Learning geology before the earthquake

The influence of faultlines in boards of directors on post-M&A firm value and performance

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Abstract: Faultlines are hypothetical dividing lines in a team, that, when activated, may have communication-disturbing repercussions on a team, as subgroup forming. The present study investigates the influence of faultlines in boards of directors on M&A success. The methodology presents a walkthrough of faultline calculations and its applications. The results are somewhat surprising. Looking at M&A success dichotomously, I find a significant relation between strong faultlines and M&A success. Especially gender and age faultlines portray this effect. This directly contradicts much of the existing literature on the subject and therefore has significant theoretical implications. Furthermore, a board could be composed in such a way as to increase the chance on post-M&A profit, by constructing faultlines.

Keywords: Demographic faultlines; board of directors; event study; M&A performance

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1. Introduction

A considerable amount of research has been devoted to the influence of diversity on team performance (e.g. Jehn, Northcraft and Neale, 1999; Garton, 1992). Though a source for task- and relational conflict, it is a great basis for creativity and creative thinking, as many different ideas and thought processes collide. However, unless a team is perfectly diverse, people who are alike tend to seek each other out. This subgroup-forming phenomenon is caused by a concept dubbed and introduced in 1998 by Lau and Murnighan: faultlines. The term, based on geological faults (fractures in the earth's crust), is explained as possibly unnoticed breaking points in a team that have the potential to crack, or 'activate', when exposed to certain external factors; not unlike an earthquake. Once activated, faultlines can cause subgroups to emerge within a team, which hampers creativity and communication efforts. Research done on faultlines is mostly based on demographic attributes, as attributes based on personality traits are simply too difficult to find and analyse perfectly.

Having been introduced 15 years ago, it is a relatively new topic. Available papers on faultlines have focused on when subgroups are likely to be formed (Veltrop, 2012), its effects on team functioning and conflicts (Molleman, 2005; Thatcher, Jehn and Zanutto, 2003) or top management team performance and its effect on the product diversification process (van Knippenberg et al., 2010; Hutzschenreuter and Horstkotte, 2013). However, to my knowledge there has not yet been extensive research on the effects of demographic faultlines in boards of directors, nor has much faultline research focussed on mergers and acquisitions (M&As). This represents a gap, as we are unsure whether potential conflicts in boards of directors will have a significant (negative) influence on its governing role, effectively deteriorating the firm's entire senior management decision making process. Furthermore, it is interesting to see if strong faultlines will have a negative effect on M&As, same as they usually do on other aspects of a firm's functioning. This research will therefore investigate the effect of faultlines in boards of directors on a firm's M&A success, through the governing role these boards play in the decision making process of top management. Thus, with this thesis, I will attempt to fill the research gap by answering the following research question:

How do demographic faultlines in boards of directors affect merger and acquisition decisions?

In this, I initially argue that faultlines in boards of directors will have a negative effect on post-M&A firm value. However, the findings indicate otherwise, as will become more apparent in the results and discussion sections. To answer the research question, focus will be put on demographic attributes as age, gender, title and experience. These attributes will not be treated as single demographic characteristics, but will be viewed collectively, taking into consideration how their alignment as a whole potentially divides a team in subgroups.

In doing so, this project contributes to the literatures on strategic management and group diversity and is relevant to academics and practitioners. In addition, it will contribute to the area of psychology, as faultline theory has an inherently psychological background. Finally, it will have some implications for users of event studies, as some minor findings on the application of proper event windows were found.

The methodology section will describe the research process, as well as the dependent variable, M&A success, the independent variable faultline strength and the control variables. Furthermore, it contains a descriptive walkthrough of the faultline strength calculations. With the findings, I distinguish between an analysis with M&A success as a continuous value and as a dichotomous variable. Interestingly, viewing M&A success dichotomously (either a profit or a loss), produces very different results from when it was viewed continuously. Theoretical and managerial implications of these results are stated in the discussion section. It seems there is no relation between faultline strength and M&A success in the sense of an existing trend, meaning the strength (or weakness) of board faultlines cannot predict the size of profits or losses. Moreover, looking at it from a dichotomous viewpoint, it is evident that higher faultlines can indeed predict the occurrence of profits or losses from M&As to a certain extent.

2. Theoretical background and hypotheses

2.1 Boards of directors

A corporation's board of directors is a team of senior managers, who are responsible for the governance of the firm. These members can be either elected or appointed, and can be either from inside the company (insider directors) or from outside the company (e.g. independent or outside directors). Insider directors in this context are translated into all directors who in any way are directly related to the corporation in question. This can be as an employee, major shareholder, or any other member who represents one of the firm's stakeholders (e.g. labour unions). Contrarily, outsider directors are directors who do not have a direct involvement with the firm and are usually from another company in a different industry.

Boards are not particularly different from regular teams when studying its diversity. However, its influence can be studied in relationship with the performance of the organization as a whole. Important aspects of that performance are influenced directly by the top management team, but equally important, influenced indirectly by the board's governing powers (Carpenter, Geletkaycz and Sanders, 2004). Corporate law in the United States grants directors the formal authority to approve management initiatives, to evaluate managerial performance, and to allocate rewards and penalties to management on the basis of criteria that are supposed to reflect shareholders' interests (Fama and Jensen, 1983). Some organization theorists argue that because the board possesses these powers, they set the premises of managerial decision making by the top management team (e.g., Mizruchi, 1983). That is, chief executive officers (CEOs), who are a part of any board, as well as any top management team, learn what the frame of mind of the board is, conduct themselves in a manner compatible with these dispositions, and implement decisions that correlate with the board's concepts of strategy. The important aspect of performance in this research, which is indirectly influenced by the board of directors, is the performance directly related to M&A decisions. The change in the firm's performance after making an M&A investment is assessed in relation to the board's composition. Forbes and Milliken (1999) propose a model of strategic decision-making effectiveness in boards of directors that argues the importance of boards' cohesiveness. As will become evident in the section on group diversity and faultlines, group cohesiveness suffers significantly from strong faultlines.

The process of information elaboration is essential to performance in teams dealing with complex problems and decisions, non-routine challenges and a great variety of complex information (van Knippenberg et al., 2010). Therefore, good communication to facilitate this process is of great importance in any higher level management team.

2.2 Group diversity and faultlines

Diversity, or heterogeneity, is defined as the condition or quality of being diverse, different or varied. Team diversity has been subject to a wide range of research, with both negative and positive aspects coming to light. Diversity amongst team members decreases social contacts and social integration (Blau, 1977; O'Reilly et al. 1989) and may be a source of task conflict and interpersonal conflict (Jehn, et al., 1999). However, it is widely acknowledged that social interaction among diverse perspectives can lead to the emergence of new insights, as conceptual thinking is being restructured within the groups (Levine and Resnick, 1993). It is thus a great source of creativity. The more people differ amongst each other, the stronger the team diversity is, and the greater the aforementioned consequences are. However, this research has received criticism for only looking at diversity from one dimension, which potentially causes researchers to overlook the combined and interactive effects of multiple dimensions of diversity (van Knippenberg and Schippers, 2007; Jiang et al., 2012). In an attempt to open up diversity research and look at it from a different dimension, Lau and Murnighan developed the term group faultlines.

Group faultlines, or simply called faultlines, are hypothetical dividing lines that may split a diverse group into subgroups based on one or more attributes of the group members (Lau and Murninghan, 1998). It is a relatively new term, as it was introduced in 1998 by Lau and Murnighan, who published an article on the dynamics of subgroup forming in the development of organizational groups. Faultlines can be formed on the basis of many different kinds of attributes, the most prominent and easiest to analyse of which are demographic attributes. Age, sex, race and job tenure are all examples of attributes on which demographic faultlines can be based. Another demographic attribute that is sometimes used in research as a potential cause of faultline forming is formal education. However, as reasoned by Barkema (2007), by the time managers reach higher echelons in their corporation, they have gained so much experience in different work settings that their formal education, which typically took place decades before, is no longer a good proxy for differences in cognitive characteristics. When they tested it they indeed found no evidence of faultlines based on formal education.

An alignment of multiple demographic attributes may cause social categorization and intergroup relationships within a team. The most likely demographic attributes favouring a division into subgroups are those which are beyond the control of the people themselves, as gender, race, age, tenure and experience (Pelled et al., 1999). Although tenure, experience and age do change over time, it is impossible for people to return to a previous stage, making it beyond their control as well (Pelled et al., 1999). Faultlines may also be based on non-demographic characteristics, like personality traits and other social features of a person's character. However, because of the high complexity associated with finding such personality traits in a high number of people, the focus of this study will be on demographic attributes.

As with diversity, the strength of a faultline can vary. As more attributes align themselves in the same way, the faultline is strengthened (Lau and Murninghan, 1998). For example, if a group of four people consists of two young Asian females and two middle-aged Caucasian males, the group's potential faultline is strong. However, if that group would consist of 1, an Asian woman in her twenties; 2, a black man in his twenties; 3, a black woman in his fifties and 4, an Asian man in his fifties, the potential for faultlines is still there, but it is significantly weaker. It would be weaker because the possible faultlines that could be formed (based on sex for 1-3 and 2-4, age for 1-2 and 3-4 or race for 1-4 and 2-3) would be based on the alignment of one attribute in three possible ways, as opposed to the alignment of three attributes in the first example. Thus, not only must the various attributes of a group be considered, but also the alignment of those attributes among the members, and the number of potentially homogeneous subgroups (Thatcher et al., 2003).

In theory, faultlines can only exist in teams that are moderately diverse, as teams with no diversity whatsoever will form one cohesive (uncreative) group, whereas groups that are completely diverse will have no attributes to base subgroups on (Lau and Murnighan, 1998). In practice however, inactivated faultlines are always there, as no person is perfectly the same, nor perfectly different. A team could be perfectly diverse in terms of demographic characteristics, but for other characteristics, based on personality traits, there will always be some similarity on which faultlines can be based. The chance that these dormant faultlines will be activated and cause subgroups to emerge depends on the strength of the faultline.

Group faultlines are relevant for all sorts of group performance, because it hampers creativity and communication. This causes important decisions to be made with less premeditation, which is an impermissible problem in the complex decision-making process of boards of directors. Lau and Murnighan (2005) suggest that the most important negative effect of faultlines is likely to be communication. With strong faultlines, communication between subgroups can generate conflict, scorn, and poor performance; with weak faultlines, communication should improve performance. This theory has been tested often, with mostly similar results (among others, Thatcher et al, 2003; Molleman, 2005). Only rare cases have concluded differently, as with Van Knippenberg et al. (2010), who found that faultlines may have either positive or negative influences, depending on how highly shared the corresponding case's objective is. A highly shared objective can capitalize on faultlines, whereas faultlines may be absolutely detrimental for a hardly shared objective.

When subgroups are formed, people expect support from the members of their subgroup. Thus, fewer ideas are thrown in the group, as they will be pitched per subgroup, not per individual. Individuals become biased toward their subgroup's members. Therefore, each subgroup's position will be strengthened, making disagreements and other conflicts within the entire group more difficult to solve (Lau and Murnighan, 1998). Strong emotional subgroup attachments may then become potential sources for interpersonal or relationship conflict (Jehn, 1995).

Furthermore, Lau and Murnighan (1998) state that, when there are differences in size of subgroups, the larger subgroup is much more likely to push its ideas through than the smaller subgroup. The reason for this is that members of smaller subgroups may not speak up, as they are afraid to be put down by the larger subgroups. Stasser, Taylor, and Hanna (1989) found that information is shared more freely when members of the group have reason to believe that other members hold the same point of view. This also means that when a larger part of the team does not hold the same opinions, smaller subgroups may not be inclined to speak up and voice their disagreement. Moreover, smaller subgroups may be more likely to use covert power tactics, whereas larger subgroups may be more likely to use overt power tactics. These differences between subgroups of different sizes cause the larger subgroup not to notice that the team is not as much in agreement as initially seems on the surface. Thus, when these disagreements eventually come to light, they may seem unexpected and last longer because of a lack of understanding among the members of the subgroups (Lau and Murnighan, 1998).

2.3 Mergers and acquisitions

Mergers and acquisitions, also commonly referred to as M&As, are a type of external expansion investment, that grows a business overnight, as opposed to gradually, through corporate combinations (Kalra, 2013). Though mergers and acquisitions are usually used interchangeably, they mean slightly different things. When a firm purchases and takes over another company, it is called an acquisition. The target company no longer exists from a legal point of view. With a merger, two firms go forward as one, forming a new entity.

The main principle of an M&A is to create a value larger than the cost of making the merger or acquisition. This is commonly accomplished by gaining synergies, typically described as the 'one plus one makes three' effect. Two firms together are more valuable than two separate firms. However, M&As are rarely successful, because of the extreme management difficulty it poses to organize such a major company re-structuring. This links back to faultlines, as it is interesting to see if the communicative difficulties that accompany strong faultlines will be detrimental for post-M&A firm performance.

Hambrick et al. (1996) argued that a decision about an expansion may involve all the firm's senior executives, as opposed to other decisions that may involve only a subset of the top team. This makes the choice of M&A decisions a particularly appropriate setting for this research.

2.4 Hypotheses

All in all, faultlines disturb the information elaboration process through hampered creativity and communication. Furthermore, strong faultline settings hamper important strategic decisions and innovations, which require communication within boards and the consensus of most or all team members (Barkema, 2007; Li and Hambrick, 2005). Therefore, I expect a negatively moderating correlation with faultline strength in boards of directors and the success of mergers and acquisitions.

Hypothesis 1: Ceteris paribus, demographic faultline strength in boards of directors will negatively moderate the success of mergers and acquisition decisions made.

In addition to a negative moderation, it is interesting to investigate whether board faultlines can function as a predictor of the occurrence of either a profit or a loss after a merger or acquisitions. The expectation here is similar. It is expected to find a negative relation between faultline strength in boards of directors and the chance of a merger or acquisition being successful.

Hypothesis 2: Ceteris paribus, demographic faultline strength in boards of directors significantly affects the chance of gaining a profit or a loss from a merger or acquisition by moderating the firm's M&A decisions proficiency, where stronger faultlines increase the chance on a loss and weaker faultlines increase the chance on a profit.

The difference with the first hypothesis here is that *Hypothesis 1* looks for the profitability of an M&A. It tries to answer the question *can a company earn a larger profit with a weaker board faultline?* It looks for a trend of profitability correlating to faultline strength. The second hypothesis looks at it from a simpler, dichotomous viewpoint. It attempts to answer the question *does a company have a higher chance of gaining a post-merger profit with weaker board faultlines?*

This research attempts to investigate these hypotheses as completely as possible. The next section demonstrates the research process.

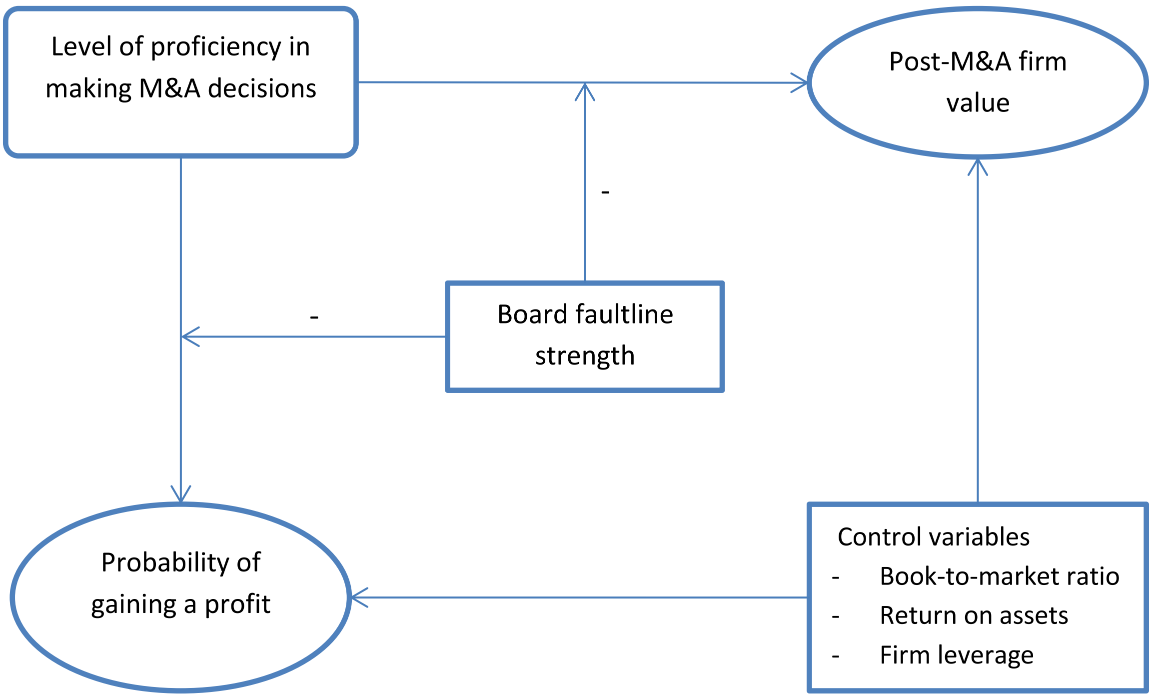


Figure 1: Visual representation of the hypothesized relationships

3. Methodology

3.1 Research process

In this research the theory testing approach was applied, because much theory has been developed on (high ranking management team) faultline influences, the most prominent of which was done by Lau and Murnighan in 1998 and 2005. However, there are still many areas in which these developments can be tested, as they are very broad. For example, the theories have been tested on firm performance through return on assets (Hutzschenreuter and Horstkotte, 2013; Knippenberg et al., 2010; Thatcher, Jehn and Zanutto, 2003), but we cannot be sure to get the same result when tested on other aspects of firm performance, as geographic acquisition decision success rates. In addition, research on faultlines in upper echelon management typically investigates the effects of top management team decisions on performance, as opposed to those of boards of directors. Furthermore, many of these papers have used a logarithm developed by Thatcher et al. (2003) to compute the faultline strength (FLS). However, I believe this method to be inferior to that derived by Shaw (2004), which will be elaborated upon in later sections of the methodology.

3.1.1 Sample and data collection

Firms

As stated, the information on team composition was obtained from boards of directors. Only firms from the drugs industry were selected (SIC = 283). Using a Thomson SDC database from 2010, which contained a list of companies, 173 drugs-related companies were identified. 19 of these companies had no available information, as they had been acquired sometime between now and 2010. 18 of these 19 companies were acquired by one of the other 154 remaining pharmaceutical companies. Two of the 154 remaining companies were acquired also, yet still had board information available, though their boards consisted of a mere three and four members. Uncertainty existed with regard to their operational activity, because of their ‘acquired’ status. They were still included in the FLS calculations as a precaution. Faultline strength was computed for these 154 companies, though not all of them were eventually used in the study, because of a lack of performed M&As, which will become apparent in the section on *Mergers and acquisitions* on the next page.

Boards

Of these 154 companies, outgoing directors that constitute the sample of this research were identified through LexisNexis. LexisNexis provides reliable up to date information on the names of many boards and their members. However, the database does not contain demographic information. Therefore, after the identification, these members' demographic characteristics were found using the investing.businessweek.com website. This website contains, among other things (e.g. stock information) an excellent database of boards of directors and their demographic qualities. As with LexisNexis, the information on this site is perfectly up to date, containing information up to January 2014. Using two databases with perfect timely information assures the precision of the information. The information of the two databases was matched manually, to validate its precision. Finally, occasional missing data points (e.g. a member's missing age or joining year) were filled up as proficiently as possible using the most recent annual reports of the particular missing board members' companies. These reports were usually from 2013, with some being from 2012.

The initial plan was to utilize demographic attributes as advised by Lau and Murnighan (1998; 2005); age, sex, race and job tenure. However, race appeared to be rather difficult to identify, as information on countries of origin and racial backgrounds could only be gathered by contacting each firm directly, which would be beyond the scope of this research in time consumption. Race was replaced by title, because differences in influence and the significance in mutual acquaintance between team members were expected to influence group dynamics. In this context, the title category can be seen as a team member's group-functioning; what functions do they fulfil and how they are positioned in the team. Job tenure was still used, but renamed to experience, as it brings out more of the essence of why this attribute is added, which is to match people together that have worked alongside each other for an extended amount of time. More on the demographic decisions made and their categorization is stated in next sections.

Using statistical software (Stata & SAS), this data was used to calculate the overall faultline strength per company, as well as the FLS per attribute. More on this process is stated in section 3.2.2, where a manual walkthrough of the process is presented, to illustrate how it was coded into Stata and SAS. Using Thomson SDC, the faultline information was then matched with relevant M&A data over the past 8 years. The companies were categorized on their least experienced member. Thus, for example, if a team consists of five members with more than 10 years of experience and one member with only 1 year of experience, the entire board is categorized as having 1 year of experience, as the entire faultline dynamic may be changed by the addition of a new member (Lau & Murninghan, 1998). Then, the event dates of the M&As were matched with the board information, and if an event occurred with a different board than the one today (e.g. the acquisition was in 2011, but the board changed in 2012, making the board information from 2014, which is the information obtained, irrelevant), the board of that period was looked up and the FLS computed for the relevant board.

Mergers and acquisitions

Finally, Datastream was used to find firm-level data to analyse firm performance. Performance was primarily assessed through stock prices, as this is the most prominent measure of firm performance (Zollo and Meier, 2008). Of the 154 companies that were analysed for FLS, 59 companies had performed M&As with their current board, with 239 mergers and acquisitions. The effect of these M&As on firm value was calculated by means of an event study, more on which will be discussed in section 3.3. A regression analysis was performed on the M&A outcomes and the FLS per company, to investigate whether a relation between FLS and M&A performance could be found. The process and the outcomes are stated in the results section.

