The Effect of CEO Overconfidence on Stock Price Crash Risk

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Abstract

This thesis examines the relationship between CEO overconfidence and stock price crash risk. First, a mechanism is developed which explains the relationship between CEO overconfidence and stock price crash risk by using CEO communication. After that the findings of Kim, Wang and Zhang (2016) are subjected to a series of robustness tests using several different measures for stock price crash risk and CEO overconfidence, a wider timespan and more control variables. There will be sixteen proxies for stock price crash risk, seven for CEO overconfidence, a sample with data between 1996 and 2016 and three additional control variables. By doing this it is found that the proxies used by Kim, Wang and Zhang (2016) are significantly related, while some of the additional measures for stock price crash risk and CEO overconfidence are not significantly related. Therefore, it is concluded that the Kim, Wang and Zhang (2016) findings are not robust. Finally, it is also found that the effect of CEO overconfidence does not depend on how common CEO overconfidence is in an industry.

Keywords: *Overconfidence, managerial bias, crash risk, CEO communication*

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1. Introduction

The influence of behavioral finance has grown over the last period. Behavioral economists found that people have systematic biases in the way they think and therefore they are not making decision following the rational-agent models (Kahneman, 2003). Rabin (1998) found that psychology could be useful for making suitable economic assumptions in economic theorizing. Therefore, behavioral economists are looking at psychological explanations for deviations from the behavior described by rational-agent models. One of the most widely found deviations from rationality is overconfidence. Overconfidence is used to explain a lot of market anomalies such as hubris, market bubbles, financial collapses (Johnson & Fowler, 2011). It is also tried to explain stock prices which became above the rational value with overconfidence. Stock prices which became above the rational value can result in subsequent crashes of stock prices (Kim, Wang, & Zhang, 2016; Schrand & Zechman, 2012).

Existing literature has shown that overconfident people tend to overestimate their own knowledge, abilities, the precision of their own information and to be overly optimistic about the future and their ability to control this future (Goel & Thakor, 2008). Due to that overconfident people overestimate future cashflows and returns. For that reason, overconfident investors are trading more, take more risk, are willing to pay more for an investment and do not diversify their portfolio enough (Malmendier & Tate, 2005a). The effect of overconfidence on individual traders is found widely (Barberis & Shleifer, 2003; Barber & Odean, 2001; Bleck & Liu, 2007; Klayman, Soll, González-Vallejo, & Sema, 1999).

However, there is so far little evidence of the effect of CEO's overconfidence on the financial markets in the aggregate. There is just one paper on the effects of CEO overconfidence on financial markets, by Kim, Wang and Zhang (2016). Kim, Wang and Zhang (2016) found that CEO overconfidence is positively related to firms-specific stock price crash risk. This thesis will subject the findings of Kim, Wang and Zhang (2016) to a series of robustness tests using several different measures for stock price crash risk and CEO overconfidence, a wider timespan and more control variables.

These additional robustness checks are necessary for several reasons. The first reason is that the research of Kim, Wang and Zhang (2016) is the only research that found a relationship between CEO overconfidence and financial markets. Further, one of the proxies for stock price crash risk used by Kim, Wang and Zhang (2016) is only looking at a firm's weekly return falling below a benchmark, based on firm's industry, but this proxy can indicate that there has been a crash when a stock is just very volatile. This proxy is using a fall of 3.2

standard deviations below the firms mean weekly returns as a benchmark for stock price crashes and by doing this, it selects the lowest 0.1% of the sample. But why is this part of the sample indicated as a crash? Next, the proxy for overconfidence used, the so-called holder67 proxy, is based on CEO option holding, while Bayat, Salehnejad and Kawalek (2016) found that proxies for CEO overconfidence based on CEO option holding does not really measure CEO overconfidence. Further, Kim, Wang and Zhang (2016) are only using a limited number of control variables, whereas the literature suggests several important additional variables to control for.

For that reason, the analysis done Kim, Wang and Zhang (2016) will be repeated and extended. Stock price crash risk will be measured in sixteen different ways (Kim et al only used 3 measures). These will be described later. Data for these proxies is gathered from the CRSP database and from the database from French (2017). For measuring CEO overconfidence, the "holder 67", "holder 100" and "net buyer" proxies of Malmendier and Tate (2005a) are used. These proxies are based on CEO-characteristics and are all CEO level proxies. The data for these proxies is gathered from Execucomp. There will also be four proxies based on the measures of Schrand and Zechman (2012). These proxies are based on firm level data, two of these proxies are firm-level proxies and two are CEO-level proxies. The data for these proxies is gathered from Compustat. This means that there will be seven proxies for overconfidence in total, while Kim, Wang and Zhang (2016) used only three proxies. Further, in addition Kim, Wang and Zhang (2016) also cash reserves, R&D expenses and CEO age will be used as control variables. Another added part is a novel mechanism which is developed to describe the relationship between CEO overconfidence and stock price crash risk. This mechanism is not described by Kim, Wang and Zhang (2016). The final addition I make to the Kim, Wang and Zhang (2016) paper is the investigation of different impacts of CEO overconfidence within different industries. The industries are based on the "5 industry portfolio" developed by French (2017).

Overconfidence is more common in some industries (Baker, Bloom, & Davis, 2016; Engelen, Neumann, & Schwens, 2015). Due to that it is expected that investors in these industries know that CEOs are overconfident and therefore are these industries be less sensitive stock price crashes that other industries (Engelen, Neumann, & Schwens, 2015; Malmendier & Tate, 2005a). But it could also be that this relationship is the other way around. It can also be easier to distinguish overconfident CEOs from non-overconfident CEOS in industries with less overconfident CEOs, investors will notice the overconfident CEO earlier and take this into account. Therefore, industries with less overconfident CEOs can also be less sensitive to stock price crashes (Peng & Xiong, 2006).

By doing the analysis it became clear that I had the same results as Kim, Wang and Zhang (2016) when the same proxies for CEO overconfidence and stock price crash risk are used, except for the regressions between negative skewness and the proxies based on the criteria of Schrand and Zechman (2012). These were insignificant in my data sample. But, a lot of regressions with additional proxies did not have significant results. For instance, the CRASH_SMALL proxy was only significant when it is combined with the net buyer proxy and the COUNT_CRASH_MEDIUM proxy was only significant in combination with the HOLDER100 and NETBUYER proxies. Further, it does not matter which control variables are included, the results are the same when only the control variables of Kim, Wang and Zhang (2016) are used and when also the additional control variables are used. The final conclusions are that the Kim, Wang and Zhang (2016) findings are not robust and that the effect of CEO overconfidence is not affected by how common CEO overconfidence is in an industry.

In addition to the previous described contribution to the Kim, Wang and Zhang (2016) article, this study also relates to several strands of existing literature. First, this thesis relates to the literature of stock price crash risk. There have been several theoretical and empirical studies which has found a variety of contributing factors to firm-specific crash risk (Hutton, Marcus, & Tehranian, 2009; Kim, Li, & Zhang, 2011; Kim, Wang, & Zhang, 2016). Like the study of Kim et al. (2016) I try to offer a psychological founded explanation for stock price crash risk. But as described above, in addition to Kim, Wang and Zhang (2016), the results provided in this thesis are more robust. Second, this study relates to the growing body of behavioral economic explanations for managerial behavior. In this paper, a novel mechanism is developed to describe the relationship between CEO overconfidence and stock price crash risk.

The next chapter will describe the existing literature about overconfidence and stock price crashes, will relate this literature to each other, will develop a novel mechanism to describe the relationship between CEO overconfidence and stock price crashes, it and will develop the hypotheses. There will be a description of the data, construction of the proxies and methodology in the third chapter. After that the results of the tests will be described and it will be explained what this means. The final chapter will give a final discussion and conclusion.

2. Literature overview

2.1. Overconfidence

This part of the text will give an overview of the existing literature about overconfidence. First, a definition of overconfidence is given, after that the causes of overconfidence are described and finally the implications of overconfidence are given.

2.1.1. Definition of overconfidence

Overconfidence can be defined in three ways: 1. overestimation of your own actual performance, 2. over placement of your own performance relative to others and 3. excessive precision in your beliefs (Moore & Healy, 2008). An example of the first definition can occur in guessing the score of a test, a lot of economic students tend to think that they got a higher grade then they get (Grimes, 2002). A widely-used example of the second definition is about people's driving ability. According to the experiment done by Svenson (1981), half of the US drivers think that they are among the safest 20 percent of drivers and half of the Swedish drivers think that they are in the safest 30 percent of drivers. But this cannot be true, only 20 percent of the drivers can be in the safest 20 percent of drivers. The third definition can be illustrated with the estimation of distance. For example, someone must estimate the distance between two places and a, for instance 90 percent, confidence interval afterwards. Most of the time people tend to estimate the confidence intervals too narrow (Moore & Healy, 2008).

In general, it can be said that overconfidence is the overestimation of your own abilities. Therefore, from now we see CEO overconfidence as a CEO who is overestimating her own abilities.

2.1.2. Causes of overconfidence

In the previous paragraph, it is described that overconfident people have too positive feelings about their own abilities. But not everybody is having the same level of overconfidence, the reason for this is that not everybody is having the same positive feelings about their own abilities. The level of overconfidence can be explained in several ways.

According to Burt (1997), a greater level of overconfidence is related to more "constrained" networks. A constrained network is a small social network where people have strong connections with people within the network and weak connections with people outside their network. People in these networks have more biased views than people in the less "constrained" networks. Due to this, there is a bigger chance that people in a "constraint" network are too optimistic about their own abilities relative to people in a less "constrained" network (Burt, 1997).

