97.8%	2498	94.6%	32.8%
2004	3768	10.7%	2748	7.9%	2580	7.5%	4.8%
2005	3822	30.0%	2900	28.8%	2772	28.7%	9.7%
2006	3868	11.0%	2977	9.3%	2876	9.1%	9.7%
2007	3918	-11.4%	3030	-11.5%	2967	-11.7%	-6.9%

3.3.2 Market capitalization

The size of the company has been showed to affect the stock market returns in many other studies (see e.g. Banz, 1981 and Fama and French, 1992). The small companies are a significant part of the sample in this study as well. In Table 4 the stocks in the sample in year 2005 have been categorized by their size according to the same categorization used by Fama and French (2008). As we can see, the micro- and small-caps have much smaller market capitalization than the large-caps and they form a significant proportion of all companies in the sample. Because the stock market returns are calculated as equal-weighted average, the small stocks have a strong effect on the average stock returns. The negative side of the small stock dominance is that value drivers that act as proxies for the size seem to perform better than they would if there were less small companies in the sample. In addition, any practical attempts to follow the investment strategies suggested in this study might be impossible because of liquidity constraints on small stocks. In particular, shorting very small stocks is often impossible.

On the other hand, using the market-weighted returns would emphasize the large-caps extremely heavily (Fama and French, 2008). The disadvantages of this approach would be even more devastating. Individual mega-caps would have a dominating effect over all the small companies combined. Thus, a single company specific issue could affect the value driver performance significantly in a given year. Another way to decrease the size effect would be to omit smaller companies from the sample or run the analyses separately for different company sizes. This approach would cut the sample size dramatically as we see in Table 4. By omitting all companies with significantly lower market-caps than the average, we would end up omitting a greater part of the sample. Therefore, the sample is analyzed as a whole in order to maximize the sample size. This is particularly important for value drivers that impose strict data requirements themselves, such as the PEG ratio. As a conclusion, the equal-weight method without any size omissions or categorizations is chosen despite the dominance of small companies in the sample. However, the size effect is closely monitored throughout the study, and whenever needed sensitivity analysis is performed to separate the size effect from the performance of the value driver.

Table 4 Distribution of market capitalization in the sample in year 2005

Companies in the sample (Compustat+CRSP) separated by their market capitalization in year 2005. The percentile limits adopted from Fama and French (2008.)

Size category	Percentile	No of Stocks	Limits (m$)	Average Size
Micro-caps	0-20%	764	0 - 87	41.8
Small-caps	20-50%	1147	87 - 406	212.2
Large-caps	50-100%	1911	406-	6070.8
All		3822		3109.0

Table 5 further clarifies the effect of the market capitalization on the stock returns. The companies are sorted according to their market capitalization into five portfolios. In Panel A all companies are included in the sample, and the smallest companies in the buy portfolio produce 26% higher stock market returns than the largest companies in the sell portfolio. The smaller stocks experience a higher likelihood of extreme returns as well, because the average return of the buy portfolio is much higher than the respective median return. In other words, the high extreme returns can be found in the smallest companies. In Panel B the micro-caps are omitted from the sample. The omission is done by removing the bottom 20th percentile in terms of market capitalization each year. We can see that the size effect halves after the omission. The hedge return between the buy and sell portfolio is only 12% anymore. In Panel C the micro- and small-caps are both omitted. This is conducted by removing the bottom 50th percentile in terms of market capitalization from the sample. Again the size effect almost halves and now the effect calculated using median returns is almost non-existent. Naturally, the sample size is also halved. As a conclusion, in the following analyses the examination is started by using the full sample in determining the value driver performance. If the size distribution in the portfolios seems uneven, the size effect is diminished by omitting the micro-caps from the sample. The decrease in the size effect after omitting the next 30 % of stock is not significant enough when considering the respective decrease in the sample size.

Table 5 The portfolio returns after sorting the stocks by their market capitalization 1975-2007

Each year the stocks are assigned into 5 portfolios each consisting of the same amount of stocks. The assigning is done by sorting the stocks according to their market capitalization. The stocks with the lowest market capitalization are included in the buy portfolio and vice versa. From each year the average and median returns of every portfolio are calculated. The averages or medians are averaged over all the years in the sample (1975-2007). Also the average market capitalization (size) of the stocks in each portofolio is reported. N is the average number of stocks in the sample.

	Sell	Reduce	Hold	Accumul.	Buy	All	N	Buy vs. Sell
Panel A: All stocks included								
Average return	16%	19%	22%	27%	42%	25%	2930	26%
Median return	12%	13%	13%	14%	19%			6%
Average size (m$)	5552	425	143	53	15	1238		
Panel B: Micro-caps omitted (below 20th percentile)								
Average return	16%	18%	21%	23%	28%	21%	2343	12%
Median return	12%	13%	13%	12%	14%			2%
Average size (m$)	6717	617	234	105	48	1544		
Panel C: Micro- and small-caps omitted (below 50th percentile)								
Average return	15%	17%	18%	20%	22%	18%	1464	7%
Median return	12%	13%	13%	13%	13%			1%
Average size (m$)	9867	1245	551	300	177	2428		

The size effect is not an issue when dealing with analyst forecasts and recommendations. As mentioned in section 3.2.4, there is a natural selection bias towards bigger companies when using analyst data, because analysts tend to follow only large established companies. Therefore, the micro-cap omission is not needed when using analyst data. Table 6 describes the distribution of market capitalization with analyst data using the same absolute size categories as Table 4. As we can see, the number of micro-caps followed by analysts is significantly lower than in the full sample. Only 7% of companies followed by the analyst fall into this category (compared to 20% in the full sample). The effect can be seen in the average market capitalization as well, which is up to $800 million higher in the analyst sub-sample. All in all, the micro-cap omission is not needed when using the analyst data because of the analyst selection bias towards larger companies.

Table 6 Distribution of market capitalization in the analyst data subsample in year 2005

Companies in the sample (Compustat+CRSP+IBES) separated by their market capitalization in year 2005. Same category limits as in Table 4.

Size category	Limits (m$)	No of Stocks	% of Sample	Average Size
Micro-caps	0 - 87	215	7%	55.4
Small-caps	87 - 406	887	31%	222.9
Large-caps	406-	1798	62%	6174.9
All		2900	3426.4	3909.7

4 VALUE DRIVER PERFORMANCE USING BACKWARD-LOOKING DATA AND PERFECT FORESIGHT

In this chapter the sorting method is used to test value drivers using historical figures and perfect foresight. The value drivers are first calculated using only historical items. In this setting the analyses are close to the classic anomaly studies. The purpose of this examination is to provide us the lower limit on the returns that should be expected later in the study. If one is able to gain higher returns using historical rather than forward-looking data, there is no sense in trying to forecast the future fundamentals. Next the same value drivers are calculated using the future financial figures, i.e. taking advantage of the perfect foresight. This analysis provides us an upper limit that anyone could ever achieve by forecasting future fundamentals. The objective of this chapter is to establish the upper and lower limit of returns achievable using the tested value drivers in practice and to find out which value drivers would work best if forecasts were unbiased and accurate. In the second phase of this study, these limits are compared against the performance of the analyst forecasts.

4.1 Performance of backward-looking value drivers

In this section the value driver performance is tested using only historical items, i.e. the perfect foresight is not yet applied. The historical value drivers are calculated based on fiscal year-end financial statements for year Y-1 (dated at the latest December 31st). The value driver performance is determined by one year buy-and-hold returns starting from April 1st in year Y and ending on March 31st in year Y+1. The four month slack between the financial statements date and starting the holding period is due to the delay related to publishing the financial statements as mentioned in section 3.1.2. The exact formulas used in calculating the value drivers are presented in Appendix 1.

4.1.1 Backward-looking value driver performance using full sample

First, the backward-looking value drivers are tested with all the companies in the sample. The results are shown in Table 7. For each value driver the average return over the full examination period (1975-2007) is reported individually for each portfolio. From these figures we can examine how large difference there is between the buy and sell portfolio returns and whether the portfolios in between behave coherently. The difference between the buy and sell portfolios, i.e. the hedge return, is reported in the 'Buy vs. Sell' column. The next row is the respective median returns. In many cases the median returns provide better results than average returns, because extreme stock returns have less influence in the median calculation method.

The average market capitalization is reported in the third row. This can be used to examine whether any portfolio is dominated by smaller or larger companies. As mentioned earlier, smaller companies tend to provide higher returns. Therefore, whenever needed the size effect is separated from the value driver performance by omitting micro-caps (bottom 20^{th} percentile in terms of market capitalization) from the sample. These results are shown in Table 8 in section 4.1.2.

The fourth row includes the average values of the value driver under review for each portfolio. These values can be used to check how much the portfolios differ from each other in terms of the value driver used in creating them. Extremely large or low values in the buy and sell portfolio indicate that additional analysis omitting extreme value driver values could be in order. These sensitivity analyses are performed in section 4.1.3.

Finally, the last row of the results reports the buy vs. sell diagnostics. The first measure "% of Max" compares the current hedge return against the highest hedge return ever possible in the same sample as explained in section 3.1.3. However, this measure is mainly used in the context of perfect foresight, because when using historical fundamentals, the percentages remain quite low as there is no knowledge of the future used in generating the value drivers. The two last figures reported in the table are related to the t-test conducted to test statistically the difference between the buy and sell portfolio return. Here the returns from all years are combined together using the yearly average returns as describe in section 3.1.3. The significance level of rejecting the null hypothesis (no difference in portfolio returns) is reported together with the actual t-stat value. Also the alternative hedge return, i.e. the difference in portfolio returns using the combined yearly data, is reported here. The reporting format of the value driver performance remains the same throughout the study.

Table 7 Backward-looking value driver performance using full sample

Backward-looking value driver performance in 1975-2007. The value driver is calculated for every stock separately using historical fundamental data dated at the latest December 31st the previous year (Y-1) for all years in the sample. Each year the stocks are sorted according to the value driver and assigned to the five equally sized portfolios. The buy portfolio consists of the best 20% of stocks ranked by the value driver and vice versa. The portfolio returns are calculated by using a one year buy-and-hold period starting on April 1st (Y = 0) and ending on March 31st (Y+1) taking the average or median of the returns of all the stocks in the portfolio. Finally, the portfolio returns from different years are combined by averaging them. Also the average market capitalization (size) is reported for all portfolios. The buy vs. sell (hedge) return is calculated as the difference between the buy and sell portfolio returns. The item "% of max" is the proportion of the value driver hedge return from the largest possible hedge return achievable by sorting the stocks according to their stock returns directly. The t-stat is the t-value of the t test testing the statistical significance of the difference in buy and sell portfolio returns (10%, 5% and 1% significance levels marked with *). The difference in averages is an alternative way to calculate the hedge return used in the t-test.

