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Analysts' Expectations and Stock Returns on the London Stock Exchange

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Abstract: This study examines the anomaly between stock returns and analysts' forecasts, with reference to previous findings in the US market. We replicate La Porta's (1996) study, where he finds that betting against analysts' forecasts tends to be a good strategy, as the stocks that analysts are most optimistic about earn poor returns relative to the stocks that analysts are most pessimistic about. We discover that his findings do not hold in a different market, the UK, even when taking into consideration the risk exposure of portfolios formed on a long-term growth basis. While analysts do exaggerate their predictions, affected by a series of positive or negative news, the results suggest that their expectations are not representative of all markets.

Keywords: Analysts' expectations, Efficient Markets, Representativeness Heuristics

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1 Introduction

1.1 Purpose

The purpose of this thesis is to investigate the extent to which there exists an anomaly between analysts' expectations and stock returns in the UK market, comparing this with previous findings in the US market. The anomaly we are referring to is the surprising finding in the latter that stocks which analysts are the most optimistic about, in terms of long-term growth in earnings, earn poor returns when compared to the stocks which they are the most pessimistic about, even when taking into consideration various risk factors. Previous research has attributed this anomaly to a representativeness heuristic, which shapes the subjective probability we assign to certain events occurring. While, in general, these heuristic techniques are useful, they can lead to predicable and systematic errors.

In order to test if these findings still hold, we constructed portfolios ranked by analysts' expectations in each year, from 2003 to 2016, and thereafter computed their yearly returns post formation. Our research was inspired by La Porta (1996), who found that in the US, from 1982 to 1991, betting against analysts' extreme optimism was, on average, a good idea. If the first stage of our research confirmed the anomaly, our next step was set as investigating whether this could be explained by standard measures of risk, or whether it could be attributed to biases in evaluation, originating from the representativeness heuristic.

We thus seek to answer the following questions:

"Is the contrarian strategy of betting against analysts' predictions effective in the UK market?"

&

"If so, can the predictability of stock returns be attributed to biases in evaluation?"

1.2 Background

It has become increasingly accepted that developed capital markets contribute to, or at least facilitate, economic development and, hence, the long-term growth of per capita income. In a study conducted by Rajan and Zingales (1998), financial development, measured by stock market size and credit level, is shown to contribute to the efficient allocation of resources. For example, the study demonstrates that industries experiencing high growth, such as the pharmaceutical industry, and are thus in need of external financing, grow at a higher rate relative to mature industries, such as tobacco, in countries with developed financial markets. The reverse is true for countries with low financial development. Understanding how financial markets work is, therefore, essential to efficiently allocating capital and avoiding any welfare loss that could arise from inefficient allocations.

The standard neoclassical economic theories that try to explain how markets behave are grounded in the common assumption of the rationality of agents. 'Rationality' here refers to the understanding that investors are, on average, rational, trying to maximise some predetermined utility function in each economic decision they face. Over the past 40 years, the field of behavioural finance, incorporating elements from psychology in financial theory, has gained popularity due to its ability to propose convincing alternative explanations to various anomalies found in financial markets that cannot be plausibly explained from the rational agent perspective. Nobel laureate Daniel Kahneman, through his studies with Amos Tversky, has disputed the standard rational, utility maximising agent model. Together, they developed the Prospect Theory, showing that individual preferences and choices differ significantly from what is predicted by Expected Utility Theory in situations involving risk. In Kahneman and Tversky's (1979) study, subjects weighed up outcomes that were certain as opposed to outcomes that were merely probable. The results demonstrate risk aversion when facing choices with certain gains and risk seeking when facing choices with certain losses, with the conclusion that the subjects, therefore, ended up making sub-optimal choices, at best.

A great part of Kahneman's work has focused on the factors affecting individual decision making, mainly cognitive biases in evaluation due to misconceptions or neglect of standard statistics. These misconceptions have also been examined by other scholars, such as De Bondt and Thaler, whose 1985 study show that stocks that have experienced the highest depreciation perform better in subsequent periods relative to stocks that have experienced the highest appreciation, which perform poorly in subsequent periods. The authors attribute these findings to investors overreacting to recent news and thus, in line with the representativeness heuristic, they become excessively optimistic (pessimistic) about stocks that have experienced a series of good (bad) news, underweighting the base rate frequency, that is, the general probability of a firm sustaining such performance.

In light of these critiques of the notion of the rational agent, the focus of the current thesis lies on analysts' expectations and their potential overreactions, examining how these relate to actual stock outcomes and the validity of contrarian strategies.

1.3 Scope of Investigation

The scope of our research is limited to analyst expectations and returns in the UK. We focus on analysts' long-term growth forecasts in earnings per share, for companies listed on the London Stock Exchange. Our sample period ranges from 2003 to 2016. We exclude the years prior to 2003 due to the scarce availability of data during the dot-com crisis. We include the 2008 financial crisis which, according to the International Monetary Fund, was "the largest financial shock since the Great Depression" (GFSR 2011, p. 1), to evaluate the extent of analysts' overreaction and the performance of contrarian strategies in bull and bear markets.

1.4 Contribution

Our research contributes to existing literature in two key ways. Firstly, we provide a comparative analysis of analysts' overreactions found in previous research with those in the UK over recent years. We find that the attribution of cognitive biases stemming from representativeness heuristics hold when examining a different market, thus supporting this aspect of the existing literature. Secondly, however, we find that analysts' expectations are not representative of the market's – results that are consistent over time even when taking into account various risk measures. Therefore, we highlight that contrarian strategies seeking to exploit investors' errors in expectations are not as effective as previous research has shown.

The remainder of this thesis is structured as follows. Section two provides a literature review of relevant concepts to the current research and outlines our theoretical framework, presenting the most important findings in the behavioural finance field over the past 30 years and how these findings relate to our research. In section three, we present our hypothesis. Section four describes the methods used to obtain our results, which we then present and discuss in section five.

2 Literature Review

Over the past two decades, analyst expectations have gained popularity in financial literature, mainly due to their availability, as they are publicly available, and the fact that, being stated expectations, they can provide a tangible measure of market expectations. This section critically reviews the literature in this field most relevant to the current topic of study.

2.1 Efficient Market Hypothesis

In his 1970 publication, *Efficient Capital Markets: A Review of Theory and Empirical Work*, Eugene Fama, building on previous theories and empirical work, developed the weak, semi-strong and strong Efficient Market Hypotheses (EMH). In general, all these hypotheses state that current market prices are "right", meaning that they reflect all available information, but to various degrees. Under the weak EMH, investors cannot take advantage of historical information as this is already reflected in the current price. The semi-strong EMH states that investors cannot take advantage of current publicly available information, as this is also reflected in current prices. Lastly, the strong EMH states that investors cannot take advantage of "insider" information, which is also reflected in current prices. The peculiarity of the EMH is that it cannot be tested with certainty due to the "joint hypothesis problem", whereby it cannot be discerned whether prices are not reflecting their fundamental value or whether the discounting model used is incorrect. Shiller (1980) challenged the EMH, showing that the historical volatility of stock prices had been too extreme to be explained by the discounting of any new publicly available information about future dividends, but could, rather, be explained by the marginal rate of substitution of historical consumption levels, used as a proxy for real interest rates.

The general implication of the EMH is that since prices reflect their fundamental value, it is impossible to beat the market, in the sense of earning higher returns without incurring any extra risk. In the context of the current study, therefore, EMH is relevant in leading to the argument that betting against analysts' extreme expectations should not earn any excess risk adjusted returns, as stocks prices already reflect their fundamental value.

2.2 Behavioural Finance

As mentioned in the introduction, over the last half-century psychology has been incorporated into economic research to provide alternative explanations for anomalies in financial markets that have not been convincingly explained from the rational agent perspective. For example, Kahneman and Tversky (1972) discuss the implications of the representativeness heuristic. Among the central factors affecting representativeness heuristics, and central to the current research, are the illusion of validity and base-rate neglect. The illusion of validity refers to the confidence with which individuals predict outcomes when the "input variable" affecting the outcome has been consistent or redundant, even if simple statistics tell us that the accuracy of predictions decrease as variables are correlated. The neglect of base-rate frequency refers to the confidence with which individuals assign probabilities based on specific information about a particular event, which might not be relevant, while neglecting the general probabilities of events of such types occurring. As Kahneman and Tversky (1971) point out: "apparently, acquaintance with formal logic and with probability theory does not extinguish erroneous intuitions" (p. 109).

2.3 Market Anomalies

With respect to the various theories proposed by Kahneman and Tversky, a great deal of financial research has raised the question of whether the anomalies found in financial markets can be attributed to the cognitive biases discussed. For example, contrary to what could be expected from the weak form EMH, De Bondt and Thaler (1985) find that the stocks which have experienced the highest depreciation in price in a given year outperform the stocks which have experienced the highest appreciation in the subsequent year, by as much as 25%. These results suggest that stock prices follow a predictable adjustment in price, in turn indicating that superior risk adjusted returns can be earned by examining historical prices. However, Zarowin (1990) finds that the performance of the various stocks is driven by size, rather than past prices.

Conversely from the study of De Bondt and Thaler, Jegadeesh and Titman (1993) find the reverse to be true if the window for calculating returns is shortened to six months. Both Daniel et al. (1998) and Barberis et al. (1998), show that stock prices overreact to a series of positive or negative news while underreacting to current news, suggesting that rational investors could take advantage of the price differential to earn risk-free profits. Contrary to the law of one price, Shleifer et al. (1991) find that close-end funds trade at a discount in relation to the assets they hold.

La Porta (1996) analyses analysts' expectations and discovers that the stocks which analysts are most optimistic about in terms of long term growth earn poor returns relative to the stocks which they are most pessimistic about. These results hold even after taking into consideration market risk or firm-specific risk; moreover, the abnormal returns around earnings announcement dates suggest that analysts' expectations are shared by the market. Gennaioli et al. (2017) replicate La Porta's study and find that his discoveries hold in todays' US market. La Porta's (1996) finding, that analysts exaggerate their predictions affected by a series of positive or negative news regarding the stock, is consistent with the findings regarding overreaction from De Bondt and Thaler (1985).

However, among the studies mentioned in this section related to analysts' expectations, those of La Porta (1996) and Gennaioli et al. (2017) focus on the US stock market, mainly due to the greater availability of data and thus greater samples. The interest of the current research lies in analysts' expectations in the UK as no previous studies have, to our knowledge, focused on this particular market. In addition, as our sample ranges from 2003 to 2016, we were able to capture the effect of expected growth rates during bull and bear market conditions in the UK, as opposed to La Porta (1996), whose sample period is limited to bull markets.

3 Explanatory Models and Hypothesis

This section discusses the detailed explanatory models for the findings presented in the literature review and uses these to construct the hypothesis for the current study.