Another explanation can be found in culture, some cultures tend to be more overconfident than others (Weber & Hsee, 2000). According to House (2004, p. 57), culture is the "shared motives, values, beliefs, identities and interpretations of meanings of significant events that result from common experiences of members of collectives and are transmitted across generations". Several scientists have found that the level of overconfidence differs across cultures. According to Yates, Lee and Bush (1997), overconfidence in general knowledge is typically less strong for Western people than for Asian people. The explanation for this can be that cultures perceive risk different, have other risk preferences and due to that people in make different decisions in different cultures (Weber & Hsee, 2000). According to Yates, Zhu, Ronis, Wang, Shinotsuka and Toda (1989), overconfidence occurs when people are only looking for information which confirms their expectation and fail to see information which contradicts their expectations. People in different cultures have different abilities to see the contradicting evidence and to look critically (Yates, et al., 1989). The investigation of Krawczyk and Wilamowski (2016) into overconfidence of marathon participants confirmed the finding that people in Asian cultures tend to be more overconfident than other cultures, since people in these cultures overestimate their performance in the marathons more than others.

The next explanation for differences in the level of overconfidence are different individual characteristics (Klayman, Soll, González-Vallejo, & Sema, 1999; Forbes, 2005). According to Simon, Houghton and Aquino (2000) and Forbes (2005): most people suffer from several cognitive biases such as overconfidence, illusion of control and belief in the law of small numbers, these biases enable us to deal quickly with the large volumes of information and are natural phenomenon. But due to these biases, we make mistakes in our decisions. The cognitive biases are more pronounced by certain people than by others. According to Chatterjee (2009), CEO overconfidence is for example associated with certain psychological characteristics and observable experience. The psychological characteristics which influence overconfidence are conscientiousness, emotional instability, agreeableness, extraversion and openness[1] (Peterson, Smith, Martorana, & Owens, 2003). Observable experience is affecting a

[1] According to Peterson and colleagues (2003), an CEO who is conscious in making decisions, not influenced by emotions when she is making decisions, willing to agreements with their management group, social but not dominant and interested in unusual thought processes are expected to make better decisions.

CEO’s behavior by the values of the executive, education background, cognitive structures, thinking styles, functional backgrounds and company tenures (Chatterjee, 2009). Another characteristic which is connected to overconfidence is narcissism (Chatterjee, 2009).

A fourth explanation for the levels of overconfidence can be gender (Barber & Odean, 2001). Barber and Odean (2001) found that men trade 45 percent more than women and trading reduces men’s net returns more than women’s net return. The clarification for this can be that men feel more competent in financial matters (Prince, 1993), have a stronger self-serving attribution bias (Gervais & Odean, 2001) and feel more confident in a market when there is unambiguous feedback (Lenney, 1977). For these reasons, men are more likely to feel overconfident than woman.

A final explanation for the level of overconfidence can be people’s mood (Hirshleifer & Shumway, 2003; Nofsinger, 2005). There are several thoughts about the impact of mood on people’s overconfidence. In general, it is thought that when mood is positive, people are making decisions more biased by optimisms and when mood is negative, peoples decisions are stronger biased by pessimism (Nofsinger, 2005). This implies that people with a positive mood are more overconfident than people with a negative mood.

2.1.3. Implications of overconfidence

Overconfidence can have several effects on the economy. It is found that overconfident people tend to overestimate their knowledge, underestimate risks and exaggerate their ability to control events (Nofsinger, 2001). Due to that people become blind to negative information, belief that their information is superior (Zacharakis & Shepherd, 2001), trade excessively (Odean, 1998), diversify their portfolio too little (Chen, Kim, Nofsinger, & Rui, 2007), take too much risk (Odean, 1998) and hoard bad news (Bleck & Liu, 2007).

The first mentioned implication of overconfidence was that overconfident people become blind to negative information (Zacharakis & Shepherd, 2001). This is also called the “good news-bad news’ effect (Eil & Rao, 2011). This effect implies that people put more weight on good news than on bad news. The unfavorable information is discounted more than favorable information and therefore favorable information is having a bigger impact on beliefs than unfavorable information (Eil & Rao, 2011).

The second implication is that people belief that their own information is superior to the information of others (Zacharakis & Shepherd, 2001). This implies that people do not incorporate all the available information. When somebody thinks that she is having exclusive information about a firm, this person thinks that her information is superior to the information of others. The information of others is ignored for that reason (Zacharakis & Shepherd, 2001).

The next implication of overconfidence is that people trade excessively. Odean (1998) showed that investors with discounted brokerage accounts[2] trade excessively[3], even after eliminating the trades that can be motivated by liquidity demands, tax- loss selling, portfolio rebalancing, or a move to lower-risk securities. Chen et al. (2007) had a similar finding: they found that Chinese investors in brokerage accounts make poor decisions. They sell stocks that perform well and buy stocks that underperform, while it would sometimes be better to keep the well performing stocks. This implies that they are trading excessively. As described before, a similar finding had been found by Barber and Odean (2001). They found that men, who are expected to be more overconfident than women, trade 45 percent more than woman.

Too little diversification is the fifth implication of overconfidence. Overconfidence people tend to be too confident about the performance of some stocks. Therefore, they invest too much in these stocks, while diversification would be much safer (Ritter, 2003).

The next implication can be linked to the previous implication. Overconfident people tend to take too much risk, since overconfident people think that they have superior information and have the illusion of controlling the situation (Nofsinger, 2001; Odean, 1998). For this reason, they think that they know future returns and therefore they will only invest in a small number of assets of which they feel confident that they will perform well. By doing this they face a lot of risk due to under-diversification.

The final implication of overconfidence is bad news hoarding. This means that managers tend to hide bad news, but the bad news will all come out in one time (Bleck & Liu, 2007). Overconfident CEOs overestimate future returns and do not see or believe the bad news and therefore, they are not able to evaluate the true intrinsic value of the projects (Hribar & Yang, 2015). Unconsciously, due to that they are also hiding the bad news for the investors (Bleck & Liu, 2007). Bad news can be hoarded when a firm is not completely transparent (Jin & Myers, 2006; Kim, Li, & Li, 2014). When a firm's CEO is overconfident, a firm's insiders should also hide the information from the investors, otherwise CEO overconfidence will not influence investor's beliefs (Jin & Myers, 2006). When the insiders are not absorbing the information, but instead they are sharing this with outsiders, then the outside world will

[2] A discounted brokerage account attracts overconfident people, since customers can trade for themselves without agency concerns (Odean, 1998; Glaser & Weber, 2007; Chen, Kim, Nofsinger, & Rui, 2007).

[3] People trade excessively when their return is reduced through trading (Odean, 1998).

already know that an overconfident CEO is not conveying the true situation. According to Jin and Myers (2006), all the firm-specific news, good or bad, will come out at once and will be absorbed in investor's beliefs. The amount that insiders are willing to absorb is limited. When insiders had to absorb too much bad news, they will give up absorbing bad news and it will all come out together (Jin & Myers, 2006).

Bad news hoarding is a widely used as an explanation for stock price crashes. For instance, Kim, Li and Li (2014) found that firms which commit to high transparency standards engage less in bad news hoarding and that these firms face lower crash risk than firms which did not commit to these high transparency standards. According to Kim, Li and Zhang (2011), the positive relation between tax avoidance and stock price crash risk is stronger when bad news can be hoarded.

2.2. Stock price crashes

This part of the text will give an overview of the existing literature of stock price crashes. First the definition of stock price crashes is given, after that the causes of stock price crashes are described and finally the implications of overconfidence are given.

2.2.1. Definition of stock price crashes

There is no good definition of a stock price crash. Mishkin and White (2002) gave the following hard to operationalize definition: *"When you see it, you know it"* (Mishkin & White, 2002, p. 2). This indicates that you know that there was a stock price crash afterwards, but not during the crash. A more precise definition and measurement of a crash is very difficult (Mishkin & White, 2002).

Out of the previous paragraph follows that a stock price crashes if the price of an assets is falling a lot. But how much and how fast should a stock price fall before you can call it a crash? A common way to operationalize stock market crashes is to look at falls in weekly returns that exceed a certain number of standard deviations. One measure by Hutton, Marcus and Theranian (2009) proposes a fall in weekly returns of 3.09 standard deviations below the mean firm-specific returns over the fiscal year. Such an event occurs in about 0,1% of the weekly returns in their sample which is a useful benchmark for a crash[4]. This benchmark for a stock price crash is also used by Kim, Wang and Zhang (2016)[5], Bradshaw, Hutten and Tehranian (2010) and Chen, Hong and Stein (2001).

2.2.2. Why stock prices become too high

According to Sornette (2009) stock prices can crash when there have been "systematic instabilities" in the market. A build-up phase in which systematic instabilities develop precedes the actual crash, but it does not trigger it. Usually some short-term mechanism triggers price crashes, but these mechanisms can differ widely (Sornette, 2009). These will be discussed in the next paragraph.

Systematic instabilities can occur whenever arbitrage does not work effectively. Due to the limitations of arbitrage, the price of a stock might not reflect all the available information and therefore the price might not be right. Markets can become instable when there is uncertainty about the true value of assets due to asymmetric information. A shock to the financial system or underlying economy can increase the information asymmetry and due to these funds may not always be channeled efficiently to the best investment opportunities (Mishkin, 1997). Some investors think that stock prices will increase while others think that they will decrease. Optimistic investors will push up the price, by buying up the stock. While pessimistic investors cannot counterbalance this due to the short selling constraints (Brunnermeier, 2016). For this reason, pessimistic investors are moved out of the market. This will lead to an increase in stock prices until it subsequently crashes.

