MARISKA DOUWENS-ZONNEVELD

# Animal Spirits and Extreme Confidence

## No Guts, No Glory?

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## No Guts, No Glory?

Instinctief Handelen en Extreem Vertrouwen

Zonder Lef Geen Succes?

Thesis

to obtain the degree of Doctor from the
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by

Maria Geertruida Zonneveld
born in Limmen

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Acknowledgements

Animal spirits and confidence are the key ingredients of the dissertation that lies in front of you. Surprisingly, my pregnancy did not reinvigorate such “mood effects”, but caused an upward shift of my sentiment curve. It also showed me the edge of reason, at the benefit of sellers of baby products.

In my former occupation as equity analyst, I closely encountered three kinds of economic actors i.e. managers, investors and analysts and collected a wealth of anecdotal evidence on their behavior, myself including. Although my timing of entering the investment industry just months after the burst of the dotcom bubble in 2000 may seem unfortunate, it contributed to a wide collection of different stories. It reinvigorated a “spontaneous urge” to dig further into the question how human behavior impacts finance decisions and the resulting outcomes.

Along the somewhat unpredictable or random walk of writing a dissertation, my sentiment swung from bullish to bearish and vice versa. It seems like running a marathon, which is a very lonely process, but with many people cheering for you at the sideline. Sometimes, you feel the pain, but then a euphoric feeling takes over and keeps you going. The big pitfall of doing research is that you no longer keep your feet on the ground, but rather sink into the vast pool of theory, data and models. Reality checks are no longer embedded in your work flow, but have to be actively chased at. The people on the sideline are crucial for staying connected with the “real” world, for getting refueled with new energy and for reaching the finish line.

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It goes without saying that I am heavily indebted to my family, for giving their unconditional support and love. You deserve my full attention, but sometimes my thoughts were miles away. The good part of being the youngest sibling in the family or so-called “jongste poppetje” is that you are taken care of when you do not yourself, and you do not even have to ask for it. Mom, I highly admire the energy and devotion that you put in not only raising us as kids, but our offspring as well. You are a true “multi-tasker” from whom we can learn a lot. You keep your head cool, but your heart warm. Dad, your entrepreneurial spirit is all around in the house and you show us the benefits of hard work and perseverance. For those to whom I qualified myself as the so-called “koude kant”, your warm gestures are a big support. Special thanks to Jeroen, who took the dare to picture my ideas, as shown on the cover page.

Dear Enrico and Juliette, I am blessed with having you as part of me and my life. You refilled me with new energy and restored the balance between head and heart. Enrico, our shared interest in economics brought us together when the exchange of books was still in person rather than via the Internet! You more or less decided for me to proceed when I was having doubts, as I would otherwise never forgive myself. Even while fully loaded with work yourself, you stuck to your promise to work from home on Fridays and taking care of our precious. Juliette, you do not always stick to the rules of rational behavior and your preferences seem inconsistent across time or across the persons who look after you. It suggests that our unpredictability is an innate human trait, clearly not to be sorry for!

One of the main takeaways of this project is that moving to extremely low rather than extremely high confidence is detrimental for our well-doing and well-being, let alone any multiplier effects. I sincerely hope that this awareness is contagious and translates into more acts of confidence going forward.

Mariska Douwens-Zonneveld, Amsterdam 2012

# 1 Introduction

## 1.1 Research Scope

Following the financial meltdown in 2008, the “homo economicus” has suffered another blow, from which we have yet to fully recover. Every opportunity seemed a free call option with only upside potential, thus translating into risk seeking behavior and moral hazard. All kinds of economic actors, e.g. consumers, investors, managers, financial intermediaries and government bodies, fell prey to these human traits. Countervailing power was heavily eroded, but instead economic reality caught up with the fads. This has happened before in economic history, which raises the question on the persistence of the impact of human behavior on economic decisions.

There is ample anecdotal evidence on behavioral distortions, but we will narrow our focus to three types of economic actors e.g. managers, investors and financial intermediaries. When assuming that the latter two fully rely on their own judgment rather others, the moves of company management and its competitors should be their prime concern. Their competitive advantage lies in understanding and anticipating such events and whether or not one should read something in these between the lines.

For instance, a change in segment reporting seems a frivolous event with no major market impact. However, the financial community may consider such changes, which rendered the prior years’ sales and profit breakdowns useless, rather suspicious than a way of improving transparency[1]. It could even trigger price reactions, albeit not necessarily irrational if the new structure fuels second thoughts on the company’s cash flow generation. In addition, diversifying acquisitions could raise the eyebrows, as investors are better able to accomplish diversification themselves. Such moves could stem from management’s overconfidence or from catering to investors’ needs who themselves are irrational. It raises the question if and to what extent interaction between management and investor sentiment may affect decisions and stock price behavior.

In addition to the primary goal of providing an opinion on the company’s financial health and its stock valuation based on (past) company events, analysts and investors[2] may also be interested in so-called soft attributes, such as management characteristics. This can translate into hefty stock price reactions when board changes are announced. One could earmark management as confident, aggressive or overconfident respectively as conservative[3] or diffident by recalling a list of management’s wise or stupid actions from

[1] Especially if management feels that their shares undervalued, they can defend such changes in segment reporting by pointing at the similarity of this new structure versus (higher valued) peers

[2] This excludes the so-called “quants” who tend to be focused on realized rather than expected numbers as to wipe out any bias.

[3] These wordings are also used by Malmendier and Tate (2008) in their press-based approach of overconfidence

the past. From this list, one could implicitly infer a probability of similar actions or positive momentum or the risk of mean-reversion. In particular, extreme events tend to come up easily to one's mind, so one has to be careful to properly weigh these.

Perfect expectations aside, investors and analysts face the challenge of how to respond to news which does not comply with their current view, especially when the news is negative. The easiest response is to give management the benefit of the doubt and hope for the best. This wishful thinking implies underreaction to news. However, when results keep disappointing, patience is put up to the test. Frustration accrues, which can result in an overreaction to the next disappointment, which could just happen to mark the tipping point. One has to choose between biting the dust and revising an opinion early and the risk of losing credibility or money by hanging on too long on old ideas.

The careful reader will have detected various biases and heuristics enclosed in these stories. If systematic rather than random, such distortions can spill over to real and financial markets and drift us away from an optimal resource allocation. In this dissertation, we explore how these non-rational factors, which Keynes (1936) qualified as "animal spirits", can not only be detected, but also how these may impact performance. We consider performance from a broad perspective, which can refer to both financial and operating performance. We capture the former by return measures for (specific) capital providers, while operating performance refers to how well someone is doing his job. The latter is used for equity analysts and measured by forecast accuracy. In particular, the wide coverage on overconfidence and the neglect of both diffidence and the use of heuristics in economic decision making caught our eyes.

More specifically, we seek to develop a measure for managerial confidence that, unlike current literature, captures both the upper and the lower confidence extremes. As diffidence hardly attracts any research attention, one could get the impression that this phenomenon has no major economic impact, which is tested in this dissertation. Conversely, overconfidence has been widely investigated, including its impact on corporate decisions. However, its impact on financial performance is hardly covered, which we seek to address in this dissertation. Our findings indicate that particularly extremely low rather than high levels of confidence hurt financial performance, including risk adjusted stock returns, In addition, we also put more color on our confidence measure by exploring whether or not there are specific company, industry or time characteristics.

By nature, the measurement of a human bias is subjective, but we seek to mitigate this by not only earmarking one particular corporate decision as a sign of confidence, but taking various corporate decisions into account instead. Another advantage of this multidimensional approach is that mitigating or spill-over effects also become pronounced in the overall score. As more information is required, this comprehensive approach comes at the cost of sample observations. The overall low scores in our sample of large US firms suggest that mitigating factors are at work. In the last chapter, we will also discuss countervailing power mechanisms.

In addition to contributing to the string of research on managerial (over)confidence bias, we also dig into an area which seems hardly touched in economic literature, such as the use of heuristics by equity analysts. Analyst (over)optimism, strategic bias and over- or underreaction to news has been widely documented, but these effects could be (partly) captured by an underlying driver, such as anchoring and adjustment. The jury is not out whether or not this specific rule-of-thumb can cause extreme confidence as well[4], but this is not relevant for our empirical analysis of analyst forecast errors. A distinctive feature f our approach is that we disentangle anchoring from (insufficient) adjustment. Next to our contribution to the hardly covered use of heuristics in analyst forecasts, our large sample enables us to perform analyses on lower or non-aggregate levels, such as the analyst, firm or industry. Furthermore, we also allow for strategic bias or higher estimates for firms with lower transparency i.e. strategic bias and asymmetric attitudes to short and long-term risk.

Overall, we find that what we qualify as innate optimism or optimism that is not reflected in the chosen anchor[5] itself is persistent, except on the firm level. Furthermore, our results point to anchoring, except when analyst forecast errors are considered from an industry perspective or when the anchor is a negative number. Also, we find an overall tendency for less pessimism for small firms, which corroborates with strategic bias. With regard to the adjustment process, we mostly find underreaction to recent news with asymmetric responses to good and bad news. We also find this asymmetry in long and short-term risk measures. While long-term risk is considered upside potential, short-term risk is seen as downside. These results imply that analyst forecasts are affected by both human biases and the use of heuristics, which could result from the fact that they need to satisfy the needs of various internal and external clients.

## 1.2 Research Structure

This dissertation is comprised of several parts, as summarized in figure 1.2.1. First, we provide a theoretical background on the decision making process and rationality or the lack thereof. Subsequently, we discuss extreme forms of management confidence and how this may impact financial performance. Lastly, we investigate the use of heuristics in analyst forecasts. We explore to what extent anchoring and adjustment may impact analyst forecast errors or accuracy. Some argue that the inefficient adjustment to information or too high emphasis on one's anchor is a sign of overconfidence. Alternatively, it is intuitive to think that the refuge to such rules shows a lack of confidence in one's own judgment. As earlier discussed above, there is no consensus on how to interpret the use of this specific

[4] We refer to Block and Harper (1991) for a detailed discussion on anchoring and overconfidence in estimates.

[5] For instance, one could chose peak earnings as an anchor for an earnings forecast

heuristic. In summary, we explore to what extent extreme forms of confidence, from either a management or an analyst's perspective, may impact financial or operating performance.

In chapter two, we discuss theoretical concepts and empirical findings on psychological biases and the use of heuristics in decision making. Although there is extensive research in this field, we keep our focus on the most commonly cited human errors in behavioral finance.

In chapter three, we proceed with an overview of theory and empirical research on irrationality in finance. We discuss optimal behavior for managers, investors and financial intermediaries e.g. maximization of net present value respectively the risk-return tradeoff and how biases and the use of heuristics can cause deviations from this optimum. In addition to the common distinction between irrational investors and irrational managers, we also distinguish financial intermediaries as a separate category. In the next chapters, we will further dig into behavioral distortions, or specifically extreme confidence and anchoring and adjustment.

In chapter four, we narrow our scope to the overconfidence bias and we construct a degree of confidence variable. Although widely documented, research on overconfidence is mainly aimed at unfolding its impact on corporate decisions or investment and acquisitions in particular. We take a reverse approach in which the Rotterdam adage of "actions speak louder than words" is imperative. We take those decisions as a starting point and infer a degree of confidence from a wide array of investment, financing and operational actions. Conversely, when narrowing the scope to only one course of action for earmarking companies as overconfident, mitigating and leveraging effects to other decisions are ignored. In addition to including various dimensions, we define confidence as a (five-point) scaled rather than a binary variable. Instead of only looking at extreme high levels of confidence or overconfidence, it also enables us to measure the impact of extreme low confidence.

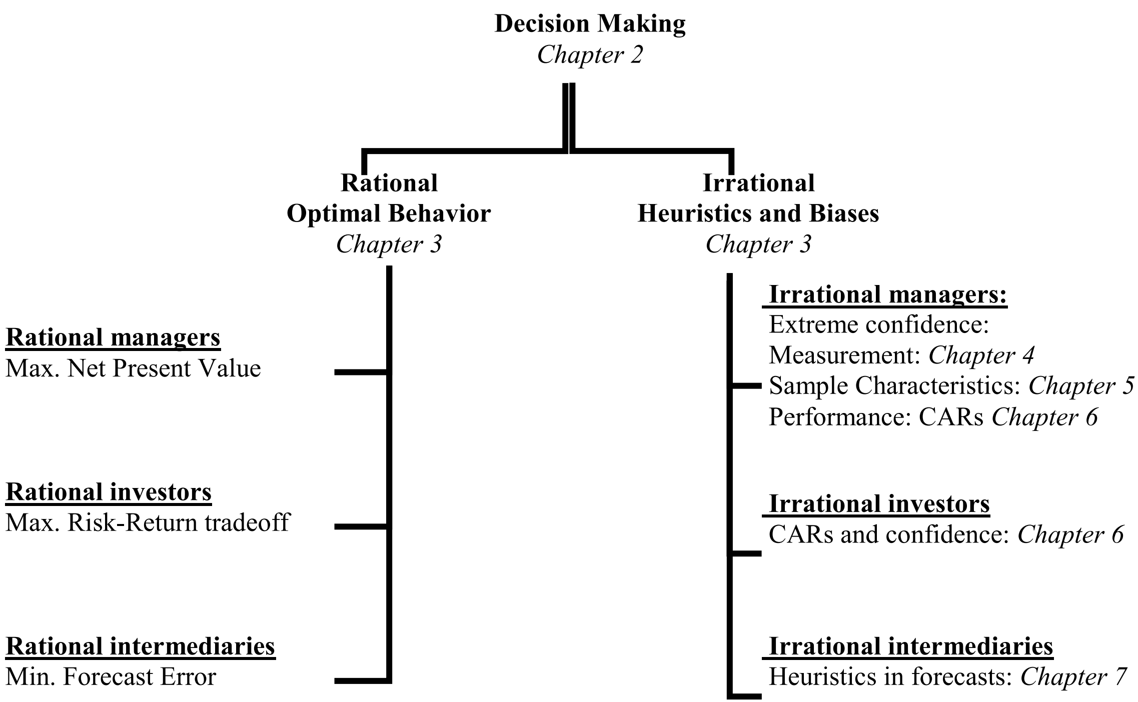
Chapters five to seven comprise our empirical analysis. In chapter five, we empirically explore the characteristics of extreme confidence companies, including time and industry characteristics. In addition, we extend our analysis of company confidence to financial performance, which is defined as the return to the capital providers. Regardless of the direction of the confidence bias, moving to extreme situations of confidence suggest suboptimal decisions and hence lower performance.

In chapter six, we proceed with performance characteristics and explore if moving to extreme confidence levels translates into abnormal stock returns for varying time horizons. We explore if the market already anticipates such moves or only reacts to such moves. We also include a measure of investor confidence to allow for spill-over effects of managerial and investor confidence.

In chapter seven, we move from biases to the use of heuristics. Specifically, we look at the use of the anchoring and adjustment heuristic and its impact on analyst performance or forecast errors. We explore if analysts use prior year earnings as an anchor for current year's forecasts, controlling for innate bias, risk appetite and insufficient adjustment to past news events. In addition to analyzing analyst forecast accuracy on an aggregate basis by performing pooled panel regressions, we redo the analysis on lower levels e.g. the analyst, firm and on the industry level.

Lastly, we conclude with a brief summary and discussion how to interpret our findings in today's and tomorrow's environment.

**Figure 1.2.1: Dissertation Structure**




Note: Max. stands for maximizing, min. for minimizing. CARs stand for Cumulative Abnormal Stock Returns.

# 2 Decision making under uncertainty

## Abstract

In this chapter, we discuss various stages in the decision making process and what violations of rationality may occur. We narrow our scope to widely documented biases and heuristics in financial decisions and leave the underlying motivational factors behind these distortions to psychologists. Given the high amount of decisions that we face these days, we may easily forget that this is a continuing and complex process. It consists of several stages, which offer also room for retrospection before moving forward. Even when a decision is made, the process continues as the generated feedback ploughs back into our beliefs and preferences i.e. we learn from our experiences. As an alternative to expected utility theory, we discuss Kahneman and Tversky's prospect theory (1979), which gives room to non-rational factors in our decisions. This theory can be regarded as one of the main drivers behind the paradigm shift away from efficient markets.

## 2.1 Introduction

*"Like Prometheus, they defied the gods and probed the darkness in search of the light that converted the future from an enemy into an opportunity. The transformation….has channeled the human passion from games and wagering into economic growth, improved quality of life, and technological progress."*

*From the introduction of "Against the Gods" by Peter Bernstein (1996)*

As Bernstein (1996) notes, emerging ideas on risk, its measurement and its consequences fuelled a paradigm shift away from posing our future at the mercy of divine powers. The genie is left out of the bottle, but it also increases complexity by adding a wealth of decisions covering the future instead of only the (near) present. This decision power does not only increase our responsibility, but also creates new risks, such as getting disconnected with the present or becoming irrational. A big shock can enforce a reality check, but history suggests that, sooner or later, such learning effects fade out as irrational behavior is very persistent.

The big challenge in investigating irrational behavior is not only how to define and measure it, but also how to unfold its impact on decision making and performance, including interaction effects. Before we move to the measurement and impact of non-rational factors, we provide an overview of the decision making process and possible distortions due to human errors.

## 2.2 Stages in decision making

Figure 2.3.1 at the end of this chapter summarizes the stages in decision making and how human errors may distort these. In this section, we will briefly describe rational decision making, as shown in the left-hand side of the figure. In the next section, we will discuss possible noise in this process, as indicated by the right-hand side of figure 2.3.1.

Preceding any decision, we start with a set of ex ante preferences and beliefs. In the widely used definition of economics by Robbins (1932)[6], the scarcity of means force us to set priorities before making decisions. Von Neumann and Morgenstern (1944) make the concept of rational preferences more explicit by defining several requirements: completeness, transitivity, independence and continuity. In addition, time, risk and social preferences can be incorporated in their theoretical framework. With regard to beliefs, rationality requires that we consider all possible options of satisfying our needs given

[6] Robbins (1932) defines economics as "the science which studies human behaviour as a relationship between ends and scarce means that have alternative uses"

budgetary, legal, time and legal constraints. In addition, all relevant information, both public and private, is collected and properly processed to ensure consistency.

The next step is to translate a set of ex ante beliefs and preferences into specific goals. The widely used expected utility theory advocates that we should aim at maximum final wealth. Deviations from this situation, which we denote as a challenge, provoke action in order to close this gap. For instance, one could seek to address certain constraints, or, which is easier, just redefine priorities.

One could have different views on discrepancies between the target and current situation. In this respect, Kahneman and Lovallo (1993) distinguish between a broad and a narrow view respectively between an inside and outside view. If both a broad and outside perspective is adopted, the risk of cognitive errors is lowest. The former implies that challenges are not considered on a standalone basis, but seen as part of a bigger set of opportunities. The latter indicates that mere statistical probabilities rather than subjective probability estimates are used in the decision making process.

Before making a final decision, additional data can be gathered to update beliefs and preferences, conditional on time and budgetary constraints. Absent any bias, views are updated according to Bayes' rule, which is indeed a widely adopted assumption in economics.

Finally, a decision is made, but the whole process does not end here. In addition, rational decision makers should properly process feedback for evaluating decisions, updating beliefs, preferences and taking corrective action if needed.

Although our discussion suggests a very orderly and predictive process of distinct stages of decision making, those stages may comingle or even be skipped in reality, due to time or cognitive constraints in reality. As Keynes (1936) already remarked, sometimes, our "animal spirits" or "a spontaneous urge to action" just take over. Afterwards, we may seek to rationally justify such actions to comfort people that we were in control rather than acted because we just felt for it.

## 2.3 Violation of rationality in decision making

The stages in the decision making process as discussed in the prior section all involve human judgment and hence bear the risk of irrationality. When a decision maker acts in line with a certain decision or normative model, but uses biased input, he is qualified as biased. Alternatively, if a he properly forms preferences and beliefs, but uses a wrong decision model, he can be qualified as irrational. Even if both the input and decision follow the rules of rationality, irrationality may occur with regard to the processing of feedback. Field and experimental studies have indeed unfolded several inconsistencies resulting from cognitive errors and resource constraints. We will briefly discuss some well-known biases and types of heuristics and subsequently relate these to the different stages in decision making as shown in the right-hand of figure 2.3.1.

First of all, we note that our set of ex ante beliefs and preferences is not fixed, but a moving object instead. When we come of age and are able to make informed rather than instinctive or impulsive decisions, our beliefs and preferences[7] change accordingly. For a child, less abstract needs prevail, such as quenching thirst or security, while more abstract needs like self-fulfillment gain in importance when we grow older. Regardless of how we learn i.e. by inductive or deductive reasoning, both ways entail a risk of human error.

Our preferences may be distorted by inconsistencies related to timing, risk attitude or social pressure. DellaVigna (2009) highlights that self-control problems can cause a preference for a combination of a short-term gain and long-term pain to the alternative of a short-term pain and long-term gain. Conversely, there is also evidence of hyperbolic discounting or the use of higher discount rates for near future payoffs than for far future payoffs. With regard to risk, various experiments have shown that people do not have a linear risk attitude, but underweight merely probable outcomes vs. certain ones. Allais (1953) described this phenomenon as the certainty effect. Also, risk aversion does not prevail when people are faced with certain losses. Instead risk-seeking behavior or an all or nothing approach tends to be followed in such situations. Lastly, social pressure can cause people to drift away from their own preferences.

With regard to the formation of our beliefs, cognitive constraints, such as bias or the use of heuristics, could have a distorting impact. Current literature[8] provides a long list of biases, which can also interact. For instance, optimism, the illusion of control and the better-than-average-effect all fuel overconfidence. If things go right, self-attribution and confirmation bias can make us feel better than average and give us the illusion of control. Conversely, in adverse situations others are blamed or the event is ignored, the latter of which is referred to as cognitive dissonance.

In order to deal with budget and time constraints, one could resort to the use of heuristics. In their pioneering work on decision making under uncertainty, Tversky and Kahneman (1974) distinguish three types of heuristics for estimating probabilities and outcomes. These comprise representativeness, availability and anchoring and adjustment, all of which can be related to cognitive biases[9].

[7] We define ex ante beliefs and preferences as the set of beliefs and preferences when a challenge arises and has to be tackled

[8] We refer to Larwood and Whittaker (1977) on self-serving bias in organizations and overly optimistic planning, Weinstein (1980) on overoptimism about future life events and the illusion of control, Svenson (1981) on our driving skill perceptions (better than average effect), Alicke (1985) on positive traits and the illusion of control, while negative traits are externalized. Shefrin (2007) provides an extensive overview

[9] None of these biases are attributable to penalties or to motivational effects like wishful thinking

The representativeness heuristic implies that probabilities are evaluated by the degree to which a certain event is representative of or resembles another event. This can translate into base rate neglect i.e. the gambler's fallacy, sample size neglect i.e. the false belief that the full population characteristics are reflected in a small sample as well, a lingering belief in the law of small numbers i.e. failure to see a sequence of events as random, the inclusion of irrelevant information and misconceptions of regression and causality. The availability heuristic implies that the probabilities of events are estimated by the ease with which such observations come to one's mind. Biases, such as familiarity, salience and imaginability[10] , can inflate perceived probabilities of these events. Finally, the anchoring and adjustment heuristic refers to distortions caused by starting from an initial value and subsequently making adjustments to find the answer. As adjustments are insufficient, different starting points yield different estimates, which are biased towards the initial value. It results into miscalibration or too narrow confidence intervals. Furthermore, probabilities of simultaneous events are overestimated, while those of separate events are underestimated. All in all, these distortions in beliefs and preferences could induce persons to pursue other goals than maximization of final wealth.

Examples of alternative goals comprise the maximization of the *change* in wealth, minimization of regret or the completion of an acceptable percentage of a certain objective. Simon (1956) came up with the term satisficing, a blend of satisfying and sufficient, to describe the latter phenomenon. When we narrow the scope to a manager, alternative goals could entail maximizing status and compensation, a preference for small short-term gains to large long-term gains, minimizing the risk of being replaced or catering to investor needs (social pressure).

After defining goals, discrepancies between the current and target situation can be detected. As earlier discussed, Kahneman and Lovallo (1993) distinguish various perspectives from which such challenges can be viewed. The risk of bias is highest if a narrow and inside view is taken. The former implies that challenges are considered on a standalone basis with no interaction or covariance with other (future) opportunities. Closely related to this, challenges can be framed in a certain way, which implies that only selective elements instead of the whole environment are included. An inside view also reinvigorates the risk of bias, as challenges are seen only from the decision maker's point of view. This can induce anchoring to current values or extrapolation of recent trends instead of the use of mere statistical or objective probability rates.

Biases and the use of heuristics can also dampen learning effects or rational processing of feedback. Negative feedback can be ignored for false reasons, a phenomenon known as cognitive dissonance, or used to blame others. Alternatively, self-attribution

[10] Kahneman and Tversky (1974) also mention effectiveness of a search set and illusory correlation

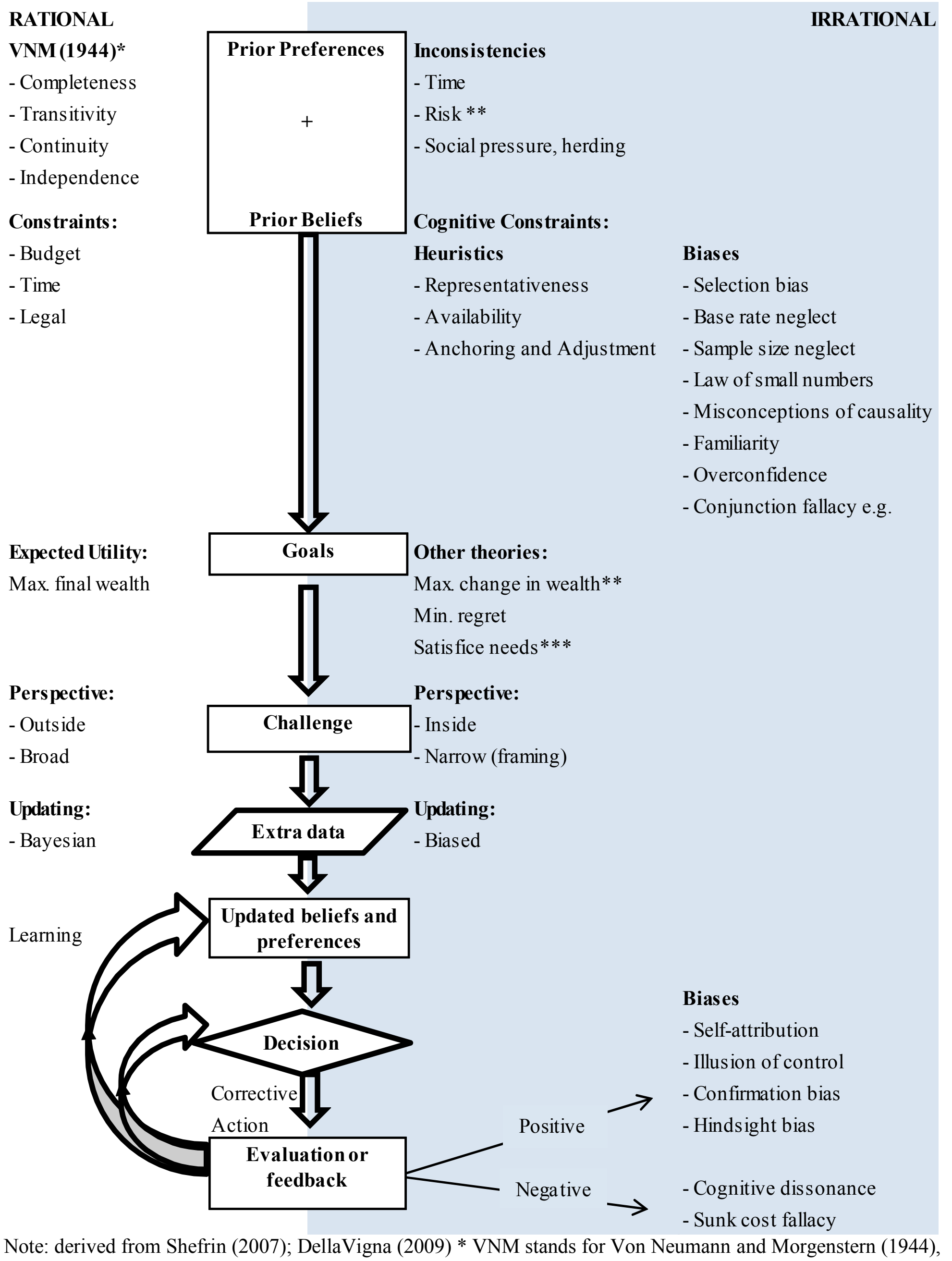
could result into taking credits for positive outcomes or hindsight bias can fuel the false belief that one already knew the outcome. It also implies that only feedback that confirms current beliefs is taken into account.

As a response to widely documented violations of expected utility theory, alternative theories on decision making emerged. The pioneering work of Kahneman and Tversky (1979), denoted prospect theory, addresses violations with regard to risk. It marked a turning point in economics by explicitly allowing for human errors when decisions are made under uncertainty. Unlike expected utility theory, prospect theory is not a normative theory, but only descriptive of how decisions are made under uncertainty. Based on various experiments, they argue that people use a relative rather than absolute definition of utility. This is also embedded in their theory, which defines utility as gains and losses versus a reference point rather than a final state of wealth. Closely related to this, Thaler (1980) detects the endowment effect, which implies that the value of a good given up is perceived higher than the value of acquiring that good. This also implies that one's starting position or reference point matters when determining value. In line with experimental outcomes on risk attitude, prospect theory uses decision weights instead of mere statistical probabilities when calculating value. These weights are mostly lower, except in loss-making situations or very unlikely events, such as winning a lottery or losing your home in a fire. In the latter situations, overweighing tends to occur.

As prospect theory aims to mirror the outcomes of revealed rather than rational preferences and beliefs, its value function has a different shape than that of expected utility curve. The main difference is that the former captures asymmetry in responses to positive and negative changes of wealth by its concavity in the gains area, convexity when losses occur and a steeper slope for losses than for gains. In this way, Kahneman and Tversky (1979) show that utility is higher when gains are segregated and losses combined. If there is a combination of gains and losses, value is highest when small losses are combined with larger gains and when small gains are segregated from larger losses.

In the next chapter, we will narrow our scope to three types of economic agents, i.e. investors, managers and financial intermediaries. We will discuss literature on optimal behavior and violations thereof. Furthermore, we will specify our view on efficient behavior for these agents, on which we will build our empirical analysis in chapters five to seven.

**Figure 2.3.1 : Stages in Decision Making**




Note: derived from Shefrin (2007); DellaVigna (2009) * VNM stands for Von Neumann and Morgenstern (1944), ** See prospect theory by Kahneman and Tversky (1979), *** Simon (1956) introduced this term, a blend of satisfy and suffice. Max. (Min.) stands for maximizing (minimizing).

# 3 Irrationality in finance


## Abstract

In this chapter, we follow up on the most common distinction in behavioral finance which is made between irrational managers and irrational investors. In addition to managers and investors, we also include irrational intermediaries as a separate category. For each of these actors, we discuss theories on optimal behavior and how biases and the use of heuristics can distort the picture. We define net present value maximization as an optimal strategy for managers, requiring returns consistent with Carhart's (1997) four factor model as efficient for investors and finally mean forecast error minimization as the main priority for intermediaries. Although most studies only assume one type of actor to be irrational if any, spill-over effects between different actors may occur as well. We therefore conclude this chapter with some thoughts on contagion and herding behavior.

## 3.1 Introduction

*"The market can stay irrational longer than you stay solvent."*

*Attributed quote to Keynes by Harrod (1951)*

In the attributed quote to Keynes, the possibility of rational agents not living up to their reputation is addressed. As a result of limits to arbitrage or other constraints[11], such as regulation, the lack of perfect substitutes or noise trader risk, mispricing may persist. For instance, insider trading rules hamper the so-called strong form of market efficiency, which implies that even inside information is reflected in prevailing asset prices. These rules prohibit "buying or selling stock in breach of a fiduciary duty or other relationship of trust and confidence while in possession of material, non-public information." Also, the weak and semi-strong forms of market efficiency are subject to debate. DeLong et al. (1990) show that the long breath and persistence of noise traders can make it too risky for arbitrageurs to bet against the market for restoring the equilibrium.

Alongside limits to arbitrage, the existence of market anomalies suggests that the EMH does not hold. These phenomena fuel a string of research on irrational market participants. Barberis et al. (1998) note that cross-sectional tests may be able to reject the efficient market hypothesis. However, results can be conflicting and ambiguous. We will discuss this in more detail in section 3.4 when we address irrational investors. On an aggregate or portfolio basis, inefficiencies are clearly harder to detect or not long-lived. Still, Bouman and Jacobsen (2002) find persistence of the so-called "Halloween indicator", which implies that returns from May up to and including October are structurally lower than in the other six months of the year. Baker and Wurgler (2002) find support that rational managers exploit such inefficiencies by timing the market. Fama and French (1992, 1996) dismiss these results and argue that these patterns reflect differences in riskiness instead of market inefficiency.

In addition to limits to arbitrage and the existence of market anomalies, the recognition that distortions in human behavior may be very persistent rather than faded out on an aggregate basis, fuelled a paradigm shift away from the prevailing "homo economicus". Long before the development of the efficient market hypothesis (EMH) by Fama (1970), economists acknowledged the role of subjective elements in decision making. Keynes (1936) introduces the concept of "animal spirits", while March and Simon (1958) highlight human limitations and develop the bounded rationality concept. Still, the role of irrational human behavior in economics stayed marginal until Kahneman and

[11] In this case, budgetary constraints are the restraining factor, but time constraints from regular performance evaluation can also render a bet against inefficient markets unattractive.

Tversky (1979) developed prospect theory. This descriptive theory challenges the widely accepted expected utility theory, which used to be imperative when analyzing decision making under uncertainty.

Notwithstanding empirical backing, behavioral finance continues to be at a competitive disadvantage compared to modern finance, for which data availability, data cost and the hard to measure subjective elements are to blame. In addition, Bernstein (1996) adds that "it has been criticized for representing the Theory Police rather than a separate school of thought." Also, within behavioral finance, the research coverage between irrational investors and irrational managers is highly imbalanced. Irrational managers get clearly less attention, while Heaton (2002) remarks that the impact of individual biases on corporate decisions is easier to detect than those on stock valuation. He points at the infrequent nature and noisy feedback of major corporate decisions, which makes the learning curve flatter. As a result, inefficiencies are not easily arbitraged[12] away. In the next sections, we will discuss various types of economic agents who are prone to behavioral distortions i.e. managers, investors and their intermediaries or analysts.

## 3.2 Irrational managers

### 3.2.1 Introduction

*"It is the optimistic denial of uncontrollable uncertainty that accounts for managers' views as themselves as prudent risk takers and for their rejection of gambling as a model of what they do."*

*Kahneman and Lovallo (1993)*

Risk attitude is a key ingredient when defining confidence levels, as it could translate into too low hurdle rates when evaluating the net present value of investments. Based on interviews with managers, March and Shapira (1987) find that managers consider risks as controllable or modifiable[13], which makes their skills relevant. Furthermore, they tend to view risk from a downside perspective rather than upside potential. However, according to the standard rational model of economics, managers are just gamblers when making business decisions. Their role and added value is restricted to updating probability beliefs of the gambles in a consistent or Bayesian way and to maximizing expected utility. Kahneman and Lovallo (1993) summarize the ambivalence of managers, who are prone to the conflicting biases of "unjustified optimism and

[12] Takeovers are a costly mechanism for addressing inefficiencies
[13] In the words of March and Shapira (1987), managers seek to change the odds

unreasonable risk aversion". Management's too optimistic beliefs or "bold forecasts" do not translate into their "timid" decisions, due to their risk preferences.

Similar to stock markets, we can argue that on an aggregate level, such as the industry, all the parties' information involved should be reflected. In addition to public information, this entails insider, including competitor sensitive, information. This can become a competitive edge that pays off in better financial performance when properly used. Cash-strapped companies can fall into a downward spiral of getting lower quality information, thus increasing the probability of bad decisions and underperformance compared to sector peers. Goel and Thakor (2008) argue that overconfident CEOs underinvest in acquiring project relevant information, thus increasing project selection errors and the quality of information used to judge the CEO.

If some managers do not act rationally, we could assume that their actions are random, thus not impacting overall resource allocation when assuming efficient markets. Otherwise, arbitrage in the form of management replacement or corporate takeovers should occur. However, high transaction cost could render such actions very costly. Some researchers doubt the impact of management on the firm. March and Simon (1958) propose that organizations create functions which effectively limit discretion and diminish the importance of any one individual's characteristics. Population ecologists like Hannan and Freeman (1977) argue that environmental and organizational constraints contain managerial impact. Conversely, the findings of Haleblian and Finkelstein (1993) imply that top management teams and CEO dominance positively contribute to performance in certain industries. Bertrand and Schoar (2003) also find support for management impact on a wide range of investment, financial and organizational decisions.

We adopt the view that managers indeed matter and so does the risk of irrationality on their behalf. This leaves capital providers as a cost-effective source for pushing managers to take rational decisions. In order to infer the optimal behavior for the firm, we need a normative theory on the optimal allocation of real assets[14]. This brings us to the theory of the firm as developed by Jensen and Meckling (1976) and its offspring.

### 3.2.2 Optimal behavior for the firm

The firm's very existence is justified in its mission statement, which is usually concise. It transforms into a strategic blueprint when measurable objectives are defined of which progress can be monitored. In Anglo-Saxon countries, shareholder value maximization tends to be the adage. Alternatively, firm value maximization or other objective functions with a more explicit risk target could be imperative. The latter could prove very useful for entities performing a critical social function, such as financial

[14] Strictly speaking, managers do not only allocate real assets, but also intangible assets such as human capital. In addition, they can also engage in financial asset allocation by taking financial stakes in other companies

institutions. Jensen and Meckling (1976) briefly describe some theories on firm behavior before discussing their own well-known approach, which we extend by including alternative theories.

Coase (1937) is among the first to define a theory around the firm and argues that its optimal size is based on the transaction cost of organizing production compared to the market. Alternatively, one could adopt a portfolio approach, by defining the firm as a portfolio of real assets. We could argue that the current value of a standalone real asset is given by the investment outlay, but estimating its future or expected net present value is more complicated than that of tradable financial assets. In addition to a higher heterogeneity of real assets, pricing information is less readily available if at all or can be heavily distorted by illiquid markets[15]. This also makes it hard to calculate correlations between different assets. Furthermore, the benefits of diversification as highlighted by Markowitz (1952) are traded off against the potential loss of control, scale and expertise (including market share or competitive edge), all of which are hard to quantify. Furthermore, these portfolio optimization models implicitly assume that firms can lend or borrow resources indefinitely at a fixed rate, thus making capital structure irrelevant, which brings us to Modigliani and Miller (1958). When we construct our company confidence measure in chapter four, we will relax this assumption and explicitly take into account a firm's financial slack when judging management's action.

Modigliani and Miller (1958) focus on the hurdle rate or the cost of capital to determine the optimal investment level. They argue that if the objective is to maximize market value of the firm, the hurdle rate for each investment is equal in all cases and not dependent on its funding. This assumption of capital structure irrelevance is closely related to the Capital Asset Pricing Model (CAPM) assumption that investors have an indefinite ability to tap funds at a fixed rate, which equals the risk-free interest in a CAPM-framework. However, due to market imperfections, such as the tax benefits of debt, bankruptcy and transaction costs, capital structure indeed seems relevant for the firm's investment decisions and valuation.

Alchian and Demsetz (1972) explicitly include monitoring cost in the firm's decisions on investment, which result from the fact that production is a joint effort. Jensen and Meckling (1976) criticize this view, as outsiders like suppliers and customers are not explicitly taken into account. In response, they develop a theory of the ownership structure for deriving an optimal scale or investment level for the firm. The authors emphasize that a firm is not an individual but "a legal fiction" where contractual relations align conflicting objectives of its stakeholders. In this framework, an insider's risk attitude towards underdiversification[16] and the net agency cost of outside equity[17] and debt funding can be

[15] There are few so-called pure asset players listed

[16] Underdiversification occurs when the manager puts his money in this firm rather than spread it over other ones

explicitly taken into account. These agency costs do not only comprise monitoring costs, but also include bonding costs and the residual loss or lower firm value from making suboptimal decisions.

Myers (1977) follows up on Jensen and Meckling (1976) by making the cost of suboptimal investment explicit. He infers that the optimal debt level is inversely related to the share of growth opportunities, which can be qualified as a discretionary item. Conversely, current assets in place are non-discretionary and should be financed with debt. In the latter case, debt positively relates to profitability and operating leverage. When assuming shareholder instead of firm value maximization, risky debt reduces the current market value of a firm holding real options. These real options increase collateral value and imply a transfer of wealth from equity to bond holders, as the latter do not downwardly adjust their required rate of return. In order to prevent this, underinvestment to the optimal level may occur. As real options are riskier than their underlying value, Myers (1977) argues that instead of using a constant cost of capital, different discount rates should be used for cash flows from current assets and from future investment. For firms with valuable growth options, a CAPM based discount rate would overestimate the correct hurdle rate.

Myers and Majluf (1984) take this a step further and investigate the financing options for firms with growth opportunities when capital structure is indeed relevant. Their model is based on information asymmetry between management and shareholders, which can result in firms refusing to issue stock and hence giving up value enhancing investments. In order to prevent such situations, managers may prefer to create financial slack or show a preference for internal funds. If external funds have to be attracted, debt is preferred to equity, also in line with pecking order theory.

The above mentioned views on the firm's optimal investment level or size[18] primarily focus on the required rate of return of the capital providers. However, the needs of other stakeholders have to be "satisficed" or sufficiently met as well. As we have seen in the US automotive industry, you cannot keep squeezing the margins of your suppliers at your own company's benefit. It would prevent the latter from getting their activities funded and hence lead them into bankruptcy. Also, we see that public outcry or product boycotts can be harmful to firms that do not respect labor rights and hence cause their staff to be "nickel and dimed"[19] .

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[17] Apart from their funding role, outside equity providers perform no other functions in the organization unlike inside equity holders
[18] Size is similar to cumulative investments, so these objectives are similar
[19] We borrowed this term from Barbara Ehrenreich (2001)

### 3.2.3 Biases and heuristics in management behavior

Shefrin (2007) provides an extensive overview on biases and the use of heuristics in finance, which includes a string of examples how to detect and correct distortions in human behavior. In academic research on irrational managers, we see a high interest for the optimism and overconfidence biases. Despite measurement and validation problems common to any psychological trait, these biases may attract such a high attention as they trigger action rather than inaction.

Roll (1986) was among the first to embed hubris in company decision making or specifically, in corporate takeover activity. As Hayward and Hambrick (1997) commented, Roll does neither specify the definition of hubris nor the ways to test it. Roll simply state that hubris causes bidders to overpay for their targets, as synergy benefits are too optimistic. Such valuation errors could stem from overestimated return expectations, underestimated risk respectively overestimated ability to control risk. As a result, the market value changes of the target (increase) respectively the acquirer (decrease) or the new combination (slight decrease).

Hayward and Hambrick (1997) follow the dictionary when defining hubris as exaggerated pride or self-confidence. Still, this definition requires further specification in order to measure it. They test Roll's hubris hypothesis by using several indicators for hubris. These comprise the acquirer's recent performance, recent media praise, a CEO's self-importance as measured by the relative cash and non-cash salary compared to the second highest executive and a composite factor constructed from these three indicators. All indicators seem positively related to acquisition premiums paid, especially when corporate governance is weak, thus supporting the hubris hypothesis. In addition, hubris seems negatively related with subsequent stock performance.