3.1 Explaining Market Anomalies

To begin with, De Bondt and Thaler attribute their findings relating to the highest-depreciating stocks outperforming the highest-appreciating stocks to overreaction. They argue that investors had revised their expectations excessively in light of recent events (earning announcements), neglecting the idea that expectations should be: "moderated by considerations of predictability" (p.793). Zarowin (1990), however, later argued that the stocks labelled as "winners" – earning them poor returns in subsequent periods – are in general larger than the "loser" stocks. The latter perform better as they are smaller-sized companies, thus being riskier and requiring a higher return. He also demonstrated that the years in which "winner" stocks are smaller than "loser" stocks, the winners outperform the latter. The results are thus driven by risk factors and are not to be attributed to investor overreaction.

Daniel et al. (1998) argue that investors are quasi-rational in the sense that they are Bayesian in the way they update probabilities, but overconfident of their privately produced information while neglecting public information. This echoes Bem's (1965) attribution theory, which posits that information confirming previous predictions, increase confidence, while information disproving previous predictions only mildly affects confidence and is attributed to bad luck rather than erroneous predictions. The self-attribution bias is then the cause of momentum in security prices, which is then reversed as security prices fall in line with their fundamental value as new information is released.

Barberis et al. (1998) instead attribute their findings regarding investors' overreactions and underreactions to the representativeness heuristic. In their model, investors update their estimates according to recent news. When earnings follow a positive trend, investors raise the likelihood of the stock being in a "trending" regime; conversely, when the trend is negative they raise the likelihood of the stock being in a "mean-reverting" regime, thus causing prices to drift from their fundamental value.

Shleifer et al. (1991) argue that even if the discount at which close-end funds seem to be trading at can attributed to agency costs, capital gains tax liabilities or the illiquidity of the assets held by these funds, these factors neither explain the fluctuation in discounts over time nor the correlation in discounts among the different funds. Rather, Shleifer et al. argue that the sentiment of irrational investors hinders rational investors from anticipating noisy traders' "mood", and thus from taking advantage of the price differential, ultimately making close-end funds a riskier asset due to their increased volatility. The rational objection to all of the above findings can be summed up as the "no free lunch" principle: if prices do not reflect the true fundamental value of a security, rational traders could – and would – quickly take advantage of the opportunity presented by the price differential caused by irrational traders, and the price would fall back in line with the security's true value. Apart from the noise-trader risk discussed by Shleifer, arbitrage strategies can be costly if the risk associated with the security is too high and substitute securities are imperfect. The implementation cost of the arbitrage strategies can also be prohibitive. The cost of borrowing securities to short them depends on the period of time for which the investor intends to hold on to the stock, which might not be known in advance. In addition, as there are securities who have a short-sale constraint, arbitrage strategies cannot always be implemented. Thus, the limitations of arbitrage can fail to eliminate mispricing.

La Porta (1996) attributes his findings to analysts' and investors' extreme pessimism (optimism) about firms that have experienced a series of bad (good) earnings announcements, to be in line with the representativeness heuristic. As expected, growth forecasts increase, and returns decrease accordingly. Considering the explanatory models discussed in this section, in this study we seek to investigate whether the anomalies discovered by La Porta (1996) still hold, and if they are caused by biases in evaluation that can be attributed to the representativeness heuristic. The reason for focusing on La Porta's study (1996), apart from its' relevant focus on analysts' expectations, is that no previous study has focused on expectations outside of the US market and one could plausibly think that the biases discussed would only apply to naïve investors, but not to experienced professionals. However, there exist numerous biases that could potentially affect analysts' evaluations. For example, as Michaely and Womack (1999) show, biased forecasts can be driven by conflicts of interest between the forecasting firm and the forecasted company. This conflict of interest could also be the reason why Easterwood and Nutt (1999) find that analysts' forecasts overreact to positive news but seem to underreact to negative news. Regardless of whichever biases might be at work, if analysts' forecasts are affected by the representativeness heuristic, a pattern of overreaction to a series of positive or negative earnings news should still be present. If, then, their expectations are representative of the market's, the contrarian strategy of betting against analysts' expectations proposed by La Porta should earn superior returns. However, if analysts' expectations are not shared by the market, which is on average rational, prices will reflect the fundamental value of the stocks and thus there should be no relationship between forecasts and returns. These two latter possibilities are the primary concerns of this research.

3.2 Hypothesis Development

Under the standard neoclassical assumption that investors are on average, rational, then stock prices should reflect all the publicly available information. If, however, analysts' expectations are not rational, in the sense that their forecasts are affected by the cognitive biases that stem from the representativeness heuristic previously discussed, we should then expect analysts to overestimate (underestimate) the long-term growth potential of stocks that have experienced a series of positive (negative) growth in earnings, neglecting the general probability of firms sustaining such growth. If, then, analysts' expectations are representative of the market's, the stocks that have been labelled as high growth stocks should earn poor returns in subsequent periods, as they are likely to have been overvalued. The reverse should then hold for stocks that have been labelled as low growth stocks.

If, on the other hand, analysts' expectations are not rational, in the same manner as above, but their expectations are not representative of the market's, the relationship between returns and long-term growth forecasts could be expected to be weak for high and low growth stocks. Finally, in a scenario where analysts' expectations are rational and representative of market expectations, if their forecasts are uncorrelated with risk factors, then there should be no clear relationship between stock returns and forecasts.

The advantage of working with expected growth rates is that, as they are stated expectations, we can test the overreaction hypothesis. As previously mentioned, if analysts' expectations are deemed rational (as the market's) and uncorrelated with risk, we would not be able to predict stock returns based on expectations.

In light of these assumptions and the preceding critique of the explanatory models for market anomalies, we constructed the following hypothesis:

H.1 Analysts' expectations are rational, not correlated with risk factors, and therefore unable to explain stock returns.

4 Method

4.1 Data

All the data used for this study were gathered in Datastream, from the Thomson Reuters database, and include companies in the UK that are listed on the London Stock Exchange, reporting earnings in sterling. For each year from 2003 to 2016, we gathered data on all companies, active and dead, that had long-term growth estimates for at least one year. We chose the median long-term growth (LTG) estimate as, according to Thomson Reuters, this is the representative consensus forecast. LTG is defined as the yearly growth in earnings per share (EPS) over the company's next full business cycle, which period ranges from three to five years[1].

The returns on individual stocks were drawn from the total return index, where returns were calculated under the assumption that any received dividend had been reinvested in the stock. Total assets are defined as the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets. Market capitalisation is defined as the closing share price on the day forecasts are released, multiplied by the total number of outstanding shares. Operating income is defined as the difference between sales and operating expenses. Net income is defined as the yearly income minus preferred dividends. Since the number of outstanding shares varies over time and several companies lacked this data in different periods, we chose to use net income as a proxy for EPS. Since the book value of equity was not available, we calculated this by multiplying 'book value per fully diluted share' with 'common shares', using the latter to calculate book value per fully diluted share, in line with Thomson Reuters. Return on equity is defined as 'Net income – bottom Line – preferred dividend requirement' divided by the average of the previous year's and the current year's equity. Cash flow, or 'funds from operations', is defined as the sum of net income and all non-cash charges or credits. Basic EPS refers to the earnings based on average common shares for the 12 months ended in the last fiscal year.

4.2 Methodology

We began by constructing ten decile portfolios in December of each year, ranked by analysts' median long-term growth forecasts. The reason for choosing December was that Thomson

[1] Previous research has proposed the market interpret the LTG forecast horizon as somewhere between five and 10 years. See Sharpe (2004).

Reuters surveys analysts around the middle of the month, and estimations are made available to the market around the third week of the month. The accounting variables we assigned to each firm were the ones available in December of each year. The returns for each portfolio constructed in December represented the return on the portfolio in the subsequent calendar year. The yearly return of each portfolio was computed by compounding monthly returns. Portfolios were equally weighted and rebalanced monthly. The reason for choosing equally weighted portfolios was that these have historically performed better than ones weighted according to market capitalisation.[2] If any individual stock included in a portfolio was missing data for a variable in a certain month, the missing value was replaced with the average value, in that month, of the portfolio it had been assigned to. All variables were winsorised at the 1% and 99% level to replace any extreme values that might have been reported erroneously. Portfolios were constructed to assess the validity of the superior performance of the contrarian strategy of betting against analysts' expectations, discussed by La Porta (1996). To assess the persistence of the strategy we reported yearly returns per portfolio as well as portfolio geometric average returns over the sample period.

4.3 Cross-Section Regression

If analysts are subject to the judgment biases previously discussed and thus exaggerate their predictions, given that analysts' expectations are representative of the market's, stock returns should then be predictable as high-growth stocks are likely to be the ones being overvalued, while the reverse would hold for low-growth stocks. To test our hypothesis of rational expectations, under which we should not be able to predict stock returns, we ran a cross-section regression of returns on different firm characteristics, including LTG forecasts.

[2] Plyakha, Uppal and Vilkov (2012) show that equally weighted portfolios with monthly rebalancing outperformed both value weighted and price weighted portfolios from 1967 to 2009 in the US.

4.3.1 Regression Model

$$Y_{i,t+1} = \beta_0 + \beta_1 BM(+)_{i,t} + \beta_2 \log(size_{i,t}) + \beta_3 EP(+)_{i,t} + \beta_4 CP(+)_{i,t} + \beta_5 \log(LTG_{i,t}) + \varepsilon_{t+1}$$

Where:

$Y_{i,t+1}$: Return of firm i at time $t + 1$.

$BM(+)_{i,t}$: Book value to market value of equity of firm i at time t.

$Size_{i,t}$: Natural logarithm of market capitalisation of firm i at time t.

$EP(+)_{i,t}$: Earnings to market value of equity ratio of firm i at time t.

$CP(+)_{i,t}$: Cash flow to market value of equity ratio of firm i at time t.

$LTG_{i,t}$: Natural logarithm of LTG forecast of firm i at time t.

For BM, EP and CP we include only positive ratios, if the ratio is negative, the value is set to 0.

We included various firm characteristics as we wanted to capture the unique relationship between LTG forecast and returns, thus controlling for other variables that might explain stock performance. For example, Fama and French (1992) find that book-to-market equity has strong predictive power with regard to stock returns as it captures firm risk. A firm with a low book-to-market value could thus be interpreted as riskier compared to high book-to-market firms – since price incorporates future growth prospects, low book-to-market firms have worse growth prospects and would thus require a higher return. We also controlled for size because, as Zarowin (1990) argued, this is the major factor contributing to the lower returns earned by "winner" stocks. As these stocks are less risky, in subsequent periods they require a lower return contra "loser" stocks. The lower relative performance can thus not be attributed to market overreaction. EP refers to the ratio of earnings to market value of equity, where a higher ratio signals a higher dividend paying ability. CP represents the firms' cash flow to market value of equity, which we also included in the regression as, contrary to EP, cash flows are harder to manipulate than earnings, which can be affected by accounting methods.