There are several explanations for the limitations of arbitrage. The first explanation for the failing arbitrage are short selling constraints (Miller, 1977; Xiong & Yu, 2011). Miller predicted a long time ago, in 1977, that short selling constraints can lead to overpricing. Short selling makes it possible for investors who do not own an asset to participate in the market, due to this the price will reflect full information. Pessimistic investors who do not own an asset are not able to influence prices when there are constraints on short selling and the price will not reflect the true value (Miller, 1977). Xion and Yu (2011) tested this idea in China, they found that investors are having heterogenous beliefs about returns when there is a ban on short selling

[4] It will also be tested whether the effect of overconfidence on stock price crash risk is different when a stock price crashes if the weekly returns fall with 2.5 and 4.5 standard deviations below the mean firm-specific returns over the fiscal year.
[5] Kim Wang and Zhang (2016) used 3.2 standard deviations as a benchmark for a stock price crash, but the results for these two benchmarks are the same.

financial warranties. Investors who think that the price will increase further will buy the asset, because they think that they have the option to resell the warrant to someone else in the future for even a higher price (Xion & Yu, 2011).

Due to short selling constraints, it can be that news is not incorporated efficiently, since optimistic investors ignore bad news and pessimist investors have limited ability to bring back the price. Reducing the costs of short selling increases efficiency of incorporating news, bad news will faster be incorporated in the price (Diamond & Verrecchia, Constraints on short-selling and asset price adjustment to private information, 1987)[6].

News can also not be incorporated efficient due to the biased self-attribution. Traders tend to overvalue private information and only consider information that confirms private information. Due to this public information that contradicts their private information is neglected. Therefore, it is possible that prices do not reflect all available information and that some assets are overvalued (Daniel, Hirshleifer & Subrahmanyam, 1998). When prices increased, people received a lot of positive information, therefore they are too optimistic and think that prices keep increasing until they subsequently crash.

The third explanation for failing arbitrage are the short horizons of investors. According to Shleifer and Vishny (1990) investors want to have sure returns. Their model for firm investments contains three periods and two investment projects (short-term and long-term projects). They assume that firm managers with poor management performance are more likely to be replaced. Since long term projects can be mispriced more, investing in long term projects can threaten their jobs. For that reason, firm managers are more likely to invest in short term assets (Shleifer & Vishny, 1990). The same reasoning also holds for investors, they also want sure returns and therefore they also more likely to invest in short-term projects. The demand for short-term project will always be higher than the price of long-term projects and therefore it is possible that a mispricing in short-term assets survive.

Another interpretation of the effect of investor's short horizons on the failing arbitrage is given by Abreu and Brunnermeir (2003). They found that investors do not know how other rational investors will behave. More precise, investors do not know whether other investors will withdraw their money or not. A price will not fall when only one investor withdraws her money, prices will only fall if a group of investors withdraws their money. Therefore, an investor will make a loss when she withdraws while others do not. Because of that one single investor is too

[6] The idea of slower incorporation of news with short selling constraints is supported by the research of Beber and Pagano (2013)about the crisis of 2007-2009.

risk averse to withdraw her money. For that reason, it can be that no investor will withdraw her money and arbitrage is failing (Abreu & Brunnermeier, 2003).

The final reason explanation failing arbitrage is called style investing. Investors are categorizing assets in different categories, the assets in these categories are expected to move together. When other assets in a category increases than a certain asset within this category will also increase. Therefore, when the demand for some assets in a category is increasing, the demand for all the assets within the category will increase and due to this the price of all the asset will increase, even when it is rational to expect the price of an asset to decrease (Barberis & Shleifer, 2003).

2.2.3. Mechanisms triggering stock price crash

The above described explanations for stock prices becoming above the fundamental value show that it is possible that stock prices stay too high for a period. Further, one of the described consequences of overconfidence was bad news hoarding, but the amount an insider can hoard is limited. When insiders should absorb too much bad news, they will give up absorbing bad news and it will all come out together (Jin & Myers, 2006). This shows that stock prices can be too high for a while, but it will always become clear that prices became too high and stock prices will crash after that (Jin & Myers, 2006; Sornette, 2009).

A stock price will crash when it becomes clear to everybody that the price is not right. A lot of people will start selling the assets and prices will drop. According to Sornette (2009), a short-term mechanism will make clear that that prices do not display real value. By doing that, the short-term mechanism will trigger the stock price crash. The short-term mechanism, described by Sornette (2009), which can trigger the crash can be for instance a news article, an investor who starts to sell or simply an announcement by the firm. In the Jin and Myers (2006) model, a stock price will crash when insiders are no longer willing to absorb bad news. When this is the case, insiders will give signals to the outside world, for instance by starting to sell stocks of that firm or some announcement. The mechanism which triggers a stock price crash be very small. Only one sentence in an article which raises suspicion can be enough to trigger a stock price crash (Hamm, Li, & Ng, 2012).

2.2.4. Implications of stock price crashes

The goal of the central banks should be to treat price stability and financial stability as consistent and reinforcing objectives (Bernanke & Gertler, 2000). Crashes of stock prices can destabilize the real economy, since a crash can result in a large loss of wealth (Mishkin & White, 2002). Long run price stability is designated to be the goal of central bank policy and maximum economic growth will be reached when this is combined with financial stability (Bernanke & Gertler, 2000). If there are stock price crashes, financial and price stability is not reached and maximum economic growth will not be reached. To reach the long-run price stability, central bank's monetary policy needs to react in an optimal manner to stock price movements (Mishkin & White, 2002).

A consequence of a stock price crash is moral hazard (Bernanke & Gertler, 1989; Mishkin & White, 2002). Bernanke and Gertler (1989) showed that firms have low net worth after a crash, therefore these firms can lose very little. For that reason, firms are very likely to take more risk after a crash. The risk they take is not on their own company, since it has a very low net worth, but on the lender. This can lead to a contraction in lending and a crash of the whole financial system (Bernanke & Gertler, 1989).

An additional problem of the moral hazard problem are possible bank runs (Mishkin & White, 2002). When a firm is taking too much risk and fails to fulfill its requirements, a bank is losing her money. Depositors can start to fear that they will lose their money when a bank is losing money (Mishkin & White, 2002). When the fear becomes too big, the depositors will withdraw their money and a bank can collapse. This can result in a distrust between banks, a contraction in lending and a crash of the whole financial system (Diamond & Dybvig, 1983).

The above described consequences of stock price crashes show that the consequences could be disastrous. Therefore, it is important that central bank's monetary is reacting to stock price movements (Mishkin & White, 2002).

2.3. Overconfidence and Stock Price Crashes

2.3.1. Mechanism between CEO overconfidence and stock price crash risk

In addition to Kim, Wang and Zhang (2016), a novel mechanism is developed to describe the relationship between CEO overconfidence and stock price crash risk. The developed mechanism contains of five steps, it starts with an overconfident CEO and ends with a stock price crash. Important for developing the mechanism between CEO overconfidence and stock price crash risk are the earlier findings that overconfident people become blind to negative information (Eil & Rao, 2011; Zacharakis & Shepherd, 2001) and hoard bad news (Bleck & Liu, 2007; Jin & Myers, 2006).

The starting point of the developed mechanism is an overconfident CEO. As mentioned before, an overconfident CEO is overestimating his own abilities. Further, someone who is overconfident is ignoring negative feedback. The blindness for negative information results in bad news hoarding (Bleck & Liu, 2007). Due to this, overconfident CEOs have too positives beliefs about their firm's performance and they will overestimate future cash flows.

The next step in the process is CEO communication. A CEO is expected to be a good leader and should communicate the future course of the organization to the shareholders (Bolton, Brunnermeier, & Veldkamp, 2008). When a CEO is overconfident, the overoptimistic forecasts of CEOs will be included in the communication of future course which the CEO gives to investors. The negative feedback a CEO received is hoarded and will not be included in the communication of the CEO. Therefore, overconfident CEO's communication does not reflect the real situation (Bolton, Brunnermeier, & Veldkamp, 2008). Overconfident CEOs believe that they are conveying the true performance of the firm and think that they are maximizing shareholders wealth by continuing projects with a negative net present value and hiding negative feedback, because they are not able to evaluate the true intrinsic value of the projects (Hribar & Yang, 2015).

This leads to the next step. When investors get the positive signals of the CEO and do not receive other signals. Investors will believe that future cash flows will be higher and that stock prices are too low. Therefore, investors will belief that it is profitable to invest in a firm's stocks. This leads to an increase in the demand for stocks and due to that, a firm's stock prices will also increase.

After a while, it becomes clear that the CEO had overestimated future cash flows and some short-term mechanism will reveal that stock prices became too high. When investors start to know that prices have become too high, all the bad news that has been hoarded will come out together and the stock price will crash (Sornette, 2009).

Figure 1: Mechanism between CEO overconfidence and stock price crash risk

2.3.2. Different industries

Earlier research has found that some industries are more innovative, proactive and risk taking than others, these sectors face more uncertainty and overconfidence (Engelen, Neumann, & Schwens, 2015). Examples of industries with more uncertainty are defense, healthcare and infrastructure construction (Baker, Bloom, & Davis, 2016).

CEO communication can have a big impact on uncertainty. But investors have limited attention, which leads to category learning. Therefore, investors are processing more market and sector-wide information than firm-specific information (Peng & Xiong, 2006). This implies that investors are making decisions based on style categories (Barberis & Shleifer, 2003). Since investors know that some industries face more uncertainty and overconfidence than others, they adjust their expectations for whole industries. Therefore, if a CEO is overconfident in an industry with a lot of overconfidence, investors think that the CEO is overconfident beforehand. This will make investor sentiment less positive and due to that it will not have much effect on the price (Malmendier & Tate, 2005a). But when a CEO is overconfident in an industry without much overconfidence, investors will not recognize that the CEO is overconfident. Investor will believe that CEOs know the true value sentiment and investor sentiment will be much more positive (Malmendier & Tate, 2005a). For that reason, an overconfident CEO has a stronger effect on stock prices in markets without a lot of CEO overconfidence.

The argument of category learning can also be explained the other way around. Investors are thinking in categories, due to that investors know the common expectations of an industry. A CEO will be recognized as overconfident when her expectations are deviating from these common expectations (Peng & Xiong, 2006). For that reason, an overconfident CEO has a less strong effect on stock prices in markets without a lot of overconfident CEOs.