Malmendier and Tate (2005, 2008) explore if there is a relation between overconfidence and investment, including acquisitions. They consider overconfidence from a returns rather than a risk perspective[20]. They define overconfidence as overestimating returns and use two overconfidence measures. One proxy is based on option exercise behavior or actually the lack of exercising deep in the money options and the other one is based on business press characterization. In their 2005 paper, they find that investment by overconfident CEOs is more sensitive to cash flow, especially in equity-dependent firms. In a later study, they find that acquisitions are 65% more likely to happen if a CEO is qualified as overconfident, especially if there are no financial constraints i.e. no external financing is required. Overconfident CEOs are more likely to use cash rather than stock as takeover currency when the firm has a low valuation vs. peers. Also, the market reaction seems more negative than an acquisition by a non-overconfident CEO, which

[20] The authors assume constant relative risk aversion (CRRA) in their model

seems further aggravated by a diversifying move. These empirical findings support Myers and Majluf's (1984) pecking order theory and Roll's (1986) hubris hypothesis.

Ben-David et al. (2007) consider overconfidence from a risk perspective and use the degree of miscalibration of the CFO's views on the expected performance of the market index and company stock as a proxy. They separate optimism from overconfidence with the former implying that the mean is overestimated, while the latter implies that volatility is underestimated. The results from their survey indeed confirm miscalibration, as realized market returns fall within the CFO's 80% confidence interval only 38% of the time i.e. confidence intervals are indeed too narrow[21]. As overconfident CFO's use lower discount rates in their net present value calculations, they also invest more. In addition, they use higher financial leverage with a longer duration, have lower dividend payouts and are more likely to buy back shares. Finally, they find empirical support for the argument put forward by Hayward and Hambrick (1997) that stock momentum impacts CEO hubris. CFOs tend to be more confident after periods of high stock market (S&P 500) returns, while past returns of their own stock also seem to have an impact.

Goel and Thakor (2008) also adopt a risk perspective and argue that overconfident managers can both underestimate risk and deliberately opt for more risk in order to increase the probability of getting promoted. The reasoning behind this is that manager's perceived ability is inferred from the average pay-off of their decision(s), while the risk associated with these decisions cannot be disentangled. Their model shows that an overconfident manager is more likely to be promoted than a rational one, thus suggesting that overconfidence is persistent in companies. These biases can make managers believe that their firms are undervalued, encourage overinvestment and risk taking and fuel a preference for internal to external finance, consistent with pecking order theory.

Concluding, current literature offers various proxies for overconfidence, such as merger and acquisition behavior e.g. the number, size and acquisition premium paid, option exercise behavior by CEOs, characterization by the business press, miscalibration of management's expectations on returns, relative CEO compensation, CEO prominence and past stock performance. Overconfidence or specific forms thereof can be considered from a first-order returns perspective (too high) or second-order risk perspective (too low) or both. We are not aware of research that defines management overconfidence from a third or fourth moment perspective. The former or skewness would imply a higher focus on the occurrence of more extreme values. Overconfidence would imply negative skewness or a lower expected frequency of negative events than under a normal distribution, thus inflating the mean. The latter or kurtosis can be reconciled with underestimated variance.

[21] In other studies on miscalibration on different topics such as those of Svenson (1981) on driving skills, similar percentages are found

In addition to adopting a single or narrow perspective, current literature makes no distinction between different degrees of confidence. Furthermore, the relation between overconfidence and corporate decisions gets most attention, in particular investment - acquisitions included - and financing. However, in order to qualify a corporate decision as irrational (ex post), we need to incorporate performance measures as well. In chapter four, we will further elaborate on our view on company confidence and develop an alternative measure.

## 3.3 Irrational investors

### 3.3.1 Introduction

*"How do we know when irrational exuberance has unduly escalated asset values? ... We should not underestimate or become complacent about the complexity of the interactions of asset markets and the economy."*

*Alan Greenspan in a speech to the American Enterprise Institute for Public Policy Research on December 5th 1996*

While managers are in charge of allocating real assets, investors allocate the money. When analyzing irrationality, it is easier to assume that only one of these actors is assumed to be irrational, but in his 1996 speech, Greenspan already warns for spill-over effects. As we have yet to fully recover from the financial market meltdown in 2008, the risk of contagion has become evident. We would also rather fine-tune Greenspan's question to "How do we know ex ante when irrationality is about to take over?" Is it possible to define red flags when we move on the verge of irrationality, so collective corrective action can be taken? The big difficulty is that today's prices are an aggregate of our beliefs and preferences, so it is hard to detect where irrationality is hidden, unless it has infected us in total. We refer to Hirshleifer (2001) for an extensive overview about irrational asset pricing, while we limit ourselves to some main findings on irrational investor behavior in the next section.

### 3.3.2 Optimal investment behavior

Markowitz (1952) was the first to develop a theory on the optimal investment portfolio by building on the benefits of diversification. In his framework, Markowitz explicitly rejects the rule that investors maximize discounted expected returns, as this ignores variance, which is "an undesirable thing". He showed that when combining different assets, overall portfolio risk or variance could be lowered without compromising disproportionately on returns. By combining assets or portfolios, one could plot a line or efficient frontier, which provides the highest (mean) return given a certain amount of risk or variance. By definition, the market portfolio is efficient and lies on this line. Markowitz' portfolio theory is a key ingredient of the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965).

The CAPM infers the optimal risk-return ratio by combining a risk-free asset with the market portfolio and argues that only systematic or non-diversifiable risk is rewarded. Unlike investments in real assets, the CAPM assumes that investors are indeed able to lend and borrow unlimited amounts at the risk free rate. This indefinite borrowing capacity at a fixed (risk free) rate implies that investors do not need to create financial slack now for future investment[22].

Alternative asset pricing models can incorporate additional risk factors, such as the two additional factors distinguished by Fama and French (1992, 1996) e.g. size and book to market value, to which Carhart (1997) added a fourth factor of recent stock price momentum. Another well-known asset pricing model is developed by Ross (1976) and known as Arbitrage Pricing Theory or APT. While the CAPM (-based) model(s) captures sensitivity to the market portfolio, APT enables the inclusion of various economic factors. When asset prices diverge from the model-implied return, arbitrage will restore the gap. A more simple and non-regression based model is the Dividend Discount and Gordon Growth Model developed by Gordon (1959, 1962) [23], In addition to model modifications, alternative objective functions like minimizing downside risk, maximizing tracking error e.g. result in different optimal asset allocations.

### 3.3.3 Biases and heuristics in investor behavior

There is a string of academic research on irrational investor behavior, but we limit ourselves to some well-known studies, the results of which can be conflicting. De Bondt and Thaler (1985) empirically found stock return patterns which cannot be reconciled with efficient markets. The winner-loser effect or the reversal of stock returns over a three to five year period suggests that investor overreact at first, which is corrected in later years. On a shorter horizon, however, Jegadeesh and Titman (1993) found an opposite effect of underreaction to news. This causes stock momentum on a short horizon of three to twelve months. Under- and overreaction could stem from various biases or the use of heuristics, such as summarized in figure 2.3.1 in the previous chapter.

Daniel et al. (1998) propose a theory of securities that incorporates both market under- and overreaction, based on two well-known psychological biases: investor overconfidence and self-attribution. They define overconfidence as overestimating the precision of one's forecast or private signal, which results into overreaction to private

[22] Open end funds can resort to alternative, but more expensive means of finance by issuing new shares
[23] We refer to the Appendix for more details on the Gordon Growth model (1962)

signals and underreaction to public signals. Alongside a constant confidence level, they introduce a dynamic element in their analysis by including self-attribution. The latter causes asymmetric shifts in investors' confidence as a function of their investment outcomes. Events that confirm an individual's beliefs and actions tend to boost confidence too much, thus intensifying overreaction. On the contrary, disconfirming events weaken confidence too little. Their model incorporates these effects and predicts short-run momentum and long-term reversals in stock prices.

Barberis et al. (1998) explain overreaction and underreaction by the use of representativeness heuristics respectively the conservatism bias. They define a dynamic or learning model in which actual earnings follow a random walk, but individuals believe that earnings either follow a steady growth trend e.g. extrapolation or are mean-reverting e.g. the gambler's fallacy. The investor is Bayesian when updating his beliefs, but uses an inaccurate model of the earnings process.

Another well-known market anomaly is the phenomenon that Mehra and Prescrott (1985) described as the equity premium puzzle. They state that the level of risk aversion necessary to explain the large differences in returns between stocks and (risk-free) T-Bills would have to be implausible high and is hard to reconcile with rationality[24]. Benartzi and Thaler (1995), solve this so-called equity premium puzzle by explicitly incorporating mental accounting. The frequency with which investors make up the balance or count their profits and losses impacts their risk appetite. Investors suffer from myopic behavior as they use a narrow time frame for measuring portfolio performance. The authors find that people will have to evaluate their portfolios every 13 months to make them indifferent between the US historical distributions of returns on stocks and bonds.

Odean (1998A) tests the disposition effect[25] or investors' tendency to hold losing stocks too long and sell winners too early. In analyzing trading records for 10,000 accounts at a discount broker from 1987-1993, Odean finds empirical support that investors indeed have a strong preference for realizing winners rather than losers. This behavior does not seem to stem from rebalancing portfolios, avoidance of relatively higher trading costs of lower priced stock or by a rational belief of reversal in subsequent periods. However, the results can be complied with prospect theory, which implies high decreases in value from losses and higher increases in value from small gains relative to large gains. Alternative explanations are that investors fall prey to the gambler's fallacy or an irrational belief in mean reversion. This could translate into cognitive dissonance and/or overoptimism that the tide will turn for the better for the losers.

[24] In the model by Mehra and Prescott (1985), this risk aversion parameter can take up a value of up to 10, whereas previous estimates and theory imply that this coefficient should be close to one. Still, their model fails to explaining the puzzle when allowing for such a high risk aversion

[25] Shefrin and Statman (1985) introduced this term

In another paper, Odean (1998B) investigates how overconfidence can impact financial markets. Odean (1998B) distinguishes between price takers, insiders or market makers and infers how trading volumes, market depth, expected utility, expected returns, price quality and volatility could be affected. He finds that impact on the market can be very different if at all and is conditional on who wrongly processes the information or overly relies on its own information when overconfident. In a later study, Barberis and Odean (2001) empirically investigate overconfidence for which they use excessive trading as a proxy. They find that overconfidence is a gender trait or more prevalent at men, who thus heavily erode stock returns by not recouping their high transaction costs.

Closely related to availability heuristics, Shefrin (2007) identifies affect or familiarity heuristics. This could explain wide empirical evidence of home bias or overrepresentation of domestic stocks in international investment portfolios. Also, one could argue that the availability heuristic fuels bubbles by taking recent performance of a stocks in a certain sector as indicative for peers as well. During the Internet bubble, adding dotcom to your company name could pay off in significant abnormal price appreciation as indicated by Cooper et al. (2001). In later work (2005), they found that the opposite of removing any connection with the dotcom era also paid off in higher abnormal returns.

Fama and French (1992, 1996) dismiss behavioral explanations and argue that these patterns reflect a compensation for risk instead. In other words, the model for predicting asset prices is misspecified instead of markets being inefficient. The main challenge is how to deal with this joint hypothesis problem of choosing the right asset price model and properly forecasting its parameters. Furthermore, it is not always easy to disentangle ex ante from ex post information i.e. there is a risk of hindsight bias. Both stated and revealed preferences are based on utility, but differ in timing and measurement. Stated preferences are inferred from surveys or intended instead of actual decisions. Albeit more forward looking or ex ante, well-known shortcomings of survey-based research, such as strategic behavior or biased responses could have a distorting impact. People do not always put their money where their mouth is. Conversely, revealed preferences are an ex post measure and based on real acts which speak louder than words.

### 3.3.4 Interaction between investors and managers

Not only rational investors, but also rational managers can exploit stock price distortions. Shleifer and Vishny (2003) find support for stock market driven acquisitions, as a predator's high stock valuation makes preys look cheap. Furthermore, negative abnormal returns following seasoned equity offerings or initial public offerings are widely documented, which also suggests that management indeed exploits the opportunities of overvalued stock. Baker and Wurgler (2002) find that rational or smart managers have a persistent impact on capital structure by timing the (irrational) market. This is also supported by Huang and Ritter (2009) who find more equity issues when the (implied) cost of equity is low.

On the negative hand, inefficient markets could cause managers to use wrong hurdle rates for investments. This can be interpreted as an irrational response to an irrational phenomenon. Stein (1996) proposes a market-based approach when managers maximize short-term stock prices or when it faces financial constraints. Otherwise, the fundamental asset risk approach is to be preferred.

## 3.4 Irrational intermediaries

### 3.4.1 Introduction

As expectations of individual investors cannot be directly observed in the market, analyst forecasts can be used instead. Stickel (1992) and Chen et al. (2005) suggest a higher market impact of more accurate analysts, thus implying that if an analyst has persistent bias in his estimates and hence incurs larger forecast errors, investors will take him less seriously. Abarbanell (1991) also raises the question if analyst earnings estimates are a good proxy for market expectations, as some research suggests a reverse relation in which the sign and magnitude of analyst forecast revisions are positively related with (sign and magnitude) of past price changes rather than the other way around. Trueman (1994) and Campbell and Sharpe (2009) suggest that market participants may adjust for cognitive errors and reporting strategy of analysts. Especially when looking at analyst recommendations, the number of positive outweighs the number of negative[26] recommendations by far. This could even trigger contrarian reactions to news, such as upward adjustments in forecasts, but downward price movements.

### 3.4.2 Optimal behavior for financial analysts

Francis and Philbrick (1993) state that sell-side analysts operate in a multi-task environment and have to perform a balancing act of optimally weighing - often conflicting - interests of many internal and external clients. Paradoxically, these different input factors of the analyst's utility function can cause earnings forecasts to be biased without being irrational from the analyst's point of view. We refer to this as strategic bias. Regardless, analysts can still beat time-series models in forecasting earnings[27] and market efficiency may be preserved as well.

Incentive mechanisms, management relations and reputation concerns are considered the main drivers behind strategic bias in analyst behavior. Francis and Philbrick

[26] We note that in the investor community, "NEUTRAL" or "HOLD" recommendations are usually considered a so-called "institutional SELL".

[27] We refer to Brown et al. (1987), Fried and Givoly (1982), Affleck-Graves et al. (1990)

(1993) find that following less favorable stock recommendations, analysts issue optimistic earnings forecasts to improve management relations. Das et al. (1998) also see management relations or access to non-public information as critical and find this translated into higher optimism for lower predictability firms. Hence, forecast bias is instrumental to improving forecast accuracy[28]. Lin and McNichols (1998) and Dugar and Nathan (1995) argue that underwriter and/or banking relationships fuel optimism, which could pay off in future corporate deals.

Driven by similar motives as strategic bias, McNichols and O'Brien (1997) put forward self-selection bias. This implies that analysts report their true unbiased beliefs, but cherry-pick stocks with a favorable[29] outlook and exclude stocks with bleak prospects. In statistical terms, this practice truncates the left tail of the earnings distribution and hence inflates the mean.

Gu and Wu (2003) also focus on the shape of the earnings distribution and argue that skewness could may render analyst forecast bias, including pessimism, rational. If the analyst's objective is to minimize mean absolute forecast error, negative (positive) earnings skewness results in analyst optimism (pessimism). In such situations, the usually higher (lower) median rather than mean forecast is most optimal and accurate.

### 3.4.3 Biases and heuristics in analyst behavior

Analyst bias or its upward version or analyst optimism in particular, is a widely documented phenomenon[30]. It could be a deliberate strategy to win management's favor, a rational response to skewed earnings distributions or reflect cognitive errors. Only the latter can be categorized as irrational. Paradoxically, Richardson et al. (2004) find both optimism and pessimism in analyst forecasts, conditional on the forecast horizon. Both effects can be explained by strategic bias or focus on good relations with management. For longer-term forecasts, analysts tend to be too optimistic, while they "walk-down" their estimates to a level that management can beat when the announcement date approaches.

In addition to the possibility that inflating forecasts could be an analyst objective itself, analysts could be prone to irrationality or make cognitive errors. Tversky and Kahneman (1974) describe how various heuristics and associated biases may distort expectations about probabilities and cause over- or underreaction to news. This implies that irrational behavior of analysts spills over to investors as well. Earlier, we discussed

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[28] We refer to Lim (2001)

[29] Other arguments beyond a firm's outlook impact the decision to follow (drop) coverage on the firm, such as potential corporate deal flow and the analyst's visibility or potential market impact, which is likely to be bigger for thinly rather than widely covered stocks

[30] We refer to Fried and Givoly (1982), Butler and Lang (1991), Francis and Philbrick (1993), Abarbanell (1991), Stickel (1990), Lys and Sohn (1990)., La Porta (1996)

that there is also research that investors are smarter and adjust for bias, albeit they may not sufficiently do so.

In their pioneering work on the behavioral impact on market expectations, Froot and Frankel (1989) empirically show overreaction or excessive speculation to exchange rate expectations. Underreaction and overreaction are also widely investigated in equity markets and empirical results can be conflicting. Although these models measure the stock market rather than analyst reaction, these can be easily modified by taking (scaled) forecast related variables as dependent variables.

With regard to earnings news, De Bondt and Thaler (1990) empirically find analyst overreaction, but Mendenhall (1991) finds opposite results of underreaction. Trueman (1994) reconciles this ambiguity in a model which predicts underreaction to extreme and overreaction to small earnings surprises. He also allows for asymmetric price reactions to good and bad earnings news, as investors can anticipate such distortions in analysts' forecasting behavior. Similarly, Easterwood and Nutt (1999) allow for asymmetric responses to (unexpected)[31] earnings information, which is lacking in previous models[32]. They argue that overreaction, underreaction and optimism should be disentangled before concluding whether analysts either irrationally process earnings-relevant information or suffer from strategic bias. Their evidence of overreaction to good and underreaction to bad news complies with systematic optimism. Conversely, both strategic and selection bias suggest that optimism is opportunistic and a predefined goal. When looking at reactions to analyst forecast errors, Ali et al. (1992) and Abarbanell and Bernard (1992) find support for analyst underreaction. In this chapter, we use quarterly earnings surprises as a proxy for recent analyst forecast errors.

Similarly, Lys and Sohn (1990), Klein (1990) and Abarbanell (1991) provide empirical evidence of underreaction to past stock price news. However, Fried and Givoly (1982) find a reverse causal relation that earnings forecasts and revisions impact share prices. Also, Chen et al. (2005) find that analysts have a bigger market impact the longer their track record and the better their forecast accuracy. Abarbanell and Lehavy (2003) include both earnings and stock momentum news in the equation and find both under- and overreaction, conditional on whether the news positive or negative[33]. Also, they find a relation between the shape of the forecast error distribution[34] and unexpected accruals, thus suggesting that management plays a role as well.

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[31] They define unexpected prior earnings change as the change in excess of the average earnings change over the preceding three years

[32] They refer to Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999), who base their model on the representativeness and anchoring heuristics respectively overconfidence and self-attribution respectively the dominance of momentum traders vs. news watchers

[33] Easterwood and Nutt (1999) also make a distinction between good and bad news

[34] They explicitly investigate middle and tail asymmetry of the forecast error distribution

Research on the underlying drivers or the heuristics used for forming expectations is, however, scarce. Affleck-Graves et al. (1990) specifically test the impact of judgmental heuristics on analyst forecasting skills compared to time-series earnings models and non-experts. The latter use the same information as the time-series model i.e. historical earnings, but can also apply heuristic rules when forming earnings expectations. Analysts are superior to both and heuristics indeed seem to have an impact, as optimism bias is also present in non-expert forecasts. This also complies with Tversky and Kahneman (1974) who show that decisions of both naive and expert people show systematic biases from the use of judgmental heuristics. Amir and Ganzach (1998) argue that heuristics, or specifically optimism[35], representativeness and anchoring, jointly influence earnings forecasts and forecasting errors. They attribute overreaction to forecast changes to representativeness and underreaction to forecast revisions[36] to anchoring. They find asymmetry of overreaction to positive and underreaction to negative forecast modifications, with longer forecast horizons amplifying the effects.

Consistent with anchoring and adjustment, Campbell and Sharpe (2009) find that expert consensus forecasts on macro-economic variables are systematically biased toward the value of previous months' releases. However, the market seems to properly account for this by only reacting to surprises beyond those caused by anchoring and adjustment. Cen et al. (2010) explore the impact of anchoring on earnings forecast errors and asset prices and find higher (lower) forecast errors for firms with EPS estimates below (above) the anchor. They reason that when analysts anchor to the industry median forecast, they are reluctant to issue a forecast well away from this number, even if their information implies that they should deviate. Unlike Campbell and Sharpe (2009), Cen et al. (2010) find that the stock market does not correct for this bias, as risk adjusted returns are lower (higher) for below (above) median EPS firms.

## 3.5 Irrationality multiplied

So far, we have only considered irrationality for an isolated group of economic actors, or specifically managers, investors or intermediaries. On the one hand, we could argue that other parties serve as a countervailing power and hence indeed keep irrationality within certain limits. For instance, Baker and Wurgler (2002) find that managers exploit overvalued stock by issuing new equity i.e. by timing the market. On the other hand, interaction within and between various agents can feed a positive feedback mechanism. Such herding behavior is not irrational by definition and can be a self-fulfilling prophecy.

[35] Amir and Ganzach (1998) use the term leniency to indicate optimism
[36] They relate forecasts to realized prior period earnings (denoted forecast changes) and to prior period forecasts (denoted forecast revisions) and refer to both when using the term forecast modifications

If we all behave like the "homo economicus", this results in Pareto efficiency. The other side of the coin is that irrational behavior could solicit irrational responses, thus resulting in a real impact on the allocation of resources away from the optimal level.

Stein (1996) highlights the threat of using improper discount rates in capital budgeting decisions by using market-based hurdle rates instead of a long-term fundamental rate. Closely related to this, management could feel pressured to cater to investor's needs, even if these are not rational. Baker et al. (2004) wonder if this argument could account for the conglomerate waves in the 1960s. When irrationality becomes widespread rather than isolated, we can significantly drift away to extreme situations. The illusion of control, confirmation bias and self-attribution bias, can cause successes to be wrongly claimed and reinvigorate irrational moves. Sooner or later, reality will catch up with the facts rather than the fads.

Such extremes have proved to be not that rare in history. Following the Tulip and South sea bubble centuries ago, another financial meltdown occurred from which we have yet to recover. After just entering this millennium with unprecedented high stock valuations, markets collapsed shortly hereafter. After a cool down period of the dotcom bubble, a real estate and financial market boom and bust followed. The dark side of bubbles also became pronounced in fraudulent practices, such as the huge Ponzi-scheme of Madoff. Before moving back to normal[37], such shocks can trigger disproportionate responses in the process of resetting our prior false beliefs and preferences. It brings us back to those basic questions whether the real value is hidden in the promise of the future or in what we have on hand today.

## 3.6 Our view on optimal behavior

So far, we have discussed various concepts on optimal behavior for firms, investors and financial intermediaries. In this thesis, we make the following assumptions in order to qualify behavior as irrational. If the use of human biases or heuristics still contributes or does not necessarily jeopardize the realization of an optimal situation, we do not consider it irrational,

With regard to management, we assume maximization of the net present value (NPV) of the firm as its primary goal. This requires a proper assessment of current cash flow generation, of future growth opportunities and the cost of capital. In addition to disagreement in literature between using a constant rate vs. a time-varying or business-varying risk rate, one could disagree between using the current implied risk premium or the long-term risk premium. In our NPV-based approach, we assume a constant cost of capital, thus implying a constant relative risk aversion which is proportionate to time

[37] In statistical terms, we can refer to this as mean reversion

unlike hyperbolic discounting. If the market would show a disproportionate negative value impact of a bad investment, this would encourage managers to maintain the current status quo rather than to take risks. Similarly, for companies trading close at their critical reference point, such as the peer group multiple, it could make sense to minimize downside risk by following a cautious strategy.

With regard to rational investors, we adopt the view that it should not be possible to earn cumulative abnormal returns by using all publicly known information i.e. we assume semi-strong market efficiency. In addition to the four factors in Carhart's (1997) model, we consider the company's confidence level or change thereof as publicly known information.

Our approach to optimal analyst behavior is mostly driven by practical reasons i.e. data availability and considers minimization of squared forecast errors as the primary goal. Although it may be intuitive to think that negative forecast errors in particular or too high earnings estimates are taken negatively by the investment community, we do not assume such asymmetry. As seasonality can make quarterly earnings forecasts more volatile, one could refrain from using squared errors and instead take the year to date net forecast error. Paradoxically, the earlier discussed strategic bias or deliberate forecast error could result in lower forecast errors overall, as it enables better management access and company information. Due to quarterly earnings releases, it is easy to track the accuracy of equity analysts. Conversely, there is no such reality-check for credit analysts, unless a company does indeed move into financial distress. An example of indirect evidence that other objectives may have prevailed is the ban of Internet analyst Henry Blodget from the investment industry and what has become known as "the global settlement case of state attorney Eliot Spitzer. The ten largest investment banks were charged a USD 1.4bn fine to settle issues of conflict of interest within their businesses during the Internet boom. More severe regulation followed in order to contain such behavior and to force analysts to provide an accurate view on the companies under coverage.

## 3.7 Summary

In this chapter, we have discussed both theoretical and empirical work on irrationality of different economic actors, or specifically managers, investors and financial intermediaries. Among these actors, irrational managers are thinly covered. It continues to be a thorny issue to judge whether an agent is indeed acting irrational, as his objective function is very hard to unveil if at all. Furthermore, we have to rely on revealed beliefs and preferences rather than stated ones when empirically investigating these behavioral distortions. It is easier to judge the rationality of decisions ex post than ex ante, due to the benefit of hindsight. We adopt the following view with regard to rationality. We consider net present value maximization of the firm as optimal for managers, a risk-return tradeoff consistent with Carhart's (1997) four factor model as efficient for investors and finally the minimization of forecast errors as an optimal strategy for intermediaries.

With regard to human biases, overconfidence and optimism bias are most widely covered. However, different definitions and proxies are used, which makes it more difficult to compare these measures with each other. Research on the use of heuristics is skewed to irrational investor behavior, while it is hardly investigated for financial intermediaries, such as security analysts. This may seem surprising, as analysts can be considered a major supplier of information to investors and their expectations may even be put on par with those of investors.

In chapter four, we will narrow our scope to company confidence. We infer a composite degree of confidence measure from various corporate actions by leveraging on the insights of current theory and empirical research. Our approach differs from prior research as we do not only consider confidence from the upper extreme, but also consider lower confidence levels. Furthermore, we take a reverse approach by inferring confidence from corporate decisions and by explicitly exploring performance characteristics.

# 4 An alternative company confidence measure


## Abstract

In this chapter, we infer a comprehensive degree of confidence measure from corporate decisions on operations, investment and funding for large US companies. Our approach differs from current research as it measures different degrees of confidence instead of only the upper extreme, while we also take a multidimensional approach for inferring our confidence measure. We do not only link overconfidence to one specific corporate action, but take a more comprehensive approach. We argue that only if executive management exhibits extreme high or low confidence across different types of corporate decisions, they can be assigned with an extreme confidence degree.

## 4.1 Introduction

The previous chapters revealed that it is a big challenge to define and measure human biases, their interaction and their impact on financial decisions. In current research on biased management behavior, we see a high interest for overconfidence and – closely related with this – hubris. Despite various definitions and proxies, overconfidence or specific forms thereof is commonly viewed from a single or a narrow perspective. Most studies make no distinction between different degrees of confidence, but only focus on overconfidence or the upper extreme. Either explicitly or implicitly, overconfidence comprises other biases, such as the ability to earn higher returns i.e. the better-than-average effect or the illusion to better control risk.

In current literature, overconfidence is inferred from a wide array of predominantly ex post information. This comprises merger and acquisition behavior e.g. the number, the size and acquisition premium, CEO option exercise behavior, characterization by the business press, surveys on the miscalibration of risk and return expectations, the CEO's importance as reflected in relative compensation and prominence in the annual report or from the firm's past stock performance. After earmarking firms or people as overconfident from these actions, the impact on corporate decisions is investigated and capital budgeting decisions in particular catch a lot of attention. Although ex ante information can predict rather than explain corporate behavior, it is hard to get sufficient unbiased data.

In this chapter, we add to current research by developing a more comprehensive and multidimensional measure of confidence. Instead of a sole focus on the upper extreme, we examine differences between the upper and lower ends. Although the term confidence is subjective by definition, we seek to mitigate this by using various instead of only a single corporate action for assigning confidence levels. This is in line with Ben David et al. (2007), who investigate the relation between overconfidence and a range of corporate policies on capital spending, M&A behavior, funding and shareholder payout. In addition, the inclusion of several dimensions can absorb interaction effects between different decision variables. On the one hand, this approach implies an extra hurdle for arriving at extreme confidence levels when there are mitigating factors. On the other hand, positive feedback mechanisms could prove otherwise.

The chapter is organized as follows. First, we discuss our definition of confidence and how this compares to prior research. Inspired by a body of research on both overconfidence and corporate decision making, we define seven confidence indicators for inferring a total confidence score. We conclude the chapter with an overview on our methodology of assigning a degree of confidence by each indicator. In chapters five and six, we will empirically test our multidimensional confidence measure.

## 4.2 Our definition of confidence

We seek to incorporate both return and risk characteristics in our definition of confidence. Strictly speaking, overestimating returns refers to overoptimism, while underestimating risk or return variability captures overconfidence. However, these two biases cannot be easily disentangled and current literature on overconfidence considers these aspects more or less interchangeable as well. We require that our definition can be compared to alternative definitions of overconfidence, but also easily modified to a definition of low confidence or diffidence as well. In addition, we are looking for a comprehensive meaning that captures the many forms how confidence may materialize.

We define high confidence as overestimating the potential to create value i.e. to realize positive net present value by perceiving oneself better than average and more in control. As a result, management overestimates returns, underestimates risk or both, all of which can inflate net present value (NPV) calculations. Next, we expect these beliefs to materialize in behavior, such as a search for growth by bold[38] investments, acquisitions and diversification. Cash availability and the degree of operating leverage are restraining factors in this respect. As external funds are undervalued in the view of highly confident manager, confident managers follow a pecking order with a preference for internal funds or low dividend payouts to attracting debt, while equity issuance is seen as the last resort for funding new projects. If, however, management sees *no* further positive NPV projects going forward i.e. the optimum level of investment has been achieved, they could resort to investing in their own company or undertake share buybacks. We would also expect higher confidence to translate into more aggressive earnings forecasts and a bigger risk of missing these, which makes accruals accounting more attractive.

In the prior chapter, we referred to Kahneman and Lovallo (1993) who paradoxically stated that managers are "subject to the conflicting biases of unjustified optimism and unreasonable risk aversion". Our definition of high confidence can be complied with their view as it does not ignore risk aversion, but only implies that due to high confidence (on controllability of events, return expectations e.g.), perceived risk is lower than the true, underlying risk. If high confidence was only to reflect risk, we would have similar mean returns but significantly higher variance for high confidence companies. Conversely, if high confidence was only to translate into mean returns, we would have similar variance but significantly higher returns for high confidence companies.

## 4.3 Our multidimensional approach

In our definition of confidence we take both a return and risk perspective by associating a higher degree of confidence with higher perceived net present values. Our

[38] We borrow this term from Kahneman and Lovallo (1993)

focus is on extreme levels of confidence, for which we use the terms overconfidence and diffidence respectively high and low confidence.

We use the methodology of Hayward and Hambrick (1997) for the construction of our degree of confidence measure. We take a broad set of confidence indicators, which reflect corporate decisions on operations, investment or funding. In our view, acts speak louder than words, so personal characteristics, such as compensation package, option exercise holdings, background, e.g. are only (indirectly) relevant if translated into company decisions.

Any attempt to measure a human trait like confidence involves human judgment and hence bears the risk that chosen variables and breakpoints are arbitrary. By choosing a broad set instead of a single indicator, we seek to mitigate this risk. We use a four-point scale for assigning a degree of confidence to each confidence indicator variable, thus enforcing a direction instead of allowing for neutral confidence levels. If possible, we use quartiles instead of absolute breakpoints between the four different confidence levels, as it is easier to speak of high or low levels in relative terms rather than in absolute terms. Still, we are well aware that our choice for quartiles is subjective as well and that alternative breakpoints could yield different results. The use of more stringent criteria for assigning extreme confidence levels[39] comes at a loss of observations in the extreme confidence area[40] for each indicator. As a result, the aggregated confidence scores converge. Subsequently, we aggregate the scores on each indicator. Alternatively, we also aggregate the standardized confidence indicator values or Z-scores on the separate confidence indicators to arrive at a total confidence score.

## 4.4 Acts of Confidence: the indicators

### 4.4.1 Introduction

We have identified various confidence indicators to construct our degree of confidence measure. These indicators reflect operating, investment and funding decisions, or specifically the degree of diversification, acquisition behavior, operating leverage, accruals accounting, investment and shareholder payout policy (both dividends and share buybacks). To our knowledge, only Ben David et al. (2007) consider overconfidence in a comprehensive framework that involves a range of corporate actions. They construct a model for empirically testing the effects of overconfidence on investment (including acquisitions), financial leverage and shareholder payout policy.

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[39] One could think of alternative breakpoints, such as 15%, 50% and 85% percentiles between the four different confidence levels

[40] We note that in our empirical analysis in the next chapter, we already lose a lot of observations, as we require a lot of data for each firm, thus leaving us with fewer firms in the extreme confidence area as well.

Some of the indicators that we have defined capture macro-economic developments which affect all managers simultaneously, thus pushing confidence into one specific direction. One could argue that we cannot speak of behavioral bias in such periods. We could resolve this by determining extreme confidence levels on a year by year basis instead of calculating breakpoints for the period as whole. In absolute terms, this would lead different definitions of extreme confidence instead. Also, when using a relative confidence measure, an investment level of 70% of depreciation, while the market anticipates that you will preserve your book value[41] can be earmarked as a sign of confidence if the average ratio is at 50%. However, this is not a sustainable strategy for preserving company value. Furthermore, some of these macro-effects are dampened by the scaling of our indicators to earnings or market valuation. Also, compensating effects are at work when current investments are postponed while earnings retention ratios stay high. However, when we measure returns for extreme confidence firms, we correct for such macro-economic effects in order to isolate the confidence effect.

Based on existing theoretical concepts and empirical findings, we define a relation between these indicators and the degree of confidence. Each indicator is ranked on a four-point scale, which varies from low, medium low, medium high and high confidence. We have not defined a neutral score, thus enforce a direction. The total confidence score is constructed as the aggregate of the separate scores which could end up to zero or a neutral level.

### 4.4.2 Degree of diversification

Looking from an agency theory perspective, Stulz (1990) argues that diversification could free up more internal resources which might induce overinvestment, a behavioral characteristic linked to (over)confidence. In addition, diversification by acquisitions can be associated with hubris or overconfidence (Roll 1986, Malmendier and Tate 2008). Shleifer and Vishny (1989) argue that diversified firms are more complex to manage and a way for management to entrench themselves i.e. to protect their position and increase their influence. Rajan et al. (2000) find empirical support of their model that predicts a positive relation between the misallocation of resources and the degree of diversification. This misallocation results from high divisional autonomy on reinvestment opportunities and insufficient countervailing power by top management to redirect investments to more efficient uses. This could result into both overinvestment and underinvestment on a divisional level, a phenomenon we will discuss later.

Alternatively, we could argue that diversification is a way to reduce risk and cash flow volatility. However, high risk aversion should not be put on par with low confidence.

[41]Otherwise sai,d they value the market-to book ratio equals one

The key factor is management's (mis)judgment on how he can control or mitigate risk by his decisions. If he misperceives the correlations between different activities, the variability of the new portfolio could be underestimates as well.

Following above mentioned theoretical and empirical research and our argument that even risk reduction arguments behind acquisitions leave room for high managerial confidence, we make the following assumption. Overall, we consider firms moving away from their core business as confident, either by overestimating their ability to run the newly acquired business better or by overestimating the diversification effect i.e. underestimating the true variability associated with the new company profile. This is captured in the following proposition:

*Proposition 1: The higher the degree of diversification, the higher the degree of confidence*

### 4.4.3 Acquisition policy

Acquisitions can also be associated with confidence, as these decisions involve a large amount of money and high execution risk. Theoretically, overconfidence could translate into both higher and lower acquisition spending.

One the one hand, one could argue that overconfident managers overestimate their abilities to run another business better. There is wide empirical support for the winner's curse of overpayment and negative abnormal market returns in takeover battles, thus suggesting that hubris is indeed at work. We refer to Roll (1986), Hayward and Hambrick (1997), Morck et al. (1990), Malmendier and Tate (2008) and Ben-David et al. (2007). Especially diversifying moves, which also yield a high confidence score on diversification, seem value destroying.

On the other hand, stock market inefficiency or more specifically, management's *belief* that its shares are undervalued, a characteristic associated with overconfidence, could deter them from making acquisitions if they rely on common stock as a currency. However, it is not easy if possible at all to determine which acquisition moves are foregone for this reason. Although such a sample would be reduced to companies who are fully equity-dependent, management is unlikely to admit that it has serious interest.

Alternatively, Shleifer and Vishny (2003) formulate a theory in which managers are rational and exploit inefficient capital markets. In their framework, transactions are driven by inefficient stock market valuations of the acquiring companies rather than CEO hubris. This market timing strategy is widely investigated by Baker et al. (2004) and Baker and Wurgler (2002). It assumes that management puts the interests of existing shareholders above those of new shareholders instead of treating them equally. If these new shareholders do not earn a satisfactory return given the (new) risk profile of the company, the company could face difficulties or a higher risk premium for subsequent equity issues.

In other words, exploiting overvalued stock may not seem a value enhancing strategy on the long-term. This in line with Stein (1996) who argues that the use of market implied instead of fundament rates of return is a sign of myopic behavior. In addition, management seems reluctant in admitting that their shares are overvalued, even at the peak of the stock markets in 2000.

We recognize that investors could be irrational, on both the individual and aggregate level. Even the efficient market hypothesis provides room for such distortions, conditional on their temporary nature. Both rational and irrational managers could take advantage of overvalued stock markets to go on an acquisition spree at the risk of the company's reputation of creating long-term value. As earlier discussed, we consider net present value maximization of the company's cash flows as imperative for rational behavior.

In summary, there is wide theoretical and empirical support that overconfidence translates into acquisitive behavior, while there are practical limitations regarding foregone acquisitions, the latter of which would qualify equity-dependent firms as overconfident when they refrain from making an acquisition. Therefore, we assume that highly confident management prefers to act and acquire rather than being constrained by a higher cost of equity. The degree of confidence depends on the acquisition outlay rather than the number of acquisitions, as summarized in the following proposition:

*Proposition 2: The larger the acquisition spend, the higher the degree of confidence*

We note that we do not include the impact of the method of payment. However, if the transaction is funded by a share issue, this will result in a low confidence score on the share buyback indicator. Overconfident managers would be very reluctant to issue shares, as they consider their shares undervalued.

### 4.4.4 Operating leverage

Capital intensity or operating leverage can be linked to both industry characteristics and managerial effects. We adopt the view of Hannan and Freeman (1977), who indicate that high operating leverage gives management less discretionary power with regard to investments. In this case, assets are not easily adaptable to other functions, so a long-term view is required. As a result, the investment cycle tends to follow a lumpy rather than a smooth pattern over the years. A large part of the cost base is fixed, which translates into higher earnings swings absent any managerial overconfidence effects. On the contrary, capacity reductions are easier to realize in the short-term by mothballing plants and equipment. Such low investment levels could be interpreted as low confidence. We define the following proposition when assigning a degree of confidence level to operating leverage:

*Proposition 3: The lower the operating leverage, the higher the degree of confidence*

### 4.4.5 Accruals accounting

Accounting practices and specifically earnings management could also hint at high confidence, which is likely to translate into an ambitious earnings outlook. Using the words of Schrand and Zechman (2010), "overconfident executives are more likely to borrow from the future to manage earnings because they expect future earnings will be sufficient to cover reversals." When empirically testing earnings management, Dechow et al. (1995) test several accrual-based models to distinguish between discretionary and non-discretionary accruals. Sloan (1996) empirically finds that the market overreacts to accruals or fails to see the underlying earnings quality, thus rendering the use of an accruals-based reporting strategy attractive on a short-term basis. However, the market will correct this mispricing, thus leading to a negative subsequent stock returns. Hribar and Yang (2010) argue that overconfidence can result into an optimistic bias in earnings forecasts, the issuance of a narrow forecast range and a higher probability of missing estimates. The authors find that overconfident CEOs[42] who voluntarily provide earnings guidance, engage in more aggressive accounting as measured by abnormal accruals. In this way, they could meet or even beat their ambitious earnings targets. If so, self-attribution bias could even reinvigorate their overconfidence. Schrand and Zechman (2010)[43] even find support that overconfidence may even result into fraudulent actions to cook the books to meet unrealistic high expectations. Most of these accrual items are discretionary in terms of size and timing.

Although Dechow et al. (1995) argue that it is hard to detect earnings management for "economically plausible magnitudes of one to five percent of total assets", we are most interested in the extremes and only those are awarded with the highest or lowest level of confidence. In order to determine whether or not accruals are extreme, we look at which share of the earnings component consists of accruals instead of more persistent cash flow items. Our confidence assignment is summarized in proposition four:

*Proposition 4: The higher the accruals to earnings ratio, the higher the degree of confidence.*

[42] They follow Malmendier and Tate (2005, 2008) and define overconfidence by option exercise behavior and press-portrayal

[43] Schrand and Zechman (2010) use three proxies for overconfidence i.e. one based on option exercise behavior (Malmendier and Tate 2005), one multidimensional construct as developed by Chatterjee and Hambrick (2007) and one that uses personal traits such as educational background.

### 4.4.6 Investment

Current research emphasizes the relation between overconfidence and its impact on investment and capital structure. This is not easy to detect, as in our definition, confidence could relate to both estimated returns and riskiness. The former translates into higher estimated cash flows, while the latter implies a lower hurdle rate of the project. Furthermore, there are also interaction effects between investment and capital structure, as the latter could be a constraining factor.

Heaton (2002) argues that overconfidence can materialize in both overinvestment and underinvestment, depending on a company's financial position[44]. This relationship is empirically supported by Malmendier and Tate (2005). If a company has abundant free cash flow, overconfidence can lead to overinvestment, consistent with agency theory as developed by Jensen (1986). With ample funds available for investing, the hurdle rate could be misperceived as very low i.e. the marginal instead of the risk adjusted cost of capital is used in the net present value analysis. Ben-David et al. (2007) empirically find that overconfident managers invest more, use a too low discount rate for evaluating projects and opt for higher financial leverage instead of scrutinizing investment. Stein (1996) already highlights the risk of using wrong discount rates in capital budgeting decisions, but he refers to irrational markets rather than managers. When managers pursue to maximize short-term stock valuation or need to attract funds on a short-term basis, they should use the market implied discount rates. If they afford to adopt a long-term view and face no financing constraints, the fundamental discount rate should be used.

If there is a financing deficit and – in the view of management - expensive external funds have to be attracted, overconfidence could translate into underinvestment according to Heaton (2000). This suggests that management only acts in the interest of existing shareholders, as it prevents new investors to participate in the upside of the - in the view of management -undervalued assets-in-place. However, existing shareholders would also benefit from any upside following a good investment and re-evaluation of existing assets, even if they have to share it with new shareholders.This argument of underinvestment is further weakened when only debt is attracted, which - unlike equity - entails a fixed rather than a residual claim on the value of the firm[45]. Therefore, we dismiss the argument that overconfidence translates into underinvestment.