The purpose of including the accounting variables and LTG forecasts was to predict future returns; thus, the accounting variables from December of year *t* are matched with the year-end return at time *t*+1. It should here be noted that any eventual relationship found between the various explanatory variables and returns could be argued to be caused by a model misspecification. The reasoning here would be that the variable is acting as a proxy for some omitted risk factor which, if included, would rebalance the model. For example, the anomaly of low P/E stocks earning higher risk-adjusted returns has been disputed by Ball (1978), arguing that either there has been a misspecification of the model – that is, that P/E is acting as a proxy for some omitted risk factor – or that the market portfolio used as benchmark is not mean-variance efficient. As we could not know which risk factor we might have omitted, we obviously could not test this.

4.3.2 Hypothesis Testing

To test our hypothesis of rational expectations, we ran a cross-section regression. Our null and alternative hypotheses were thus:

$$\mathbf{H_0}: \beta_5 = 0, \qquad \mathbf{H_1}: \beta_5 \neq 0$$

If analyst and market expectations were rational, the LTG forecast should not be predictive of future returns, and we should then not be able to reject the null hypothesis that forecasts have no explanatory power. The same would apply if analysts were not rational but their expectations were not representative of the market's. Our alternative hypothesis, then, states that forecasts are statistically significant and different from zero.

There are two possible, but contrasting, explanations for the eventual explanatory power of LTG forecasts. Either these forecasts are too extreme, hence non-rational, or they are a proxy for risk.

4.4 Expectations – Representativeness Heuristic

In the case of being able to reject our null hypothesis, we planned to determine to what extent extreme expectations, and thus evaluation errors, could be attributable to biases in judgment under the representativeness heuristic.

If the stocks 'labelled' as high growth-stocks earned poor returns post-portfolio formation, they were likely to have been overvalued, as discussed by De Bondt and Thaler (1985). If analysts are subject to heuristic representativeness when forecasting earnings growth, these stocks could then be expected to have experienced a series of earnings growth prior to their formation, leading analysts to overestimate the LTG forecast, not realising that the probability of sustaining such growth is low. The reverse would then hold for stocks that had experienced a series of negative earnings growth. For stocks included in the lowest and highest deciles, LLTG and HLTG, we normalised earnings to 1, three years prior to their inclusion in the corresponding portfolio, and analysed the evolution in earnings prior to and post-portfolio formation. In order to compare the evolution of earnings with the evolution in LTG forecasts, we computed the average forecasts for the LLTG and HLTG portfolios prior to and post-formation for each year.

4.5 Risk Characteristics

As our null hypothesis states that expectations are rational and not correlated with risk, if we are able to reject this hypothesis, forecasts could still be rational and simply correlated with risk. If returns and expected growth rates were found to be positively correlated after controlling for firm specific factors, then forecasts might still be rational but positively correlated with market risk and could, therefore, earn greater returns. If, on the other hand, returns and expected growth rates were negatively correlated, forecasts might be negatively correlated with market risk and, therefore, the low returns of high expected growth stocks could be seen as due to their low market risk. To evaluate the hypothesis of forecasts being correlated with market risk factors, we analysed the risk characteristics of the constructed portfolios as ranked by analysts' expectations. Specifically, we computed the standard deviations of returns, betas and returns in up and down markets for each portfolio. Betas and performance in up and down markets were computed using the FTSE All-Share Index as a benchmark for market performance.

5 Results and Discussion

5.1 Portfolios and returns

Table 1 – Descriptive Statistics for Portfolios Formed on an LTG Basis.

	LTG Decile									
	1	2	3	4	5	6	7	8	9	10
Expected growth in eps, LTG	-7%	2%	4%	6%	7%	9%	11%	13%	19%	39%
Assets (MM)	28140	23304	19102	29239	22370	20354	22234	23793	15630	20823
Market capitalization (MM)	6973	6865	7784	7934	8465	6008	7764	7777	5845	5939
Operating margin to assets	7%	8%	8%	9%	11%	11%	11%	12%	13%	11%
Return on equity	5%	13%	16%	20%	24%	23%	22%	24%	22%	13%
Percent eps positive	74%	80%	81%	88%	93%	92%	89%	91%	89%	81%
Observations	34	41	26	33	34	29	33	29	32	31

Note: We constructed decile portfolios for December of each year between 2003 and 2016, ranked by analysts' median LTG forecasts. The various accounting variables presented in the table are averages of the ones available in December of each year, that is, at the point of portfolio formation. 'Assets' refers to the book value of total assets. 'Market capitalisation' is the share price times the number of outstanding shares. 'Operating margin to assets' is the operating income divided by assets. 'Return on equity' is net income divided by the book value of equity. 'Percent positive EPS' is the percentage of companies that have positive earnings per share. 'Observations' denotes the number of companies in each decile. All variables were winsorised at the 1% and 99% levels.

Table 1 shows that the average expected growth in earnings per share, from 2003 to 2016, differs by as much as 46 % between the lowest LTG decile (LLTG) and the highest LTG decile (HLTG). The LLTG portfolio is expected to have a negative long-term growth in earnings per share (EPS), at -7%, while the HLTG portfolio is expected to grow by 39%. The average market capitalisation for the LLTG and HLTG portfolio is £6.9 billion and £5.9 billion, respectively. The operating margin for the LTG portfolio is 7%, reaching 11% for the HLTG portfolio. The LLTG portfolio contains the lowest percentage of companies with positive EPS, where 26% of firms have negative EPS, compared to 19% in the HLTG portfolio. These results differ from the findings of both La Porta (1996) and Gennaioli et al. (2017), where both studies found that the HLTG portfolio contained the lowest percentage of firms with positive EPS. While the average assets reported for each portfolio in the current research might seem excessive, even though we winsorised all the variables, our small sample size compared to those of La Porta and Gennaioli, and the overrepresentation of larger firms, arguably do not make our results surprising.

The geometric average returns for the different portfolios over the sample period are presented in figure A.1 (Appendix A). Here, we can see that the LLTG portfolio outperforms the HLTG portfolio over the sample period, but is far from the best overall performing portfolio, contrary to what La Porta (1996) finds. Table 2 presents the yearly portfolio returns.

Table 2 – Yearly Returns for Portfolios Formed on an LTG Basis.

	LTG Decile										
Year	1	2	3	4	5	6	7	8	9	10	All
2004	0.239	0.177	0.228	0.196	0.202	0.168	0.189	0.134	0.151	0.172	0.186
2005	0.123	0.253	0.312	0.202	0.222	0.187	0.221	0.236	0.300	0.161	0.222
2006	0.193	0.321	0.000	0.164	0.255	0.330	0.181	0.128	0.233	0.198	0.200
2007	-0.123	-0.077	0.024	-0.123	-0.044	0.072	-0.207	-0.014	-0.006	-0.037	-0.054
2008	-0.487	-0.337	-0.694	-0.375	-0.341	-0.564	-0.303	-0.373	-0.278	-0.474	-0.423
2009	0.849	0.793	0.778	0.592	0.408	0.588	0.570	0.230	0.501	0.710	0.602
2010	0.079	0.292	0.495	0.276	0.180	0.213	0.338	0.162	-0.021	0.422	0.244
2011	-0.187	-0.275	-0.099	-0.102	0.002	0.021	-0.039	-0.142	-0.179	-0.174	-0.117
2012	0.348	0.222	0.307	0.191	0.287	0.291	0.270	0.199	0.383	0.122	0.262
2013	0.169	0.125	0.173	0.330	0.256	0.170	0.338	0.349	0.374	0.291	0.258
2014	-0.021	-0.031	-0.095	0.062	0.055	0.014	-0.011	0.001	0.058	-0.101	-0.007
2015	0.059	-0.015	0.008	-0.049	0.104	-0.011	0.119	0.084	0.059	-0.095	0.026
2016	0.512	0.329	0.160	0.173	0.052	-0.043	-0.003	0.051	0.122	0.251	0.160
2017	0.151	0.056	0.146	0.168	0.138	0.218	0.233	0.192	0.203	0.140	0.165
All	0.092	0.098	0.064	0.097	0.111	0.081	0.112	0.071	0.115	0.076	0.000

Note: We constructed decile portfolios for December of each year between 2003 and 2016, ranked by analysts' median LTG forecasts. The table reports the yearly returns of equally weighted portfolios, rebalanced monthly. Yearly returns were calculated by compounding monthly returns. The yearly returns for each portfolio in the table are the returns appertaining to the portfolio put together in December of the previous year.

Even if the LLTG portfolio outperforms the HLTG portfolio over the sample period,[3] as previously discussed, when considering annual returns for each of the 14 years for which we developed portfolios, the LLTG portfolio outperforms the HLTG portfolio only in seven of those years. These results are substantially different from the findings of La Porta (1996), where the LLTG portfolio outperforms the HLTG portfolio in each post-formation period. In 2006, however, a year in which the HLTG portfolio outperforms the LLTG portfolio, the returns differ only marginally, by 0.43 %. The LLTG portfolio seems to perform worse in periods of market downturn, as indicated by 2006 and 2007 returns. La Porta found a constant decrease in returns for the portfolios as the expected growth rate increased. To examine the persistence of our results over the sample period, we present the geometric average returns from 2004 to 2009 and 2010 to 2017 in figure A.2 (Appendix A). The strategy of going against, instead of following,

[3] See Figure A.1 (Appendix A)

analysts' expectations can be seen to earn higher returns for the LLTG portfolio from 2010-2017, but fails to outperform the HLTG portfolio from 2004-2009. Consistent with our previous results, there is not a clear relationship between forecasts and returns, even when analysing different periods. These results lead us to believe that the explanatory power of expected growth rates might not be as strong as previous research has shown, as the returns for our portfolios emerged as quite sparse. We will further examine portfolio performance against the market in section 5.4.

5.2 Regression Results

Table 3 presents the time-series means of the coefficients obtained in each yearly regression.