2.4. Hypotheses development

In the previous paragraphs, it is described that overconfident CEO are CEOs who are overestimating their own knowledge, abilities, the precision of their own information and they are overly optimistic over the future and their ability to control the future (Goel & Thakor, 2008). For that reason, overconfident CEOs will overestimate future cashflows.

In chapter 2.2 it is described that stock prices are crashing when the price is falling a lot in a relatively short time frame, but a precise benchmark is hard to set. There are several reasons why stock prices may become too high, but all these reasons imply that that there is uncertainty about future returns and that arbitrage is not able to bring back the market the efficient price. As described above, an overconfident CEO is overestimating future cashflows of her firm and is ignoring negative feedback. For that reason, the estimations of an overconfident CEO are too optimistic. These too optimistic estimations are also communicated to the investors. Due to that, some investors will believe the CEO, demand for a stock increases and due to that the price increases. When it becomes clear that cashflows are not as high as the CEO expected, some short-term mechanism will trigger all the hoarded bad news to come out together and stock prices will crash. This results in the following hypothesis:

H1: "Firms with a CEO that scores higher on overconfidence measures will have a higher risk of subsequent stock price crashes"

In paragraph 2.3.2, it is described that CEO overconfidence is more common in some industries and that investors think in categories. Since investors know that CEOs in certain industries are more often overconfident, they think that all the CEOs in these industries are overconfident. Due to that, investors do not believe what a CEO communicates in industries with a lot of overconfident CEOs. But it can also be that overconfident CEOs are earlier and easier recognized in industries without a lot of overconfident CEOs. Therefore, the following hypotheses are formulated:

H2a: "The effect of CEO overconfidence is *larger when overconfidence is less common in an industry"*

H2b: "The effect of CEO overconfidence is smaller when overconfidence is less common in an industry"

These hypotheses will be statistically tested in the following chapters. First, the data and methodology will be described. After that the results of the regression will be described in the fourth chapter.

3. Methodology

This part of the thesis will give an overview of the methodology used to test the relationship between CEO overconfidence and stock price crash risk. First, there will be a description of the data sample. Next, there will be an overview of the proxies to measure CEO overconfidence and how to construct them. After that, it will be outlined which proxies for stock price crash risk are used and how these proxies are constructed. Finally, there will be a description of control variables and the regressions which are used.

3.1. Description of the data

This thesis will use a data sample which contains data North-American firms between 1996 and 2016[7]. This means that there will be 21 sample years, where Kim, Wang and Zhang (2016) used 17 sample years. Three different databases are used to gather the data which is necessary to do the analysis. The first database which is used is the Execucomp database from Compustat. Option holding data is downloaded from Execucomp. Only the data of CEOs is kept out this database and observations with missing option holding data are dropped. By doing this, three measures for CEO overconfidence are based on this database. Also, the data from CEO age, which is a control variable, is gathered from this database.

The second database which is used is the CRSP (The Center for Research in Security Prices). This database contains data about stock returns. Daily stock prices are gathered from this database. Again, firms with missing data for stock prices are dropped from the sample. Weekly stock returns are calculated with this data[8]. Also, data containing the “five industries portfolios” of Fama-French is used to estimate the weekly returns[9].

The final database which is used is the Compustat database with annual fundamentals, this database is used to develop some control variables. The data for the cash reserves and the R&D expenses can be downloaded directly from this database. The market-to-book ratio is developed by doing the book value per share times the number of shares divided by market value of the firm. Leverage is calculated by the amount of debt divided by the amount of equity.

[7] A lot of option holding data was not available before 1996. Therefore, it might be that the results are not representative when the regressions are done with data before 1996.

[8] Wednesday has been taken as beginning of a week to account for the week-end effect (Jaffe & Westerfield, 1985).

[9] This data is downloaded from: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Unfortunately, not all the data of the control variables was available for all the firms. Therefore, the missing values are replaced with the mean of that control variable within the same SIC-code and year. No observations are lost in the regressions with control variables by doing this[10].

After gathering the data, the datasets are matched with each other. There are two data sets in the end, one with the measures for overconfidence based on Malmendier and Tate (2005a) and one with the measure of overconfidence based on Schrand and Zechman (2012). The first dataset contains measures of overconfidence built with option holding data and includes 27,599 observations on 2,696 firms. The second dataset contains measures of overconfidence built with firm annual fundamentals data and includes 34,510 observations on 2,838 firms. A summary of the statistics can be found in the appendix, Table 11.

3.2. Proxies for CEO overconfidence

3.2.1. Different proxies

It is very hard to measure overconfidence, since it cannot be measured directly (Malmendier & Tate, 2005a). There will be several proxies which try to measure overconfidence. This thesis will be using two kinds of proxies and 7 proxies in total[11]. One kind is based on personal characteristics and the other on firm characteristics. The HOLDER67, OC_YEARLY5 and OC_CEOTENURE5 proxies are also used by Kim, Wang and Zhang (2016), while the other proxies (HOLDER100, NETBUYER, OC_YEARLY4 and OC_CEOTENURE4) are additional to test the robustness of the Kim, Wang and Zhang (2016) findings.

The HOLDER67, HOLDER100, and NETBUYER proxies for overconfidence have been developed by Malmendier and Tate (2005a). In these proxies, it is assumed that an overconfident CEO has a lot confidence in their own ability and thereby overestimate future cashflows of the firm. At the same time, they feel that the market is underestimating their ability, and therefore they expect positive returns in the future when the market catches up to their performance. Therefore, the overconfident CEO is willing to expose themselves to more

[10]Too much date is lost when the observations with missing values for the control variables are dropped.

[11] There are many more proxies for overconfidence, but these proxies will not be used in this thesis. The proxies used in this thesis are based on registry data available in databases like Execucomp, while other proxies are based on for instance survey measures or interviews.

firm-specific risk by holding on their options beyond the exercise date (Ben-David, Graham, & Harvey, 2007; Malmendier & Tate, 2005a). The holder 67 (100) proxy gives a value of 1 for all years after the CEO holds an option which is more than 67% (100%) in the money (Malmendier & Tate, 2005a). Holding an option which is 67% (100%) in the money implies that the stock price is more than 67% (100%) higher than the exercise price, which means that it is worth exercising the option. The net buyer proxy is looking at the tendency of CEOs to buy more stocks their own company. When a CEO buys more shares than she sells, she is a net buyer and when a CEO sells more shares than she buys, she is a net seller (Malmendier & Tate, 2005a).

An important advantage of these proxies is that the data, which is necessary to develop them, is available in the Execucomp database. Therefore, acquiring the data does not cost a lot of money and time. Another advantage of Malmendier and Tate's proxies is that these proxies are looking at the decisions of CEOs (Malmendier & Tate, 2005a). This is not the case with other kinds of proxies. For instance, a CEO can fill in other answers than she is thinking in a survey or it could be that others describe a CEO wrong (Malmendier & Tate, 2005b). For this reason, the proxies of Malmendier and Tate (Malmendier & Tate, 2005a) can measure overconfidence without any influence of other persons or the CEO himself.

According to Bayat, Salehnejad and Kawalek (2016), an important disadvantage of the proxies based on CEO option holding is that they may not measure CEO overconfidence accurately. When a CEO is designated to be overconfident in one firm, then the CEO should also be overconfident when he is working at another firm, since it the same CEO. But they found that CEO option holding highly correlated with firm characteristics and CEOs behave differently when they switch between firm (Bayat, Salehnejad, & Kawalek, 2016). This implies that that a CEO is who is designated to be overconfident in one firm, is in many cases not overconfident in another firm. In the end, they conclude that the option-based measures for overconfidence are overestimating overconfidence (Bayat, Salehnejad, & Kawalek, 2016).

The next proxies for overconfidence are based on firm characteristics and originally these proxies have been developed by Schrand and Zechman (2012). The first two proxies are based on the first four criteria and the next two proxies are based on all the five criteria. The criteria are:

(1) A firm has excess investments in the top quartile of firms within industries and years, Excess investments are the residual from a regression of total asset growth on sales growth.

2) The net acquisitions from the statement of cash flows are in the top quartile of firms within industries and years.

3) The debt-to-equity ratio is in the top quartile of firms within industries and years, where the debt-to-equity ratio is defined as long-term divided by total market value.

4) Either convertible debt or preferred stock is greater than zero.

5) Dividend yield is zero.

(Kim, Wang, & Zhang, 2016, p. 12)

These criteria are based on earlier research on overconfident CEOs (Schrand & Zechman, 2012). For the first criterion, it is assumed that overconfident CEOs overestimate future cashflows and underestimate the risks of a project (Ben-David, Graham, & Harvey, 2007). The second criterion is based on a finding of Malmendier and Tate (2008), they found that overconfident CEOs are more likely to overpay and to engage in value destroying acquisitions. The third criterion is based on the findings of Malmendier, Tate and Yan (2011) and Ben-David et al. (2007), which shows that overconfident CEOs are overestimating returns of investments and the investments too much financed by risky long-term debt. Also, the fourth criterion is based on the idea of overconfident CEOs who are overestimating future cashflows. For that reason, overconfident CEOs tend to invest convertible debt or preferred stock, which is considered as risky debt (Ben-David, Graham, & Harvey, 2007). The final criterion is based on the idea that overconfident CEOs are less likely to pay dividends. Instead of that, firms finance investments with this money (Ben-David, Graham, & Harvey, 2007). Therefore, these criteria are considered as characteristics of overconfidence.

The data for these four proxies are also from Compustat. Following Kim, Wang and Zhang (2016), the industry 75 percentile will be used as benchmark in the first, second and third criteria and industries will be defined by using the Standard Industrial Classification (SIC) codes. In these proxies, it is assumed that the behavior of overconfident CEO becomes visible in the firm and only an overconfident CEO believes that these firm characteristics lead to high returns (Schrand & Zechman, 2012).