In our framework, we assume the argument of attractive investment opportunities to dominate the (under)valuation of a company's risky securities, thus ruling out

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[44] One could argue that if the Efficient Market Hypothesis (EMH) holds, overinvestment would be contained in case of a financing deficit, as the market would discount this risk in higher cost of external funds. EMH also implies that the cost of external funds will not become too high to deter management from investing. It is not relevant whether or not the market is right in pricing risky assets, as it is all about management's perception

[45] However, bond holders benefit from the higher value of collateral i.e. lower default risk, which Myers (1977) describes as the asset substitution problem between stock-and bond holders

underinvestment by overconfident managers. We also adopted this argument when discussing acquisitions as an act of confidence. We argue that overinvestment can only occur if investment is indeed high, which we measure by the depreciation level and the Q-ratio[46]. Depreciation conveys information about the required level of investment or maintenance level, while the Q-ratio conveys the market's view on the company's growth and associated investments. Furthermore, we expect management to use a lower hurdle rate if there is no financing deficit[47], thus overstating the value that they belief to create. This is translated into the following proposition:

*Proposition 5: the higher the investment level, the higher the degree of confidence, especially if there is no financing deficit i.e. a lower hurdle rate is used*

### 4.4.7 Dividend policy

Contrary to interest payments, (common) dividend is not a contractual obligation, but an item at management's discretion. Hence, managerial bias could have an impact. Alongside overconfidence, other irrational elements can impact dividend policy. Lintner (1956) cites inertia, conservatism and anchoring to the existing dividend rate as key dividend drivers. Alternatively, Bhattacharaya (1979) uses the bird in the hand fallacy as an explanation for a preference of dividends to share price appreciation. Closely related to this, Thaler (1999) emphasizes the role of mental accounting or the way how we organize information. Alternatively, Baker and Wurgler (2004) argue that catering to investor needs could determine a firm's payout strategy.

Brav et al. (2005) find empirical evidence that dividend and investment decisions are taken simultaneously, while decisions on share buybacks are made hereafter. Consistent with the latter, we isolate dividends from share buybacks. However, we do not assume a perfect correlation between dividend and current investment either and therefore introduce dividend as a separate confidence indicator[48]. This corroborates with findings by Fama and French (2002) that short-term changes in investment and earnings are absorbed by higher debt rather than lower dividends. When we perform an empirical analysis of our confidence indicator in the next chapter, we find a low positive correlation between dividend payout and high investment. This could suggest a positive view on the profitability of both current and future assets. Alternatively, in order to mitigate agency concerns from overinvestment, management could ease this by increasing the dividend

[46] This ratio could be used as a proxy for the company's growth potential as expected by the market
[47] We refer to Stein (1996) who explores "how to set hurdle rates for capital budgeting decisions in an irrational world"
[48] We believe the horizon of executive management could also have an impact. A CEO close to retirement might not be concerned with future investment opportunities, but rather op for making big moves now

payout without compromising on investment. However, we find no significant correlation between dividend changes and investment.

Similar to acquisitions and investment, both a negative and positive relation between overconfidence and dividend payout could occur. If overconfidence on profitability prevails, we would expect higher dividends, consistent with signaling, pecking order and tradeoff theory[49]. Empirical results are ambiguous though. Grullon et al (2002) and Benartzi et al. (1997) do not find that dividend payouts predict future profitability. Brav et al. (2005) only find a weak relation, which primarily works in one direction i.e. in good times. In bad times, dividends tend to be sticky rather than being cut, which is also empirically supported by Fama and French (2002). Alternatively, we could state that overconfidence on investment opportunities dominates overconfidence on profitability. This implies that dividends are lower in order to create financial slack.

We use the following approach to assign a degree of confidence level. We distinguish between first order (dividend level) and second order (dividend change) effects. Regardless of the payout level and based on research that dividends tend to be sticky in bad times[50], we consider a dividend cut as a sign of low confidence. In all other cases of stable or rising dividend, we consider both the payout level and the financing deficit before assigning a confidence score. We adopt the view that dividend or earnings retention ratios reveal information about future investment plans rather than profitability, thus following the results of Grullon et al. (2002), Brav et al. (2005) and Ben-David et al. (2007). Therefore, it is closely (inversely) related to the investment indicator discussed earlier. We do neither assume perfect (negative) correlation between current and future investment nor relate dividend to a company's growth profile. All in all, we define the following propositions:

*Proposition 6a: firms with a dividend cut, regardless of the payout ratio, have a low degree of confidence*

*Proposition 6b: the lower the dividend payout ratio, the higher the degree of confidence, especially if there is no financing deficit i.e. a lower hurdle rate is used*

### 4.4.8 Share buybacks

If Modigliani and Miller's dividend irrelevance theorem (1958, 1961) would hold, dividend and share buybacks are perfect substitutes. Grullon and Michaely (2002) find

[49] As agency costs are already incorporated in tradeoff theory, we do not consider it separately

[50] One could argue that if firms cut their dividends, this is driven by the current situation rather than long-term issues. As anecdotal evidence, we mention how shocked the market reacted when "widow stock"General Electric announced a dividend cut in 2009.

empirical support for the substitution hypothesis, but Fama and French (2001) do not, albeit different calculations could be to blame for this discrepancy. Brav et al. (2005) find that share buyback decisions follow investment and dividend, which corroborates with rejecting the substitution hypothesis. If the substitution hypothesis would hold, our propositions on overconfidence and dividend policy could be extrapolated to share buybacks as well. In their model, Ben-David et al. (2007) also assume that overconfident managers consider dividends and share buybacks separately. Their empirical results show that overconfident managers are more active in share buybacks.

Despite the lack of conclusive evidence on the substitution hypothesis, we argue that dividends cannot be put on par with share buybacks due to differences in calculations, regulation[51] and market timing. Brav et al. (2005) find that CFOs prefer share repurchases to dividends, as these are more flexible for timing the market and enhancing earnings per share. Market timing is hard to reconcile with overconfidence, as it implies that stock is issued when it is overvalued, a conclusion unlikely to be drawn by overconfident management. Malmendier et al. (2010) indeed find hat overconfident managers are less likely to use equity for covering financing needs, while Ben-David et al. (2007) do not find a significant relation between market timing and share buybacks. Ikenberry and Vermaelen (1996) also implicitly mention market timing arguments. They state that share buybacks expand the company's investment opportunity set by offering management the option to use the firm's resources when they see a mispricing vs. their "insider" valuation of the firm.

Although there is a timing difference between share buyback decisions on the one hand and investment and dividends on the other hand, we follow a similar reasoning as Ben-David et al. (2007). Higher buybacks imply a higher degree of confidence, especially if there are abundant internal funds. This is summarized in proposition seven:

*Proposition 7: The higher the amount of share buybacks, the higher the degree of confidence, especially if there is no financing deficit.*

### 4.4.9 Financial leverage

In chapter three, we discussed how to determine a firm's optimal size or investment level and we implicitly assumed capital structure a means rather than an end. In other words, we do not consider capital structure as an explicit company goal. However, when we empirically test our degree of confidence measure, we will introduce a control variable that captures a firm's excess financial leverage compared to the average of the industry.

[51] One could think of the 1986 Tax Reform Act. Also, prior to 1983, there were more constraints on share buybacks, as these could be interpreted as insider trading

In the world of Modigliani and Miller, capital structure is irrelevant for a company's value. Although there is ample literature on capital structure on a standalone basis, studies on overconfidence and its impact on financial leverage decisions are still in a developing stage. Theoretical frameworks include tradeoff theory, agency theory, pecking order theory and target adjustment theory. In order to derive an optimal capital structure, one could distinguish between optimism about the current assets in place and optimism about future assets or growth.

Following tradeoff theory, a bullish view on the profitability or bankruptcy risk of the current assets in place should translate into higher financial leverage and vice versa. Higher or less volatile earnings or lower bankruptcy risk imply a higher tax base and higher agency costs[52], thus calling for higher debt. Conversely, pecking order theory states that if management sees many investment opportunities going forward i.e. has high confidence in future growth, they may keep financial leverage low to create financial flexibility. This can be reconciled with agency theory as well, as low financial leverage implies less monitoring and therefore more room for overconfidence to have an impact. Hackbarth (2008, 2009) captures these ideas in a theoretical model and analyzes the effects of optimism and overconfidence on the interaction between financing and investment decisions. His model can explain what Graham (2000) described as the debt conservatism[53] puzzle, but managerial traits can mitigate bondholder-shareholder. In other words, debt or the overhang of debt can lead to suboptimal delay of investment, but mildly biased managers can overcome this as they tend to invest earlier than rational managers[54].

In their empirical study on the optimal capital structure, Shyam-Sunder and Myers (1999) find more support for the pecking order than for the target-adjustment or trade off model. Frank and Goyal (2003) extend the study of the former, but only detect some weak support for pecking order behavior at large firms[55]. Fama and French (2002) also find more support for the pecking order than the tradeoff theory. If expected earnings variations are short-term, management is more likely to accept temporarily higher leverage rather than to opt for structurally lower leverage ratios. Graham (2000) empirically finds persistence in debt conservatism for large, profitable companies with growth options.

Malmendier et al. (2010) find empirical support that internal financing is preferred to external funding, thus implying low financial leverage. However, if management is faced with many attractive investment opportunities and a financing deficit, it may prefer higher financial leverage to postponing these projects into the (far) future. As management

[52] This assumes that higher profitability translates into higher free cash flows which is not necessarily the case if accruals or the tax burden increase as well

[53] Debt conservatism implies underutilization of debt relative to the tax benefits and a strong preference for internal to external financing. Graham uses the so-called kink variable to measure debt conservatism

[54] Hackbarth refers to this as the leverage and timing effects

[55] When they control for conventional leverage factors, the effect evaporates.

is evaluated on a regular basis, or at least once a year, the tradeoff between long-term and short-term results also makes the option of deferring projects less attractive. In such a situation, overconfident companies will use about one third more debt than their (rational) peers and issue less frequent equity. Ben-David et al. (2007) also empirically find that overconfidence translates into higher debt levels with longer maturity. As long as management still prefers internal funds to debt and uses new equity as a last resort, it complies with pecking order theory.

## 4.5 Summary and discussion

In this chapter, we have outlined the principles that underlie our comprehensive degree of confidence measure by using a similar methodology as Hayward and Hambrick (1997). As we do not only consider the higher end of the extreme, we use the terms lower and higher confidence respectively diffidence and overconfidence. We infer our confidence measure from a broad set of confidence indicators reflecting corporate decisions on operations, investment or funding. These indicators are inferred from current theoretical and empirical research on managerial (over)confidence. In our view, acts and even deliberate inaction, speak louder than words, so personal characteristics, such as compensation package, option exercise holdings, education background, e.g. are only (indirectly) relevant if translated into company decisions.

Based on both theoretical and empirical insights, we translate the values of the confidence indicators into a confidence degree on a four-point scale. If possible, use quartiles instead of more arbitrary absolute breakpoints for assigning a degree of confidence. Although we consider financial leverage means to an end instead of a separate firm objective, we do include financial slack as one of the underlying drivers behind investment, dividend and share buyback. Table 4.5.1 summarizes the confidence indicator variables and the assignment of confidence levels to each of these, but we refer to appendix I for a more detailed variable description.

In the next chapter, we perform an empirical analysis and investigate the characteristics of extreme confidence companies. We do not only explore these company attributes on a pooled basis, but also examine these across time and across industries. We also extend the analysis to company performance, for which we use various measures.

**Table 4.5.1: Degree of confidence calculation**

| Indicator: | Variables | Confidence Score | | | |
|---|---|---|---|---|---|
| | | -2 | -1 | +1 | +2 |
| **Diversification** | Number of segments | 1st quartile (1 segment) | 2nd quartile (2 segments) | 3rd quartile (3 segments) | 4th quartile (>=4 segments) |
| **Acquisition** | Acquisition spend to total assets | < = 0 | 0-5% | 5-10% | >10% |
| **Operating leverage** | Fixed assets to total assets | 1st quartile | 2nd quartile | 3rd quartile | 4th quartile |
| **Accruals** | Accruals/ EBIT | 1st quartile | 2nd quartile | 3rd quartile | 4th quartile |
| **Investment** | Capex/depreciation to Tobin's Q (INVEST); financing deficit (DEF) | Low INVEST + DEF | Low INVEST + no DEF or Medium INVEST + DEF | Medium INVEST + no DEF or High INVEST + DEF | High INVEST + no DEF |
| **Dividend** | Yoy change dividend per share (DIV); dividend payout (PAYOUT); financing deficit (DEF) | DIV cut or high PAYOUT + DEF | High PAYOUT + no DEF Medium PAYOUT + DEF | Medium PAYOUT + no DEF or Low PAYOUT + DEF | Low PAYOUT + no DEF |
| **Share buyback** | Net share buyback (SBB) to market cap; financing deficit (DEF) | Low SBB + DEF | Low SBB + no DEF Medium SBB + DEF | Medium SBB + no DEF High SBB + DEF | High SBB + no DEF |

Note: Number of segments is based on the two-digit SIC code, excl. segments with sales < =0 or a SIC code of 0. The acquisition ratio equals items 129/6. We use absolute breakpoints as the 25%, 50% and 75% percentile are all (close to) zero. Operating leverage equals fixed to total assets (items 8/6). Accruals equals the change in non-cash current assets less the change in non-interest bearing current liabilities less depreciation (items (4-1)- (5-34) -14). We adjust EBIT (item 178) by multiplying this year's EBIT margin (items 178/12) with last year's asset turnover (items 12/ 6). Low investment comprises the first quartile, medium the second and third quartiles and high investment the fourth quartile. Capex to depreciation equals items 128/14. Tobin's Q is proxied by the market to book value of assets. Market value of total assets equals total assets less stockholders equity less deferred tax assets plus the market value of common stock (fiscal year closing price * shares outstanding) and preferred stock (items 6-216-35+199*25+130). Financing gap equals income before extraordinary items, discontinued operations and preferred dividend plus depreciation less common dividend less capex (items 237+14-21-128) less the lower of zero or net debt. (= negative if there is net cash). Net debt equals long-term debt plus current debt less cash (items 9+34–1). Financing gap is winsorized at (minus) one times the enterprise value (EV). EV equals the sum of the market value of equity, preferred stock and net debt (items 199*25+130+9+34–1). Dividend per share equals item 26. Dividend payout equals common dividend divided by income before extraordinary items, discontinued operations and preferred dividend (items 21/237). Low dividend comprises the first quartile, medium the second and third quartiles and high dividend the fourth quartile. Share buybacks are net of share issues and scaled to market capitalization (items (115-108)/(199*25). Low share buybacks comprise the first quartile, medium the second and third quartiles and high dividend the fourth quartile.

# 5 Empirical analysis of company confidence


## Abstract

In this chapter, we empirically investigate if extreme degrees of company confidence translate into significantly different company characteristics, including performance. Contrary to prior research, we do not only focus on the upper extreme or overconfidence, but also include diffidence. In addition, we consider industry respectively time characteristics and company confidence, which can be considered a rough validity test of our degree of confidence measure. We find significant differences in the characteristics of low and high confidence firms in terms of size, book-to-market equity ratio, financial leverage compared to the industry average and performance. Low confidence firms tend to be smaller, more distressed, less conservatively financed and, except for the new millennium, yield a lower return on invested capital with higher variability. Differences in industry representation are not very pronounced between the confidence extremes. Low confidence firms seem mostly overrepresented in dynamic or rapidly changing industries like technology and telecom. High confidence firms are also well represented in these sectors, but have even more exposure to consumer non-durables and manufacturing. Narrowing the scope to performance, we find that differences in returns on invested capital are most pronounced in the eighties, but remain high in subsequent decades.

## 5.1 Introduction

As discussed earlier, most research on management overconfidence focuses on its impact on a certain company decision, in particular investment. Conversely, the evolution of overconfidence across time and across industries is hardly covered. We believe that such a reality check[56], although with hindsight, adds to our knowledge as well and could make us aware of possible red flags. In addition, the impact of overconfidence on company performance or valuation is hardly covered, while this would provide a link to investor behavior as well. We have to interpret our results with caution as hindsight bias may lead to judging certain behavior as irrational ex post, while this was not necessarily so ex ante.

In the previous chapter, we developed a framework for assigning degrees of confidence and briefly touched upon the benefits of our measure compared to alternative ones. We argued that it would be less subjective, as more dimensions are included before concluding whether or not extreme confidence is exhibited. Furthermore, we do not share the implicit assumption that diffidence is not very interesting. Although it implies inaction rather than action, this does not imply that there is no impact on corporate performance either. Similar to other confidence proxies, we use ex post information, thus rendering it less suitable for predictions and validity tests.

It is important to note that irrational managers should not be put on par with agency problems, as suboptimal or even detrimental decisions of the former may not be a deliberate action. Irrational managers may unjustly believe that they are acting in the company's best interest, so some remedies to address agency problems, such as stock options, may not work[57]. However, tight corporate governance, legislation like the Sarbanes Oxley Act and a well-functioning market for corporate control may be effective countervailing power mechanisms to contain managerial biases. If so, we would find that compensating rather than reinforcing factors are at work within the different company decisions, thus topping off extreme confidence scores. Our results indeed point at mitigating factors rather than a positive feedback mechanism.

In order to make our measure more intuitive, we explore if it translates into specific company, time-series and industry characteristics, while also extending the scope to corporate performance. We can empirically test if returns to capital providers are systematically different for biased firms. In this chapter, we only explore gross stock returns and return on invested capital. In the next chapter, we specifically explore if stock holders can earn abnormal stock returns by investing in extreme confidence firms. Hackbarth (2009) shows that a mild bias might be seen as positive, as it offsets underinvestment stemming from risk aversion. If overconfidence was only to reflect risk or

[56] One could consider this a quick-and-dirty validity test
[57] This is also suggested by Malmendier and Tate (2005)

miscalibration, we would have similar mean returns but significantly higher variance for overconfident firms and vice versa for diffident firms. Conversely, if overconfidence was only to reflect returns, we would have similar variance but significantly higher mean returns for overconfident firms and vice versa for diffident firms. Alternatively, we could argue that extreme situations of confidence lead to suboptimal decisions and hence lower returns on invested capital, regardless of the direction of the bias[58].

We find an asymmetric relation of lower returns on invested capital for diffident compared to overconfident firms, thus rejecting the latter hypothesis. The difference in mean returns is even significant in the 2000 years, which was a very turbulent decade. We entered the new millennium with peak stock valuations, while by the end of this decade, a major financial and housing market collapse occurred. Based on our findings, we conclude that incorporating both risk and return into the definition of confidence indeed seems justified.

The structure of this chapter is as follows. First, we discuss our sample, followed by the methodology that we follow. For details on the company confidence measure, we refer to chapter four. Next, we present and discuss the common sample and extreme sample characteristics, including industry, time-series and performance related variables. Finally, we conclude and provide suggestions for further research.

## 5.2 Sample Description

In our empirical analysis, we focus on well-covered companies, or specifically S&P 500 firms from 1980-2008. Although changes in the S&P 500 index occur throughout the year, we take the calendar year-end as a cut-off point for determining the sample for the coming year. We have excluded regulated utilities (SIC codes 4900-4999) and financials (SIC codes 6000-6999), due to specific income statement and balance sheet characteristics. Earlier empirical studies on (over)confidence use a similar sample of large cap firms in the same industries over a similar period. Malmendier et al. (2010) arrive at a share of 13% overconfident firms in a sample of Fortune 500 firms from 1980 to 1994, while Hribrar and Yang (2010) have a share of 11% overconfident observations in a sample comprised of 572 Fortune 500 firms from the year 2000 up to and including 2004. On the one hand, we could argue that if our confidence variables compensate each other, the share of extremely high confidence firms could be less than the share found in earlier research or 20% when assuming symmetry between extremely high and low confidence scores. On the other hand, we could argue that the share of extreme confidence scores is higher than in previous research if our confidence variables have a reinvigorating effect. Beforehand, we do not

[58] Hackbarth (2009) shows that a mild bias might be seen as positive as it offsets underinvestment from risk-aversion

know what the case is, and therefore choose the 10% and 90% percentile as breakpoints for determining the two confidence extremes.

As we require a wide range of input variables, we incur a high risk of missing data otherwise. In addition to calculating the variables underlying the seven confidence indicators, we have added additional control variables e.g. size or market capitalization, excess financial leverage compared to the industry level, the book-to-market equity or BEME-ratio and finally stocks returns. We retrieve our data from the Compustat database, except for stock prices, when the CRSP database is used. Our sample matches those used in other empirical studies on overconfidence in terms of firms (large caps) and period covered. Hambrick (1995) remarks that these industries are highly regulated, which restrains managerial discretion.

We start our analysis with an unbalanced panel of 11,391 observations from 900 firms, of which only 100 have observations for the full period. We require each observation to have values on all seven confidence indicators, which results in a final sample size of 5,416 (47.55%) observations in total. In order to avoid such a loss of observations, we could apply less stringent criteria and instead calculate the average of the indicator scores that are available. In our view, this makes the companies not comparable, as their confidence level is derived from a different set of actions. It also results in a higher weight of widely available variables from just over 14% to up to 100%. Alternatively, we could opt to estimate missing data, but this seems less useful for hard to predict or more discretionary events like acquisitions and accruals accounting[59].

## 5.3 Methodology

The first part of our analysis comprises the calculation of our degree of confidence measure. We calculate the confidence indicators as defined in chapter four and then assign a degree of confidence score for each indicator following the propositions in chapter four. We refer to appendix I for more details on variable descriptions and calculations. We use a four-point scale, from minus two for the lowest and plus two for the highest confidence level, thus enforcing a direction. If possible, we use quartiles for determining breakpoints between the four different confidence levels[60]. We pool all observations over the full period to increase the number of observations and lower impact of outliers, which could be year-related. This approach assumes that the definition of low and high confidence stays constant rather than varying over the years. This could result in years with hardly any confident firms or vice versa. However, for the 1980-2008 period as a whole, we thus

[59] Especially on these variables, we lack data

[60] The use of alternative breakpoints such as 15, 50 and 85% percentiles significantly reduces the number of extreme confidence scores on the separate indicators and hence reduces the variation in the aggregated confidence scores.

assume that 20% of our sample will consist of extreme confidence. In other words, we allow for years in which firms could be perfectly rational, but do not assume such situations to be steady i.e. assume that such ideal situations will be disrupted.

Next, we aggregate the separate confidence indicator scores to arrive at a total score, which lies between -14 and +14. It could also add up to zero unlike the separate indicator scores, as we enforced a direction for the latter. Observations with missing values for one or more confidence indicators are excluded from our sample.

The second part comprises the analysis of the high or top 10% scores and low or bottom 10% confidence scores. We first discuss the descriptive statistics for the full period and then explore how confidence evolves over time and industries. We break up the period into three parts, comprising the eighties, the nineties and the 2000 years. In addition to the possibility that confidence levels can be time-dependent, industry characteristics can be an important driver. In order to avoid a high dispersion over many sub industries, we use the SIC codes for assigning firms to one of the 12 Fama-French industry groups, as defined on Kenneth French's website. As we have excluded utilities and financials from our dataset, this leaves us with ten industry groups.

In the last part of our empirical analysis, we investigate the relation between our confidence measure and company performance. We use a hybrid measure, defined as the return on invested capital at market value (ROIC MV), which captures both backward looking (accounting) and forward looking (market) information. We run a pooled panel regression (Ordinary Least Squares), specified by the following regression equation:

$$ROIC\_MV_{i,t} = \alpha_0 + X'_{i,t}\, B_1 + \beta_2 \times D_{HIGH,i,t} + \beta_3 \times D_{LOW,i,t} + \varepsilon_{i,t}$$

**Equation 5.3.1**

The constant term α could be interpreted as a benchmark return, such as the risk-free rate. The matrix *X'* comprises control variables i.e. size, BEME-ratio, excess leverage and the twelve Fama French industry groups. We use a period fixed model i.e. adjust ROIC MV for the average return for year *t* over all cross-sections. In this way, we seek to capture the opportunity set in a certain year, which can be considered an important input factor for managers. In addition, we could include firm fixed effects to allow for a firm's "natural" rate of return. We argue that this could be a feasible approach for firms in mature industries, but consider this less feasible for firms in more volatile or new industries. Finally, D is a dummy variable, the subscript of which indicates whether or not a company has an extremely high or low confidence level. Furthermore, we use White adjusted standard errors to correct for heteroskedasticity[61].

## 5.4 Results

### 5.4.1 Individual Sample Characteristics

Table 5.4.1 shows the descriptive statistics of each of the confidence indicators separately. With the exception of acquisitions, we have used quartiles for defining breakpoints between low, medium low, medium high and high values of a certain confidence indicator variable. However, due to a discrete distribution and/or additional constraints regarding the financing gap or the sign of a dividend change, the confidence scores are not necessarily evenly distributed over the four levels for each variable. Only for the accruals and operating leverage indicators, all of which have no discrete distribution, extreme scores capture a share of 25%. For the other confidence indicators, the proportion of high scores is lower.

We find that conservative accounting seems to dominate, as negative accruals comprise over half of the observations. The low occurrence and modest size of share buybacks suggests that this item is considered more discretionary rather than embedded in a company's objectives. Especially for ad hoc events, such as large acquisitions or share buybacks, high scores are scarce. As earlier documented by Fama and French (2002) and Brav et al. (2005), we find support that dividends are sticky on the downside, as the median change is zero. In addition, diversification yields little high scores, as most S&P 500 firms are highly focused or active one or two segments only. This translates in a high amount of low scores. Furthermore, the low frequency of extreme scores on the investment indicator is striking, for which the financing gap is to blame. The restrictive impact of financial slack is less dramatic for dividend payout and share buybacks, although extreme scores still capture less than half or 35-40% of observations. Also, the median investment level is somewhat low when compared to maintenance levels and market expectations[62].

In the next section, we will narrow our scope to the common sample, thus only including observations which yield data on all confidence indicators.

[61] If observations of the same firm in different periods are highly correlated with each other, the use of clustered standard errors is preferred

[62] We related investment to depreciation level and Tobin's Q ratio

**Table 5.4.1: Descriptive Statistics Confidence Variables (Individual Sample)**

| | Accruals | Acq | Div Change | Segments (Divers.) | Div Payout | Fingap | Invest | Oplev | Sharebb |
|---|---|---|---|---|---|---|---|---|---|
| Mean | -6.19% | 3.05% | 9.06% | 1.9570 | 39.42% | 1.54% | 99.31% | 36.20% | 0.61% |
| Median | -3.03% | 0.00% | 0.00% | 2.0000 | 33.93% | 1.64% | 78.25% | 32.11% | 0.00% |
| Share of high scores | 25.00% | 8.04% | 20.62% | 10.68% | 20.62% | nm | 8.14% | 25.00% | 20.80% |
| Share of low scores | 25.00% | 51.63% | 16.68% | 46.28% | 16.68% | nm | 2.87% | 25.00% | 13.95% |
| N | 10,760 | 10,206 | 11,291 | 11,353 | 10,782 | 10,996 | 10,272 | 11,342 | 7,233 |

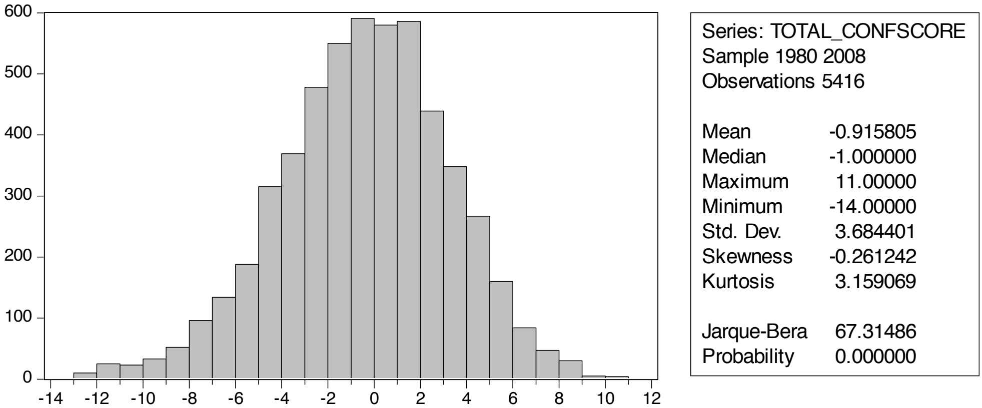
Note: Accruals equal the change in non-cash current assets less the change in non-interest bearing current liabilities less depreciation (items (4-1) - (5-34) -14) and are scaled to adjusted EBIT. Adjusted EBIT equals this year's EBIT margin (items 178/12) times last year's asset turnover (items 12/ 6). Acquisitions are scaled to total assets (items 129/6). Dividend (per share) change is calculated by the year on year change in item 26. The number of segments or the degree of diversification (divers.) is based on the number of different two-digit SIC code, excluding segments with sales < =0 or a SIC code of 0. Dividend payout (Div Payout) equals common dividend divided by income before extraordinary items (XO), discontinued operations and preferred dividend (items 21/237). Financing gap (Fingap) equals income before XO, discontinued operations and preferred dividend plus depreciation less common dividend less capex (items 237+14-21-128) plus net cash if positive. Excess cash equals cash less current and long-term debt (1-9-34). The financing gap is winsorized at (minus) one times the enterprise value (EV). EV equals the sum of the market value of equity, preferred stock and net debt (items 199*25+130+9+34–1). Invest equals capital expenditures (capex) to depreciation (128/14). Tobin's Q is calculated as the market to book value of assets. Market value of total assets equals total assets less stockholders equity less deferred tax assets plus the market value of common stock and preferred stock (items 6-216-35+199*25+130). Operating leverage equals property, plant and equipment, scaled to total assets (items 8/6). Share buybacks are net of share issues and scaled to market capitalization (items (115-108)/(199*25).

### 5.4.2 Common Sample Characteristics

As we require a score on all seven confidence indicators, we lose more than half of our observations and arrive at a final sample of 5,416 observations of 754 cross-sections over 29 years. Figure 5.4.1 summarizes the distribution characteristics of this sample.

The Jarque-Bera statistic and the shape of the distribution curve indicate that the total confidence scores are not normally distributed[63]. We arrive at a negative mean score, but also have longer tails on the left i.e. a higher share of observations lies to the right of the low mean. We use 10% and 90% percentiles for determining the breakpoints for the low and high confidence sample. As the total score is discretely distributed with -14 and +14 as extremes, the share of high respectively low confidence firms is higher and amounts to 11.04% (598 observations) respectively 10.38% (562 observations). High scores on (a) certain indicator(s) are restrained by the additional conditions we have set or cancelled out by low scores on the other confidence indicators. Although the picture is more balanced for scores of each confidence indicator separately, lower scores still dominate the picture.

**Figure 5.4.1: Total Confidence Score distribution**




Note: total confidence is calculated as the sum of the separate confidence scores on each confidence indicator i.e. accruals, acquisitions, investment, dividend, diversification, operating leverage and share buyback.

[63] We use Eviews which does not calculate excess kurtosis, but instead provides the normal kurtosis (which should be 3 in case of a normal distribution

Table 5.4.2 summarizes the common sample correlation statistics for the various confidence variables. Needless to say, these correlations do not reveal how causality runs between two variables. Furthermore, we would like to clarify our definition of financing gap, as this could be easily misinterpreted. Similar to the tendency to consider risk only from a negative perspective or downside, the term financing gap could suggest that we only refer to a deficit. However, in our definition, a positive number implies a financing surplus. We use the financing gap as a measure to what extent the company is able to fund its current capital expenditures from maintenance capital expenditures or depreciation, current ordinary income and excess cash if any. Working capital changes, acquisition spending, dividend and the cumulative funding shortfall of investments in the past i.e. the net debt position is not included in our definition. Most correlation coefficients are low or not significant. The high negative correlation between the financing gap on the one hand and investment, operating leverage respectively dividend payout on the other hand is partly due to construction.

**Table 5.4.2: Pearson correlation matrix confidence indicators (Common Sample)**

| **Variable** | Accruals | Acq | Div. Change | Diversification | Div. Payout | Fin. Gap | Invest | Oplev | Sharebb |
|---|---|---|---|---|---|---|---|---|---|
| Accruals | 1 | | | | | | | | |
| Acq | [a] 0.0027 | 1 | | | | | | | |
| Div Change | [a] -0.0116 | [a] -0.0023 | 1 | | | | | | |
| Diversification | -0.0210 [a] | 0.0294 | [a] -0.0047 | 1 | | | | | |
| Div. Payout | -0.1278 | -0.0317 | 0.0479 | 0.2007 | 1 | | | | |
| Fin. Gap | 0.1335 | [a] 0.0214 | -0.0972 | -0.1194 | -0.2883 | 1 | | | |
| Invest | [a] -0.0195 | -0.0576 | [a] -0.0112 | 0.1751 | 0.0425 | -0.3639 | 1 | | |
| Oplev | [a] -0.0035 | -0.1192 | [a] 0.0121 | 0.0629 | 0.1672 | -0.3827 | 0.4113 | 1 | |
| Sharebb | 0.0361 | -0.0324 | [a] 0.0141 | -0.0461 | -0.0548 | 0.1834 | -0.1619 | -0.1279 | 1 |

Note: [a] not significant. Accruals equal the change in non-cash current assets less the change in non-interest bearing current liabilities less depreciation (items (4-1) - (5-34) -14), scaled to adjusted EBIT. Adjusted EBIT equals this year's EBIT margin (items 178/12) times last year's asset turnover (items 12/ 6). Acquisitions are scaled to total assets (items 129/6). Dividend (per share) change is calculated by the year on year change in item 26. Diversification is based on the number of segments using the two-digit SIC code, excl. segments with sales < =0 or a SIC code of 0. Dividend payout equals common dividend divided by income before extraordinary items (XO), discontinued operations and preferred dividend (items 21/237). Financing gap equals income before XO, discontinued operations and pref, dividend plus depreciation less common dividend less capex (items 237+14-21-128) plus net cash if positive. Excess cash equals cash less current and long-term debt (1-9-34). The financing gap is winsorized at (minus) one times the enterprise value (EV). EV equals the sum of the market value of equity, preferred stock and net debt (items 199*25+130+9+34–1). Invest equals capex to depreciation (128/14). Tobin's Q is calculated as the market to book value of assets. Market value of total assets equals total assets less stockholders equity less deferred tax assets plus the market value of common stock and preferred stock (items 6-216-35+199*25+130). Operating leverage equals property, plant and equipment, scaled to total assets (items 8/6). Share buybacks are net of share issues and scaled to market capitalization (items (115-108)/(199*25).

Correlation is highest (0.4113) between the investment to Tobin's Q ratio and operating leverage. Endogeneity[64] could be to blame, as capital expenditures and depreciation, the numerator of investment to Q, is related to fixed assets or the numerator of operating leverage. This may also account for the high negative correlation of investment respectively operating leverage and the financing gap. In addition, both calculations include the book value of total assets. Although highly capital intensive firms incur are more likely to incur high investment outlay on an absolute level, this is not necessarily the case when comparing it with its market-to-book ratio. However, when high operating leverage firms are associated with less growth or a low Q ratio, this indeed increases the risk of overinvestment relative to the market's expectations. Both operating leverage and investment show negative correlation with share buybacks, the latter of which we indicated a more discretionary item in chapter four. If capital intensity and investment are at high levels, this implies less room for discretionary items. Similarly, one could also consider acquisitions a more opportunistic event. In addition, if firms are highly capital intensive, their industry[65] targets may be as well, thus making these more expensive[66].

Albeit to a lesser extent, investment also shows relatively high positive correlation with diversification or the number of different business segments. This suggests that fixed assets cannot be easily used for unrelated business activities. Furthermore, we highlight the possibility that the widely documented conglomerate discount causes markets to easily consider investment levels (too) high. As a result of higher investment requirements, financial slack also diminishes for more diversified firms. We also see a positive correlation between dividend and diversification. This could reflect the benefits of diversification i.e. lower volatility of cash flows on an aggregate basis, thus making higher dividends more sustainable..

We find a positive relation between the financing gap on the one hand and accruals, acquisitions respectively share buybacks. Conversely, correlation between the financing gap and dividend changes respectively dividend payout is significantly negative. Strictly speaking, dividends, acquisitions and share buybacks do have an impact on the financing gap on a cumulative basis by reducing the net cash position if any. A positive relation between the financing gap and accruals may seem contradictory to our view of more aggressive bookkeeping when confidence is high in order to keep up with high earnings expectations. Higher accruals imply a higher discrepancy between reported and cash earnings, thus suggesting a negative relation. However, while book value changes in working capital changes are incorporated in our accruals calculation following Sloan

[64] The correlation of investment respectively dividend with the financing gap also reflects endogeneity
[65] Note that we earlier indicated that firms tend to be highly focused, thus making expansion in related businesses more likely
[66] This assumes that these targets are not trading at distressed market values i.e. below book value

(1996), lack of data on cash changes in working capital made us decide to exclude this item from our financing gap calculation. The positive relation with more ad hoc events, such as acquisitions (insignificant) and share buybacks (significant), is intuitive i.e. such actions follow investment and are more likely to occur if sufficient slack is available. The negative relation of dividend changes respectively dividend payout with the financing gap corroborates with our view that these items do not move at par with financial slack, but tend to be sticky and set together with investment levels. Earlier, we referred to results by Fama and French (2002) that short-term changes in investment and earnings are absorbed by higher debt rather than lower dividends. The different relations between dividend-related variables and share buybacks confirm our assumption that these are no perfect substitutes, but convey different messages. While share buybacks are more opportunistic and a way of addressing current stock mispricing in the view of management, dividend policy can be considered part of a firm's long-term strategy on its future investment plans.

### 5.4.3 Extreme Confidence drivers

In order to get a better view how the different indicators impact the extreme confidence scores, we have calculated the amount of high confidence scores respectively low confidence scores as a percentage of total. The cumulative numbers in the last column of table 5.4.3 show that high scores are clearly less frequent (17.0% vs. 25.5%) than low scores. Overall, the characteristics are similar to the individual sample, with high scores clearly underrepresented, except for accruals and operating leverage.

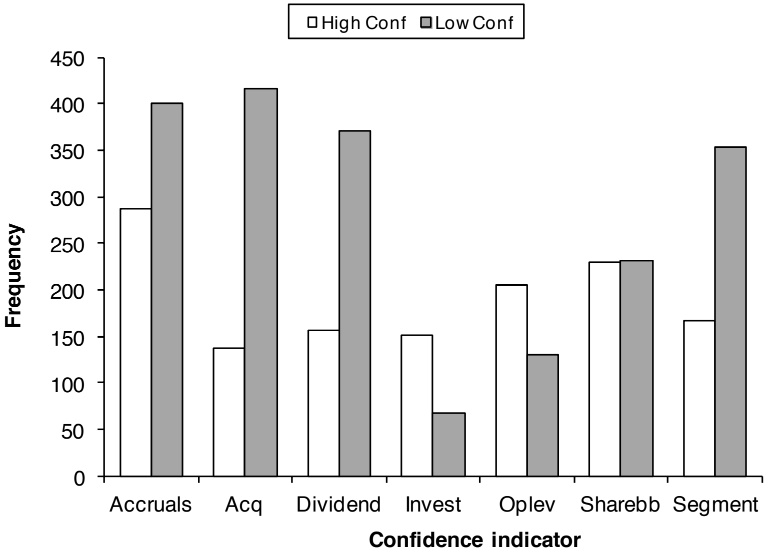
**Table 5.4.3: Share of Extreme Confidence Scores (Common Sample)**

| | Accrual | Acq | Div | Invest | Oplev | Sbb | Segment | Cum. |
|---|---|---|---|---|---|---|---|---|
| Highscore (%) | 24.78 | 7.94 | 20.64 | 9.47 | 25.59 | 20.44 | 10.01 | 16.98 |
| Lowscore (%) | 23.19 | 54.32 | 14.55 | 1.51 | 21.82 | 13.81 | 49.11 | 25.47 |
| N | 5,416 | 5,416 | 5,146 | 5,416 | 5,416 | 5,416 | 5,416 | 37,912 |

Note: The columns refer to the seven confidence indicators that we have identified. Accrual reflects the non-cash items in the income statement, scaled to adjusted EBIT. Adjusted EBIT equals this year's EBIT margin (items 178/12) times last year's asset turnover (items 12/ 6). Acq stands for acquisitions, scaled to total assets. Dividend (Div) includes both first order (the payout level) and second order itms (dividend change). Investment (Invest) is related to historical investment i.e. depreciation and the market's growth expectations as reflected by Tobin's Q. Oplev stands for operating leverage ratio, Sbb for net share buybacks as a % of total market capitalization and Segment is the number of business segments or a measure for diversification. The last column shows the cumulative numbers or total amount of high respectively low scores on all seven confidence indicators.

Figure 5.4.2 illustrates that particularly accruals, acquisitions or specifically the lack thereof, dividend policy and degree of diversification drive the extreme low confidence companies. With regard to high confidence, the accruals indicator has a high contribution, while the share of the other indicators is more balanced.

**Figure 5.4.2: Extreme Confidence drivers**




Note: Accruals reflect the non-cash items in the income statement, scaled to EBIT. Acq stands for acquisitions to total assets. Dividend includes the payout level and dividend change. Investment (Invest) is related to depreciation and Tobin's Q. Oplev stands for operating leverage ratio, Sbb for net share buybacks compared to total market capitalization and Segment is the number of business segments i.e. a measure for diversification.

### 5.4.4 Descriptive Statistics Extreme Confidence Samples

Table 5.4.4 shows the descriptive data from observations pooled[67] by confidence level, or more specifically the two extremes and the neutral confidence level. We observe that the low confidence sample comprises 1) smaller firms with 2) a higher book-to-market equity ratio, 3) less conservative financing than high confidence firms but leverage below the industry's, 4) higher valuation multiples, 5) a lower return on invested capital at market value (ROIC MV) and 6) lower mean raw annual stock returns[68]. We perform an analysis of variances (ANOVA), to investigate whether or not differences between the two confidence extremes are indeed significant, the results of which are summarized in table 5.4.5. We note that there are some small differences within the extreme confidence sample

[67] We lose some observations by including valuation multiples and stock returns

[68] Specifically, Fama and French (1992) form portfolios based on the BM-ratio at the end of fiscal year t and the size (market capitalization) as of the end of June on t+1. Annual returns are calculated as of January in the following year t+2. We also take the annual return two years later

vs. table 5.4.4, as we no longer require data on stock returns. Overall, differences with regard to size, BEME-ratio, excess leverage, returns on invested capital and valuation multiples are indeed all significant.

The smaller mean[69] size of low confidence firms (USD 6,620m vs. USD 8,597m market capitalization) could suggest that the lower amount of available resources at smaller firms dominates less tight control mechanisms compared to larger firms. In other words, investment and acquisition spend may be lower. This may also result into a higher focus or lower degree of diversification.

If we interpreted the BEME ratio as a proxy for growth, the higher BEME ratio for low vs. high confidence firms (0.6200 vs. 0.5419) suggests that their growth prospects are lower. An alternative interpretation is that the higher BEME ratio for the low confidence sample implies that these stocks are more distressed. Indeed, we find a very high share (210 or 37.37%) of negative earnings in the low confidence sample. This corresponds to 58.5% of all negative earnings observations (359), of which four are awarded the highest confidence degree. The higher share of loss making firms is for the low confidence sample is also visible in the significantly lower mean EBIT margin of low confidence firms compared to high confidence ones (12.05% vs. 5.63%) at the 1% level[70]. This lower profitability may also explain why confidence moves to such extreme low levels, albeit the opposite does not seem to occur. In a multifactor model, a lower growth profile or distressed earnings could translate into a higher ROIC MV to prevent economic value destruction. Conversely, in a CAPM-framework, such stocks could have lower correlation with the market, thus translating into lower required returns when only market risk is rewarded.

For low confidence firms, we arrive at significantly higher median valuation multiples as measured by EV/EBITDA (10.13x vs. 7.68x) and PE (71.43x vs.16.07x). As firms with negative earnings or EBITDA are winsorized at the 99% level, this inflates the valuation ratios. As earlier indicated, the high values for the low confidence sample, in particular the PE ratio, are due to a very high share of negative earnings in the low confidence sample.