Table 3 – Cross Section Regression of Returns on Firm Characteristics

	BM(+)	Size	EP(+)	CP(+)	LTG
Mean	-0.0624				
t-stat	-1.2881				
Mean		-0.0014			
t-stat		0.3157			
Mean			0.5059		
t-stat			1.0390		
Mean				0.0072	
t-stat				-0.2725	
Mean					-0.0024
t-stat					0.0215
Mean	-0.1006	-0.0109			-0.0064
t-stat	-1.5944	-0.3046			-0.1199
Mean	-0.1061	-0.0109		0.0654	-0.0056
t-stat	-1.6366	-0.2983		0.1377	-0.0976
Mean	-0.1092	-0.0124	0.6525	-0.0370	-0.0049
t-stat	-1.6624	-0.4140	1.1258	-0.0911	-0.0463

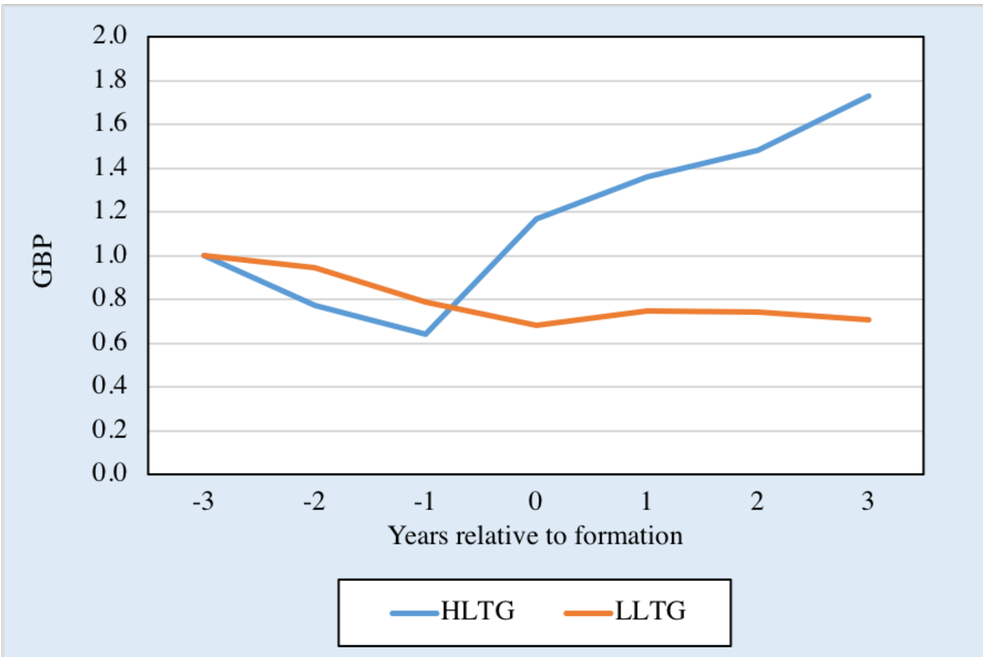
Note: A cross-section regression was run for each year from 2003 to 2016, with the one-year return in December at time t+1 as the dependent variable and firm characteristics in December at time t as independent variables. 'BM(+)' is the ratio of the book to market value of equity in December if positive, 0 if negative. 'Size' is the natural logarithm of the market value of equity in December. 'EP(+)' is the ratio of earnings to the market value of equity in December if positive, 0 if negative. 'CP(+)' is the ratio of cash flow to the market value of equity in December if positive, 0 if negative. 'LTG' is the natural logarithm of LTG forecast in December.

Since the returns for the different portfolios were quite sparse, as evident from table 2, it is arguably not as surprising that the LTG forecasts were not statistically significant and thus unable to explain stock returns. This meant that we were not able to reject the null hypothesis pertaining to rational expectations. Book to market value of equity emerged as the strongest predictor of returns, even if this was not significant over the sample period. Tables B.1 (Appendix B) and C.1 (Appendix C) present the regression results for 2003 to 2008 and 2009 to 2016. In these two periods, BM is the only significant variable that appears from 2009 to 2016. As book to market value of equity increases, the returns are negatively affected. This differs from Fama and French's (1999) results, which find the opposite to be true. Overall, the results from our cross-section regression point towards the rationality of analysts as well as the market, since we were not able to reject the null hypothesis of the LTG forecast having an explanatory power equal to zero. Apart from expectations of analysts making predictions in a rational manner, there is another plausible explanation for why the null hypothesis holds: while analysts may be biased in their expectations, they are not representative of the market's own expectations. As discussed in section three, there exist several biases that can affect forecasts, such as conflicts of interests between analysts and the forecasted firm. However, independent of which other biases might be at work, if analysts are biased as a consequence of the representativeness heuristic, we should be able to see the patterns of their overreacting or underreacting to a series of positive or negative news, as documented in previous research. To disentangle these contrasting rational-irrational views, the next section assesses the role of representativeness heuristics in shaping analyst expectations.

5.3 Representativeness Heuristic

As previously shown, on average the LLTG portfolio in this study was found to outperform the HLTG portfolio, but this outperformance was not constant over the sample period. However, as the LLTG portfolio was the portfolio with the lowest prospects but seldom the worst performing portfolio,[4] and the HLTG portfolio was the portfolio with the greatest prospects but seldom outperformed the others, if expectations are shaped by representativeness it could be expected that analysts would revise their expectations regarding the companies included in the two portfolios in line with the latter's recent performance.

Figure 1 – Evolution of EPS



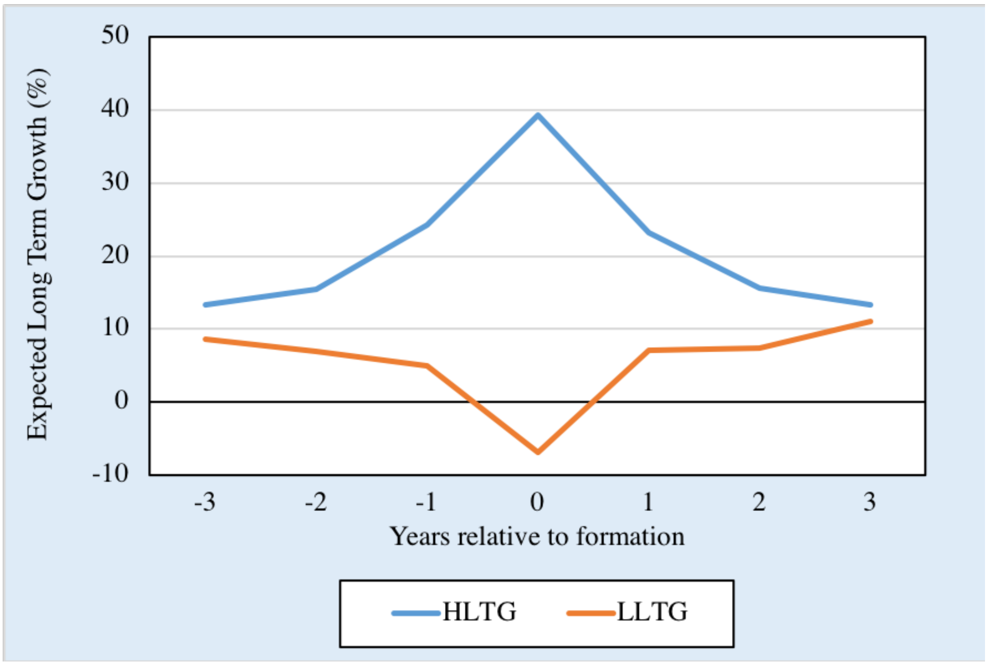
Note: We constructed portfolios for December of each year from 2003 to 2016, ranked by analysts expected long-term growth (LTG) in EPS. We normalised EPS to 1 three years prior to portfolio formation, and here report the average evolution in EPS for the stocks included in the highest (HLTG) and lowest (LLTG) decile portfolios, from *t*-3 to *t*+3.

Figure 1 demonstrates that the LLTG portfolio is on a downward spiral in terms of EPS three years prior to portfolio formation. While the HLTG portfolio also experiences a decrease in EPS three years prior to its formation, it then undergoes explosive growth one year prior to formation Following portfolio formation, the trend for the LLTG portfolio seems to reverse, while the HLTG portfolio continues to grow but at a lower rate relative to the year prior to portfolio formation. If analysts are biased in their evaluations, subject to the representativeness heuristic, they would overestimate the growth in earnings of a firms that had experienced

[4] The LLTG portfolio was the worst performing one in 2005 and 2011.

explosive growth, neglecting the base-rate frequency of firms that were able to sustain such growth in the long term. The firms in the HLTG portfolio are thus representative of high growth firms; however, as these firms are rare in absolute terms, the probability of sustaining such growth remains small. In figure 2, consistent with the previous discussion, we can see that the base-rate neglect causes analysts excessively to update their forecasts in light of recent changes in earnings. The following figure presents the realised return for the HLTG and LLTG portfolios.

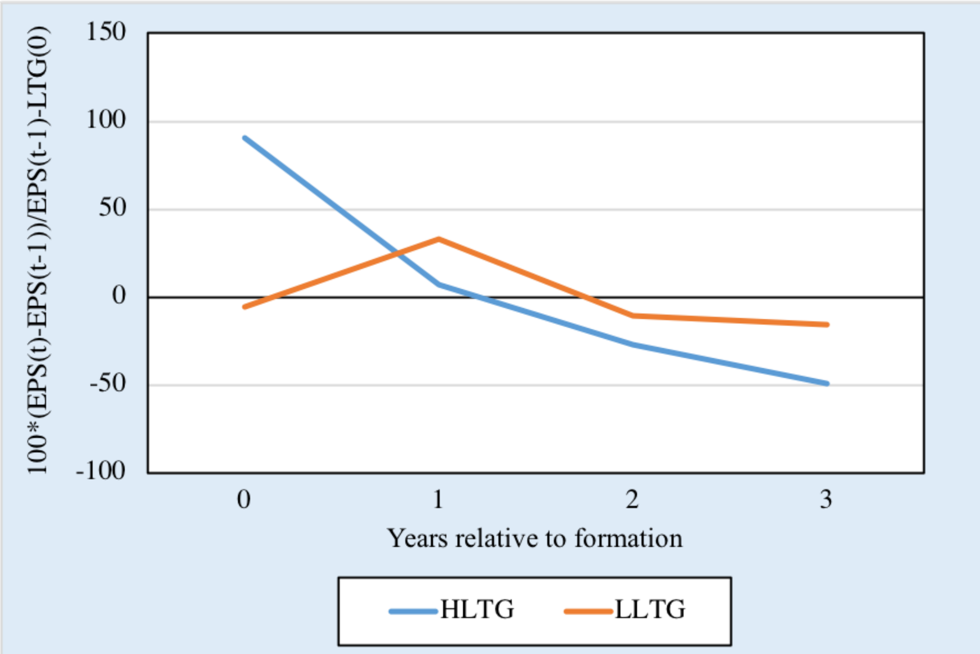
Figure 2 – Evolution of LTG



Note: We constructed portfolios for December of each year from 2003 to 2016, ranked by analysts' expected long-term growth (LTG) in EPS. Here, we report the mean LTG forecast for the highest (HLTG) and lowest (LLTG) decile portfolios, from *t*-3 to *t*+3.