As described before, two of the proxies which are developed by using the criteria of Schrand and Zechman (2012) are based on only the first four criteria and two of the proxies are based on the all the five criteria. The reason that this distinction is made is that not paying dividend can also be a characteristic of firm's industry instead of a characteristic of an overconfident CEO (Schrand & Zechman, 2012). This could also be the case with the debt-equity ratio, in some industries it is more common to finance your company with debt. But this is solved for the debt-equity ratio by taking the upper quartile of a firms SIC-code (Schrand & Zechman, 2012).

The advantage of the proxies based on firm characteristics is also that the data is widely available, therefore it the data is easy and cheap to collect. Further it can also measure overconfidence endogenous, without any influence of the CEO himself or another person.

A disadvantage of proxies based on firm characteristics is that they do not measure the decisions of a CEO directly like Malmendier and Tate's (2005a) measures do. These proxies are combining several characteristics to determine whether a firm's CEO is overconfident or not. But does that mean that a CEO is overconfident? It could also be that one criteria are met by coincidence, or that for instance all firms in a whole industry are having a lot of debt or is not paying dividend. This problem is solved in two ways. First, a CEO is not denoted as overconfident when only one criterion is met, at least two out of four (OC_YEARLY4 and OC_CEOTENURE4) or three out of five (OC_YEARLY5 and OC_CEOTENURE5) criteria should be met before a CEO is denoted as overconfident. Second, the problem with the industry characteristics is solved by picking the upper quartile of a firms SIC-code instead of the upper quartile of the whole sample.

3.2.2. Constructing the proxies

Execucomp does not provide data about the option grant specific exercise prices. Therefore, the average exercise price should be estimated using the method of Core and Guay (2002). First, the average exercise value per option is calculated, this is equal to the average value of the unexercised options[12] minus the year end close price of a stock[13],[14]. After that the average moneyness is calculated, this is equal to the average value of the unexercised options divided by the average exercise value per option. The final step is to develop the holder67 and holder100. When the average moneyness is bigger than 2/3 or 1, the holder67[15] and holder100[16] get value of 1 after an CEO gets a moneyness which is bigger than 67% or 100%.

The original proxy of Malmendier and Tate (2005a) had as a criterion for being overconfident that a CEO should hold options which are 67% or 100% in the money at least

[12] Execucomp variables: avvalue=opt_unex_exer_est_val/opt_unex_exer_num
[13] Execucomp variables: PRCCF
[14] Execucomp variables: avexercise=prccf-avvalue
[15] HOLDER67 in the analysis.
[16] HOLDER100 in the analysis.

twice. But according to Hirshleifer, Low and Teoh (2012), it does not make a statistical difference between the regression with holding an option which in the money once or twice. Therefore, following Hirshleifer, Low and Teoh (2012) and Kim, Wang, Zhang (2016) a CEO is overconfident when he or she is holding an option which is 67% or 100% in the money at least once[17].

The "net buyer" proxy is called NETBUYER and is developed in the following way: First, it is calculated how many shares a CEO has bought or sold [18]. Next, it is calculated in how many years a CEO has bought more shares than she sold. Finally, the "net buyer" variable is created. This variable gives value 1 if a CEO buys more shares than she sells in three or more years[19].

The following four proxies are based on firm characteristics and specifically on the criteria of Schrand and Zechman (2012) which are described above. Two of the proxies are based on the first four criteria and two are based on all the described criteria. A single criterion gets value 1 when the criterion is met.

The OC_YEARLY4 proxy is based on the first four criteria and is a firm-level proxy. This means that overconfidence is related to a firm and not to a CEO. This variable get value of 1 when at least 2 of the criteria are met. The OC_CEOTENURE4 proxy is also based on the first four criteria, but is a CEO-level proxy. It is developed the same way as the OC_YEARLY4 proxy, the only difference is that overconfidence is related to the CEO by following the steps of Campbell et al. (2011). Due to that, when a firm meets the criteria for being overconfident in one year, the CEO at that moment is overconfident for all years afterwards[20].

The sixth and seventh proxy for overconfidence are almost the same as the fourth and fifth proxy. Where the fourth and fifth measure are based on the first four criteria, the sixth and seventh measure are based on all the five criteria. These proxies get value 1 when at least three of the five criteria are met, where the previous two proxies get value one when at least two of

[17] It is also tested whether there is a statistical difference between the benchmark holding an option which is 67% or 100% in the money one or two times, but there were no differences between these results

[18] Execucomp variables: deltashares = shrown_excl_opts - L1. shrown_excl_opts

[19] The original proxy of Malmendier and Tate (2005a) is slightly different, it requires the CEO to be a "net buyer" three times in the first five sample years. The proxy of Malmendier and Tate (2005a) does not give other results as this proxy.

[20] The OC_CEO4 proxy gets value 1 when the company meets at least 2 of the 4 criteria are met and in all years after the company met the criteria when the company is having the same CEO.

the four criteria are met. The OC_YEARLY5 proxy is a firm-level proxy like the OC_YEARLY4 proxy, and the OC_CEOTENURE5 proxy is a CEO-level proxy like the OC_CEOTENURE4 proxy. The OC_CEOTENURE5 proxy is also related to the CEO by following the steps of Campbell et al. (2011).

3.3. Proxies of stock price crash risk

3.3.1. Different proxies

As mentioned before, a stock price is crashing when it is falling a lot, but it is hard to define a good benchmark. There are several proxies which try to measure the risk of stock price crashes. All these measures are based on historical stock prices. Data for stock price crash risk is gathered from the CRSP database and there will be seven measures for stock price crash risk. The CRASH_MEDIUM and NCSKEW proxies are also used by Kim, Wang, Zhang (2016)

The first proxy will be CRASH_MEDIUM. This proxy can have two values, yes (1) or no (0). This proxy is having the value one if a stock has crashed once during the year. A stock price crashes if the weekly return falls 3.09 standard deviations below the mean firm-specific returns over the fiscal year (CRASH_MEDIUM)[21]. According to Hutton, Marcus and Theranian (2009), a benchmark of 3.09 standard deviations is useful because it is giving the lowest 0.1% of the population.

The next two measures are almost the same as the first proxy. The only difference is that those proxies have value 1 when a firm's weekly return has fallen 2.5 (CRASH_SMALL) or 4.5 (CRASH_LARGE) standard deviations below the mean firm-specific returns over the fiscal year. The benchmark of 2.5 standard deviations is giving the lowest 0.62% of the distribution, while the proxy with 4.5 standard deviations as a benchmark for a stock price crash is giving the lowest 0.003% of the distribution (Walker, 2017). These additional benchmarks are chosen, because 2.5 standard deviation benchmark is less strict and the 4.5 standard deviation benchmark is stricter than the MEDIUM benchmark.

[21] Kim, Wang and Zhang (2016) used 3.2 standard deviations as a benchmark. But this is not giving 0.1% of the distribution, it is giving 0.07% of the distribution (Walker, 2017). It is tested whether the outcome of the regressions with 3.2 and 3.09 standard deviations as a benchmark for a crash differ, but the outcomes are qualitatively similar.

The next three proxies are equal to the times a stock price of a firm crashes during a year with the same three different benchmarks for a crash as the previous proxy. I have not found any other articles which were using these proxies. But when there is a positive relationship with CRASH, there should also be a relationship with the number of crashes during year.

The next three proxies are counting the times a stock price of a firm has crashed and discounting this with the times a stock price of a firms has jumped during a year. These proxies can have multiple possible outcomes. A stock price crashes if the weekly return falls 2.5 (CRASH_SMALL), 3.09 (CRASH_MEDIUM) or 4,5 (CRASH_LARGE) standard deviations below the mean firm-specific returns over the year, the same way as with the proxy "crash". A stock price jumps when the weekly return increases with 2.5, 3.09 or 4,5 standard deviations above the mean firm-specific returns over the year. The idea behind these proxies is that is does not matter when a stock price crashes, if it is also increasing again. The return of a stock is not low when a stock crashes once and is jumps once, instead, the return becomes too low when the stock price crashed more times than it increased. Therefore, the higher the value of NET_COUNT, the higher the change that a stock is having a low return and that the stock price crashes. This proxy is used because it is distinguishing itself from the CRASH and COUNT_CRASH proxies. These proxies are only looking at stock price crashes. But it can be the case that a stock is just very volatility. A stock that both crashes and jumps can be due to a lot of uncertainty in the environment.

The next proxy will be the ratio of crashes to jumps. The higher the value of this proxy, the more crasher there are relative to jumps. I have also not found any other articles which used this proxy before. But when the NET_COUNT proxies are having a significant relationship with the overconfidence proxies, then these proxies should have a significant effect either, since it is distinguishing itself in the same way from the CRASH and COUNT_CRASH proxies as the NET_COUNT proxy.

The next proxy is different from the previous proxies, this proxy is counting the times a stock jumps during a year. This proxy is also not used in other papers before. As mentioned before, a stock jumps when the return of a stock increases with more than the benchmark for a jump. When a positive relationship between CEO overconfidence and the CRASH, COUNT_CRASH, NET_COUNT and COUNT_RATIO is expected, then it is expected that there is no significant relationship between the proxies for overconfidence and the number of jumps. Overconfidence is positively related to stock price volatility and not with stock price crashes when the number of jumps is also having a positive relationship with the proxies for overconfidence.

The last proxy for stock price crash risk is also used by Kim, Wang and Zhang (2016) and will be negative skewness. Skewness is measuring the asymmetry of a probability distribution, negative skewness implies that the tail on the left side is longer than the tail on the right side of the distribution (Chen, Hong, & Stein, 2001). This means that there is a probability of a big negative return (Hong & Stein, 2003). The idea that is underneath the negative skewness proxy is that when a stock is negatively skewed, then there will be more negative outliners of residual returns then positive. This means that a stock is more likely to crash when the returns are negatively skewed (Chen, Hong, & Stein, 2001).