For both samples, financial leverage is low relative to the industry. High confidence firms in particular have less excess leverage (-7.49% vs.-1.84% of total assets) compared to their peers. The results of Malmendier and Tate (2005) imply that overconfident firms are more likely to use debt for covering a financing deficit than rational ones. Ben-David et al. (2007) also find that overconfidence translates into higher debt with longer maturity. However, this does not rule out more conservative balance sheet characteristics than the

[69] Median market capitalization amounts to USD 1,659m and USD 3,663m for low respectively high confidence firms

[70] Using NOPLAT (Koller et al. 2010) instead of EBIT margin does not materially change results

industry's ones, unless confidence levels are primarily driven by sector characteristics. Also, our findings are consistent with pecking order theory that internal financing is preferred to external financing. If we do not take the industry but the mean leverage of the neutral confidence sample (-14.29%) as a proxy for the rational debt level, financial leverage is significantly less conservative. The fact that our sample represents bigger and more mature firms with bigger free cash flow generation, while our industry debt ratio includes all firms could also explain these results. However, this is contrary to Myers (1977), who states that the optimal debt level is inversely related to the share of growth opportunities to total firm value, thus implying higher rather than lower financial leverage for more mature firms.

In terms of performance, we would expect extreme situations of confidence to lead to suboptimal decisions and hence lower returns on invested capital, regardless of the direction of the bias. However, our results only show a lower return for low confidence firms, while higher confidence companies significantly yield higher returns. The latter result supports Hackbarth's (2009) arguments that a mild overconfidence bias might be seen as positive, as it offsets underinvestment from risk-aversion.

If high confidence was only to reflect risk as some might argue, we would have similar mean returns but significantly higher variance for higher confidence firms. Conversely, if high confidence was only to reflect mean returns, we would have similar variance but significantly higher returns for higher confidence firms.

None of the above hypotheses were supported in our results i.e. both the mean and the variance of our performance metric are significantly different between the confidence samples, as shown in table 5.4.5.We find that the low confidence sample earns a lower mean return on invested capital at market value (ROIC MV), with a mean ROIC MV of 2.81% or significantly lower than the 6.94% earned by high confidence firms. Conversely, Malmendier and Tate (2005) do not find abnormal returns for overconfident managers for which differences in measurement may be to blame. They define abnormal returns as returns in excess of the S&P 500, i.e. they assume a beta of one and exclude other risk factors. As it takes five years from the option grant date before a CEO is qualified as overconfident, there is also a long time lag. We claim extreme confidence in the year for which we have calculated the confidence indicators, while not allowing for a time lag i.e. we match with the same ROIC MV of the same year. In the next chapter, we will release this and also allow for a time lag of up to a year after the fact.

If we would compare these returns to the mean return of 5.98% (not shown) for neutral confidence firms, both are significantly different at the 1% level. Overall, the mean ROIC MV is low and unlikely to meet the WACC, unless the market anticipates growth[71].

[71] Based on a WACC of 7-8%, it would imply 2-3% growth, which seems not very aggressive

When we narrow our scope to raw annual stock returns following extreme confidence levels, we find no significant difference (not shown in ANOVA-table) between the extreme confidence samples[72]. The median stock return for low confidence is even a bit higher. The rational explanation for this higher stock return is that it reflects a higher compensation for risk, while the irrational explanation implies that the market overreacted to bad news, which is reversed in subsequent years.

The lower ROIC MV for low confidence firms could reflect a numerator effect or low earnings after tax. Looking at the denominator, we highlight that debt conservatism vs. the industry is less for low confidence than for high confidence firms. This implies a lower weighted average cost of capital or WACC, as even a higher credit spread would make debt not as expensive as equity. A lower WACC lowers the threshold with regard to required growth rate or required ROIC in order to create value[73]. The better financial position of higher confidence firms is partly due to construction, as we associated high financial slack with higher confidence levels, as summarized in table 4.7.1.

[72] Raw returns are not adjusted for market or other risk factors. Fama and French (1992) form portfolio's based on the BM-ratio at the end of fiscal year t and the market capitalization as of the end of June on t+1. Annual returns are calculated as of January in the following year t+2. We also take the annual return two years later.

[73] For reasons of parsimony, most WACC calculations only incorporate market risk and a correction for financial leverage (by using the levered beta), while excluding the size and value premium. Higher financial leverage lowers the WACC until default risk becomes too high and pushes the cost of debt.

**Table 5.4.4: Descriptive Statistics by confidence level**

| | High confidence | | Neutral | | Low confidence | | Total | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **Median** | **Mean** | **Median** | **Mean** | **Median** | **Mean** | **Median** |
| **Sales in $ m** | 7,258 | 3,948 | 6,718 | 3,026 | 6,055 | 2,318 | 6,368 | 3,004 |
| **Total Assets in $ m** | 6,323 | 3,359 | 6,112 | 2,689 | 5,636 | 2,077 | 5,898 | 2,577 |
| **BEME ratio** | 0.5481 | 0.4645 | 0.4906 | 0.4065 | 0.6196 | 0.5170 | 0.5415 | 0.4334 |
| **PE** | 22.3312 | 15.9771 | 30.2793 | 19.2643 | 166.1853 | 67.1107 | 50.4915 | 19.7783 |
| **EV/EBITDA** | 8.2953 | 7.6178 | 10.1151 | 8.3874 | 19.0670 | 10.0975 | 11.5343 | 8.5720 |
| **Excesslev/TA** | -0.0763 | -0.0616 | -0.1479 | -0.1065 | -0.0203 | -0.0016 | -0.1198 | -0.0806 |
| **Stockret FY2** | 0.0903 | 0.1111 | 0.0928 | 0.1109 | 0.0839 | 0.1169 | 0.0854 | 0.1116 |
| **ROIC MV** | 0.0697 | 0.0624 | 0.0587 | 0.0547 | 0.0277 | 0.0310 | 0.0555 | 0.0529 |
| **N** | 556 | 556 | 524 | 524 | 508 | 508 | 4,896 | 4,896 |

Note: Only observations included for which a total confidence score can be calculated, with no negative invested capital or a |ROIC MV| >1. ROIC MV stands for return on market value adjusted capital and equals (1-cash tax rate) times EBIT (item 178), divided by invested capital at market value. Cash tax rate equals income tax less accrued and deferred taxes (item 16-305-126), divided by pre-tax income (item 170). If not between 0 and 1, the income tax cash rate is used or else a 35% default rate. Invested capital (item 37) includes market instead of book equity. Sales and Total Assets equal items 12 and 6. BEME-ratio equals book to market equity. Book equity is total stockholders' equity less preferred stock plus deferred tax assets (items 216 –130 + 35). Market equity equals shares outstanding times price (items 25*199). PE equals price divided by earnings per share before exceptionals (items 199/58),. Enterprise value (EV) equals the sum of market equity, preferred stock and net debt (items 199*25+130+9+3-1), EBITDA equals item 13. Both PE and EV/EBITDA are winsorized at the 1% and 99% level of observations with positive EPS (EBITDA). Firms with losses are attributed the maximum multiple, similar to those with marginal profitability. Excess leverage equals net debt to EBITDA [(items 9+34–1)/(item 13)] minus the industry debt ratio (based on two digit SIC code), multiplied by EBITDA to total assets. If EBITDA <=0 and net debt <=0, net debt to EBITDA is set at 0. If EBITDA is <=0 and net debt>0, excess leverage is set at net debt to total assets. We winsorize excess leverage at (minus) one times total assets. Stock return FY 2 is the annual stock return in year t+2.

**Table 5.4.5: ANOVA High vs. Low Confidence cs**

| | Mean | | | | Median | | Variance |
|---|---|---|---|---|---|---|---|
| | SIZE | BEME ratio | Excess leverage | ROIC MV | PE | EV/EBITDA | ROIC MV |
| **High conf** | 8,597 | 0.5419 | -0.0749 | 0.0694 | 16.0784 | 7.6770 | 0.0347 |
| **Low conf** | 6,620 | 0.6200 | -0.0184 | 0.0281 | 71.4312 | 10.1348 | 0.0588 |
| **Significance of Difference** | **[a)] | *** | *** | *** | *** | *** | *** |

Note: SIZE equals market equity in USD m. Market equity equals shares outstanding times price (items 199*25); BEME-ratio equals book to market equity. Book equity is total stockholders' equity less preferred stock plus deferred tax assets (items 216 –130 + 35). PE equals price divided by earnings per share before exceptionals (items 199/58). EV or enterprise value equals the sum of market equity, preferred stock and net debt (items 199*25+130+9+3-1), and scaled to EBITDA (item 13). Both PE and EV/EBITDA are winsorized at the 1% and 99% level of observations with positive EPS (EBITDA). Firms with losses are attributed the maximum multiple, similar to those with marginal profitability. Excess leverage equals net debt to EBITDA [(items 9+34–1)/(item 13)] minus the industry debt ratio (= based on two digit SIC code) times EBITDA to total assets. If EBITDA <=0 and net debt <=0, net debt to EBITDA is set at 0. If EBITDA is <=0 and net debt>0, excess leverage is set at net debt to total assets. We winsorize excess leverage at (minus) one times total assets. ROIC MV or return on market value adjusted capital equals (1-cash tax rate) times EBIT (item 178) divided by invested capital at market value. Cash tax rate equals income tax less accrued and deferred taxes (item 16-305-126) divided by pre-tax income (item 170). If not between 0 and 1, we use the income tax cash rate or otherwise a default rate of 35%. Invested capital (item 37) includes market instead of book equity. We exclude observations with negative invested capital or a | ROIC| >1.Asterisks indicate significance levels of 10 (*), 5 (**) and 1% (***);a) if we would take the natural logarithm of a firm's marketcapitalization, the difference would be significant at the 1% level.

### 5.4.5 Time characteristics

As illustrated in figure 5.4.3, the firms in our sample have a low degree of confidence over the 1980-2008 period as a whole, although we see variation over time. The mean total confidence score never comes into positive territory for our sample. On an aggregate level, management's deeds seem conservative, although their beliefs may be more outspoken. It is striking to see the confidence dip as of the second year of each decade. Like our resolutions in January, we start optimistically, but are caught by the fact going forward.

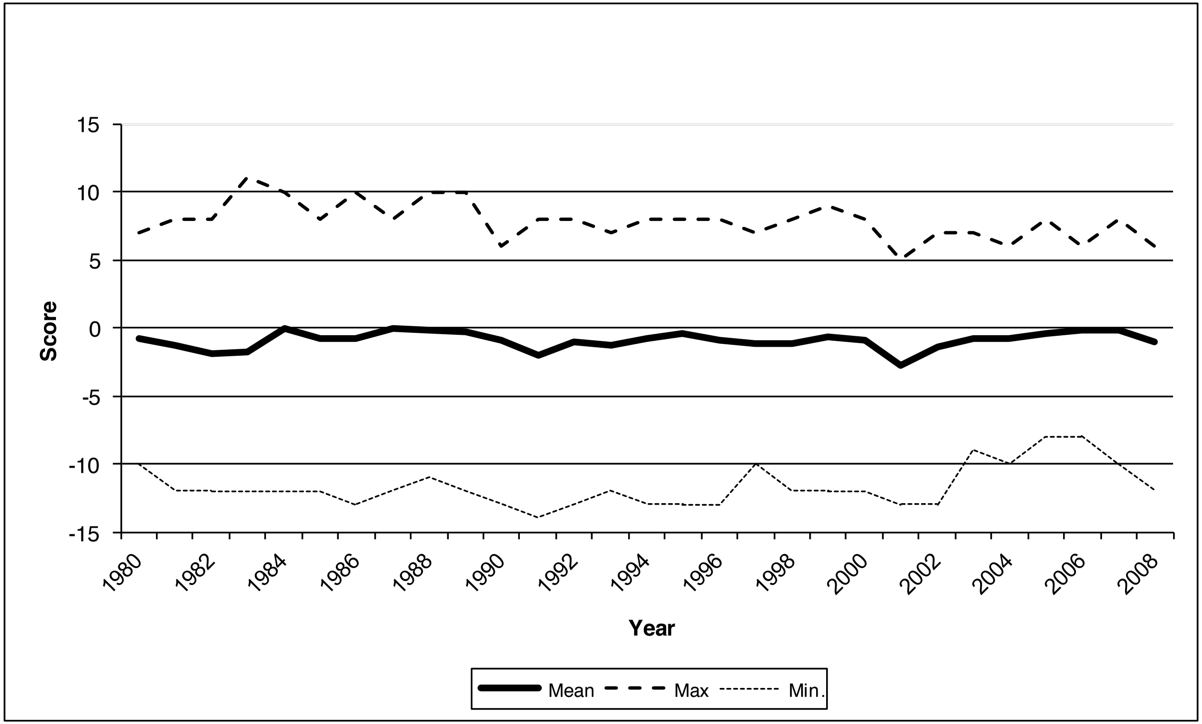
Figure 5.4.4 shows the share of extremely high and low confidence firms by year. As to be expected, we see a high negative correlation (-0.6544) between the year on year change in the number of high confidence firms and low confidence firms.

Figure 5.4.5 puts the distribution of high and low confidence firms over the 1980-2008 time period into a historical perspective. Changes in the proportion of high to low confidence firms corroborate with major financial market shocks and waves. For instance, the confidence boost in 2005 is clearly visible and so is the financial market shock in 2008. The figure suggests that confidence levels move in sync with macro-economic developments, which is indeed very intuitive. Such "collective behavioral bias" could be corrected for in the confidence indicator itself, but this would result into different, year-related absolute definitions. and a big influence of fads, such as the Internet or real estate boom. In more detail, we can make the following observations of confidence across time. The start of our sample period is marked by the Savings and Loans crisis and a recessionary environment with high inflation following the second oil crisis in 1979. The share of high confidence firms of the total for which a confidence score can be calculated plummets by over 40%, while the proportion of low confidence firms nearly doubles (+88%) from 1980 to 1982. It is not until 1984, the year in which Reagan was re-elected after his expansionary fiscal policy, that we see the proportion of high to low confidence reverse in favor of the former. The October crash in 1987 is not visible in the figure, which suggests it was an isolated event rather than a leading indicator for the "state of the union".

When we move to the nineties period, we see another shock at the start of this decade, when the First Gulf War (1990-1991) broke out. In 1991, the share of high confidence firms was half that of 1989, while the share of low confidence firms was 59% higher. The ratio of high vs. low confidence firms stays low and only gradually improves as of 1994. The impact of the Asian crisis (1997-1998) seems limited, although this could be thanks to low interest rates and the hot issue markets in technology and Internet. The peak of the technology and dotcom bubble is achieved in 1999, which shows a strong uptick in the proportion of high to low confidence companies.

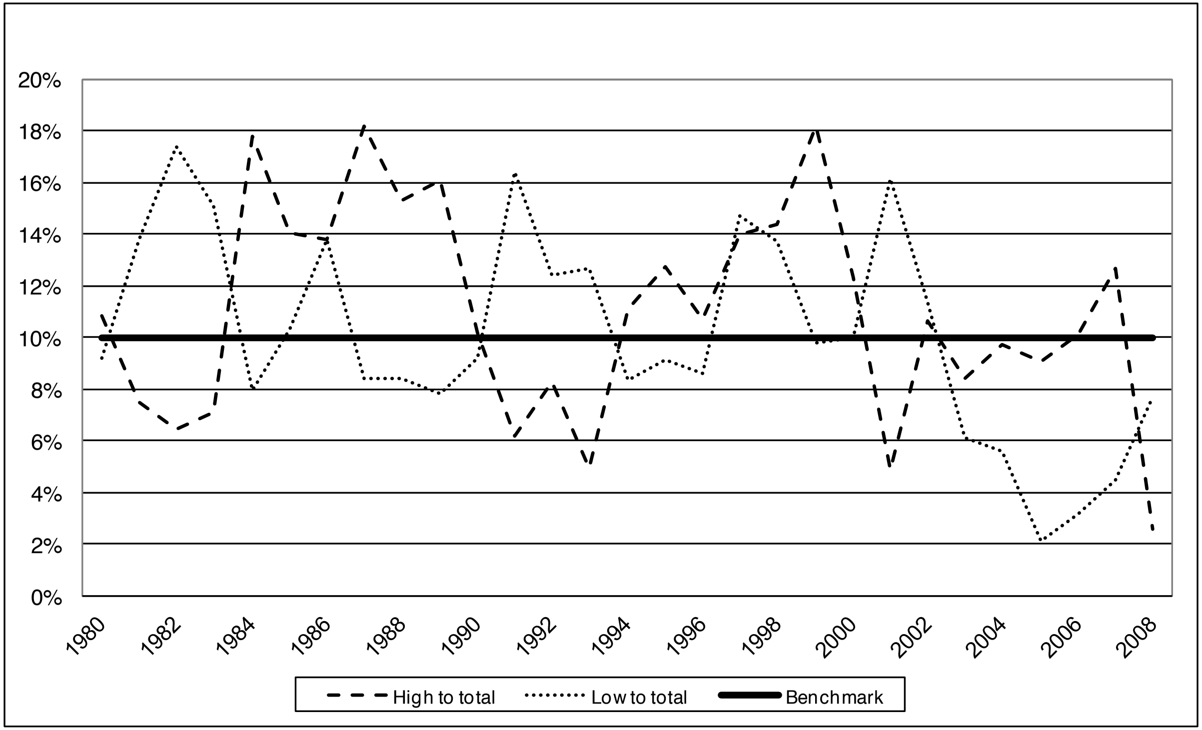
The new century starts with a confidence dip with the dotcom crash and the September 11th attacks in 2001 and the tide turns for the better as of 2003. A period of bullish real estate and financial markets follows, with the housing market crashing in 2007. One year later, the collapse of Lehman Brothers triggered a financial market meltdown, of which the effects still filter through.

**Figure 5.4.3: Confidence per year**



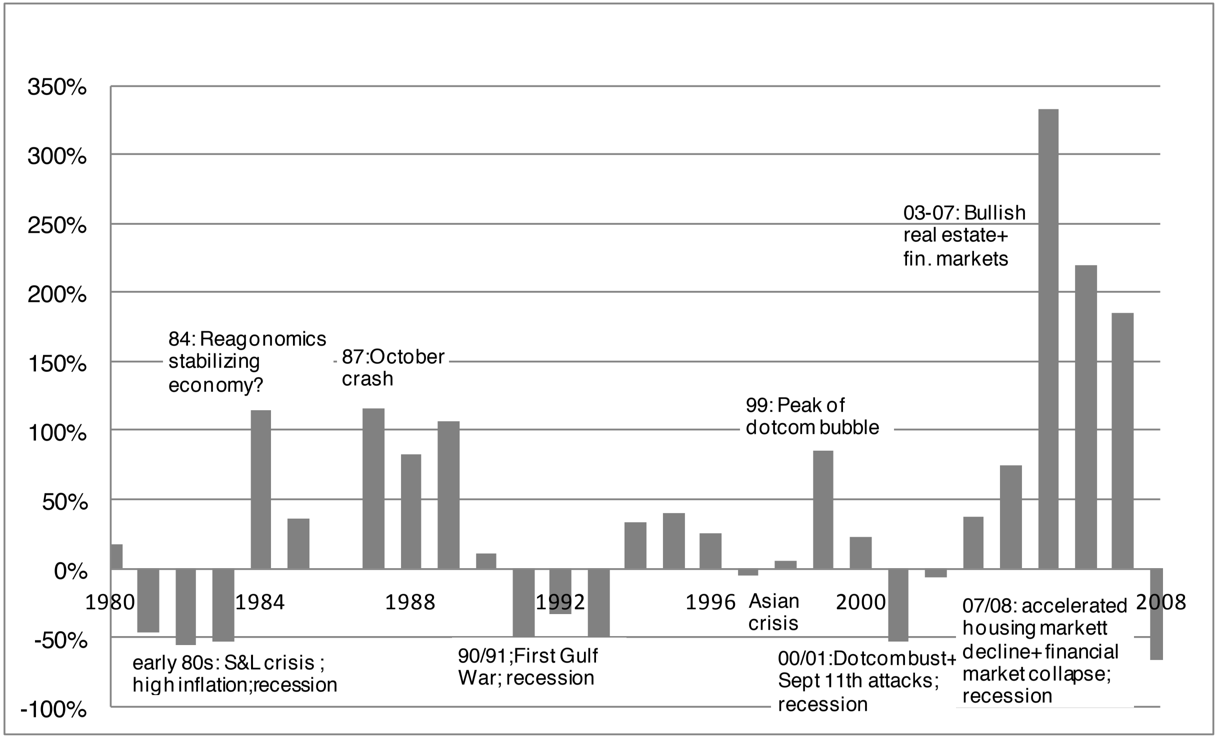

Note: total confidence is calculated as the sum of the separate confidence scores on each confidence indicator i.e. accruals, acquisitions, investment, dividend, diversification, operating leverage and share buyback

**Figure 5.4.4: Share of high to low confidence firms by year**




Note: As we take the top and bottom 10% scores for the full sample for assigning a high or low degree of confidence, we take this as a benchmark. The share of high and low confidence firms is related to the total firms for which a confidence score can be calculated in a certain year.

**Figure 5.4.5: Confidence and historical events**




Note: We calculate the share of high (low) confidence firms in a certain year by dividing the number of high (low) confidence firms by the total number of firms for which a confidence score can be calculated. Subsequently, we relate the share of high confidence firms to the share of low confidence firms less 100% to calculate to which extent high firms are overrepresented (positive outcome) or underrepresented (negative outcome). We relate outcomes to major (economic) events for the US.

In order to explore performance differences across time, we have also explored return on invested capital (ROIC MV) characteristics by sub period i.e. the eighties, the nineties and the 2000 years[74]. We analyze differences both within and between the two confidence extremes, the results of which are summarized in table 5.4.6.

**Table 5.4.6: Analysis of Variance Mean ROIC MV by sub period**

| Confidence level | Period | 80s | | 90s | | 00s | |
|---|---|---|---|---|---|---|---|
| High | Mean | 0.0813 | | 0.0585 | | 0.0550 | |
| | Difference prior period | NA | | -0.0228 | *** | -0.0036 | |
| Low | Mean | 0.0322 | | 0.0243 | | 0.0240 | |
| | Difference prior period | NA | | -0.0079 | | -0.0003 | |
| High -/- Low | Mean difference | 0.0491 | *** | 0.0343 | *** | 0.0310 | *** |

Note: High respectively Low corresponds to the top (bottom) 10% confidence scores. ROIC MV as defined in table 5.3. Column 2 (4) shows the probability that the ROIC MV of the high (low) confidence sample is equal to the previous period. The last column shows the probability that within a certain period; the ROIC MV of the high confidence samples equals that of the low confidence sample. The 2000 years cover up to and including 2008. Asterisks indicate statistical significance with at the 10% (*), 5% (**) or 1% (***) level.

We find that for the high confidence sample, the mean ROIC MV significantly differs for the eighties compared to the nineties. Conversely, there is no significant difference between the 2000 years and the nineties. For the low confidence sample, there is no significant difference in ROIC MV between the different decades at all. We note that the number of observations for both confidence samples are clearly higher in the eighties and follows a steep decline in the subsequent decades.

When we look at difference between extreme confidence firms within a certain subperiod, we observe significant differences in mean returns on invested capital for the two confidence extremes by decade, albeit most pronounced in the eighties.

### 5.4.6 Industry characteristics

We have also investigated if certain industries are over- respectively underrepresented in the high and low confidence samples, which is shown in figure 5.4.6. We find a positive correlation coefficient of 0.5236 (not shown) between the industry representation of the high and the low confidence sample. In other words, if an industry is overrepresented in the high confidence sample, it also tends to be overrepresented in the low confidence sample and vice versa, albeit to a much lower extent. Both samples are underrepresented in Energy, Chemicals and Healthcare. High confidence firms are mostly

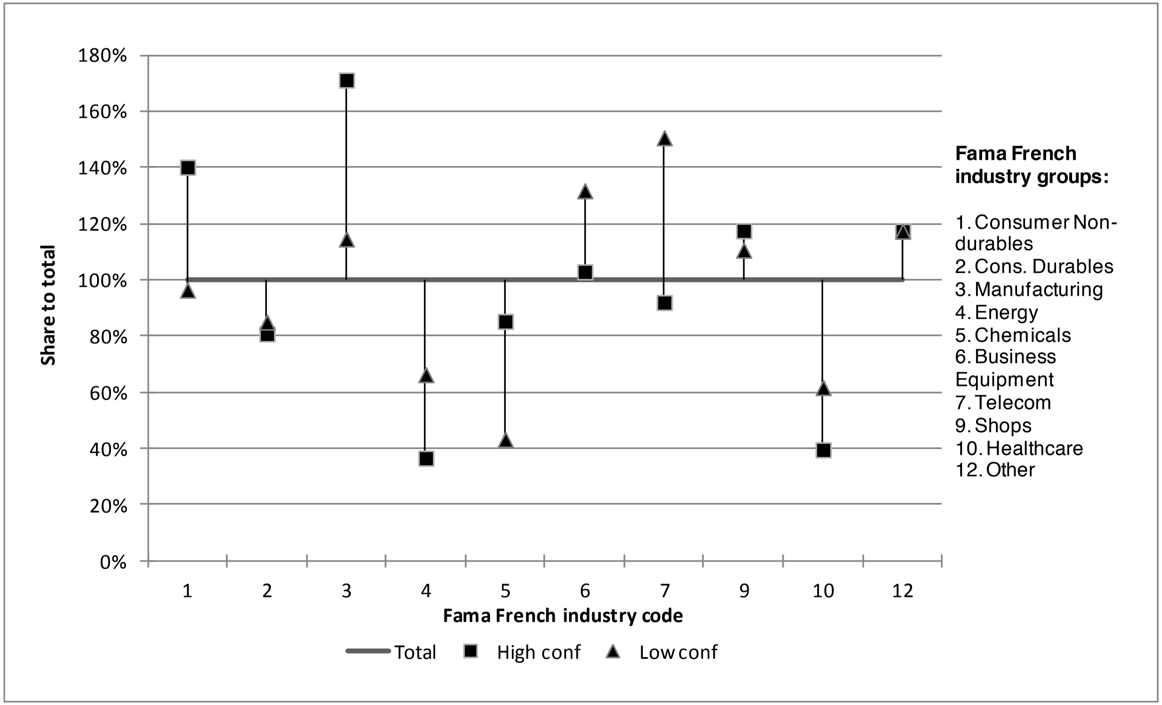
[74] For a concise description of major historical market events from 1961 to 2000 linked to investor sentiment, we refer to Baker and Wurgler (2006).

overrepresented in consumer non-durables [75] and manufacturing, while low confidence firms show a high overrepresentation in business equipment and telecom or more dynamic industries[76]. The higher focus or less diversification, a lower likelihood of overinvestment in faster growing industries and a higher reliance on human rather than fixed capital, the costs of which are expensed rather than capitalized (accruals) may account for this.

[75] Non-durables include food, tobacco, textiles, apparel, leather, toys e.g

[76] This is not synonymous to young industries

**Figure 5.4.6: Extreme confidence by industry**




Note: We use the twelve Fama French industry groups as indicated on the website of Kenneth French. Industry groups 8 (utilities) and 11 (financials) are excluded from the sample. High (low) stands for high (low) confidence observations. Points above (below) the 100% line represent over (under)representation vs. the total sample in terms of sales.

### 5.4.7 Pooled Panel Regression Results

Tables 5.4.7 and 5.4.8 summarize the output of the pooled panel (OLS) regression with return on invested capital or ROIC MV as the dependent variable. We pool all our observations for the 1980-2008 period. Overall, we can explain about 30% of the ROIC MV, to which our confidence dummies contribute 5.93%. We find positive and significant coefficients on size, BEME ratio, the high confidence dummy and industry groups 1 (consumer non-durables), 2 (consumer durables), 3 (manufacturing), 5 (chemicals), 7 (telecom) and 9 (shops). We find a negative coefficients on industry group 6 (business equipment) and a positive one on group 10 (healthcare), neither of which is significant though. Coefficients are significantly negative on excess leverage and the low confidence dummy.

The positive relation between size and ROIC MV indicates that bigger firms earn a higher ROIC MV than smaller ones, although the effect is small. For instance, a 10% higher market capitalization[77] would increase ROIC MV by only 0.02% in absolute terms. The negative impact of a higher denominator or size is more than offset by a positive numerator i.e. higher EBIT after tax. Fama and French (1992) found a negative size effect, but this was related to (forward looking) stock returns, while our ROIC metric concerns all capital providers and also includes backward looking information.

Although we find a significant positive relation between the book-to-market equity ratio and ROIC MV, the coefficient is low. For a stock at a BEME-ratio of 0.50, a 10% increase in market capitalization would, ceteris paribus, decrease ROIC MV by only 0.06% in absolute terms. The inclusion of excess leverage vs. industry peers marginally increases explanatory power. We find a negative coefficient that translates into a 0.14% lower ROIC MV in absolute terms when financial leverage to total assets is 10% higher than peers.

The opposite signs of the dummy coefficients imply asymmetry in returns vs. the benchmark. We find a significant positive relation between the high confidence dummy and ROIC MV. If confidence is high, this adds 1.17% to ROIC MV in absolute terms. Conversely, ROIC MV is 2.74% lower in absolute terms when a firm is qualified as low confident. Both relations are significant.

[77] Note that we measure size as the natural logarithm of total market capitalization

**Table 5.4.7: Pooled Panel Regression confidence dummies**

| Dependent variable: ROIC MV (1980-2008) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Constant | 0.0316 | *** | 0.0302 | *** | 0.0160 | * | 0.0258 | *** |
| | (0.0076) | | (0.0078) | | (0.0084) | | (0.0081) | |
| LNSIZE | 0.0022 | *** | 0.0020 | ** | 0.0026 | *** | 0.0016 | ** |
| | (0.0008) | | (0.0008) | | (0.0008) | | (0.0008) | |
| BEME | 0.0102 | ** | 0.0127 | *** | 0.0129 | ** | 0.0129 | *** |
| | (0.0047) | | (0.0049) | | (0.0051) | | (0.0049) | |
| EXCESS LEV | | | -0.0146 | *** | -0.0176 | *** | -0.0140 | *** |
| | | | (0.0037) | | (0.0037) | | (0.0035) | |
| $D_{HIGH}$ | | | | | | | 0.0117 | *** |
| | | | | | | | (0.0015) | |
| $D_{LOW}$ | | | | | | | -0.0276 | *** |
| | | | | | | | (0.0028) | |
| Industry effects | No | | No | | Yes | | Yes | |
| Period effects | Yes | | Yes | | Yes | | Yes | |
| Adjusted $R^2$ | 0.1971 | | 0.2093 | | 0.2441 | | 0.3033 | |

Note: Method: Pooled Panel OLS regression with period fixed effects. The dependent variable equals the return on invested capital at market value. Dummies reflect high (low) confidence sample. LNSIZE equals ln(market equity). Market equity equals shares outstanding times price (items 199*25); BEME-ratio equals book to market equity. Book equity is total stockholder's equity less preferred stock plus deferred tax assets (items 216 –130 + 35). Excess leverage equals net debt to EBITDA [(items 9+34–1)/(item 13)] minus the industry debt ratio (based on two digit SIC code) times EBITDA to total assets. If EBITDA <=0 and net debt <=0, net debt to EBITDA is set at 0. If EBITDA is <=0 and net debt>0, excess leverage is set at net debt to total assets. Excess leverage is winsorized at (minus) one times total assets. ROIC MV or return on market value adjusted capital equals (1-cash tax rate) times EBIT (item 178) divided by invested capital at market value. Cash tax rate equals income tax less accrued and deferred taxes (item 16-305-126) divided by pre-tax income (item 170). If not between 0 and 1, we use the income tax cash rate or otherwise a default rate of 35%. Invested capital (item 37) includes market instead of book equity. We exclude observations with negative invested capital or a | ROIC| >1.Asterisks indicate significance levels of 10% (*), 5% (**) and 1% (***).

**Table 5.4.8: Specification industry effects and ROIC MV**

| **Dependent variable: ROIC MV (see table 5.4.5)** | | | | |
|---|---|---|---|---|
| Constant | 0.0160 | * | 0.0258 | *** |
| | (0.0084) | | (0.0081) | |
| FF_1 | 0.0203 | *** | 0.0198 | *** |
| | (0.0042) | | (0.0040) | |
| FF_2 | 0.0092 | * | 0.0110 | ** |
| | (0.0055) | | (0.0050) | |
| FF_3 | 0.0124 | *** | 0.0124 | *** |
| | (0.0043) | | (0.0040) | |
| FF_4 | 0.0072 | | 0.0066 | |
| | (0.0057) | | (0.0056) | |
| FF_5 | 0.0174 | *** | 0.0160 | *** |
| | (0.0045) | | (0.0044) | |
| FF_6 | -0.0031 | | -0.0009 | |
| | (0.0045) | | (0.0042) | |
| FF_7 | 0.0104 | ** | 0.0114 | ** |
| | (0.0053) | | (0.0055) | |
| FF_9 | 0.0104 | *** | 0.0105 | *** |
| | (0.0041) | | (0.0039) | |
| FF_10 | 0.0012 | | 0.0027 | |
| | (0.0043) | | (0.0041) | |
| $D_{HIGH}$ | | | 0.0117 | *** |
| | | | (0.0015) | |
| $D_{LOW}$ | | | -0.0276 | *** |
| | | | (0.0028) | |
| Adjusted $R^2$ | 0.2441 | | 0.3033 | |

Note: Method: Pooled Panel OLS regression with period fixed effects. ROIC MV equals the return on invested capital at market value. Dummies reflect high (low) confidence sample. Asterisks indicate statistical significance at the 10% (*), 5% (**) or 1% (***) level. White period adjusted standard errors in brackets. Variables as defined in table 5.4.5. FF_# refers to the twelve Fama French industry groups. Industry groups 8 and 11 i.e. utilities and financials are excluded. Industry group 12 = miscellaneous and reflected in the constant term.

## 5.5 Robustness checks

As a robustness check, we redo our analysis by replacing the confidence dummies by aggregating[78] the separate Z-scores on the seven confidence indicators. For brevity, we call this alternative variable the Z-score. In formula terms, the Z-score for each firm in a certain year (firm and period identifiers are excluded for readability) is calculated as follows:

$$
\begin{aligned}
&Zscore = Zscore_{accruals} + Zscore_{acq} - Zscore_{oplev} + Zscore_{sic} + \\
&\tfrac{1}{2}\left[Zscore_{invest} + Zscore_{fingap}\right] + \tfrac{1}{2}\left[Zscore_{sharebb} + Zscore_{fingap}\right] + \\
&\tfrac{1}{3}\left[Zscore_{div\_change} - Zscore_{payout} + Zscore_{fingap}\right]
\end{aligned}
$$

**Equation 5.5.1**

The seven right-hand terms refer to the confidence indicators i.e. accruals, acquisitions, operating leverage, diversification, investment, share buyback policy and dividend policy. For more details on the variable calculations, we refer to Appendix I. As we have introduced additional constraints such as the financing gap and the change in dividend, we arrive at nine variables in total which are normalized and aggregated. When we assume a negative relation between a confidence indicator variable and confidence, the Z-score is subtracted i.e. dividend payout and operating leverage. If an indicator is based on several variables, such as the dividend indicator (dividend change, dividend payout and financing gap), each element is equally weighted.

Unlike the determination of the extreme confidence portfolios, we no longer enforce a positive or negative direction i.e. zero scores are now possible for each confidence indicator separately. Table 5.5.1 summarizes the pooled panel regression (OLS) results of our alternative confidence variable i.e. the Z-score.

[78] As shown in Equation 5.5.1, we subtract rather than add the Z-scores related to dividend respectively operating leverage

**Table 5.5.1: Pooled Panel Regression Confidence Z-score**

| **Dependent variable: ROIC MV (1980-2008)** | | | | | |
|---|---|---|---|---|---|
| Constant | * | 0.0258 | *** | 0.0262 | *** |
| | | (0.0081) | | (0.0091) | |
| LNSIZE | *** | 0.0016 | ** | 0.0018 | ** |
| | | (0.0008) | | (0.0009) | |
| BEME | ** | 0.0129 | *** | 0.0122 | ** |
| | | (0.0049) | | (0.0053) | |
| EXCESS LEV | *** | -0.0140 | *** | -0.0153 | *** |
| | | (0.0035) | | (0.0036) | |
| $D_{HIGH}$ | | 0.0117 | *** | | |
| | | (0.0015) | | | |
| $D_{LOW}$ | | -0.0276 | *** | | |
| | | (0.0028) | | | |
| Z-score | | | | 0.0018 | *** |
| | | | | (0.0005) | |
| Industry effects | | Yes | | Yes | |
| Period effects | | Yes | | Yes | |
| Adjusted $R^2$ | | 0.3033 | | 0.2586 | |

Note: Method: Pooled Panel OLS regression with period fixed effects. The dependent variable equals the return on invested capital at market value. Dummies D reflect high (low) confidence sample. Z-score refers to the sum of normalized confidence variables. LNSIZE equals ln (market equity). Market equity equals shares outstanding times price (items 199*25); BEME-ratio equals book to market equity. Book equity is total stockholders' equity less preferred stock plus deferred tax assets (items 216 –130 + 35). Excess leverage equals net debt to EBITDA [(items 9+34–1)/(item 13)] minus the industry debt ratio (based on two digit SIC code) times EBITDA to total assets. If EBITDA <=0 and net debt <=0, net debt to EBITDA is set at 0. If EBITDA is <=0 and net debt>0, excess leverage is set at net debt to total assets. We winsorize excess leverage at (minus) one times total assets. ROIC MV or return on market value adjusted capital equals (1-cash tax rate) times EBIT (item 178) divided by invested capital at market value. Cash tax rate equals income tax less accrued and deferred taxes (item 16-305-126) divided by pre-tax income (item 170). If not between 0 and 1, we use the income tax cash rate or otherwise a default rate of 35%. Invested capital (item 37) includes market instead of book equity. We exclude observations with negative invested capital or a | ROIC| >1. Asterisks indicate significance levels of 10 (*), 5 (**) and 1% (***).

When we replace our confidence dummies by our Z-score variable, adjusted $R^2$ is lower at 26%. Our Z-score variable adds 1.45% (not shown) to explanatory power. The constant term and coefficients on size, BEME ratio, excess leverage and industry groups remain similar, also in terms of significance. We find a significant positive relation between the Z-score and ROIC MV at the 1% level. This suggests that not only extreme confidence characteristics are reflected in performance, but that any change in confidence may have an impact on returns on invested capital.

Alternatively, we have introduced a one-year lag of the independent variables for addressing endogeneity and a possible delayed impact of the degree of confidence on performance[79]. The introduction of a one-year lag causes a loss of explanatory power to just over 20%, but overall the constant term and coefficients are similar in terms of size and significance. The coefficient on the BEME flips to negative, but is no longer significant. Also, neither excess leverage nor industry group 7 (Telecom) is now significant. The coefficients on the confidence dummies or Z-score are smaller but all remain significant at the 1% level for the confidence dummies respectively 5% level for the Z-score confidence variable.

## 5.6 Summary and discussion

In this chapter, we have calculated a degree of confidence for S&P 500 companies over the 1980 to 2008 period, which was inferred from corporate decisions on operations, investment and funding. Looking at the extremes, we find significant differences in the characteristics of low and high confidence firms in terms of size, book-to-market equity ratio, financial leverage vs. the industry average and performance. Lower confidence firms tend to be smaller, more distressed, less conservatively financed and, except for the new millennium, yield a lower return on invested capital with higher variability.

In order to capture time characteristics, we use a long period that covers almost three decades i.e. from 1980 to up and including 2008. Our results indicate that the share of high to low confidence firms coincides with major economic events across time. We observe that the proportion of high vs. low confidence firms deteriorates during major shocks, such as the Savings and Loans crisis, the First Gulf war, the dotcom crash and September 11th attacks in 2001 and the collapse of the financial markets in 2008. Neither the October 1987 nor the Asian crisis in the late nineties seem to have heavily affected confidence and instead seemed isolated events. However, in the late 90s, there were some mitigating factors, such as the low interest environment and hot issue market in technology and Internet. Also, the boom and bust of the housing and financial market is visible.

It is striking to see that the number of low confidence companies plummets to very low levels as of the mid-nineties, both compared to historical levels and compared to the amount of high confidence companies. Is this thanks to animal spirits in action or do we have to redo the math and enforce another correction to restore the balance? We have also

[79] Fama and French (1992) also have a one- to two-year difference between annual stock returns (measured from Jan –Dec fiscal year +2) and the cut-off points for measuring the independent variables i.e. the BEME ratio (end of fiscal year) and size (end of June fiscal year +1).

analyzed industry characteristics, but it is hard to find a common denominator. Low confidence companies seem to have a higher representation in dynamic or rapidly changing industries like technology and telecom. We find that high confidence firms have high exposure to consumer non-durables and manufacturing.

Finally, we have investigated if there is a relation between our confidence measure and company performance. We use a hybrid measure, defined as the return on invested capital at market value (ROIC MV) that captures both backward looking (accounting) and forward looking (market) information. We expect extreme situations of confidence to lead to suboptimal decisions and hence lower returns on invested capital, regardless of the direction of the bias. Hackbarth (2009) argues that a mild bias might be seen as positive, as it offsets underinvestment from risk-aversion.

The descriptive statistics show an asymmetric relation with significantly lower returns for low confidence companies vs. high confidence ones. Differences in returns between the confidence extremes are most pronounced in the eighties, fade out in the nineties and evaporate in the new millennium. Overall, we consider returns very low, which can only be justified if growth prospects look bright or investors requiring modest returns. The use of a Z-score instead of a dummy variable for extreme levels of confidence does not violate the positive relation between the degree of confidence and performance, which also remains significant. This suggests that not only extreme levels of confidence have an impact on performance, but any level.

Instead of using a hybrid dependent variable like ROIC MV which incorporates both book and market values, we could opt for a pure market performance measure, such as stock returns. In the next chapter, we will investigate if the move to an extreme confidence level yields abnormal stock returns using a multifactor model. In addition, we include investor sentiment indicators to explore the interaction between the degree of confidence and investor sentiment.

# 6 Does extreme confidence yield extreme stock returns?

## Abstract

In this chapter, we contribute to current research by empirically investigating if companies that move to extreme levels of confidence also earn cumulative abnormal stock returns (CARs), adjusted for investor sentiment as well. Over the 1980-2008 period as a whole, we find that a long-short strategy in high-low confidence firms could pay off if in high abnormal returns of 6.21% and 9.47% if well-timed one to two years in advance. In the years after changing to extreme confidence levels, CAR differences between extreme degrees of confidence are not significant, except for the nineties. Then, investing in high confidence firms has a significant negative pay-off. On a standalone basis, we find highly negative CARs to up to -13.22% prior or during a move to the lower confidence tail, thus implying that low rather than high confidence is detrimental to stock performance. We find a significant positive relation with CARs and investor sentiment, the latter of which also significantly interacts with company confidence, albeit conditional on the CAR window.

## 6.1 Introduction

*"Markets can remain irrational longer than you can remain solvent"*

*Attributed quote to Keynes in a biography by Harrod (1951)*

One of the key assumptions underlying the efficient market hypothesis or EMH is that economic agents have rational expectations and maximize utility. Irrational behavior is arbitraged away or does not have a long-lived impact. This implies that this non-fundamental risk should not be awarded with persistent abnormal returns. In chapter three, we discussed that limits to arbitrage and the widely documented existence of market anomalies imply that this assumption is violated in practice.

When we value a risky asset, we do not only have to deal with market participants, but with company management as well, including their interactions. The option to rely on the market for readdressing irrational management behavior can become costly, both in terms of money and time, as reflected in Keynes' words. DeLong et al. (1990) state that "a departure from rationality or noise creates unpredictability, uncertainty and non-fundamental risk regarding the length and extremeness of market distortions[80]". Although they referred to investors, this may also apply to irrational managers. As a result, abnormal return opportunities may arise, which can be very persistent instead of just a temporary mispricing.

Earlier, we already discussed how extreme company confidence can impact performance, for which we used a hybrid measure that contained both accounting and market information. We found that amongst other differences, lower confidence firms tend to yield a lower return on invested capital with higher variability, except for the new millennium. This seems hard to reconcile with a lower risk profile, as lower confidence tend to be more distressed and smaller.