3.1.2 Variables

I empirically study how demographic faultlines influence the making of M&A decisions under the governance of boards of directors. Accordingly, I measure the relation between a board's faultline strength and the correlating firm's performance value differentiation, as a direct result of a merger or acquisition.

The dependent variable was M&A success, with as measurable variables the differentiation in firm value after a merger or acquisition. This result on firm performance is measured by means of an event study. Within the event study, the dependent variable was stock price and de independent variables were the firm's estimated returns and the market return of local market indices. Measurable variables here were the abnormal and cumulative abnormal returns during the event window of the merger or acquisition, measured by comparing differentiation in stock price with the estimated returns and market returns. For the first hypothesis, these abnormal returns were used in their original continuous state. For Hypothesis two, they were transformed into a dichotomous state, indicating a either a loss or a profit with a dummy variable. The independent variable was faultline strength in boards of directors, computed using an algorithm developed by Shaw (2004). It takes into consideration how multiple demographic characteristics and their alignment may divide a team into subgroups when combined, as opposed to single demographic attributes individually.

3.1.3 Control variables

Because M&A success may be caused indirectly by several firm characteristics, several control variables were used to test the relative impact of faultline strength more accurately. To accommodate for the frequently used control variable of organization size (van Knippenberg et al., 2010), the *book-to-market ratio* and the *return on assets* were used as control variables. Furthermore, each firm's leverage, or *debt-to-assets ratio* was used, as a firm's financial structure may influence M&A results, because of arbitrage opportunities through tax shields. Regression analyses were applied linearly without the control variables, and multiply with these variables.

Below, all variables were condensed into a table, specifying variable types, scale types and operationalization.

Descriptive table 1: Overview of variables

Variable	Variable type	Scale type	Operationalization
Faultline strength	Independent	Ratio	The probability a faultline will be activated.
Cumulative abnormal returns (continuous)	Dependent	Ratio	Stock price differentiation within the event window, as compared to before the event.
Cumulative abnormal returns (dichotomous)	Dependent	Categorical	Cumulative abnormal returns, categorized into two different values, indicating either a profit or a loss.
Book-to-market ratio	Control	Interval	Determines the value of a firm by comparing its book value to the market value.
Return on assets	Control	Ratio	An indication of a firm's profitability. Calculates how much net income was generated from invested capital.
Debt-to-assets ratio	Control	Interval	The financial structure of the firm. Assesses how much of the firm's assets are financed using debt, as opposed to equity financing.

3.2 Calculating faultline strength

The next step in the process is to calculate the faultline strength (FLS) between the members of the identified boards of directors. The FLS is the cornerstone of this research, as it is ultimately coupled with all future measures of performance. In their article from 1998, Lau & Murnighan presented a simplified measure of FLS, with which they identified the strength in ranges, from non-existent and very low to very strong, by means of intuitive classification (Shaw, 2004). Though ground breaking at its time, this measure is too simplistic to get a useable variable for this research. Fortunately, scholars have found other measures of FLS since then, which obtain useable measures of faultline strength in percentages (Thatcher et al., 2003; Shaw, 2004).

3.2.1 Differences in faultline strength measurements

Some differences in measurement exist between these scholars' methodologies. Thatcher's method has been used widely (e.g. Molleman, 2005; Hutzschenreuter and Horstkotte, 2013), as it is a quick way of determining the FLS. However, it only takes relatively small groups into consideration of approximately 4-6 members, because of the limitations of the method. If a team would consist of more than 6 members, it is a reasonable assumption the group might split into more than 2 subgroups (Thatcher et al., 2003). Measuring group 'splits' with more than two subgroups would require a process that is too computationally complex for their algorithm. Their algorithm only accounts for the strongest group split, dividing the team into two subgroups (Thatcher et al., 2003). This would constitute a problem in this research, as many of the boards reach more than 10 members, some of which have as many as 16 members.

Furthermore, Thatcher's method does not take all possible combinations of internal alignment and cross-subgroup alignment into consideration, but merely identifies the strongest possible split and looks at the potential breaking chance from there. Therefore, using thatcher's algorithm, you can always only account for the emerging of a faultline based on the one most likely attribute. Thus, the nature of its calculations makes Thatcher's method less thorough. It has the potential to lose reliability in the outcome of the strength measurement, as more potential subgroup splits reside in other attribute combinations and therefore the results cannot be trusted fully.

For example, consider a group of students, the faultlines strength of which is measured on 4 attributes: gender, age, education and nationality. As stated by Lau & Murnighan (1998), faultlines are based on one of several attributes, and you are to calculate the internal alignment (IA) and cross-subgroup alignment (CG) of all combinations with all possible attributes as basis to calculate the chance of a faultline emerging.

In our example, a faultline could perhaps be based on gender. This means that the subgroups are into male groups and female groups. If males are very similar to one another with regard to the other attributes, the faultline is stronger. Naturally, the same goes for the female group. Thus, we calculate the internal alignment of males and age, males and education and males and nationality and do the same for the alignment of the females with age, education and nationality. Furthermore, if males are different from females with regard to all other attributes, the faultline is stronger as well. Thus, we calculate the cross-subgroup alignment by looking at similarities in attribute composition *between* males and females. So far, Thatcher and Shaw's algorithm are approximately equally useful.

However, we cannot always know which attribute will eventually be the basis for the faultline, should the group be broken into subgroups. Therefore, to fully capture the likelihood that a faultline emerges, we need to calculate the IA for all possible combinations with all possible attributes as basis. This means the IA of all age-groups over education, all age-groups over nationality and all age-groups over gender must be calculated to measure the IA with age as basis. The same goes for all areas of education and all nationalities that are considered in the particular research to calculate the IA with education and nationality as basis respectively. Moreover, we need to calculate the cross-subgroup alignment; if people in the male group are similar to people in the female group on other attributes (males have approximately the same age, education and nationality as females), the likelihood of a faultline emerging is smaller than it would be with less or no attribute overlap (males differ in age, education and nationality from females). The cross-subgroup alignment measurement must be done for all possible category combinations. As Thatcher's method merely considers the strongest group-split to calculate FLS, whereas Shaw considers all possible splits, Shaw's measure is far superior in its reliability.

Thus, Shaw looks at it more elaborately, as he takes internal alignment and cross-subgroup alignment into consideration between every possible split, as opposed to Thatcher's single strongest split. In addition, it takes into consideration the possibility of the emergence of more than two subgroups, whereas Thatcher's algorithm is not complex enough to go beyond two subgroups. Furthermore, Shaw's method controls for group size by nature of the calculations. Therefore, Shaw's method of calculating FLS suits this research better. In his 2004 paper, Shaw presents 5 steps in which to calculate FLS. To clarify the method further, all steps will be discussed below. All these steps were applied in this thesis, and are therefore not merely presented in general, but specifically as how they were applied in this research.

3.2.2 The five steps to calculating faultline strength

3.2.2a Determining attributes and categories

The first step is to determine the attributes on which the FLS must be calculated. These must be selected on theoretical considerations and must be coded into numeric values so that they can be used in the calculations. As this research investigates boards of directors, the following four attributes have been used: Gender, age, title and experience. Gender and age are two of the most prominent attributes and should be used in any research pertaining faultlines (Lau & Murnighan, 2005). Title is used partly because of its wide availability, but mostly it is used because of the expectation that the role people play in a group and how they link to the firm will affect the dynamics in a group. A board member from inside the company will, for example, likely have a closer relationship with others from inside the company than with members whom originate from other companies, because of their previously established personal relation. Finally, experience is an important factor for faultline strength calculations, as people are very likely to form subgroups with people they know personally (Lau & Murnighan, 1998). Thus, when new people join the group after some years of having the same board, it is likely the relationship between these new and old members will form a faultline (Lau & Murnighan, 1998). In this context, experience constitutes the amount of years a member has spent on this particular board. It is thus possible that a member with 5 years of experience has spent 10 years of his life as a director, be it the first 5 years were on a different board. It signifies to some extent, for as far as it is possible, a potential division based on personality traits. This is because the essence of the experience attribute's inclusion lies in that people who have worked together for a longer period of time are likely to know each other personally, and may form subgroups on the basis of that interpersonal knowledge, as opposed to people who do not have that knowledge and will therefore constitute the other subgroup.

Though used as an attribute in many existing papers (e.g. Barkema, 2006; Jiang et al., 2012), nationality has not been used as an attribute, as almost all companies are from the USA (approximately 97.5 percent), and it would be too time-consuming to research all directors' nationalities, merely for the occasional outlier constituting a person from outside the US. This is because, to be seen as a potential dividing line, an attribute must vary over at least two people in a group. This was too unlikely in this sample to be worth the tremendous effort of obtaining each person's nationality through personal contact with the firm.

After deciding on which attributes the FLS will be calculated, the next step was to code them into categories, so that they can be used in the upcoming calculations. Naturally, one must be careful to categorize the attributes into categories that properly reflect and represent the potential dividing lines among group members. For this research, the aforementioned attributes were categorized as follows. Gender (two levels, coded male = 1; female = 2), age (four levels, coded below 50 = 1; 50 to 59 = 2; 60 to 67 = 3; 68 or above = 4), title (three levels, coded leading directors = 1; Inside directors = 2; Outside directors = 3) and years of experience (four levels, coded 0 to 3 = 1; 4 to 7 = 2; 8 to 11 = 3; 12 or above= 4). According to Shaw (2004), an approach for determining the number of perceived attribute categories is to examine taxonomic research related to the attributes that are being investigated. For these attributes, a combination of this (e.g. for age) and a categorization through logical thinking (e.g. for title and experience) was used to decide on the categories, whereas the categorization of gender was dichotomous. Below, the thought processes are being elaborated upon further.

As seen above, age is coded into four unevenly distributed levels. The age of 67 was used for the border between code 3 and 4, as this is the retirement age in the United States, as stated on the website of the Social Security Agency. It is reasonable to expect the demographic quality of being retired (of regular duties besides being a board director) to potentially be a significant cause for subgroup forming. Moreover, Stata was used to tabulate and graph some attributes, after which the other proper fitting intervals were chosen, considering an as even as possible relative division among the categories. Several interval categorization decision (e.g. age, experience) were made by deriving logical conclusions from those statistics.

The directors' titles are coded into three levels. Firstly, leading directors constitute the directors that have a slight edge in influence over the rest of the board. These are (vice) chairmen, CEOs, lead directors, founders and presidents. They constitute a category because their superior level of influence separates them from the group, which makes them more likely to vary from the rest dynamically, and potentially stick together in case of a title-related group split. As seen above, another division is set between the 'regular' directors, on the difference between insiders and outsiders. An inside director is someone who is directly connected to the organization, either as an employed executive, a major shareholder or a representative of other stakeholders. Outside directors are, contrarily, members who are not otherwise engaged with the organization. Outsiders usually have their primary affiliation with another organization and serve on the board on merely a part-time basis (Forbes & Milliken, 1999). Therefore, they have limited direct exposure to the firm and the other (inside) directors. Because of this limited exposure, it is assumable that inside directors and outside directors represent a potential faultline basis.

Finally, experience is coded into four levels. The experience levels notably have a short time span of four years per category. This is firstly because of the relatively short total span of years, as the members of above 20 years of experience are so rare they are an outlier. Secondly, the essence of the experience attribute's presence in this research is the forming of subgroups with people you know personally. As it takes a limited amount of years to get to know someone better, it is a logical derivative to keep the intervals between categories relatively short. There is likely almost no identifiable difference in subgroup forming between people that work together for 16 years or longer as opposed to working together for 12 years. This near non-existing difference is the reason for the 12 year and above timespan being the final category in experience.

3.2.2b Internal alignment calculation

The third step contains the calculation of the internal alignment; the first series of calculations in determining the FLS. Every faultline is based on one attribute, and the IA calculates "the extent to which members within a particular subgroup are similar to one another on all other relevant attributes" (Shaw, 2004). As mentioned above, it is impossible to predict which attribute will form the basis of the faultline, should it emerge. Therefore, to calculate faultline strength it is necessary to calculate the possibility of a faultline to emerge from every possible attribute as base. First, the general explanation of the formulas is given, which will end with a complete real-life example to clarify the process. To calculate the IA, one basic formula is used to calculate three different outcomes; once to calculate the observed IA, once to calculate perfect alignment and once to calculate total nonalignment. This formula is as follows:

$$IA_{base/x} = \frac{\Sigma(O-E)^2}{E}$$

Wherein $IA_{base/x/obs}$ is the observed internal alignment of one category of the base attribute across the x attribute's categories, O is the observed amount of one category of the base attribute in the particular category of the x attribute and E is the expected amount of one category of the base attribute in the particular category of the x attribute. To clarify, consider the following example:

$$IA_{m/age/obs} = \frac{\Sigma(O_{mi}-E_{mi})^2}{E_{mi}}$$

Here, we calculate the observed male alignment index across age categories. Gender is thus the base, and we calculate the alignment of one of the base attribute's categories, males, with one of the other attributes, age. The O variable, O_{mi}, stands for the observed number of males in the i^{th} age category, whereas the E variable E_{mi} stands for the expected number of males in the i^{th} age category.

The perfect alignment and the total nonalignment are calculated in a similar fashion, as they use the same formula. For the perfect alignment, all 'observed' base attributes (O) are in one particular category of the x attribute. For example, if we have a subgroup of 8 males, and age has four categories, to calculate the perfect alignment, one age category will be filled with all 8 males. The 'O_{mi}' variable will equal 8 for one category and 0 for the other categories; $IA_{perfect}$ is then 24.0, as the formula will look like this:

$$IA_{m/age/perfect} = \frac{(8-2)^2}{2} + \frac{(0-2)^2}{2} + \frac{(0-2)^2}{2} + \frac{(0-2)^2}{2} = 24.0$$

For the total nonalignment, the observed variable is as close to the expected variable as possible, for as far as the combination of the amount of subgroup members and the amount of categories allows it. Thus, the outcome will always approximate 0.0 as closely as possible for the particular attribute composition. If we use the same example, to calculate the total nonalignment, each age category will be filled with $\frac{8}{2} = 2$ males for the perfect nonalignment. Thus, the 'O' variable will equal 2 for each category; $IA_{nonalign}$ will then equal 0, as the equation will look like this:

$$IA_{m/age/nonalign} = \frac{(2-2)^2}{2} + \frac{(2-2)^2}{2} + \frac{(2-2)^2}{2} + \frac{(2-2)^2}{2} = 0.0$$

However, if we only have 6 males, all categories will have at least 1 male, whereas two age categories will have 2 males. It is thus impossible to get an absolute nonalignment of 0, as the amount of males can simply not be divided perfectly amongst the amount of categories. Naturally, we cannot have one and a half male representing a category. In this case, $IA_{nonalign}$ will equal 0.67, as the equation will look like this:

$$IA_{m/age/nonalign} = \frac{(2-1.5)^2}{1.5} + \frac{(2-1.5)^2}{1.5} + \frac{(1-1.5)^2}{1.5} + \frac{(1-1.5)^2}{1.5} = 0.67$$

As seen above, it is important to remember that the total nonalignment will not always equal 0.

As stated by Shaw (2004), with the 'observed IA' formula, we measure the extent to which the male distribution is different from a purely random distribution of males across age groups. An index of the extent to which the observed IA was similar to a perfect alignment is therefore needed. This is calculated by subtracting the $IA_{nonalign}$ from the IA_{obs} and dividing the result by the maximum difference (MaxDiff), where MaxDiff = ($IA_{perfect} - IA_{nonalign}$). Thus:

$$IA_{m/age} = \frac{(IA_{m/age/obs} - IA_{m/age/nonalign})}{MaxDiff}$$

Similar formulas can then be used to calculate the IA of females across age categories. After that, the average gender alignment in age categories is needed, which is calculated by getting the average of the two outcomes:

$$IA_{gen/age} = \frac{(IA_{m/age} + IA_{f/age})}{2}$$

This process must be repeated with the other attributes; title and experience. These are calculated similarly as seen above, with the same general formulas:

$$IA_{gen/title} = \frac{(IA_{m/title} + IA_{f/title})}{2}$$

$$IA_{gen/exp} = \frac{(IA_{m/exp} + IA_{f/exp})}{2}$$

Finally, we can use these outcomes to calculate the internal alignment of the faultline, should it be formed with gender as a subgroup basis:

$$IA_{gender} = \frac{(IA_{gen/age} + IA_{gen/title} + IA_{gen/exp})}{3}$$

Similar formulas can be used to measure internal alignment based on subgroups formed with each of the other attributes as basis. The outcomes of these formulas can then be used to calculate the overall group internal alignment index, as follows:

$$IA_{overall} = \frac{(IA_{gender} + IA_{age} + IA_{title} + IA_{experience})}{4}$$

Appendix A summarizes all combinations between attributes across their categories per board, necessary to determine the internal alignment in this research. To clarify the process, one calculation will be written out fully with a real-life example.

Internal alignment calculations on a real-life example

In this section, the process of calculating the IA will be clarified by working through it on a real-life example. The steps followed in this guide correlate with the explanatory steps presented in section 3.2.2b. For this guide, the company Amylin Pharmaceuticals, inc. is used, number 12 by listing in the database. The composition of its board has a nice attribute distribution, making it the perfect example to illustrate the process. Amylin has a board consisting of 9 members, with the following distribution of attributes:

Table 1: Composition data of Amylin Pharmaceutical's board of directors

Team id	Member	Gender	Age	Title	Experience
12	1	M	62	Chairman	5
12	2	M	66	Outside director	15
12	3	M	70	Outside director	11
12	4	F	64	Outside director	9
12	5	M	67	Outside director	9
12	6	M	62	Director	7
12	7	F	58	Director	7
12	8	F	61	Director	5
12	9	M	43	Director	5

Following the coding of the attributes as seen in section 3.2.2a we arrive at a distribution as follows:

Table 2: Coded composition data of Amylin Pharmaceutical's board of directors

Team id	Member	Gender	Age	Title	Experience
12	1	1	3	1	2
12	2	1	3	3	4
12	3	1	4	3	3
12	4	2	3	3	3
12	5	1	3	3	3
12	6	1	3	2	2
12	7	2	2	2	2
12	8	2	3	2	2
12	9	1	1	2	2

The IA must be calculated with each attribute as basis, combined individually with all of the other attributes. The basic formula, as seen in section 3.2.2b is used throughout the process, and applied to a total of 39 sets of equations, as seen in the tables in appendix B.

Gender as basis

Firstly, gender will be considered the basis attribute. Thus, we will calculate the internal alignment for when the subgroup forming would be based on gender. There are two categories in this base attribute: males (coded 1) and females (coded 2). The goal is to individually calculate the alignment of all attributes in both male and female subgroups. We start with male alignment in age subgroups, making the used formula as follows:

$$IA_{m/age/obs} = \frac{\Sigma(O_{mi} - E_{mi})^2}{E_{mi}}$$

To fill in this equation, the observed frequencies of males in each age category must be identified, and the expected frequency calculated. As there are 6 males over 4 age categories, the expected amount of males per category is $\frac{6}{4} = 1.5$ males. As evident in table 2, the observed males and females across age categories are as follows:

Table 3: Observed frequencies – gender in age categories

Gender	Age category	Other variables

	Age 1	Age 2	Age 3	Age 4	Subgroup n	Expected
Males	1	0	4	1	6	1.5
Females	0	1	2	0	3	0.75

This information is now used to fill out the basic formula, determining the observed IA for males across age categories:

$$IA_{m/age/obs} = \frac{(1-1.5)^2}{1.5} + \frac{(0-1.5)^2}{1.5} + \frac{(4-1.5)^2}{1.5} + \frac{(1-1.5)^2}{1.5} = 6.0$$

If there were perfect alignment of males across age categories, then

$$IA_{m/age/perfect} = \frac{(6-1.5)^2}{1.5} + \frac{(0-1.5)^2}{1.5} + \frac{(0-1.5)^2}{1.5} + \frac{(0-1.5)^2}{1.5} = 18.0$$

If there were total nonalignment of males across age categories, then

$$IA_{m/age/nonalign} = \frac{(2-1.5)^2}{1.5} + \frac{(2-1.5)^2}{1.5} + \frac{(1-1.5)^2}{1.5} + \frac{(1-1.5)^2}{1.5} = 0.67$$

As stated above, to adjust for differences in number of categories and subgroup sample sizes, the final group internal alignment index for males across age categories is calculated with the $IA_{m/age}$ formula (Shaw, 2004). The MaxDiff variable is equal to $IA_{perfect} - IA_{nonalign}$, making it 17.33. Then, the adjusted IA_{obs} formula is:

$$IA_{m/age} = \frac{6-0.67}{17.33} = 0.3076$$

The subgroup IA index ranges in value from 0.0 to 1.0, with 0.0 indicating maximal nonalignment and 1.0 indicating maximal alignment within a subgroup across a set of attribute categories (Shaw, 2004). Of course, this is only one side of the gender attribute as basis, and to calculate the alignment of gender across age categories, the female alignment must also be calculated. This is done in like manner. Using the information from table 3, the observed frequencies can be identified and the expected frequencies calculated. As there are 3 females across 4 categories, the expected amount of females per category is 0.75. Thus:

$$IA_{f/age/obs} = \frac{(0-0.75)^2}{0.75} + \frac{(1-0.75)^2}{0.75} + \frac{(2-0.75)^2}{0.75} + \frac{(0-0.75)^2}{0.75} = 3.67$$

The next step is once more to compute the perfect alignment and the total nonalignment. As these equations are practically identical to the ones for the male perfect alignment and total nonalignment, they won't be repeated. If there were perfect alignment of females across age categories, then $IA_{f/age/perfect} = 9.0$. If there were total nonalignment, $IA_{f/age/nonalign} = 1.0$. With this information we can calculate the female alignment across age categories, which is the observed IA, from which the total nonalignment is subtracted, divided by MaxDiff, which comes to $IA_{f/age} = 0.3338$. $IA_{m/age}$ and $IA_{f/age}$ are averaged to arrive at the gender alignment across age categories.

$$IA_{gen/age} = \frac{0.3067 + 0.3338}{2} = 0.3207$$

Calculating the complete internal alignment with gender as basis requires this same set of calculations with the title and experience attributes as well. To shorten the process, unnecessary repetition is excluded. Therefore, the $IA_{nonalign}$ and $IA_{perfect}$ values, as well as the MaxDiff variable will merely be stated instead of calculated and elaborated upon fully. Therefore, the observed frequency tables will include the $IA_{nonalign}$ and $IA_{perfect}$ values from here on out.