Value Driver		Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
P/B									
	Average Return	18%	20%	22%	26%	31%	24%	13.1%	2923
	Median Return	7%	10%	13%	15%	18%		11.5%	
	Average Size	2829	1824	1149	767	422	1398	-570%	
	Average P/B	14.36	2.65	1.71	1.17	0.62	4.10		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			8.8%			16.45***	13.8%		
P/E									
	Average Return	19%	19%	20%	23%	28%	22%	8.5%	2292
	Median Return	7%	11%	13%	16%	18%		11.1%	
	Average Size	2013	2364	1986	1476	967	1761	-108%	
	Average P/E	163.33	21.62	14.91	10.97	5.73	43.32		
	Buy vs. Sell Diagnostis		*% of Max*			t-stat	*diff. in averages*		
			6.6%			8.6***	7.3%		
PEG									
	Average Return	17%	19%	21%	23%	25%	21%	7.5%	1386
	Median Return	11%	14%	14%	14%	15%		3.8%	
	Average Size	3920	2660	1673	1500	875	2126	-348%	
	Average PEG	8.91	0.83	0.43	0.20	0.05	2.08		
	Buy vs. Sell Diagnostis		*% of Max*			t-stat	*diff. in averages*		
			6.1%			7.91***	6.6%		

(Table 7 continues)

(Table 7 continues)

Value Driver		Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
P/RI[1]									
	Average Return	19%	19%	20%	23%	28%	22%	9.0%	1770
	Median Return	9%	12%	14%	16%	18%		8.9%	
	Average Size	1925	2909	2615	1868	1182	2100	-63%	
	Average P/RI	385.18	40.82	26.22	18.19	8.97	95.88		
	Buy vs. Sell Diagnostis		*% of Max*			t-stat	*diff. in averages*		
			7.0%			8.24***	7.4%		
D/E									
	Average Return	23%	22%	24%	22%	28%	24%	4.8%	2965
	Median Return	13%	14%	13%	8%	13%		-0.9%	
	Average Size	1439	1894	1871	1063	696	1393	-107%	
	Average D/E	6.16	0.62	0.29	0.09	0.01	1.44		
	Buy vs. Sell Diagnostis		*% of Max*			t-stat	*diff. in averages*		
			3.2%			4.79***	3.9%		
Growth									
	Average Return	23%	21%	20%	19%	22%	21%	-0.6%	2033
	Median Return	12%	14%	14%	13%	12%		0.1%	
	Average Size	1322	1931	2916	2252	1184	1921	-12%	
	Average Growth	-0.61	-0.29	-0.14	0.06	5.01	0.81		
	Buy vs. Sell Diagnostis		*% of Max*			t-stat	*diff. in averages*		
			-0.5%			-0.59	-0.5%		
ROE									
	Average Return	30%	24%	22%	21%	22%	24%	-7.6%	2905
	Median Return	10%	13%	14%	14%	12%		2.6%	
	Average Size	358	698	1219	1839	2935	1410	88%	
	Average ROE	-0.90	0.04	0.12	0.18	0.70	0.03		
	Buy vs. Sell Diagnostis		*% of Max*			t-stat	*diff. in averages*		
			-5.1%			-9.06***	-9.3%		

[1] RI is estimated as EBIT*1-0.35) - Invested Capital * 0.07.

* significant at 10% level, ** 5% and *** 1%

The best value driver when using only historical value drivers seems to be the P/B ratio, which is in line with the results of the anomaly literature discussed in section 2.1.1. The hedge return is up to 13.1%, which is considerable especially when taking account that no forward-looking fundamentals were used here. All the five portfolios act very coherently. The average return increases gradually as we move on from the sell portfolio towards the buy portfolio. The median returns are somewhat lower than the average returns, but the overall effect is very similar to using average. The median as the calculation method still results in coherent portfolios and a hedge return of 11.5%. The statistical significance of the hedge return is very clear with all common significance levels. As we can see, however, the size is heavily correlated with the portfolios. It seems that the P/B ratio works also as a proxy for the market capitalization. The low P/B companies tend to be significantly smaller than the companies with a high P/B ratio. The average size in the sell portfolio is up to eight times larger than in the buy portfolio. Probably a large part of the performance of the P/B ratio is related to its proxy as size. Therefore, the results are rerun in section 4.1.2 after omitting the micro-caps from the sample.

The P/E ratio is the second best backward-looking value driver tested in this study. Calculation of the ratio requires positive net earnings, and thus the number of companies in the sample is somewhat lower, 2,292 on average. However, exactly as the value vs. growth anomaly suggests the driver is able to create an 8.5% hedge return. The lower tail of the portfolio returns remains relatively flat, but otherwise the portfolios are coherent. The median portfolio returns lead to even higher hedge return of 11.1%, which is already very close to the performance of the P/B ratio. The extreme returns are offsetting the portfolio returns in this case. The difference in the portfolio returns is statistically significant. The sell portfolio has over twice as large companies as the buy portfolio, but the size does not follow the P/E ratio linearly. The highest market capitalization is in the reduce portfolio. By all standards the size effect is not as strong with the P/E ratio as with the P/B ratio. Still the performance of the P/E ratio is tested without micro-caps in section 4.1.2.

The PEG ratio incorporates the growth aspect into the P/E ratio. Theoretically speaking this value driver could be able to identify potential high P/E stocks that would still have investment value through high growth opportunities. The value driver is calculated by dividing the P/E ratio with earnings growth percentage. The PEG ratio is able to generate a 7.5% hedge return, but the return remains slightly below the hedge return of the plain P/E ratio. In terms of median return the value driver underperforms the P/E ratio even more clearly. The disadvantage of this value driver is that it decreases the sample size significantly. In addition to requiring positive earnings the value driver requires also positive earnings growth. This cuts the average number of companies in the sample down to 1,386. The hedge return is still statistically significant despite the smaller sample. The size is a considerable part of this value driver as well. Although there is hardly room to decrease the sample size by omitting micro-caps, this is still done in section 4.1.2.

The price-to-residual income (P/RI) ratio performs surprisingly well despite the rough approximations used in calculating it. The exact calculation methods are explained in Appendix 1, but in short the residual income is estimated by deducting a 7% cost of capital from the operating profit. The cost of capital is calculated from invested capital and the tax rate is assumed to be 35%. The P/RI ratio can be considered as a more sophisticated P/E ratio that takes into account also the cost of capital. The idea is to include only earnings that really increase shareholder value. The advantage of this value driver is its strong link to valuation theory. Indeed, after these heavy approximations the P/RI ratio is still able to create a 9% hedge return just above the normal P/E ratio. The median hedge return is slightly below the respective return of the P/E ratio. All in all, the P/RI shows clear potential as a backward-looking value driver, but would require much more sophisticated estimation methods.

Return on equity (ROE) behaves oddly as a value driver. Using the ROE calculated from historical fundamentals leads to negative hedge return. Counterintuitively, the previously more profitable companies lead to lower stock market returns the next year. This is also controversial to some other studies made on profitability (see e.g. Haugen and Baker, 1996). The most likely reason for this phenomenon is the apparent correlation with ROE and size. Small companies seem to have smaller ROE percentages, which allocates them to the sell portfolio using this value driver. Despite the low ROE percentage, these smaller companies seem to outperform larger ones so significantly that the overall results get reversed. The extreme returns play a significant role here as well. Using the median in calculating portfolio returns actually results in a positive buy vs. sell return. Even when using the median, the portfolios do not behave coherently and the value driver does not seem to explain future stock returns very well. The value driver is thoroughly tested in the following sections with sensitivity analysis in order to understand why the value driver creates negative returns.

Also plain earnings growth (marked Growth in Table 7) is tested as a value driver. In the context of previous studies this value driver seems controversial. On the one hand, growth as such is usually a sign of a successful company. On the other hand, the anomaly studies found that high growth companies tend to be overpriced on the markets. The value companies provided significantly higher stock returns in the long-run. In this study, historical earnings growth shows no potential as a backward-looking value driver, because the value driver does not create any kind of buy vs. sell returns in one way or another. The difference between buy and sell portfolio is statistically insignificant with all common significance levels. The returns are oddly distributed, because the highest average returns are with the buy and the sell portfolios, but the highest median return is with the hold portfolio. Also the size peaks at the hold portfolio, and therefore, the value driver is tested also after omitting the micro-caps.

The D/E ratio creates a small positive hedge return in this sample, but the level of performance is significantly below the P/B or P/E ratios. This is in line with the previous studies as mentioned in section 2.3. However, the value driver has difficulties in creating any kind of difference between the median returns. All in all, the value driver shows relatively low performance as backward-looking value driver and its capability of capturing forward-looking information is very weak as well. Therefore, it is excluded from the following phases of the study.

4.1.2 Backward-looking value driver performance after omitting the micro-caps

In this section the same analysis is repeated after omitting the micro-caps, i.e. the lowest 20th percentile in terms of market capitalization, from the sample. As we saw in the previous section, all the value drivers were more or less correlated with the size. Therefore, all value drivers are recalculated after omitting the micro-caps. The results are shown in Table 8. Naturally, the sample sizes in all value drivers decrease by 20% after the operation. However, the sample size of all value drivers remains at a sufficient level for statistically significant results.

Table 8 Backward-looking value driver performance after omitting the micro-caps

Similar calculation methods as in Table 7, but now the bottom 20th percentile of smallest stocks in terms of market capitalization (micro-caps) have been omitted from the sample.

Value Driver		Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
P/B									
	Average Return	17%	17%	20%	21%	24%	20%	6.9%	2338
	Median Return	7%	10%	12%	14%	16%		9.5%	
	Average Size	3258	2183	1484	1067	728	1744	-347%	
	Average P/B	16.29	2.87	1.88	1.31	0.73	4.62		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			5.3%			8.99***	6.9%		
P/E									
	Average Return	17%	17%	18%	20%	23%	19%	6.7%	1866
	Median Return	7%	11%	13%	15%	18%		10.6%	
	Average Size	2293	2823	2395	1797	1320	2126	-74%	
	Average P/E	156.06	22.05	15.39	11.51	6.42	42.28		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			5.8%			6.26***	4.9%		
PEG									
	Average Return	16%	18%	19%	19%	21%	19%	5.3%	1108
	Median Return	11%	14%	14%	13%	15%		3.6%	
	Average Size	4586	3241	2093	1908	1432	2652	-220%	
	Average PEG	9.74	0.91	0.49	0.24	0.07	2.29		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			4.8%			5.7***	4.7%		
P/RI[1]									
	Average Return	17%	17%	18%	20%	23%	19%	6.5%	1440
	Median Return	8%	11%	13%	16%	17%		8.5%	
	Average Size	2204	3452	3034	2365	1612	2533	-37%	
	Average P/RI	361.87	41.64	27.20	19.28	10.17	92.03		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			5.7%			5.4***	4.8%		
ROE									
	Average Return	21%	20%	20%	19%	20%	20%	-0.4%	2323
	Median Return	7%	12%	14%	13%	12%		5.4%	
	Average Size	574	1071	1562	2287	3300	1759	83%	
	Average ROE	-0.80	0.06	0.13	0.19	0.73	0.06		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			-0.3%			-1.72*	-1.6%		

[1] RI is estimated as (EBIT*1-0.35) - Invested Capital * 0.07.

* significant at 10% level, ** 5% and *** 1%

The most dramatic effect after omitting the micro-caps is the decrease in the performance of the P/B ratio. The P/B ratio was the most heavily size-correlated value driver. Thus, its performance almost halves after omitting the micro-caps. This is logical after considering the high returns related to micro-caps shown in section 3.3.2. The hedge return decreases to 6.9%, but still remains statistically significant. The hedge margin calculated using median does not fall as much as the average hedge margin, which implies that the micro-caps also included stocks that distorted the results through extreme stock returns. The P/B ratio still remains correlated with market capitalization even after omitting the micro-stocks. However, as we saw in section 3.3.2 omitting the micro-caps is enough to eliminate most of the size effect. To validate this the performance of the P/B ratio is calculated omitting bottom 50th percentile, and the results are reported in Table 9. The average hedge return drops only an additional 2% and the median hedge return stays almost the same. Indeed, the micro-cap omission seems to be enough to eliminate most of the size effect. As a conclusion, the P/B ratio seems to be relatively good backward-looking value driver even without the size effect.

Table 9 Performance of the backward-looking P/B ratio after omitting micro- and small-caps

Similar calculation methods as in Table 7, but now the bottom 50th percentile of smallest stocks in terms of market capitalization (micro-caps) have been omitted from the sample.