In this chapter, we narrow our scope to market-based performance indicators, or specifically abnormal stock returns. Our expectation is that when adjusting for risk-adjusted returns, the performance gap between high and low confidence firms widens even further. As the information that we use for calculating our confidence indicator is all publicly available, albeit revealed with some delay after the fiscal year end, semi-strong market efficiency suggests that prices should reflect this information shortly after release[81].

[80] Although DeLong et al (1990) refer to the financial market, one could also take a broader definition and include real markets as well.

[81] It should be contained in the annual report, which is released shortly after the FY figures. When the book year coincides with the calendar year, one can expect this information by March/April when the annual report is released.

Apart from comparing cumulative abnormal stock returns (CARs) between firms that move to the most extreme company confidence levels, we also allow a role for investor sentiment and its interaction with company sentiment. As the market may anticipate a move to extreme confidence levels, but may also underreact or overreact to such news, we take various windows for calculating CARs. Causality could run from (lagged) market sentiment to management's confidence but also the other way around. For instance, Shleifer and Vishny (2003) empirically find a positive relation between merger and acquisition activity and stock valuation. However, so-called "bellwether" stocks like Intel can also heavily impact market sentiment.

The chapter is organized as follows. First, we discuss some limitations of current research on overconfidence. Subsequently, we describe our sample and methodology. Apart from reporting plain results on abnormal stock returns between the confidence extremes for the 1980-2008 period as a whole, we explore the characteristics by decade as well as possible interaction between investor sentiment and company sentiment. In addition, we include the overall stock market environment in the picture, for which we use the implied equity risk premium as a proxy. Similar to chapter five, we also perform a robustness check by using an alternative measure for calculating total confidence. Finally, we end the chapter with a summary and discussion of our main findings.

## 6.2 Shortcomings of current research

In literature on irrational management behavior, overconfidence and its impact on corporate decisions attracts most attention. The big challenge is how to measure overconfidence, while extending the analysis to performance would provide a link to investors. Empirical tests of the detrimental impact of suboptimal decisions by biased management on company or shareholder value are scarce if performed at all. Malmendier and Tate (2005, 2008) calculate excess returns vs. the S&P 500 by overconfident CEOs[82], to test whether or not insider trading instead of overconfidence could be a rational argument why they are underdiversified. The authors mutually exclude positive excess returns and overconfidence though. They find no excess returns on average, although there is a negative announcement effect of acquisitions. Based on these results, the authors dismiss the insider trading argument. However, we note that these may have to do with the long time lag of five years, before a CEO who failed to exercise options is qualified as confident.

Goel and Thakor (2008) show that, up to a certain point, management overconfidence can enhance company value by compensating for risk aversion. However, for extreme forms of overconfidence, the impact is detrimental, due to over- or

[82] Malmendier and Tate (2005) define an overconfident CEO as one who has excessive exposure to his firm by holding instead of exercising in the money options

underinvestment. We are not aware of any literature on the culprit of extreme forms of diffidence. Assuming symmetry, we would also expect higher required returns for any form of extreme confidence. However, we only documented very low returns on invested capital for low confidence firms in the previous chapter, which may suggest asymmetry. The sign of the CARs is not clear though, as it depends on the source of the low returns on invested capital i.e. whether it reflects a denominator or a numerator effect. As the market value of equity represented the biggest component in the denominator, this could imply that the market has not yet fully discounted the stock or underreacted to news. However, overreaction is also possible if the market heavily discounted the shares in previous periods, while earnings recovery has yet to occur i.e. the numerator depresses return on invested capital. In the latter situation, positive CARs are possible.

In chapters four and five, we constructed an indirect measure of a company's confidence level and linked this to return on invested capital. We constructed a composite confidence measure from seven confidence indicators covering a wide range of corporate decisions on operations, investment and funding. As a result, companies were only marked as high or low confident if they exhibited this behavior consistently in those seven areas. We expected extreme confidence levels to lead to suboptimal decisions and hence lower returns on invested capital (ROIC), regardless of the direction of the bias[83]. However, amongst other differences, we found a significantly lower and more volatile performance for the bottom vs. the top confidence deciles, thus suggesting asymmetry.

In this empirical study, we use Carhart's (1997) four factor model and analyze if 12- month cumulative abnormal returns (CARs) within and between the two confidence extremes are significantly different for various windows i.e. the year prior, the year itself and the two years after moving to an extreme low or high confidence level. In other words, we explore the profitability of a long strategy in either of the confidence extremes and a long-short strategy in the high- low extreme. The base case of efficient markets implies that it is not possible to persistently earn abnormal returns based on historical, recent market or even inside information. As our confidence measure entails various indicators on which news could be released throughout the year, this implies many price moving events and hence opportunities for abnormal returns if adjustments are insufficient. Apart from biases, investors may suffer from the use of heuristics.

Financial market booms and busts across time imply that confidence is highly contagious rather than an isolated phenomenon. Akerlof and Shiller (2009) referred to this as the confidence multiplier. Baker and Wurgler (2006) already investigated the standalone impact of investor sentiment on cross-sectional stock returns, but we also explore if

[83] Hackbarth (2009) shows that a mild bias might be seen as positive as it offsets underinvestment from risk-aversion

interaction between company confidence and investor sentiment significantly impacts CARs.

The relation between investor and management confidence is not straightforward. For instance, management may have good reasons to ignore or even defy market signals given their inside information, thus implying a non-existent or negative relation. Alternatively, there could be an asymmetric relation, conditional on management's risk attitude and dominance of either confirmation bias or cognitive dissonance. If risk seeking, we would expect management to overweigh positive and to underweigh respectively ignore negative investor sentiment, while the opposite is more likely to occur if they are highly risk averse.

## 6.3 Data and methodology

For the first set of data, we use our confidence measure as calculated for the S&P 500 firms from 1980 up to and including 2008 in chapters four and five. In our analysis, we use the 10% and 90% percentile as breakpoints for determining the two confidence extremes. The few companies (34) that move from one extreme to the other in the subsequent year are excluded, which does hardly affect our results. Furthermore, we only look at the *change* in confidence vs. the previous year, for which we use dummies. This approach enables us to track returns in the period before and after such a change. Conversely, if we take the absolute confidence level and no change takes place in the prior or post period, we cannot determine whether returns reflect the past, current or future situation, For companies that remain qualified as extremely high or low confident in the subsequent year, the confidence change dummy takes a value of zero. The reason for doing so is that we calculate CARs over different monthly time windows of [-12, -1], [0, 11], [12, 23] and [24, 35], with zero corresponding to the month January of the year in which a move to extreme confidence takes place[84]. This methodology significantly reduces the observations in the extreme confidence samples by roughly 50%, as confidence levels tend to be steady for a while.

The second set of data comprises total monthly returns of these S&P 500 companies over 1979-2008. We only extract return data of common stock i.e. exclude share codes 10 and 11[85] from the CRSP database. We use these data for calculating abnormal stock returns following Carhart's (1997) four factor model, in which the return in excess of the risk-free rate, denoted R, is explained by the excess market return (RMRF), size (SMB), distress (HML), prior year momentum (PR1YR) and some noise as denoted by the error term. This

[84] Alternatively, we could correct t-values for this problem by dividing these by the square root of the maximum amount that an observation could pop up (i.e. four times).
[85] Sometimes, firms have more than one PERMNO code, due to different classes of stock or other technical reasons. In that case, we take the class which is most traded by the public

is shown by equation 6.3.1 (next page). The subscripts $t$ = 1,2,…T and $T$ correspond to the total months for which we have stock returns data and the subscript $i$ identifies the firm.

$$R_{i,t} = \alpha_{i,T} + b_{i,T} RMRF + s_{i,T} SMB + h_{i,T} * HML + p_{i,T} * PR1YR_t + e_{i,t}$$

**Equation 6.3.1**

First, we have to estimate the factor sensitivities for each company, by regressing monthly stock returns from the same period on the monthly factor premiums[86] by using an ordinary least squares approach. The error terms or residuals correspond to the monthly abnormal returns, which are accumulated for the full year. We thus assume perfect hindsight and no change in factor exposure across the years. Note that in the TMT (Technology Media and Telecom) bubble, we saw a large drop in market beta for non-TMT stocks, while this was reversed in later periods. Such temporary distortions are not reflected in our coefficients, but translate into the error term[87]. We require data for the full year in order to be included. Investors could have anticipated the very low mean returns on invested capital for low confidence firms by depreciating the stock in previous months. Alternatively, it could take some time before the market finds out about the confidence level, as some information[88] is revealed after the fiscal year-end.

When we assume positive risk premiums on the four factors[89], the smaller size and higher book-to-market ratio imply higher (required) stock returns for the lower confidence firms. Furthermore, we expect market beta to be positive for these S&P 500 firms[90], which also translates into higher returns. It is intuitive to think that momentum is negative for low confidence stocks, but we doubt whether this factor could mitigate the higher required returns from the other three factors. Taking into account the lower raw annual stock returns that we found in earlier research, we would expect negative risk adjusted returns or CARs for the low confidence firms.

We use an analysis of variance or ANOVA to test whether or not CAR differences are significant between the confidence extremes in the year before, the year itself and the two years after the change to extreme confidence. In addition, we explore how CARs evolve over different sub periods comprising the eighties, nineties and the 2000 years.

86 These factor premiums are extracted from Kenneth French' website.
87 If we would use year-fixed effects, such year-related distortions would translate into a higher constant term
88 In particular, working capital changes i.e. changes in accruals are hard to predict, as these can be very volatile and subject to management's discretion.
89 This seems very logical, but we note that only in three out of thirty years, all factor premiums are positive. Excluding momentum, only six out of thirty years have positive premiums on all three factors simultaneously.
90 We find a market beta of 1.12 and 1.10 for the low and high confidence firms. The sample includes three companies with a negative beta

Furthermore, the CAR difference between the two confidence extremes is put into a time and general stock market perspective. We use the forward (excess) earnings yield as a proxy for general stock market conditions. When long-term growth expectations and expected dividend payout ratios hardly change[91], the change in earnings yield should mirror the change in the equity risk premium. The latter is illustrated in the appendix, where we discuss Gordon (1962) growth model.

We calculate the actual and expected earnings yield for the market by using IBES data on earnings forecasts for as many companies as possible in a certain year, so beyond the S&P 500. In addition, we require at least five estimates before including a forecast. Most earnings forecasts are only one to two years ahead, while there is a high amount of missing data on long-term growth. Sufficient data on dividend estimates are not available until 2003. We supplement the forecast data with realized data from the (merged) Compustat/CRSP data with regard to earnings and dividends per share, fiscal year-end shares outstanding, fiscal year-end closing price and the share price on the date at which the consensus forecast was calculated (April 15th). We cannot perfectly reconcile the three different databases, but the loss of data is limited to less than two percent.

Next, we perform panel regressions for explaining CARs, which allows us to add additional control factors when explaining abnormal stock returns. We neither assume cross-section fixed nor period fixed effects, as abnormal returns *should* not be company or time dependent but noisy instead. In other words, we assume that smart investors will prevent companies from consistently beating or underperforming Carhart's model. However, we face a joint testing problem in this case and omitted risk factors could render Carhart's model less useful for specific companies.

Similar to our descriptive analysis, we take different time windows for calculating cumulative abnormal returns i.e. one year prior, the current year, next year and two years after the extreme confidence year. The right-hand terms or independent variables includes the change in the high (low) confidence dummy takes a value of one when a company moves from the mainstream confidence level to the top (bottom) 10%. As we discussed earlier, observations from one extreme to the other are excluded, while those implying no change in the degree of confidence level take a dummy value of zero. Apart from including the change in the confidence dummy, we control for the twelve[92] Fama-French industry groups. Finally, we also add lagged investor sentiment and its interaction with company confidence.

In current literature, there are various proxies for investor sentiment. Brown and Cliff (2004) consider a comprehensive set of sentiment proxies, which consists of both

[91] For the market as a whole, such an assumption is not uncommon

[92] As our sample excludes utilities and financials due to their specific balance sheet characteristics and regulatory environment, we are only left with ten industry groups

direct and indirect variables. Also, they distinguish between institutional investor sentiment and those of individual investors and test the relation of sentiment with subsequent stock returns. Baker and Wurgler (2006) also construct a composite sentiment variable from various indirect investor sentiment proxies in earlier literature and clean for business cycle effects as well. Their measure allows for lagging effects between these variables and investor sentiment. They find significant evidence that, when adjusting for Carhart's (1997) four factors, investor sentiment may indeed have a significant impact on cross-sectional stock returns. The effect seems higher, the more subjective and the more difficult to arbitrage a stock is. These data can be retrieved from Wurgler's website[93] and we include these in our regression equation. We refer to the appendix for more details about these investor sentiment proxies. These factors are all summarized in the following regression equation:

$$CAR_{i,t} = \alpha_{0i,t} + \beta_{1i,t} D_{low,i,t} + \beta_{2i,t} D_{high,i,t} + \beta_{3i,t} SENT_{t-1} + \beta_{4,i,t} SENT_{t-1} D_{low,i,t} \\ + \beta_{5,i,t} SENT_{t-1} D_{high,i,t} + FF\_industry \times X' + \varepsilon_{i,t}$$

**Equation 6.3.2**

*CAR* stands for the cumulative abnormal stock return, the constant term *α* also captures the industry group one, the dummies *D* refer to the direction of the confidence change, the term *SENT* refers the clean sentiment indicator of Baker and Wurgler (2006) in the prior year *t-1* followed its interaction with company confidence. Finally, we correct for industry effects[94], while the error term captures the unexplained part.

In our robustness check, we will define an alternative confidence variable or the change in the standardized individual confidence score on each of the seven indicators, abbreviated as the Z-score. We calculate mean CARs for different windows for each of the Z-score deciles and use an F-test to calculate whether or not mean CARs are simultaneously different among deciles.

## 6.4 Results

### 6.4.1 Cross-sectional differences in CARs

In chapter five, we reported significant differences between low and high confidence companies, with the former having 1) a smaller size, 2) a higher book-to-market equity ratio, 3) less conservative financing, albeit still underleveraged vs. the

[93] Data are updated until 2007

[94] As our sample excludes financials and utilities, Fama French industry groups 8 and 11 are not represented in our sample.

industry, 4) higher valuation multiples, 5) a lower and more volatile return on invested capital at market value and 6) lower raw annual stock returns[95]. Although a high share of cheap (debt) financing or low required returns could justify lower returns on invested capital, this explanation seems implausible for low confidence firms. Even with 100% debt financing, it is hard to believe that debt holders would be sufficiently compensated for their risk with a required return of less than 3% [96] after tax, especially when bearing in mind that these companies tend to be more distressed. Assuming efficient markets, this implies that the dip in ROIC is temporary and should reverse. If this view on recovery proves wrong, the market value of invested capital should depreciate until the required return hurdles are met, hence creating negative CARs.

**Table 6.4.1: Performance Characteristics by confidence level**

| | **Change to Highconf** | | **Change to Lowconf** | | **Change to Neutral** | |
|---|---|---|---|---|---|---|
| | Mean | Median | Mean | Median | Mean | Median |
| AT | 6,624 | 3,307 | 6,045 | 2,123 | 6,694 | 2,929 |
| EBITMARGIN | 0.1157 | 0.1049 | 0.0573 | 0.0539 | 0.1239 | 0.1055 |
| ROIC_MV | 0.0679 | 0.0610 | 0.0349 | 0.0317 | 0.0580 | 0.0550 |
| PRE12M_CAR | -0.0028 | 0.0088 | -0.0968 | -0.0808 | 0.0017 | -0.0027 |
| CAR_FYEAR | -0.0174 | -0.0088 | -0.0657 | -0.0598 | -0.0242 | -0.0236 |
| POST12M_CAR | -0.0360 | -0.0395 | -0.0055 | -0.0096 | -0.0173 | -0.0083 |
| POST24M_CAR | -0.0105 | -0.0204 | 0.0140 | 0.0097 | -0.0240 | -0.0271 |
| N | 247 | 247 | 231 | 231 | 313 | 313 |

Note: AT stands for total assets, ROIC MV for return on invested capital at market value, CAR refers to annual cumulative abnormal return, which is measured 12 months before, during and after the year in which a degree of confidence was calculated. Using seven confidence indicators on investment, operating and financial decisions, we calculate a total degree of confidence score. The top (bottom) 10% belong to the high (low) confidence sample, while zero scores are qualified as neutral.

Although each of the sub samples is much smaller or about half that in chapter five, company characteristics are similar as shown in table 6.4.1. Within each confidence sample, we only include observations which have data on all financial variables. Low confidence firms are indeed smaller and have much lower profitability. We stress that low

[95] Specifically, Fama and French (1992) form portfolio's based on the BM-ratio at the end of fiscal year t and the size (market capitalization) as of the end of June on t+1. Annual returns are calculated as of January in the following year t+2. We also take the annual return two years later.

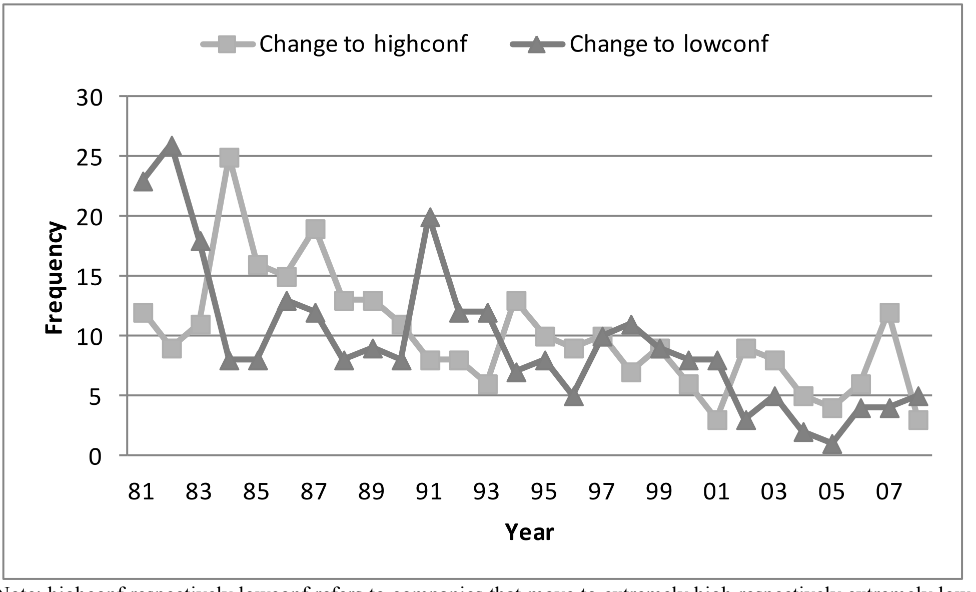
[96] We found mean returns on invested capital at market value of 2.81% and 6.94% for low respectively low confidence firms over the 1980-2008 period.(Chapter 5)

EBIT margins or related profitability measures were not used as criteria for assigning a degree of confidence level. Overall, return on invested capital at market value (ROIC MV) is low and below six percent for the total sample (not shown in table). Unless required returns are low, this suggests that the market anticipates future growth.

Figure 6.4.1 shows the frequency of the number of firms that move to extreme confidence areas. In total, we only have 280 respectively 267[97] observations of firms that move to extremely high respectively extremely low confidence areas in a certain year. The positive correlation (0.1769) implies that years with a higher frequency of one extreme, also tend to have a higher frequency of the other extreme.

[97] Note: the higher amount of observations vs. table 6.4.1. is due to the fact that we no longer require data on financial metrics, such as sales, margins and stock returns.

**Figure 6.4.1: Frequency of movements to extreme confidence**




Note: highconf respectively lowconf refers to companies that move to extremely high respectively extremely low confidence levels.

Table 6.4.2 shows the outcome of the Analysis of Variances (ANOVA) between the two extreme confidence levels. We note that the number of observations is approximately 10% higher for each window for each confidence sample compared to table 6.4.1, as we only require data on CARs for this specific window instead of all windows. This explains the differences in mean CARs.

We find that for the high confidence sample, CARs are all negative, but not significantly different from zero for either window. This suggests that insider trading does not pay off for overconfident firms, as the results of Malmendier and Tate (2005) also indicated. For the low confidence sample, however, we see a clearly different pattern. CARs are significantly negative in the year prior and low confidence year itself, despite the fact that we include momentum in the equation. As momentum is determined by looking at prior 12 month raw returns[98] i.e. not adjusted for risk, this might be to blame. However, we see an improvement in the two years hereafter, when CARs even turn positive, albeit not significant.

[98] Formally, prior year momentum is constructed as the equal weight average of the firms with the highest 30% eleven-month returns lagged one month less the equal weight average of the firms with the lowest 30% eleven-month returns lagged one month. See Carhart (1997) and Kenneth French' website.

Apart from within sample CARs, we also examine whether the difference in mean CARs between extreme samples is significant. In other words, we test if a long-short strategy could earn significantly positive CARs. We find that 12 months prior to moving to an extreme confidence level, CARs of the low confidence sample are significantly lower at -9.56% vs. -0.08% for high confidence firms, thus implying a gap of 9.47%. In the low (high) confidence year itself, the CAR gap narrows to 6.21%, both of which are negative at -8.20% (-1.99%). However, in the next 12-24 months, the loser (winner) turns out to be less of a loser or even a winner (loser) with CARs of -0.31% (-2.25%) respectively 1.50% (-1.23%). Consistent with De Bondt and Thaler (1985), we find a reversal pattern for abnormal stock returns of diffident companies after two years[99], but CAR differences are not significant in either year. In the next section, we will explore if these significant differences also hold within specific periods, i.e. the eighties, the nineties and the 2000 years.

**Table 6.4.2: mean CARs confidence extremes (1980-2008)**

| **Mean CAR** | High Confidence | N | Low Confidence | | N | High-/- Low | | N |
|---|---|---|---|---|---|---|---|---|
| PRE12M | -0.0008 | 279 | -0.0956 | *** | 266 | 0.0947 | *** | 545 |
| FYEAR | -0.0199 | 280 | -0.0820 | *** | 267 | 0.0621 | ** | 547 |
| POST12M | -0.0225 | 270 | -0.0031 | | 252 | -0.0194 | | 522 |
| POST24M | -0.0123 | 250 | 0.0150 | | 232 | -0.0273 | | 482 |

Note: Using seven confidence indicators on investment, operating and financial decisions, we calculate a total degree of confidence score. The top (bottom) 10% belong to the high (low) confidence sample. CAR refers to annual cumulative abnormal return, which is measured 12 months before, during and after the year in which a degree of confidence was calculated. The asterisks identify significance level at 10% (*), 5% (**) and 1% (***).

[99] If we would take the start of the confidence change year, reversal takes place after three years.

### 6.4.2 Period characteristics of extreme confidence CARs

When we analyze period characteristics, we divide the samples into three sub periods i.e. the eighties, nineties and 2000 years. We also explore different time windows with regard to cumulative abnormal stock returns. The results are summarized in table 6.4.3.

**Table 6.4.3: Analysis of Variance in mean CARs by sub period**

| Subperiod | Mean | High Confidence | | Low Confidence | | High minus Low | |
|---|---|---|---|---|---|---|---|
| Eighties | PRE12M | 0.0235 | | -0.0957 | *** | 0.1193 | *** |
| | FYEAR | 0.0085 | | -0.0663 | ** | 0.0748 | ** |
| | POST12M | -0.0060 | | 0.0072 | | -0.0132 | |
| | POST24M | 0.0142 | | 0.0092 | | 0.0049 | |
| Nineties | PRE12M | -0.0287 | | -0.1026 | *** | 0.0740 | ** |
| | FYEAR | -0.0229 | | -0.1322 | *** | 0.1093 | ** |
| | POST12M | -0.0575 | * | -0.0305 | | -0.0270 | |
| | POST24M | -0.0485 | * | 0.0450 | | -0.0935 | * |
| 2000 Years | PRE12M | -0.0133 | | -0.0773 | | 0.0640 | |
| | FYEAR | -0.0825 | ** | -0.0028 | | -0.0798 | |
| | POST12M | -0.0036 | | 0.0406 | | -0.0442 | |
| | POST24M | -0.0149 | | -0.0593 | | 0.0444 | |

Note: Using seven confidence indicators on investment, operating and financial decisions, we calculate a total degree of confidence score. The top (bottom) 10% belong to the high (low) confidence sample. CAR refers to annual cumulative abnormal return, which is measured 12 months before, during and 12 after the year in which a degree of confidence was calculated. The asterisks identify significance level at 10% (*), 5% (**) and 1% (***).

On a standalone basis, prior and current year CARs for firms moving to low confidence are no longer significantly negative in the 2000 years, while the opposite is true for high confidence firms. Furthermore, CAR differences between extreme confidence groups seem period specific as well and with no longer significance for the new millennium. However, we note that we have fewer observations, as we only have data until 2008, thus making it more challenging to achieve significance. Furthermore, this was a very turbulent decade which started with high valuations and ended with the collapse of Lehman Brothers in 2008.

In more detail, we first discuss CARs for the high respectively low confidence firms on a standalone basis, which is followed by a comparison of the CAR differences between the two extremes by each sub period.

For the eighties, CARs are positive (significantly negative) a year prior to the extremely high (low) confidence year and in the year itself. The sign shifts in the next years, but is not significant though. For the high confidence firms, CARs turn negative in the year after changing to high confidence and positive hereafter, but none of these are significantly different from zero.

The nineties show a very weak performance with negative CARs prior, during and after the high confidence year, although only the latter is significant. In the years after moving to the high confidence sample, CARs are in significant negative territory at -5.75% and -4.85%. The low confidence firms perform very poorly with negative CARs in the double digit region, which cannot be compensated by the positive, albeit insignificant CAR of 4.50% two years later.

For the 2000 years, none of the CARs are significant for the low confidence sample, regardless of the time window. The high confidence firms continue their weak stock performance, with negative CARs across the board. Only in the high confidence year itself, it is significantly negative and sizable at -8.25%.

When we explore the CAR differentials between the extreme confidence samples, we arrive at the following results. For the eighties and nineties, there is a significant positive gap when we take a long position in high confidence and a short position in low confidence firms if we anticipate it well; the gap is only positive in the twelve months prior to and in the confidence year itself (for which realized data are released in the next year). Hereafter, the gap is no longer significant and tends to move to negative territory. Only for the nineties, we find a significant negative gap between high and low confidence firms in the 24 months following an extreme confidence year i.e. a reversal pattern. We note that the number of confident firms is not clustered at the late nineties at the time of the dotcom bubble, which could have been a possible explanation. Especially the high confidence companies showed a very weak stock performance in this period. For the 2000 years, low confidence firms no longer show a significant performance differential vs. high confidence firms. The difference in current and post 12 month CARs are in favor of the low confidence firms albeit not significant and partly reversed in the last period.

### 6.4.3 Extreme confidence CARs and general market developments

In this section, we compare CARs of extreme confidence stocks with general stock market developments, which we proxy by the implied earnings yield, including a forward measure. The descriptive statistics are shown in tables 6.4.4 and 6.4.5. In addition, we add some major economic events to give more color to our findings, as illustrated in figures 6.4.2 and 6.4.3.

In summary, we find that in most years, the mean CAR difference between confidence extremes is positive. Years in which high confidence firms underperformed seem to coincide with major economic shocks. This higher sensitivity to negative events may results from the significantly lower B/M ratios of high confidence stocks, which imply higher growth expectations. Furthermore, we find a positive correlation of 0.3247 between the high minus low returns gap and the equity risk premium.

The descriptive statistics in tables 6.4.4 and 6.4.5 show that the dividend payout can be highly volatile, mainly due to a (lagged) denominator effect. Also, the scarcity of forward looking dividend per share and long-term estimates becomes clear. One has to be cautious in looking at total market value, as it depends on sufficient analyst coverage. The dotcom bubble is clearly visible, which was accompanied with many IPOs and increased analyst coverage. One might have expected the highest PE ratio for the 1999 peak year as well, but the big multiples in excess of 100 were restricted to a specific industry rather than a market-wide phenomenon. Therefore, the inflating impact of a market-wide recession on the price-to-earnings ratio could be more severe than a bubble in a certain industry, as the former implies that expected earnings are depressed across all industries.

### Table 6.4.4: Dividend Payout, Forward PE and Size 1980-2008

| Year | Dividend payout prior year | Forward PE | Market Value in USD m |
|---|---|---|---|
| **1980** | 36.28% | 6.23 | 742,159 |
| **1981** | 40.40% | 8.27 | 1,077,163 |
| **1982** | 42.59% | 6.81 | 955,100 |
| **1983** | 52.67% | 11.62 | 1,345,694 |
| **1984** | 50.38% | 10.67 | 1,348,924 |
| **1985** | 45.27% | 10.56 | 1,586,179 |
| **1986** | 53.47% | 18.12 | 2,392,026 |
| **1987** | 58.83% | 18.64 | 2,486,141 |
| **1988** | 52.06% | 13.51 | 2,228,360 |
| **1989** | 46.63% | 11.81 | 2,498,598 |
| **1990** | 50.96% | 13.68 | 2,707,214 |
| **1991** | 61.10% | 16.64 | 6,189,999 |
| **1992** | 69.14% | 22.45 | 3,489,665 |
| **1993** | 63.15% | 21.21 | 3,952,814 |
| **1994** | 52.87% | 17.60 | 4,166,723 |
| **1995** | 41.78% | 14.95 | 4,705,464 |
| **1996** | 40.46% | 17.57 | 6,173,399 |
| **1997** | 37.76% | 17.30 | 7,305,970 |
| **1998** | 38.74% | 24.85 | 10,901,912 |
| **1999** | 44.25% | 29.55 | 25,854,885 |
| **2000** | 38.76% | 27.98 | 14,981,078 |
| **2001** | 38.52% | 27.60 | 13,192,734 |
| **2002** | 88.62% | 59.44 | 12,060,021 |
| **2003** | 63.06% | 31.18 | 9,620,843 |
| **2004** | 37.10% | 21.53 | 12,901,264 |
| **2005** | 32.74% | 17.76 | 13,448,326 |
| **2006** | 39.75% | 17.73 | 13,613,966 |
| **2007** | 30.42% | 16.25 | 17,546,959 |
| **2008** | 41.39% | 18.29 | 15,689,047 |

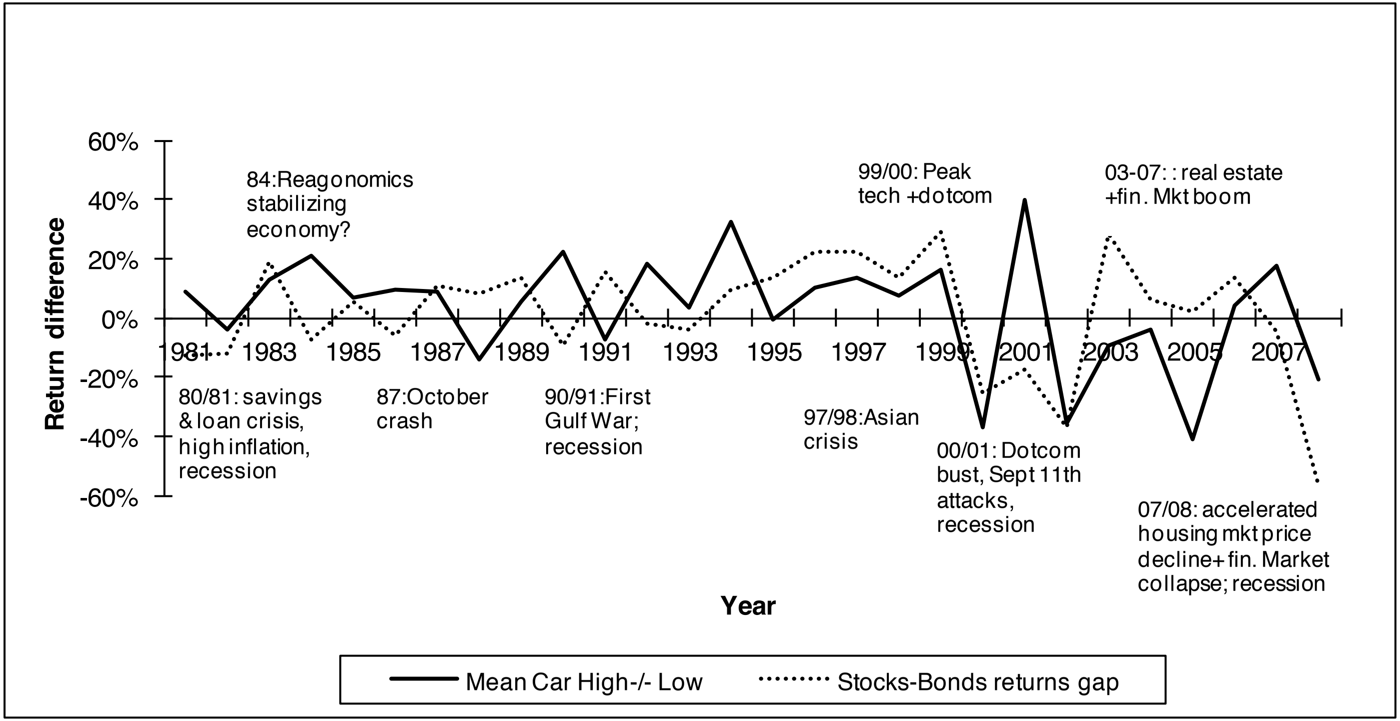
Note: Calculations are on an aggregate basis. including all companies with sufficient coverage i.e. a minimum of five earnings estimates on the highest frequency data item (i.e. EPS +1) as provided by I/B/E/S. Forward PE is calculated as the aggregated market capitalization, divided by the aggregated one-year ahead earnings forecast.

**Table 6.4.5: Number of Earnings per Share (EPS) estimates**

| Year | # LTG | # EPS +1 | # EPS +2 | # EPS +3 | # DPS +1 | # DPS +2 | # DPS +3 |
|---|---|---|---|---|---|---|---|
| **1980** | NA | 841 | 109 | NA | NA | NA | NA |
| **1981** | NA | 1,018 | 218 | NA | NA | NA | NA |
| **1982** | 544 | 1,064 | 334 | NA | NA | NA | NA |
| **1983** | 679 | 1,093 | 455 | NA | NA | NA | NA |
| **1984** | 786 | 1,247 | 677 | NA | NA | NA | NA |
| **1985** | 797 | 1,325 | 667 | 1 | NA | NA | NA |
| **1986** | 783 | 1,317 | 712 | 2 | NA | NA | NA |
| **1987** | 881 | 1,455 | 768 | 3 | NA | NA | NA |
| **1988** | 734 | 1,387 | 694 | 2 | NA | NA | NA |
| **1989** | 792 | 1,470 | 882 | 6 | NA | NA | NA |
| **1990** | 761 | 1,455 | 915 | 7 | NA | NA | NA |
| **1991** | 1,624 | 2,828 | 1,944 | 30 | NA | NA | NA |
| **1992** | 852 | 1,432 | 1,065 | 17 | NA | NA | NA |
| **1993** | 904 | 1,596 | 1,180 | 20 | NA | NA | NA |
| **1994** | 976 | 1,836 | 1,344 | 24 | NA | NA | NA |
| **1995** | 982 | 1,864 | 1,365 | 19 | NA | NA | NA |
| **1996** | 1,107 | 2,025 | 1,459 | 32 | NA | NA | NA |
| **1997** | 1,220 | 2,190 | 1,619 | 26 | NA | NA | NA |
| **1998** | 1,355 | 2,284 | 1,722 | 33 | NA | NA | NA |
| **1999** | 2,700 | 4,664 | 3,480 | 90 | NA | NA | NA |
| **2000** | 1,299 | 2,206 | 1,655 | 45 | 1 | 1 | NA |
| **2001** | 1,062 | 1,893 | 1,344 | 22 | NA | NA | NA |
| **2002** | 1,195 | 1,750 | 1,439 | 17 | NA | NA | NA |
| **2003** | 1,168 | 1,736 | 1,415 | 75 | 102 | 25 | 4 |
| **2004** | 1,061 | 1,943 | 1,738 | 158 | 209 | 130 | 5 |
| **2005** | 1,029 | 2,053 | 1,863 | 180 | 208 | 127 | 7 |
| **2006** | 894 | 2,161 | 1,963 | 278 | 303 | 237 | 22 |
| **2007** | 857 | 2,302 | 2,161 | 365 | 380 | 327 | 29 |
| **2008** | 581 | 2,300 | 2,128 | 473 | 485 | 457 | 140 |

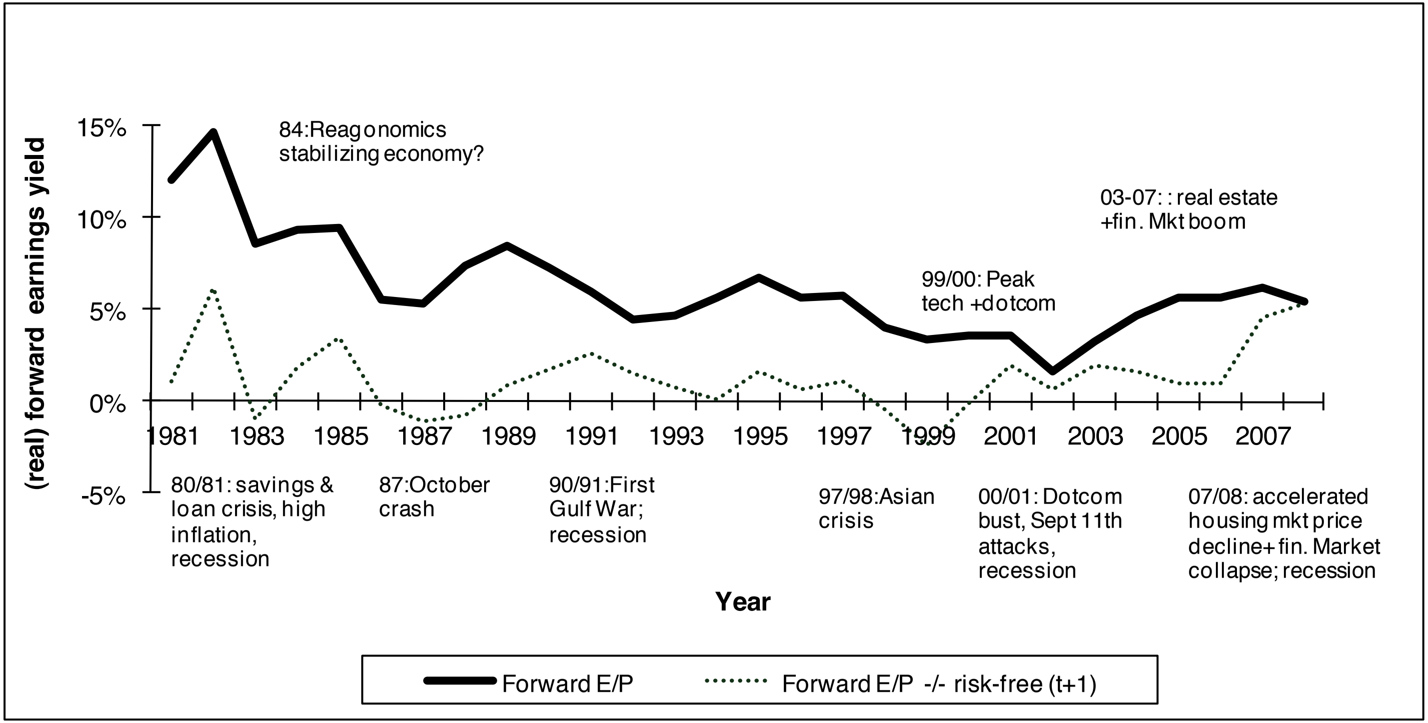
Note: LTG stands for long-term earnings growth. EPS (DPS) for earnings (dividends) per share, while suffices +1, +2 respectively +3 refer to the forecast horizon in years. NA stands for Not Available.

**Figure 6.4.2: Excess Returns High and Low Confidence Firms**




Note: asset return differentials and major historical events. The solid line refers to abnormal returns between the highest and lowest confidence deciles.
The dashed line shows the equity risk premium or the difference between stocks and T-bonds or equity risk premium (data retrieved from Damodoran's website).

**Figure 6.4.3: Forward Earnings Yield 1980-2008**




Note: The solid line shows the forward earnings yield (E/P). This equals consensus estimate of next year's earnings on an aggregate basis divided by the current share price i.e. the date on which consensus was constructed (April 15th). The dashed line shows the excess forward earnings yield in the current year t or the forward earnings yield less the expected risk-free rate for next year t+1. We have set the expected risk-free rate equal to the realized return on T-Bills (Damodaron 2011) for year t+1.

The solid line in figure 6.4.2 illustrates the mean CAR difference between high and low confidence firms and the stock-bond return difference or the equity risk premium. The latter variable is retrieved from Damodaron's website. High confidence firms underperformed low confidence firms in the following periods. In 1982, the aftermath of the oil and savings and loans crisis took its toll. In 1987, the stock markets crashed in October, although this seemed an isolated event. In 1991, the First Gulf War began and the US went into a recession. In 2000, the dotcom bubble burst and the heavily inflated stock market showed a sharp correction. In 2002, a recession followed the September 11th attacks, and high confidence companies underperformed in the subsequent three years as well. As of 2006, the housing and financial markets were flourishing and high confidence companies outperformed, until the financial meltdown in 2008.

Figure 6.4.3 shows the forward earnings yield (solid line), including the yield in excess of the risk-free rate (dotted line). Although the earnings yield in the early eighties seems very attractive, the picture is less rosy when correcting for the highly inflationary environment. At a quick glance, one could become very pessimistic when looking at the high frequency of bad events, as mentioned in the lower part of the graph. Also, the excess earnings yield is low with an arithmetic mean of only 1.27% for the period, albeit this ignores the long-term growth potential of stocks. The trough level of the excess earnings yield (-2.38%) coincided with the peak of the dotcom bubble in 1999. Conversely, when the housing and financial markets collapsed in 2007 and 2008, excess earnings yield moved to the mid-single digit region.

### 6.4.4 Pooled Panel Regression results

When we perform pooled panel regressions with CARs as the dependent variable, we take four different windows. These include up to one year before the move to an extreme confidence level, to the year of change itself and up to two years hereafter. The regression approach enables us to filter out other possible drivers behind CARs, such as industry effects and investor sentiment. Table 6.4.6 shows the regression results in the year in which a move to extreme confidence levels occurred and the contribution of each variable to explanatory power.

We note that the constant term partly captures an industry effect[100]. Excluding this, efficient markets require a constant of zero or no persistence in abnormal returns. The highly negative coefficient of -5.70% on the low confidence dummy is significant, both in statistical and economic terms. This continues to be the case when additional control factors are added. The positive coefficient on the high confidence dummy is not significant though. The sensitivity to prior year investor sentiment is positive and significant, also in

[100] Specifically, it captures Fama French industry group 1 i.e. non-durable consumer goods

economic terms. When we use the average investor sentiment score of 0.34, it would enhance CAR by some 80 basis points. This positive relation suggests that the momentum factor does not fully capture investor sentiment or future expectations. We find no significant interaction between company and investor sentiment.

**Table 6.4.6: CARs in the year of confidence change**

| **Method: Pooled Panel Regression (OLS) 1980 - 2008**<br>**Dependent Variable: CAR_FYEAR** | | | | | | | |
|---|---|---|---|---|---|---|---|
| CONSTANT | -0.0029 | -0.0062 | | -0.0118 | | -0.0127 | |
| | (0.0068) | (0.0076) | | (0.0077) | | (0.0078) | |
| $D_{high}$ | | 0.0056 | | 0.0067 | | 0.0047 | |
| | | (0.0150) | | (0.0155) | | (0.0183) | |
| $D_{low}$ | | -0.0570 | *** | -0.0514 | *** | -0.0358 | * |
| | | (0.0189) | | (0.0193) | | (0.0214) | |
| SENT(-1) | | | | 0.0248 | *** | 0.0276 | *** |
| | | | | (0.0062) | | (0.0068) | |
| SENT(-1)* $D_{high}$ | | | | | | 0.0056 | |
| | | | | | | (0.0219) | |
| SENT(-1)* $D_{low}$ | | | | | | -0.0371 | |
| | | | | | | (0.0235) | |
| Industry effects | Yes | Yes | | Yes | | Yes | |
| Year effects | No | No | | No | | No | |
| Adjusted $R^2$ | 0.0045 | 0.0112 | | 0.0151 | | 0.0154 | |
| N | 5,111 | 3,860 | | 3,827 | | 3,827 | |

Note: Observations pooled for the 1980-2008 period. Dependent variable is the cumulative abnormal stock return in the year in which a company moves to the top (bottom) confidence decile. Asterisks denote significance at the 10% (*), 5% (**) and 1% level (***). FF_industry groups as defined by Fama and French. excl. utilities and financials (groups 8 and 11). Industry group 1 (non-durable consumer goods) is captured by the constant term. ENT(-1) refers to the sentiment indicator in the prior 12 months, cleaned for business cycle effects as defined by Baker and Wurgler 2006. Sentiment data are available up to and including 2007. White adjusted standard errors in brackets.