3.3.2. Constructing the proxies

Some steps need to be done before the proxies for crash risk can be developed. First, daily stock price data is downloaded from CRSP. Second, the daily stock prices are transformed into weekly stock prices[22], with the week starting on Wednesday. Third, the return of the stocks is calculated. Next, the daily returns of the Fama-French value weighted industry index are downloaded and turned into weekly data. After that, expected stock returns are calculated with the following formula.

$$\begin{aligned} r = \alpha + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_5 r_{m,t+2} + \beta_6 r_{i,t-2} \\ + \beta_7 r_{i,t-1} + \beta_8 r_{i,t} + \beta_9 r_{i,t+1} + \beta_{10} r_{i,t+2} + \varepsilon \end{aligned} \quad (1)$$

In this formula is r_m the return on the CRSP value-weighted market index in week t and r_i is the return on the Fama-French value-weighted industry index in week t. The return is estimated with the observed, lagged and lead returns. The lagged and leaded terms are included to allow for nonsynchronous trading (Dimson, 1979). The next thing which should be done before the proxies can be built, was to estimate the residuals. The residuals are used to is estimated the real return with the following formula.

$$W_{j,t} = \ln(1 + \varepsilon_{j,t}) \quad (2)$$

The next step was to calculate the mean return and the standard deviation per firm-year.

[22] This is done by using the ASCOL command in STATA

After that the proxies for stock price crash risk can be built. The first proxy for stock price crash risk is the variable CRASH, this variable is built with three different benchmarks for a crash, these benchmarks are 3.09, 2.5 and 4.5 standard deviations. The first step in developing the CRASH variable was to determine the benchmarks for a crash. The benchmarks are equal to the mean weakly returns less 3.09, 2.5 or 4.5 standard deviations per firm-year. When a stock's weekly return becomes lower than this benchmark, the stock crashes. The variable CRASH has value 1 if a firm's weekly return has dropped at least once below the benchmark of that firm in a certain year. The proxy with a 2.5 standard deviations as a benchmark for a crash is called CRASH_SMALL, the proxy with 3.09 standard deviations as a benchmark for a crash is called CRASH_MEDIUM and the proxy with 4.5 standard deviations as a benchmark for a crash is called CRASH_LARGE.

After the CRASH proxies, the COUNT_CRASH proxies are developed. These proxies are almost equal to the CRASH proxies. The only difference is that these proxies can not only get value 0 and 1, these proxies get the value of the total amount of crashes during a year for a firm. The proxy with a 2.5 standard deviations as a benchmark for a crash is called COUNT_CRASH_SMALL, the proxy with 3.09 standard deviations as a benchmark for a crash is called COUNT_CRASH_MEDIUM and the proxy with 4.5 standard deviations as a benchmark for a crash is called COUNT_CRASH_LARGE.

The next proxies which are developed are the COUNT_JUMP proxies. These proxies are counting the times a stock's weekly return comes above the benchmark. The benchmark for a jump is the mean weakly return plus 3.09, 2.5 or 4.5 standard deviations per firm-year. The proxy with a 2.5 standard deviations as a benchmark for a jump is called COUNT_JUMP_SMALL, the proxy with 3.09 standard deviations as a benchmark for a jump is called COUNT_JUMP_MEDIUM and the proxy with 4.5 standard deviations as a benchmark for a jump is called COUNT_JUMP_LARGE.

After that the NET_COUNT proxies are developed. These proxies are the result of the number of crashes minus the number of jumps within the same benchmark for a crash and a jump, for instance NET_COUNT_MEDIUM is the result of COUNT_CRASH_MEDIUM minus COUNT_JUMP_MEDIUM. Thus, a value of 2 on the NET_COUNT proxies implies that a stock has crashed 2 times more than it has crashed. The NET_COUNT proxy with a benchmark for crashes and jumps of 3.09 standard deviations is called NET_COUNT_MEDIUM, 2.5 standard deviations is called NET_COUNT_SMALL and 4.5 standard deviations is called NET_COUNT_LARGE.

The last proxies which are based on the COUNT_CRASH and COUNT_JUMP proxies are the COUNT_RATIO proxies. These proxies are calculated with the following formula:

$$\frac{Crashes}{Jumps} = \ln\left(\frac{1 + \mathrm{COUNT\_CRASH}}{1 + \mathrm{COUNT\_JUMP}}\right) \tag{3}$$

A value bigger than 0 implies that a stock has crashed more times than it has jumped and a value smaller than 0 means that a stock has jumped more times than in has crashed. The natural logarithm of the ratio is taken to make the linear interpretation more straightforward, since the ratio is not linear. The COUNT_RATIO proxy with a benchmark for crashes and jumps of 3.09 standard deviations is called COUNT_RATIO_MEDIUM, 2.5 standard deviations is called COUNT_RATIO_SMALL and 4.5 standard deviations is called COUNT_RATIO_LARGE.

The final proxy for stock price crash risk will be negative skewness. This proxy is called NCSKEW, for “negative coefficient of skewness”. This proxy is calculated by taking the negative of the third moment of weekly returns, and dividing it by (the sample analog to) the standard deviation of daily returns raised to the third power. This implies that we have for a certain stock *i* over period t:

$$NCSKEW_{it} = -(n(n-1)^{\frac{3}{2}}\Sigma W_{j,t}^{3})/((\mathrm{n}-1)(\mathrm{n}-2)\left(\Sigma W_{j,t}^{2}\ \right)^{\frac{3}{2}}) \tag{4}$$

Where W(j, t) is the firm-specific weekly returns for each sample year; and n is the number of observations on weekly returns in the sample year. The higher the value of NCSKEW, the higher the increase in negative volatility.

3.4. Description of the methodology

3.4.1. Control variables

The analysis also contained some control variables. This is to control for influences of these variables on stock price crashes and CEO overconfidence. The included control variables are: market to book ratio and financial leverage which are also used by Kim, Wang and Zhang (2016). In addition, there will be some extra control variables. This will be CEO age, a firm’s cash reserves, earnings per share and research and development expenses which are also widely used as control variables (Engelen, Neumann, & Schwens, 2015; Goel & Thakor, 2008; Schrand & Zechman, 2012). The data for the control variables is all yearly data and will also be downloaded from Compustat and CRSP database.

The market to book ratio is a useful control variable because it is trying to identify securities which are undervalued or overvalued. According to Fama and French (1993), the book to market ratio is correlated with the expected returns. When the book to market ratio is smaller than one, the market value is bigger than the book value. When this is the case, it is likely that the firm is overvalued. Due to this the is it likely that the value of stocks will decrease and that stock prices crash (Fama & French, 1993).

The second control variable is financial leverage. Financial leverage is measuring the part of a firm which is financed by debt. When financial leverage is high, a firm is for a big part financed with debt. Firms with high leverage should have high cash flows to pay the dividends over their debt, which they do not always have. Therefore, firms with high leverage are more likely to face stock price crashes (Kim, Li, & Li, 2014). Further, financial leverage is also correlated with CEO overconfidence. An overconfident CEO overestimates future cashflows and is therefore willing to finance a big part of the CEO with debt, which is riskier than equity (Ben-David, Graham, & Harvey, 2007).

In addition to the control variables which are also used by Kim, Wang and Zhang (2016), I also add some additional control variables. First, the regression will also be controlled for CEO age. Earlier research has found that younger CEOs are less likely to do an acquisition than older CEOs. The reason for that is that older CEOs are more experienced and trust more on their own ideas that younger CEOs (Yim S. , 2013). This implies that older CEOs are more likely to be overconfident than younger CEOs (Chen, Hong, & Stein, 2001). A contradicting finding has been found by (Ferris, Jayaraman, & Sabherwal, 2013). Ferris, Jayaraman and Sabherwal (2013) found CEO overconfidence is inversely related with age, since a that a firm with a younger CEO is more likely to do an announcement of acquiring a firm. This implies that older CEOs are more cautious (Ferris, Jayaraman, & Sabherwal, 2013). Both findings are confirmed by Krawczyk and Wilamowski (2016). They investigated overconfidence in a sample of one million marathon participants. They found that the level of overconfidence was U-shaped. The youngest and oldest participants were most overconfident, while the participants between 40 and 50 years old were least overconfident (Krawczyk & Wilamowski, 2016)[23].

Another extra control variable is cash. Firms with a lot of cash are risk averse, they are always able to pay when they should pay (Malmendier & Tate, 2008; Opler, Pinkowitz, Stulz, & Williamson, 1999). Firms with a lot of cash reserves can always fulfill their paying obligations, therefore, there is less risk that these firms go bankrupt and there firms are seen as a safe investment opportunity (Opler, Pinkowitz, Stulz, & Williamson, 1999). Further, Callen and Fang (2015) found that stock price crashes are more likely to occur when firms are more likely to go bankrupt in the future.

The final control variable are the research and development expenses. Earlier research has found that firms with overconfident CEOs are more likely to have high research and development expenses, since overconfident CEOs are likely to overestimate the future cash flows of the expenses (Hirshleifer, Low, & Teoh, 2012). Further, firms with high research and development expenses have the risk of very low earnings, because it is uncertain if the investments have a positive outcome (Hirshleifer, Low, & Teoh, 2012). When investors know that a firm is having low earnings, then stock prices will fall. This implies that firms with high research and development expenses also face higher stock price crash risk.

3.4.2. Regressions

The data analysis will be done by using STATA. The dependent variable in all the regressions will be the proxy stock price crash risk and the independent variables will be the proxy for overconfidence and the control variables. All the proxies for overconfidence have a value of 1, when a CEO is overconfident, or 0, if a CEO is not overconfident, therefore these measures will be included as a dummy (Malmendier & Tate, 2005a).