Value Driver		Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
P/B									
	Average Return	15%	14%	17%	18%	20%	17%	4.7%	1574
	Median Return	8%	10%	12%	13%	16%		8.1%	
	Average Size	4364	3185	2110	1680	1305	2529	-234%	
	Average P/B	12.79	3.13	2.06	1.43	0.83	4.05		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			4.2%			3.96***	3.5%		

The P/E ratio does not suffer from the size-effect as much as the P/B ratio, which can be seen in Table 8. After omitting the micro-caps the performance of the P/B and P/E ratio are very close to each other. Actually in terms of median hedge return the P/E ratio is already better backward-looking value driver. ROE is the last value driver, where significant changes can be seen after omitting the micro-caps. When using the full sample this value driver produced significant negative hedge returns. After omitting the micro-caps the average hedge return is practically zero. This indicates that the negative hedge return was mostly due to the strong size-effect in the driver. The larger companies tended to have higher ROE values than the smaller companies. As a conclusion, however, ROE shows no potential as a backward-looking value driver, because it is incapable of creating a statistically significant hedge return.

The changes in the performance of the other value drivers after omitting the micro-caps are smaller. These were also moderately correlated with market capitalization and therefore their performance slightly decreases as the micro-caps are omitted. The changes are, however, relatively small. The pecking order of the rest of the value drivers remains the same after omitting the micro-caps.

4.1.3 Backward-looking value driver performance after omitting extreme observations

The last sensitivity analysis conducted for the backward-looking value drivers is the omission of extreme value driver observations. For most value drivers the data is already somewhat filtered for extreme values, because the value drivers have strict restrictions on how they must be calculated. For example, the P/E ratio requires positive earnings and the P/B ratio requires positive book value. In addition, any database related errors to negative prices are already omitted. However, the value drivers can still get abnormally high or low values. In some cases these values could be due to one-off situations or database errors, and there could be a risk that these would distort the overall results.

Thus, the results are rerun after omitting 1% of the highest and the lowest value driver observations. This method is quite rough for the buy vs. sell return, because it directly affects the composition of the buy and the sell portfolio. However, it also reveals if the overall results are heavily affected by extreme value driver values. The extreme observation omission is conducted for the data sample where the micro-caps are already omitted. In other words, these results represent as clean a sample as possible. The results are shown in Table 10.

Table 10 Backward-looking value driver performance after omitting micro-caps and extreme value driver observations

Similar calculation methods as in Table 7, but now the bottom 20th percentile of smallest stocks in terms of market capitalization (micro-caps) and 1% of the highest and the lowest value driver values have been omitted from the sample.

Value Driver	Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
P/B								
Average Return	16%	18%	20%	21%	24%	20%	7.1%	2290
Median Return	7%	10%	12%	14%	16%		9.1%	
Average Size	3319	2157	1491	1073	755	1759	-339%	
Average P/B	6.83	2.84	1.88	1.32	0.78	2.73		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		5.5%			9.66***	7.4%		
P/E								
Average Return	16%	17%	18%	20%	24%	19%	7.0%	1831
Median Return	7%	11%	12%	15%	18%		10.8%	
Average Size	2352	2848	2361	1798	1375	2147	-71%	
Average P/E	71.00	21.85	15.40	11.58	6.82	25.33		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		6.1%			6.71***	5.3%		
PEG								
Average Return	16%	18%	19%	19%	21%	19%	5.3%	1087
Median Return	11%	14%	14%	13%	14%		3.5%	
Average Size	4662	3209	2085	1894	1485	2667	-214%	
Average PEG	4.02	0.90	0.49	0.24	0.07	1.15		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		4.8%			5.33***	4.7%		
P/RI[1]								
Average Return	17%	17%	18%	21%	23%	19%	6.5%	1412
Median Return	8%	11%	13%	16%	17%		8.5%	
Average Size	2252	3416	3057	2388	1663	2555	-35%	
Average P/RI	175.42	41.20	27.21	19.42	10.82	54.82		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		5.7%			5.23***	4.8%		
ROE								
Average Return	21%	20%	20%	19%	20%	20%	-0.4%	2276
Median Return	7%	12%	14%	13%	13%		5.2%	
Average Size	601	1083	1558	2253	3410	1781	82%	
Average ROE	-0.26	0.07	0.13	0.19	0.39	0.10		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		-0.3%			-1.46***	-1.4%		

[1] RI is estimated as EBIT*(1-0.35) - Invested Capital * 0.07.

* significant at 10% level, ** 5% and *** 1%

The effect of the extreme observations on the value driver performance seems to be relatively small. After omitting 1% of the highest and lowest value driver values the hedge margins remain more or less the same as in Table 8 where only micro-caps were omitted. Naturally, the extreme observation omission affects most the buy and sell portfolio where the omissions were made, but even in these the changes are only minimal. The biggest changes can be seen in the average values of the value drivers in each portfolio. As expected, the average value drivers are significantly closer to each other after omitting the extreme observations. Consequently, it seems that stocks with extreme value driver observations do not mean extreme stock returns.

There is one more sensitivity analysis that can be done for the value driver performance. The importance of extreme stock returns in anomaly studies has been widely discussed. Researchers have shown that classic anomaly studies are very dependent for small number of extreme stock returns (see e.g. Knez and Ready, 1997). These studies have been conducted by omitting extreme stock returns (e.g. 1% of the highest and lowest stock returns) from the sample altogether. In this study, the effect of the extreme stock returns is mostly studied by looking at the median returns of the portfolio returns. This diminishes significantly the effect of the extreme stock returns. The median approach is better also in the sense that it can be easily applied in practice as well. If the dominance of extreme stock returns needs to be eliminated, the reporting can be based on median returns. Omitting the extreme stock returns has a direct effect on the buy vs. sell returns, because it by definition omits any extreme stock returns that have a significant effect on the results. In Table 11 we can see the P/B and P/E ratio after omitting the extreme stock returns in addition to the previous omissions of micro-caps and extreme value driver observations.

Table 11 Backward-looking value driver performance after omitting micro-caps, extreme value driver observations and extreme stock returns

Similar calculation methods as in Table 10, but now in addition to micro-caps and extreme value driver observations also extreme stock returns are omitted from the sample.

Value Driver		Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
P/B									
	Average Return	15%	15%	18%	19%	22%	18%	6.6%	2243
	Median Return	7%	10%	12%	14%	16%		8.7%	
	Average Size	3408	2190	1487	1084	764	1787	-346%	
	Average P/B	6.74	2.82	1.87	1.31	0.78	2.70		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			5.7%			10.45***	6.5%		
P/E									
	Average Return	14%	16%	17%	19%	22%	18%	7.8%	1797
	Median Return	7%	11%	13%	15%	18%		10.5%	
	Average Size	2403	2900	2371	1808	1391	2175	-73%	
	Average P/E	70.15	21.70	15.35	11.57	6.82	25.12		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			7.4%			9.91***	6.2%		

As we can see, now the average portfolio returns are changed by few percentage points towards the median returns. Still the buy vs. sell returns remain relatively stable. It is interesting that after omitting the extreme stock returns the P/E ratio actually seems to perform better than the P/B ratio. However, the extreme stock return omission can be considered as questionable sensitivity tool as it uses hindsight over future stock returns in omitting the stocks. In the following phases of this study, the effect of the extreme stock returns is examined only through median returns.

4.1.4 Conclusions on the performance of backward-looking value drivers

The purpose of examining the value drivers using only historical fundamentals was to create a certain lower limit for the results in the next stages. We saw that one can achieve 7-13% hedge returns just by using backward-looking value drivers. In the next stages, this level of buy vs. sell return can be considered as the lower limit that the value driver has to exceed. Otherwise it would be better for the investor to skip forecasting and just use easily available historical fundamentals in creating the portfolios.

The best backward-looking value driver was the P/B ratio. However, the P/B ratio had also the strongest link with the market capitalization. As we saw in Table 8 significant part of the hedge return was actually due to the size-effect. As such this is not a problem since we are only looking for value drivers that are able to create high hedge returns, but in the next phase when perfect foresight is applied the situation will become more complicated. Then there are two powerful forces possibly affecting the results: the size effect and the new knowledge not yet incorporated in the stock price.

The second best backward-looking value driver was the P/E ratio. It suffered also from the size effect, but significantly less than the P/B ratio. Interestingly, the more the sample was cleaned from possible biases the more the P/E ratio improved its performance compared to the P/B ratio. In the following phases when the value drivers are turned into forward-looking, the P/E ratio offers the best capabilities of incorporating future expectations into the value driver.

There were also other value drivers that showed clear potential. First, the PEG ratio resulted in statistically significant hedge return, but it was still outperformed by the ordinary P/E ratio. The difference between the value drivers, however, was very small and thus, the PEG will be tested in the following phases as well. Perhaps the most interesting finding was the strong performance of P/RI ratio despite the rough approximations made in calculating it. When using the full sample it actually outperformed the P/E ratio by a small margin. The value driver shows good potential but it would certainly require more sophisticated calculation methods.

Finally, earnings growth and ROE showed no real potential for backward-looking value drivers. These value drivers contain good forward-looking characteristics and therefore they will be tested in under perfect foresight as well. The D/E ratio showed only moderate performance as backward-looking value driver and its capability of incorporating future forecasts is so low that it will be excluded in the following phases of this study.

4.2 Performance of forward-looking value drivers using perfect foresight

In this section the analysis is taken further by using future fundamentals in calculating the value drivers. This examination should provide us with the upper limit for the buy vs. sell return that one could ever achieve by utilizing the tested value drivers. The methodology is similar to the previous section. However, now the measure "% of Max", i.e. the value driver's capability of capturing as large proportion of the maximum hedge return as possible, is used as the primary decision criterion.

4.2.1 Forward-looking value driver performance using full sample

Similarly to the previous section, the analysis starts by examining the results using the full sample. These results are presented in Table 12. Later the micro-caps and the extreme value driver observations are excluded in sections 4.2.2 and 4.2.3. The exact formulas used in calculating the value drivers are presented in Appendix 1.

Table 12 Performance of the forward-looking value drivers using perfect foresight and full sample

This table summarizes the forward-looking value driver performance in the sample during 1975-2007. The value driver is calculated for every stock separately using next year's fundamental data dated at the latest December 31st (Y = 0). Each year the stocks are sorted according to the value driver and assigned to five equally sized portfolios. The buy portfolio consists of the best 20% of stocks ranked by the value driver and so on. The portfolio returns are calculated by using a one year buy-and-hold period starting on April 1st (Y = 0) and ending on March 31st (Y+1) taking the average or median of the returns of all the stocks in the portfolio. Finally, the portfolio returns from different years are combined by averaging them. Also the average market capitalization (size) is reported for all portfolios. The buy vs. sell (hedge) return is calculated as the difference between the buy and sell portfolio returns. The item "% of max" is the proportion of the value driver hedge return from the largest possible hedge return achievable by sorting the stocks according to their stock returns directly. The t-stat is the t-value of the t-test testing the statistical significance of the difference in buy and sell portfolio returns. The difference in averages is an alternative way to calculate the hedge return used in the t-test.