We have also tested for asymmetry to the confidence dummies respectively interaction terms. The Chi square-test that the coefficient of the interaction term with low confidence is minus that of the high confidence yields a high p-value of 0.3461, so we cannot reject symmetry. Neither can we reject symmetry between the standalone sensitivities to extremely high respectively low confidence changes (p-value of 0.1549).

Table 6.4.7 summarizes the regression output when CARs prior respectively after a change to extreme confidence are taken as dependent variables. Overall, we only observe a few differences, such as a significant positive coefficient to the interaction term with high confidence in the year after the change. For this window, the coefficient to the low confidence also becomes positive, albeit not significant. Another year later, however, the CAR reversal to positive territory for low confidence firms indeed becomes significant, as tables 6.4.1 and 6.4.2 also indicate. Apart from other factors, confidence extremeness seems to have an important impact on stock performance.

**Table 6.4.7: CARs prior (post) a change to extreme confidence**

| **Method: Pooled Panel Regression (OLS) 1980- 2008** | | | | | | |
|---|---|---|---|---|---|---|
| **Dependent Variable CAR:** | **PRE12M** | | **POST12M** | | **POST24M** | |
| CONSTANT | -0.0152 | ** | -0.0300 | *** | -0.0354 | *** |
| | (0.0067) | | (0.0086) | | (0.0092) | |
| $D_{high}$ | 0.0195 | | -0.0078 | | 0.0188 | |
| | (0.0177) | | (0.0159) | | (0.0196) | |
| $D_{low}$ | -0.0608 | *** | 0.0220 | | 0.0490 | ** |
| | (0.0160) | | (0.0217) | | (0.0239) | |
| SENT(-1) | 0.0386 | *** | 0.0266 | *** | 0.0339 | *** |
| | (0.0071) | | (0.0067) | | (0.0073) | |
| SENT (-1)* $D_{high}$ | -0.0246 | | 0.0558 | ** | -0.0069 | |
| | (0.0194) | | (0.0228) | | (0.0288) | |
| SENT(-1)* $D_{low}$ | -0.0501 | * | 0.0102 | | -0.0209 | |
| | (0.0272) | | (0.0258) | | (0.0305) | |
| Industry effects | Yes | | Yes | | Yes | |
| Year effects | No | | No | | No | |
| Adjusted $R^2$ | 0.0165 | | 0.0112 | | 0.0116 | |
| N | 3,820 | | 3,584 | | 3,294 | |

Note: Dependent variables are the cumulative abnormal stock returns in the year prior to respectively after moving to the top (bottom) confidence decile. Asterisks denote significance at the 10% (*), 5% (**) and 1% (***) FF_industry groups as defined by Fama and French, excl. groups 8 and 11 (utilities and financials). Industry group 1 (non-durable consumer goods) is captured by the constant term. SENT(-1) refers to the sentiment indicator in the prior 12 months, cleaned for business cycle effects as defined by Baker and Wurgler 2006. Sentiment data are available up to and including 2007. White adj. standard errors in brackets.

In more detail, the table above shows that the negative coefficient on the low confidence dummy is significant 12 months prior to this move, both in statistical and economic terms. Including investor sentiment and its interaction with company confidence, a move to low confidence reduces CARs by 6.08%. This can be reinvigorated by its interaction with investor sentiment, which is both statistically and economically significant; if we use the average sentiment score of 0.34, CARs will be reduced by 1.71% in the year prior to moving to low confidence levels. The inclusion of Baker and Wurgler's investor sentiment variable renders statistically significant coefficients of up to 3.86% on a stand-alone basis. Its economic impact is mitigated by the low average sentiment score over the period as a whole, but still adding a little over one percent to CARs[101]. The interaction with high confidence is also negative, but not significant. The coefficient of the change in high confidence dummy is positive at 1.95%, but insignificant. We have tested for symmetry of the confidence coefficients respectively their interaction with investor sentiment and the low probability values show that we can reject this.

Moving to the CARs 12 months after the year of high (low) confidence, the sign on the low confidence dummy flips to positive (2.20%), but is not significant. The coefficient on the high confidence dummy is negative, but continues to be insignificant. We cannot reject symmetry for the standalone coefficients on extreme confidence (p-value of 0.2434), but the tests suggest asymmetry with regard to the two coefficients on the interaction terms at the 10% level (p-value of 0.0716). Another year later or two years after the change to extreme confidence, the coefficient to the low confidence dummy turns significantly positive at 4.90%, thus signaling a reversal effect. We can also reject symmetry with regard to moving to the high confidence level.

### 6.4.5 Robustness checks

We test for robustness by taking current year instead of prior year sentiment and by using an alternative confidence score. We find that the use of current year investor sentiment does not materially change our results. We still find a significant positive relation between the investor sentiment indicator and CARs, although explanatory power remains low at one to two percent. In other words, a large amount of the cumulative abnormal returns is left unexplained by our model. This leaves random noise or model misspecifications as the main explanation for these abnormal returns. Due to these explanations, the latter of which can be qualified as the joint hypothesis problem, we cannot reject market efficiency, even while CARs are sizeable.

As an alternative to our extreme confidence dummies, we take the change in the sum of all standardized confidence indicator scores, which we abbreviate as the change in Z-score. In chapter five, we provided the following formula for estimating the Z-score:

$$
\begin{aligned}
Zscore = {} & Zscore_{accruals} + Zscore_{acq} - Zscore_{oplev} + Zscore_{sic} + \\
& \tfrac{1}{2}\left[Zscore_{invest} + Zscore_{fingap}\right] + \tfrac{1}{2}\left[Zscore_{sharebb} + Zscore_{fingap}\right] + \\
& \tfrac{1}{3}\left[Zscore_{div\_change} - Zscore_{payout} + Zscore_{fingap}\right]
\end{aligned}
$$

**Equation 6.4.1**

[101] Data are retrieved from Wurgler's website and updated until 2007. Using all available years, the average (clean) sentiment would be close to zero.

We note that we lose a few observations, as we could not calculate a payout ratio for a few stocks with a dividend decrease. This lack of data, or specifically ordinary operating income was not a major issue before, as the dividend decrease itself was already sufficient to assign the lowest confidence level. Payout and financing deficit were only relevant for companies with stable or higher dividends year-on-year. First, we explore whether or not relations between CARs and confidence variables are similar i.e. comparing the output of table 6.4.8 with table 6.4.6. Next, we compare the CAR differences between extreme Z-score change deciles in table 6.4.9 with the gap in CARs between extreme confidence samples as shown in table 6.4.2. If high swings in Z-scores occur within the non-extreme confidence area instead of between the non-extreme and extreme confidence area, we would arrive at different outcomes.

In summary, we find a significant relation between company confidence and CARs, regardless of the confidence measure used. However, the impact on CARs seems most pronounced for moves to extreme low confidence levels. Furthermore, the significant positive relation between investor sentiment and CARs is not conditional on either the confidence measure or CAR window. The CAR difference between extremes is significantly positive in the year prior and the year of change for both confidence measures. The difference is somewhat lower between extreme Z-score deciles in the year before, but higher in the year of change itself. For years hereafter, the differences in CARs between extremes is no longer significant, which is mainly due to improving returns of the lowest confidence firms.

**Table 6.4.8: Robustness test CARs and Z-score change**

| CAR: | PRE12M | | FYEAR | | POST12M | | POST 24 M | |
|---|---|---|---|---|---|---|---|---|
| CONSTANT | -0.0168 | ** | -0.0137 | * | -0.0291 | *** | -0.0311 | *** |
| | (0.0066) | | (0.0077) | | (0.0085) | | (0.0090) | |
| ZSCORE Δ | 0.0092 | *** | 0.0047 | ** | -0.0042 | * | 0.0010 | |
| | (0.0028) | | (0.0024) | | (0.0025) | | (0.0026) | |
| SENT(-1) | 0.0353 | *** | 0.0271 | *** | 0.0319 | *** | 0.0338 | *** |
| | (0.0065) | | (0.0062) | | (0.0062) | | (0.0071) | |
| SENT(-1) * ZSCORE Δ | 0.0025 | | 0.0047 | ** | 0.0009 | | 0.0001 | |
| | (0.0037) | | (0.0024) | | (0.0036) | | (0.0037) | |
| Industry effects | Yes | | Yes | | Yes | | Yes | |
| Year effects | No | | No | | No | | No | |
| Adjusted $R^2$ | 0.0186 | | 0.0187 | | 0.0114 | | 0.0116 | |
| N | 3,775 | | 3,773 | | 3,533 | | 3,251 | |

Note: Dependent variable is the cumulative abnormal return in the year prior to moving to an extreme confidence level, the year itself and the year hereafter. Asterisks denote significance at the 10% (*), 5% (**) and 1% level (***). FF industry groups as defined by Fama and French, excl. utilities and financials (groups 8 and 11). Industry group 1 (non-durable consumer goods) is captured by the constant term. SENT refers to the sentiment indicator cleaned for business cycle effects as defined by Baker and Wurgler (2006).White adjusted standard errors in brackets. The symbol Δ refers to change.

Although we already highlighted our main findings from the robustness test, we proceed with a more detailed discussion of our findings as shown in table 6.4.8. With regard to the CARs in the 12 months prior to the change to extreme confidence, we find a positive and significant coefficient of 0.92% to the Z-score change. As the average[102] change in Z-score is close to zero, it is tempting to say that the economic impact is negligible. However, there is a high standard deviation of 2.13, which implies a close to two percent impact on CAR when the Z-score is one standard deviation away. There is no major interaction with investor sentiment.

In the year of change itself, the coefficient to the Z-score change diminishes to 0.47%, but continues to be significant. The negative CAR impact becomes even higher if investor sentiment was positive in the prior year. This may seem counterintuitive, as one might expect a dampening effect of positive investor sentiment. A possible explanation

[102] Both the mean and median change in the Z-score are close to zero

could be that when investors are in a good mood, they want to see this translated into actions as well and dissociate from conservative management. If sentiment is positive (negative), this effect is aggravated (offset) by the significant interaction term. With an average sentiment indicator of only 0.34 for the 1979- 2007 period, an increase in the Z-score by one standard deviation would increase CAR by 30 basis points[103].

When we move to the CARs 12 months after the extreme confidence year, the coefficient on the Z-score shifts signs and turn significantly negative at -0.42% on a standalone basis at the 10% level. The coefficient on the interaction term is no longer significant. Another year later, only standalone investor sentiment and the constant term remain significant.

Concluding, when we narrow our scope to significant results, we find no major differences when we use the change in the Z-score instead of the extreme confidence dummies. For both confidence measures, we only find a significant CAR difference between extremes in the year prior and in the year of change itself, in favor of the highest confidence firms. This suggests that standardization of the components of the confidence indicators, does not lead to major different outcomes.

[103] Note that our Z-score variable is the aggregate of separate Z-scores and it is not standardized itself. Therefore, its value does not correspond to the standard deviation

Table 6.4.9: ANOVA mean CARs by Z-score change decile

| DECILE | Mean CAR PRE12M | Mean CAR FYEAR | Mean CAR POST12M | Mean CAR POST24M |
|---|---|---|---|---|
| 1 | -0.0603 | -0.0851 | 0.0066 | -0.0295 |
| 2 | -0.0637 | -0.0411 | -0.0097 | -0.0143 |
| 3 | -0.0299 | 0.0023 | -0.0283 | -0.0454 |
| 4 | -0.0327 | -0.0309 | -0.0135 | -0.0402 |
| 5 | -0.0079 | -0.0406 | -0.0518 | -0.0610 |
| 6 | -0.0320 | -0.0416 | -0.0469 | -0.0390 |
| 7 | -0.0005 | -0.0491 | -0.0506 | -0.0348 |
| 8 | 0.0054 | -0.0169 | -0.0513 | -0.0210 |
| 9 | 0.0257 | -0.0329 | -0.0424 | -0.0106 |
| 10 | 0.0001 | -0.0069 | -0.0298 | -0.0112 |
| **ANOVA F-test mean CARs:** | | | | |
| Equal means all deciles | No (***) | No (***) | No (**) | Yes |
| Equal means decile 1 and 10 | No (***) | No (***) | Yes | Yes |
| Equal means deciles 2 to 9 | No (***) | Yes | Yes | Yes |
| **Mean difference:** | 0.0604*** | 0.0782*** | -0.0364 | 0.0182 |
| Deciles 10 -/- 1 | | | | |
| High -/- Low conf | 0.0947*** | 0.0621** | -0.0194 | -0.0273 |

Note: CAR stands for cumulative abnormal return, which is measured 12 months before, during and 12 months after the year in which a degree of confidence was calculated. Asterisks below the variable denote significance at the 10% (*), 5% (**) and 1% level (***). High respectively Low conf refers to the differences in CARs when high respectively low confidence dummies are used instead (table 6.4.2).

Based on the mean CAR differences between extreme Z-score changes, we arrive at the following results. For CARs 12 month prior to a certain change in the Z-score, we find that the mean CARs significantly differ between the highest (0.0001) and lowest Z-score change decile (-0.0603). This CAR difference is less extreme than the results in table 6.4.2, which were based on regressions with extreme confidence dummies. Based on that non-standardized measure, firm that moved to extremely low confidence levels realized a CAR of -9.56%. The results of F-test statistics imply that mean CARs of the non-extreme deciles, also significantly differ from each other and widely vary from -6.37% to 2.57%.

In the (change in) Z-score year itself, the mean CAR of the lowest decile deteriorates by over 2% in absolute terms to -8.51%. The gap with the mean CAR of the highest decile widens, as the standalone decrease of this decile is less severe at -0.69%. The negative CAR for the low confidence dummy sample of -8.20% in table 6.4.2 is comparable to that of the lowest Z-score decile. Conversely, the highest decile performs better than its high confidence dummy counterpart (-0.69% vs. -1.99%). The CAR difference of 7.82% is significant between the two extreme deciles, while those between the other eight deciles are not significant. The latter vary from -4.91% to 0.23%.

Moving another year ahead, CARs for the top decile deteriorate to -2.98%, while the bottom decile has a slight positive CAR of 0.66%. The CAR difference is not significant and neither are the mean CARs of the other deciles. We can only reject equality of all ten means together. Earlier, we also saw the worst performance (-0.60%) for high confidence dummy firms twelve months following the confidence year, albeit not significantly different from zero. Similarly, the low confidence dummy firms moved to positive with a mean CAR of 0.72%, or comparable to that of the lowest decile.

Finally, after two years, the CARs of the highest decile remain negative at -1.12% vs. -2.95% for the lowest decile, but the difference stays insignificant. Although there is a high difference with the stand alone CARs of 1.50% when using low confidence dummies, this value was not significant either. CAR differences for the remaining deciles are not significantly different from each other either and vary from -6.10% to -1.06%.

## 6.5 Summary and Discussion

Current research only focuses on the upper confidence extreme or overconfidence and investigates its impact on corporate decisions rather than performance or company valuation. It is widely documented that overconfidence has a detrimental impact on company decisions which suggests a negative impact on stock returns as well. In this chapter, we seek to address this. We have explored the relation if moving to extreme confidence levels results in cumulative abnormal stock returns, both on a standalone basis and in comparison with the other confidence extreme.

In chapter five, we already found very low returns on invested capital for low confidence firms, where we used the market value of equity in the denominator. This could have implied that a markdown had yet to occur i.e. that the denominator was still inflated. If so, we would expect negative abnormal returns following a move to low confidence. However, our results do not support this underreaction hypothesis, as we find that significant negative CARs precede rather than follow a move to low confidence. This leaves the numerator effect or depressed earnings as the main explanation of the low returns on invested capital. Indeed, we calculated much lower EBIT margins and a high share of loss-making in our low confidence sample.

Our empirical study shows that extremely low rather than extremely high confidence is the culprit to stock performance, adjusted for several common risk factors. Although it takes until the next year before all variables for calculating our degree of confidence score are publicly known, the markets seem to anticipate this well in advance. Our results suggest that the market heavily discounts companies that move to the lowest confidence level on the rumor rather than on the fact, as CARs are mostly negative in the year of such a move and 12 months prior to that. In the year in which a firm moves to an extremely low confidence level and the twelve months prior to that, we find significantly negative CARs of up to –13.22% in the nineties. Part of this is reversed after two years for this sub period, thus suggesting that overreaction took place. Ironically, this was the decade when stock market valuation reached unprecedented peaks. For other sub periods or for the 1980-2008 as a whole, we do not find significant support for such overreaction or a reversal in CAR in later periods.

Conversely, we find no significant standalone CARs when companies move to the highest confidence area, thus suggesting that this may not be put on par with suboptimal and value destructing actions. Alternatively, one could argue that investors expect management to be driven by animal spirits and high confidence, as this is also the way how they are selected according to Goel and Thakor (2008). We did not find strong support for interaction with investor sentiment, but on a standalone basis, this variable seems an important factor.

We conclude that it is only with perfect hindsight and good timing that one could exploit a profitable strategy consisting of a short position of firms that move to diffidence and a long position in firms that become overconfident. Even then, the persistence of such a strategy is questionable, as it did not work out in the new millennium.

# 7 Anchoring and Adjustment in Analyst Forecasts


## Abstract

In this chapter, we investigate how heuristics, specifically anchoring and adjustment, may distort analyst forecasts. We test to what extent analysts anchor to a variable which contains both firm-specific and time-series information, such as prior year earnings. To disentangle anchoring from adjustment, we control for variables that trigger adjustments from the starting point, such as risk appetite and news. We also allow for asymmetric responses by separating good news from bad. Our empirical analysis differs from prior research by exploring how sensitivities to these variables may differ at different levels e.g. forecast horizon, analyst, firm or the industry. Our results suggest that innate bias, anchoring to prior year earnings, risk attitude and responses to recent news are conditional on the level of analysis. This could explain why market reactions are not always in sync with analyst forecast errors. Innate optimism prevails on the industry and analyst level. We find no support for anchoring by analysts with a long track record or across industries, which suggests a more bottom-up approach. Furthermore, long-term volatility is considered an upside opportunity, while short-term risk is taken more cautiously. Finally, we mostly find underreaction to news, whether good or bad, albeit we find weak support for asymmetric responses.

## 7.1 Introduction

*"… I looked at the business first. If I look at the price first, I get influenced by it."*

*Warren Buffett explains his investment approach in an interview with FOX Business Network, 19 October 2007*

In the lines above, investor Warren Buffett articulates the pitfall of anchoring to a certain starting value, such as a company's current stock price when making investment decisions. I this chapter, we also focus on the use of anchoring and adjustment heuristics by security analysts, which is a topic that has not attracted a lot of research attention so far. Conversely, as outlined in chapter three, analyst optimism bias in earnings forecasts is widely investigated. Similarly, analyst under- or overreaction to news events, such as past results or past stock performance, attracts a lot of research interest.

In this chapter, we take a more comprehensive approach on the underlying process on how analysts set their forecasts. Following Trueman (1994), weak analysts tend to be followers and in order to prevent such a qualification, an analyst is pressured to issue an updated view before the crowd does. As financial analysts work in a very dynamic environment with severe time constraints, these could induce them to using heuristics when setting or updating their forecasts, especially when they walk out before the rest. Specifically, we will look at anchoring and adjustment heuristics, but we also correct for other cognitive distortions or biases in analysts' earnings forecasts.

As analysts perform a balancing act of keeping many internal and external parties satisfied, we believe that these cognitive distortions should not be isolated but taken together. Although overoptimism serves company management, the sales and corporate finance department, it hurts investors and his reputation of being a good forecaster. As an analyst covers a portfolio of stocks, this gives him leeway to leave an overall good impression at all parties involved. For instance, for so-called maintenance stocks in his universe i.e. stocks that he needs to cover but in which he or his employer have no competitive edge with regard to deal flow, it is easier to be somewhat more pessimistic and skeptical. Conversely, for the stocks that he "owns", he will probably follow a different approach. Investors also look through this game of coverage on a company by "house banks" compared to less dependent parties. Regulation Fair Disclosure (Reg FD) also forces investment banks to disclose whether or not they have done substantial business with the company under coverage and the analyst's rating track record. Combined with the large fines charged to the investment banking industry during the Internet boom, this could have changed equity analyst behavior as well.

As earlier discussed, research on analyst behavior tends to narrow its focous on a single behavioral bias, such as overoptimism or under- and overreaction to news. Although these topics are widely covered, we see, however, little interest in the analysts'view on long-term and short-term risk and how the use of heuristics may affect their behavior. As earlier mentioned, the analysts' time pressure makes the use of heuristics more attractive. With regard to anchoring, we are only aware of work in progress by Cen et al. (2010). After performing interviews[104] with equity analysts, they define the absolute median industry EPS as an anchor. This implies that analysts neither rescale EPS figures to a common denominator nor account for other firm-specific differences such as operating or financial leverage[105]. We expect analysts to be less naïve and define another anchor variable. Apart from exploring whether anchoring occurs on an aggregate level, we explore to what extent this is present on the analyst, firm and industry level.

This study provides insight in the underlying process behind the production of analysts' earnings forecasts and resulting forecast errors. We construct an extensive dataset that covers widely covered stocks from 2000 to 2009. This period was characterized by analyst scandals following the burst of the dotcom bubble that provoked legislative changes in the industry. Unlike earlier research, we do not only consider one specific cognitive error in their issued forecasts, but instead allow for various human factors to have an impact. Our empirical results confirm the latter is the case or more specifically that one should be aware of innate optimism, anchoring, aversion to short-term risk but high appetite for long-term risk and a tendency to underreact to recent news. However, sensitivities to these factors are conditional on the level of analysis, i.e. the aggregate, analyst, firm or industry level.

Apart from the fact that investors can incorporate such behavioral distortions[106], company management could also use this information. Brown and Caylor (2005) argue that as of 1996[107], management focus has shifted from avoiding earnings losses or earnings declines to avoiding negative earnings surprises. If management is more aware of innate biases, anchors and how analysts react to certain news, they could incorporate this in their communication strategy. As long as these behavioral biases enable the analyst to keep many different parties content without compromising too much on their overall forecast error or reputation, it seems a rational strategy to follow.

This chapter is organized as follows. First, we discuss our dataset and methodology. Next, we discussed the pooled regression results, followed by the analyst-, firm- and sector

[104] This reference points was inferred from interviews with six analysts
[105] By taking prior year EPS, we assume that these characteristics do not dramatically change year-on-year
[106] Campbell and Sharpe (2009) find that the market incorporates such biases, while Cen et al. (2010) do not find empirical support for such a correction by the market
[107] Their study covers the 1985-2002 period

specific regressions. Furthermore, we also perform several robustness checks. The last section concludes and makes suggestions for further research.

## 7.2 Data and Methodology

### 7.2.1 Introduction

In order to test whether analysts fail to properly process news, we perform regressions with actual EPS, forecast EPS and forecasting error as dependent variables. Although most research focuses on taking forecast errors as dependent variable in the regressions, we would not only like to show to what extent analysts underweight or overweigh certain information, but also if the coefficient signs are consistent between actual and forecast EPS. This also shows the absolute importance of each type of information, or specifically the anchor variables.

Inspired by the wide coverage on analyst bias, the over- and underreaction effect and our previous working practice in equity sales and research, our independent variables cover anchoring, risk attitude and adjustment to news. All variables are based on publicly available information. Daniel et al. (1998) argue that if analysts are overconfident, they tend to underweight public and overweigh their private information. This implies a positive relation between the absolute forecast error and these publicly known variables.

### 7.2.2 Variable and Data description

First, we will briefly describe the anchor, risk and news variables. Subsequently, we will discuss how and which data we capture for our analysis and separately discuss the issues that we face with the non-pooled or micro-level regressions.

Our anchor variable comprises prior year earnings per share, which suggests that analyst cater to investors' needs of "fixating" on earnings, which is empirically supported by Sloan (1996). We also test for robustness by substituting prior year EPS with the mean consensus EPS in the prior quarter. Both anchor variables are publicly known, so following Daniel et al. (1998), we could argue that if we detect anchoring or a too high weight to the anchor variable, this is hard to comply with analyst overconfidence. Tversky and Kahneman (1974) discuss how anchoring may cause miscalibration – a proxy for overconfidence. Block and Harper (1991) directly test if there is a relation between (extreme) confidence levels and anchoring and find no higher overconfidence for people who use anchors vs. non-users.

The risk proxies cover both long-term and short-term risk and comprise past five-year EPS volatility respectively consensus forecast dispersion. The news variables which trigger analysts to update their forecasts consists of recent quarterly earnings surprises i.e.

prior quarter forecasting errors and a stock's momentum vs. the market over the past three months. Finally, we add a control variable for company size as well.

We retrieve detailed forecast and realized or actual earnings per share (EPS) data from the adjusted (for stock splits, stock issues, stock dividends, share buybacks e.g.) detailed IBES file[108]. We only consider the 2000-2009 period. Forecast errors are defined as the difference between the actual and forecast EPS. Our main focus is on annual EPS forecasts issued in four forecast windows of up to 90 days, up to 180 days, up to 270 days or more than 270 days and less than 365 days ahead of the earnings release date.

We apply several restrictions on the sample. As forecast horizons beyond a year are based on earnings estimates rather than realized earnings for the prior year, we exclude these. In addition, we only include firms with a fiscal year-end coinciding with the calendar year-end, so each forecast window refers to a similar period or calendar quarter. This mitigates the impact of specific events in a certain quarter. We do not take the fiscal year-end but the earnings announcement date for calculating forecast windows, as earnings information remains uncertain until disclosed.

Next, we require minimum analyst coverage of at least five annual EPS estimates by different analysts in each forecast window. As alternative to prior year EPS, we use prior quarter consensus, which we consider not very meaningful if based on less than five observations. In addition, we require at least five different analysts for each quarterly EPS forecast (not necessarily the same), so there is ample quarterly information for updating full year EPS forecasts. If analysts issue more than one forecast in a certain window, we only keep the most recent one. As a result, the self-selection bias highlighted by McNichols and O'Brien (1997), or the initiation respectively drop of coverage when news becomes favorable respectively bad, could have an impact on our results.

We also use individual forecast data for calculating earnings forecast dispersion, which is defined as the difference between the highest and lowest estimate. For the longest forecast window of up to a year, we set the forecast dispersion in the prior quarter, the one in which prior year earnings also have to be estimated, at zero. This implies that when prior year EPS have not been revealed yet, most effort is put in this year's forecast rather than next year's EPS. This dispersion measure could be seen as a proxy for short-term earnings risk, while EPS volatility over the past five years is a long-term risk measure. The former changes when we move another quarter or forecast window ahead, while the latter is unchanged throughout the year and could also be considered an anchor variable[109].

[108] Detailed earnings estimates are not available until 1982. We are well aware of rounding errors in IBES, but believe this problem is mitigated for detailed forecasts vs. summary forecasts, as the former are rounded at four rather than two digits.

[109] Kahneman and Tversky (1974) state that anchoring not only happens when the starting point i.e. prior year EPS is given, but also when incomplete computations are made

Long-term earnings risk or volatility is calculated as the standard deviation of realized (adjusted) EPS figures, as revealed by IBES[110].

Quarterly earnings surprises convey information whether or not the company is on track on realizing its full year targets. We note that this quarterly news variable can be very volatile and reverse in subsequent quarters. Hence, analysts might not change their annual estimates at par with quarterly results. We define EPS surprise as the difference between the actual and forecast quarterly EPS in the prior period, scaled to beginning of quarter stock price.

Stock momentum is the other news variable, which is calculated for the three months preceding the activation date of an analyst's annual earnings forecast in a certain forecast window. We use a simple market factor or CAPM model, although we argue that analysts have sufficient leeway to pick a benchmark (sector or multifactor based) that supports their investment case better. For each month, we calculate the excess (log) returns as the difference between (log) returns and the equal weighed (log) market return, which are aggregated for three consecutive months. We only look at ordinary common stock (share codes 10 and 11) with a minimum share price of USD 5.00 i.e. we exclude REITs, ADRs, preferred stock and penny stocks. Finally, we also control for size, which we measure by the natural logarithm of the firm's market capitalization.

Using the above mentioned variables, we perform pooled regressions with (scaled) actual EPS, forecast EPS and the difference between the two or forecast error (FE) as dependent variables[111]. We estimate the following panel regression equation:

$$DEPVAR_{x,t} =$$

$$\alpha_0 + \beta_1 *(1-D_{LOSS})*EPS\_PRIOR_{x,t-1} + \beta_2 *(D_{LOSS})* EPS\_PRIOR_{x,t-1} + \beta_3 *EPSVOL_{x,t} + \beta_4 *(D_{GOOD\_EPS})* SURPRISE_{i,x,t-1} + \beta_5 *(1-D_{GOOD\_EPS})* SURPRISE_{i,x,t-1} + \beta_6 *DISP_{x,t-1} + \beta_7 *(D_{GOOD\_MOM})*MOM_{x,t} + \beta_8 *(1- D_{GOOD\_MOM})*MOM_{x,t} + \beta_9 *LNSIZE + \varepsilon_{i,x,t}$$

**Equation 7.2.1**

The left-hand side variable *DEPVAR* refers to the dependent variable which comprises the annual EPS forecast *(EPSFC)* respectively the actual EPS *(EPS_ACTUAL)* or the difference between the two i.e. the forecast error (FE) The dependent variables comprise prior year annual earnings per share or EPS_PRIOR, past five year annual EPS volatility *(EPSVOL)*, prior quarter EPS surprise as denoted by SURPRISE, forecast dispersion of prior quarter consensus *(DISP)*, momentum *(MOM)* and size *(LNSIZE)*. Also,

[110] We do not use Compustat EPS data, as definitions may differ from IBES

[111] Although actual earnings should not be impacted by heuristics, one could determine what optimal weight should have been used to minimize mean (or median if quantile regression is used) forecast error.

we have included dummies, denoted with *D*, for firms that were loss-making in the prior year, for good and bad earnings surprises respectively stock momentum. Easterwood and Nutt (1999) follow a similar approach in an attempt to reconcile the ambiguous results of both over- and underreaction in prior research. Such a distinction allows us to test for asymmetric responses to good respectively bad news. The subscripts $i$, $x$ and $t$ refer to the analyst, firm and estimation quarter. The latter ranges from 1 (1Q00) to 40 (4Q09).

In order to avoid endogeneity problems, we use a one period lagged quarterly EPS surprise. All dependent variables, except size and momentum, are scaled to start of the quarter stock price and winsorized at the 1% and 99% level. As we use adjusted quarterly EPS forecasts from IBES, we also have to use the adjusted share price when scaling variables to price. Although we require minimum (unadjusted) share prices of at least USD 5.00 per share by the end of the month when calculating excess returns, adjusted shares prices at the start of the quarter could fall below USD 5 per share, thus boosting the scaled earnings yield ratio. If we would scale forecast dispersion to the absolute mean consensus forecasts, it could be seen as a rough proxy for the shape of the anticipated earnings distribution[112]. The term MOM captures stock momentum in the three months prior to the analyst's forecast activation date.

### 7.2.3 Model modifications for non-pooled regressions

The main restriction of the pooled regression analysis is that it is a "one size fits all" solution, yielding only one set of coefficients applicable to every analyst, firm, year, industry and forecast horizon. Although we could add a bias per analyst-firm pair or per year by including cross-section respectively period fixed effects, it does not allow for cross-section or time varying weights. Therefore, we also perform separate regressions by analyst respectively industry, firm or forecast horizon. We use the Fama and French classification of 48 industry groups based on the SIC codes.

However, as we lack sufficient data on prior year EPS losses on the analyst, firm or industry level, we can no longer allow for asymmetry to this anchor variable. Due to this negative earnings skewness[113], we modify the regression equation by no longer distinguishing between profitable and loss-making firms. As negative skewness is less of an issue for prior quarterly EPS surprises and stock momentum, we still allow for asymmetric reactions to these news items. Still, we lack sufficient data for some analysts or firms, which corroborates with underreaction (bandwagon) rather than a random walk or mean reversion caused by overreaction model. A bandwagon effect implies that the signs

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[112] We refer to Gu and Wu (2003) who discuss earnings skewness and forecast bias

[113] See Gu and Wu (2003), as earlier discussed. Note that survivorship and selection bias could also be to blame for negative earnings skewness, as companies that structurally underperform will turn into penny stocks or no longer attract sufficient analyst coverage and hence drop from our sample

remain similar in subsequent periods, while randomness would imply that we would more or less the same amount of positive and negative signs, unless the sample size is small. However, continuation of both analysts and good coverage on firms i.e. at least five analysts follow the firm per quarter, is the main challenge to our sample.

### 7.2.4 Drivers Behind Forecast Errors

When we use actual or forecast EPS as the dependent variable, the rational expectations hypothesis suggests that the constant term is positive and above the risk-free rate, unless high future growth compensates for this. Looking at the difference between the two or the widely used forecast error, the constant term should be zero in the absence of- what we refer to as - innate forecast bias. One could refer to this as a person's nature or optimism or pessimism, albeit the jury is not out whether this is indeed a biological or a learned trait. We define innate bias as a residual or bias beyond that caused by anchoring and adjustment errors or strategic drivers. The widely documented optimism bias suggests a negative constant term or innate optimism, although we have to remark that most studies do not include as many variables in the equation as we do.

We could analyze the superiority of analyst predictions relative to time-series models by taking the commonly used seasonal random walk model as an alternative to analysts' EPS predictions. Such models assume no relation between prior year and current (expected) EPS, albeit not ruling out temporary distortions. Conversely, mean reversion models assume a negative relation and momentum models a positive relation between past and future EPS. If analysts indeed attach a too high weight to the anchor variable than the proper weight, this translates into a negative coefficient to the prior year EPS when taking forecast error as dependent variable. Hence, the overweighing to the anchor translates into more negative forecast errors when prior year earnings are positive.

The firm's risk profile[114] and the analyst's risk attitude determine the relation of these risk proxies with future (expected) earnings. Higher earnings risk translates into more extreme results, both in the positive and negative direction. Risk seekers rather see risk as an upside potential, while risk-averse people are focused on the downside. The signs of the coefficient to the risk proxies reveal which risk appetite prevails.

With regard to the news variables, the rational expectations assumption that earnings are i.i.d. and unbiased implies a one-on-one positive relation between annual (forecast) EPS and the prior quarter EPS surprise. Deviations from par suggest over-and underreaction to this news. Momentum could convey information about the current year's (expected) EPS, which should translate into a significant coefficient in our regression. Abarbanell (1991) points to empirical evidence suggesting a positive association between

[114] This includes a company's internal hedge or ability to absorb earnings volatility, as determined by its operating leverage, financial leverage and, to a limited extent, accounting practices

earnings estimates and prior price changes. If there is no relation with current year estimates, momentum could convey information about a firm's long-term growth or cost of capital instead. When we focus on the forecast errors, under- and overreaction suggests positive respectively negative coefficients of prior quarter earnings surprise and momentum. Abarbanell (1991) and Abarbanell and Lehavy (2003) find a positive relation between past share price and earnings forecasts. If analysts would be indifferent to whether news is good or bad, the coefficients on the interaction terms would be similar.

The size variable could pick up strategic bias, such as the importance of management access or hunt for corporate deals. Alternatively, size could also be closely related to analyst following. However, as we set stringent conditions for the latter, it is hard to interpret the size coefficient in this perspective. If small firms are less predictable due to a lower availability of public information, Das et al. (1998) suggest that strategic bias could be more important. This would translate into more positive EPS forecasts or more negative forecast errors for smaller firms. The negative relation between forecast error and size can also be reconciled with Fama and French (1992), who argue that size is a proxy for risk and that small firms are riskier than big ones. If, however, underwriter and banking relationships are the main drivers behind strategic bias as Lin and McNichols (1998) and Dugar and Nathan (1995) argue, it could be more beneficial to please large firms with optimistic forecasts, as these are more likely to engage in corporate deals. Also, if smaller firms are associated with higher growth than large ones, current earnings yield forecasts could be lower. Then, the optimism bias is present in the future or long-term growth rather than in the current year's earnings estimate, thus falling out of the scope of our model. Similarly, if growth rates and required rates of returns do not differ between big and small companies, market inefficiency could cause lower (higher) earnings yields for the firms with more positive (negative) forecast bias.

Table 7.2.1 summarizes the expected relation between the price-scaled forecast error, which is most widely used as dependent variable in prior research, and the independent variables that we have defined. Our commonly used forecast error definition as the difference between the actual and forecast EPS, implies that a negative forecast error corresponds to too optimistic analyst forecasts and vice versa.

**Table 7.2.1: FC Error and (exp.) relation with input variables**

| Variables | Price-scaled Forecast Error | Comment |
|---|---|---|
| Constant c | <0 (>0) implies innate optimism (pessimism) | For mature, low growth firms, c > risk-free rate |
| *Coefficients to:* | | |
| Prior year EPS | <0 corroborates with anchoring | >0 implies momentum; insignificance implies random walk |
| EPS volatility (5 yr) | <0 implies risk seeking; >0 implies risk aversion | Risk could be considered an upside opportunity or a downside risk * |
| Dispersion prior Q | <0 implies risk seeking; >0 implies risk aversion | Risk could be considered an upside opportunity or a downside risk * |
| Prior Quarterly EPS surprise | <0 (>0) implies over(under)reaction | Asymmetric reaction if coef good surprise <> coef bad surprise |
| Prior Q stock momentum | <0 (>0) implies over(under)reaction | Asymmetric reaction if coef good surprise <> coef bad surprise |
| Size (start of Q) | >0 corroborates with strategic bias | With less public info for small firms, management access is more important** |

Note:FC stands for forecast, exp. Stands for expected. Q stands for quarter, coef for coefficient and <> for not equal to. Forecast error = actual -/-forecast EPS.*Trueman (1994) suggests that if volatility is higher, so is the probability that weak analysts incorporate (inaccurate) private info rather than exhibit herding behavior.**Lim (2001) finds support for higher forecast bias for smaller firms.

## 7.3 Results

### 7.3.1 Descriptive Statistics

We end up with a final dataset of 237,058 observations that meet our analyst coverage criteria of at least five quarterly and five annual EPS estimates by different analysts. We lose 1% of observations to 235,185 when matching our firm with CRSP price data, based on (N)CUSIPS.

The descriptive statistics of the individual sample in table 7.3.1 show that the median (mean) size of the firms in the individual sample is large at three to just below eight USD billion (USD 12-27 billion). When requiring firms to have data on all variables, we lose roughly half of the observations to 121,691, but size characteristics remain similar. The high market valuations at the start of 2000 reflect the unprecedented peak valuation during the dotcom bubble, which also affected mature companies. We note that due to our requirements of a five-year EPS history, young Internet firms fall out of our sample. Furthermore, the impact of the financial market meltdown after the Lehman Brothers' collapse in September 2008 is also clearly visible in the (start of) 2009 market valuations.

The cross-section characteristics of the common sample as summarized in tables 7.3.2 and 7.3.3 show a very low number of observations in 2000. Particularly, the limited analyst coverage in the third quarter of 2000 is to blame. A possible explanation could be that following the dotcom bust, business models had to be redefined and this high uncertainty could have made analysts reluctant to issue forecasts. During the period, the number of firms and analysts gradually increases, with the exception of small dip in 2008.

To summarize the main results of table 7.3.3, we find that the mean forecast error is negative and significant, thus consistent with overoptimism. The median forecast error is close to zero, in line with results of Abarbanell (2003). The skewness to big firms and optimistic forecasts could result from strategic motives if indeed bigger firms generate higher fees and trading commissions for affiliated parties. Earnings volatility is high, but is not scaled to price. Furthermore, we use (stock split, issuance, stock dividend e.g.) adjusted rather than reported figures.

**Table 7.3.1: Individual sample characteristics EPS forecasts**
**Period: 2000-2009**

| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean size | 26,718 | 21,483 | 18,609 | 16,753 | 18,362 | 19,735 | 19,566 | 20,685 | 16,356 | 11,566 | 18,062 |
| Median size | 7,661 | 6,676 | 6,188 | 5,646 | 5,981 | 7,085 | 6,368 | 6,400 | 4,534 | 3,103 | 5,461 |
| Max size | 458,394 | 309,815 | 299,820 | 341,362 | 318,054 | 394,008 | 398,312 | 521,071 | 510,904 | 415,274 | 521,071 |
| Min. size | 117 | 51 | 44 | 62 | 120 | 14 | 113 | 88 | 44 | 29 | 14 |
| # of analyst-firm-quarter pairs | 9,866 | 17,683 | 16,617 | 19,467 | 22,284 | 25,045 | 25,971 | 27,660 | 35,239 | 35,353 | 235,185 |
| # of analyst-firm pairs | 4,265 | 7,192 | 6,808 | 7,630 | 8,364 | 9,229 | 9,478 | 10,164 | 12,576 | 12,600 | 41,986 |
| # of firms | 198 | 345 | 333 | 359 | 422 | 479 | 511 | 563 | 731 | 678 | 1,490 |
| # of analysts | 1,806 | 2,137 | 2,096 | 2,141 | 2,245 | 2,289 | 2,340 | 2,420 | 2,590 | 2,501 | 6,865 |

Note: Size equals the number of outstanding shares times the closing price at the first trading day of the calendar year. Size figures are denominated in USD millions.

**Table 7.3.2: Common Sample characteristics EPS forecasts (1)**
**Period: 2000-2009, N= 121,691**

| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean size | 26,940 | 21,351 | 18,270 | 16,192 | 19,059 | 21,306 | 21,518 | 23,395 | 22,207 | 13,818 | 19,962 |
| Median size | 6,768 | 7,688 | 7,163 | 6,463 | 6,051 | 7,586 | 7,064 | 8,399 | 8,788 | 4,009 | 6,832 |
| Max size | 458,394 | 291,004 | 221,034 | 341,362 | 318,054 | 394,008 | 398,312 | 521,071 | 510,904 | 415,274 | 521,071 |
| Min. size | 147 | 176 | 186 | 171 | 143 | 160 | 136 | 142 | 85 | 119 | 85 |
| # of analyst-firm-quarter pairs | 4,730 | 8,348 | 7,885 | 9,204 | 12,625 | 14,852 | 14,888 | 16,253 | 14,084 | 18,822 | 121,691 |
| # of analyst-firm pairs | 2,238 | 3,658 | 3,455 | 3,916 | 5,035 | 5,946 | 5,979 | 6,392 | 5,543 | 7,288 | 23,590 |
| # of firms | 133 | 220 | 217 | 231 | 302 | 348 | 354 | 388 | 335 | 445 | 930 |
| # of analysts | 1,168 | 1,416 | 1,418 | 1,555 | 1,712 | 1,824 | 1,798 | 1,890 | 1,719 | 1,919 | 5,073 |

Note: Size equals the number of outstanding shares times the closing price at the first trading day of the calendar year. Size figures are denominated in USD millions.