In figure 2, consistent with the previous discussion, we can see that the base-rate neglect causes analysts excessively to update their forecasts in light of recent changes in earnings. The forecast for the LLTG portfolio is less severely affected than the forecast for the HLTG portfolio, which is reasonable since the performance of the former portfolio is not as volatile as the latter's. The evolution of EPS and the LTG forecast is thus in line with the trend predicted by the representativeness heuristic. The results suggest then that analysts exaggerate their forecasts in light of recent shifts in earnings. The explosive growth in earnings for the HLTG firms leads analysts to overestimate the probability of the firms' long-term growth capacity. The following figure presents the realised returns for the HLTG and LLTG portfolios.

Figure 3 – Realised growth



Note: We constructed portfolios for December of each year from 2003 to 2016, ranked by analysts' expected long-term growth (LTG) in EPS. Here, we report the realised growth in relation to LTG forecast at *t*=0 for the highest (HLTG) and lowest (LLTG) decile portfolios.

As illustrated in figure 3, the realised growth for the HLTG portfolio at the point of its formation is well above the growth forecast at this same point, while the LLTG portfolio performs slightly worse leading up to its formation in relation to what was forecast. After formation, the realised returns shift dramatically. The negative forecast errors for the HLTG portfolio grow large, consistent with the findings of Easterwood and Nutt (1999), showing that analysts overreact to positive news. However, the LLTG portfolio performs better than expected after formation, contrary to the latter's findings that analysts underreact to negative news. Figures B.1-B.3 (Appendix B) present the results for the evolution of EPS, LTG and realised growth for the portfolios formed in the 2003-2008 period, while figures C.1-C.3 (Appendix C) include the results for portfolios formed in the 2009-2016 period. In the 2003-2008 period, the results are similar to those for the whole sample period, but the reversal of forecast trends and forecast errors is not as severe. The opposite holds for the 2009-2016 period, suggesting that forecast errors might be less severe during recessions as forecasts are typically more conservative in those periods.

Thus far, the results show that the contrarian strategy of betting against analysts' expectations does not earn superior returns, which is different to what previous research has shown. Not surprisingly, then, the cross-section regression of stock returns on LTG forecasts indicates that forecasts are not significant in explaining returns. This, in turn, confirms our null hypothesis of analysts' expectations being rational, representative of the market's expectations and not correlated with risk, and thus unable to explain stock returns. However, in our investigation of the evolution of EPS and forecasts, the patterns observed strongly suggest that analysts exaggerate their forecasts, following the trend predicted by the representativeness heuristic. Since the contrarian strategy is not as effective as previously shown, but rather it is the case that analysts exaggerate their predictions, these results imply that analysts' expectations are not representative of the market's expectations. In order to further eliminate any doubt regarding the performance of the contrarian strategy, which might still be superior depending on the risk associated with it, the next section presents the risk characteristics of portfolios formed on an LTG basis.

5.4 Risk Characteristics

Table 4 – Risk Characteristics of Portfolios

	LTG Decile										
	1	2	3	4	5	6	7	8	9	10	All
Std. Dev.	0.115	0.137	0.183	0.080	0.056	0.128	0.056	0.060	0.066	0.075	0.070
Beta	1.200	1.107	1.259	0.992	0.956	1.206	0.985	0.969	0.955	1.140	1.076
Worst 20%	-0.056	-0.044	-0.052	-0.042	-0.041	-0.052	-0.041	-0.045	-0.042	-0.049	-0.046
Ret < 0	-0.032	-0.027	-0.029	-0.024	-0.023	-0.031	-0.023	-0.025	-0.023	-0.031	-0.027
Ret > 0	0.035	0.033	0.033	0.030	0.030	0.033	0.031	0.027	0.031	0.033	0.032
Best 20%	0.055	0.054	0.061	0.050	0.051	0.060	0.055	0.047	0.051	0.057	0.054

Note: In December of each year between 2003 and 2016 we form decile portfolios ranked by analysts' median LTG forecasts. For each portfolio we compute the standard deviation of returns from 2004 to 2017. Beta was calculated by regressing each portfolio against the FTSE All-Share Index weighted by market capitalisation. 'Worst' (20%) and 'Best' (20%) are the average return of the worst and best performing stocks, respectively, in each portfolio. 'Ret < 0' and 'Ret > 0' represent the average monthly return of portfolios when the FTSE All-Share Index return is negative and positive, respectively.

Table 4 highlights the risk characteristics of the various portfolios formed on an LTG basis. The table shows that the standard deviation of returns for the LLTG portfolio, together with portfolio six, is the highest. The HLTG portfolio is less volatile compared to the LLTG portfolio, but other portfolios exhibit an even lower volatility. The LLTG portfolio also has a higher beta compared to the HLTG portfolio, and thus performs better in bull markets but worse in bear markets, as evident from the average monthly returns in market up- and downturns.

These results differ quite significantly from those of La Porta (1996) and Gennaioli et al. (2017), who both find a persistent increase in beta as expected growth increases. While portfolio nine has the lowest beta amongst all the portfolios, it is also the best performing portfolio over the sample period, which seems contradictory. Its superior return can thus not be attributed to a higher level of risk. Portfolio three has a high beta but performs poorly over the sample period. Portfolio seven performs well over the sample period but has a low beta. These results suggest that betas might not be an appropriate measure for risk. Indeed, the use of beta as a risk measure has been criticised, as it assumes that the upside and downside potential of an investment are equal in relation to the market, and also because it provides an unreliable risk measure of future performance. Fama and French (1992) find that betas alone are not sufficient in explaining stock returns.

As our portfolio formation period ranged from 2003 to 2016, in order to further dissect the role of betas in up and down markets we examined betas during and after the financial crisis. Table B.2 (Appendix B) shows the betas and standard deviations of returns for portfolios formed from 2003 to 2008 for the 2004-2009 period. Table C.2 (Appendix C) shows the betas and standard deviations of returns for portfolios formed from 2009 to 2016 for the 2010-2017 period. As can be seen, the standard deviations of returns and betas are spread over both sample periods. The LLTG portfolio has a higher beta compared to the HLTG portfolio in both periods, suggesting a higher market risk. Table D.1 (Appendix D) shows, for portfolios formed from 2011 to 2016, the betas and standard deviations of returns for the 2012-2017 period, with the equally weighted FTSE 100 index as benchmark, instead of the FTSE All-Share Index we have used for the other tables. The results here suggest that the LLTG portfolio is less risky than the HLTG portfolio, contrary to the previous results. Since the LLTG portfolio also performs better than the HLTG portfolio in the 2010-2017 period, this suggests that the superior return is not driven by a higher market risk. As we see from the different tables, the results differ quite significantly depending on which benchmark is used. When the market capitalisation FTSE All-Share Index is used as a benchmark, the LLTG's portfolio returns can be attributed to higher market risk. However, when the equally weighted FTSE 100 index is used as the benchmark, the portfolio's superior performance does not seem to be driven by higher market risk. The results should thus be interpreted with caution. As we used the FTSE All-Share Index as the benchmark and it is market capitalisation weighted, the results might not be fully representative since the portfolio weighting of the benchmark differs from the weighting used when building our portfolios. An equally weighted FTSE All-Share Index was not available for our research, and the equally weighted FTSE 100 index was only available from 2012 and so not applicable to our whole sample period. The FTSE 100 index might also not be the best benchmark for ascertaining overall market performance as it only includes the 100 largest companies listed on the London Stock Exchange. Overall, regardless of which benchmark is used, in our research the LLTG portfolio was not the best performing one even when considering market risk, contrary to what both La Porta (1996) and Gennaioli et al. (2017) found.

6 Conclusion

6.1 Summary and Interpretation of Results

This study has investigated whether the anomaly relating to stock returns and analysts' forecasts in the US stock market – which, in previous studies has been attributed to market overreaction caused by the representativeness heuristic – is also present in a different market, that of the UK.

Our study found that the contrarian strategy seeking to exploit analyst overreactions is not consistent over time. The cross-section regression conducted of stock returns on LTG forecasts demonstrated that the forecasts were not significant and thus unable to explain stock returns. As we were unable to reject the null hypothesis of rational expectations, but given the ongoing reality that analysts seem to overreact to news and excessively update their forecasts, our results suggest that analysts are biased by the representativeness heuristic when forecasting expected growth rates in EPS, but that their expectations are not representative of the market's own expectations. When taking into consideration the risk characteristics of the portfolios formed on an LTG basis, the results varied depending on which market benchmark was used; overall, however, no strong link was found between returns and expected growth rates when accounting for risk, thus confirming the ineffectiveness of the strategy.

One of the greatest criticisms of the cross-section regressions of returns, apart from model misspecifications, is related to data-mining. The way in which a study models its data in order to obtain results will obviously has a great effect on the various relationships found, which might induce the labelling of certain findings as significant when, in fact, they are simply a casualty resulting from sorting and rearranging the data. The best argument against data-mining problems, then, is the consistency of results over time. In the current research, this consistency was found for the case of analysts' biased expectations, but not with regard to the accuracy of employing contrarian strategies.

Both La Porta (1996) and Gennaioli et al. (2017) find that analysts exaggerate their predictions, in line with the representativeness heuristic, and that analysts' expectations are shared by the market. In line with this, the contrarian strategy seeking to exploit errors in analysts' predictions earns superior returns, even when accounting for risk. Our study, however, shows that while analysts are subject to the biases stemming from the representativeness heuristic, their overreaction – and, thus, expectations – is not shared by the market, inducing the contrarian strategy to work poorly, even when accounting for risk. The striking differences found compared to the two previous studies, can be argued to have been caused by differences in sample size. La Porta has an average of 90 observations in each portfolio each year, roughly three times more than our sample, while Gennaioli averages around 245 observations per portfolio each year. The number of LTG observations obviously depend on the number of listings in the market they are drawn from. The London Stock Exchange total listings amount to 2022, compared to the combined listings of the New York Stock Exchange and the Nasdaq, which amount to 5458, where La Porta's and Gennaioli's samples were taken from. As companies with greater market capitalisation are overrepresented in our sample, our results might be subject to sampling bias. Our results might thus not reflect the true relationship in the "population", as some observations might have a greater probability of being part of the sample, which then results in a non-random sample. It can be argued that analysts might not have the same incentive to follow smaller companies, therefore we cannot be certain that our results are transferable to a broader scope. This sampling bias also applies to La Porta (1996).

6.2 Implications for Future Research

The contradiction between the findings of De Bondt and Thaler (1985) and those of Jegadeesh and Titman (1993), where the returns of winner and loser stocks are affected by the length of time used to calculate portfolio returns, lead us to believe that our results could differ significantly if we were to apply different time horizons when calculating returns. This suggests that future research should focus on the effect of the temporality of returns.

In general, the sparse returns obtained when forming portfolios on an LTG basis point towards analysts' expectations not being shared by the market as, otherwise, the stocks which analysts were most optimistic about should have returned poorly in subsequent periods, while the reverse would hold for the stocks which analysts were most pessimistic about. However, in order to assess with greater confidence the degree to which analysts' forecasts are not representative of market expectations, future research should focus on event studies of returns around earnings announcement dates. If a reversion of forecasts does not match returns after earnings announcements, we could argue with greater confidence that analysts' forecasts are not representative of market expectations and thus cannot be used as a proxy for market expectations.