Value Driver	Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
PEG								
Average Return	11%	20%	29%	39%	61%	32%	49.9%	1340
Median Return	8%	16%	23%	29%	40%		31.6%	
Average Size	4022	2764	1698	1358	749	2118	-437%	
Average PEG	8.74	0.90	0.50	0.28	0.11	2.10		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		37.3%			40.18***	48.5%		
PE-G[1]								
Average Return	4%	11%	20%	33%	52%	24%	48.5%	1983
Median Return	-3%	6%	16%	26%	34%		36.2%	
Average Size	1569	2959	2612	1460	1170	1954	-34%	
Average PE-G	80.03	20.20	0.18	-22.63	-574.01	-99.27		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		38.5%			50.78***	48.0%		
P/E								
Average Return	7%	15%	23%	32%	55%	26%	47.3%	2222
Median Return	-2%	8%	15%	22%	34%		36.6%	
Average Size	2032	2593	2065	1429	830	1790	-145%	
Average P/E	146.56	18.88	13.19	9.67	4.87	38.63		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		34.7%			45.44***	46.0%		
P/RI								
Average Return	13%	18%	24%	34%	59%	29%	46.2%	1700
Median Return	4%	11%	17%	25%	38%		34.3%	
Average Size	2111	3108	2677	1783	1082	2152	-95%	
Average P/RI	362.03	36.06	23.13	15.82	7.45	88.89		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		32.9%			37.96***	44.8%		

(Table 12 continues)

(Table 12 continues)

Value Driver	Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
ROE								
Average Return	10%	14%	21%	27%	42%	23%	32.0%	2854
Median Return	-7%	5%	13%	18%	26%		33.1%	
Average Size	392	684	1213	1790	3063	1428	87%	
Average ROE	-0.64	0.04	0.11	0.17	0.62	0.06		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		21.5%			27.57***	29.8%		
P/B								
Average Return	11%	18%	22%	27%	38%	23%	26.9%	2846
Median Return	1%	8%	11%	15%	22%		20.4%	
Average Size	3054	1796	1063	755	454	1425	-572%	
Average P/B	10.39	2.32	1.57	1.11	0.60	3.20		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		18.2%			31.12***	28.4%		
Growth								
Average Return	18%	14%	18%	28%	39%	23%	21.4%	2890
Median Return	2%	3%	12%	20%	23%		20.8%	
Average Size	682	1121	2357	1845	1038	1409	34%	
Average Growth	-6.17	-0.38	0.04	0.34	6.41	0.04		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		14.3%			18.05***	17.6%		
PB-ROE[2]								
Average Return	10%	13%	20%	27%	45%	23%	35.0%	2859
Median Return	-7%	4%	13%	19%	29%		35.9%	
Average Size	434	762	1313	1950	2677	1427	84%	
Average PB-ROE	70.74	-1.93	-9.58	-15.20	-51.81	-1.48		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		23.5%			30.15***	32.7%		
10xPB-ROE[3]								
Average Return	10%	11%	17%	26%	51%	23%	41.4%	2859
Median Return	-7%	0%	9%	18%	33%		40.5%	
Average Size	1581	1911	1550	1180	912	1427	-73%	
Average PB-ROE	184.32	19.44	7.92	1.39	-17.34	39.22		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		27.8%			36.42***	38.6%		

[1] Calculated as normal PEG ratio but instead dividing by earnings growth the P/E ratio is subtracted by growth.
[2] Calculated by subtracting the ROE (as percentage) from the P/B ratio
[3] Calculated as PB-ROE, but P/B is magnified by 10 in order to make the two figure more comparable
* significant at 10% level, ** 5% and *** 1%

The best value driver using perfect foresight is the PEG ratio. The traditional form of the value driver is able to create a 49.9% hedge return, which is up to 37.3% of the maximum return. An alternative format of the PEG ratio, where the P/E ratio is subtracted instead of being divided by the growth rate, is able to generate even slightly higher proportion of the maximum return (38.5%). To distinguish the two ratios from each other the PEG ratio using subtraction is called the PE-G ratio in Table 12. The PE-G ratio is better also in the sense that it has less strict requirements for the data. The growth rate can be negative as well, and the sample size is therefore significantly higher when using this format. The size effect is also more subtle with the PE-G ratio. The average size of the companies in the sell portfolio is slightly higher than in the buy portfolio, but the biggest companies are in the portfolios in the middle portfolios. Still the portfolio returns behave coherently between all the five portfolios. As a conclusion, the PE-G ratio works really well with perfect foresight.

The plain P/E ratio performs relatively well too. The hedge return is 47.3%, which constitutes 34.7% of maximum return. Overall the results are very similar to the PE-G ratio. The 4% difference in the proportion of theoretical maximum return can be considered relatively low at least when compared against the complexity that increases when incorporating the growth rate to the value driver. It seems that the GARP framework works under perfect foresight, but the advantage is perhaps not significant enough to justify the complicated calculation related to PEG or PE-G ratios. On the other hand, the size effect is clearly stronger in the P/E ratio than with the PE-G ratio.

The forward-looking P/RI ratio is estimated here in a similar manner as the backward-looking version. Now the EBIT is just taken from the next year’s financial statements. Again, the P/RI ratio performs surprisingly well when considering the heavy approximations used in calculating it. The P/RI ratio results in a high hedge return of 46.2% (32.9% of max) staying just behind the ordinary forward-looking P/E ratio. The buy portfolio of this value driver contains significantly smaller companies than the buy portfolio.

The earnings growth rate showed absolutely no potential as a backward-looking value driver, but it is able to incorporate some future information. When applied with perfect foresight the value driver is able to create a 21.4% hedge margin, which is clearly statistically significant.

By looking at the average size of companies in the portfolio, we can see that there are two forces in play here. The buy portfolio actually has higher average size than the sell portfolio. It seems that now the effect of perfect foresight over the next year's net earnings is slightly stronger than the opposite size effect. In the next section earnings growth will be tested after omitting the micro-caps.

The P/B ratio does not improve its performance much under perfect foresight. As expected, it cannot incorporate future information in it very well. The only future fundamental used in calculating the value driver is the book value of equity in the next year. In practice this means that future performance is available only in the retained earnings, which is of course less informative than whole net earnings for example. The hedge return is still higher (27.1%) than when using historical fundamentals (13.1%). However, in terms of capability of capturing as much as possible from maximum return available the value driver stays clearly behind the PEG or P/E ratios. Similarly to the backward-looking P/B ratio the value driver is heavily correlated with size.

ROE improves its performance the most from its backward-looking version. Now the value driver is able to achieve a 32% hedge return (21.5% of max). This is particularly significant because now the size is clearly reversed in the portfolios. The buy-side portfolios contain systematically larger companies than the sell portfolios. Thus, the future information content is very strong in the next year's ROE, because it is able to achieve the high hedge return even with the opposing size-effect. This phenomenon is further studied in the next section where micro-caps are omitted from the sample.

The last two value drivers in Table 12 are more experimental by their nature. An interesting combination from the viewpoint of this study would be the P/B ratio and ROE as mentioned in section 2.3.1. However, the most obvious way of combining them by dividing P/B ratio by ROE leads to the regular P/E ratio. The PB/ROE value driver can be expressed in the following form (P/bvps)/(eps/bvps), which simplifies to regular forward-looking P/E. One alternative is to use similar kind of subtraction as was done with PE-G. However, this is also problematic as P/B ratio and ROE have usually very different magnitudes. P/B ratios vary somewhere between 0-5 and ROE between +/- 50%. Ideally the two figures should be scaled to the same magnitude before calculating any combined figure using subtraction. The two last items in Table 12 test these kinds of value drivers. The first one is PB-ROE figure as such and the second item is calculated by magnifying the P/B ratio by 10 in order make it better adjusted for ROE. In Table 12 we can see that the magnification by 10 works relatively well and it increases the hedge return relatively close to the P/E ratio (41.4%). The plain PB-ROE as such does not work as well, because now the ROE dominates the combination too heavily. Still the hedge return is 35.0%, which can be considered relatively good. Of the two combinations the 10xPB-ROE seems to be the better one. The examination of these two value drivers is, however, only preliminary in the sense that for any practical applications the weights between the two parameters would have to be carefully adjusted for optimal results. Nevertheless, these results show that the PB and ROE combination does have good potential for forward-looking value driver. The advantage of this value driver is that it might be able to take the advantage of the value vs. growth anomaly using the strongest value driver, the P/B ratio, but still adjust for forecasts related to next years earnings through ROE.

4.2.2 Forward-looking value driver performance after omitting micro-caps

In this section the forward-looking value driver results are rerun after omitting micro-caps, i.e. the bottom 20th percentile in terms of market capitalization. The method is similar to section 4.1.2, where the same sensitivity analysis was done for backward-looking value drivers. The forward-looking value driver performance after omitting micro-caps can be seen in Table 13.

Table 13 Performance of the forward-looking value drivers using perfect foresight after omitting micro-caps

Similar calculation methods as in Table 12, but now the bottom 20th percentile of smallest stocks in terms of market capitalization (micro-caps) have been omitted from the sample.

Value Driver		Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
PEG									
	Average Return	10%	19%	26%	34%	46%	27%	36.1%	1071
	Median Return	8%	16%	21%	26%	33%		25.1%	
	Average Size	4638	3377	2049	1899	1253	2643	-270%	
	Average PEG	9.61	0.99	0.57	0.33	0.14	2.33		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			31.3%			38.18***	35.5%		
PE-G									
	Average Return	2%	10%	19%	30%	42%	21%	39.6%	1585
	Median Return	-2%	6%	16%	24%	29%		31.2%	
	Average Size	2116	3527	3071	1859	1613	2437	-31%	
	Average PE-G	77.49	19.31	1.00	-18.88	-519.69	-88.17		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			35.3%			49.39***	39.3%		
P/E									
	Average Return	6%	14%	20%	28%	41%	22%	35.2%	1777
	Median Return	-3%	8%	14%	21%	28%		31.1%	
	Average Size	2479	3067	2479	1836	1303	2233	-90%	
	Average P/E	142.39	19.21	13.70	10.32	5.68	38.26		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			29.8%			42.31***	34.0%		
P/RI									
	Average Return	10%	15%	21%	29%	44%	24%	33.3%	1359
	Median Return	3%	10%	15%	22%	32%		29.1%	
	Average Size	2547	3548	3336	2348	1646	2685	-55%	
	Average P/RI	329.10	36.90	24.27	17.11	8.82	83.24		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			28.0%			35.24***	31.9%		
ROE									
	Average Return	5%	12%	19%	24%	36%	19%	31.5%	2282
	Median Return	-7%	5%	13%	17%	24%		31.8%	
	Average Size	585	1022	1553	2168	3581	1782	84%	
	Average ROE	-0.53	0.06	0.12	0.18	0.65	0.10		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			24.2%			32.36***	30.3%		
Growth									
	Average Return	11%	10%	16%	25%	33%	19%	22.6%	2311
	Median Return	0%	3%	13%	20%	21%		21.2%	
	Average Size	939	1545	2895	2079	1328	1757	29%	
	Average Growth	-5.17	-0.30	0.07	0.33	6.18	0.22		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			17.3%			22.07***	19.1%		

In general the results are in line with the similar sensitivity analysis performed for the backward-looking value drivers. Those value drivers that are positively correlated with market capitalization lose some of their hedge returns. Interestingly, however, this time the value drivers that are negatively correlated with size, such as ROE, stay mostly just unaffected by the omission. The PE-G ratio is still the best forward-looking value driver and the regular forward-looking P/E ratio also performs well.

Although the average hedge returns decrease for most of the value drivers after omitting the micro-caps the proportion of maximum return is less affected. The reason for this phenomenon is that the maximum hedges return available decreases also significantly after omitting the micro-caps that produce the highest stock returns. This also emphasizes the goodness of the '% of max' as criterion for choosing the best forward-looking value drivers.

The earnings growth and ROE are interesting forward-looking value drivers in the sense that they have two opposing effects embedded in them. The first one is the future information content that both value drivers can incorporate relatively well. The opposing force is the size-effect as both value drivers are negatively correlated with market capitalization. Indeed, earnings growth is able to marginally improve its performance after omitting the micro-caps especially when looking at the measure '% of Max'. ROE is also able to improve the proportion of maximum return that it captures, but in terms of absolute hedge margin, the value driver remains on the same level. As a conclusion, it seems that the effect of new information in these value drivers is much stronger than the plain size-effect.