**Table 7.3.3: Common Sample Characteristics EPS forecasts (2)**
**Period: 2000-2009, N= 121,961**

| | Mean | Median | Maximum | Minimum |
|---|---|---|---|---|
| EPS_ACTUAL a,b) | 5.22% | 5.69% | 21.31% | -36.37% |
| EPSFC a,b) | 5.57% | 5.85% | 19.98% | -26.19% |
| FE a,b) | -0.35% | 0.01% | 42.78% | -46.39% |
| EPS_PRIOR a) | 5.75% | 5.68% | 92.76% | -135.51% |
| EPSVOL | 0.82 | 0.50 | 34.69 | 0.03 |
| DISP a) | 1.47% | 0.42% | 456.27% | 0.00% |
| SURPRISE a) | 0.05% | 0.00% | 83.92% | -22.65% |
| MOM | -2.73% | -1.81% | 104.85% | -207.57% |
| SIZE (USD m) | 19,962 | 6,832 | 521,071 | 85 |
| FC horizon | 181 | 187 | 365 | 0 |

Note: a) variable scaled to share price if at least USD 5.00. b) winsorized at 1 and 99%. EPSFC stands for EPS Forecast, FE for forecast error, DISP for dispersion in consensus EPS in the prior quarter (high-/low annual EPS estimate), EPSVOL for past 5-year EPS volatility, MOM for past 3month cumulative outperformance vs. the market index, SURPRISE for quarterly EPS surprise in the prior quarter. SIZE equals outstanding shares times closing price at the first trading day of the calendar year. FC horizon equals days before the actual earnings announcement.

Table 7.3.3 indicates that the earnings yield amounts to five to six percent on average, implying a price-earnings ratio of 17 to 19. This seems a hefty valuation multiple, but this can be compensated by the firm's future growth potential. The mean forecast error may seem small at -0.35%, but when we multiply this by the price-earnings ratio, it implies an error of about six percent of EPS. Although exceptional, momentum can exceed -100% in the case that the market is significantly up, while the stock is hammered. Although not revealed in the table, losses in the prior year occur in only 6.19% of the observations, which is partly due to the fact that we exclude penny stocks. This low percentage could hint at self-selection bias or analysts dropping coverage when news flow becomes bad.

We find slightly more positive than negative or zero forecast errors (50.41% vs. 49.59%[115]), thus pulling the median forecast error to zero. This compares to Brown et al. (1987) who detect negative skewness in analyst forecast errors. Conversely, Abarbanell and Lehavy (2003) find slight positive skewness or analyst pessimism with a share of 48% positive and 52%[116] negative or zero forecast errors. The symmetry that we find could result from more effective earnings expectations management and legislative changes like

[115] This 49.59% consists of 45.58% negative forecast errors and 4.01% zero forecast errors
[116] This number consists of 40% negative forecast errors and 12% zero forecast errors

the Sarbanes Oxley Act. Furthermore, we also find more negative than positive momentum (55.33% to 44.77%) compared to the market index, which suggests that selection bias does not play a major role in our sample. In other words, analysts do not seem to restrict their coverage to stocks with positive momentum.

In line with prior research, we also find a higher magnitude of negative forecast errors (mean of -1.53% vs. +0.81%), which pulls the mean into negative territory (-0.35%). Also, the frequency of large negative vs. large positive surprises is higher, while we do not detect middle asymmetry i.e. a higher amount of small positive surprises vs. small negative surprises. We also put these forecast errors into historical perspective as shown by graphs 7.3.1 and 7.3.2. These suggest that more negative forecasts errors coincide with major event, such as the September 11th attacks in 2001, the slowdown in the US housing markets as of 2007 and finally the financial crisis as of 2008. The forecast dispersion is quite stable until 2007, but significantly widens hereafter. This divergence suggests higher uncertainty and, with hindsight, could be considered a red flag. In addition, the denominator effect or stock de-rating could also have contributed to this widening gap.

Finally, table 7.3.4 shows the correlation matrix. Overall, correlation coefficients between the dependent and independent variables are low, which mitigates the risk of multicollinearity. However, we find a high a correlation between actual respectively forecast EPS and prior year EPS respectively prior period consensus EPS. This suggests that it seems a logical move to use the latter[117] as anchor variables. Correlation of the anchor variables with forecasting error is low though, thus suggesting that the adjustment process rather than the starting point is mainly to blame for these EPS inaccuracies. The low negative[118] correlation between forecast error and the earnings forecast is surprising, as the latter is part of the definition of the former. This can only be explained if changes in forecasts are joined by changes in actual EPS, so there is a combined instead of standalone effect on forecast error. However, if forecasts tend to be static or do not change[119], this does not mean that actual EPS does not come in higher or lower either. Furthermore, we observe positive correlation between our long-term and short-term risk proxies, i.e. EPS volatility and forecast dispersion, and between the news variables i.e. prior quarter EPS surprise and stock momentum.

[117] Note that we substitute prior year EPS by prior period consensus EPS when testing for robustness
[118] Our definition of forecast error implies that the higher the forecast vs. the actual number, the more negative the forecast error
[119] One could argue that analysts do not like major earnings revisions, as this implies that you were wrong in your assumptions about the company

**Figure 7.3.1: Forecast Dispersion by year**

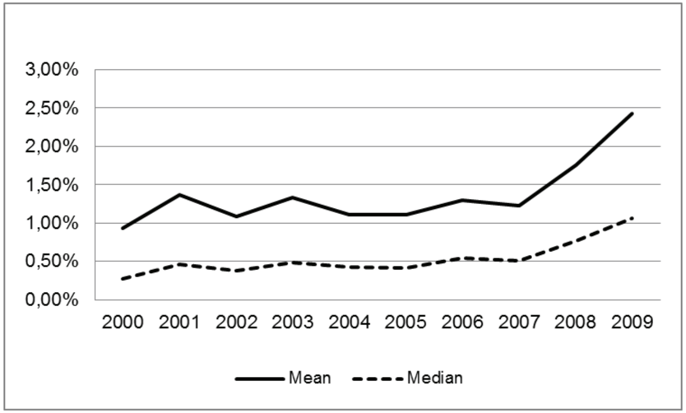
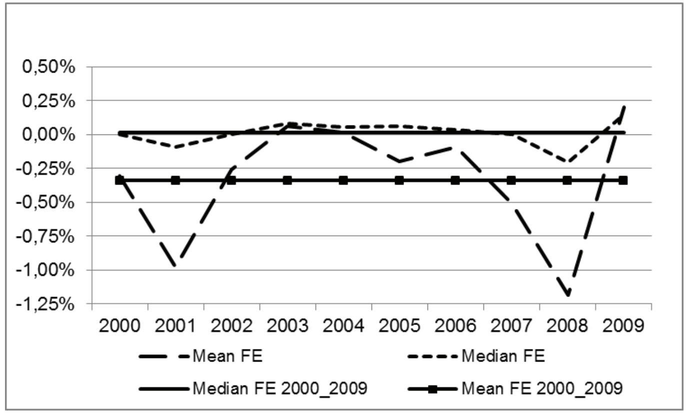



**Figure 7.3.2: Forecast Error by year**




Note: Forecast dispersion and forecast errors are scaled to the start of quarter share price (min. USD 5.00). Dispersion equals max. -/- min annual EPS forecast in the prior quarter.

**Table 7.3.4 : Correlation matrix**

| Variable | EPS_REAL | EPSFC | FE | EPS_PRIOR | EPSVOL | DISP | CONSENS | MOM | SURPRISE | LNSIZE |
|---|---|---|---|---|---|---|---|---|---|---|
| EPS_REAL [a, b)] | **1.0000** | 0.8984 | 0.2930 | 0.5705 | 0.2018 | 0.0340 | 0.7793 | 0.1598 | 0.1318 | 0.1507 |
| EPSFC [a, b)] | 0.8528 | **1.0000** | -0.0068 | 0.6398 | 0.2266 | 0.0204 | 0.8649 | 0.1238 | 0.0993 | 0.1451 |
| FE [a, b)] | 0.5156 | -0.0077 | **1.0000** | -0.0133 | -0.0077 | 0.0177 | -0.0237 | 0.1140 | 0.1270 | 0.0418 |
| EPS_PRIOR [a)] | 0.4051 | 0.5121 | -0.0644 | **1.0000** | 0.2571 | 0.1272 | 0.7707 | -0.0039 [c] | 0.0091 | 0.0835 |
| EPSVOL | -0.0216 | 0.0236 | -0.0802 | 0.0121 | **1.0000** | 0.2040 | 0.2468 | -0.0087 | 0.0503 | 0.0881 |
| DISP [a)] | -0.1136 | -0.1099 | -0.0373 | 0.0440 | 0.0886 | **1.0000** | 0.0768 | 0.0159 | 0.2649 | -0.0907 |
| CONSENS [a)] | 0.6769 | 0.8116 | -0.0353 | 0.6876 | 0.0226 | -0.1348 | **1.0000** | 0.0345 | 0.0761 | 0.1282 |
| MOM | 0.1602 | 0.1218 | 0.1070 | -0.0032 [c] | -0.0157 | -0.0004 [c] | 0.0204 | **1.0000** | 0.1113 | -0.0022 [c] |
| SURPRISE [a)] | 0.1076 | 0.0731 | 0.0861 | -0.0206 | 0.0140 | 0.0816 | 0.0132 | 0.0665 | **1.0000** | 0.0267 |
| LNSIZE | 0.1670 | 0.1667 | 0.0463 | 0.0883 | 0.0522 | -0.0621 | 0.1453 | -0.0073 | 0.0119 | **1.0000** |

Note: Ordinary (Spearman) correlations on the left (right) of diagonal and calculated by balanced sample (N=121,691). [a)] variables are price-scaled, conditional on a minimum share price of USD 5.00. [b)] winsorized at 1 and 99%. . [c)] coefficient insignificant. EPSVOL refers to EPS volatility in the prior five years, DISP stands for forecast dispersion or the maximum less minimum forecast, CONSENS refers to the annual EPS consensus estimate in the prior quarter, based on >=5 forecasts, MOM for past 3 months' stock momentum, SURPRISE for prior quarter EPS surprise, LNSIZE for the natural logarithm of a firm's market capitalization.

### 7.3.2 Pooled regression analysis

Table 7.3.5 summarizes the pooled regression results with EPS forecasts as the dependent variable. It shows that by only including prior year EPS, we can explain some 23% of the annual EPS forecast. Overall, each variable adds explanatory power to up to one third of the forecast EPS, in particular the inclusion of momentum. The constant term is also significantly positive as expected, albeit declining to 1.33% when more variables are added. Although this is well above zero, Treasury Bills would yield higher returns, thus suggesting innate pessimism rather than optimism with regard to current earnings potential[120].

Except for positive events, all coefficients are significant and their signs can be reconciled with earlier work and theory. Coefficients for prior year EPS are positive and both economically and statistically significant. The higher coefficient for prior year losses compared to prior year profits indicates that analyst tend to be more cautious when starting from a bad year, which seems very intuitive as well.

With regard to risk, results are ambiguous with a positive coefficient for past five-year EPS volatility and a negative coefficient for forecast dispersion. It suggests that analysts interpret long-term risk as upside potential and short-term uncertainty as downside risk. Similarly, the negative coefficient for prior quarter earnings is counterintuitive, but not significant. However, analysts could have strategic reasons to lower full year EPS forecasts following a better than expected quarter, as this enables management to continue positive EPS surprises. Alternatively, management itself may downplay expectations rather than inflate earnings expectations. Richardson et al. (2004) empirically tested this "earnings-guidance game" and indeed found evidence of long-term optimism and short-term pessimism. The coefficient for good momentum is neither stable in terms of direction nor significant.

Finally, the significant positive size coefficient implies higher forecast for bigger firms, thus supporting the strategic bias arguments of Lin and McNichols (1998) and Dugar and Nathan (1995). Economic significance of size is also high, as it captures half of the earnings yield for the average-sized firm.

[120] However, one could be optimistic on future earnings growth or on the cost of capital

**Table 7.3.5: Pooled Regression Results EPS Forecast**

| Sample: 2000Q1 2009Q4 (40 periods included); Dependent Variable EPSFC [a)] | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| C | 0.0408 | *** | 0.0391 | *** | 0.0387 | *** | 0.0383 | *** | 0.0415 | *** | 0.0133 | *** |
| $(1-D_{LOSS})$*EPS_PRIOR [a)] | 0.2626 | *** | 0.2788 | *** | 0.3100 | *** | 0.3189 | *** | 0.3423 | *** | 0.3436 | *** |
| $D_{LOSS}$ *EPS_PRIOR [a)] | 0.3924 | *** | 0.4256 | *** | 0.3981 | *** | 0.3773 | *** | 0.4309 | *** | 0.4142 | *** |
| EPSVOL | | | 0.0020 | *** | 0.0022 | *** | 0.0024 | *** | 0.0016 | *** | 0.0014 | *** |
| DISP [a)] | | | | | -0.1211 | * | -0.1016 | * | -0.0839 | * | -0.0814 | * |
| $D_{GOOD\_EPS}$*SURPRISE [a)] | | | | | | | -0.0676 | | -0.0800 | | -0.0641 | |
| $(1-D_{GOOD\_EPS})$*SURPRISE [a)] | | | | | | | 0.8759 | *** | 0.9754 | *** | 0.9395 | *** |
| $(D_{GOOD\_MOM})$*MOM | | | | | | | | | -0.0005 | | 0.0047 | |
| $(1-D_{GOOD\_MOM})$*MOM | | | | | | | | | 0.0505 | *** | 0.0475 | *** |
| LNSIZE | | | | | | | | | | | 0.0031 | *** |
| Cross-section fixed effects | no | | no | | no | | no | | no | | no | |
| Period fixed effects | no | | no | | no | | no | | no | | no | |
| Adjusted $R^2$ | 0.2296 | | 0.2469 | | 0.2652 | | 0.2768 | | 0.3236 | | 0.3320 | |
| N | 224,519 | | 172,489 | | 172,489 | | 138,116 | | 122,200 | | 122,200 | |

Note: a) refers to price-scaled variables, conditional on a min. share price of USD 5.00 and winsorized at the 1 and 99% level. DUM stands for dummy, EPSVOL for annual EPS volatility over the past five years. DISP stands for forecast dispersion (highest -lowest estimate). SURPRISE equals the difference between actual and forecast quarterly EPS in the prior quarter. MOM stands for the past cumulative market outperformance in the past 3 months. LNSIZE equals the natural log of a firm's market value. Asterisks identify significance levels of 1% (***), 5% (**) and 10% (*), based on White cross-section adjusted standard errors. Regression based on Ordinary Least Squares method.

**Table 7.3.6: Pooled Regression Actual, FC EPS and FC error**

| **Dependent variable:** | **EPS_ACTUAL** [a, b)] | | **EPSFC** [a, b)] | | **FE**[a, b)] | | **FE**[a, b)] |
|---|---|---|---|---|---|---|---|
| C | 0.0107 | ** | 0.0133 | *** | -0.0054 | *** | -0.0018 |
| $(1-D_{LOSS})$*EPS_PRIOR [a)] | 0.2769 | *** | 0.3436 | *** | -0.0380 | ** | -0.0197 |
| $D_{LOSS}$*EPS_PRIOR [a)] | 0.4414 | *** | 0.4142 | *** | -0.0183 | | -0.0441 |
| EPSVOL | 0.0001 | | 0.0014 | *** | -0.0015 | ** | -0.0003 |
| DISP [a)] | -0.0919 | * | -0.0814 | * | -0.0066 | | -0.0164 |
| $D_{GOOD\_EPS}$*SURPRISE [a)] | 0.0243 | | -0.0641 | | 0.1501 | | 0.0644 |
| $(1-D_{GOOD\_EPS})$*SURPRISE [a)] | 1.4226 | *** | 0.9395 | *** | 0.4917 | *** | 0.5940 |
| $(D_{GOOD\_MOM})$*MOM | 0.0048 | | 0.0047 | | 0.0020 | | -0.0057 |
| $(1-D_{GOOD\_MOM})$*MOM | 0.0708 | *** | 0.0475 | *** | 0.0231 | *** | 0.0165 |
| LNSIZE | 0.0039 | *** | 0.0031 | *** | 0.0009 | *** | 0.0004 |
| Adjusted $R^2$ | 0.2680 | | 0.3320 | | 0.0367 | | 0.0475 |
| Observations | 122,201 | | 122,200 | | 121,691 | | 80,184 |
| Period fixed effects | no | | no | | no | | no |
| Cross-section fixed effects | no | | no | | no | | no |
| ALL FC WINDOWS | yes | | yes | | yes | | no |
| FC WINDOW unequal to 4 | no | | no | | no | | yes |

Note: a) refers to price-scaled variables, conditional on a minimum share price of USD 5.00. b) refers to variables that are winsorized at the 1 and 99% level. DUM stands for dummy, EPSVOL for annual EPS volatility over the past five years. DISP stands for forecast dispersion (highest -lowest estimate). SURPRISE equals the difference between actual and forecast quarterly EPS in the prior quarter. MOM stands for the past cumulative market outperformance in the past 3 months. LNSIZE equals the natural log of a firm's market value. Asterisks identify significance levels of 1, 5 and 10% (***, **,*). White cross-section adjusted standard errors. FC stands for Forecast

We have disentangled how each of the independent variables impacts actual respectively forecast EPS. For those coefficients that are statistically significant, signs are the same between the two regressions. The contradictory signs for positive earnings surprises are not significant, which could be conditional on the magnitude[121].

When we analyze the difference between the two or the forecast error, we find a significantly negative constant term, thus implying innate optimism. Moving to the anchor variable or prior year EPS, only positive prior year EPS numbers have significance. The negative coefficient implies that by anchoring too heavily to prior year earnings, forecasts become too optimistic. Similar to Gu and Wu (2003), we find a significantly positive coefficient for size. This higher pessimism or less optimism for bigger firms translates into higher than expected realized EPS figures or positive respectively less negative forecast errors.

With regard to the risk proxies, dispersion is no longer significant, but its long-term counterpart is. It suggests that past years' earnings volatility is too much considered an upside opportunity rather than downside risk, thus leading to inflated forecasts.

Similar to the standalone actual and forecast EPS regressions, coefficients for good events, either earnings or stock-price related, are not significant and imply underreaction rather than the widely documented overreaction effect. Conversely, the positive coefficients for bad events are significant and imply underreaction to these negative events, in line with prior empirical evidence, such as Ali et al. (1992) and Abarbanell and Bernard (1992).

### 7.3.3 Time varying regression analysis

Including year-effects in the regression, explanatory power of the forecast error more than doubles to 7.35%. Following major events, such as September 11th in 2001 and the US housing market and financial crisis in 2007 and 2008, we see a more negative forecast-error adjustment. The results of the Wald-test imply that the year-coefficients are significantly different from each other at the 1% significance level.

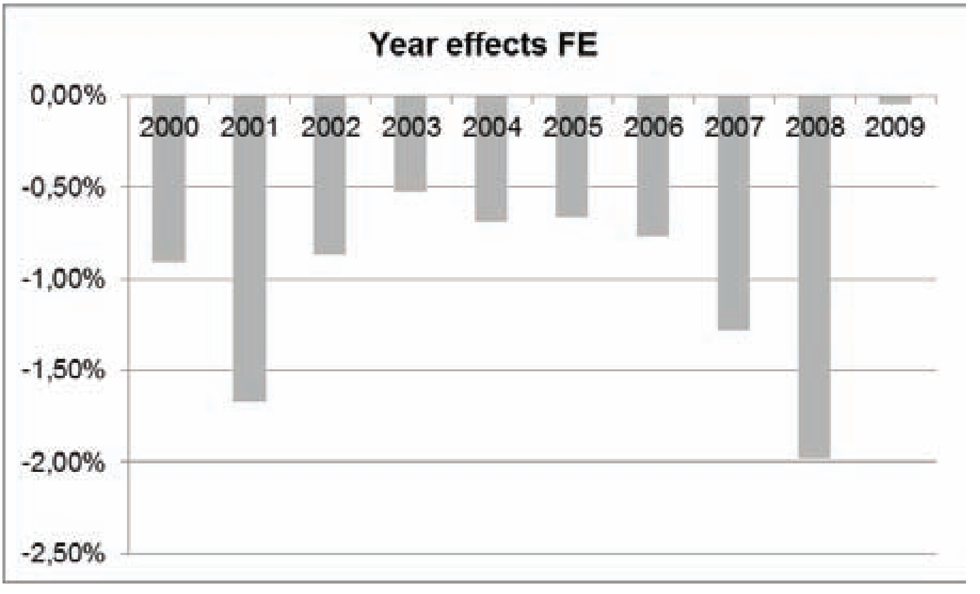
[121] Trueman (1994) and Abarbanell and Lehavy (2003) suggest that this ambiguity could be related to the size of the earnings surprise

**Table 7.3.7: Regression Forecast Error and Year Effects**

| **Dependent variable: Forecast Error** | | |
|---|---|---|
| $(1-D_{LOSS})$*EPS_PRIOR | -0.0482 | *** |
| $D_{LOSS}$*EPS_PRIOR | -0.0044 | |
| EPSVOL | -0.0014 | ** |
| DISP | -0.0080 | |
| $D_{GOOD\_EPS}$*SURPRISE | 0.1288 | |
| $(1-D_{GOOD\_EPS})$*SURPRISE | 0.4782 | *** |
| $(D_{GOOD\_MOM})$*MOM | 0.0102 | ** |
| $(1-D_{GOOD\_MOM})$*MOM | 0.0210 | *** |
| LNSIZE | 0.0013 | *** |
| FPE_YEAR=2000 = C(10) | -0.0091 | *** |
| FPE_YEAR=2001 = C(11) | -0.0167 | *** |
| FPE_YEAR=2002 = C(12) | -0.0087 | *** |
| FPE_YEAR=2003 = C(13) | -0.0052 | *** |
| FPE_YEAR=2004 = C(14) | -0.0069 | *** |
| FPE_YEAR=2005 = C(15) | -0.0066 | *** |
| FPE_YEAR=2006 = C(16) | -0.0077 | *** |
| FPE_YEAR=2007 = C(17) | -0.0128 | *** |
| FPE_YEAR=2008 = C(18) | -0.0198 | *** |
| FPE_YEAR=2009 = C(19) | -0.0005 | |
| Adjusted $R^2$ | 0.0736 | |
| | | |
| **Wald-test that Year Coefficients C(10) to C(19) are equal** | | |
| Test Statistic | Value | Probability |
| F-statistic | 8.1102 | 0 |

Note: Forecast Error is scaled to a min. share price of USD 5.00 and winsorized at 1 and 99%. D stands for dummy, EPSVOL for annual EPS volatility over the past five years, DISP for forecast dispersion (high-low). SURPRISE for the actual less forecast quarterly EPS in the prior quarter. MOM is the cumulative market outperformance of the stock in the past 3 months. LNSIZE equals the natural log of a firm's market value. Asterisks imply significance levels of 10, 5 and 1% (*, **, ***). White cross-section adjusted standard errors.

**Figure 7.3.3: Year-effects Forecast Errors 2000-2009**




Note: FE stands for Forecast Error, which is scaled to the share price.

We have also investigated the impact of varying the forecast horizon and its impact on the forecast error. We run separate regressions for a sample excluding forecast window four i.e. forecasts one-year ahead, for which we set the default earnings dispersion at zero. In other words, when we run separate regressions by forecast horizon, we only include horizons up to 270 days ahead. The results are summarized in table 7.3.8.

Despite the loss of observations, explanatory power is similar or strongly improves when narrowing the forecast window. We can better explain forecasting error the shorter the forecast horizon. The constant term or innate optimism bias found earlier is no longer significant, except for forecasts from 180 to 270[122] days ahead. The latter could have to do with the fact that most companies will not have reported their half-year results yet by that time, which can be considered a first reality check for the analysts' full year forecasts. If any, bias is caused by anchoring and adjustment or strategic concerns (size).

When we pool all observations for the three forecasts windows together i.e. forecasts of no more than three quarters ahead, we find the following results. Anchoring to the prior year EPS is significant for longer forecast horizons when it concerns profits. For shorter horizons up to 180 days ahead, analysts seem to hang on too heavily on the prior

[122] The mean (median) forecast horizon amounts to 200 (193) days ahead for forecast window 3, 111 (104) days ahead for forecast window 2 and 42 (37) days for forecast window 1.

year loss and this pessimism results into positive forecast errors. For medium to long-term forecast horizons, the size coefficient is small but positive, thus implying less pessimism for smaller firms. If smaller firms are less predictable due to less publicly available information, a more positive or less negative analyst stance could pay off in better management access, as Das et al. (1998) argue.

Analysts do not seem to take a consistent approach towards risk during the forecast cycle. For longer forecast horizons, long-term risk or EPS volatility is too much considered an upside opportunity, thus leading to too optimistic forecasts and disappointing actual results. Conversely, for short-tem horizons of no more than 90 days ahead, EPS volatility is too much considered a downside. The short-term risk appetite as reflected by the dispersion measure seems more consistent. When statistically significant, dispersion is overly considered an upside opportunity rather than a downside risk. Our findings of bigger negative annual EPS surprises for stocks with higher forecast dispersion could also result from a higher use of (wrong) private information by weaker analysts. Trueman (1994) argued that weak analysts are more inclined to use their private information instead of herding when earnings volatility is greater. However, economic significance is very low of these risk variables.

When we move to the news events, we find a significant sensitivity to bad prior quarter earnings surprises and, to a lesser extent, bad stock momentum. Similar to findings by Abarbanell and Lehavy (2003), analysts seem to underreact to both. Surprisingly, we also find underreaction to positive quarterly earnings surprises for short forecast horizons of 90 days or less ahead. This reluctance could stem from strategic reasons i.e. analysts pleasing management by giving them room to beat estimates at the full year results announcement. We also find signs of overreaction to good momentum for the short forecast horizons.

**Table 7.3.8: Impact FC horizon on FC Error**

| | Dependent variable: Forecast Error [a, b)] | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| CONSTANT | -0.0054 | *** | -0.0018 | | -0.0060 | *** | 0.0009 | | 0.0001 | |
| $(1-D_{LOSS})$*EPS_PRIOR | -0.0380 | ** | -0.0197 | | -0.0297 | *** | -0.0283 | *** | 0.0004 | |
| $D_{LOSS}$*EPS_PRIOR | -0.0183 | | -0.0441 | *** | -0.0163 | | -0.0682 | *** | -0.0518 | *** |
| EPSVOL | -0.0015 | ** | -0.0003 | | -0.0013 | *** | 0.0001 | | 0.0003 | *** |
| DISP | -0.0066 | | -0.0164 | ** | -0.0046 | | -0.0143 | *** | -0.0654 | *** |
| $D_{GOOD\_EPS}$*SURPRISE | 0.1501 | | 0.0644 | | 0.1116 | | -0.0051 | | 0.3938 | *** |
| $(1-D_{GOOD\_EPS})$*SURPRISE | 0.4917 | *** | 0.5940 | *** | 0.4199 | *** | 0.7169 | *** | 0.7367 | *** |
| $(D_{GOOD\_MOM})$*MOM | 0.0020 | | -0.0057 | | 0.0050 | * | -0.0168 | *** | -0.0054 | *** |
| $(1-D_{GOOD\_MOM})$*MOM | 0.0231 | *** | 0.0165 | *** | 0.0236 | *** | 0.0212 | *** | 0.0040 | *** |
| LNSIZE | 0.0009 | *** | 0.0004 | | 0.0007 | *** | 0.0002 | ** | 0.0001 | |
| | | | | | | | | | | |
| Adjusted $R^2$ | 0.0367 | | 0.0475 | | 0.0365 | | 0.0700 | | 0.1072 | |
| Observations | 121,691 | | 80,184 | | 28,097 | | 28,692 | | 23,395 | |
| | | | | | | | | | | |
| FC WINDOW: | All | | 1,2,3 | | 3 | | 2 | | 1 | |

Note: No period or cross-section fixed effects. Note: Subscripts refer to a) price-scaled variables, conditional on a min. share price of USD 5.00, b) winsorized at the 1 and 99%. D stands for dummy, EPSVOL for annual EPS volatility over the past five years. DISP stands for forecast dispersion (high-low). SURPRISE equals actual minus forecast quarterly EPS in the prior quarter. MOM equals cumulative market outperformance in the past 3 months. LNSIZE equals the natural logarithm of a firm's market capitalization. Asterisks identify significance levels of 1% (***), 5% (**) and 10% (*). White cross-section adjusted standard errors.

### 7.3.4 Cross-sectional regression analysis forecast errors

We have redone the regressions on three separate levels comprising analyst, industry and firm specific data. For brevity and comparability with other research, we narrow our discussion to forecast errors only. The lack of continuation of both analysts and firms causes a high loss of observations. When requiring a common sample of at least 25 respectively 50 observations per analyst, we only keep 1,374 (27%) respectively 693 (14%) out of 5,073 analysts. For firms, the picture looks better, as we end up with 57% (535 out of 930 firms) when requiring at least 50 observations on all variables. With regard to industries, we lack sufficient data on industry groups 1, 5, 16 and 20, which comprise agriculture, tobacco products, textiles and fabricated products. Listed companies with good analyst coverage are hard to find in these specific sectors.

**Table 7.3.9: Descriptive Statistics non-pooled FE regressions**

| **Dependent var: FE** [a)] | **Share of significant values** | | | | |
|---|---|---|---|---|---|
| **Panel A: Analyst_min25** | **-/-** | **0** | **+** | **Net** | **Median coefficient** |
| CONSTANT | 15.14% | 76.35% | 8.52% | -6.62% | -0.0030*** [c)] |
| EPS_PRIOR [a)] | 17.98% | 65.57% | 16.45% | -1.53% | -0.0082** [c)] |
| EPSVOL | 16.96% | 77.00% | 6.04% | -10.92% | -0.0012*** [c)] |
| DISP [a)] | 8.30% | 83.77% | 7.93% | -0.36% | 0.0140*** [c)] |
| GOOD_SURPRISE [a)] | 3.13% | 89.59% | 7.28% | 4.15% | 0.2680*** [c)] and *** from coef bad |
| BAD_SURPRISE [a)] | 4.29% | 88.65% | 7.06% | 2.77% | -0.0155 [b)] and *** from coef good |
| GOOD_MOM | 4.95% | 90.32% | 4.73% | -0.22% | 0.0036*** [b)] and ** from coef bad |
| BAD_MOM | 3.28% | 86.83% | 9.90% | 6.62% | 0.0055***[c)] and ** from coef good |
| LNSIZE | 7.86% | 76.56% | 15.57% | 7.71% | 0.0004*** [c)] |
| **Panel B: Analyst_min 50** | | | | | |
| CONSTANT | 18.04% | 74.03% | 7.94% | -10.10% | -0.0035*** [c)] |
| EPS_PRIOR [a)] | 18.47% | 63.49% | 18.04% | -0.43% | -0.0019 [c)] |
| EPSVOL | 22.22% | 71.86% | 5.92% | -16.31% | -0.0016*** [c)] |
| DISP [a)] | 12.27% | 79.51% | 8.23% | -4.04% | -0.0002 [b)] |
| GOOD_SURPRISE [a)] | 2.74% | 87.45% | 9.81% | 7.07% | 0.3294*** [c)] and *** from coef bad |
| BAD_SURPRISE [a)] | 5.05% | 86.00% | 8.95% | 3.90% | 0.0082 [b)] and *** from coef good |
| GOOD_MOM | 6.49% | 89.90% | 3.61% | -2.89% | 0.0025*** [b)] and *** from coef bad [b)] |
| BAD_MOM | 2.16% | 83.98% | 13.85% | 11.69% | 0.0077*** [c)] and *** from coef good [b)] |
| LNSIZE | 7.22% | 72.73% | 20.06% | 12.84% | 0.0004*** [c)] |

| **Panel C: Industry** | **-/-** | **0** | **+** | **Net** | **Median coefficient** |
|---|---|---|---|---|---|
| CONSTANT | 38.64% | 34.09% | 27.27% | -11.36% | -0.0054 [b)] |
| EPS_PRIOR [a)] | 34.09% | 22.73% | 43.18% | 9.09% | 0.0068 [b)] |
| EPSVOL | 59.09% | 20.45% | 20.45% | -38.64% | -0.0024 ** [b)] |
| DISP [a)] | 27.27% | 40.91% | 31.82% | 4.55% | 0.0055 [b)] |
| GOOD_SURPRISE [a)] | 2.27% | 47.73% | 50.00% | 47.73% | 0.3820*** [b)] and * from bad |
| BAD_SURPRISE [a)] | 11.36% | 54.55% | 34.09% | 22.73% | 0.0873 [b)] and * from good |
| GOOD_MOM | 15.91% | 50.00% | 34.09% | 18.18% | 0.0054** [b)] and not sign. from coef bad |
| BAD_MOM | 13.64% | 29.55% | 56.82% | 43.18% | 0.0090*** [c)] and not sign. from coef good |
| LNSIZE | 22.73% | 34.09% | 43.18% | 20.45% | 0.0010[b)] |
| **Panel D: Firm** | | | | | |
| CONSTANT | 23.74% | 36.82% | 39.44% | 15.70% | 0.0266*** [b)] |
| EPS_PRIOR [a)] | 35.14% | 33.46% | 31.40% | -3.74% | -0.0294* [b)] |
| EPSVOL | 34.39% | 35.14% | 30.47% | -3.93% | -0.0010 [b)] |
| DISP [a)] | 22.62% | 43.55% | 33.83% | 11.21% | 0.0267** [b)] |
| GOOD_SURPRISE [a)] | 18.88% | 61.68% | 19.44% | 0.56% | 0.0217 [c)] and not sign. from coef good |
| BAD_SURPRISE [a)] | 16.82% | 71.40% | 11.78% | -5.05% | -0.0807 [b)] and not sign. from coef bad |
| GOOD_MOM | 21.87% | 58.50% | 19.63% | -2.24% | 0.0003 [b)] and ** from coef bad |
| BAD_MOM | 23.93% | 56.07% | 20.00% | -3.93% | -0.0017** [b)] and ** from coef good |
| LNSIZE | 37.94% | 38.50% | 23.55% | -14.39% | -0.0027*** [b)] |

Note a) refers to price-scaled variables, conditional on a minimum share price of USD 5.00, winsorized at 1 and 99%. b) mean not significant from zero. c) mean significantly different from zero and -/- , 0, and + stand for negative, negligible or positive significance at the 5% level . Net = % sign. positive -/- % sign. negative

Panels A and B in table 7.3.9 show the characteristics of the analyst-specific regression. There is a striking difference with regard to innate bias or the constant term. For analysts for whom we have fewer observations, we see more innate optimism, while the opposite is true for analysts for whom we have more observations. Furthermore, the former tend to anchor to prior year EPS. If the latter uses a (more complex) bottom-up approach for constructing estimates[123], the separate components of prior year EPS are relevant rather than the aggregated number.

Except for the risk proxies and good momentum, the majority of coefficients are significantly positive rather than negative. We have tested if the constant and median coefficients are significantly different from zero[124] and if there is a significant difference between bad and good news events. Trueman (1994) argues that when explanatory power is very high[125] i.e. when error terms are low when explaining an analyst's individual forecasts, this could be a sign of herding. He also argues that a low coefficient on historical earnings volatility suggests herding. In our analyst-specific regression, however, we find a significant coefficient on past earnings volatility, although the term is not significant when performing industry or firm level regressions.

Except for bad EPS surprises, all (median) coefficients are significant and we also find asymmetry between good and bad news. In line with prior research by Easterwood and Nutt (1999) and Abarbanell and Lehavy (2003), we find underreaction to negative news i.e. the positive coefficient suggests a higher EPS shortfall given negative EPS or stock momentum. However, we also find that analysts underreact rather than overreact to positive news. On an individual basis, we have more negative coefficients on positive stock momentum, but the associated overstated EPS forecasts are more than offset by underestimated EPS for the other positive coefficient stocks with good momentum. The size coefficient is also relevant on an analyst level and the positive coefficient corroborates with strategic bias driven by management access rather than potential fees from corporate deals.

On the industry level (Panel C), we find neither significant innate optimism nor less cautious earnings estimates for smaller firms. Size effects if any seem to balance out, as neither the median nor mean coefficient are significant. In addition, the insignificant positive coefficient for prior year EPS suggests no anchoring to this variable on the industry level. It could imply that industry forecasts are built from bottom up and based on macro-economic variables, legislation and market structure. EPS volatility or long-term

[123] One could think of this as starting with estimating volumes and prices per product group, and estimating the cost price by estimating raw material prices, wage inflation and labor productivity, marketing e.g.
[124] If earnings forecasts are the dependent variable, we test if the median coefficient for the earnings surprise differs from one
[125] The mean (median) adjusted $R^2$ equals to 18% (15%) on the analyst_min50 level. On the firm level, mean and median adjusted $R^2$ are around 50%.

risk is significant and tend to be perceived as upside potential, unlike short-term risk (not significant). Regardless of the direction of the news, we find underreaction and asymmetric responses to recent EPS surprises.

Finally, panel D shows the results when performing regressions on a firm-by-firm level. The median constant term implies innate pessimism, although the mean does not significantly point south. We also detect anchoring and a size effect. The negative size coefficient implies optimism, which is lower rather than higher the smaller the firm. The risk attitude seems more cautious, with no significant optimism towards long-term risk and a too prudent view on the short-term risk proxy. We only find significant overreaction to bad momentum, which is more intense than the (under)reaction to good momentum.

Overall, we find conflicting results with regard to innate bias, anchoring, risk attitude and responses to recent news for the pooled, time varying and cross-sectional regressions. This could also explain why market reactions are not always in the same direction as analyst forecast errors. Except for the firm regressions, we find that innate optimism prevails. We do not find support for anchoring for analysts with a long track record on well-covered firms or across industries. This could suggest a more bottom-up approach for constructing EPS estimates. The risk proxies reveal that long-term volatility is considered an upside opportunity, while short-term risk or forecast dispersion is taken more cautiously. Finally, we mostly find underreaction to news, whether good or bad, albeit the degree of underreaction is conditional on the direction i.e. asymmetry. Table 7.3.9 summarizes the findings of our pooled and cross-sectional regression results with forecast error as the dependent variable.

**Table 7.3.10: Summary Forecast Error Regression**

| | Pooled regression | Analyst_25 | Analyst_50 | Industry | Firm |
|---|---|---|---|---|---|
| **Bias and anchoring:** | | | | | |
| Innate bias? | Yes, optimism | Yes, optimism | Yes, optimism | Not sign. optimism | Yes, pessimism |
| Anchoring past year EPS? | Yes, if profit | Yes | Not sign. | No | Yes |
| Strategic bias small firms? | less pessimism | less pessimism | less pessimism | not sign. Less pessimism | less optimism |
| **Risk focus:** | | | | | |
| long-term | risk = upside | risk = upside | risk = upside | risk = upside | risk =not sign.upside |
| short-term | risk =not sign.upside | risk=downside | risk=not sign. upside | risk = not sign. Downside | risk=downside |
| **Reaction to news:** | | | | | |
| Good EPS | not sign.underreaction | underreaction | underreaction | Underreaction | not sign. underreaction |
| Bad EPS | Underreaction | not sign. overreaction | not sign. underreaction | not sign. Underreaction | not sign. overreaction |
| Good momentum | not sign. Underreaction | underreaction | underreaction | Underreaction | not sign. underreaction |
| Bad momentum | Underreaction | underreaction | underreaction | Underreaction | overreaction |
| Asymmetry? | to both EPS + mom news | to both EPS + mom news | to both EPS + mom news | only to EPS news | only to mom news |

Note: No fixed effects included. Relationships inferred from median coefficient and its significance, using White adjusted standard errors. Analyst_25(50) refers to the min.required observations per regression. Mom stands for momentum.

### 7.3.5 Robustness checks

As a robustness check, we have substituted prior year (annual) EPS by the consensus EPS forecast as constructed from the prior quarter for the firm, which is also publicly known information. We avoid endogeneity issues by using consensus in the prior quarter. Trueman (1994) states that analysts have a tendency to release forecasts closer to prior earnings expectations rather than fully incorporate their private information. This herding behavior is particularly more likely to happen the weaker the analyst and the less volatile earnings are. Amir and Ganzach (1998) also argue that analysts' earnings may not be independent from each other, but rather anchored to previously issued forecasts by other brokers. Campbell and Sharpe (2009) also find that expert consensus forecasts on macro-economic variables are systematically biased toward the value of releases in previous months.

For each forecast window, we calculate a consensus estimate, which is based on the most recent forecasts of the analysts following the firm in that quarter. If an analyst issues a forecast for the firm in the prior forecast window, but does not follow up in the current one, he is no longer included. IBES would include forecasts until they are notified that the stock is no longer covered, thus increasing the risk of stale forecasts in its summary statistics. By using only recent estimates, we believe that the risk of stale estimates is mitigated[126].

As analysts are more reluctant to forecast losses, we no longer distinguish between a negative and positive value of the anchor. Logically, we follow the same approach when comparing the regression results with the prior year EPS anchor, as shown in table 7.3.11.

Furthermore, we exclude forecasts to up to a year ahead, we set the prior quarter consensus (i.e. five quarters before the earnings release date) at the prior year EPS. This suggests that analyst do not make sophisticated estimates of earnings in year t+1, until the EPS for year t is released. If the anchoring and adjustment weights are indeed time, firm and analyst invariant and consensus would already fully reflect these heuristics and biases (innate, selection or strategic), none of the other regression coefficients or the constant term should be significant[127].

[126] Trueman (1994) states that in order for consensus forecasts to be an informative measure for market expectations, simply averaging individual forecasts is inappropriate, as one should account for the timing of an earnings forecast. Chen et al. (2005) attach more weights to more recent forecasts.
[127] By construction, we have set consensus equal to prior year EPS for forecast windows beyond nine months to up to a year ahead, so exclude this forecast window when comparing coefficients with those based on prior year EPS

**Table 7.3.11: Robustness test consensus EPS anchor variable**

| **Dependent variable: Forecast Error [a, b)]** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| CONSTANT | -0.0010 | | -0.0013 | | -0.0043 | ** | -0.0047 | ** |
| EPS_PRIOR [a)] | -0.0289 | *** | | | -0.0330 | *** | | |
| CONSENSUS [a)] | | | -0.0310 | ** | | | -0.0273 | * |
| EPSVOL | -0.0002 | | -0.0001 | | -0.0002 | | -0.0001 | |
| DISP [a)] | -0.0149 | ** | -0.0200 | ** | -0.0166 | ** | -0.0211 | *** |
| $D_{\_GOOD\_EPS}$*SURPRISE [a)] | 0.0852 | | 0.0891 | | 0.0434 | | 0.0546 | |
| (1-$D_{GOOD\_EPS}$)*SURPRISE [a)] | 0.5764 | *** | 0.5989 | *** | 0.5962 | *** | 0.6130 | *** |
| ($D_{GOOD\_MOM}$)*MOM | -0.0056 | | -0.0057 | | -0.0008 | | -0.0004 | |
| (1-$D_{GOOD\_MOM}$)*MOM | 0.0164 | *** | 0.0168 | *** | 0.0162 | *** | 0.0160 | *** |
| LNSIZE | 0.0003 | | 0.0004 | * | 0.0007 | *** | 0.0007 | *** |
| | | | | | | | | |
| Adjusted $R^2$ | 0.0469 | | 0.0440 | | 0.0902 | | 0.0852 | |
| Cross-section fixed effects | no | | no | | no | | no | |
| Period fixed effects | no | | no | | yes | | yes | |
| N (excl. forecasts>270 days ahead) | 80,184 | | 80,389 | | 80,184 | | 80,389 | |

Note: We replace anchor variable prior year EPS by prior quarter consensus forecast. For forecasts >3 quarters ahead, consensus is set at prior year EPS. The subscripts refer to a) price-scaled variables, conditional on a minimum share price of USD 5.00, b) winsorized at the 1 and 99% level. D stands for dummy, EPSVOL for annual EPS volatility over the past five years. DISP stands for forecast dispersion (highest -lowest estimate). SURPRISE equals the difference between actual and forecast quarterly EPS in the prior quarter. MOM stands for the past cumulative market outperformance in the past 3 months. LNSIZE equals the natural log of a firm's market value. Asterisks identify significance levels of 1% (***), 5% (**) and 10% (*). White cross-section adjusted standard errors.