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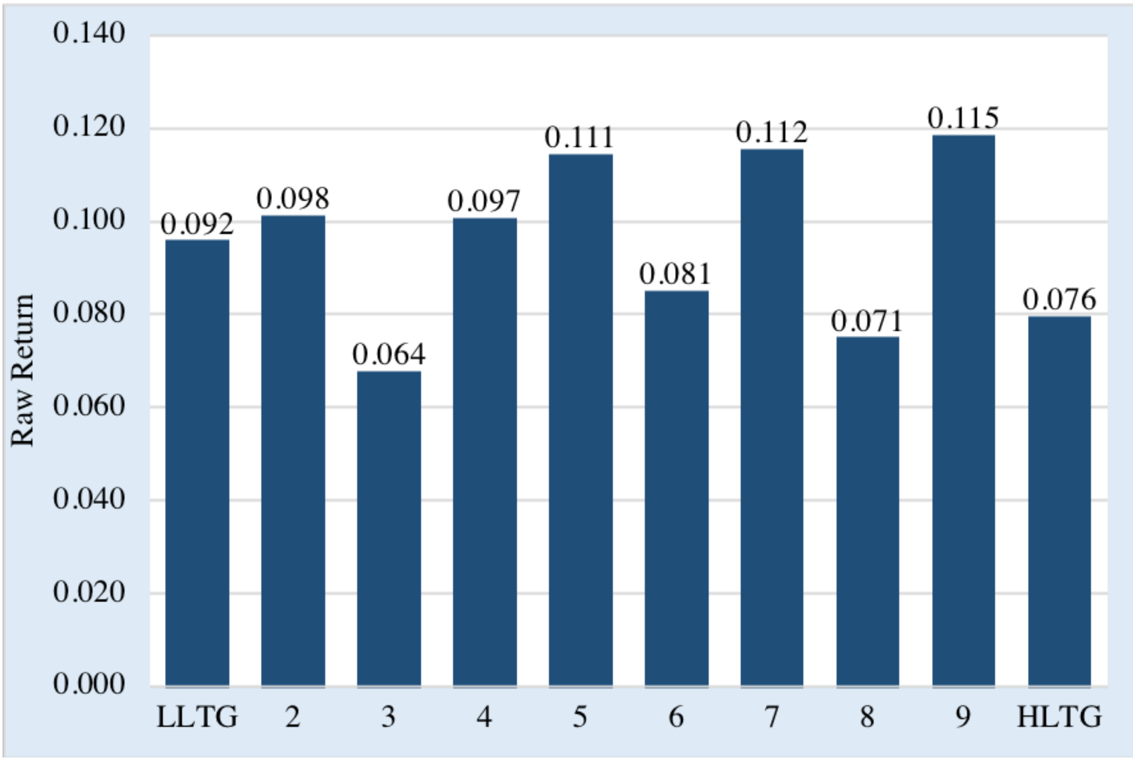
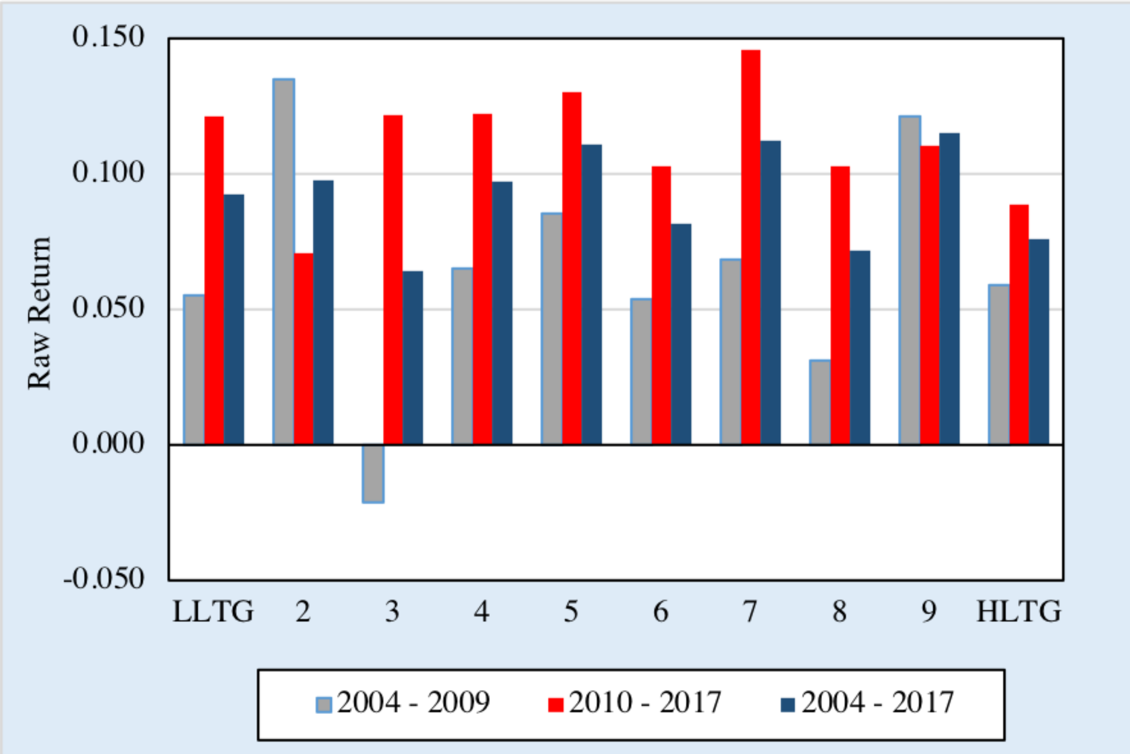
Appendix A

Figure A.1



Note: We constructed portfolios for December of each year from 2003 to 2016, ranked by analysts' expected long-term growth (LTG) in EPS. Here, we report the geometric average one-annual return over the subsequent year for each portfolio.

Figure A.2



Note: We constructed portfolios for December of each year from 2003 to 2016, ranked by analysts expected long-term growth (LTG) in EPS. Here, we report the geometric average one-annual return over the subsequent year for each portfolio for the 2004-2009, 2010-2017 and 2004-2017 periods.

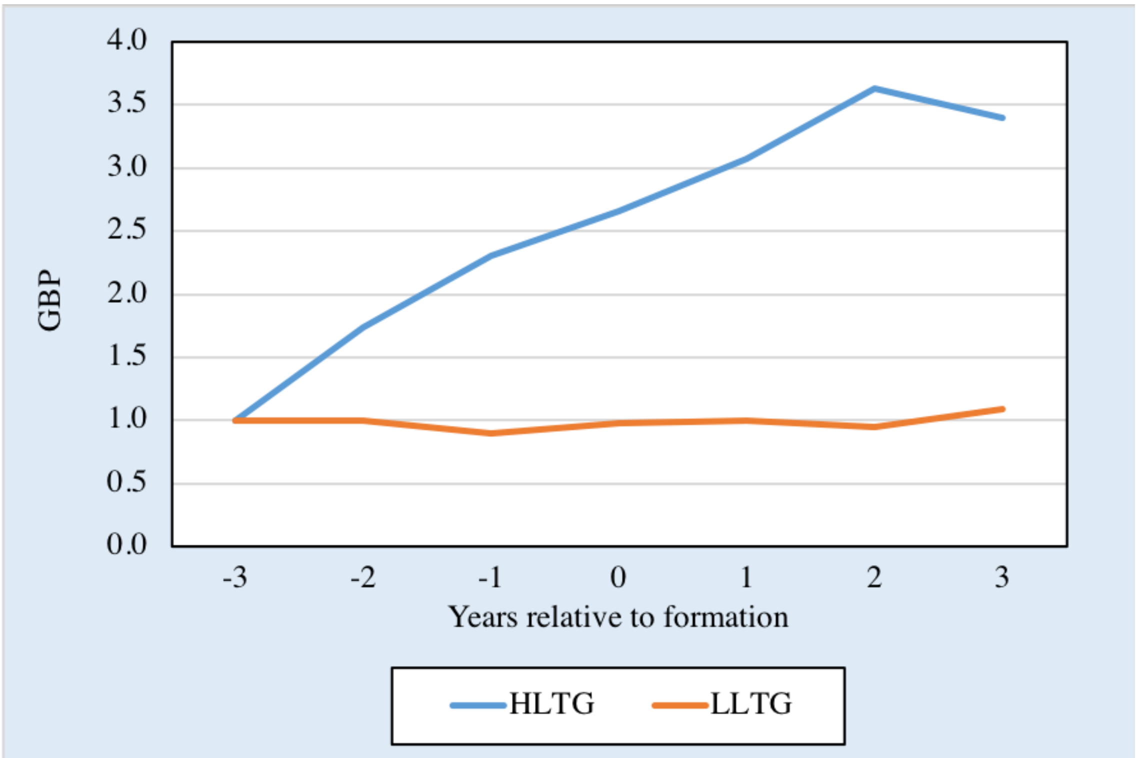
Appendix B

Table B.1 – Cross Section Regression of Returns on Firm Characteristics

	BM(+)	Size	EP(+)	CP(+)	LTG
Mean	-0.0386				
t-stat	-0.4494				
Mean		0.0008			
t-stat		0.5929			
Mean			0.7077		
t-stat			1.3988		
Mean				0.1993	
t-stat				0.4972	
Mean					-0.0202
t-stat					-0.5484
Mean	-0.0660	-0.0043			-0.0292
t-stat	-0.9959	0.4212			-0.7926
Mean	-0.0725	-0.0052		0.1795	-0.0268
t-stat	-1.0669	0.3474		0.4165	-0.7186
Mean	-0.0716	-0.0069	0.7261	0.0855	-0.0272
t-stat	-0.9385	0.1779	1.3228	0.1311	-0.7013