Table 4: Observed frequencies – gender in title categories

Gender	Title category			Other variables			
	Title 1	Title 2	Title 3	Subgroup n	Expected	$IA_{nonalign}$	$IA_{perfect}$
Males	1	2	3	6	2	0	12
Females	0	2	1	3	1	0	6

As before, we start with the male category. In this scenario, as seen in observed frequency table 4, $IA_{nonalign}$ is 0.0, $IA_{perfect}$ is 12.0 and MaxDiff is also 12.0. Next, we utilize the general formula to calculate the observed IA:

$$IA_{m/title/obs} = \frac{(1-2)^2}{2} + \frac{(2-2)^2}{2} + \frac{(3-2)^2}{2} = 1.0$$

And the adjusted IA:

$$IA_{m/title} = \frac{1-0}{12} = 0.0833$$

As for the female category, $IA_{nonalign}$ is 0.0, $IA_{perfect}$ is 6.0 and MaxDiff is also 6.0. As usual, with that and the observed frequencies, we can fill in the necessary variables in the general formulas, to arrive at an observed IA of 2.0 and an adjusted IA of 0.3333. As before, the average of these adjusted values is taken to complete the calculation of the gender IA across title categories:

$$IA_{gen/title} = \frac{0.0833 + 0.3333}{2} = 0.2083$$

To finalize the IA calculations with gender as basis, we go through the same process a final time to calculate the IA of gender across experience categories.

Table 5: Observed frequencies – gender in experience categories

Gender	Experience category				Other variables			
	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Subgroup n	Expected	$IA_{nonalign}$	$IA_{perfect}$
Males	0	3	2	1	6	1.5	0.67	18.0
Females	0	2	1	0	3	0.75	1.0	9.0

The observed frequencies, perfect alignment and total nonalignment variables are filled into the general formulas, to arrive at an adjusted IA of

$$IA_{m/exp/obs} = \frac{(0-1.5)^2}{1.5} + \frac{(3-1.5)^2}{1.5} + \frac{(2-1.5)^2}{1.5} + \frac{(1-1.5)^2}{1.5} = 3.33$$

$$IA_{m/exp} = \frac{3.33 - 0.67}{17.33} = 0.1537$$

As for the female categories, the observed IA is 3.67, whereas the adjusted IA is 0.3338, averaging at

$$IA_{gen/exp} = \frac{0.1537 + 0.3338}{2} = 0.2437$$

Now that the IA of gender across all other attributes is calculated, these three results can be put together to calculate the internal alignment of gender as basis attribute, as seen in the IA_{gender} formula in section 3.2.2b:

$$IA_{gender} = \frac{0.3207 + 0.2083 + 0.2436}{3} = 0.2575$$

To get the IA of Amylin's board, we need to calculate IA_{age}, IA_{title} and IA_{exp} as well, which are the internal alignment indexes with age, title and experience as basis respectively, to average the results and arrive at $IA_{overall}$. To avoid repetition once more, the full calculations of these variables will not be included in this example. This concludes the calculation of a team's internal alignment.

$$IA_{overall} = \frac{0.2575 + 0.029 + 0.2685 + 0.1713}{4} = 0.1816$$

3.2.2c Cross-subgroup alignment calculations

The fourth step in determining the FLS is calculating the cross-subgroup alignment over the attributes. This is necessary, because apart from the similarity between people that form a subgroup, it is important to consider the similarity of those people with the other subgroups, as cross-group similarities could greatly reduce the significance of the internal alignment, should it exist. Males can be very similar to each other in other attributes, but if the females are equally as similar in these features, there will be no reason for subgroup forming. Fortunately, the calculation of the CG is slightly more straightforward than that of the IA. As with the IA, the general calculations will be explained, after which one real-life example will be demonstrated to clarify the process.

The goal is to get a frequency count of subgroup members in each attribute category and to find match-ups. These match-ups, or cross-products, are easily found by multiplying the amount of members in one category from one subgroup by the amount of members in that category from another subgroup. For example, say two leading directors are above 67 years old (Albert and Bob) and three outside directors are above 67 years old (Charles, David and Evelyn). Then, there are $(2 \times 3) = 6$ matchups between leading directors and outside directors in the 4th age category (Albert & Charles, Albert & David, Albert & Evelyn, Bob & Charles, Bob & David and Bob & Evelyn).

However, this cross-product score provides information about the CG only *"to the extent that we can compare the number of actual match-ups to those that would occur in a situation of perfect alignment"* (Shaw, 2004). Therefore, the amount of observed match-ups must be divided by the maximal amount of match-ups, which occurs at perfect alignment. Thus, if there are a total of five leading directors (three of which are in reality not in the 4th age category) and 4 outside directors (one of which is in reality not in the 4th age category), the maximal amount of match-ups is $5 \times 4 = 20$, which is the amount by which 6 must be divided for the adjustment.

In addition to this 'perfect-alignment adjustment', the outcome must be adjusted for subgroup sizes, so that it is applicable to all sizes of teams. To accomplish this, normalized weights must be calculated by multiplying all non-redundant combinations of subgroups and adding all outcomes together to get the denomination. Next, all non-redundant combinations are divided by that denomination to get the normalized weight. The CG measured before can then be multiplied by the normalized weights, to arrive at the cross-subgroup age alignment indices. This way, alignment levels of bigger subgroups are given higher relative significance.

Cross-subgroup calculations on a real-life example

The case of Amylin Pharmaceuticals will once more be used as an example. As with the IA illustration, the distribution of attributes from table 2 is used. As the CG calculations are much more straightforward than that of the IA, only a portion of the equations will be projected here. For that, the cross-subgroup alignment of age categories over title categories will be a sufficient clarification of the process.

Table 6: Observed frequencies – age in title categories

Age	Title category			
	Leading directors (LD)	Inside directors (ID)	Outside directors (OD)	Subgroup n
Age 1 = Below 50	0	1	0	1
Age 2 = 50s	0	1	0	1
Age 3 = 60-67	1	2	3	6
Age 4 = Above 67	0	0	1	1

Firstly, the cross-products (CPs) will be calculated for each non-redundant match-up and adjusted for the perfect alignment. As mentioned, this is accomplished by multiplying the observed frequencies and dividing them by the perfect alignment score. The following formula represents this process, using age category 1 and age category 2 as an example match-up:

$$CP_{a1/a2/title} = \frac{[(N_{a1/LD} \times N_{a2/LD}) + (N_{a1/ID} \times N_{a2/ID}) + (N_{a1/OD} \times N_{a2/OD})]}{N_{a1} \times N_{a2}}$$

Where CP is the cross product, a1 and a2 represent age categories 1 and 2 respectively, LD, ID and OD represent the title categories 1, 2 and 3 respectively and N stands for frequency. Thus, with the observed frequencies in place, the calculations look like this:

$$CP_{a1/a2/title} = \frac{[(0 \times 0) + (1 \times 1) + (0 \times 0)]}{1 \times 1} = 1.0$$

$$CP_{a1/a3/title} = \frac{[(0 \times 1) + (1 \times 2) + (0 \times 3)]}{1 \times 6} = 0.33$$

$$CP_{a1/a4/title} = \frac{[(0 \times 0) + (1 \times 0) + (0 \times 1)]}{1 \times 1} = 0.0$$

$$CP_{a2/a3/title} = \frac{[(0 \times 1) + (1 \times 2) + (0 \times 3)]}{1 \times 6} = 0.33$$

$$CP_{a2/a4/title} = \frac{[(0 \times 0) + (1 \times 0) + (0 \times 1)]}{1 \times 1} = 0$$

$$CP_{a3/a4/title} = \frac{[(1 \times 0) + (2 \times 0) + (3 \times 1)]}{6 \times 1} = 0.5$$

The normalized weights (W) are calculated by adding up all multiplied non-redundant match-ups and dividing each individual match-up by the outcome:

$$W_{denom/title} = (1 \times 1) + (1 \times 6) + (1 \times 1) + (1 \times 6) + (1 \times 1) + (6 \times 1) = 21$$

$$Wt_{a1/a2/title} = \frac{(1 \times 1)}{21} = 0.04762$$

$$Wt_{a1/a3/title} = \frac{(1 \times 6)}{21} = 0.28571$$

$$Wt_{a1/a4/title} = \frac{(1 \times 1)}{21} = 0.04762$$

$$Wt_{a2/a3/title} = \frac{(1 \times 6)}{21} = 0.28571$$

$$Wt_{a2/a4/title} = \frac{(1 \times 1)}{21} = 0.04762$$

$$Wt_{a3/a4/title} = \frac{(6 \times 1)}{21} = 0.28571$$

These weights are put in so that combinations with higher observed subgroup sizes will relatively contribute more to the eventual outcome of the cross-subgroup alignment. Finally, the CG can be calculated by multiplying the cross-products with the normalized weights, so that they are adjusted for subgroup size:

$$CG_{a1/a2/title} = 1 \times 0.0476 = 0.04762$$

$$CG_{a1/a3/title} = 0.33 \times 0.28571 = 0.09524$$

$$CG_{a1/a4/title} = 0 \times 0.0476 = 0.0$$

$$CG_{a2/a3/title} = 0.33 \times 0.28571 = 0.09524$$

$$CG_{a2/a4/title} = 0 \times 0.0476 = 0.0$$

$$CG_{a3/a4/title} = 0.5 \times 0.28571 = 0.14286$$

By adding all outcomes together we arrive at the overall cross-subgroup title alignment for age subgroups:

$$CG_{age/title} = 0.04762 + 0.09524 + 0.0 + 0.09524 + 0.0 + 0.14286 = 0.38096$$

As with the IA, the CG index values vary in value between 0.0 and 1.0, 0.0 meaning no cross-group alignment and 1.0 meaning complete alignment. The CG of 0.381 seen above indicates a mediocre cross-subgroup alignment for these two attributes. The further the CG approximates 0.0, the stronger the faultline will be when combining this number with the IA. The method of this combination is discussed in the next section. To finalize the process of calculating the complete cross-subgroup alignment of a team, these calculations must be done for all attribute combinations. In this research, these are as follows.

- Gender groups
  - $CG_{gender/age}$ = gender groups across age categories
  - $CG_{gender/title}$ = gender groups across title categories
  - $CG_{gender/exp}$ = gender groups across experience categories
  - CG_{gender} = overall CG for gender groups (average of previous three equations)
- Age groups
  - $CG_{age/gender}$ = age groups across gender categories
  - $CG_{age/title}$ = age groups across title categories
  - $CG_{age/exp}$ = age groups across experience categories
  - CG_{age} = overall CG for age groups (average of previous three equations)
- Title groups
  - $CG_{title/gender}$ = title groups across gender categories
  - $CG_{title/age}$ = title groups across age categories
  - $CG_{title/exp}$ = title groups across experience categories
  - CG_{title} = overall CG for title groups (average of previous three equations)
- Experience groups
  - $CG_{exp/gender}$ = experience groups across gender categories
  - $CG_{exp/age}$ = experience groups across age categories
  - $CG_{exp/title}$ = experience groups across title categories
  - CG_{exp} = overall CG for experience groups (average of previous three equations)

Thus, after making this set of calculations for all these attribute combinations, the overall CG was found by averaging CG_{gender}, CG_{age}, CG_{title} and CG_{exp}. As with the IA, the CG equations are coded into Stata so that the cross subgroup alignment may be calculated for each company at once, per attribute as well as overall. However, it is not yet finished, as the IA and CG must be combined to get to the original objective: the faultline strength measurement.

3.2.2d Combining the internal alignment and cross-subgroup alignment

These methods are constructed in to allow for the outcomes to be used in multiple ways. The FLS can be assessed relative to a single attribute (e.g. gender), or the overall FLS can be obtained by combining all outcomes, as illustrated before. As the goal of this research is to find the FLS before we know which attribute is the subgroup basis, only the latter was used. Since a strong FLS is characterized by a high IA and a low CG, the reciprocal of the CG index was used to calculate the overall FLS, making the formula for faultline strength as follows:

$$FLS = IA \times (1 - CG)$$

Wherein FLS naturally represents the overall faultline strength. For this research, this equation is applied by averaging the IA for all attributes together, and then averaging the CG for all attributes, after which they are combined as in the equation. A different approach yielding almost identical results is to average the IA for each attribute as basis, then average the CG for each attribute, combining them as in the equation above, but per attribute, so that the FLS per attribute is computed. Finally, these are averaged to get the overall FLS. The first approach was chosen, so that the eventual results would contain the overall IA and overall CG results, as well as the FLS. However, using the second approach would essentially not limit the research and is not discouraged; it is simply a choice.

As can be derived by nature of the formula, if either IA or (1-CG) equals 0, the faultline strength will as well. The index varies in size from 0.0 to 1.0, where 0.0 indicates non-existing faultline strength, meaning likely no subgroups will form. A score nearing 1.0 indicates a very high possibility of a subgroup emerging. These extremes are very unlikely to occur though, as they require unobtainable heights of diversity and homogeneousness.

This concludes Shaw's five steps to calculating the FLS. As evident by the process, calculating the faultline strength for a team is an elaborate process to perform on a large amount of teams. These calculations were coded into SAS, so that they may be applied automatically on an unlimited amount of teams. The FLS was coded using a program created by scholars Y. Chung, J.B. Shaw and S.E. Jackson in 2006, which can be found online. A link will be provided in the bibliography. In order to use this program, all attribute data must be categorized, coded and sorted sequentially in Excel, by company ID and member ID. Table 2 is an example of what the sorted data of one team looks like.

3.3 Firm performance measurement

The next step in the process was to find the influence of faultline strength on firm performance. This was done by means of an event study. An event study is a method to assess the impact of an event on the performance value of a firm. The goal is then to create an estimate on what the firm performance would have looked like *without* the investment, to compare with what happened *with* the investment. The initial task is to define the events and identify the event window, which is the period over which security prices of the firms will be examined (MacKinlay, 1997). After establishing the event period, it is necessary to determine from which index the independent variable will be drawn. Finally, the events impact is measured by means of the firm's abnormal return, which is drawn by comparing the estimated returns with the actual returns in the event window (MacKinlay, 1997).

3.3.1 The event study

It was considered to recover board data on each necessary year, so that each event between 2006 and 2014 could be used. However, it proved to be insurmountable to collect board data on all necessary years within the time-scope of this research. To overcome this inconvenience, the events constitute all M&As between 2006 and 2014, within the scope of the particular firm's board. Thus, for example, if a board's least experienced member joined in 2011, all M&As between 2011 and 2014 for that board's firm are used. Should the unexperienced member have joined two years ago, merely all M&As between 2012 and 2014 are used for that firm. This way, assurances are in place that each board's faultline strength correlates with the right events.

DataStream was used to collect the variables for the event study. The company's SEDOL codes were used to identify companies. Firms whose SEDOLs could not be identified by DataStream were deleted from the study. This came down to a total of four firms. The dependent variable constitutes daily stock price data on all firms that had at least one merger or acquisition in the past eight years, within the period between now and the year the least experienced member joined the team. Four events were dropped because there was no stock value available from when the event took place. This came down to a total of 55 out of the 154 firms, with 225 M&As. Furthermore, daily local market indices were collected, and used to compute the independent variable: market return. Of the 55 firms, 54 firms used the S&P 500 composite market index and 1 (the only Canadian firm, Valeant) used the S&P/TSX composite market index

Event windows of 7 days and of 2 days were used: for the former five days before and one day after the event, for the latter the day of the event and the day after the event. The window was drawn as shortly after the event as possible, one day, as this will produce the most accurate post-investment representation. The longer one measures past the initial event, the less one can be sure the outcomes are caused by the event. Five days before the event are used to allow for a working week of speculation between the likely produced rumors of the event's occurrence in the near future, and the actual announcement day. For the 2 day event window, no speculation days were accounted for.

An estimation window of 30 days was used: from 60 days before the event to 30 days before the event. The returns in the estimation window are used to establish what performance may have looked like *without* the event. These are then compared to the returns computed within the event window, which represent the returns *with* the event. These results are then combined with the results from the market indices, to calculate the abnormal returns.

Stata was used to run the event study. The coding is presented in appendix D, whereas the most important results and their usage in the regressions are presented in the following section.

3.4 Validity and reliability

Validity

The obtained board data was transformed into a list of several values related to faultline strength (appendix D). All of these values were obtained by running the data through a program, which was created partially by James Shaw, the scholar who developed the measure. In his article describing the measure, Shaw (2004) gives solid reasoning for why this measure makes for a good representation of a team's faultline strength, as described in section 3.2.1 of this thesis. As for post-M&A firm performance, stock price value is the most prominent way to measure firm value (Zollo and Meier, 2008) and has been used in many papers (e.g. Hendricks and Singhal, 2005; Mayew and Venkatachalam, 2012). Triangulation was applied when gathering board composition data. Where the initial research instrument was insufficient, annual reports were gathered to fill in the empty spots.

Drawn conclusions were kept internally valid by stating the limited potential of the results. It was acknowledged that a maximum of 5% of the dependent variable's variance could be predicted by the independent variable's strength. As the dependent variable's variance was measured by merely one independent variable, and further accompanied only by control variables, alternative explanations for the variance are ruled out.

External validity is slightly skewed, as it is unknown whether the results may be partially explained by industry characteristics. All measurements were performed on boards from firms in the drugs industry.

Reliability

The present study was conducted in a concise and reliable matter. No researcher bias exists; all obtained and noted data was double checked before usage. Board data was collected from a website and insured of its reliability by comparing the obtained names with names in the highly esteemed database LexisNexis. In addition, data on age, title and experience was verified by pulling up annual reports from approximately 40 randomly selected boards out of the total 154 boards. The data on firm performance was obtained through another respected database. The stock price and control variable values were obtained through Thomson Reuters DataStream, whereas the identified events were obtained from Thomson Reuters' SDC. The respondent reliability was somewhat skewed, as only the firms with available board data (firms that were acquired in the past years were excluded) and only firms that performed a merger or acquisitions with the current board were included into the study. Thus, if a firm acquired another firm in 2011, but the latest joined member joint in 2012, this firm was excluded from the research. In the future, board data from multiple years should be collected to verify that it would yield similar results. As none of the data was collected by performing face-to-face interviews, the results were reliable pertaining to the circumstances.

4. Results

This section is dedicated to discussing the gained results after performing a regression analysis on the dependent variable faultline strength, and the independent variable M&A success. The analysis was performed through Stata, with a simple linear regression between the dependent and independent variables, which was supplemented with a multiple regression analysis containing several control variables. Once again, the coding is presented in appendix C.

4.1 Preliminary analyses and results

Firstly, the preliminary results of the faultline analysis will be discussed. After running Shaw's FLS algorithm through SAS, multiple variable values were obtained; the IA and CG per category individually and the FLS per attribute. The categorical values were manipulated further, to gain the internal alignments per attribute and overall, the cross-subgroup per attribute and overall and the FLS overall. This was done by using the averaging methods presented in section 3.2.2. All of these values can be found in appendix D.

The most important values, the overall IA, overall CG and overall FLS are presented in table 9 on the next page for all companies that were used in the event study. For the regression, merely the overall FLS variable will be used, as the IA and CG variables have no particular meaning individually. They were included here so that any uncertainty regarding the legitimacy of the FLS variable may be eliminated. This is possible by performing the FLS calculation as presented in the section 3.2.2d.

Statistical values as mean and standard deviation for these outcomes are summarized below; the first representing all boards, while table 8 summarizes the statistics for boards of firms that were used in the event study. As evident from the results, the means and standard deviations for these are mere identical. Thus, it can be assumed that the 55 used companies are a good representative of the total 154 companies with regard to faultline strength. This assumption is backed up by the normal distribution indicators in figure 2 and 3.