4.2.3 Forward-looking value driver performance after omitting extreme value driver observations

In this section the extreme value driver observations are omitted from the sample in the same manner as in section 4.1.3. The 1% highest and lowest values of the value drivers are omitted. The omission is done for the sample where micro-caps have already been omitted. Thus, this sample should be as clean as possible from these biases. The results are shown in Table 14.

Table 14 Performance of the forward-looking value drivers using perfect foresight after omitting micro-caps and extreme value driver observations

Similar calculation methods as in Table 12, but now in addition to micro-caps also 1% of the highest and lowest value driver observations are omitted.

Value Driver		Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
PEG									
	Average Return	10%	19%	26%	34%	46%	27%	36.0%	1049
	Median Return	8%	16%	21%	25%	33%		25.2%	
	Average Size	4653	3390	2047	1907	1304	2660	-257%	
	Average PEG	3.85	0.98	0.57	0.33	0.15	1.18		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			31.3%			37.72***	35.6%		
PE-G									
	Average Return	3%	10%	20%	29%	41%	21%	38.9%	1552
	Median Return	-2%	7%	16%	24%	29%		30.6%	
	Average Size	2122	3579	3082	1873	1634	2458	-30%	
	Average PE-G	61.30	18.81	1.03	-18.19	-134.27	-14.26		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			35.1%			49.09***	38.5%		
P/E									
	Average Return	6%	15%	20%	28%	41%	22%	35.1%	1740
	Median Return	-2%	8%	14%	21%	29%		30.9%	
	Average Size	2580	3045	2483	1854	1354	2263	-91%	
	Average P/E	56.41	19.04	13.70	10.39	6.06	21.12		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			29.8%			41.76***	34.0%		
P/RI									
	Average Return	11%	16%	21%	28%	44%	24%	33.7%	1331
	Median Return	3%	10%	15%	22%	33%		29.6%	
	Average Size	2574	3574	3372	2362	1709	2718	-51%	
	Average P/RI	132.65	36.47	24.27	17.26	9.44	44.02		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			28.3%			35.1***	32.4%		
ROE									
	Average Return	5%	12%	19%	24%	35%	19%	30.3%	2236
	Median Return	-7%	5%	13%	17%	24%		30.6%	
	Average Size	601	1031	1558	2156	3668	1803	84%	
	Average ROE	-0.22	0.06	0.12	0.18	0.34	0.10		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			23.7%			32.09***	29.5%		
Growth									
	Average Return	11%	10%	16%	25%	34%	19%	22.7%	2264
	Median Return	0%	3%	12%	19%	21%		21.4%	
	Average Size	948	1560	2920	2082	1369	1776	31%	
	Average Growth	-2.26	-0.29	0.07	0.32	1.98	-0.03		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			17.5%			22.25***	19.3%		

Similarly to the sensitivity analysis performed on the backward-looking value drivers the effect of omitting extreme value driver observations is very weak for forward-looking value drivers as well. Again the value driver averages in the buy and sell portfolio move closer to each other but in terms of portfolio returns the changes are minimal. The effect could have been stronger when using the forward-looking value drivers, because the fundamentals used in calculating the value drivers play a bigger part here. However, this seems not to be the case. All in all, it is clear that the results are relatively insensitive to extreme value driver observations and therefore in the following phases of the study this particular sensitivity analysis is not conducted anymore.

4.2.4 Conclusions on the performance of value drivers using perfect foresight

The buy vs. sell returns of the value drivers increase dramatically when perfect foresight is applied. This is natural as information from the future is included in the value drivers that surely cannot yet be reflected in the stock prices. The best value drivers can generate almost up to 40% of the theoretical maximum return. Naturally, if any common forecast errors were included, the hedge returns would decrease respectively. In the next phase of this study, the value driver performance is tested with real analyst data. The idea is to see whether any hedge returns are left when using real forecasts that have errors and biases in them. This analysis also gives us one measure of how good forecasts analysts are able to make.

The key finding of this section was that the PEG or PE-G value drivers were the most sensitive to the new information available. They are the best value drivers to incorporate unbiased accurate forecasts and generate stock recommendation based on those forecasts. However, the regular forward-looking P/E ratio did not perform much worse. The advantage of the P/E ratio is its simplicity, a characteristic that should not be underestimated. In fact, the difference between the P/E ratio and the PEG ratio was so small that justifying the use of the more complex PEG ratio is somewhat difficult. In addition, the PEG ratio did underperform the PE ratio in its backward-looking version. This could imply that the better performance of the forward-looking PEG ratio is merely due to its ‘hyper-sensitivity’ to future earnings, but not its so-called growth-at-reasonable-price (GARP) features. Later, in the context of real forecasts hyper-sensitivity could become an issue since then the value driver would be hyper-sensitive to forecasts errors as well.

Finally, two more value drivers showed some good forward-looking value driver potential. Again the P/RI ratio was able to achieve good results despite the heavy approximations used in calculating it. The strong link to shareholder value seems to be important for the value drivers. Also the combination of P/B and ROE could probably be further developed into a good forward-looking value driver, with a similar kind of GARP framework as in the PEG ratio. However, the exact calculation methods need to be heavily tested first. Developing both of these value drivers provide excellent topics for future research.

5 PERFORMANCE OF VALUE DRIVER GENERATED RECOMMENDATIONS USING ANALYST FORECASTS

In this section, the analyst forecasts are applied to the forward-looking value drivers presented above. This examination reveals if the EPS forecasts of the analysts contain valuable information that could be turned into profitable investment recommendations by using the value drivers tested in this study. The recommendations generated using value drivers are later called *auto-recommendations*. Secondly, these auto-recommendations are compared against real consensus recommendations of the analysts. The purpose of this examination is to see whether a simple value driver based sorting method could generate better recommendations than the analysts' current ad hoc methods.

The data sample is smaller in these analyses because the EPS forecasts in the IBES database are available only from 1984 onwards. Moreover, the EPS is the only forecast item widely available in the database, which restricts the number of value drivers that can be tested with real analyst data. The analyst recommendations are available in the database only from 1994 onwards, which cuts the observation period to only 13 years. Shorter observation period means that the sample is more vulnerable to single economic up- and downturns. The dot-com bubble in the beginning of the millennium explains the most radical stock returns in these samples and therefore additional sensitivity analysis is conducted to controlling the effect of the dot-com bubble.

The analyst forecasts and recommendations are taken from March each year. The buy-and-hold period starts from April 1st as previously. Using the analyst data gathered in March means that the consensus forecasts and recommendations should be available at the portfolio formation day. The exact formulas used in calculating the value drivers are presented in Appendix 1.

5.1 Profitability of auto-recommendations using analyst forecasts

In this section the IBES analyst EPS forecast data is used to generate auto-recommendations. The idea is to assign the stocks into five portfolios in a similar manner as in the previous chapter. This time, however, the forecasts for forward-looking value drivers are taken from real analyst consensus forecasts. As we saw in section 3.3.2 the dominance of micro-caps is not a critical issue when using analyst data, because the data sample itself is biased towards bigger companies as analysts do not generally follow the smaller stocks. Therefore, the micro-caps are not omitted from the sample when using analyst data.

5.1.1 Auto-recommendation profitability using full sample

First, the profitability of the auto-recommendations generated using analyst EPS forecasts are calculated using the full sample. All value drivers that showed clear potential in the previous chapter have been included if the value driver can be calculated using only earnings forecasts. Some interesting value drivers such as the P/RI had to be left out, because the IBES database does not contain enough observations for other items than EPS. The results of auto-recommendation profitability using the full sample are shown in Table 15.

Table 15 Profitability of auto-recommendations using analyst EPS forecasts

Profitability of auto-recommendations calculated based on forward-looking value drivers in 1984-2007. The value drivers use the analysts' consensus EPS forecasts for the next year (EPS Y1). The consensus forecasts are taken from March (Y=0) each year. The stocks are sorted according to the value driver and assigned to the five equally sized portfolios. The portfolio returns are calculated by using a one year buy-and-hold period starting on April 1st (Y = 0) and ending on March 31st (Y+1) taking the average or median of the returns of all the stocks in the portfolio. Finally, the portfolio returns from different years are combined by averaging them. Also the average market capitalization (size) is reported for all portfolios. The hedge return is calculated as the difference between the buy and sell portfolio returns. The item "% of max" is the proportion of the value driver hedge margin from the largest possible hedge margin achievable by sorting the stocks according to their stock returns directly. The t-stat is the t-value of the t-test testing the statistical significance of the difference in buy and sell portfolio returns. The difference in averages is an alternative way to calculate the hedge margin used in the t-test.

Value Driver	Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
P/E								
Average Return	15%	15%	17%	18%	21%	17%	6.5%	2106
Median Return	4%	8%	11%	13%	14%		10.3%	
Average Size	2656	3045	3109	2398	1821	2606	-46%	
Average P/E	69.04	21.26	16.10	12.93	9.27	25.72		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		5.2%			5.55***	5.2%		
PEG								
Average Return	15%	16%	17%	15%	18%	16%	2.8%	1270
Median Return	10%	11%	10%	8%	9%		-1.7%	
Average Size	5012	4324	2766	2205	1743	3210	-188%	
Average PEG	14.96	1.41	0.86	0.51	0.24	3.59		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		2.3%			2.34**	3.2%		
PE-G								
Average Return	17%	17%	17%	17%	17%	17%	-0.8%	1838
Median Return	10%	12%	12%	10%	7%		-2.6%	
Average Size	2131	3790	3865	2412	2053	2850	-4%	
Average PE-G	70.91	19.18	5.89	-9.32	-416.09	-65.90		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		-0.7%			0.15	0.2%		
Growth								
Average Return	18%	18%	17%	16%	16%	17%	-1.8%	1798
Median Return	11%	12%	11%	10%	7%		-4.2%	
Average Size	1486	3043	4387	3408	2164	2897	31%	
Average Growth	-52.24	0.15	27.31	66.44	1067.70	221.85		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		-1.5%			-1.8*	-1.7%		
ROE								
Average Return	21%	18%	17%	18%	17%	18%	-4.7%	2384
Median Return	5%	11%	11%	11%	10%		5.4%	
Average Size	514	1243	1675	2483	5627	2308	91%	
Average ROE	-0.38	0.07	0.12	0.17	0.51	0.10		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		-3.4%			-5.92***	-7.0%		

[1] Calculated as normal PEG ratio but instead dividing by earnings growth the P/E ratio is subtracted by growth.

* significant at 10% level, ** 5% and *** 1%

The best value driver using the analyst forecasts is the ordinary forward-looking P/E ratio. However, compared to the buy vs. sell returns achieved under perfect foresight, the hedge return of 6.5% cannot be considered very high. This tells that the analyst forecasts are hardly perfect or anywhere near it. This was expected since any real forecasts suffer from serious forecasting errors and biases that are not present when using the perfect foresight method. Interestingly, the forward-looking value drivers using analyst forecasts have serious difficulties in outperforming the backward-looking value drivers calculated in the beginning. The backward-looking P/E ratio was able to produce an 8.3% hedge margin in section 4.1.1. However, the figure is not exactly comparable since the sample is not the same. As mentioned earlier, the analysts do not follow the smallest companies, and this skews the sample towards bigger companies. In Table 16 the backward-looking P/E ratio is recalculated with the same sample as in Table 15. As we can see, now the hedge return of the backward-looking P/E ratio drops to 5.0% (median 9.6%), which is slightly lower than the 6.5% (median 10.3%) achieved by analyst forecasts. This implies that analyst forecasts have some new information content compared to purely historical fundamental analysis, but the information value is alarmingly low. From the viewpoint of the analysts the issue is particularly alarming when the performance of the analyst forecasts is compared to results of the perfect foresight method, which showed the great potential of the value drivers, assuming that forecasts accuracy was significantly better.