Overall, we cannot better explain forecasting errors by substituting prior year EPS by consensus estimates[128] . Unless we include period fixed effects, the constant term is no longer significantly negative when excluding forecasts horizons of more than 270 days ahead i.e. forecast window four. The negative coefficient to the anchor variables indeed suggests that the market too heavily weights on this number. We still find significant underreaction to bad news and a size effect, so this seems a persistent among analysts rather than balancing out on the aggregate level.

As an alternative to EPS volatility data, we have also calculated the five-year historical volatility in return on equity for the 48 industry groups, as defined by Fama and French. In order to calculate return on equity, we have retrieved data from the Compustat database (items ibcom and ceq) and require common equity to be positive. The inclusion of this alternative long-term earnings volatility measure increases the number of observations as we lacked IBES-data of five-year EPS history for a large amount of firms. The use of industry statistics enables us to keep young companies on board with no or a very short earnings history.

[128] Due to lack of sufficient observations for some analyst-firm pairs, we only show period fixed and no cross-section fixed effects

**Table 7.3.12: Robustness check: alternative risk measure**

| | Dependent variable: Forecast Error (FE) [a)] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | FIRM | | INDUS | | FIRM | | INDUS | |
| CONSTANT | -0.0054 | *** | -0.0169 | *** | -0.0088 | *** | -0.0185 | *** |
| $D_{\_LOSS}$ *EPS_PRIOR [a)] | -0.0183 | | 0.0088 | | -0.0071 | | 0.0157 | |
| (1-$D_{\_LOSS}$)*EPS_PRIOR [a)] | -0.0380 | ** | -0.0290 | * | -0.0535 | *** | -0.0428 | *** |
| EPSVOL | -0.0015 | ** | | | -0.0014 | * | | |
| INDUSVOL_ROE | | | 0.0438 | *** | | | 0.0384 | * |
| DISP [a)] | -0.0066 | | -0.0107 | | -0.0113 | ** | -0.0154 | ** |
| $D_{GOOD\_EPS}$* SURPRISE [a)] | 0.1501 | | 0.2070 | | 0.0869 | | 0.1403 | |
| (1-$D_{GOOD\_EPS}$) *SURPRISE [a)] | 0.4917 | *** | 0.4350 | *** | 0.5267 | *** | 0.4749 | *** |
| ($D_{GOOD\_MOM}$)*MOM | 0.0020 | | 0.0012 | | 0.0084 | | 0.0076 | |
| (1-$D_{GOOD\_MOM}$)*MOM | 0.0231 | *** | 0.0189 | *** | 0.0220 | *** | 0.0162 | *** |
| LNSIZE | 0.0009 | *** | 0.0008 | *** | 0.0013 | *** | 0.0012 | *** |
| Cross-section fixed effects | no | | no | | no | | no | |
| Period fixed effects | no | | no | | yes | | yes | |
| Adjusted $R^2$ | 0.0367 | | 0.0371 | | 0.0881 | | 0.0852 | |
| N | 121,691 | | 153,408 | | 121,691 | | 153,408 | |

Note: a) FE is price-scaled, conditional on a min. share price of USD 5.00 and winsorized at the 1 and 99% level. D stands for dummy, EPSVOL for annual EPS volatility over the past five years. INDUSVOL_ROE equals the 5-year historical volatility of return on equity for the 48 industry groups. DISP stands for forecast dispersion (high -low). SURPRISE equals actual minus forecast quarterly EPS in the prior quarter. MOM equals cumulative market outperformance in the past 3 months. LNSIZE equals the natural log of a firm's market value. Asterisks identify significance levels of 10, 5 and 1 % (*, **, ** *). White cross-section adjusted standard errors.

Overall, the sign of significant coefficients and the constant term are the same, except for the long-term risk proxy. Forecast errors become more negative the larger the firm's earnings volatility, while becoming more positive when industry risk is used in the equation. This suggests that industry risk is perceived as a downside and firm-specific risk as an upside opportunity. The cautious view on industry risk is partly offset by underestimated short-term risk or forecast dispersion.

Our final robustness check is also inspired by Trueman (1994), who suggests that reactions could be different for extreme earnings surprises. We narrow our scope to extreme quarterly EPS surprises in the prior quarter, which is publicly known information, and define extremeness as the top and bottom decile EPS surprises. As we already divided the sample in extremely high and extremely low EPS numbers respectively extremely positive and extremely negative quarterly forecast errors, we no longer have a dummy that refers to the direction of the EPS surprise.

**Table 7.3.13: Robustness check: Extreme earnings surprises**

| Dependent variable: Forecast Error a) | | | | |
|---|---|---|---|---|
| **Sample:** | **Extremely high EPS SURPRPISE** | | **Extremely low EPS SURPRISE** | |
| C | 0.0015 | | -0.0077 | *** |
| $(D_{\_LOSS})$*EPS_PRIOR a) | -0.0609 | *** | -0.0374 | *** |
| $(1\text{-}D_{\_LOSS})$*EPS_PRIOR a) | 0.0118 | ** | -0.0493 | *** |
| EPSVOL | -0.0005 | ** | 0.0009 | *** |
| DISP a) | -0.0136 | *** | -0.0179 | * |
| SURPRISE a) | -0.0397 | | 0.4820 | *** |
| $(D_{GOOD\_MOM})$*MOM | -0.0152 | *** | -0.0044 | |
| $(1\text{-} D_{GOOD\_MOM})$*MOM | 0.0272 | *** | 0.0263 | *** |
| LNSIZE | 0.0002 | | 0.0009 | *** |
| | | | | |
| Adjusted $R^2$ | 0.0259 | | 0.0663 | |
| N | 11,476 | | 11,258 | |
| | | | | |
| **Descriptives sample** | **Mean** | **Median** | **Mean** | **Median** |
| EPS_ACTUAL a) | 0.0588 | 0.0744 | 0.0297 | 0.0489 |
| EPS_PRIOR a) | 0.0648 | 0.0709 | 0.0638 | 0.0699 |
| EPSFC a) | 0.0584 | 0.0721 | 0.0396 | 0.0528 |
| FE_P5 a) | 0.0004 | 0.0019 | -0.0099 | -0.0014 |

Note: The subscript a) refers to price-scaled variables, conditional on a minimum share price of USD 5.00. In addition, we have winsorized FE at 1 and 99%. D stands for dummy, EPSVOL for annual EPS volatility over the past five years. DISP stands for forecast dispersion (highest -lowest estimate). SURPRISE equals the difference between actual and forecast quarterly EPS in the prior quarter. MOM stands for the past cumulative market outperformance in the past 3 months. Asterisks identify significance levels of 1% (***), 5% (**) and 10% (*). White cross-section adjusted standard errors.

First of all, we remark that the prior year EPS is not materially different between extremely positively and extremely negatively surprising firms. In other words, negative (positive) surprises are not necessarily preceded by bad (good) years. The negative coefficients for prior year losses in both subsamples suggests that analysts tend to be too conservative in those situations, thus leading to positive or less negative forecast errors. Conversely, when prior year earnings are positive, analysts on negatively surprising firms tend to anchor too heavily to this, unlike the extremely positively surprising firms. Other differences regarding extremely negative surprises stem from underreaction to prior quarter earnings surprises and momentum. This is only partly offset by a conservative stance to EPS volatility and positive size effect. Extremely positive surprises are higher when prior year profits are higher, albeit partly offset by a too positive view on risk, overreaction to good momentum and underreaction to bad momentum.

## 7.4 Summary and Discussion

In this chapter, we empirically investigated the impact of heuristics or specifically anchoring and adjustment on analysts' earnings forecasts. Apart from determining the most optimal weights for the anchor, risk and news variables on an aggregate basis, we investigated time and cross-sectional differences. Overall, our findings imply the use of heuristics and various biases are incorporated in analysts' earnings forecasts for which their multi-task environment may be to blame. Otherwise said, as analysts have to please many internal and external clients, they may fall prey to such cognitive errors.

We find signs of innate optimism in analysts' EPS forecasts, except when firm-specific regressions are run or when forecast horizons are no more than half a year ahead. The former could result from our narrow scope to widely covered firms. For such firms, it is more difficult to establish a close relation with management as investor relation officers come in between. This makes it easier to issue more critical or less optimistic estimates and hence could account for the significant pessimism in our firm results. This is further supported by our findings of more pessimism or less optimism for bigger firms. The fading out of optimism for shorter forecast horizons could imply that analysts perform a reality check after the release of the half-year results.

Conversely, anchoring to prior year EPS seems most pronounced on the firm-level, although we note that on the analyst level, we have not included their full coverage, but only the widely followed stocks. On the industry level and among well-represented analysts in the sample, signs of anchoring are absent or weak. This could suggest that a more complex bottom-up approach is used. Instead of taking last year's prices, volumes, cost base, taxes and financing structure as a starting point, estimates evolve from identifying macro-economic factors, demand and supply trends, raw material price developments, capacity utilization, labor productivity, wage developments e.g.

Furthermore, we find ambiguous results with regard to risk. Long-term risk or EPS volatility is perceived a positive element or upside potential, while short-term risk is taken negatively. March and Shapira (1987) find that managers tend to view risk from a downside perspective rather than upside potential, but do not link this to forecast horizon.

Our evidence mainly points at underreaction to news and asymmetry between good and bad news. The underreaction to bad momentum is larger than to good momentum, while the underreaction to bad earnings is often insignificant and below the underreaction to good earnings. Moving to extreme earnings surprises, those that are extremely negative in the prior quarter, filter through in negative annual EPS surprises as well. Too heavy anchoring to prior year profits and underreaction to quarterly news, including stock momentum is to blame. Overreaction is only found to bad news in the firm-specific analyses.

The use of consensus EPS as an anchor does not materially change results on an aggregate basis and implies that this alternative measure does not neutralize innate bias, different risk attitudes or improper reactions to news. Conversely, the use of an industry- instead of company specific long-term risk measure translates into higher innate optimism. This is offset by a too conservative view on this long-term risk proxy, which is opposite the optimistic view on its company specific risk measure.

Finally, when we narrow our scope to the most extreme quarterly earnings surprises, we find too much pessimism when losses were incurred in the prior year and underreaction to negative momentum, regardless of the sign of the extreme surprise. Also, we find a too high reliance on prior year profits for negatively surprising firms, while short-term risk and prior quarter earnings surprises are underestimated.

# 8 Summary and directions for future research


## Abstract

Inspired by ample anecdotal evidence from the investment industry, we felt “a spontaneous urge” to investigate irrationality at company management, investors and financial intermediaries. This dissertation was focused on extreme management confidence, abnormal stock return opportunities and anchoring and insufficient adjustment to news by security analysts. Our research was exploratory in nature and based on data from the past three decades from the 80s, 90s and the 2000 years. However, in the next sections, we will put our results into today’s and tomorrow’s context and suggest directions for further research.

## 8.1 Measurement and impact of extreme confidence

### 8.1.1 Main results and findings

This study investigates to what extent extreme confidence of either management or security analysts may impact financial or operating performance. We construct a multidimensional degree of company confidence measure from a wide range of corporate decisions. We empirically test this measure for large US companies from 1980 -2008 and find significantly different company and performance characteristics between confidence extremes. Diffident firms tend to be smaller, more distressed, less conservatively financed and, except for the new millennium, yield a lower return on invested capital with higher variability.

In addition, we find significantly lower, mostly negative, risk adjusted stock returns preceding and in the year of change to low confidence vs. the ones that move to upper confidence level. The new millennium shows an opposite pattern though. This turbulent decade started with unprecedented peaks in stock valuation and ended with huge asset markdowns. Following shifts to extreme confidence levels, we find weak support of return reversals, albeit insufficient to compensate in full. The strategy "Buy on the Rumor, Sell on the Fact" could pay off, but requires perfect foresight of company confidence levels a year in advance

Extreme confidence could also distort earnings forecasts as analyst may overly rely on an anchor or make insufficient adjustments. Innate bias, anchoring to prior year earnings, risk attitude and responses to recent news are conditional on the level of analysis. Innate optimism prevails on the industry and analyst level. We find no support for anchoring by analysts with a long track record or across industries, which suggests a bottom-up approach. Long-term risk is considered as upside and short-term risk as downside potential. There is also a tendency to underreact to news, the extent of which seems conditional on the direction.

In the next sections, we will take a closer look at our main results and put these in today's and tomorrow's perspective.

### 8.1.2 Diffidence deserves more attention

Any bias is a human trait and with it comes the challenge of finding an unbiased or objective way of measuring it. We attempted to do so by taking various corporate actions as a starting point, subsequently combining this information with theoretical and empirical research on overconfidence and hence inferring a degree of confidence. In our definition of high (low) confidence, we included both risk and return characteristics, which resulted in overestimating (underestimating) the net present value of certain management actions.

Unlike prior research, we did not only narrow our scope to overconfidence, but also explicitly included its negative or diffidence. In our view, this area demands more attention, particularly as we found that diffidence can have a major negative impact on a company's performance as measured by return on invested capital and abnormal stock returns. Conversely, we did not find such negative effects for overconfidence.

Although diffidence is more likely to translate into a passive stance and probably for this reason considered less attractive from a research perspective, this does not imply that there is no impact on the bottom line either. Conversely, we found that diffidence is detrimental for performance based on both accounting and market-based measures. Although this may be a sufficient justification for devoting more research attention in this area, the fear of being qualified as "Dr. Doom" may have a deterring effect. However, this is not about bringing the bad news, but rather how to prevent such undesirable situations from diffidence to materialize. Take the example of countervailing power, such as investors pushing management to embark on share buyback programs or risky projects instead of sitting on a cash pile. However, this resistance is not institutionalized and management cannot be formally held to give in to such demands. As investors themselves are not immune to bias either, it may sometimes be a better strategy to ignore or exploit such market signals, as Baker et al. (2004) argue.

### 8.1.3 Countervailing powers to confidence …

Although corporate governance is an institutionalized mechanism and a potential source of countervailing power to management, it tends to be focused on addressing agency problems. It contains management's locus of control or their freedom to make bold moves like acquisitions. In additional, risk management and compliance systems should act as a countervailing power to contain excessive behavior.

We could extend our analysis by adding a measure for measuring the existence of countervailing powers, such as the governance score developed by Gompers et al. (2003). They combine a large set of governance provisions into an index which is used as a proxy for shareholder strength. In the extremes, they distinguish democracies (G-score <=5) and dictatorships (G-score >=14). They empirically investigate the relation between this index and corporate performance and find that a long-short strategy in low-high governance score portfolios clearly pays off. It generates high abnormal returns of 8.5% a year based on Carhart's (1997) four factor model.

We would predict that companies which score low on this metric i.e. those who do not restrict shareholder's power are less prone to extreme forms of confidence in both directions. We empirically found significantly lower profitability in terms of EBIT margin and return on invested capital and a higher distress risk as indicated by a higher share of loss making firms and higher book equity to market equity ratio for the lower confidence extreme. As diffidence in particular seems more detrimental than overconfidence, we would expect that higher shareholder involvement mitigates the risk of moving to this negative territory. In other words, we would also predict asymmetry or higher underrepresentation of diffident compared to overconfident companies when the corporate governance score is low and vice versa when the corporate governance score is high.

### 8.1.4 …and reinvigorating powers to confidence

Contrary to mitigating factors to confidence extremes, we can also observe organizational procedures that encourage high confidence, such as the selection process for electing new CEOs. Goel and Thakor (2008) develop a model that shows that an overconfident manager is more likely to become CEO. Furthermore, management share and options plans are mainly criticized for inducing risky behavior. However, the structure of compensation contracts could also be an effective tool to prevent management from exhibiting low confidence, as the latter is likely to be penalized by negative abnormal stock returns. In the model by Goel and Thakor (2008) an even more dramatic scenario in which the CEO is dismissed when extremely confident or extremely diffident. We could empirically test if this is the case, although it may be hard to have sufficient observations to achieve significance. We could increase this by assuming that takeovers of extreme confidence firms where the CEO moves to a non-executive function as a special case of forced resignation.

In forthcoming work by Gervais et al. (2011), the authors investigate how compensation contracts could optimally adjust to overconfidence effects on the firm. They model that if a manager is mildly overconfident, firm value increases by offering less convex contracts or a lower share of performance-based compensation. Conversely, when a manager exhibits extreme overconfidence, highly convex contracts are more optimal, as these are overvalued by the manager. This may seem hard to defend as the high share of variable compensation is also blamed for being the culprit behind the 2008 financial crisis, from which we have yet to recover. The absence of claw back provisions i.e. repayment of (part) of bonuses when things go sour, encouraged excessive risk taking and myopic behavior in search of short-term gains. We could also incorporate the structure of the compensation contract of the CEO respectively all executive members to empirically test if there is a relation with our degree of confidence measure.

In addition to internal procedures, there is a role for government bodies. In this respect, take the example of the Sarbanes-Oxley Act in 2002. This new legislation made senior executives individually responsible for accuracy and completeness of corporate financial reports, but it also tempered their animal spirits. This may have affected the results of our period specific regressions, which showed no significant CAR differences between confidence extremes and highly negative CARs for high confidence firms on a standalone basis in the same year. Conversely, the government can also encourage entrepreneurship by offering subsidies or guarantees. During the financial crisis, government guarantees were put in place to induce banks to perform their core business of lending. However, such measures also carry the risk of moral hazard by offering a bail-out option when things go wrong.

### 8.1.5 Extensions of our measure: dynamism and other industries

Over the 1980-2008 period as a whole, we found that the average company confidence level was low, which may not bode well for the future. Looking at 2008, the picture was very gloomy with a very low proportion of high confidence firms. We do not dare to speculate if we have reached another tipping point, or that we will face some steady years with little changes in the share of high vs. low confidence firms. Paradoxically, the number of low confidence firms was not that high either, but the exclusion of financials, for technical reasons, could be to blame. In order to extend our degree of confidence to financials as well, the take example of redefining investment by including human capital (wage costs) rather than production, plant and equipment. Instead of operating leverage, tier capital ratios could be considered. Segments could be divided into traditional banking or savings and loans business, insurance and investment banking, while accruals could be replaced with bad loan provisioning practices.

Furthermore, our degree of confidence measure is fairly static, although we allowed for interaction with prior period investor sentiment. However, we could add more dynamics based on self-attribution, as Daniel et al. (1998) used in their investor behavior model. This bias implies that confidence is reinvigorated when decisions turn out very well, the latter of which can be inferred from higher compensation, higher stock valuation, a good earnings track record with positive surprises or positive press coverage. Conversely, if feedback is negative, one may blame others or the environment for this, thus leaving the manager's own confidence level intact.

## 8.2 Performance Measurement

### 8.2.1 Disentanglement of risk and return expectations

In our definition of confidence we adopted a risk-return perspective. Alternatively, confidence could be defined from a risk only or returns-only perspective. In our approach, there was no need to disentangle whether corporate decisions were driven by too optimistic forecasts on either cash flows, or growth or the discount rate. It is clear that such a distinction is more of a challenge and requires more direct input from executives and insight of their personal characteristics. Although listed companies share their vision on the market developments and margin potential during analyst meetings and strategy updates, we expect reluctance with regard to more detailed information on projects. Competitors are also listening and such transparency also makes executives vulnerable when such specific targets are communicated. Since the Sarbanes-Oxley Act, we would expect listed companies to be more transparent in communicating more details en masse, as it becomes too risky to share such information "off the record" in one-on-one meetings with investors.

Goel and Thakor (2008) argue that overconfident managers underinvest in acquiring project relevant information, thus increasing the risk of selecting bad projects and scrutinizing the quality of information that is used to evaluate the CEO. One could argue that management has little leeway to do so, as auditors will require impairments or provisions when investments do not live up to expectations. However, they can give management, who are also their principals, the benefit of the doubt before requiring such dramatic charges. We could empirically test this by constructing a transparency measure that reflects whether or not management frequently communicates on projects or a portfolio thereof i.e. provides segments guidance and targets. In addition, the information that a company provides when making acquisitions, such as price paid, valuation multiples, payback time given a certain cost of capital e.g. could be included in this measure as well.

### 8.2.2 On abnormal return measurement

As far as investors are concerned, information on risk appetite and attitude is easier to extract, as we could take the implied option inferred volatility as a proxy. Furthermore, the widely used factor risk premiums on French' website could be used as an ex post indicator. As we looked for the best model fit or factor loadings on market risk, size, book-to-market and momentum for the full period data rather than on a subsample of data, we more or less assumed that factor loadings would not be time-varying by firm. In other words, a move to extreme confidence levels is just a temporary drift away from its mean risk profile, to which it will revert in the long-term. Alternatively, if we would have estimated factor sensitivities by using a sub sample of observations before a change to an extreme confidence level, this may have led to distortions as well.

We are well aware of the joint testing problem i.e. the risk of misspecification of the model rather than irrational behavior by investors. Overall, our confidence and investor sentiment variables can only explain a minor part of the cumulative abnormal returns, thus implying that either there is a lot of noise or that there are some additional systematic factors that are yet to be identified. For instance, take the example of temporary drifts from speculative behavior.

Our implicit assumption that the long-term risk profile is the key ingredient of any market valuation model implies that fundamentalists dominate speculators. Although we include time-varying required returns as risk premiums vary, allowing for different factor loadings would make the model more dynamic. In such a framework, we could also add a dominant role of speculators from time to time. However, it continues to be a challenge to predict tipping points i.e. when one type of investor starts to dominate the other. We would predict a higher difference in returns between confidence extremes when speculators dominate the market.

Finally, we could look at bond returns as an alternative to stock returns. However, we have to be cautious in comparing bond returns, as characteristics i.e. duration, provisions, credit rating, may heavily differ among and within companies. Next to being standardized, shares and associated derivatives are also very liquid, thus reducing the risk of market inefficiencies. Although diffident or passive management seems negative for shareholders, one could argue that bond holders may encourage such behavior, thus implying lower credit spreads. However, as we find that diffidence is associated with more distressed situations of lower profitability, we would expect higher spreads instead.

## 8.3 Earnings forecast errors

### 8.3.1 Analysts to blame…

Although the lower-level i.e. the analyst, firm and industry specific regressions strongly contribute to explaining analyst forecasting errors, there is still room left for improvement. The results of our study indicate that the level of analysis is an important determinant whether or not innate bias, anchoring and (insufficient) adjustment and under- or overreaction occurs. We can come to different conclusions, such as that innate optimism at the analyst level, while we observed pessimism at the firm level. The latter implies that firms tend to positively surprise, which may be for a reason, such as building a good track record. We also found that long-term risk is considered as upside opportunity, while short-term risk is seen as a downside threat.

We could extend our regression analysis by adding stock recommendations as a dummy variable, as these may also have an impact on analyst estimates. We argue that earnings cuts (increases) are more difficult for stocks on which the analyst has a positive (negative) stance. Paradoxically, optimistic estimates can coincide with a sell recommendation but for very different reasons. It could be fuelled by the need to restore management relations, or on the negative hand, put more pressure on management; as the earnings bar is raised, it negative earnings surprises become more likely, thus supporting the analyst's negative stance. However, it remains a challenge to unfold the analyst's true underlying view, as this could disrupt the fragile equilibrium of the various parties he or she is involved with.

If we would have less strict criteria on coverage, we could include smaller firms and the individual analyst's full stock coverage instead of only stocks that are well covered by others as well. Moving to a balanced panel would also enable a time-series analysis by firm or by analyst and the ability to add dynamics in the framework, such as firm or analyst reputation. The less negative the earnings surprises respectively the more accurate the earnings forecast, the better the reputation.

Furthermore, a larger sample would enable us to look how so-called lower levels forecast errors develop by forecast horizon. In the pooled regressions, we already saw that innate bias was only present at long forecast horizons of up to 270 days ahead, while it moved to pessimism for shorter forecast horizons, albeit not significant. In addition, anchoring was also most pronounced for longer forecast horizons, while prior year EPS seems less important after some releases of interim results. These announcements are usually accompanied with more specific earnings guidance, which can become the new anchor. In order to test this, we could include management's earnings guidance as reported in press releases or in conference calls. This also brings us to forecast and earnings management practices, which could also be to blame for analysts' forecast errors.

### 8.3.2 …or management to blame?

In this dissertation, we only attributed forecast errors to the analysts, but management could also have an important impact by influencing the reported numbers and by managing expectations. We only briefly discussed this when we discussed accruals as an indicator for confidence. Gu and Wu (2003) also looked at accruals, or specifically the unexpected part of it, when controlling for earnings management. It should not be put on par with fraud, which is an excessive form of earnings management.

Earnings management has been widely covered in literature. In their study from 1985 to 2002, Brown and Caylor (2005) detect a major shift in management focus to avoiding negative earnings surprises as of 1996. Before, management's main priority was to avoid earnings losses or year on year earnings declines. As possible explanations of this shift, they mention a higher market impact of missing forecasts and better analyst coverage and precision. Matsumoto (2002) and Burgstahler and Eames (2006) also explicitly mention the phenomenon that management downplays analyst expectations in order to beat these hereafter. This would result in a higher frequency of zero or positive surprises and a smaller frequency of small negative surprises.

Forecast management is less explored, as it also requires hand-collection of data, as unlike analysts' forecasts, earnings guidance is not widely gathered in databases. In addition to press releases, one could use the transcripts of conference calls, from which even more information can be revealed. In press releases, the company's determines what is communicated, while in the conference, analysts can guide what topics are more discussed in detail.

### 8.3.3 Forecast errors and market impact

Our results show that underreaction to news, both earnings and stock price related, is also an important driver behind analyst forecast errors. The extent of this underreaction seems dependent on the direction, with higher sensitivity to bad news events. However, this does not imply that the stock market response in the same way. If analysts would be a good proxy for investor expectations, we would expect a similar pattern. Alternatively, we could argue that as investors do not work in what Francis and Philbrick (1993) referred to as "a multi-task environment", but only deal with their own goals, bias is not instrumental to them. In other words, investors adjust for such biases before making investment decisions. In current literature, we find support for both views.

Fried and Givoly (1982) find that analyst forecast errors are more closely related with security price movements, thus suggesting that analysts' forecasts are a better substitute for market expectations than time-series models. When measuring the market impact of equity analysts, Chen et al. (2005) find that investors attach bigger weights on the accuracy of an analyst i.e. his forecast error the longer his track record. Abarbanell and Bernard (1992) also find that analysts underreact to prior earnings news, but this can only explain half of the post-earnings announcement drift. With regard to macro-economic news and forecasts thereof, Campbell and Sharpe (2009) find that the market adjusts for anchoring in consensus forecasts and react to surprises that cannot be attributed to such cognitive errors. However, the use of consensus estimates assumes an equal weighing of each analyst forecast, while Chen et al. (2005) suggest that investors differentiate among analysts based on their forecast accuracy. Although these studies emphasize one specific type of cognitive errors, i.e. reaction to prior news or the use of anchoring and adjustment heuristics, we have cleaned analyst forecast errors for various errors, including the direction of the news and time-varying risk. We could extend our analysis by testing to what extent post-earnings announcement drift can be explained by expected and unexpected forecast surprises. For calculating the expected surprise component we use the coefficients from our pooled or lower level regression results.

## 8.4 Concluding remarks

Without being extensive, we highlighted various ideas for further research in the areas that we discussed in this study. Apart from exploratory analyses, we consider a move to predictive models as one of the main challenges for the future of behavioral finance. Although we could develop ex ante measures of preferences and expectations of economic actors, they do not always put the money where their mouth is. Hence, we believe that actions or the aggregate of revealed preferences and beliefs speak louder. As our degree of confidence is based on revealed rather than planned actions, a forward looking view on the different components could be used for flagging tipping points in a firm's stock performance. Also, if we could better predict forecast behavior of each individual analyst and firm-specific biases in forecasts, we may better anticipate the market's reaction to earnings news. Ironically, this would kill one of the main drivers, i.e. market anomalies, behind behavioral finance. Our animal spirits will, however, prevent such predictable situations. These animal spirits should be kept alive, as lack thereof or extreme low levels of confidence seem the major threat to performance. No guts, no glory.

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# Appendices

# Appendix I: List of variables (in alphabetical order)

**Note: Items refer to Compustat**

**Accruals.** We follow Sloan (1996) and calculate accruals as the change in non-cash working capital (items 4+34-1-5) less depreciation (items 14) and scale this to adjusted EBIT. Similar to Sloan, we exclude debt in current liabilities from working capital. We winsorize the accruals ratio at (minus) one.

**Acquisitions.** We scale acquisition spend to total assets at the start of the year (items 129/6).

**Adjusted EBIT.** In order to correct for potential distortions by end of year acquisitions or divestments, we adjust EBIT. This equals this year's EBIT margin multiplied by last year's asset turnover.

**Adjusted Earnings per Share (EPS)**. These EPS numbers are retrieved from the detailed IBES database and are adjusted for stock splits, share issues, share buybacks, stock dividends e.g

**Asset turnover.** This equals total assets to sales (items 12/6).

**Cumulative Abnormal Return (CAR).** The cumulative abnormal stock return is calculated on a monthly basis and equals the (natural logarithm of the) return in excess of the predicted return by using Carhart's (1997) four factor model. The monthly CARs are aggregated to arrive at an annual cumulative abnormal return for the full year.

**Degree of diversification.** We determine the degree of diversification by counting the number of different business segments, based on the two-digit SIC codes . In case of missing data, we look at the number of segments in the prior and following year and if acquisitions or divestments have taken place during this period.

**Dispersion (DISP)**. Dispersion is is a short-term risk proxy and equals the difference between the highest and the lowest EPS estimate, measured by quarter and based on all available individual forecasts. This measure is scaled to the share price, conditional on a minimum (adjusted) share price of USD 5.00.

**Dividend change**. First, we calculate the change in dividend per share (item 26).

**Dividend payout ratio**. We calculate this ratio by scaling common dividend to income before extraordinary items, discontinued operations and preferred dividend (items 21/237). If a firm is loss-making i.e. the denominator is negative and a dividend is paid, we set the payout ratio at one. The payout ratio is winsorized at values between zero and one.

**EBIT margin**. This equals Earnings before interest and tax (EBIT) to sales (Items 178/12).

**Enterprise Value (EV).** EV equals the sum of the market value of equity, preferred stock and net debt (items 25*199+130+9+34–1).

**Enterprise Value to EBITDA ratio**. For the enterprise value (EV) to EBITDA ratio, we use our earlier calculations of EV respectively EBITDA and winsorize at the 1% and 99% percentile for observations with positive EBITDA. Similar to negative earnings firms, those with negative EBITDA are assigned the highest EV to EBITDA multiple.

**EPSVOL**. This is a long-term risk proxy and equals the volatility in adjusted EPS (as documented in IBES) in the past five years.

**Equity risk premium**. This equals the return difference between stocks and T-bonds. Data retrieved from Damodoran's (2011) website.

**Excess leverage (EXCESS LEV).** We control for financial leverage, specifically excess leverage vs. the industry average. First, we scale net debt (items 9+34–1) to EBITDA (item 13) and relate this to the industry average, based on the two digit SIC code. Next, we multiply the difference by the EBITDA to total assets ratio (items 13/6). For loss making firms with net cash, we assign a net debt to EBITDA of zero. In case of losses and net debt, we set excess leverage to net debt to total assets. Excess leverage is winsorized at (minus) one times total assets.

**Financing gap (FINGAP)**. Financing gap equals income before extraordinary items, discontinued operations and preferred dividend plus depreciation less common dividend less capex (items 237+14-21-128) less the lower of zero or net debt. (= negative if there is net cash). The financing gap is winsorized at (minus) one times the enterprise value (EV).

**Forecast Error (FE)**. We use the commonly used definition of actual minus forecast EPS and scale this difference to the share price, conditional on a minimum (adjusted) share price of USD 5.00.

**Forward PE**. This ratio is calculated for the market as a whole and equals the aggregated market capitalization of all stocks for which one-year ahead earnings estimate data is available, scaled to the aggregated one-year ahead estimated earnings. The latter equals the earnings per share estimate for year t, multiplied by the number of shares outstanding at the end of the prior book year (t-1).

**Growth (BEME-ratio).** We also include growth as a control variable which we proxy by the book equity to market equity (BEME) ratio. Book equity is total stockholders' equity less preferred stock plus deferred tax assets (items 216 –130 + 35). Market equity equals shares outstanding multiplied by price (items 25*199). We omit observations with negative book equity or a market capitalization below USD 20m.

**Invested capital at market value**. This equals invested capital (item 37) but includes market equity (items 199*25) instead of book equity (items 216 –130 + 35).

**Investment-to-Q-ratio (INVEST).** First, we relate the capital expenditures to depreciation (items 128/14), which indicates if a company is increasing its tangible production capacity. Second, we scale this number to the market's growth perception which we proxy by the widely recognized Tobin's Q ratio.

**MOM**. This variable measures the stock's return in the past three months.

**Net debt.** This equals long-term debt plus current debt less cash (items 9+34–1).

**Operating leverage (OPLEV)**. We calculate operating leverage by scaling fixed assets to total assets (items 8/6).

**Price to Earnings ratio (PE).** This ratio equals price divided by earnings per share before exceptional items (items 199/58). and is winsorized at the 1% and 99% percentile of observations with positive earnings. Firms with negative earnings are attributed the maximum PE ratio, similar to those with marginal profits.

**Return on invested capital at market value (ROIC MV)**. The numerator of this measure consists of EBIT (item 178) less cash tax. (1-cash tax rate) times EBIT (item 178), divided by invested capital at market value. Cash tax rate equals income tax less accrued and deferred taxes (item 16-305-126), divided by pre-tax income (item 170). If not between 0 and 1, the income tax cash rate is used or else a 35% default rate. We winsorize ROIC MV at (minus) one.

**Return on equity (ROE)**. This equals income before extraordinary items, discontinued operations and preferred dividend, divided by common equity (items 237/60). Observations with negative common equity are excluded.

**Share buybacks (SHAREBB)**. Share buybacks are net of share issues and scaled to market capitalization (items (115-108)/(25*199).

**(LN)SIZE.** We take the widely used (natural logarithm of a) company's market capitalization (items 199*25) and exclude book values below USD 20m.

**SURPRISE**. This equals the share price-scaled forecast error of quarterly EPS or the difference between the actual and forecast quarterly EPS. We only included observations with a minimum (adjusted) share price of USD 5.00.

**Tobin's Q ratio**. This ratio is calculated as the market to book value of total assets. Market value of total assets equals total assets less stockholders equity less deferred tax assets plus the market value of common stock and preferred stock (items 6-216-35+199*25+130).

**Z-score.** This robustness variable equals the aggregate of the separate Z-scores on each confidence indicator. If an indicator consists of several underlying variables, the normalized scores of each variable is equally weighed. In formula terms:

$$
\begin{aligned}
Zscore = {} & Zscore_{accruals} + Zscore_{acq} - Zscore_{oplev} + Zscore_{sic} + \\
& \tfrac{1}{2}\left[Zscore_{invest} + Zscore_{fingap}\right] + \tfrac{1}{2}\left[Zscore_{sharebb} + Zscore_{fingap}\right] + \\
& \tfrac{1}{3}\left[Zscore_{div\_change} - Zscore_{payout} + Zscore_{fingap}\right]
\end{aligned}
$$

# Appendix IIa: Investor sentiment proxies

## Brown and Cliff (2004)

Brown and Cliff (2004) explore how investor sentiment relates to near-term stock market returns. They consider a comprehensive set of sentiment proxies, both direct and indirect, explore the relations among these variables and test the relation of sentiment with subsequent stock returns. In their paper, they summarize the main direct and indirect measures of investor sentiment. Also, they distinguish between individual and institutional investors.

The direct or survey-based measure for individual investor sentiment is inferred from a weekly poll as of July 1987 by the American Association of Individual Investors. Among each of its members, it asks where the stock market will be in six months; up, down or unchanged. The direct proxy for institutional investor sentiment is inferred from the Investor Intelligence's weekly bull-bear spread by investigating approximately 150 market letters and available on a monthly basis as of 1965.

The indirect measure is composed of the following components:

- Advance/Decline ratio or the issues up vs. issues down, can be adjusted by standardizing with average volumes
- Monthly percentage change in margin borrowing (published by Fed)
- Short interest and short sales
- Ratio of put-call trading volume (from the CBOE)
- Expected vs. current volatility
- Closed-end fund discount
- IPO first day returns and number of IPOs
- Mutual fund redemptions

Brown and Cliff (2004) face some difficulty when constructing this composite measure, as some correlations between de direct and indirect sent measures are counterintuitive. In order to deal with this, they filter data a single state variable via the Kalman filter and then perform a principal component analysis. They only use the first and second Principal Component in their investor sentiment variable.

All in all, they find that institutional sentiment seems to impact individual investors, but not the other way around. Only some weak evidence of a delayed impact of the level institutional sentiment on large cap stock returns, Furthermore, they find a negative relation between the change in professional investor sentiment and subsequent returns of small stocks on a monthly basis.

# Appendix IIb: Investor sentiment proxies

## Baker and Wurgler (2006)

Baker and Wurgler (2006) also construct a composite investor sentiment measure and investigate how investor sentiment could impact cross-sectional differences in stock returns. Their indirect proxy for investor sentiment is based on the common variation in six underlying proxies for sentiment. The authors make no explicit distinction between fundamentalists and speculators or between individual and common market sentiment. The six proxies that Baker and Wurgler include are respectively:

- the closed-end fund discount (CEFD) to net asset value
- the NYSE share turnover (TURN)
- the number of IPO's (NIPO)
- the average first-day returns on IPO's (RIPO)
- the equity share in new issues (S) and
- the premium of dividend payers vs. non-payers (PD-ND).

They perform a principal component analysis with the six proxies and their lags as variables and end up with a sentiment index consisting of current standardized variables CEFD (negative sign), NIPO's (positive sign), S (positive sign) and lagged standardized variables RIPO (positive sign), turnover (positive sign) and PD-ND (negative sign). The signs of these (lagged) variables are intuitive. In addition, they also calculate a clean sentiment proxy in which common business cycle effects are removed. Data can be retrieved from Wurgler's website.

Overall, the authors find that the impact of market-wide investor sentiment on the cross-section of stock returns is larger the more subjective and the more difficult to arbitrage a stock is. Higher subjectivity suggests more room for behavioral bias to have an impact.

## Appendix III: Gordon growth model (1962)

The Gordon (1962) growth model for valuing a company's stock can be summarized by:

$$P_0 = \frac{D_1}{k - g}$$

where $P_0$ equals the current share price. $D_1$ equals next period's dividend, $k$ refers to the cost of equity and g to the perpetual growth in earnings. When data on expected dividend are scarce or lacking, we could proxy next period's dividend by multiplying last period's dividend payout d with the expected earnings per share ($EPS_1$) or:

$$P_0 = \frac{d_0 \times EPS_1}{k - g} \rightarrow k = d_0 \times \frac{EPS_1}{P_0} + g$$

When we reshuffle the terms in such a way that we have $k$ on the left side and the terms on the right side of the equation are E/P. dividend payout ratio and long-term growth respectively. Differentiating $k$ to dividend payout respectively PE ratio and growth gives:

$\Delta k = EPS/P * \Delta d_0 + d_0 \, \Delta \, (EPS/P) + \Delta g$

If both the dividend payout and the long-term growth rate remain unchanged, it follows that only the change in earnings yield drives a change in the required rate of return.

# Nederlandse samenvatting (Dutch summary)

In deze studie onderzoeken we hoe irrationaliteit in financiële beslissingen gemeten kan worden en hoe dit prestaties beïnvloedt, zoals het rendement op geïnvesteerd vermogen, abnormale aandelenrendementen en de nauwkeurigheid van winstverwachtingen. We beschouwen verschillende type actoren, te weten managers, beleggers en aandelenanalisten en bespreken kort welk gedrag voor hen optimaal is. Voor managers definiëren we maximalisatie van de netto contante waarde van de vrije kasstromen als optimaal. Voor beleggers beschouwen we het streven naar rendementen in lijn met de blootstelling aan de vier risicofactoren als onderscheiden door Carhart (1997) als optimaal. Tenslotte definiëren we voor aandelenanalisten de minimalisatie van de gemiddelde voorspellingsfout als optimale strategie.

Aan de hand van bestaande theorie en empirisch onderzoek ontwikkelen we een alternatieve maatstaf om de mate van management vertrouwen te meten. Hierbij zijn daadwerkelijk genomen en niet geplande beslissingen op diverse vlakken leidend. Naast onze multidimensionale aanpak, beschouwen we niet alleen een extreem hoge graad van vertrouwen, maar ook een extreem lage graad als vertrouwen. Over de periode 1980 tot en met 2008, vinden we duidelijk onderscheidende ondernemingskarakteristieken en prestatieverschillen tussen deze extremen, welke we als volgt kunnen samenvatten.

Ondernemingen met extreem laag vertrouwen zijn kleiner, hebben een lagere marktwaardering ten opzichte van de boekwaarde, grotere druk op de winstgevendheid, minder conservatieve balansverhoudingen en hebben een lager en meer volatiel rendement op geïnvesteerd vermogen. We vinden duidelijk lagere en veelal negatieve abnormale aandelenrendementen voorafgaand en tijdens een verschuiving naar een extreem lage vertrouwensgraad ten opzichte van het andere extreem. Echter, dit lijkt niet te gelden voor het nieuwe millennium, waardoor de winstgevendheid van een dergelijke long-short strategie niet persistent lijkt. Een groot deel van de abnormale aandelenrendementen blijft onverklaard, eveneens na toevoeging van een indicator voor het sentiment van beleggers. Dit impliceert dat de markt niet structureel inefficiënt is.

Tenslotte onderzoeken we of en in hoeverre analisten te veel vasthouden aan een anker in hun winstschattingen en of inconsistenties ten opzichte van risico en recent nieuws leiden tot hogere voorspellingsfouten. De resultaten verschillen naar gelang het niveau van de analyse i.e. geaggregeerd, per analist, per sector of per bedrijf. In de meeste gevallen vinden we een neiging tot natuurlijk optimisme en het vasthouden aan de winst in het voorgaande jaar als ijkpunt. Daarnaast vinden we een positieve houding ten opzichte van lange termijn risico, terwijl korte termijn risico eerder als negatief wordt ervaren. We vinden een onderreactie op nieuws, met name recente koersontwikkelingen, terwijl ook de aard van het nieuws bepalend kan zijn voor de mate van onderreactie.

## About the author

Mariska Douwens-Zonneveld earned a Master's degree in Business Economics at the Vrije Universiteit in Amsterdam in 2000. While working in the financial industry as an equity analyst on Dutch stocks, she also achieved a Master of Financial Analysis at the Vrije Universiteit Amsterdam. After a short period as assistant controller at a large retailer, she decided to move back to equity research in 2004. In 2007, she moved to New York City for a job in equity sales. After returning from New York City in 2009, she embarked upon the so-called Mature Talent program at the Erasmus School of Economics to do research in behavioral finance. As of 2012, she works as fund manager credits at a large administrator and asset manager for pension funds.

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## ANIMAL SPIRITS AND EXTREME CONFIDENCE
## NO GUTS, NO GLORY?


This study investigates to what extent extreme forms of confidence, from either a management or an analyst's perspective, may impact financial or operating performance.

We construct a multidimensional degree of company confidence measure from a wide range of corporate decisions. We empirically test this measure for large US companies from 1980-2008 and find significantly different company and performance characteristics between confidence extremes. Diffident firms tend to be smaller, more distressed, less conservatively financed and, except for the new millennium, yield a lower return on invested capital with higher variability. When adjusting stock returns for risk, the performance differences prior to moving to extreme confidence become even more pronounced.

Analysts' earnings forecasts may also be distorted by extreme confidence or overly relying on an anchor and insufficient adjustments. Innate bias, anchoring to prior year earnings, risk attitude and responses to recent news are conditional on the level of analysis. Innate optimism prevails on the industry and analyst level. We find no support for anchoring by analysts with a long track record or across industries, which suggests a bottom-up approach. Long-term risk is considered as upside, but short-term risk is seen as downside. There is also a tendency to underreact to news, whether good or bad. If we could better predict individual analyst's forecasts, we may better anticipate market reactions to earnings news. Our animal spirits will prevent this from happening and should be kept alive, as lack thereof seems the main culprit to performance. No guts, no glory.



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