Table 7: Statistics for all boards' faultline strength

Variable	Sample size	Mean	Std. Dev.	Min	Max
IA overall	154	.2629	.0665	.1279	.487
CG overall	154	.4968	.1453	.2596	.9167
FLS overall	154	.1357	.0478	.0231	.2803

Notes: all values have been rounded to a maximum of four decimals

Table 8: Statistics for used boards' faultline strength

Variable	Sample size	Mean	Std. Dev.	Min	Max
IA overall	55	.2675	.0604	.1403	.3899
CG overall	55	.4828	.1479	.2819	.9109
FLS overall	55	.1405	.0498	.0297	.2421

Notes: all values have been rounded to a maximum of four decimals

Table 9: Faultline values for all firms included in the event study

Team ID	IA overall	CG overall	FLS overall	Team ID	IA overall	CG overall	FLS overall
2	0.329386264	0.471164048	0.16190359	83	0.325520813	0.482202381	0.165087387
8	0.275249273	0.301587313	0.190394431	84	0.258487642	0.575892866	0.12111786
10	0.233484685	0.607142866	0.103530727	87	0.204119176	0.374338627	0.127003908
11	0.140277773	0.313624352	0.097058713	94	0.208854169	0.625198424	0.091617063
12	0.181579411	0.402520597	0.107866868	101	0.312191367	0.470674694	0.16438444
13	0.25526768	0.478769839	0.127304077	103	0.18773742	0.385978848	0.117130198
18	0.336391807	0.439781755	0.175816089	107	0.264802933	0.412450403	0.160314322
21	0.336259931	0.758680582	0.093351953	108	0.301504612	0.322016448	0.203717992
22	0.231327161	0.396521151	0.137171626	109	0.295497477	0.446075827	0.152417839
23	0.295450509	0.910879612	0.03519376	115	0.295312434	0.453995824	0.162476316
30	0.196180552	0.608465612	0.096528694	118	0.271450192	0.398691237	0.149939477
31	0.203059703	0.416749358	0.118595488	123	0.340954423	0.311979175	0.235188589
39	0.250327945	0.483063281	0.125433698	125	0.280324072	0.336259931	0.181148425
41	0.220949069	0.414917022	0.128665775	127	0.258487642	0.5121032	0.126881406
44	0.257754624	0.325488687	0.173903316	132	0.380324066	0.537037015	0.217378557
47	0.245340705	0.382523149	0.1553974	133	0.32069087	0.683333337	0.104134023
50	0.32005623	0.411180556	0.184896782	137	0.2821334	0.385858595	0.162131608
52	0.273504287	0.301587313	0.185570985	138	0.294863313	0.408193707	0.174517557
56	0.166898146	0.762037039	0.035423096	143	0.258322328	0.618055582	0.112532154
62	0.389975071	0.388065189	0.242120177	144	0.314064413	0.592881918	0.152363226
64	0.17488426	0.631944418	0.064149305	152	0.288631916	0.421266228	0.166285679
66	0.174857557	0.39312169	0.102549404	154	0.33267197	0.421675086	0.196522117
68	0.355902791	0.725000024	0.12019676	156	0.218956679	0.381995887	0.131444231
69	0.313806206	0.476172119	0.170284539	157	0.195138887	0.840277791	0.029706791
71	0.202777773	0.667129636	0.067869082	163	0.314508438	0.422293454	0.180526629
72	0.230555564	0.75	0.060185187	165	0.208526239	0.487301588	0.100903422
74	0.341512352	0.318121672	0.228815496	168	0.199537039	0.281944454	0.144791663
77	0.364799976	0.430134684	0.206657916				

To get the best results, it is desirable to have a normally distributed FLS, so that weak as well as strong board faultlines may be tested for their effects on firm performance. As evident from the figure below, faultline strength was indeed normally distributed for the 154 companies, with only a slight skew to the right in the center. This is evident in the histogram, through which a near-perfect bell curve runs. When performing the same tests to the list of FLSs from the remaining 54 teams, we get similar results. Though the bell curve is notably less steep, it still has a clear bell form, indicating normal distribution. Therefore, firm performance can be investigated in relation to a near equal amount of weaker and stronger faultlines. Thus, t-t est values will be valid.

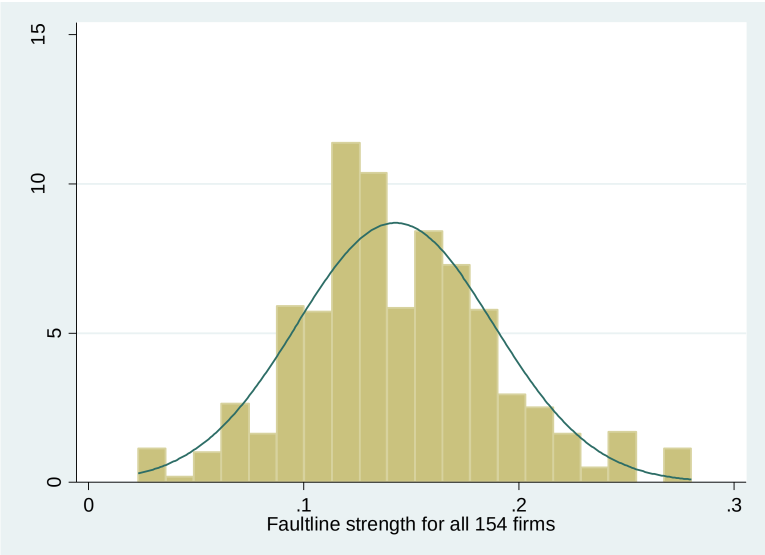
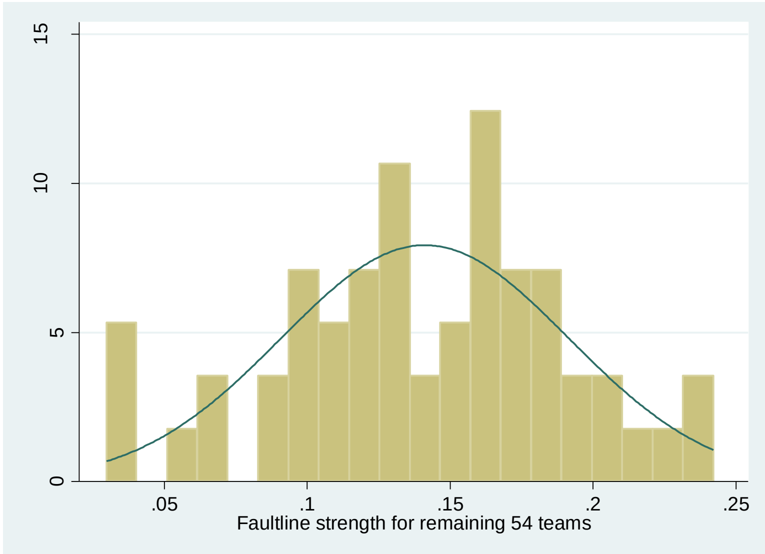


Figure 2: Faultline strength normal distribution - all firms



Figuur 3: Faultline strength normal distribution - event firms

After running the event study through Stata, multiple results were produced. It is common practice to determine the event window empirically, to be assured of the most reliable possible outcome, as it is impossible to be sure of when investors obtained the information (Wiles and Danielova, 2009). By empirically looking for the best event window, we allow ourselves some uncertainty in that regard. With the pre-determined event window of seven days, abnormal returns were calculated against the local market indices. Averaging them per day in the event window produced a graph as seen in figure 4, in which the direct effect after the event is demonstrated nicely. Here, the negative numbers in the legend represent the days before the event, 0 the day of the event, and 1 the day after the event. It is clear that on the days of the event and after the event the abnormal return level was much higher than the days before. The slight abnormal returns of the 5 days before the event date indicates that it may be wise to reduce the event window to a mere two days: days 0 and 1.

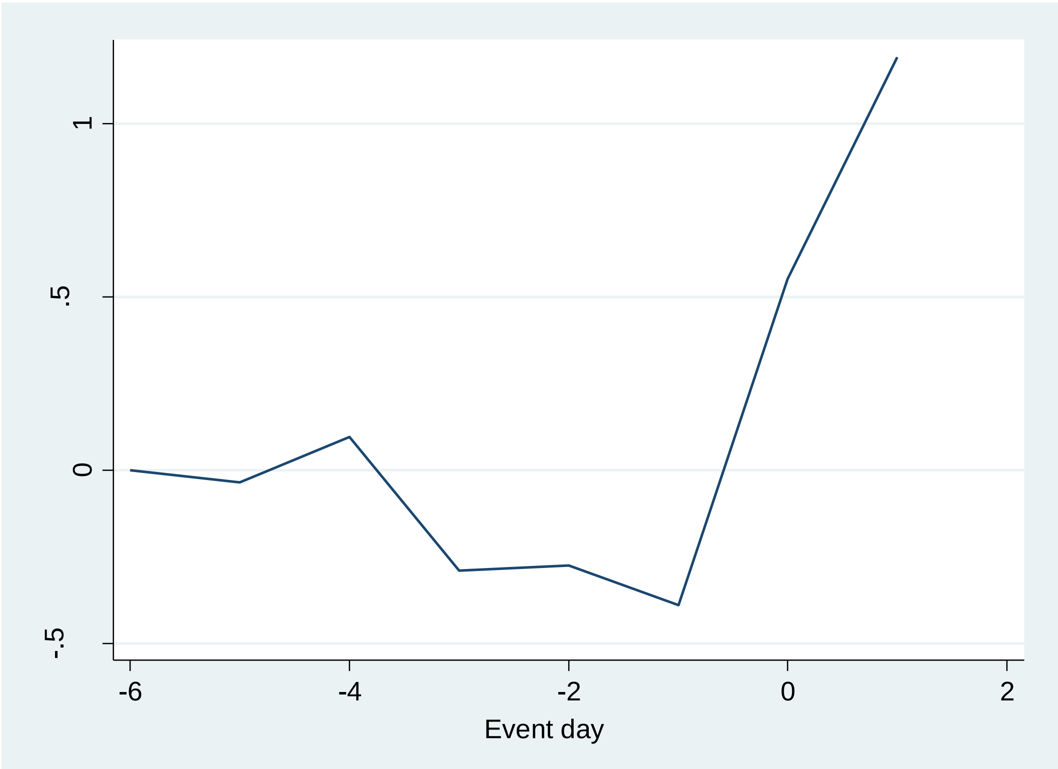


Figure 4: Average abnormal returns per event day

This is further backed up by an event study by Homburg, Vollmayr and Hahn (2014). They empirically determine that an event window of day 0 to day 1 produces the most significant t-test and z-test statistics for an event study designed to assess firm value. The event study by Wiles & Danielova has drawn different conclusions regarding the event window. However, as the nature of their event study is different than the current study (the worth of product placement), the conclusions drawn by Homburg et al. are regarded as correct for this research. Therefore, this study will be executed in two ways: with an event window of 7 days (-5 to 1), as well as 2 days (0 to 1), to see which yields the best results. Table 10 demonstrates the results with regard to the Cumulative Average Abnormal Return (CAAR) with different event windows.

Table 10: Descriptive results for different event windows

Event window	Sample size	CAR	CAAR	Positive abnormal returns (%)
-5 to 1	225	1.19	0.0053	121 (54)
0 to 1	225	1.58	0.007	119 (53)

Note: The CAAR equals the Cumulative Abnormal Returns (CAR) divided by the sample size

The statistics in figure 4 and table 10 are merely a mean though, as multiple firms produced negative results, when cumulating all event windows' abnormal returns. This is evident from the table in appendix E, where cumulative abnormal returns (CARs) for all firms are presented, for an event window of 7 days, as well as 2 days. For the different event windows, 100 firms for days -5 to 1 and 102 firms for days 0 to 1 produced negative abnormal returns. Furthermore, 4 events produced an abnormal return of 0, because of a lack of available stock price data at the time of the event. These events were excluded from the study.

4.2 Regression analyses and results

The goal for this thesis is to see if there is a correlation between faultline strength and M&A success. This is done with a regression analysis, by effectively looking for a significant correlation between faultline strength and the abnormal returns that were the result of these M&As, where it is expected to find negative cumulative abnormal returns with high faultline strength. The regression analysis was performed in Stata, for both event windows, with as dependent variable cumulative abnormal returns, and as independent variable faultline strength.

Multiple checks were performed to confirm that these results would be unbiased. Mistakes as wrongly inserted numbers or missing values in the database were non-existent. Figure 5 shows a scatterplot, which illustrates how the results are distributed in relation to each variable. As evident from the lower two matrices, the cumulative abnormal returns from either size event windows do not predict any particular outcome. They seem rather randomly distributed. In addition, there were a certain amount of outliers present. To accommodate for the outliers, variables were remove on the 1% level. Thus, all values from 2% to 99% of the total values remained in the study.

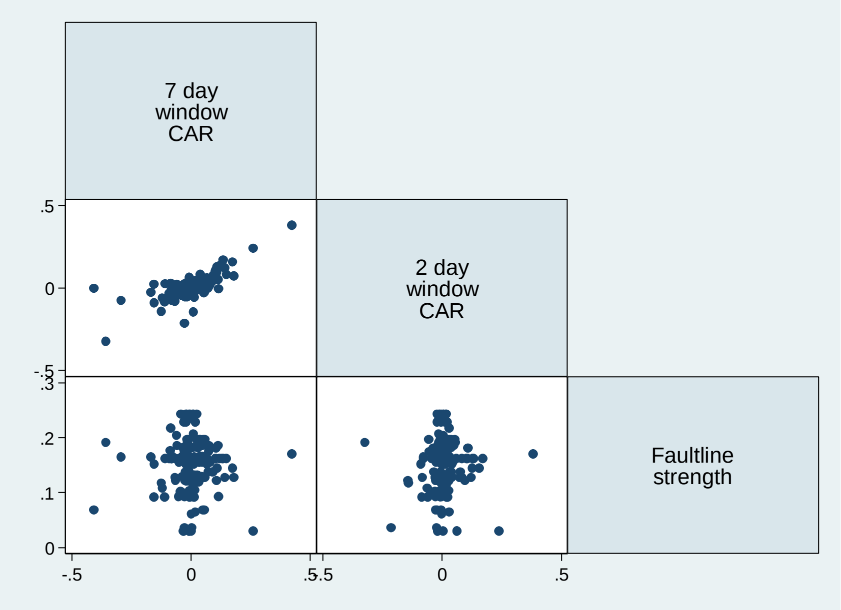


Figure 5: Result distribution

Table 11 illustrates the initial results. As evident from the p-value, which is higher than the 0.05 permitted p-value level, there is no significant relation between faultline strength in boards of directors and the success of the M&A decisions that are influenced by these boards. A p-value of .553 illustrates a 55.3% chance that the results were based on chance. Thus, looking purely at the outcomes of faultline strength and abnormal return, there is no identifiable relationship between the two. However, here is merely looking for a trend of lower abnormal returns with higher faultline strength.

Table 11: Initial regression analysis with continuous values

Regression analysis	Coefficient	Std. Error	t-test	p-value	R-squared	95% conf. interval	
FLS in 7 day window-CAR	.0625	.1052	.59	.553	.0016	-.1448	.2698
FLS in 2 day window-CAR	.0576278	.0732	.79	.432	.0028	-.0244	.021

Notes: For neither event window a significant relationship could be identified.

Looking at it more abstractly, the cumulative abnormal return variable may be transformed into a dichotomous variable, being '0' when the return is negative and '1' if it is positive. This way, actual losses or profits may be identified. Here, it is expected to find a negative performance with higher faultline strength and vice versa. The difference is that we are not merely looking for higher performance with lower FLS and lower performance with higher FLS, but at M&A decisions resulting in an actual loss or profit for the company.

The dichotomous regression analysis is presented in table 12, once again for both event windows. For the 7 day event window the results remain the same: there is no indication that the higher faultline strength causes the cumulative abnormal returns to be negative in the event window of 7 days. The p-value is .715, which is well above the required <.05 value. However, the event window of 2 days now contains very different outcomes. As the p-value is below the .05 level, the relationship is significant. This indicates a correlation between FLS and M&A success, given a dichotomous distribution of the abnormal returns. However, the relationship is different than initially expected. The coefficient of 1.6562 (which is significantly different from 0, as the t-test value is large enough) indicates a positive relationship between FLS and M&A success. This means that if a firm's board has a stronger faultline, the firm is more likely to actually produce better decisions regarding the initializing of mergers and acquisitions. This is in direct contrast with the initial thought that it would produce negative M&A decisions. The R-squared value of 0.0199 means that approximately 2% of the variance of the cumulative abnormal returns is caused by faultline strength. As predicted by Homburg et al. (2014), the event window containing day 0 and day 1 was a better indication of the abnormal returns than the 7 day event window with days -5 through 1.

Table 12: Initial regression analysis with dichotomous values

Regression analysis	Coefficient	Std. Error	t-test	p-value	R-squared	95% conf. interval	
FLS in 7 day window-CAR	.2908	.795	.37	.715	.0006	-1.276	1.8576
FLS in 2 day window-CAR	1.6562	.786	2.11	.036	.0199	.1070	3.2054

Note: cumulative abnormal returns are dichotomous: 0 for negative and 1 for positive abnormal returns.

A summary of the regression results is presented table 13. With this outcome, the hypotheses will be rejected. More on this and the effect it has on the outcome of the research is presented in the discussion section. However, the control variables will first be added, to create a more accurate regression analysis.

Table 13: Linear regression results

	Continuous values		**Dichotomous values**	
Variables	**7 day window**	**2 day window**	**7 day window**	**2 day window**
Faultline strength	0.0625	0.0576	0.291	1.656**
	(0.105)	(0.0732)	(0.795)	(0.786)
Observations	221	221	221	221
R-squared	0.002	0.003	0.001	0.020

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Adding control variables

These initial regression results are a start, but can be improved by adding the aforementioned control variables. These variables will improve the results, as their unchanged nature will eliminate the possibility that the abnormal returns are based on these company characteristics. As mentioned in the methodology, the outcomes of the regression will be controlled by each firm's return on assets (ROA), leverage and book-to-market ratio (b/m) at the year of the event and the previous year.

As evident from table 14, the result of the controlled regression varies little from the initial regression results. The decrease in observations from 221 to 167 firms is caused by missing data on the control variables. No data on ROA or the firm's financial structure was obtainable for the year 2014, and some additional firms lacked the information on other years as well.

As was the case initially, faultline strength does not have a significant relationship with the cumulative abnormal returns resulting from mergers and acquisitions on the continuous level.

However, though the 7 day window is deteriorating further in its significance (from a p-value of .553 to a p-value of .825), the 2 day window-CAR has improved significantly. Unfortunately, this improvement is not strong enough, as there is still no significant identifiable relation between FLS and the CAR. The same is true for the dichotomous CAR values; whereas the 7 day window-CAR has deteriorated further to .974, the 2 day window-CAR has improved to the .01 significance level. This further demonstrates the stronger accuracy of the 2 day event window as compared to the 7 day event window. The adjusted R-squared value of 0.0505 indicates that approximately 5% of the variance of the dichotomous CAR value in an event window of 2 days is accounted for by the model.

Table 14: Multiple regression with control variables

	Continuous CAR values		**Dichotomous CAR values**	
Variables	**7 day window CAR**	**2 day window CAR**	**7 day window CAR**	**2 day window CAR**
Observations	167	167	167	167
Faultline strength	-0.0248	0.0880	0.0345	2.864***
	(0.112)	(0.0708)	(1.060)	(1.025)
P-value (linear p-value)	0.825 (.553)	0.215 (.442)	0.974 (.715)	0.006 (.036)
Book-to-market ratio	0.776**	-0.0108	2.198	-1.177
	(0.352)	(0.223)	(3.333)	(3.222)
Previous year b/m	-0.994***	-0.166	-1.660	-2.340
	(0.284)	(0.180)	(2.689)	(2.599)
Return on assets	-0.000470	0.000303	-0.00227	0.000812
	(0.000405)	(0.000256)	(0.00383)	(0.00370)
Previous year ROA	0.000537	-0.000275	0.00466	-0.000346
	(0.000508)	(0.000321)	(0.00480)	(0.00464)
Leverage	-0.0415	-0.0126	0.641*	-0.182
	(0.0375)	(0.0237)	(0.354)	(0.343)
Previous year leverage	0.0727*	0.0223	-0.432	-0.0810
	(0.0400)	(0.0253)	(0.378)	(0.366)
Adjusted R-squared	0.0570	0.0128	0.0085	0.0505

Notes: Standard errors in parentheses, except state otherwise. *** p<0.01, ** p<0.05, * p<0.1

In conclusion, with the addition of the control variables, the dichotomous cumulative abnormal returns with the event window interval of day 0 and day 1 remains the only dependent variable that can significantly be predicted by faultline strength in boards of directors. This means that while there is no visible trend of the FLS influencing or predicting the height of the cumulative abnormal returns from M&As, it is a significant predictor of a company's profit or loss as a result of their merger or acquisition. In contrast to initial expectations however, this predictor is very positive, directly contradicting existing research on faultlines and their effects on firm performance. Therefore, it is found faultlines have a different effect on boards of directors than on other upper echelon teams, as for example, the firm's top management team. Both hypotheses remain rejected. To help explain this result, the controlled regression was performed with faultline strength for each attribute individually. This way, it will become evident which attribute's faultlines cause the positive effect on post-M&A firm value. In knowing that, it will open up possibilities for firms to steer their boards into gaining stronger faultlines in those particular areas.

Regression on faultline strength per attribute

A total of sixteen additional regressions were performed. These consisted of a multiple regression with control variables for each of the four attributes; gender, age, title and experience. These were performed with four different dependent variables: cumulative abnormal returns with event windows of 7 and 2 days, continuously and dichotomously. Once again, none of the regressions with the 7 day event window-CAR were significant. Thus, the focus will be placed on regressions with as dependent variables the 2 day event window-CARs, continuously and dichotomously. Results are presented in table 15 on the next page.

Let us first discuss the continuous values. When looking at the overall faultline strength, the relation was insignificant with a p-value of 0.215 (as evident in table 14). However, looking at the faultline strength of individual attributes, it is evident the FLS of age does portray a significant positive relation with cumulative abnormal returns from M&As at the <0.1 level. This indicates that it is possible that a faultline in age particularly could affect the height of a profit or loss, where a faultline is deemed positive for the profit. 2.69% of the variance in cumulative abnormal returns is explained by the age faultlines, as presented by the adjusted R-squared value.

At the dichotomous level, more interesting outcomes come to light. It is especially the gender and age attributes that significantly influence the post-M&A firm performance. They explain 2.9% and 3.2% of the variance of the dichotomous CAR value in an event window of 2 days respectively. Here we a see significant positive relation at the <0.05 level for both attributes. These results mean that though the overall FLS has a very significant relation with the CAR dichotomously (as seen in table 14), it is especially the gender and age faultlines that cause this significant relation. Thus, more specific implications for managers can be drawn from the results, as can be seen in the discussion section.