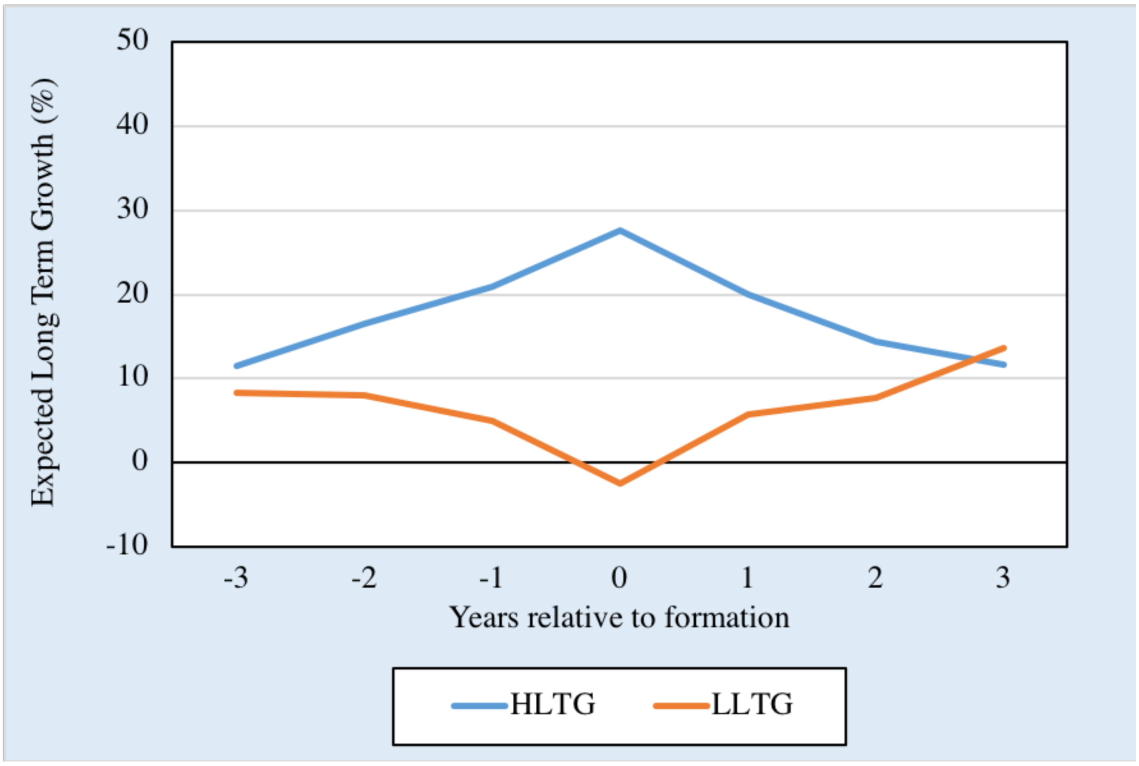
Note: A cross-section regression was run for each year from 2003 to 2008, with the one-year return in December at time *t*+1 as the dependent variable and firm characteristics in December at time *t* as independent variables. 'BM(+)' is the ratio of the book to market value of equity in December if positive, 0 if negative. 'Size' is the natural logarithm of the market value of equity in December. 'EP(+)' is the ratio of earnings to the market value of equity in December if positive, 0 if negative. 'CP(+)' is the ratio of cash flow to the market value of equity in December if positive, 0 if negative. 'LTG' is the natural logarithm of LTG forecast in December.

Figure B.1 – Evolution of EPS



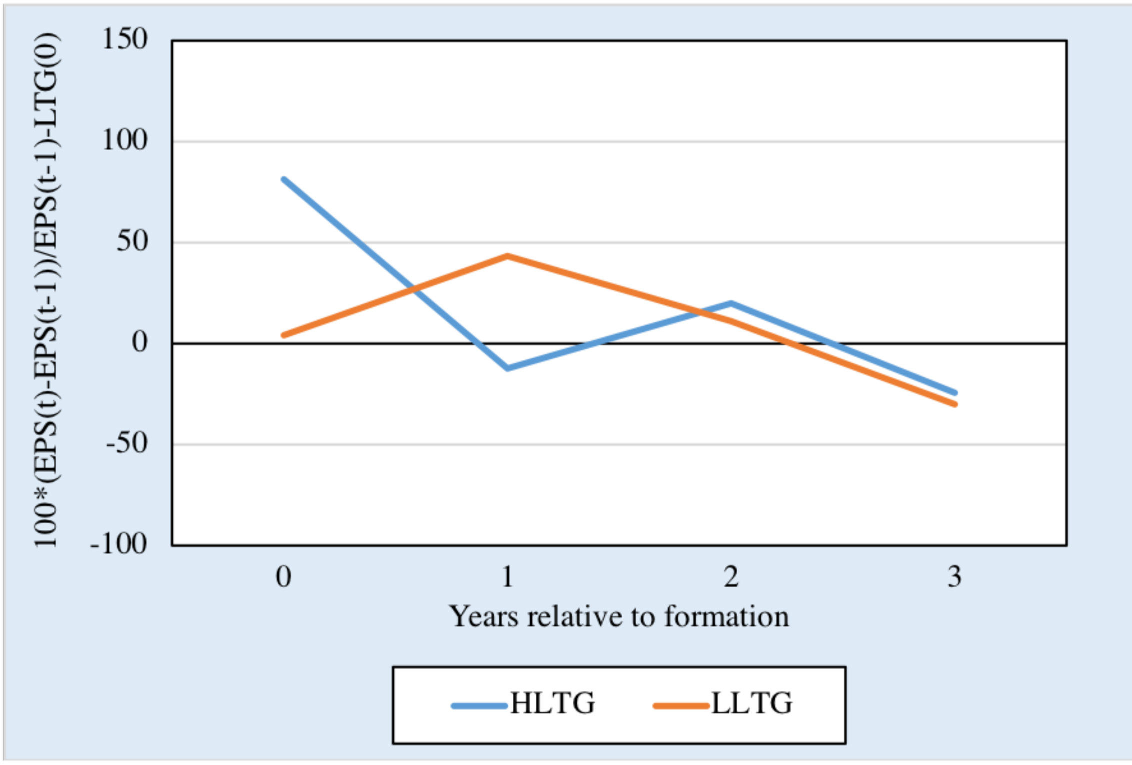
Note: We constructed portfolios for December of each year from 2003 to 2008, ranked by analysts' expected long-term growth (LTG) in EPS. We normalised EPS to 1 three years prior to portfolio formation, and here report the average evolution of EPS for the stocks included in the highest (HLTG) and lowest (LLTG) decile portfolios, from *t*-3 to *t*+3.

Figure B.2 – Evolution of LTG



Note: We constructed portfolios for December of each year from 2003 to 2008, ranked by analysts' expected long-term growth (LTG) in EPS. Here, we report the mean LTG forecast for the highest (HLTG) and lowest (LLTG) decile portfolios, from *t*-3 to *t*+3.

Figure B.3 – Realised growth



Note: We constructed portfolios for December of each year from 2003 to 2008, ranked by analysts' expected long-term growth (LTG) in EPS. Here, we report the realised growth in relation to the LTG forecast at t=0, for the highest (HLTG) and lowest (LLTG) decile portfolios.

Table B.2 – Risk Characteristics of Portfolios

	LTG Decile										
	1	2	3	4	5	6	7	8	9	10	All
Std. Dev.	0.191	0.233	0.312	0.135	0.084	0.206	0.094	0.091	0.083	0.106	0.113
Beta	1.237	1.245	1.612	1.090	1.075	1.494	1.089	0.992	0.976	1.184	1.196
Worst 20%	-0.058	-0.051	-0.082	-0.049	-0.056	-0.079	-0.053	-0.052	-0.042	-0.064	-0.058
Ret < 0	-0.038	-0.033	-0.050	-0.034	-0.034	-0.052	-0.036	-0.033	-0.028	-0.040	-0.038
Ret > 0	0.033	0.040	0.041	0.031	0.034	0.043	0.032	0.026	0.034	0.035	0.034
Best 20%	0.056	0.061	0.076	0.049	0.050	0.071	0.058	0.034	0.053	0.050	0.056

Note: In December of each year between 2003 and 2008 we form decile portfolios ranked by analysts' median LTG forecasts. For each portfolio we compute the standard deviation of returns from 2004 to 2009. Beta was calculated by regressing each portfolio against the FTSE All-Share Index weighted by market capitalisation. 'Worst (20%)' and 'Best (20%)' represent the average return of the worst and best performing stocks in each portfolio, respectively. 'Ret < 0' and 'Ret > 0' denote the average monthly return of portfolios when the FTSE All-Share Index return is negative and positive, respectively.

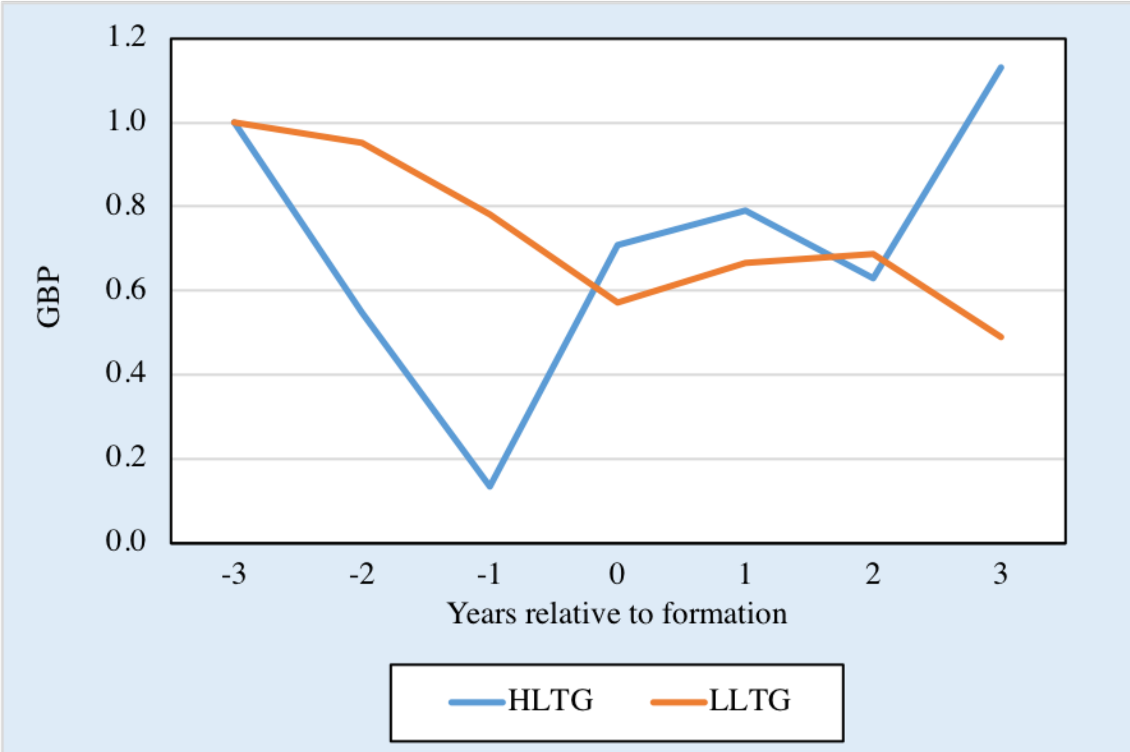
Appendix C

Table C.1 – Cross Section Regression of Returns on Firm Characteristics

	BM(+)	Size	EP(+)	CP(+)	LTG
Mean	-0.0803				
t-stat	-1.9171				
Mean		-0.0031			
t-stat		0.1078			
Mean			0.3545		
t-stat			0.7691		
Mean				-0.1368	
t-stat				-0.8499	
Mean					0.0109
t-stat					0.4490
Mean	-0.1265	-0.0159			0.0106
t-stat	-2.0432	-0.8490			0.3847
Mean	-0.1313	-0.0151		-0.0202	0.0104
t-stat	-2.0639	-0.7826		-0.0714	0.3682
Mean	-0.1374	-0.0165	0.5973	-0.1289	0.0118
t-stat	-2.2054	-0.8580	0.9781	-0.2376	0.4449