Table 16 Performance of the backward-looking P/E ratio using the IBES sample

Backward-looking P/E ratio performance with the same sample as in Table 15. The calculation method is the same as in Table 7, where the performance of backward-looking value drivers was tested. This time the sample is restricted to companies that have consensus EPS forecasts available. In other words, these results are directly comparable to the auto-recommendation profitability reported in Table 10.

Value Driver		Sell	Reduce	Hold	Accum.	Buy	All	Buy vs.	N
P/E									
	Average Return	15%	15%	16%	18%	20%	17%	5.0%	1863
	Median Return	5%	9%	11%	12%	14%		9.6%	
	Average Size	3044	3709	3104	2451	1769	2815	-72%	
	Average P/E	186.00	25.56	17.89	13.32	7.07	49.96		
	Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
			4.1%			3.3***	3.6%		

Otherwise the P/E ratio seems to be perform relatively well under analyst forecasts as well. The median buy vs. sell return is significantly higher than the average hedge return, which indicates that extreme stock returns diminish the gap between buy and sell portfolios. One possible reason is the small number of growth companies that actually turn out to be worth the high P/E ratio. These would significantly increase the average return of the sell portfolio, which is indeed 10% higher than the respective median return. Although the average size in the sample is significantly higher when using the analyst forecasts, there is still a certain level of correlation between the average size and the portfolios. The smallest companies are emphasized in the buy portfolio although the difference is not very big.

Surprisingly, the other value drivers in Table 15 underperform the P/E ratio by a wide margin. In particular the performance of the PEG and PE-G ratios is disappointing. The PEG ratio clearly underperforms the P/E ratio when using the analyst data. Under perfect foresight the situation was the other way around. Perhaps the PEG ratio is already too sensitive to the future forecasts and therefore the value driver adjusts too precisely to the overoptimistic and biased forecasts.

The growth and ROE value drivers result in negative hedge returns as they did when they were applied in their backward-looking forms. The hedge return of growth is statistically insignificant and no investment strategies could be conducted using only that value driver. ROE results in higher negative return, but as its backward-looking version it is highly correlated with size. The stocks in the sell portfolio are ten times smaller than the stocks in the buy portfolio. As a conclusion, ROE's performance remains at the same low level as in previous analyses.

5.1.2 Auto-recommendation profitability after omitting the dot-com bubble

Barber et al. (2003) show that the dot-com bubble that burst in 2001 has significant effects on any study using analyst forecasts. They show that the accuracy of analyst recommendations deteriorated significantly during the dot-com boom and bust. Their main argument is that additional sensitivity analysis is needed, where year 2000 and 2001 are omitted as outliers in analyst accuracy. In this section the forward-looking value drivers using analyst data are tested in a similar manner. In Table 17 the forward-looking P/E ratio performance is presented at a detailed year-level. As we can see, the buy vs. sell return varies quite much between the years. However, years 1999 and 2000 are clear exceptions. In year 1999 the value driver creates a negative buy vs. sell return of -70%. Respectively in year 2000 the value driver creates a positive buy vs. sell return of 64%. These hedge returns are clearly non-typical in the data. The extreme years, i.e. 1999 and 2000, in this study are one year off from the years identified by Barber et al. (2003). One possible explanation for this is that Barber et al. (2003) rebalanced their portfolio daily in their study. Therefore, their results place the extremes exactly to the right days, months and years. In this study a one year buy-and-hold period is used and the period starts from April and ends in March the next year. For example, the S&P 500 index peaked at March 2000, which is still calculated under year 1999 in this study.

Table 17 Performance of the forward-looking P/E ratio using analyst forecasts at year-level

Portfolio returns of the P/E ratio at a year-level. The calculation method and sample is similar to Table 15. The portfolio returns for all portfolios are presented for each year. N denotes the number of stocks in the sample each year.

Year	Sell	Reduce	Hold	Accum.	Buy	All	Buy vs. Sell	N
1984	2%	11%	18%	24%	27%	16%	25%	1442
1985	24%	29%	34%	37%	45%	34%	21%	1493
1986	16%	20%	16%	22%	24%	20%	8%	1454
1987	-11%	-9%	-4%	-4%	-10%	-8%	1%	1554
1988	10%	15%	16%	19%	21%	16%	11%	1586
1989	17%	14%	11%	9%	7%	12%	-10%	1629
1990	19%	16%	16%	9%	8%	14%	-11%	1646
1991	19%	16%	20%	23%	28%	21%	10%	1684
1992	10%	10%	17%	18%	18%	15%	9%	1803
1993	11%	11%	9%	7%	12%	10%	1%	1990
1994	13%	13%	12%	11%	6%	11%	-7%	2238
1995	42%	29%	28%	27%	26%	30%	-16%	2399
1996	-3%	9%	12%	13%	20%	10%	22%	2587
1997	42%	42%	44%	44%	51%	45%	8%	2823
1998	1%	-8%	-12%	-14%	-20%	-11%	-21%	2864
1999	102%	49%	48%	47%	31%	55%	-70%	2644
2000	-42%	-12%	4%	19%	21%	-2%	64%	2503
2001	13%	18%	27%	35%	51%	29%	38%	2297
2002	-31%	-22%	-22%	-18%	-11%	-21%	19%	2014
2003	84%	75%	68%	68%	97%	79%	14%	2116
2004	0%	3%	13%	18%	23%	11%	23%	2327
2005	30%	28%	24%	23%	25%	26%	-5%	2443
2006	7%	7%	12%	15%	16%	11%	10%	2511
2007	-14%	-8%	-7%	-9%	-2%	-8%	13%	2495
Average	*15%*	*15%*	*17%*	*18%*	*21%*	*17%*	*7%*	*2106*

The dynamics of the dot-com effect are quite clear. During the steepest boom on the markets the value driver approach could not explain the stock returns and the buy vs. sell return became significantly negative. In other words, companies with already high P/E ratios outperformed the low P/E stocks in the dot-com boom. However, when the bubble burst the value driver quickly improved its performance as the high P/E stocks turned out to be bad investments after all. As Barber et al. (2003) suggest the dot-com years seem like outliers in this study as well. Therefore, the results are rerun after omitting years 1999 and 2000 from the sample. These results can be seen in Table 18.

Table 18 Profitability of auto-recommendations using analyst EPS forecasts after omitting years 1999-2000

Performance of forward-looking value drivers with analyst data after omitting years 1999 and 2000. Otherwise the calculation method and the sample is the same as in Table 15 (1984-2007).

Value Driver	**Sell**	**Reduce**	**Hold**	**Accum.**	**Buy**	**All**	**Buy vs.**	**N**
P/E								
Average Return	14%	14%	16%	17%	21%	16%	7.4%	2063
Median Return	5%	9%	11%	13%	15%		9.5%	
Average Size	1881	2794	3143	2487	1928	2446	2%	
Average P/E	62.02	20.89	16.11	13.07	9.44	24.31		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		6.3%			8.53***	7.0%		
PEG								
Average Return	15%	16%	15%	15%	17%	16%	1.8%	1250
Median Return	12%	12%	10%	9%	9%		-3.0%	
Average Size	4154	4127	2771	2118	1802	2994	-130%	
Average PEG	15.32	1.40	0.86	0.51	0.24	3.67		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		1.6%			*1.46*	*1.9%*		
Growth								
Average Return	16%	17%	17%	15%	16%	16%	-0.7%	1765
Median Return	11%	12%	12%	11%	8%		-2.7%	
Average Size	1486	3043	4387	3408	2164	2897	31%	
Average Growth	-51.30	0.60	27.45	66.40	1078.82	224.36		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		-0.7%			*-0.45*	*-0.4%*		
ROE								
Average Return	18%	17%	16%	17%	16%	17%	-1.7%	2325
Median Return	5%	11%	11%	11%	11%		6.4%	
Average Size	514	1243	1675	2483	5627	2308	91%	
Average ROE	-0.34	0.08	0.12	0.17	0.49	0.10		
Buy vs. Sell Diagnostis		*% of Max*			*t-stat*	*diff. in averages*		
		-1.3%			*-2.64****	*-2.6%*		

Although the individual buy vs. sell returns in years 1999 and 2000 were very dramatic the performance of the value drivers does not change significantly after omitting these years from the sample. The overall buy vs. sell return of the P/E ratio increases 1 percentage point to 7.5%. The biggest effect can be seen in ROE, where the negative buy vs. sell return almost disappears. Although the changes in the value driver performance after omitting 1999 and 2000 were found to be minimal in this study, Barber et al. (2003) still have a good point in warning other researchers about the dangers involved in those years. In this study the two years nicely balance each other out as the buy vs. sell return was -70% in year 1999 and then +64% in year 2000. Thus, when both are included or omitted from the sample there are no significant distortions. However, if the buy-and-hold period is chosen unfortunately and wrong years are omitted (e.g. in this study year 2000 and 2001) the results would get heavily biased, because the counter-effect would be neglected. The conclusion of this sensitivity analysis is that years 1999 and 2000 can be included in sample as long as they are both included in their full extent.

5.1.3 Conclusions on the profitability of auto-recommendations using analyst forecasts

Despite the many potential forward-looking value drivers identified in section 4.1.1 only the P/E ratio seemed to have serious investment value when real analyst forecasts were applied. Perhaps the biggest disappointment was the PEG ratio which lost all its potential when tested with analyst data. The other potential value drivers could not be tested because the only item widely available in the IBES analyst data was the earnings per share forecasts.

The performance of the P/E ratio was not great either. The forward-looking P/E ratio with analyst forecasts outperformed the backward-looking version of the value driver only marginally. Thus, the usefulness of analyst forecasts can be considered somewhat questionable. As we saw in the context of perfect foresight, however, there is great potential if the forecasts would be accurate and unbiased.

5.2 Auto-recommendations vs. analysts' consensus recommendations

In this section, the auto-recommendations calculated using the value drivers are compared against the analysts' real stock recommendations. The purpose is to see whether using a value driver based recommendation model could be used to improve the consensus recommendations. The data sample is again smaller than in the previous analyses as the analyst recommendations are available only from 1994 onwards. The consensus recommendation is derived from the number of strong buy, buy, hold, underperform, and sell recommendations issued by the analysts in March each year. The buy-and-hold period starts on April 1st as before. The consensus forecasts is calculated as an average after assigning number 1 for sell recommendations and number 5 for strong buy recommendation.

5.2.1 Auto-recommendation vs. analyst's consensus recommendation profitability using full sample

First, the auto-recommendations created by the forward-looking value drivers using analyst forecasts are compared against the consensus recommendations using the full sample. These results are shown in Table 19.

Table 19 Auto-recommendation vs. consensus recommendation profitability using full sample

The auto-recommendation profitablity of the forward-looking value drivers using analyst forecasts is compared to the profitablity of the analyst consensus recommendations. The data is from years 1994-2007. The value driver performance is calculated similarly as in Table 15 using the analyst forecasts. The consensus recommendations are calculated from the analyst recommendations by weighting the buy recommendations by 5 and the sell recommendations by 1. The average of the given recommendations is used as the consensus recommendation. In calculating the profitability of the analyst recommendations the stocks are sorted according to the consensus recommendations into five equally weighted portfolios. The recommendation distribution is heavily skewed towards buy, but in this analysis the bias is corrected by making five portfolios with the same amount of stocks in each one. The EPS forecasts and stock recommendations are taken from March (Y =0). The buy-and-hold period starts from April 1st (Y=0) and ends on March 31st (Y+1).