Table 15: Multiple regression with control variables – individual attribute's faultline strength

	2 day window-CAR – Continuous				2 day window-CAR - Dichotomous			
Variables	**gender**	**age**	**title**	**experience**	**gender**	**age**	**title**	**experience**
Observations	167	167	167	167	167	167	167	167
FLS gender	0.0353				0.998**			
	(0.0338)				(0.494)			
FLS age		0.0908*				1.468**		
		(0.0461)				(0.679)		
FLS title			0.0453				0.418	
			(0.0466)				(0.689)	
FLS experience				-0.0386				0.875
				(0.0405)				(0.595)
P-value	0.298	0.051	0.332	0.341	0.045	0.032	0.545	0.143
Book-to-market ratio	0.0180	-0.0450	-0.0841	-0.0633	-0.439	-2.032	-2.282	-1.003
	(0.227)	(0.221)	(0.230)	(0.225)	(3.318)	(3.248)	(3.393)	(3.313)
Previous year b/m	-0.187	-0.153	-0.196	-0.223	-3.093	-2.719	-3.465	-3.069
	(0.178)	(0.178)	(0.178)	(0.179)	(2.603)	(2.616)	(2.626)	(2.628)
Return on assets	0.000315	0.000268	0.000284	0.000283	0.00112	0.000176	0.000542	0.00105
	(0.000256)	(0.000254)	(0.000256)	(0.000257)	(0.00375)	(0.00374)	(0.00379)	(0.00377)
Previous year ROA	-0.000209	-0.000266	-0.000198	-9.37e-05	0.00197	0.00150	0.00279	0.00129
	(0.000312)	(0.000311)	(0.000312)	(0.000321)	(0.00457)	(0.00458)	(0.00461)	(0.00471)
Leverage	-0.0152	-0.00712	-0.0105	-0.00988	-0.239	-0.0326	-0.0766	-0.0412
	(0.0243)	(0.0233)	(0.0236)	(0.0235)	(0.355)	(0.343)	(0.349)	(0.346)
Previous year leverage	0.0237	0.0134	0.0300	0.0284	-0.0215	-0.148	0.0987	0.0373
	(0.0252)	(0.0257)	(0.0252)	(0.0251)	(0.369)	(0.379)	(0.373)	(0.369)
Adjusted R-squared	0.01	0.0269	0.0091	0.0089	0.0288	0.0323	0.0062	0.0173

5. Discussion

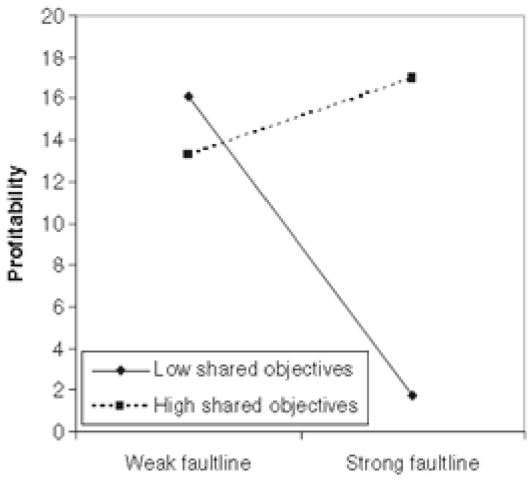
In this study, the impact of faultline strength in boards of directors on M&A performance is investigated. The study extends faultline theory and research by demonstrating that faultlines in boards of directors have contrary effects to faultlines in other aspects of upper echelon management, as top management teams. Where other researchers on faultlines have suggested a negative effect on creativity and communication, and therefore on team performance (e.g. Jehn, 1995; Hutzschenreuter & Horstkotte, 2013), the current research found a significant positive relation between faultline strength and M&A performance.

5.1 Theoretical implications

The effect of board faultlines was measured on the influence on post-M&A abnormal returns in two different ways. First, viewing cumulative abnormal return as the continuous variable that it is, faultlines in boards of directors where investigated as a moderating variable to M&A success. The results indicate no moderating relationship between the variables, when using the overall FLS as the independent variables. Thus, whether the overall possibility of a faultline emerging in a board is high or low, it will not influence the magnitude of its firm's profit or loss.

However, the regression analysis on the faultline strength per individual attributes shows that a faultline in age categories, thus splitting the team into groups based on age, does positively moderate M&A success. This indicates that when a firm's board contains strong or weak faultlines in age, it does influence the magnitude of its profit or loss, where strong age faultlines correlates positively with higher profits.

The results of the dichotomous regression analysis aimed to investigate hypothesis 2 had more promising implications. These indicated a significant relation between faultline strength and the occurrence of either a profit or a loss. As discussed in the results section, this relationship opposed initial expectations. As exemplified by the work of many scholars, I expected to find a negative relationship with faultline strength and firm performance. However, the 2.864 coefficient with a p-value of <0.01 indicates a very positive influence of strong faultlines. This may be caused by a phenomenon that was theorized by Knippenberg et al. (2010). They state that with high shared objectives, having strong faultlines in your team is slightly preferable for profitability. Contrarily, with low shared objectives, strong faultlines are absolutely detrimental



for your profitability. As making a decision regarding mergers and acquisition may involve all senior executives (Hambrick et al., 1996), it can be considered as a highly shared objective within a firm. Though their research was based on top management teams, it may also apply to boards of directors. The image on page 41 was taken directly from Knippenberg's (2010) paper, and illustrates the differences in levels of shared objectives.

Another possible explanation for this outcome may be related to the nature of boards of directors and their roles within the firm. It is possible that the nature of board teams is significantly different from other upper echelon teams after all; allowing faultlines to be capitalized on. This was initially assumed not to be the case, but the results suggest otherwise. Faultlines are said to create conflict within a team, which is difficult to forego or solve, since it is often between unified subgroups that support their members (Jehn, 1995; Lau & Murnighan, 1998). Most boards from this dataset were filled with managers of considerable age (approximately 57% being older than 60, and 91% older than 50 years old) and it is possible that their large amount of work experience has prevented them from having petty conflicts, or from capitalizing on the size of their subgroups to suppress the smaller groups, which it is said may happen in regular teams (Lau & Murnighan, 1998). Future research should aim to investigate these curious board characteristics further, to find strong reasoning behind this claim.

Additionally, since within the scope of M&As the main role of boards of directors is to govern the decision making process of other upper echelon management teams, the division of a board in subgroups may be positive. Arguably, having two or three viewpoints (for each subgroup) instead of a viewpoint for each team member may facilitate the governing process, as decisions are gained faster and more easily, without many conflicts arising for the aforementioned reasons.

Regardless of the possible explanation of this unexpected result, it may be stated that a firm should consider their board of directors' faultline strength before committing to an M&A. As evident from the regression using individual attributes' faultline strength, one should pay special attention to gender and age faultlines. Subgroups divided on the basis of these attributes positively relate to the chance of gaining a profit, whereas the title and experience attributes do not share this quality. It is important to note that its influence on post-M&A firm performance is rather small and should be considered with a range of other quality-assessing factors.

All in all, the outcome of hypothesis 2 has theoretical implications for faultline research in board of directors, in that stronger faultlines improve the chance of gaining a post-M&A profit. With the adjusted R-squared value of approximately 0.05, the results suggest that about 5% of the variance of a post-M&A chance on a profit or loss are caused by the faultline strength in a firm's board. Before entering into a merger or acquisition, a firm could look at their board of directors' faultline strength as an indicator to ascertain the solidity of their decision making.

Implications for event study users

As stated in the results section, the regression analysis was performed on event study outcomes with two event windows, one of 7 days (five days before the event, the event day itself and one day after) and one of 2 days (the event day and one day after), so that it could be decided empirically which would produce the most accurate results. As evident in the results, for both the continuous and the dichotomous regressions, the 7 day event window-results produced very insignificant results, growing even more insignificant with the addition of control variables. Contrarily, the 2 day window produced insignificant results (though less extreme) for the continuous regression, but highly significant results when performed dichotomously. Both 2 day window-results grew stronger with the addition of the control variables, further proving their legitimacy. Therefore, this research has minor theoretical implications for event studies. Building on the results, I would advise event study users to empirically assess which event window is superior, as they may provide very different results. Furthermore, it may prove prudent to consider the aforementioned event window of 2 days as one of the 'candidates' for the event study. The proficiency of this event window is likely caused by the short amount of time it contains, as returns from days that approximate the event day have the smallest chance of being caused by something different than the event. Thus, by merely applying the closest days, a more accurate representation of the event's influence is showcased.

5.2 Managerial implications

From a managerial point of view, it would be wise to consider board faultlines before committing to a merger or acquisition. Though M&As are rarely profitable, at least 5% of the variance of it being either profitable or not is influenced by the board's faultline, which is a considerable amount.

Connected to this, an implication of the outcomes on team composition issues would be to attempt to increase faultline strength, especially when considering an M&A. This faultline strength must then especially be increased with regard to gender and age faultlines, as these types of faultlines could influence M&A success strongest (only age from a continuous view on abnormal returns, and both from a dichotomous point of view). This can be done by increasing team turnover, as the addition of new members increases the overall FLS, and this way a manager could steer the team into gaining stronger gender and age faultlines. However, this would significantly decrease team cohesiveness and morale. In addition, one must consider the detrimental effects these faultlines may have on other types of firm performance, besides M&As. As mentioned, it is likely board faultlines will have negative effects on low shared objectives. Furthermore, when selecting a member, the aim should go to a gender- or age-minority (e.g. women or people below the age of 50), and the candidate should only be chosen for the team if their background differs from those of the rest of the team. This strategy will also reduce entry barriers for members of these underrepresented groups. However, it would reduce the degrees of freedom in the selection process of new members, where qualified people are in high demand (van Knippenberg et al., 2010).

In conclusion, managers (or other stakeholders of the firm that have deciding power on board recruitment and composition) can indeed exercise some degree of influence on M&A success through the board's composition. However, as with many a managerial problem, it is evident that many of these board alterations constitute a trade-off with other aspects of the firm's performance and should not be taken lightly.

5.3 Limitations and future research

A limitation of the current study is its relatively small sample size. As the study was dependent on the least experienced member of each board for selecting the usable M&As, the sample size was significantly reduced. In future research, board composition data on several years per firm should be collected, so that all M&As of a certain period of time may be connected to their contributing board FLS. Fortunately, this does not affect the validity of the study, as statistical tests take sample sizes into account. Another limitation is the small number of women in the study, as well as the small number of younger members. Boards in the USA tend to contain a large percentage of senior males, which significantly reduced the possibility of a gender or (in lesser extremity) age related faultline emerging. To constitute a faultline, both subgroups (e.g. males and females) must have a minimum of 2 members, which was quite rare in the case of women. This could not be prevented however, as it reflects the reality of US-boards of directors. Furthermore, this research was conducted on drugs-related firms only. It is possible this formed a bias in the research.

According to Lau and Murnighan (1998), demographic faultlines are more likely to be strongest at the beginning of a group's life, because they become clear amongst the members right away, and therefore exist almost immediately. However, after a while people get to know each other and social aspects start to play a role. Then, demographic faultlines weaken, whereas personality-related faultlines start to take over, which tend to be much less powerful, because personality traits are generally much more divided from each other than demographics, making the chance of a strong faultline setting smaller. It may thus be wise to try to prevent demographic faultlines from being activated at the beginning of the group's lifetime, so that subgroup forming will be less strong on the long run. One way to do this is by using external forces, such as pressing deadlines and competing groups, which are likely to increase group cohesiveness and draw members' attention away from their potential subgroups and to the group as a whole (Heilman and Hornstein, 1982). A second way to achieve this goal is to create a shared objective amongst the team. As mentioned before, this attenuating factor was introduced by Knippenberg et al. (2010), who state that the negative relationship between diversity faultlines and organizational performance is weaker with higher shared objectives. However, Lau and Murnighan (1998) state that the addition of new members into established groups introduces the possibility of the resurfacing of old faultlines, the creation of new faultlines, and changes in the group's basic, underlying dynamics. It would be interesting to assess the influence the life span of a board has on the amount and success of geographic decisions made. Additionally, the addition of new members to the board would be an interesting concept to research. Therefore, I urge future research to investigate these matters further.

6. Conclusion

The present thesis extends faultline theory and research by demonstrating how faultlines in boards of directors have very different effects on firm value performance than faultlines in other upper echelon management teams. Though only a small significant relation was found between age faultlines in boards of directors and the size of a profit or loss after performing a merger or acquisition, the results suggest a predictive power in board faultlines to determine whether an M&A will make a profit or a loss. By looking at the issue dichotomously, valuable new insights may be gained, as boards may be tuned to increase faultline strength, in order to improve future M&A-related decision making processes in the firm. Especially gender and age related faultlines take an important role here. Subgroup forming with one of these attributes as basis, which is caused by the presence of strong faultlines, positively influences the chance on a post-M&A profit. This viewpoint adds to existing literature, as little faultline research has been done on boards of directors, nor on M&As.

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Appendix A – Categorized and coded board compositions

Team ID	Member	Gender	Age	Title	Experience	Team ID	Member	Gender	Age	Title	Experience
2	1	1	2	1	2	87	1	1	4	1	4
2	2	1	3	3	1	87	2	1	3	2	2
2	3	1	4	1	3	87	3	2	2	2	1
2	4	1	2	3	3	87	4	1	3	2	3
2	5	1	1	3	2	87	5	1	2	2	2
2	6	1	2	3	2	87	6	1	3	2	2
2	7	2	2	3	2	87	7	1	4	2	2
2	8	1	1	3	2	88	1	2	1	1	3
2	9	2	2	3	2	88	2	1	2	2	1
3	1	1	3	1	1	88	3	1	4	2	3
3	2	1	3	1	3	88	4	1	3	2	3
3	3	1	2	3	2	88	5	1	2	2	2
3	4	1	3	3	3	88	6	1	2	2	2
3	5	1	2	3	4	88	7	1	4	3	1
3	6	1	1	2	2	89	1	1	2	1	2
4	1	1	2	1	3	89	1	1	3	2	4
4	2	1	4	1	3	89	2	1	3	1	4
4	3	1	4	2	3	89	3	1	3	2	4
4	4	1	4	2	3	89	4	1	4	2	2
4	5	1	2	2	1	89	5	1	2	2	3
4	6	1	4	2	3	89	6	1	4	2	4
4	7	1	2	2	3	89	7	1	3	2	3
5	1	1	1	1	1	89	8	1	4	2	3
5	2	1	2	1	4	89	9	1	2	2	4
5	3	1	4	3	3	89	10	1	2	2	3
5	4	1	3	3	2	91	1	1	4	1	4
5	5	1	4	3	2	91	2	1	3	1	4
6	1	1		1	1	91	3	1	1	2	2
6	2	1	4	1	3	91	4	1	3	1	2
6	3	1	3	2	3	91	5	1	2	2	1
6	4	1	3	2	3	92	1	1	2	1	1
6	5	1	3	2	3	92	2	2	2	2	3
6	6	1	2	2	2	92	3	1	3	2	4
6	7	1	4	2	3	92	4	1	3	2	1
6	8	1	2	2	2	92	5	1	3	2	2
6	9	1	2	2	2	92	6	1	3	2	4
6	10	1		2	1	92	7	1	4	1	4
7	1	1	3	1	2	93	1	1	2	1	4
7	2	1	3	1	2	93	2	1	2	1	4
7	3	1	2	2	1	93	3	1	1	1	4

7	4	1	2	2	1	93	4	1	3	3	2
7	5	2	3	2	3	93	5	1	3	3	2
7	6	2	2	2	1	93	6	1	3	3	3
7	7	1	2	2	2	93	7	1	4	2	3
7	8	1	4	2	3	93	8	1	3	3	1
7	9	1	3	2	2	93	9	1	4	2	1
8	1	1	4	1	3	94	1	1	4	1	4
8	2	1	3	1	4	94	2	1	2	3	1
8	3	1	4	1	4	94	3	1	2	2	1
8	4	1	3	3	2	94	4	1	4	3	3
8	5	1	3	3	2	94	5	1	4	3	2
8	6	1	3	3	3	94	6	1	3	3	3
8	7	2	2	3	2	94	7	1	4	3	1
9	1	1	2	1	4	95	1	1	2	1	4
9	2	1	2	1	4	95	2	1	1	1	3
9	3	1	1	1	4	95	3	1	4	2	3
9	4	1	2	2	3	95	4	1	2	2	4
9	5	1	4	2	4	96	1	1	2	1	4
9	6	1	1	2	2	96	2	2	3	2	2
9	7	1	3	2	4	96	3	1	3	2	4
9	8	1	4	2	4	96	4	1	4	2	2
9	9	1	4	2	2	96	5	1	3	2	2
10	1	1	2	1	4	96	6	1	4	2	4
10	2	1	4	2	3	96	7	1	4	1	4
10	3	1	3	2	2	96	8	1	4	2	4
10	4	1	4	2	2	97	1	1	2	1	4
10	5	1	3	2	1	97	2	1	4	1	4
10	6	1	3	2	2	97	3	1	4	2	4
10	7	1	4	2	4	97	4	1	2	3	1
11	1	1	2	1	1	97	5	1	4	2	4
11	2	2	4	1	4	97	6	1	2	2	2
11	3	1	4	2	2	97	7	1	2	2	3
11	4	1	3	2	2	97	8	1	3	3	2
11	5	1	2	1	2	98	1	1	2	1	2
11	6	2	1	2	1	98	2	1	1	2	1
11	7	1	2	2	2	98	3	1	3	1	4
12	1	1	3	1	2	98	4	1	2	3	1
12	2	1	3	3	4	98	5	1	1	3	1
12	3	1	4	3	3	98	6	2	2	2	1
12	4	2	3	3	3	98	7	1	2	3	2
12	5	1	3	3	3	98	8	1	2	1	4
12	6	1	3	2	2	98	9	2	3	1	4
12	7	2	2	2	2	98	10	1	4	3	1

12	8	2	3	2	2	99	1	1	1	1	3
12	9	1	1	2	2	99	2	1	1	1	1
13	1	1	2	1	2	99	3	1	4	1	4
13	2	1	4	1	4	99	4	1	3	2	3
13	3	1	2	2	3	99	5	1	1	2	4
13	4	1	2	2	2	99	6	2	3	2	2
13	5	1	2	2	1	99	7	1	2	2	1
13	6	1	3	2	2	100	1	1	2	1	1
13	7	1	4	2	4	100	2	1	4	2	4
13	8	2	2	2	3	100	3	1	2	1	1
14	1	1	2	1	4	100	4	1	3	2	1
14	2	1	2	3	2	100	5	1	1	2	1
14	3	1	2	3	2	100	6	1	1	2	1
14	4	1	3	3	3	100	7	1	2	2	1
14	5	1	3	3	2	100	8	1	3	2	1
14	6	1	3	1	3	100	9	1	2	2	1
15	1	1	3	1	3	100	10	1	3	2	1
15	2	1	3	2	1	100	11	1	4	3	1
15	3	2	3	2	1	101	1	1	2	1	1
15	4	1	3	2	3	101	2	1	4	2	4
15	5	1	3	2	3	101	3	1	4	2	4
15	6	1	3	2	4	101	4	1	4	1	2
15	7	1	3	2	3	101	5	1	3	2	2
15	8	1	3	1	3	101	6	1	2	2	1
15	9	1	4	2	2	101	7	1	2	2	1
15	10	1	3	2	4	101	8	2	2	2	2
15	11	1	4	2	3	101	9	1	4	2	3
15	12	1	3	2	3	101	10	1	2	2	1
15	13	2	4	2	3	101	11	1	4	2	4
17	1	1	2	1	4	101	12	2	3	2	4
17	2	1	1	3	3	101	13	1	3	2	2
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59	4	1	4	3	3	146	6	1	2	2	3
59	5	1	2	2	1	147	1	1	3	1	1
59	6	1	4	2	3	147	2	1	1	1	1
59	7	1	2	2	3	147	3	1	3	2	2
59	8	1	2	2	3	147	4	2	2	2	2
60	1	1	1	1	2	147	5	1	3	2	3
60	2	1	3	1	1	148	1	1	2	1	2
60	3	1	2	3	1	148	2	2	4	1	4
60	4	2	3	3	2	148	3	1	3	2	3
60	5	1	3	3	2	148	4	1	4	3	2
60	6	1	3	2	1	148	5	1	3	2	2
60	7	2	2	2	1	148	6	2	3	2	1
60	8	1	3	3	2	148	7	1	2	2	1
62	1	1	2	1	4	149	1	1	3	1	4
62	2	1	3	2	2	149	2	1	2	1	4
62	3	2	2	2	4	149	3	1	2	2	2
62	4	2	2	2	1	149	4	1	4	2	2
62	5	1	4	2	3	149	5	2	3	2	1
62	6	1	3	2	2	149	6	1	4	2	1
62	7	2	2	2	1	149	7	1	3	2	1
62	8	2	2	2	2	150	1	1	3	2	2
62	9	1	3	1	2	150	2	1	3	2	1
62	10	1	4	2	2	150	3	1	2	1	4
62	11	1	3	2	2	150	4	1	2	2	2
63	1	1	3	1	4	150	5	1	1	1	3
63	2	1	4	1	4	150	6	1	1	2	3
63	3	1	4	2	2	151	1	1	2	1	4
63	4	1	4	2	4	151	2	1	4	1	4
63	5	1	4	2	4	151	3	1	4	2	3
64	1	1	3	1	2	151	4	1	4	2	3
64	2	1	2	2	1	151	5	1	4	1	4
64	3	2	3	2	2	151	6	1	4	2	4
64	4	1	3	2	2	151	7	1	4	2	3