The first three proxies for stock price crash risk, CRASH[24], can have two values: a stock has crashed (1) or a stock has not crashed (0). Therefore, a normal OLS regression will not be suited. In this case, a logistic regression is used[25]. By doing the regression it is considered that

[23] Since the level of overconfidence over age is U-shaped, it would be logical to use the normal variable for age and the squared version. But when this is done, in all the regressions the coefficients of age and half of the coefficients of age-squared become not significant. While the coefficient of age is significant in most regressions when only the normal variable is used. An explanation for this can be that CEO overconfidence is not U-shaped in this sample. Therefore, age-squared is excluded from the regressions.

[24] The precise proxies are CRASH_MEDIUM, CRASH_SMALL and CRASH_LARGE.

[25] The logistic regression is best suited to do regression with two possible outcomes

the data is clustered within around the firm. This analysis will be done with a decrease of 2.5, 3.09 and 4.5 standard deviations in a firm's weekly returns as a benchmark for stock price crashes and it will be checked whether the effect differs across industries. First, it will be tested whether there is a relationship without any control variables and later, it will also be tested if there is still a relationship when the control variables are included.

The proxies which are counting the amount of crashes can have values between 0 and 52, but only values between 0 and 6 are observed for the smallest benchmark for a stock price crash. Therefore, an ordered logit regression will better suited than a normal OLS, since a normal OLS is estimating the regression from minus infinity to plus infinity and the ordered logit regression can deal with categorical data. It is considered that the data is clustered around the firm by doing the ordered logit regression. These regressions are repeated with three different benchmarks (3.09, 2.5 and 4.5) for a stock price crash. Next, it is tested whether the found effect changes when control variables were added. Finally, there are also three regressions (one with all the three benchmarks for a stock price crash) which test whether there the effect is different between the industries.

The next three proxies for stock price crash risk are the result of the amount of crash weeks in a year minus the amount of jump weeks. This implies that these proxies can have values from -52 to 52. But looking at the distribution reveals that the values vary between -5 and 6. For this reason, an ordered logit regression will be used. Also, this proxy will be regressed with and without the control variables, and it will also be tested whether the effects are different between industries. By doing the regression it is also considered that the data is clustered around the firm.

The proxies based on the ratio of crashes to jumps can in theory have values between 3.97 and -3.97, but I observe only values between -1.79 and 1.94. Therefore, an ordered logit regression will also for used for the regression with the proxies based on the ratio of crashes to jumps. It is considered that the data is clustered around the firm by doing the regressions. Also, this proxy will be regressed with and without the control variables.

The regressions with the proxies with the COUNT_JUMP proxies are also done with an ordered logit regression, since values between 0 and 6 are observed for the COUNT_JUMP_SMALL proxies, with taken into account that the data is clustered around the firm. These regressions are done with all the three benchmarks for a jump, with and without control variables.

The final proxy for stock price crash risk will the negative skewness of weekly stock returns in a fiscal year. This variable can also have all possible values[26] and many different values occur. Therefore, this variable can be tested by using a normal OLS. Also for this proxy will be regressed with and without the control variables.

When all the above described regressions are done it will be tested whether the found effect is the same in all industries. The industries are developed by following the reasoning of French's (2017) "five industries portfolios" and are based on SIC codes, which can be seen in Table 10 in the appendix. By looking at the sample sizes, it became clear that the industry containing consumer durables, non-durables, wholesale, retail and some services (Industry "1" in STATA) was very small[27]. This industry is merged with industry "other" to solve this. By doing this, I kept 4 different industries for testing whether there are differences between the industries. In addition, it is also tested whether there are differences in the stock price crash risk and overconfidence means between the industries. When there are no differences in means of the proxies for stock price crash risk and overconfidence, it would also not make sense to test if there are differences between the industries.

It is tested whether the effect of CEO overconfidence is different within different industries by redoing the regressions including interaction terms, these are a dummy variable for the industries times the measure for CEO overconfidence. The consumer durable and other industry is the reference category in these regressions. The HOLDER67 proxy in this regression is giving the coefficient for the reference category. The interaction terms are giving coefficient which display the difference between the reference category and the industry.

[26] Most of the values are between -6.961123 (5 percentile) and 7.365686 (95 percentile).

[27] In the appendix, Table 31, it can be seen that this industry contains only 2,587 observations. This is much smaller than the other industries. Therefore, this industry is merged with the "other" industry.

4. Results

This part of the text will show the results of the regression. First, the results of the regressions with the CRASH proxies as a proxy for stock price crash risk are be described. After that the regressions, with COUNT_CRASH, NET_COUNT, COUNT_JUMP and COUNT_RATIO, are described. Next, the results of the regressions with NCSKEW as a proxy for stock price crash risk will be given. Finally, it will be checked whether there are differences between different industries.

But before the results are described, it is important that some other things are mentioned. First, a summary of the statistics can be found in the appendix, Table 10. Second, it is tested whether there is multicollinearity between the variables or not[28], if there is a constant variance[29] and if there is covariance between the variables or not[30]. The results of these tests can be found in the appendix, Table 12, Table 13 and Table 14. By doing this it is found that there is no multicollinearity, constant variance and little covariance.

4.1 Results: CRASH

The CRASH proxies are all tested with a logit regression with considering clustering around the firm. The results of the regressions with the CRASH proxies can be found in

Table 1. All the proxies for CEO overconfidence are having a positive and significant effects on CRASH_MEDIUM, which can be seen in Table 1

Table 1. Which means that a falling stock return with 3.09 standard deviations below the mean yearly return is positively related with holding options which are in the money, buying additional stocks and the firm characteristics described by Schrand and Zechman (2012). Kim Wang and Zhang (2016) also regressed the CRASH_MEDIUM proxy with the HOLDER67, OC_YEARLY5 and OC_CEOTENURE5 proxies. They found similar results for these regressions.

The economic significance of the OC_CEOTENURE5 proxies is quite big, 35.8% of the standard deviation of the CRASH_MEDIUM proxy can be explained by the OC_CEOTENURE5 proxy. The HOLDER100 proxy is having the lowest economic

[28] This is done with the estat vif command in STATA.

[29] A constant variance is one of the assumptions of a linear regression (Kutner, Nachtsheim, & Neter, 2004). The estat hettest command in STATA is used to test this.

[30] This is tested with the estat vce command in STATA.

significance, only 13% of the standard deviation of CRASH_MEDIUM can be explained with HOLDER100 proxy.

Adding the control variables to the regressions did not lead to a lot of differences in the results for the proxies based on CEO-characteristics. But the results for the proxies based on firm-characteristics did change, the OC_YEARLY4, OC_CEOTENURE4 and OC_CEOTENURE5 proxies became insignificant[31]. The OC_YEARLY4, OC_CEOTENURE4 proxies are both not used by Kim Wang and Zhang (2016). The insignificant results for the OC_CEOTENURE5 proxy is a difference with the results of Kim Wang and Zhang (2016), since they still have significant results after adding the control variables. An explanation for this can be the difference in sample years[32]. The results for the OC_YEARLY5 proxy did not change, both are still significant when the control variables are added. The results of the CRASH_MEDIUM proxy and the proxies for CEO overconfidence including the control variables can be found in the appendix, Table 15.

The results of the regressions with CRASH_SMALL can be found in
Table 1. Here, only the NETBUYER proxy is having a significant and positive effect on CRASH_SMALL. The NETBUYER can explain 24.7% of the standard deviation of CRASH_SMALL. All the other proxies for CEO overconfidence are not having significant effects on the CRASH_SMALL proxy. The CRASH_SMALL proxy is not used by Kim Wang and Zhang (2016). The insignificant results indicate that when the benchmark for a crash is low and 0.62% of the sample is indicated as a crash, then there is no longer a significant relation between CEO overconfidence and stock price crashes. The results did not change when the control variables are added to the regressions, these results can be found in Table 16 in the appendix.

The final regressions with the proxies which indicated whether there has been a crash or not is done with the CRASH_LARGE proxy. The CRASH_LARGE is using a higher benchmark for stock price crashes than the other CRASH proxies, therefore, there are less crashes in the CRASH_LARGE proxies. In
Table 1, it can be found that NETBUYER proxy and the proxies based on firm characteristics are having significant effects on CRASH_LARGE, these proxies can explain between 17.0% and 63.5% of the standard deviation of CRASH_LARGE. The HOLDER67 and HOLDER100

[31] The results are also not significant when only the control variables which are used by Kim Wang and Zhang (2016) are added.

[32] I could not test whether I will find the same effect as Kim Wang and Zhang (2016) when the same sample years are used since the option holding data was nog available before 1996.

proxy are not having significant effects on the CRASH_LARGE proxy. These findings imply that the proxies based on CEO option holding do not have a significant effect on stock price crash risk, while the NETBUYER proxy and the proxies based on firm-characteristics do have a significant effect when the benchmark for stock price crashes is higher. The HOLDER67 proxy becomes significant at the 10% level after adding the control variables, while the OC_CEOTENURE5 proxy became insignificant after adding the control variables to the regression. These results can be found in Table 17 in the appendix.

Table 1: Regression without control variables CRASH

	1	2	3	4	5	6	7
CRASH_MEDIUM							
HOLDER67	0.0748** (2.45)						
HOLDER100		0.0627** (2.25)					
NETBUYER			0.0842*** (3.12)				
OC_YEARLY4				0.0851** (2.07)			
OC_YEARLY5					0.288** (2.38)		
OC_CEOTENURE4						0.0673** (2.37)	
OC_CEOTENURE5							0.1727** (2.89)
CRASH_SMALL							
HOLDER67	0.0139 (0.34)						
HOLDER100		0.0176 (0.47)					
NETBUYER			0.0997*** (2.74)				
OC_YEARLY4				0.0568 (1.04)			
OC_YEARLY5					0.112 (0.69)		
OC_CEOTENURE4						0.0610 (1.61)	
OC_CEOTENURE5							0.115 (1.36)
CRASH_LARGE							
HOLDER67	0.0534 (1.61)						
HOLDER100		0.0453 (1.51)					
NETBUYER			0.0797*** (2.73)				
OC_YEARLY4				0.0808* (1.84)			
OC_YEARLY5					0.282** (2.35)		
OC_CEOTENURE4						0.0754** (2.46)	
OC_CEOTENURE5							0.132** (2.07)

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

4.2. Results: COUNT_CRASH

The COUNT_CRASH proxies are all tested with an ordered logit regression with taking clustering around the firm into account. The results of the regressions with the COUNT_CRASH proxies can be found in Table 2. The COUNT_CRASH proxies are not used by Kim Wang and Zhang (2016). But when there is a positive significant relationship with the appearance of a crash or not during a year, it is also expected that the COUNT_CRASH proxies are positive and significant correlated with the proxies for CEO overconfidence.