Value Driver	Sell	Reduce	Hold	Accumul.	Buy	All	N	Buy vs. Sell
P/E								
Value Driver Performance								
Average	17%	15%	18%	19%	24%	19%	2205	6.0%
Median	3%	7%	10%	11%	14%	9%		6.1%
Size	4009	4546	4414	3301	2559	3766		
Average P/E	88	12	9	7	5	30.8		
Analyst Recommendation Performance								
Average	22%	19%	19%	17%	17%	19%	2205	-5.4%
Median	11%	11%	9%	7%	6%	9%		-2.1%
Size	2129	4507	5104	5386	1705	3766		
Average P/E	31	15	15	16	16	31		
PEG								
Value Driver Performance								
Average	15%	16%	18%	16%	20%	17%	1298	4.6%
Median	8%	10%	9%	8%	9%	9%		0.6%
Size	7758	6020	3934	3253	2507	4694		
Average PEG	12.3	0.8	0.5	0.3	0.2	3.1		
Analyst Recommendation Performance								
Average	19%	17%	17%	16%	16%	17%	1298	-2.3%
Median	11%	10%	9%	7%	7%	9%		-2.0%
Size	2779	6225	6263	6323	1884	4694		
Average PEG	3.5	2.2	1.3	1.7	1.1	3.1		

As we saw in the previous section, the best value driver to be used in creating the auto-recommendation is the ordinary P/E ratio. In this smaller sample from 1994-2007 the buy vs. sell return is 6.0%, which is relatively close to the return reported in Table 15. The most interesting part of the results is that the consensus recommendations show negative buy vs. sell returns (-5.4%). In other words, the quality of analyst recommendations is extremely weak. The fact is that by investing in stocks that have lower stock market recommendations, the investor could get higher returns than investing in stocks that analysts recommend.

Another interesting fact that can be seen in Table 19 is that the analysts follow the P/E framework in making their recommendations at least to some extent. This effect has also been documented by Jegadeesh et al. (2004). In the portfolios formed after consensus recommendations the average P/E ratio of the sell portfolio is two times larger than the average P/E ratio of the buy portfolio. It seems that increasing correlation of the recommendations with the P/E ratio more systematically could improve the recommendation quality.

The other value driver that showed even remote potential in Table 15 was the PEG ratio. In this subsample as well it clearly underperforms the P/E ratio. The PEG ratio limits the number of stocks in the sample due to positive earnings and growth requirements. In this subsample the consensus recommendations have smaller negative buy vs. sell returns, but still the value driver clearly outperforms the analysts in making stock recommendations.

5.2.2 Auto-recommendations vs. consensus recommendations after omitting the dot-com bubble

In particular Barber et al. (2003) argued that the analyst recommendations were significantly inaccurate during the dot-com bubble in 2000 and 2001. As we saw in section 5.1.2, in this study the dot-com effect can be seen in years 1999 and 2000. The auto-recommendations are compared to the consensus recommendations also after omitting these years as Barber et al. (2003) suggest. These results are shown in Table 20.

Table 20 Auto-recommendation vs. consensus recommendation profitability after omitting years 1999-2000

Auto-recommendation profitability compared against the consensus recommendation profitability after omitting year 1999 and 2000. Otherwise the calculation method is similar to Table 19.

Value Driver		Sell	Reduce	Hold	Accumul.	Buy	All	N	Buy vs. Sell
P/E									
	Value Driver Performance								
	Average	15%	14%	17%	17%	23%	17%	2183	8.0%
	Median	5%	9%	10%	12%	15%	10%		5.3%
	Size	4009	4546	4414	3301	2559	3766		
	Average P/E	77.6	12.1	9.2	7.4	5.3	29.0		
	Analyst Recommendation Performance								
	Average	22%	17%	16%	15%	16%	17%	2183	-5.6%
	Median	12%	12%	10%	9%	8%	10%		-1.8%
	Size	2129	4507	5104	5386	1705	3766		
	Average P/E	30.1	14.2	14.6	14.1	14.9	29.0		
PEG									
	Value Driver Performance								
	Average	15%	16%	16%	15%	19%	16%	1285	3.5%
	Median	11%	11%	9%	9%	10%	10%		-0.6%
	Size	7758	6020	3934	3253	2507	4694		
	Average PEG	12.5	0.8	0.5	0.3	0.2	3.1		
	Analyst Recommendation Performance								
	Average	18%	17%	15%	15%	15%	16%	1285	-3.4%
	Median	12%	11%	9%	9%	8%	10%		-2.0%
	Size	2779	6225	6263	6323	1884	4694		
	Average PEG	3.5	2.2	1.3	1.8	1.1	3.1		

After omitting the dot-com effect from the sample the results are even more explicit. The gap between the auto-recommendation and consensus recommendation profitability just widens. Now the P/E ratio is able to achieve a 8.0% positive buy vs. sell return whereas the respective analyst recommendation result in a -5.6% negative buy vs. sell return. There are no dramatic changes in the profitability of the consensus recommendations after omitting the dot-com effect as suggested by Barber et al. (2003). One possible reason for the smaller effect is that this study uses a one year holding period instead daily portfolio rebalancing used by Barber et al. (2003). The longer holding period could smooth the effect, because the most flagrant overreactions might be already corrected before the next March when the consensus recommendations are gathered again. In the daily rebalancing all extremes during the year are duly accounted for.

5.2.3 Conclusions on the auto-recommendation vs. consensus recommendation profitability

The most important finding of this section was that the auto-recommendation model using the P/E ratio and analyst forecasts is able to significantly outperform the consensus recommendations of the analysts themselves. This implies that analysts would be better off in utilizing a systematic approach in making recommendations compared to their current methods. The better performance of auto-recommendations using analyst forecasts compared to analysts' own consensus recommendations means also that analysts do a better job in making forecasts than recommendations. This is actually quite natural as mentioned in Chapter 1. In making the forecasts, the analyst can concentrate on company specific issues only. The historical trends in earnings and managements assessments give some information that can be used in deriving the future forecasts. On the contrary, in making the stock recommendation the analyst has to consider the current price-level of the stock and compare it against other stocks in the market. The findings of this study suggest that equity analysts could use the auto-recommendation decision-aid tool to create better stock recommendations based on their forecasts. This would also bring a top-down approach in making the stock recommendation, which could lead to smaller biases in terms of too optimistic recommendations. When ranking the stocks systematically according to a value driver, some stocks have to be placed in the sell portfolio as well.

6 CONCLUSIONS

In this chapter, the main results of the study are summarized by repeating the research question and reflecting the empirical results on it. Next the practical implications of this study are discussed and some possible practical applications are outlined. Finally, the future research questions raised by this study are specified.

6.1 Summary of the main results

The research question in this study was *"What forward-looking value drivers provide the best basis for investment strategy using the most accurate, unbiased forecasts available?"*

Answering the research question started with a literature review where the most influential value drivers of the previous studies were identified. The list of value drivers gathered from existing literature was first applied to only historical fundamental data. These results provided us a lower limit on the returns that should be expected in the following stages. The stocks were sorted into five equally sized portfolios according to different value drivers and the average returns of the portfolios were compared. Particularly interesting was the difference between the two extreme portfolios (buy and sell), because this represents the return of an investment strategy where the buy portfolio is purchased and the sell portfolio is shorted. The best backward-looking value drivers in terms of buy vs. sell return seemed to be the price-to-book (P/B) and the price-to-earnings (P/E) ratio. Among these value drivers the distorting effect small-cap companies was relatively strong. Actually, the best historical value driver would have been the market capitalization of the company itself. A significant part of the value driver performance of the P/B and P/E ratios was due to the size effect. Still after controlling the size effect by omitting micro-caps from the sample, the P/B and P/E ratios resulted in statistically significant buy vs. sell portfolio returns.

Next, the perfect foresight method was applied to the data and the performance of the value drivers was tested with future fundamentals consisting of next year's unpublished financial figures. This time a more sophisticated value driver, the price-earnings-growth (PEG) ratio, seemed to provide the best results, but it was closely followed by the common forward-looking P/E ratio. Both ratios showed that with accurate forecasts significant, up to 50% buy vs. sell returns could be achieved. The P/B ratio could not capture much of the new available information and performed poorly. At this stage it became clear that P/E or PEG ratio were the best value drivers to be used as forward-looking value drivers.

The value drivers were further tested with real analyst consensus forecasts to see what kind of returns they could provide with non-perfect estimates on future fundamentals. This phase also provided a way to analyze the information content of equity analyst forecasts, i.e. whether analyst forecasts have investment value as such or not. The results were somewhat controversial. On the other hand, the P/E ratio with analysts' forecasted earnings resulted in 6.5% buy vs. sell return, and the return was shown to be statistically significant. However, the buy vs. sell return was only minimally higher than the buy vs. sell return achieved by the backward-looking P/E ratio, which used no forecasts at all. This questions the true information content of analyst forecasts. The perfect foresight approach applied earlier, however, clearly showed that there is great potential in using these value drivers if the forecasts would be any better. As mentioned in many studies, the analyst forecasts are generally heavily biased upwards and they suffer from many other conflicts of interests as well. The same conclusion can be made also on the basis of this study.

The final stage of this study was the comparison between the value driver generated auto-recommendations and the analysts' own consensus stock recommendations. Again the buy vs. sell returns were used as the comparison criteria. The results were undisputable. Following the analyst consensus recommendations is clearly not profitable. In fact, the analyst recommendations yielded a negative -5.4% buy vs. sell return. For the same sample the value driver method with simple P/E ratio yielded a positive 6.5% buy vs. sell return. Thus, analysts would be better off making recommendations with a systematic value driver based decision-aid rather than their current methods. Also investors would be better off entering the analyst consensus forecasts into the auto-recommendation model rather than following the analysts' own consensus recommendations.

In conclusion, this study confirmed that simple value drivers, such as the P/E or PEG ratio, sort stocks in portfolios that provide significant buy vs. sell returns. In accordance with anomaly studies, the effect is present already when applying historical data. When the perfect forecasts are applied to the value drivers the buy vs. sell returns increase significantly. This confirms that these simple value drivers could be used to systematically take advantage of good, unbiased estimates. In testing the drivers with perfect foresight, we saw that some less often used value drivers showed significant potential for explaining future stock returns. Utilizing these drivers in practice, however, requires better and more comprehensive forecasts and some more development work in terms of fine-tuning the value drivers themselves.

Finally, the information value of analyst forecasts was left questionable in this study. It seems that the forecasts are so biased that value drivers based on these figures are not even significantly better than backward-looking value drivers. However, when compared against real analyst consensus recommendations, the auto-recommendations generated using analyst forecasts outperformed the analysts' own consensus recommendations by a wide margin.

6.2 Practical implications of the study

In this study we saw that the analyst do better in making the numerical forecasts than the recommendations. Using a decision-aid tool to create auto-recommendations based on the value drivers presented in this study could increase the quality of the analyst recommendations. Systematic ranking of stocks with the value drivers could help the analysts to see the bigger picture and the implication of their forecasts in terms of other investment opportunities. On the other hand, the system could be used also into the other direction. The forecasting accuracy could be improved, if the decision-aid would alert the analyst that the current overoptimistic forecasts would put the stock into the highest buy portfolio. Adjusting the forecasts to match the analysts view on the right stock recommendation would be another practical application of the auto-recommendation model.