64	5	1	2	2	2	151	8	1	2	2	1
65	1	1	2	1	2	152	1	1	2	1	1
65	2	1	3	1	4	152	2	1	3	3	2
65	3	1	1	2	3	152	3	1	3	3	2
65	4	2	2	2	2	152	4	1	2	2	2
65	5	1	4	2	3	152	5	1	4	1	4
65	6	1	1	2	1	152	6	1	4	2	3
65	7	1	2	2	2	152	7	2	3	2	3
65	8	1	2	2	2	152	8	1	4	2	2
65	9	2	2	2	1	152	9	1	3	2	2
66	1	1	2	1	4	152	10	1	2	2	3
66	2	1	3	1	2	152	11	1	3	2	3
66	3	1	2	2	2	153	1	1	1	2	2
66	4	1	2	2	2	153	2	1	2	2	4
66	5	1	4	2	4	153	3	1	2	1	3
66	6	1	3	2	3	153	4	2	2	2	1
66	7	2	1	2	1	153	5	1	2	2	2
68	1	1	4	1	4	153	6	1	2	2	2
68	2	1	2	2	4	153	7	1	1	2	3
68	3	1	2	2	4	154	1	1	2	1	3
68	4	1	4	1	4	154	2	2	2	2	3
68	5	1	2	2	3	154	3	1	2	2	3
68	6	1	2	2	4	154	4	2	2	2	1
69	1	1	2	1	4	154	5	1	4	2	4
69	2	1	2	1	4	154	6	1	4	2	3
69	3	1	3	2	1	154	7	2	2	2	2
69	4	1	3	2	2	154	8	1	3	2	4
69	5	2	2	2	2	154	9	1	3	1	4
69	6	1	3	2	2	154	10	1	3	2	4
69	7	1	4	2	4	154	11	1	3	2	2
69	8	1	4	2	4	155	1	1	3	1	4
69	9	1	2	2	3	155	2	1	4	1	4
70	1	1	2	1	3	155	3	1	2	2	4
70	2	1	2	1	1	155	4	1	4	2	4
70	3	1	4	1	4	155	5	1	4	2	4
70	4	1	4	2	3	155	6	1	4	1	4
70	5	1	1	2	2	155	7	1	4	2	4
70	6	2	4	2	2	155	8	1	4	2	1
70	7	1	3	2	2	155	9	2	3	2	2
70	8	1	4	1	4	155	10	1	4	2	3
70	9	1	3	2	4	155	11	1	3	2	4
71	1	1	2	1	4	155	12	1	2	2	1
71	2	1	2	1	4	156	1	1	2	1	4

71	3	1	4	1	4	156	2	1	4	1	4
71	4	1	1	2	4	156	3	1	3	1	4
71	5	1	2	2	3	156	4	1	3	2	2
72	1	1	2	1	1	156	5	1	4	2	4
72	2	1	2	2	1	156	6	1	4	3	4
72	3	1	1	2	1	156	7	1	2	2	2
72	4	1	2	1	3	156	8	2	3	2	2
73	1	1	2	1	2	156	9	1	4	2	3
73	2	2	4	2	4	157	1	1	3	1	2
73	3	2	3	2	4	157	2	1	3	2	2
73	4	1	4	2	4	157	3	1	2	2	2
73	5	1	3	2	4	157	4	1	4	2	2
73	6	1	4	2	4	158	1	1	3	1	4
73	7	1	4	2	4	158	2	1	4	2	1
73	8	1	3	1	1	158	3	1	4	2	4
74	1	1	3	1	2	158	4	1	4	2	2
74	2	1	3	1	4	158	5	1	3	2	3
74	3	1	4	1	3	158	6	1	4	2	3
74	4	2	3	3	4	159	1	1	2	1	3
74	5	1	4	2	2	159	2	1	1	2	2
74	6	1	3	2	2	159	3	1	3	1	3
74	7	1	2	2	1	159	4	1	4	2	3
74	8	1	2	2	1	159	5	1	2	2	2
74	9	2	3	2	3	159	6	1	2	2	2
74	10	1	2	2	1	159	7	1	2	2	1
74	11	1	4	2	2	162	1	1	4	1	4
75	1	1	1	1	3	162	2	1	2	1	1
75	2	1	4	1	3	162	3	1	4	2	4
75	3	1	3	2	3	162	4	1	1	1	4
75	4	1	2	2	2	162	5	1	4	2	4
75	5	1	3	2	1	162	6	2	2	2	2
75	6	1	2	2	1	162	7	1	4	2	4
75	7	1	2	2	1	162	8	1	2	1	4
76	1	1	2	1	1	163	1	1	2	1	3
76	2	1	1	2	1	163	2	1	1	1	1
76	3	1	1	2	1	163	3	1	3	1	3
76	4	1	3	3		163	4	1	2	2	2
76	5	1	3	3	1	163	5	2	3	2	1
76	6	1	3	3		163	6	2	3	2	2
76	7	1	1	2		163	7	2	2	2	1
77	1	1	2	1	1	163	8	1	2	2	1
77	2	1	4	1	3	163	9	1	2	2	2
77	3	1	4	3	3	163	10	1	4	2	3

77	4	2	3	3	2	163	11	1	3	2	3
77	5	2	3	3	3	163	12	1	2	2	3
77	6	1	3	3	1	163	13	1	4	2	3
77	7	1	3	3	1	164	1	1	3	1	4
77	8	1	4	3	3	164	2	1	3	2	2
77	9	1	2	3	3	164	3	1	3	2	1
77	10	1	3	3	2	164	4	1	4	2	4
77	11	1	3	3	3	164	5	1	2	2	1
78	1	1	2	1	4	164	6	1	3	2	2
78	2	1	4	2	4	164	7	1	1	2	3
78	3	1	4	2	1	164	8	1	4	2	2
78	4	1	4	2	4	164	9	1	3	2	2
78	5	1	4	2	3	164	10	2	2	2	1
78	6	1	3	2	2	164	11	1	3	3	4
78	7	2	4	2	2	164	12	1	3	2	3
79	1	1	2	1	2	165	1	1	2	1	4
79	2	1	2	1	1	165	2	1	2	2	2
79	3	1	2	2	1	165	3	1	2	2	1
79	4	1	3	2	2	165	4	1	2	2	2
79	5	1	2	2	1	165	5	2	4	2	4
79	6	1	3	2	1	165	6	1	4	2	3
79	7	1	4	2	2	165	7	1	2	2	3
79	8	2	3	2	1	165	8	1	1	2	2
80	1	1	2	1	3	166	1	1	3	1	3
80	2	1	2	2	1	166	2	1	4	1	4
80	3	1	4	2	2	166	3	2	3	3	1
80	4	1	3	1	3	166	4	1	3	3	3
80	5	1	1	2	4	166	5	1	2	3	2
80	6	1	3	2	3	166	6	1	3	3	1
80	7	1	2	2	1	167	1	1	2	1	3
80	8	1	2	2	1	167	2	1	3	1	3
81	1	1	4	1	3	167	3	1	3	3	3
81	2	1	2	1	3	167	4	1	2	3	3
81	3	1	1	3	1	167	5	1	4	3	2
81	4	1	3	3	1	167	6	1	4	3	3
81	5	1	2	3	1	167	7	1	3	3	3
82	1	1	2	1	1	167	8	1	2	3	2
82	2	2	4	1	1	167	9	1	3	3	2
82	3	1	2	2	1	167	10	1	3	3	1
82	4	1	3	2	3	167	11	2	2	2	1
82	5	1	1	2	1	168	1	1	4	1	4
82	6	1	4	2	2	168	2	2	3	1	4
82	7	1	1	2	1	168	3	1	4	2	4

83	1	1	4	1	2	168	4	1	2	2	3
83	2	2	3	1	2	168	5	1	2	2	2
83	3	1	2	2	2	171	1	1	1	1	1
83	4	1	4	2	3	171	2	1	1	1	1
83	5	1	3	2	2	171	3	2	2	2	1
83	6	1	1	2	1	171	4	1	1	2	1
83	7	1	4	2	2	171	5	1	1	2	1
83	8	1	4	2	3	171	6	1	1	2	1
83	9	1	2	2	2	171	7	1	2	2	1
83	10	2	4	2	2	171	8	1	2	2	1
84	1	1	1	1	4	171	9	1	1	2	1
84	2	1	2	2	1	171	10	1	3	2	1
84	3	1	2	2	2	172	1	1	1	1	1
84	4	1	2	2	1	172	2	1	2	2	1
84	5	1	2	2	2	172	3	1	1	1	1
84	6	1	3	2	2	173	1	1	1	1	2
84	7	1	1	2	1	173	2	1	4	1	2
84	8	1	1	2	2	173	3	1	4	2	2
85	1	1	1	1	2	173	4	2	2	2	2
85	2	1	2	1	3	173	5	1	4	2	2
85	3	1	1	2	1	173	6	2	2	2	1
85	4	1	2	3	1	173	7	1	3	2	1
85	5	1	2	2	3	173	8	1	3	2	1
85	6	2	2	2	1						
85	7	1	2	3	3						

Appendix B – List of internal alignment calculations

Gender subgroups	Male category	Female category
Age alignment	Age alignment in male subgroups	Age alignment in female subgroups
Title alignment	Title alignment in male subgroups	Title alignment in female subgroups
Experience alignment	Exp. alignment in male subgroups	Exp. alignment in female subgroups

Age subgroups	<50 category	50-59 category	60-67 category	>67 category
Gender alignment	Gender alignment in < 50 subgroups	Gender alignment in 50-59 subgroups	Gender alignment in 60-67 subgroups	Gender alignment in >67 subgroups
Title alignment	Title alignment in < 50 subgroups	Title alignment in 50-59 subgroups	Title alignment in 60-67 subgroups	Title alignment in >67 subgroups
Experience alignment	Exp. alignment in < 50 subgroups	Exp. alignment in 50-59 subgroups	Exp. alignment in 60-67 subgroups	Exp. alignment in >67 subgroups

Title subgroups	Leading category	Inside category	Outside category
Gender alignment	Gender alignment in leading subgroups	Gender alignment in inside subgroups	Gender alignment in outside subgroups
Age alignment	Age alignment in leading subgroups	Age alignment in inside subgroups	Age alignment in outside subgroups
Experience alignment	Exp. alignment in leading subgroups	Exp. alignment in inside subgroups	Exp. alignment in outside subgroups

Experience subgroups	0-3 category	4-7 category	8-11 category	>12 category
Gender alignment	Gender alignment in 0-3 subgroups	Gender alignment in 4-7 subgroups	Gender alignment in 8-11 subgroups	Gender alignment in >12 subgroups
Age alignment	Age alignment in 0-3 subgroups	Age alignment in 4-7 subgroups	Age alignment in 8-11 subgroups	Age alignment in >12 subgroups
Title alignment	Title alignment in 0-3 subgroups	Title alignment in 4-7 subgroups	Title alignment in 8-11 subgroups	Title alignment in >12 subgroups

Appendix C – Event study and regression analysis coding for Stata 13.0

```
*******stock prices
reshape long stockprice, i(sdate) j(company_id)
destring, replace
gen datevar=date(sdate,"MDY")
sort company_id datevar

******event dates
destring, replace
gen event_date = date(event,"DMY")
sort company_id event_date

***Merge stock prices and event dates and create ‘main file’
 merge m:m company_id using "C:\Users\Nouredyn\Desktop\Master
Thesis\Database\Event Study\2006-2014\event dates.dta"
 drop _merge
 sort reference1 datevar

****indices
reshape long index, i(sdate) j(reference1) string
destring, replace
gen datevar=date(sdate,"MDY")
sort reference1 datevar


***Merge main file with indices and create ‘event study’
merge m:1 reference1 datevar using "C:\Users\Nouredyn\Desktop\Master
Thesis\Database\Event Study\2006-2014\indices.dta"
drop _merge

*******event study

destring, replace

sort company_id datevar
tsset company_id datevar

sort company_id datevar
by company_id: gen datenum=_n
by company_id: gen target=datenum if datevar==event_date
egen td=min(target), by(company_id)
drop target
gen dif=datenum-td

tsset company_id datenum
by company_id: gen ret=(stockprice-L.stockprice)/L.stockprice
by company_id: gen marketret=(index-L.index)/L.index

by company_id: gen event_window=1 if dif>=0 & dif<=1
egen count_event_obs=count(event_window), by(company_id)
by company_id: gen estimation_window=1 if dif<-30 & dif>=-60
egen count_est_obs=count(estimation_window), by(company_id)
replace event_window=0 if event_window==.
replace estimation_window=0 if estimation_window==.

tab company_id if count_event_obs<2
tab company_id if count_est_obs<30

drop if count_event_obs<2
drop if count_est_obs<30
```

```
drop count_event_obs count_est_obs

gen predicted_return=.
egen id=group(company_id)

forvalues i=1(1)N {
l id company_id if id==`i'& dif==0
reg ret marketret if id==`i' & estimation_window==1
predict p if id==`i'
replace predicted_return = p if id==`i' & event_window==1
drop p
}
***Where N is the amount of companies


sort id datevar
gen abnormal_return=ret-predicted_return if event_window==1
by id: gen cumulative_abnormal_return = sum(abnormal_return)

graph twoway line abnormal_return dif if (dif <2 & dif>-1), by(id)

graph twoway line cumulative_abnormal_return dif if (dif <2 & dif>-1),
by(id)


sort id datenum
by id: egen ar_sd = sd(abnormal_return)
gen test =(1/(N))*(cumulative_abnormal_return/ar_sd)
list company_id cumulative_abnormal_return test if dif==0

***Where N is the amount of days in the event window

reg cumulative_abnormal_return if dif==0, robust

sort dif
by dif: egen CAR=sum(cumulative_abnormal_return)
sort id datenum

twoway (line CAR dif if (dif <2 & dif>-6))


sum abnormal_return if dif==-5
sum abnormal_return if dif==-4
sum abnormal_return if dif==-3
sum abnormal_return if dif==-2
sum abnormal_return if dif==-1
sum abnormal_return if dif==0
sum abnormal_return if dif==1

sort dif id datevar
by dif: gen cum_abnormal_return_min5 = sum(abnormal_return) if dif==-5
by dif: gen cum_abnormal_return_min4 = sum(abnormal_return) if dif==-4
by dif: gen cum_abnormal_return_min3 = sum(abnormal_return) if dif==-3
by dif: gen cum_abnormal_return_min2 = sum(abnormal_return) if dif==-2
by dif: gen cum_abnormal_return_min1 = sum(abnormal_return) if dif==-1
by dif: gen cum_abnormal_return_0 = sum(abnormal_return) if dif==0
by dif: gen cum_abnormal_return_1 = sum(abnormal_return) if dif==1

gen mean_abnormal_return_min5 = cum_abnormal_return_min5/225
gen mean_abnormal_return_min4 = cum_abnormal_return_min4/225
```

```
gen mean_abnormal_return_min3 = cum_abnormal_return_min3/225
gen mean_abnormal_return_min2 = cum_abnormal_return_min2/225
gen mean_abnormal_return_min1 = cum_abnormal_return_min1/225
gen mean_abnormal_return_0 = cum_abnormal_return_0/225
gen mean_abnormal_return_1 = cum_abnormal_return_1/225

drop cum_abnormal_return_min5 cum_abnormal_return_min4
cum_abnormal_return_min3 cum_abnormal_return_min2 cum_abnormal_return_min1
cum_abnormal_return_0 cum_abnormal_return_1

rename mean_abnormal_return_min5 mean_ab_ret_m5
rename mean_abnormal_return_min4 mean_ab_ret_m4
rename mean_abnormal_return_min3 mean_ab_ret_m3
rename mean_abnormal_return_min2 mean_ab_ret_m2
rename mean_abnormal_return_min1 mean_ab_ret_m1
rename mean_abnormal_return_0 mean_ab_ret_0
rename mean_abnormal_return_1 mean_ab_ret_1

graph bar mean_ab_ret_m5 mean_ab_ret_m4 mean_ab_ret_m3 mean_ab_ret_m2
mean_ab_ret_m1 mean_ab_ret_0 mean_ab_ret_1 if id==225

sort dif company_id datevar
by dif: egen CAR=sum(cumulative_abnormal_return)
sort id datenum

gen CAAR = CAR/225
graph twoway line CAR dif if (dif <2 & dif>-7 & id==1), by(id)
sort dif
ttest CAAR by(dif)


***control variables
**merge with control variables, per year

destring, replace

gen market_value = mvy_2006
replace market_value = mvy_2007 if event_date>=17167 & event_date<=17531
replace market_value = mvy_2008 if event_date>=17532 & event_date<=17897
replace market_value = mvy_2009 if event_date>=17898 & event_date<=18262
replace market_value = mvy_2010 if event_date>=18263 & event_date<=18627
replace market_value = mvy_2011 if event_date>=18630 & event_date<=18991
replace market_value = mvy_2012 if event_date>=18994 & event_date<=19358
replace market_value = mvy_2013 if event_date>=19359 & event_date<=19723
replace market_value = mvy_2014 if event_date>=19724

gen market_value_prev = mvy_2006
replace market_value_prev = mvy_2006 if event_date>=17167 &
event_date<=17531
replace market_value_prev = mvy_2007 if event_date>=17532 &
event_date<=17897
replace market_value_prev = mvy_2008 if event_date>=17898 &
event_date<=18262
replace market_value_prev = mvy_2009 if event_date>=18263 &
event_date<=18627
replace market_value_prev = mvy_2010 if event_date>=18630 &
event_date<=18991
replace market_value_prev = mvy_2011 if event_date>=18994 &
event_date<=19358
replace market_value_prev = mvy_2012 if event_date>=19359 &
event_date<=19723
```

```
replace market_value_prev = mvy_2013 if event_date>=19724

gen book_value = bvy_2006
replace book_value = bvy_2007 if event_date>=17167 & event_date<=17531
replace book_value = bvy_2008 if event_date>=17532 & event_date<=17897
replace book_value = bvy_2009 if event_date>=17898 & event_date<=18262
replace book_value = bvy_2010 if event_date>=18263 & event_date<=18627
replace book_value = bvy_2011 if event_date>=18630 & event_date<=18991
replace book_value = bvy_2012 if event_date>=18994 & event_date<=19358
replace book_value = bvy_2013 if event_date>=19359 & event_date<=19723
replace book_value = bvy_2014 if event_date>=19724

gen book_value_prev = bvy_2006
replace book_value_prev = bvy_2006 if event_date>=17167 & event_date<=17531
replace book_value_prev = bvy_2007 if event_date>=17532 & event_date<=17897
replace book_value_prev = bvy_2008 if event_date>=17898 & event_date<=18262
replace book_value_prev = bvy_2009 if event_date>=18263 & event_date<=18627
replace book_value_prev = bvy_2010 if event_date>=18630 & event_date<=18991
replace book_value_prev = bvy_2011 if event_date>=18994 & event_date<=19358
replace book_value_prev = bvy_2012 if event_date>=19359 & event_date<=19723
replace book_value_prev = bvy_2013 if event_date>=19724

gen book_to_market_ratio = book_value/market_value
gen book_to_market_ratio_prev = book_value_prev/market_value_prev

gen roa = roay_2006
replace roa = roay_2007 if event_date>=17167 & event_date<=17531
replace roa = roay_2008 if event_date>=17532 & event_date<=17897
replace roa = roay_2009 if event_date>=17898 & event_date<=18262
replace roa = roay_2010 if event_date>=18263 & event_date<=18627
replace roa = roay_2011 if event_date>=18630 & event_date<=18991
replace roa = roay_2012 if event_date>=18994 & event_date<=19358
replace roa = roay_2013 if event_date>=19359 & event_date<=19723
replace roa = roay_2014 if event_date>=19724

gen roa_prev = roay_2006
replace roa_prev = roay_2006 if event_date>=17167 & event_date<=17531
replace roa_prev = roay_2007 if event_date>=17532 & event_date<=17897
replace roa_prev = roay_2008 if event_date>=17898 & event_date<=18262
replace roa_prev = roay_2009 if event_date>=18263 & event_date<=18627
replace roa_prev = roay_2010 if event_date>=18630 & event_date<=18991
replace roa_prev = roay_2011 if event_date>=18994 & event_date<=19358
replace roa_prev = roay_2012 if event_date>=19359 & event_date<=19723
replace roa_prev = roay_2013 if event_date>=19724

gen net_income = nety_2006
replace net_income = nety_2007 if event_date>=17167 & event_date<=17531
replace net_income = nety_2008 if event_date>=17532 & event_date<=17897
replace net_income = nety_2009 if event_date>=17898 & event_date<=18262
replace net_income = nety_2010 if event_date>=18263 & event_date<=18627
replace net_income = nety_2011 if event_date>=18630 & event_date<=18991
replace net_income = nety_2012 if event_date>=18994 & event_date<=19358
replace net_income = nety_2013 if event_date>=19359 & event_date<=19723
replace net_income = nety_2014 if event_date>=19724

gen net_income_prev = nety_2006
replace net_income_prev = nety_2006 if event_date>=17167 &
event_date<=17531
replace net_income_prev = nety_2007 if event_date>=17532 &
event_date<=17897
```

```
replace net_income_prev = nety_2008 if event_date>=17898 &
event_date<=18262
replace net_income_prev = nety_2009 if event_date>=18263 &
event_date<=18627
replace net_income_prev = nety_2010 if event_date>=18630 &
event_date<=18991
replace net_income_prev = nety_2011 if event_date>=18994 &
event_date<=19358
replace net_income_prev = nety_2012 if event_date>=19359 &
event_date<=19723
replace net_income_prev = nety_2013 if event_date>=19724

gen total_debt = dey_2006
replace total_debt = dey_2007 if event_date>=17167 & event_date<=17531
replace total_debt = dey_2008 if event_date>=17532 & event_date<=17897
replace total_debt = dey_2009 if event_date>=17898 & event_date<=18262
replace total_debt = dey_2010 if event_date>=18263 & event_date<=18627
replace total_debt = dey_2011 if event_date>=18630 & event_date<=18991
replace total_debt = dey_2012 if event_date>=18994 & event_date<=19358
replace total_debt = dey_2013 if event_date>=19359 & event_date<=19723
replace total_debt = dey_2014 if event_date>=19724

gen total_debt_prev = dey_2006
replace total_debt_prev = dey_2006 if event_date>=17167 & event_date<=17531
replace total_debt_prev = dey_2007 if event_date>=17532 & event_date<=17897
replace total_debt_prev = dey_2008 if event_date>=17898 & event_date<=18262
replace total_debt_prev = dey_2009 if event_date>=18263 & event_date<=18627
replace total_debt_prev = dey_2010 if event_date>=18630 & event_date<=18991
replace total_debt_prev = dey_2011 if event_date>=18994 & event_date<=19358
replace total_debt_prev = dey_2012 if event_date>=19359 & event_date<=19723
replace total_debt_prev = dey_2013 if event_date>=19724

gen total_assets = asy_2006
replace total_assets = asy_2007 if event_date>=17167 & event_date<=17531
replace total_assets = asy_2008 if event_date>=17532 & event_date<=17897
replace total_assets = asy_2009 if event_date>=17898 & event_date<=18262
replace total_assets = asy_2010 if event_date>=18263 & event_date<=18627
replace total_assets = asy_2011 if event_date>=18630 & event_date<=18991
replace total_assets = asy_2012 if event_date>=18994 & event_date<=19358
replace total_assets = asy_2013 if event_date>=19359 & event_date<=19723
replace total_assets = asy_2014 if event_date>=19724

gen total_assets_prev = asy_2006
replace total_assets_prev = asy_2006 if event_date>=17167 &
event_date<=17531
replace total_assets_prev = asy_2007 if event_date>=17532 &
event_date<=17897
replace total_assets_prev = asy_2008 if event_date>=17898 &
event_date<=18262
replace total_assets_prev = asy_2009 if event_date>=18263 &
event_date<=18627
replace total_assets_prev = asy_2010 if event_date>=18630 &
event_date<=18991
replace total_assets_prev = asy_2011 if event_date>=18994 &
event_date<=19358
replace total_assets_prev = asy_2012 if event_date>=19359 &
event_date<=19723
replace total_assets_prev = asy_2013 if event_date>=19724

gen firm_leverage = total_debt/total_assets
gen firm_leverage_prev = total_debt_prev/total_assets_prev
```

```
drop mvy_2006 mvy_2007 mvy_2008 mvy_2009 mvy_2010 mvy_2011 mvy_2012
mvy_2013 mvy_2014 bvy_2006 bvy_2007 bvy_2008 bvy_2009 bvy_2010 bvy_2011
bvy_2012 bvy_2013 bvy_2014 roay_2006 roay_2007 roay_2008 roay_2009
roay_2010 roay_2011 roay_2012 roay_2013 roay_2014 nety_2006 nety_2007
nety_2008 nety_2009 nety_2010 nety_2011 nety_2012 nety_2013 nety_2014
dey_2006 dey_2007 dey_2008 dey_2009 dey_2010 dey_2011 dey_2012 dey_2013
dey_2014 asy_2006 asy_2007 asy_2008 asy_2009 asy_2010 asy_2011 asy_2012
asy_2013 asy_2014

***Regression analysis

regress car_7days nfls_overall
regress car_2days nfls_overall

graph matrix car_7days car_2days nfls_overall, half

gen car_7days_dich = 0
replace car_7days_dich = 1 if car_7days>0
gen car_2days_dich = 0
replace car_2days_dich = 1 if car_2days>0

regress car_7days_dich nfls_overall
regress car_2days_dich nfls_overall

graph matrix car_2days_dich nfls_overall, half

winsor car_7days , gen(wcar_7days ) p(0.01)
winsor car_2days , gen(wcar_2days ) p(0.01)
gen wcar_7days_dich = 0
replace wcar_7days_dich = 1 if wcar_7days>0
gen wcar_2days_dich = 0
replace wcar_2days_dich = 1 if wcar_2days>0

regress wcar_7days nfls_overall
outreg2 using winsor_regression.xls, replace ctitle(7 day window)
regress wcar_2days nfls_overall
outreg2 using winsor_regression.xls, append ctitle(2 day window)
regress wcar_7days_dich nfls_overall
outreg2 using winsor_regression.xls, append ctitle(dich 7 day window)
regress wcar_2days_dich nfls_overall
outreg2 using winsor_regression.xls, append ctitle(dich 2 day window)


****with control variables

**merge with fls on team_id

winsor car_7days , gen(wcar_7days ) p(0.01)
winsor car_2days , gen(wcar_2days ) p(0.01)

gen car_7days_dich = 0
replace car_7days_dich = 1 if car_7days>0
gen car_2days_dich = 0
replace car_2days_dich = 1 if car_2days>0

regress wcar_7days nfls_overall book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev
outreg2 using controlled_regression.xls, replace ctitle(7 day window)
regress wcar_2days nfls_overall book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev
```

```
outreg2 using controlled_regression.xls, append ctitle(2 day window)
regress car_7days_dich nfls_overall book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev
outreg2 using controlled_regression.xls, append ctitle(7 day window
dichotomous)
regress car_2days_dich nfls_overall book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev
outreg2 using controlled_regression.xls, append ctitle(2 day window
dichotomous)


regress wcar_7days nfls_gender book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

regress wcar_7days nfls_age book_to_market_ratio book_to_market_ratio_prev
roa roa_prev firm_leverage firm_leverage_prev

regress wcar_7days nfls_title book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

regress wcar_7days nfls_exp book_to_market_ratio book_to_market_ratio_prev
roa roa_prev firm_leverage firm_leverage_prev

regress car_7days_dich nfls_gender book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

regress car_7days_dich nfls_age book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

regress car_7days_dich nfls_title book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

regress car_7days_dich nfls_exp book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev



regress wcar_2days nfls_gender book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

outreg2 using controlled_regression2.xls, replace ctitle(2 day window
gender)

regress wcar_2days nfls_age book_to_market_ratio book_to_market_ratio_prev
roa roa_prev firm_leverage firm_leverage_prev

outreg2 using controlled_regression2.xls, append ctitle(2 day window age)

regress wcar_2days nfls_title book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

outreg2 using controlled_regression2.xls, append ctitle(2 day window title)

regress wcar_2days nfls_exp book_to_market_ratio book_to_market_ratio_prev
roa roa_prev firm_leverage firm_leverage_prev

outreg2 using controlled_regression2.xls, append ctitle(2 day window
experience)
```

```
regress car_2days_dich nfls_gender book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

outreg2 using controlled_regression2.xls, append ctitle(2 day window
dichotomous gender)

regress car_2days_dich nfls_age book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

outreg2 using controlled_regression2.xls, append ctitle(2 day window
dichotomous age)

regress car_2days_dich nfls_title book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

outreg2 using controlled_regression2.xls, append ctitle(2 day window
dichotomous title)

regress car_2days_dich nfls_exp book_to_market_ratio
book_to_market_ratio_prev roa roa_prev firm_leverage firm_leverage_prev

outreg2 using controlled_regression2.xls, append ctitle(2 day window
dichotomous experience)
```