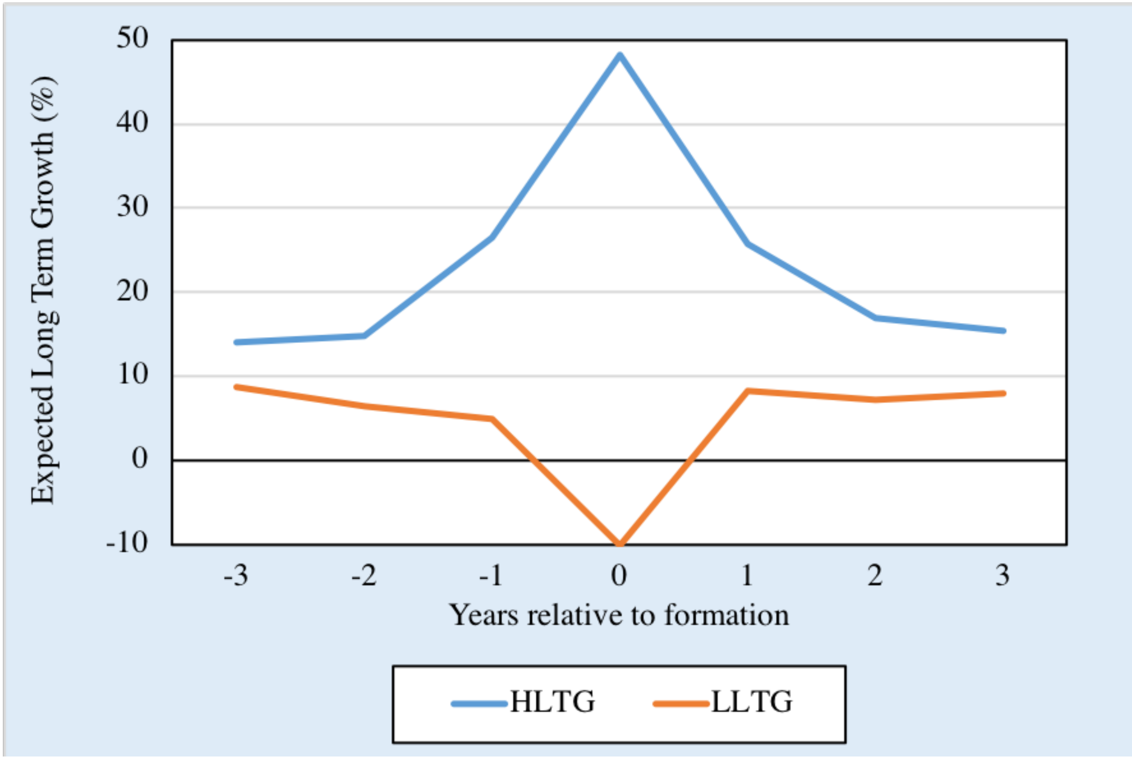
Note: A cross-section regression was run in each year from 2009 to 2016, with the one-year return in December at time *t*+1 as the dependent variable and firm characteristics in December at time *t* as independent variables. 'BM(+)' is the ratio of book to market value of equity in December if positive, 0 if negative. 'Size' is the natural logarithm of the market value of equity in December. 'EP(+)' represents the ratio of earnings to the market value of equity in December if positive, 0 if negative. 'CP(+)' is the ratio of cash flow to the market value of equity in December if positive, 0 if negative. LTG is the natural logarithm of LTG forecast in December.

Figure C.1 – Evolution of EPS



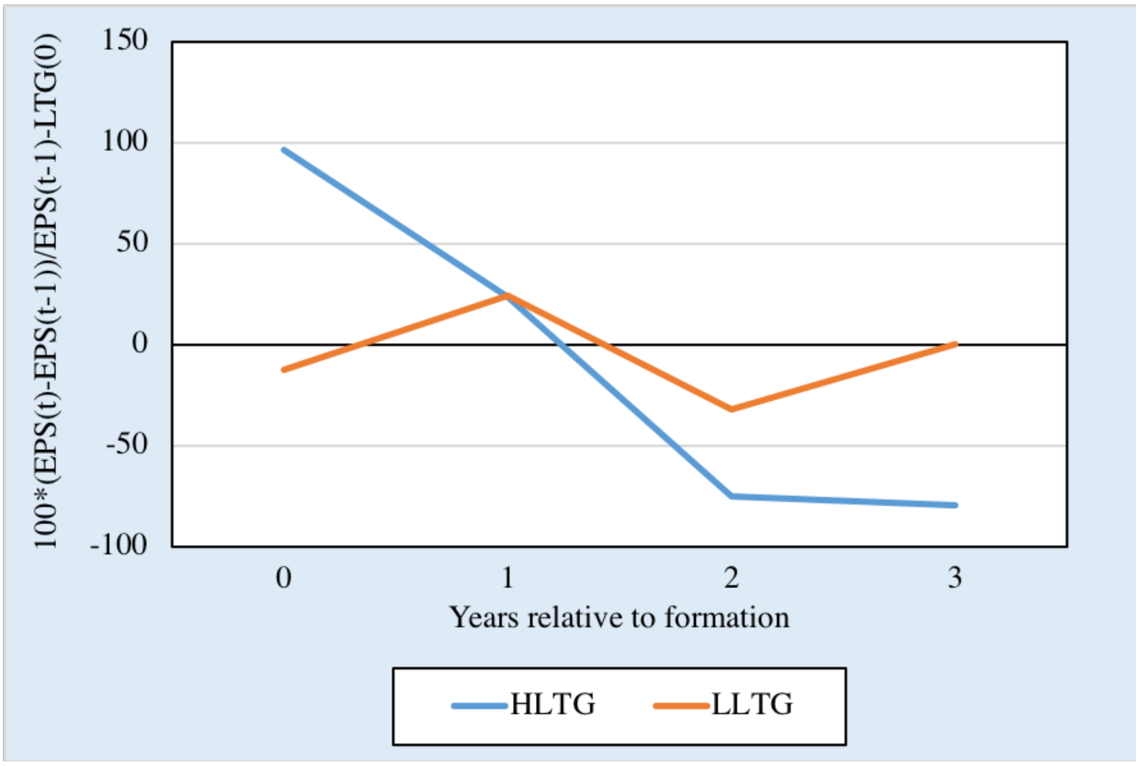
Note: We constructed portfolios for December of each year from 2009 to 2016, ranked by analysts' expected long-term growth (LTG) in EPS. We normalised EPS to 1 three years prior to portfolio formation, and here report the average evolution in EPS for the stocks included in the highest (HLTG) and lowest (LLTG) decile portfolios, from *t*-3 to *t*+3.

Figure C.2 – Evolution of LTG



Note: We constructed portfolios for December of each year from 2009 to 2016, ranked by analysts' expected long-term growth (LTG) in EPS. Here, we report the mean LTG forecast for the highest (HLTG) and lowest (LLTG) decile portfolios, from *t*-3 to *t*+3.

Figure C.3 – Realised growth



Note: We constructed portfolios for December of each year from 2009 to 2016, ranked by analysts' expected long-term growth (LTG) in EPS. Here, we report the realised growth in relation to LTG forecast at t=0, for the highest (HLTG) and lowest (LLTG) decile portfolios.

Table C.2 – Risk Characteristics of Portfolios

	LTG Decile										
	1	2	3	4	5	6	7	8	9	10	All
Std. Dev.	0.105	0.086	0.134	0.051	0.052	0.052	0.044	0.071	0.106	0.098	0.049
Beta	1.155	0.942	0.850	0.871	0.811	0.857	0.857	0.939	0.929	1.085	0.930
Worst 20%	-0.050	-0.036	-0.027	-0.033	-0.028	-0.032	-0.028	-0.037	-0.041	-0.038	-0.035
Ret < 0	-0.028	-0.023	-0.016	-0.018	-0.014	-0.016	-0.014	-0.019	-0.019	-0.025	-0.019
Ret > 0	0.037	0.027	0.029	0.029	0.028	0.026	0.030	0.028	0.030	0.031	0.029
Best 20%	0.052	0.047	0.048	0.049	0.049	0.049	0.052	0.057	0.049	0.062	0.052

Note: In December of each year between 2009 and 2016 we form decile portfolios ranked by analysts' median LTG forecasts. For each portfolio we compute the standard deviation of returns from 2010 to 2017. Beta was calculated by regressing each portfolio against the FTSE All-Share Index weighted by market capitalisation. 'Worst (20%)' and 'Best (20%)' represent the average return of the worst and best performing stocks in each portfolio, respectively. 'Ret < 0' and 'Ret > 0' denote the average monthly return of portfolios when the FTSE All-Share Index return is negative and positive, respectively.

Appendix D

Table D.1 – Risk Characteristics of Portfolios

	LTG Decile										
	1	2	3	4	5	6	7	8	9	10	All
Std. Dev.	0.111	0.084	0.069	0.057	0.068	0.062	0.059	0.085	0.092	0.129	0.047
Beta	0.930	0.878	0.861	0.838	0.822	0.933	0.835	1.053	0.917	0.979	0.905
Worst 20%	-0.031	-0.029	-0.030	-0.024	-0.024	-0.027	-0.023	-0.027	-0.019	-0.032	-0.027
Ret < 0	-0.012	-0.017	-0.023	-0.015	-0.020	-0.025	-0.019	-0.025	-0.018	-0.021	-0.020
Ret > 0	0.012	0.013	0.013	0.012	0.014	0.013	0.014	0.012	0.014	0.012	0.013
Best 20%	0.037	0.036	0.036	0.040	0.039	0.037	0.040	0.053	0.046	0.040	0.040

Note: In December of each year between 2011 and 2016 we form decile portfolios ranked by analysts' median LTG forecasts. For each portfolio we compute the standard deviation of returns from 2012 to 2017. Beta was calculated by regressing each portfolio against the FTSE 100 equally weighted Index. 'Worst (20%)' and 'Best (20%)' represent the average return of the worst and best performing stocks in each portfolio, respectively. 'Ret < 0' and 'Ret > 0' denote the average monthly return of portfolios when the FTSE 100 Index return is negative and positive, respectively.