The analyst forecasts are the only way of getting educated guesses about future performance of the stocks for many investors that do not have their own buy-side research. Thus, they have to deal with biased forecasts and especially with the biased recommendations every day. As we saw earlier, especially the recommendations have no investment value as such. Other researchers have found valuable information in the analyst recommendations, but usually it means heavy data manipulation such as looking only to downgrades in the recommendations. This makes it difficult to conduct investment strategies, because timing the transactions becomes a difficult issue. By utilizing the analyst forecasts in creating auto-recommendations based on simple value drivers, the investors could produce themselves better recommendations out of the same analyst data. Moreover, the results of this study suggest that there are good opportunities to increase the profitability of the recommendations by improving the quality of the forecasts. For example, by trying to remove the some of the most obvious biases in the analyst forecasts the investors could possibly get superior returns as suggested when using the perfect foresight method in this study. For these kinds of purposes this study offers a straightforward framework how to use own forecasts as efficiently as possible in practice. As we saw in this study, the key to high returns are quality forecasts.

6.3 Suggestions for future research

From the theoretical viewpoint, this study suggests a new framework how to study the interaction between analyst forecasts and analyst recommendations. Already in the beginning of the 1990s, the two most influential surveys on equity analysts, Schipper (1991) and Brown (1993) called for further research on this matter. So far not that many researchers have really studied the field (Bradshaw, 2002). The framework based on simple value drivers could be used to determine when the analysts tend to have their forecasts right but their recommendations wrong and vice versa. This kind of analysis could provide further insights on the biases in the analyst forecasts and recommendations.

More practically, the study could be easily extended to a larger set of value drivers. The perfect foresight method introduced in this study, can be applied to any items on the companies' income statement, balance sheet or cash-flow statement. By looking at the driver's capability of capturing the maximum buy vs. sell return, one could find good value drivers where people have not looked for them previously. As mentioned earlier, much of the literature has been focused on historical fundamentals or a restricted number of items available from analyst forecasts. Some other items might prove to be good sources of forward-looking value drivers, but they have been overlooked in other studies.

Also the existing value drivers could be further developed. Especially, the more complicated ones, such as the PEG ratio, the P/RI ratio and the PB-ROE combination, could use more innovative approaches. First of all, many of these ratios suffer from strict data restrictions such as the requirement for positive earnings or positive growth. Overcoming this by some kind of alternative functional form could provide interesting results as more companies would be included in the sample. Also issues related to the easier and more accurate estimation of the residual income could provide interesting topics for future research.

Another suggestion for future research is to improve the quality of the analyst forecasts by systematically overcoming some of the most common biases in the forecasts, such as over-optimism. Simple rules, such as cutting the forecasts of growth companies by 5% and increasing the forecasts of value companies by 5%, could result in better buy vs. sell returns as the quality of forecasts improves. Also the benchmark used in comparing the auto-recommendations could be further developed. Many investors already follow only the changes in analyst recommendations because the plain recommendations themselves provide little value as we saw in this study. Also academic research has reported that following the revisions in recommendations can lead to abnormal profits (Givoly and Lakonishok, 1979 and Womack, 1996). If all participants on the markets already look only at recommendation revisions, this would be a better benchmark for the value driver performance as well. However, these investment strategies have been accused of extremely tight requirements for perfect timing and high transaction costs (Barber et al., 2001).

The analyst recommendations could be also more specifically linked to the characteristics of the stock and surrounding environment. Jegadeesh et al. (2004) argue that analyst consensus recommendations work better for stocks with other favorable characteristics such as positive price momentum and low P/E ratio. In a similar manner the value driver performance could be studied separately for example for value and growth companies. Perhaps the value drivers could distinguish the best stocks from the worst better if the companies were more alike in other aspects. Also the financial environment such as the economic cycle has an effect on the value driver performance as we saw in 5.1.2. It could be interesting to see if some value drivers work best in upturn and other value drivers in downturns. If the economic cycle could be determined using some external variable such as GDP growth, the value driver based investment strategy could switch between the value drivers depending on the current financial environment.

Finally, the study could be extended to other markets to see if the same principles apply there as well. For example, the small size of the Finnish stock market would probably create interesting additional requirements for the tested value drivers.

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8 APPENDIX 1

Backward-looking value driver definitions

Value Driver	Formula	Description
Price-to-book (P/B)	Stock $Price_t$ / (Shareholders $Equity_{t-1}$ / Number of $Stocks_t$)	Stock $Price_t$ and Number of $Stocks_t$ from March 31st year t (CRSP), Shareholder's Equity $_{t-1}$ latest from December 31st the previous year (Compustat)
Price-to-earnings (P/E)	Stock $Price_t$ / (Net Income $_{t-1}$ / Number of $Stocks_t$)	Stock $Price_t$ and Number of $Stocks_t$ from March 31st year t (CRSP), Net Income $_{t-1}$ latest from December 31st the previous year (Compustat)
Price-earnings-growth (PEG)	Stock $Price_t$ / ((Net Income $_{t-1}$ / Number of $Stocks_t$) / (Net Income $_{t-1}$ / Net Income $_{t-2}$-1) * 100)	Stock $Price_t$ and Number of $Stocks_t$ from March 31st year t (CRSP), Net $Income_{t-1}$ latest from December 31st the previous year and Net $Income_{t-2}$ latest from December 31st the year before that (Compustat)
Price-to-residual income	Stock $Price_t$ / (($EBIT_{t-1}$ * (1-0.35) - Invested $Capital_{t-2}$ * 0.07) / Number of $Stocks_t$)	Stock $Price_t$ and Number of $Stocks_t$ from March 31st year t (CRSP), $EBIT_{t-1}$ latest from December 31st the previous year and Invested $Capital_{t-2}$ latest from December 31st the year before that (Compustat)
Debt-to-equity	Long-term Debt $_{t-1}$ / Shareholder's Equity $_{t-1}$	Long-term $Debt_{t-1}$ and Shareholder's $Equity_{t-1}$ latest from December 31st the previous year (Compustat)
Earnings growth (Growth)	(Net $Income_{t-1}$ / Net $Income_{t-2}$ - 1)	Net Income $_{t-1}$ latest from December 31st the previous year and Net $Income_{t-2}$ latest from December 31st the year before that (Compustat)
Return on equity (ROE)	Net $Income_{t-1}$ / Shareholder's $Equity_{t-2}$	Net Income $_{t-1}$ latest from December 31st the previous year and Shareholder's $Equity_{t-2}$ latest from December 31st the year before that (Compustat)

Forward-looking value driver definitions using perfect foresight

Value Driver	Formula	Description
Price-earnings-growth (PEG)	Stock Price$_t$ / ((Net Income$_t$ / Number of Stocks$_t$) / (Net Income$_t$ / Net Income$_{t-1}$-1))	Stock Price$_t$ and Number of Stocks$_t$ from March 31st year t (CRSP), Net Income$_t$ latest from December 31st the same year and Net Income$_{t-1}$ latest from December 31st the previous year (Compustat)
Price-earnings-growth substracted (PE-G)	Stock Price$_t$ / ((Net Income$_t$ / Number of Stocks$_t$) - (Net Income$_t$ / Net Income$_{t-1}$-1) * 100)	Stock Price$_t$ and Number of Stocks$_t$ from March 31st year t (CRSP), Net Income$_t$ latest from December 31st the same year and Net Income$_{t-1}$ latest from December 31st the previous year (Compustat)
Price-to-earnings (P/E)	Stock Price$_t$ / (Net Income$_t$ / Number of Stocks$_t$)	Stock Price$_t$ and Number of Stocks$_t$ from March 31st year t (CRSP), Net Income$_t$ latest from December 31st the same year (Compustat)
Price-to-residual income	Stock Price$_t$ / ((EBIT$_t$*(1-0.35)-Invested Capital$_{t-2}$ * 0.07) / Number of Stocks$_t$)	Stock Price$_t$ and Number of Stocks$_t$ from March 31st year t (CRSP), EBIT$_t$ latest from December 31st the same year and Invested Capital$_{t-2}$ latest from December 31st the previous year (Compustat)
Return on equity (ROE)	Net Income$_t$ / Shareholder's Equity$_{t-1}$	Net Income$_t$ latest from December 31st the same year and Shareholder's Equity$_{t-1}$ latest from December 31st the previous year (Compustat)
Price-to-book (P/B)	Stock Price$_t$ / (Shareholders Equity$_t$ / Number of Stocks$_t$)	Stock Price$_t$ and Number of Stocks$_t$ from March 31st year t (CRSP), Shareholder's Equity$_t$ latest from December 31st the same year (Compustat)
Earnings growth (Growth)	Net Income$_t$ / Net Income$_{t-1}$ - 1	Net Income$_t$ latest from December 31st the same year and Net Income$_{t-1}$ latest from December 31st the previous year (Compustat)
Price-to-book vs. ROE (PB-ROE)	(Stock Price$_t$ / (Shareholders Equity$_t$ / Number of Stocks$_t$)) – (Net Income$_t$ / Shareholder's Equity$_{t-1}$)	Stock Price$_t$ and Number of Stocks$_t$ from March 31st year t (CRSP), Shareholder's Equity$_t$ and Net Income$_t$ latest from December 31st the same year and Shareholder's Equity$_{t-1}$ latest from December 31st the year before that (Compustat)
Magnified Price-to-book vs. ROE (10*PB-ROE)	10* (Stock Price$_t$ / (Shareholders Equity$_t$ / Number of Stocks$_t$)) – (Net Income$_t$ / Shareholder's Equity$_{t-1}$)	Stock Price$_t$ and Number of Stocks$_t$ from March 31st year t (CRSP), Shareholder's Equity$_t$ and Net Income$_t$ latest from December 31st the same year and Shareholder's Equity$_{t-1}$ latest from December 31st the year before that (Compustat)

Forward-looking value driver definitions using analyst forecasts

Value Driver	**Formula**	**Description**
Price-to-earnings (P/E)	Stock $Price_t$ / EPS_Y1_t	Stock $Price_t$ from March 31st year t (CRSP), one year Earnings per Share (EPS_Y1_t) consensus forecast from March the same year (IBES)
Price-earnings-growth (PEG)	(Stock $Price_t$ / EPS_Y1_t) / ((EPS_Y1_t * Number of $Shares_t$) / Net $Income_{t-1}$ - 1) * 100)	Stock $Price_t$ and Number of $Stocks_t$ from March 31st year t (CRSP), one year Earnings per Share (EPS_Y1_t) consensus forecast from March the same year (IBES), Net $Income_{t-1}$ latest from December 31st the previous year (Compustat),
Price-earnings-growth substracted (PE-G)	(Stock $Price_t$ / EPS_Y1_t) - ((EPS_Y1_t * Number of $Stocks_t$) / Net $Income_{t-1}$ - 1) * 100)	Stock $Price_t$ and Number of $Stocks_t$ from March 31st (CRSP), one year Earnings per Share (EPS_Y1_t) consensus forecast from March the same year (IBES), Net $Income_{t-1}$ latest from December 31st the previous year (Compustat),
Earnings growth (Growth)	(EPS_Y1_t * Number of $Stocks_t$) / Net $Income_{t-1}$ - 1	Number of $Stocks_t$ from March 31st year t (CRSP), one year Earnings per Share (EPS_Y1_t) consensus forecast from March the same year (IBES), Net $Income_{t-1}$ latest from December 31st the previous year (Compustat),
Return on equity (ROE)	(EPS_Y1_t * Number of $Stocks_t$) / Shareholder's $Equity_{t-1}$	Number of $Stocks_t$ from March 31st year t (CRSP), one year Earnings per Share (EPS_Y1_t) consensus forecast from March the same year (IBES), Shareholder's $Equity_{t-1}$ latest from December 31st the previous year (Compustat)