Appendix D – Faultline values per attribute

Team ID	IA gen	IA age	IA tit	IA exp	IA overall	CG gen	CG age	CG tit	CG exp	CG overall	FLS gen	FLS age	FLS tit	FLS exp	FLS overall
2	0.609	0.338	0.198	0.173	0.329	0.571	0.504	0.476	0.333	0.471	0.261	0.168	0.103	0.116	0.162
3	0.040	0.306	0.370	0.250	0.241	1.000	0.281	0.440	0.519	0.560	0.000	0.220	0.207	0.120	0.137
4	0.229	0.339	0.432	0.143	0.286	1.000	0.750	0.767	0.667	0.796	0.000	0.085	0.101	0.048	0.058
5	0.042	0.167	0.296	0.167	0.168	1.000	0.478	0.333	0.478	0.572	0.000	0.087	0.198	0.087	0.093
6	0.194	0.667	0.167	0.403	0.358	1.000	0.444	0.571	0.600	0.654	0.000	0.370	0.071	0.161	0.151
7	0.294	0.225	0.389	0.392	0.325	0.452	0.330	0.429	0.317	0.382	0.161	0.151	0.222	0.268	0.200
8	0.119	0.297	0.324	0.361	0.275	0.278	0.242	0.361	0.325	0.302	0.086	0.225	0.207	0.244	0.190
9	0.117	0.417	0.396	0.271	0.300	1.000	0.673	0.556	0.405	0.658	0.000	0.136	0.176	0.161	0.118
10	0.141	0.361	0.154	0.278	0.233	1.000	0.360	0.389	0.680	0.607	0.000	0.231	0.094	0.089	0.104
11	0.171	0.139	0.120	0.131	0.140	0.233	0.426	0.389	0.206	0.314	0.131	0.080	0.074	0.104	0.097
12	0.257	0.029	0.269	0.171	0.182	0.426	0.434	0.454	0.296	0.403	0.148	0.016	0.147	0.121	0.108
13	0.109	0.245	0.195	0.472	0.255	0.476	0.356	0.500	0.583	0.479	0.057	0.158	0.097	0.197	0.127
14	0.132	0.278	0.315	0.361	0.272	1.000	0.593	0.542	0.377	0.628	0.000	0.113	0.144	0.225	0.121
15	0.403	0.228	0.447	0.541	0.405	0.561	0.611	0.697	0.693	0.641	0.177	0.089	0.135	0.166	0.142
17	0.185	0.093	0.472	0.333	0.271	0.333	0.396	0.370	0.364	0.366	0.123	0.056	0.297	0.212	0.172
18	0.331	0.392	0.048	0.574	0.336	0.396	0.494	0.345	0.524	0.440	0.200	0.199	0.032	0.273	0.176
19	0.127	0.325	0.350	0.392	0.299	1.000	0.392	0.583	0.635	0.653	0.000	0.197	0.146	0.143	0.122
20	0.047	0.201	0.250	0.207	0.176	0.286	0.414	0.367	0.238	0.326	0.034	0.118	0.158	0.158	0.117
21	0.176	0.291	0.487	0.392	0.336	1.000	0.639	0.667	0.729	0.759	0.000	0.105	0.162	0.106	0.093
22	0.125	0.364	0.191	0.245	0.231	0.259	0.339	0.397	0.591	0.397	0.092	0.241	0.115	0.100	0.137
23	0.245	0.122	0.481	0.333	0.295	1.000	1.000	0.852	0.792	0.911	0.000	0.000	0.071	0.069	0.035
24	0.107	0.151	0.185	0.361	0.201	0.444	0.377	0.500	0.360	0.420	0.059	0.094	0.093	0.231	0.119
26	0.120	0.167	0.185	0.167	0.160	1.000	0.622	0.333	0.341	0.574	0.000	0.063	0.123	0.110	0.074
27	0.074	0.250	0.222	0.194	0.185	1.000	0.356	0.583	0.500	0.610	0.000	0.161	0.093	0.097	0.088
28	0.145	0.228	0.407	0.389	0.292	1.000	0.583	0.583	0.420	0.647	0.000	0.095	0.170	0.226	0.123
29	0.109	0.389	0.358	0.364	0.305	1.000	0.614	0.533	0.397	0.636	0.000	0.150	0.167	0.219	0.134
30	0.076	0.125	0.278	0.306	0.196	1.000	0.560	0.536	0.339	0.608	0.000	0.055	0.129	0.202	0.097
31	0.109	0.242	0.212	0.250	0.203	0.429	0.294	0.417	0.528	0.417	0.062	0.171	0.124	0.118	0.119
32	0.155	0.311	0.395	0.322	0.296	1.000	0.440	0.600	0.611	0.663	0.000	0.174	0.158	0.125	0.114
33	0.431	0.417	0.185	0.169	0.300	0.333	0.472	0.378	0.333	0.379	0.287	0.220	0.115	0.113	0.184
34	0.141	0.533	0.217	0.450	0.335	0.125	0.238	0.333	0.343	0.260	0.123	0.407	0.144	0.296	0.243
35	0.153	0.058	0.333	0.306	0.212	0.300	0.190	0.302	0.294	0.271	0.107	0.047	0.233	0.216	0.151
36	0.579	0.269	0.195	0.611	0.413	0.286	0.279	0.352	0.444	0.340	0.413	0.194	0.126	0.340	0.268
37	0.037	0.361	0.704	0.528	0.407	1.000	0.312	0.452	0.280	0.511	0.000	0.248	0.385	0.380	0.253
39	0.297	0.355	0.215	0.134	0.250	0.469	0.575	0.456	0.432	0.483	0.158	0.151	0.117	0.076	0.125
40	0.107	0.222	0.198	0.214	0.185	0.389	0.534	0.433	0.278	0.409	0.065	0.103	0.112	0.154	0.109
41	0.331	0.222	0.141	0.190	0.221	0.440	0.311	0.370	0.538	0.415	0.185	0.153	0.089	0.088	0.129
42	0.244	0.440	0.292	0.492	0.367	0.333	0.496	0.375	0.460	0.416	0.163	0.222	0.182	0.266	0.208
43	0.063	0.169	0.593	0.472	0.324	0.250	0.272	0.378	0.449	0.337	0.048	0.123	0.369	0.260	0.200
44	0.019	0.318	0.361	0.333	0.258	0.333	0.226	0.353	0.389	0.325	0.012	0.246	0.233	0.204	0.174

45	0.115	0.296	0.306	0.318	0.259	0.333	0.281	0.519	0.361	0.374	0.077	0.213	0.147	0.203	0.160
46	0.274	0.313	0.166	0.417	0.292	0.333	0.354	0.306	0.403	0.349	0.182	0.202	0.115	0.249	0.187
47	0.274	0.264	0.277	0.167	0.245	0.389	0.271	0.333	0.537	0.383	0.167	0.192	0.185	0.077	0.155
48	0.153	0.333	0.306	0.058	0.212	0.467	0.556	0.583	0.467	0.518	0.081	0.148	0.127	0.031	0.097
50	0.460	0.206	0.301	0.313	0.320	0.479	0.371	0.417	0.378	0.411	0.240	0.130	0.176	0.194	0.185
51	0.084	0.444	0.333	0.253	0.279	1.000	0.362	0.556	0.472	0.598	0.000	0.283	0.148	0.133	0.141
52	0.038	0.306	0.444	0.306	0.274	0.278	0.267	0.413	0.249	0.302	0.028	0.224	0.261	0.230	0.186
53	0.141	0.240	0.198	0.492	0.268	0.417	0.395	0.548	0.360	0.430	0.082	0.145	0.089	0.315	0.158
54	0.521	0.306	0.306	0.020	0.288	0.422	0.363	0.505	0.381	0.418	0.301	0.195	0.151	0.012	0.165
55	0.130	0.249	0.201	0.519	0.275	0.444	0.383	0.542	0.606	0.494	0.072	0.153	0.092	0.205	0.131
56	0.213	0.139	0.185	0.131	0.167	1.000	0.548	0.750	0.750	0.762	0.000	0.063	0.046	0.033	0.035
57	0.238	0.389	0.148	0.151	0.232	0.452	0.453	0.405	0.506	0.454	0.131	0.213	0.088	0.075	0.127
58	0.147	0.505	0.272	0.505	0.357	1.000	0.402	0.571	0.402	0.594	0.000	0.302	0.116	0.302	0.180
59	0.129	0.310	0.457	0.319	0.304	1.000	0.353	0.517	0.389	0.565	0.000	0.201	0.221	0.195	0.154
60	0.116	0.149	0.361	0.144	0.193	0.417	0.281	0.464	0.417	0.394	0.068	0.107	0.194	0.084	0.113
62	0.525	0.445	0.144	0.445	0.390	0.357	0.310	0.426	0.460	0.388	0.338	0.307	0.083	0.240	0.242
63	0.227	0.158	0.481	0.142	0.252	1.000	0.667	0.722	0.750	0.785	0.000	0.053	0.134	0.035	0.055
64	0.206	0.278	0.120	0.096	0.175	0.667	0.611	0.667	0.583	0.632	0.069	0.108	0.040	0.040	0.064
65	0.414	0.255	0.167	0.387	0.306	0.476	0.447	0.405	0.444	0.443	0.217	0.141	0.099	0.215	0.168
66	0.107	0.222	0.148	0.222	0.175	0.222	0.442	0.467	0.442	0.393	0.083	0.124	0.079	0.124	0.103
68	0.222	0.458	0.611	0.132	0.356	1.000	0.583	0.583	0.733	0.725	0.000	0.191	0.255	0.035	0.120
69	0.113	0.496	0.407	0.239	0.314	0.458	0.376	0.476	0.595	0.476	0.061	0.310	0.213	0.097	0.170
70	0.054	0.385	0.241	0.306	0.246	0.375	0.494	0.383	0.484	0.434	0.033	0.195	0.148	0.158	0.134
71	0.171	0.139	0.370	0.131	0.203	1.000	0.474	0.611	0.583	0.667	0.000	0.073	0.144	0.054	0.068
72	0.200	0.139	0.444	0.139	0.231	1.000	0.667	0.667	0.667	0.750	0.000	0.046	0.148	0.046	0.060
73	0.466	0.243	0.277	0.125	0.278	0.583	0.294	0.278	0.218	0.343	0.194	0.172	0.200	0.098	0.166
74	0.256	0.398	0.235	0.478	0.342	0.259	0.290	0.315	0.409	0.318	0.189	0.283	0.161	0.282	0.229
75	0.100	0.361	0.395	0.306	0.290	1.000	0.550	0.400	0.392	0.585	0.000	0.162	0.237	0.186	0.146
77	0.475	0.377	0.204	0.404	0.365	0.519	0.374	0.444	0.384	0.430	0.229	0.236	0.113	0.249	0.207
78	0.161	0.111	0.118	0.222	0.153	0.556	0.337	0.389	0.701	0.496	0.072	0.074	0.072	0.066	0.071
79	0.155	0.253	0.331	0.208	0.237	0.524	0.403	0.556	0.578	0.515	0.074	0.151	0.147	0.088	0.115
80	0.106	0.325	0.350	0.389	0.293	1.000	0.569	0.500	0.565	0.659	0.000	0.140	0.175	0.169	0.121
81	0.097	0.083	0.444	0.333	0.240	1.000	0.622	0.389	0.389	0.600	0.000	0.031	0.272	0.204	0.127
82	0.149	0.417	0.247	0.058	0.217	0.333	0.563	0.433	0.349	0.420	0.099	0.182	0.140	0.038	0.115
83	0.347	0.431	0.220	0.304	0.326	0.479	0.591	0.479	0.379	0.482	0.181	0.176	0.115	0.189	0.165
84	0.181	0.306	0.173	0.375	0.258	1.000	0.479	0.429	0.396	0.576	0.000	0.159	0.099	0.227	0.121
85	0.090	0.139	0.407	0.222	0.215	0.444	0.433	0.544	0.307	0.432	0.050	0.079	0.186	0.154	0.117
87	0.174	0.361	0.101	0.181	0.204	0.333	0.370	0.333	0.460	0.374	0.116	0.227	0.067	0.097	0.127
88	0.136	0.278	0.148	0.361	0.231	0.111	0.410	0.257	0.325	0.276	0.121	0.164	0.110	0.244	0.160
89	0.136	0.456	0.256	0.407	0.314	1.000	0.451	0.537	0.425	0.603	0.000	0.250	0.118	0.234	0.151
91	0.060	0.167	0.296	0.250	0.193	1.000	0.511	0.389	0.322	0.556	0.000	0.081	0.181	0.169	0.108
92	0.132	0.181	0.210	0.222	0.186	0.278	0.274	0.400	0.511	0.366	0.096	0.131	0.126	0.109	0.115
93	0.017	0.597	0.722	0.611	0.487	1.000	0.426	0.361	0.481	0.567	0.000	0.343	0.461	0.317	0.280

94	0.098	0.283	0.148	0.306	0.209	1.000	0.385	0.505	0.611	0.625	0.000	0.174	0.073	0.119	0.092
95	0.117	0.167	0.222	0.250	0.189	1.000	0.361	0.583	0.500	0.611	0.000	0.106	0.093	0.125	0.081
96	0.174	0.269	0.340	0.234	0.254	0.429	0.373	0.528	0.533	0.466	0.099	0.169	0.161	0.109	0.134
97	0.063	0.278	0.500	0.225	0.267	1.000	0.322	0.526	0.545	0.598	0.000	0.188	0.237	0.102	0.132
98	0.064	0.370	0.417	0.336	0.297	0.313	0.431	0.379	0.265	0.347	0.044	0.211	0.259	0.247	0.190
99	0.067	0.194	0.194	0.250	0.177	0.222	0.439	0.389	0.429	0.370	0.052	0.109	0.119	0.143	0.106
100	0.192	0.767	0.528	0.113	0.400	1.000	0.768	0.686	0.600	0.763	0.000	0.178	0.166	0.045	0.097
101	0.292	0.370	0.173	0.414	0.312	0.455	0.358	0.485	0.585	0.471	0.159	0.238	0.089	0.172	0.164
102	0.333	0.111	0.222	0.111	0.194	0.833	1.000	0.833	1.000	0.917	0.056	0.000	0.037	0.000	0.023
103	0.081	0.194	0.198	0.278	0.188	0.389	0.487	0.367	0.302	0.386	0.050	0.100	0.125	0.194	0.117
105	0.091	0.125	0.194	0.417	0.207	0.278	0.417	0.488	0.452	0.409	0.066	0.073	0.100	0.228	0.117
106	0.154	0.223	0.075	0.112	0.141	0.429	0.436	0.660	0.572	0.524	0.088	0.126	0.026	0.048	0.072
107	0.118	0.158	0.331	0.451	0.265	0.476	0.403	0.417	0.354	0.412	0.062	0.095	0.193	0.292	0.160
108	0.194	0.306	0.417	0.289	0.302	0.333	0.374	0.346	0.235	0.322	0.130	0.191	0.273	0.221	0.204
109	0.323	0.186	0.070	0.603	0.295	0.407	0.487	0.350	0.540	0.446	0.191	0.096	0.046	0.277	0.152
110	0.090	0.318	0.195	0.222	0.206	0.476	0.368	0.444	0.537	0.456	0.047	0.201	0.108	0.103	0.115
111	0.120	0.500	0.370	0.128	0.279	1.000	0.407	0.583	0.389	0.595	0.000	0.296	0.154	0.078	0.132
112	0.119	0.361	0.086	0.144	0.178	0.222	0.370	0.390	0.381	0.341	0.092	0.227	0.053	0.089	0.115
113	0.188	0.009	0.176	0.139	0.128	0.333	0.344	0.370	0.380	0.357	0.125	0.006	0.111	0.086	0.082
114	0.160	0.417	0.093	0.245	0.229	0.571	0.438	0.571	0.435	0.504	0.068	0.234	0.040	0.139	0.120
115	0.280	0.328	0.304	0.270	0.295	0.467	0.373	0.442	0.534	0.454	0.149	0.205	0.169	0.126	0.162
116	0.107	0.222	0.389	0.333	0.263	1.000	0.593	0.500	0.630	0.681	0.000	0.091	0.194	0.123	0.102
117	0.188	0.444	0.171	0.301	0.276	1.000	0.688	0.556	0.667	0.728	0.000	0.139	0.076	0.100	0.079
118	0.072	0.290	0.352	0.372	0.271	0.179	0.538	0.455	0.422	0.399	0.059	0.134	0.192	0.215	0.150
119	0.256	0.139	0.111	0.194	0.175	0.375	0.272	0.370	0.265	0.321	0.160	0.101	0.070	0.143	0.118
120	0.127	0.158	0.195	0.214	0.174	0.381	0.395	0.500	0.549	0.456	0.079	0.096	0.097	0.097	0.092
121	0.116	0.194	0.324	0.250	0.221	0.333	0.407	0.375	0.481	0.399	0.077	0.115	0.203	0.130	0.131
122	0.174	0.186	0.357	0.352	0.267	0.333	0.420	0.417	0.257	0.357	0.116	0.108	0.208	0.261	0.173
123	0.394	0.297	0.256	0.417	0.341	0.356	0.295	0.333	0.264	0.312	0.254	0.210	0.171	0.307	0.235
124	0.379	0.280	0.400	0.081	0.285	0.542	0.372	0.497	0.333	0.436	0.174	0.176	0.201	0.054	0.151
125	0.194	0.539	0.139	0.249	0.280	0.247	0.369	0.287	0.443	0.336	0.146	0.341	0.099	0.139	0.181
126	0.440	0.206	0.371	0.329	0.337	0.500	0.356	0.500	0.358	0.428	0.220	0.133	0.186	0.211	0.187
127	0.153	0.276	0.395	0.210	0.258	0.476	0.500	0.489	0.583	0.512	0.080	0.138	0.202	0.087	0.127
128	0.012	0.556	0.537	0.444	0.387	1.000	0.486	0.438	0.461	0.596	0.000	0.286	0.302	0.240	0.207
132	0.056	0.444	0.741	0.281	0.380	1.000	0.347	0.472	0.329	0.537	0.000	0.290	0.391	0.188	0.217
133	0.227	0.162	0.519	0.375	0.321	1.000	0.500	0.667	0.567	0.683	0.000	0.081	0.173	0.163	0.104
134	0.120	0.214	0.173	0.194	0.175	0.333	0.282	0.500	0.585	0.425	0.080	0.154	0.086	0.081	0.100
135	0.370	0.028	0.389	0.165	0.238	0.289	0.438	0.391	0.271	0.347	0.263	0.016	0.237	0.121	0.159
137	0.037	0.458	0.360	0.273	0.282	0.267	0.461	0.414	0.401	0.386	0.027	0.247	0.211	0.164	0.162
138	0.162	0.370	0.340	0.308	0.295	0.417	0.393	0.476	0.347	0.408	0.094	0.225	0.178	0.201	0.175
139	0.243	0.131	0.213	0.051	0.159	0.367	0.294	0.357	0.413	0.358	0.154	0.092	0.137	0.030	0.103
140	0.102	0.381	0.303	0.556	0.335	0.333	0.501	0.396	0.552	0.445	0.068	0.190	0.183	0.249	0.173
141	0.184	0.361	0.407	0.132	0.271	1.000	0.438	0.708	0.533	0.670	0.000	0.203	0.119	0.062	0.096

142	0.097	0.360	0.183	0.464	0.276	0.407	0.589	0.479	0.561	0.509	0.057	0.148	0.095	0.204	0.126
143	0.087	0.444	0.284	0.218	0.258	1.000	0.625	0.508	0.339	0.618	0.000	0.167	0.140	0.144	0.113
144	0.099	0.375	0.282	0.500	0.314	1.000	0.476	0.361	0.535	0.593	0.000	0.197	0.180	0.233	0.152
145	0.153	0.299	0.426	0.308	0.296	1.000	0.567	0.639	0.425	0.658	0.000	0.129	0.154	0.177	0.115
146	0.174	0.139	0.173	0.333	0.205	1.000	0.778	0.533	0.583	0.724	0.000	0.031	0.081	0.139	0.063
147	0.144	0.111	0.296	0.250	0.200	0.250	0.237	0.333	0.300	0.280	0.108	0.085	0.198	0.175	0.141
148	0.076	0.167	0.102	0.167	0.128	0.267	0.235	0.333	0.360	0.299	0.056	0.127	0.068	0.107	0.090
149	0.081	0.306	0.309	0.444	0.285	0.444	0.349	0.367	0.304	0.366	0.045	0.199	0.195	0.309	0.187
150	0.068	0.417	0.259	0.333	0.269	1.000	0.352	0.458	0.537	0.587	0.000	0.270	0.140	0.154	0.141
151	0.166	0.220	0.457	0.408	0.313	1.000	0.583	0.600	0.410	0.648	0.000	0.092	0.183	0.241	0.129
152	0.066	0.299	0.549	0.241	0.289	0.433	0.356	0.450	0.446	0.421	0.037	0.192	0.302	0.133	0.166
153	0.187	0.236	0.101	0.278	0.200	0.500	0.633	0.556	0.640	0.582	0.093	0.087	0.045	0.100	0.081
154	0.467	0.385	0.141	0.338	0.333	0.389	0.335	0.463	0.500	0.422	0.286	0.256	0.076	0.169	0.197
155	0.185	0.369	0.367	0.298	0.305	0.303	0.414	0.630	0.561	0.477	0.129	0.216	0.136	0.131	0.153
156	0.092	0.264	0.296	0.223	0.219	0.333	0.348	0.526	0.321	0.382	0.062	0.172	0.140	0.152	0.131
157	0.261	0.167	0.222	0.131	0.195	1.000	0.583	0.778	1.000	0.840	0.000	0.069	0.049	0.000	0.030
158	0.161	0.250	0.173	0.250	0.209	1.000	0.583	0.467	0.759	0.702	0.000	0.104	0.092	0.060	0.064
159	0.118	0.131	0.383	0.306	0.234	1.000	0.615	0.500	0.423	0.635	0.000	0.050	0.191	0.176	0.104
162	0.190	0.228	0.324	0.130	0.218	0.238	0.387	0.542	0.255	0.355	0.145	0.140	0.149	0.097	0.132
163	0.397	0.389	0.196	0.276	0.315	0.400	0.503	0.444	0.342	0.422	0.238	0.194	0.109	0.182	0.181
164	0.136	0.447	0.089	0.597	0.317	0.364	0.576	0.542	0.610	0.523	0.086	0.190	0.041	0.233	0.137
165	0.178	0.208	0.086	0.361	0.209	0.381	0.392	0.524	0.653	0.487	0.110	0.127	0.041	0.125	0.101
166	0.079	0.082	0.213	0.333	0.177	0.467	0.269	0.417	0.463	0.404	0.042	0.060	0.124	0.179	0.101
167	0.158	0.345	0.375	0.291	0.292	0.133	0.399	0.358	0.350	0.310	0.137	0.207	0.241	0.189	0.193
168	0.150	0.333	0.259	0.056	0.200	0.250	0.233	0.333	0.311	0.282	0.113	0.256	0.173	0.038	0.145
171	0.302	0.361	0.530	0.119	0.328	0.667	0.559	0.792	1.000	0.754	0.101	0.159	0.110	0.000	0.093
172	0.278	0.250	0.333	0.139	0.250	1.000	0.667	0.667	1.000	0.833	0.000	0.083	0.111	0.000	0.049
173	0.479	0.611	0.277	0.178	0.386	0.389	0.472	0.444	0.422	0.432	0.292	0.323	0.154	0.103	0.218

Notes: all values have been rounded to three decimals

Appendix E – Cumulative Abnormal Returns (CAR) per event

Company ID	Team ID	Event date	7 day window-CAR	2 day window-CAR	Company ID	Team ID	Event date	7 day window-CAR	2 day window-CAR
1	62	16-05-2014	0.01335	-0.00662	114	8	08-09-2011	-0.00068	0.00036
2	62	21-04-2014	0.00621	-0.01067	115	8	27-04-2011	0.00735	-0.00509
3	62	15-07-2013	-0.00165	0.00514	116	8	01-03-2011	0.01160	0.01738
4	62	15-07-2013	-0.00165	0.00514	117	8	05-05-2010	-0.27804	-0.24361
5	62	14-06-2013	-0.01319	0.00377	118	11	08-08-2013	-0.02545	-0.01725
6	62	19-03-2013	-0.04429	0.00270	119	21	02-01-2014	-0.05114	-0.02652
7	62	07-08-2012	-0.01763	-0.00820	120	21	01-11-2013	-0.04843	-0.02151
8	62	14-01-2011	-0.01031	-0.00987	121	21	01-07-2013	0.01932	0.00668
9	157	01-12-2009	-0.03230	0.03725	122	21	02-01-2013	-0.03100	-0.01024
10	157	01-12-2009	-0.03230	0.03725	123	21	02-10-2012	0.11503	-0.00461
11	157	20-04-2009	0.01416	-0.00659	124	21	01-05-2012	-0.00686	-0.01951
12	157	05-09-2008	-0.01469	-0.00035	125	13	19-03-2013	0.20088	0.09508
13	157	05-09-2008	-0.01469	-0.00035	126	68	26-04-2012	0.00237	-0.00942
14	157	04-04-2008	-0.00423	-0.00179	127	68	30-12-2011	0.01203	-0.00157
15	165	16-02-2012	0.01435	0.01009	128	68	31-07-2008	-0.02228	0.02676
16	87	09-05-2014	0.05738	0.04664	129	68	04-05-2007	-0.00771	-0.00188
17	87	27-08-2013	0.12896	0.10861	130	83	17-04-2014	-0.16846	-0.02631
18	115	28-02-2012	-0.00814	-0.00414	131	83	16-12-2013	-0.21186	0.00393
19	156	28-12-2011	0.02071	-0.00416	132	83	24-04-2013	-0.04393	-0.01720
20	156	10-02-2011	0.03135	0.04081	133	83	08-01-2013	0.08099	-0.00169
21	156	31-01-2011	-0.03173	0.01126	134	83	26-12-2012	-0.01864	0.00732
22	107	22-01-2013	0.00562	0.00372	135	83	19-10-2012	0.04269	-0.04245
23	69	13-01-2014	0.48955	0.44749	136	83	03-08-2012	-0.02193	0.03187
24	101	01-07-2013	-0.01152	-0.01635	137	83	05-06-2012	-0.00746	0.00529
25	101	12-06-2013	-0.00771	-0.00616	138	83	23-01-2012	0.03218	-0.01211
26	101	13-12-2012	-0.02558	-0.00743	139	72	21-01-2014	0.00000	0.00000
27	101	10-12-2012	-0.01459	0.01180	140	72	01-11-2013	0.00000	0.00000
28	101	25-04-2012	0.04692	0.01443	141	72	15-10-2012	0.00272	-0.00026
29	101	10-04-2012	0.02360	0.00557	142	64	18-02-2014	0.01364	0.02481
30	101	21-04-2011	-0.01462	-0.04438	143	154	29-07-2013	-0.02508	-0.06414
31	101	08-04-2011	0.02922	0.00408	144	154	17-06-2013	0.02824	0.00282
32	101	11-03-2011	0.03810	0.02974	145	154	11-02-2013	0.05740	0.02907
33	101	24-01-2011	0.03130	0.00549	146	154	01-02-2013	0.03800	0.04269
34	12	08-11-2011	-0.18420	-0.12621	147	154	28-12-2012	0.03781	0.00520
35	108	18-12-2007	-0.04402	0.01992	148	154	13-09-2012	-0.02319	-0.00399
36	103	26-04-2013	0.00376	-0.01413	149	154	09-01-2012	0.00157	0.00683
37	39	06-02-2013	0.03352	0.02100	150	154	28-02-2014	0.01764	-0.01230
38	39	14-02-2012	-0.01953	-0.00129	151	41	28-04-2014	0.05627	0.03919
39	39	06-09-2011	-0.00688	0.00698	152	41	27-06-2013	-0.02213	-0.00027

40	39	06-09-2011	-0.00688	0.00698	153	41	01-11-2012	-0.03561	-0.01836
41	138	07-01-2013	-0.00875	-0.01154	154	41	22-10-2012	0.01746	-0.00640
42	138	23-06-2011	-0.02462	0.00330	155	41	27-02-2012	-0.01422	0.00055
43	138	17-08-2010	-0.02726	-0.00578	156	41	12-12-2011	0.02061	0.00156
44	138	04-02-2010	0.02159	-0.00623	157	41	22-11-2011	-0.01204	-0.00068
45	74	29-04-2014	-0.03054	-0.02933	158	41	20-07-2011	-0.03041	-0.00389
46	74	29-06-2012	0.01866	0.01205	159	41	07-02-2011	0.02051	-0.01893
47	74	26-06-2012	0.00813	0.00897	160	41	01-02-2011	0.03407	0.04268
48	74	06-01-2012	-0.02194	0.00514	161	41	20-10-2010	-0.01276	0.00370
49	30	17-12-2012	0.00000	0.00000	162	41	20-10-2010	-0.01276	0.00370
50	47	02-04-2014	0.00070	0.00128	163	41	12-10-2010	-0.00868	-0.00062
51	47	01-04-2014	0.01547	0.04013	164	41	01-09-2010	0.01273	0.00316
52	47	15-01-2014	0.00489	-0.01305	165	144	16-05-2012	-0.04367	-0.00878
53	47	04-10-2013	0.04728	0.02102	166	144	02-01-2012	-0.07484	-0.00936
54	47	04-10-2013	0.04728	0.02102	167	52	06-05-2013	0.04449	0.01027
55	47	29-07-2013	0.06172	-0.00189	168	52	11-01-2010	0.11307	0.05140
56	47	12-06-2013	0.01241	0.00310	169	52	08-12-2009	0.05816	0.00217
57	47	03-10-2012	0.02129	0.00047	170	168	07-11-2013	0.00569	-0.01206
58	47	13-06-2012	-0.01221	0.01145	171	168	08-11-2011	-0.00644	0.01286
59	47	26-01-2012	-0.00690	-0.01148	172	66	26-08-2013	0.01900	0.03570
60	47	04-11-2011	-0.04768	-0.00891	173	94	17-07-2013	0.05430	-0.02030
61	47	04-11-2011	-0.04768	-0.00891	174	94	10-08-2012	-0.16626	0.01272
62	47	18-08-2011	0.03266	0.00326	175	94	05-04-2012	-0.11580	-0.08834
63	47	16-02-2011	0.07122	0.01074	176	94	15-06-2011	-0.00820	0.01442
64	31	21-03-2011	0.03399	0.00482	177	22	23-04-2014	0.04307	-0.00974
65	31	09-02-2011	0.03275	0.00340	178	22	04-12-2013	0.05300	0.03606
66	71	15-05-2012	0.05678	-0.02452	179	22	04-06-2013	-0.00121	-0.01174
67	71	30-12-2011	0.03867	-0.03040	180	22	12-12-2012	0.00016	0.03742
68	71	13-07-2009	-0.46082	-0.05693	181	22	05-06-2012	0.09306	0.01626
69	163	30-07-2013	0.01242	0.01683	182	56	17-08-2010	-0.02011	-0.04400
70	163	30-07-2013	0.01242	0.01683	183	2	27-05-2013	0.16278	0.09595
71	163	25-02-2013	-0.00470	-0.02037	184	2	29-04-2013	-0.03305	0.02582
72	10	03-03-2014	-0.02458	0.00832	185	2	15-04-2013	0.02824	0.02727
73	23	09-06-2008	0.03377	-0.15326	186	2	20-03-2013	0.02377	0.01985
74	18	22-04-2014	-0.00547	-0.01748	187	2	19-11-2012	-0.00967	0.00611
75	18	03-10-2013	-0.07496	-0.03117	188	2	12-04-2012	-0.01364	0.01234
76	127	12-12-2013	0.01602	0.05997	189	2	16-12-2011	0.03421	-0.00250
77	127	25-04-2013	0.05849	0.01709	190	2	03-11-2011	0.09203	0.10739
78	127	21-05-2012	-0.02054	-0.02679	191	2	29-08-2011	0.05938	0.02245
79	127	21-05-2012	-0.02054	-0.02679	192	2	11-07-2011	0.01596	-0.00035
80	127	12-08-2010	-0.00940	-0.02332	193	2	24-02-2011	-0.12354	0.00911
81	137	28-04-2014	-0.07658	-0.01940	194	2	01-02-2011	0.05706	0.04808
82	137	08-01-2014	0.14061	0.17562	195	2	21-04-2014	0.03356	0.03247

83	137	02-12-2013	0.09728	0.10039	196	2	03-02-2014	0.02791	0.00586
84	118	13-01-2014	0.00000	0.00000	197	2	22-01-2014	-0.00808	0.01092
85	50	07-05-2014	0.06326	0.00210	198	2	16-12-2013	0.03122	0.03058
86	50	12-12-2012	0.00267	-0.00339	199	2	30-10-2013	-0.03743	-0.01786
87	50	18-07-2012	0.01867	0.00212	200	2	29-11-2012	0.00784	0.00754
88	50	08-08-2011	-0.07383	0.00460	201	2	19-11-2012	-0.00839	0.00547
89	50	22-02-2011	0.02820	0.00424	202	2	24-09-2012	-0.00515	0.01258
90	50	25-06-2010	0.05136	0.02082	203	2	03-09-2012	0.00293	0.00123
91	50	11-05-2010	0.02638	0.02738	204	2	15-06-2012	-0.06096	-0.02488
92	50	29-01-2010	0.09402	0.02456	205	2	24-05-2012	-0.02242	0.02661
93	132	02-03-2009	-0.10963	0.00378	206	2	03-05-2012	-0.07856	-0.07738
94	77	25-04-2011	0.02990	0.00738	207	2	18-04-2012	0.01208	0.00425
95	123	21-08-2013	-0.00962	-0.00583	208	2	26-03-2012	0.01400	0.00055
96	109	17-06-2013	0.00054	0.00176	209	2	13-03-2012	0.00030	-0.00763
97	109	25-01-2013	0.01025	0.00949	210	2	12-03-2012	0.02642	-0.00750
98	109	30-09-2011	0.02327	0.00976	211	2	13-02-2012	-0.02751	0.00234
99	109	18-04-2011	0.03165	0.00426	212	2	01-02-2012	-0.02780	0.02058
100	143	26-01-2011	0.00581	0.01204	213	2	21-11-2011	0.04783	0.01301
101	133	24-12-2008	0.01942	-0.00190	214	2	08-11-2011	0.03453	0.00399
102	152	09-06-2014	-0.01522	0.00011	215	2	29-08-2011	0.03670	0.01429
103	152	01-05-2013	-0.07160	-0.02563	216	2	26-07-2011	-0.03155	-0.00006
104	152	21-06-2012	0.02147	0.01519	217	2	24-05-2011	-0.06976	-0.00125
105	152	26-07-2011	-0.00797	-0.00069	218	2	24-05-2011	-0.06874	-0.00123
106	152	27-04-2011	0.04419	0.01397	219	2	29-03-2011	-0.00376	-0.00682
107	44	02-12-2011	0.07080	0.01880	220	84	22-12-2011	-0.05050	-0.01252
108	125	04-04-2014	0.00131	0.02546	221	84	27-10-2011	-0.05585	-0.06043
109	125	29-10-2013	-0.03194	0.00084	222	84	15-09-2011	-0.03472	-0.00623
110	125	14-05-2013	0.01765	0.02621	223	84	09-03-2011	0.08773	0.07585
111	125	27-02-2013	-0.00924	-0.00061	224	84	17-06-2010	0.02703	0.00067
112	125	15-02-2013	0.00775	0.00234	225	84	15-07-2008	0.00691	-0.14685
113	8	05-11-2013	0.02626	0.00359					

Notes: All CAR values were rounded to 5 decimals