In Table 2 only the HOLDER100 and NETBUYER proxy are positively correlated with COUNT_CRASH_MEDIUM. The HOLDER100 proxy can explain only 6.3% and the NETBUYER proxy can explain only 11% of the standard deviation of the COUNT_CRASH_MEDIUM proxy. This shows that most of the proxies for CEO overconfidence do not have significant relations, while the others have low economic significance. The results of the regressions with CRASH_COUNT_MEDIUM including the control variables can be found in Table 18, which can be found in the appendix. Including the control variables did not qualitatively change to the results.

The regressions with COUNT_CRASH_SMALL only give significant and positive coefficients for the NETBUYER proxy. But the economic significance of this proxy is rather low, only 6.5%. All the other proxies do not have significant coefficients in the regressions with COUNT_CRASH_SMALL. This indicates that the proxies for CEO overconfidence are not strongly influenced by the COUNT_CRASH_SMALL proxies. The results did not qualitatively change when the control variables are added to the regression, these results can be found in Table 19.

The results of the regressions with the COUNT_CRASH_LARGE proxy can also be found in Table 2. Here, the NETBUYER proxy is having a significant coefficient at the 1% level and the OC_YEARLY5 and OC_CEOTENURE4 proxies are having significant coefficients at the 10% level. The NETBUYER proxy can explain 19.6% of the standard deviation of COUNT_CRASH_LARGE, while the other proxies can explain less than 10% of the standard deviation of COUNT_CRASH_LARGE. Only the NETBUYER proxy stays significant when the control variables are added to the regressions, which means that the OC_YEARLY5 and OC_CEOTENURE4 proxies became insignificant[33]. This is seen as a

[33] It is found that the results are also not significant when only the control variables which were used by Kim Wang and Zhang (2016) are used.

logical consequence of adding the control variables, since these variables were already only significant at the 10% level.

Table 2: Regressions without control variables COUNT_CRASH

	1	2	3	4	5	6	7
COUNT_CRASH_MEDIUM							
HOLDER67	0.0503 (1.64)						
HOLDER100		0.0500* (1.76)					
NETBUYER			0.0868*** (3.06)				
OC_YEARLY4				0.00634 (0.46)			
OC_YEARLY5					0.0219 (0.57)		
OC_CEOTENURE4						0.0128 (1.05)	
OC_CEOTENURE5							-0.0146 (-0.52)
COUNT_CRASH_SMALL							
HOLDER67	0.0253 (0.80)						
HOLDER100		0.0359 (1.21)					
NETBUYER			0.0715** (2.38)				
OC_YEARLY4				0.0109 (0.55)			
OC_YEARLY5					-0.0395 (-0.72)		
OC_CEOTENURE4						0.0167 (0.88)	
OC_CEOTENURE5							-0.0501 (-1.13)
COUNT_CRASH_LARGE							
HOLDER67	0.0449 (1.32)						
HOLDER100		0.0420 (1.34)					
NETBUYER			0.0914*** (2.97)				
OC_YEARLY4				0.0130 (1.54)			
OC_YEARLY5					0.0468* (1.83)		
OC_CEOTENURE4						0.0114* (1.78)	
OC_CEOTENURE5							0.00592 (0.42)

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

4.3. Results: NET_COUNT

The NET_COUNT proxies are all tested with an ordered logit regression considering that the data is clustered around the firm. The results of the regressions with the NET_COUNT proxies can be found in Table 3. The NET_COUNT proxies are not used by Kim Wang and Zhang (2016). But CRASH and COUNT_CRASH proxies can indicate that there has been a crash, while it was just the volatility in a firm's weekly returns.

In Table 3, six out of the seven measures for CEO overconfidence are having a positive and significant influence on NET_COUNT_MEDIUM. The HOLDER67 proxy is positive, but not significant. The HOLDER100 proxy is having a positive and significant coefficient at the 10% level. The NETBUYER is positive and significant at the 5% level. The proxies based on the firm characteristics and related to the CEO are having a positive coefficient and is significant at the 1% level. The economic significance of the HOLDER100 and the NETBUYER proxy is rather low, between 3.9% and 4.9% of the standard deviation of NET_COUNT can be explained by these proxies. The economic significance of the proxies based on firm-characteristics is higher, between 50.3% and 144.1% of the standard deviation of NET_COUNT_MEDIUM can be explained by these proxies. Adding the control variables did not adjust the qualitatively alter the results, these results can be found in Table 21.

The results for NET_COUNT_SMALL are slightly different from the results of NET_COUNT_MEDIUM. The results for the proxies based on firm characteristics did not change, but the HOLDER100 and NETBUYER proxy became insignificant, which can be seen in Table 3. The economic significance of these proxies based on firm characteristics is high, since between 40.0% and 112.1% of the standard deviation can be explained by the proxies for CEO overconfidence. The results of the regressions including the control variables, which can be found in Table 22, are qualitatively not different from the results without the control variables.

It can be seen in Table 3 that the results for NET_COUNT_LARGE are quite like the results of NET_COUNT_MEDIUM and NET_COUNT_SMALL. The results for the CEO overconfidence proxies based on firm characteristics and the NETBUYER proxy are significant and positive for the NET_COUNT_LARGE proxy. The coefficients for the proxies based on CEO option holdings are not significant. The economic significance of the coefficients of the proxies based on firm characteristics is also high for the NET_COUNT_LARGE proxy, while the economic significance of the NETBUYER proxy is lower. The results did not qualitatively change when the control variables were added to the regression. The results of the regression with NET_COUNT_LARGE can be found in Table 23.

Table 3: Regressions without control variables NET_COUNT

	1	2	3	4	5	6	7
NET_COUNT_MEDIUM							
HOLDER67	0.0368 (1.52)						
HOLDER100		0.0394* (1.82)					
NETBUYER			0.0491** (2.37)				
OC_YEARLY4				0.556*** (4.19)			
OC_YEARLY5					1.446*** (5.62)		
OC_CEOTENURE4						0.505*** (3.08)	
OC_CEOTENURE5							1.442*** (7.71)
NET_COUNT_SMALL							
HOLDER67	0.00776 (0.33)						
HOLDER100		0.0122 (0.58)					
NETBUYER			0.0219 (1.08)				
OC_YEARLY4				0.539*** (4.03)			
OC_YEARLY5					1.397*** (5.33)		
OC_CEOTENURE4						0.507*** (3.10)	
OC_CEOTENURE5							1.419*** (7.62)
NET_COUNT_LARGE							
HOLDER67	0.0266 (0.94)						
HOLDER100		.02326 (0.91)					
NETBUYER			0.0655*** (2.60)				
OC_YEARLY4				0.557*** (4.22)			
OC_YEARLY5					1.410*** (5.59)		
OC_CEOTENURE4						0.516*** (3.16)	
OC_CEOTENURE5							1.463*** (7.96)

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

4.4. Results: COUNT_JUMP

The COUNT_JUMP proxies are also all tested with an ordered logit regression taking clustering around the firm into account. The results of the regressions with the COUNT_JUMP proxies can be found in Table 4. The COUNT_JUMP proxies are not used by Kim Wang and Zhang (2016). According to by Kim Wang and Zhang (2016), stock price crash risk is positively correlated with CEO overconfidence. When a positive relationship between CEO overconfidence and the CRASH, COUNT_CRASH, NET_COUNT and COUNT_RATIO is expected, then it is also expected that there is no significant relationship between the proxies for overconfidence and the COUNT_CRASH proxies.

The results for the regressions with the COUNT_JUMP proxies can be found in Here it can be seen that the proxies for CEO overconfidence based on CEO-characteristics are not having significant effects on all the COUNT_JUMP proxies and that the proxies based on firm characteristics are having a significant negative effect for all proxies. Earlier, it was found that CEO overconfidence is positively correlated with the some of the CRASH proxies. The insignificant results for the proxies based on CEO-characteristics indicate that the proxies for CEO overconfidence are correlated with stock price crashes and not with volatility. Adding the control variables to the regressions with COUNT_JUMP_MEDIUM did not change the signs and significance levels of the found effects for all the regressions, this can be seen in Table 24, Table 25 and Table 26.

Table 4: Regressions without control variables COUNT_JUMP

	1	2	3	4	5	6	7
COUNT_JUMP_MEDIUM							
HOLDER67	-0.00335 (-0.11)						
HOLDER100		-0.00500 (-0.18)					
NETBUYER			0.0256 (0.94)				
OC_YEARLY4				-0.550*** (-4.20)			
OC_YEARLY5					-1.424*** (-5.62)		
OC_CEOTENURE4						-0.492*** (-3.05)	
OC_CEOTENURE5							-1.457*** (-7.83)
COUNT_JUMP_SMALL							
HOLDER67	0.0231 (0.72)						
HOLDER100		0.0326 (1.10)					
NETBUYER			0.0426 (1.46)				
OC_YEARLY4				-0.529*** (-4.03)			
OC_YEARLY5					-1.437*** (-5.59)		
OC_CEOTENURE4						-0.490*** (-3.06)	
OC_CEOTENURE5							-1.469*** (-7.72)
COUNT_JUMP_LARGE							
HOLDER67	0.0209 (0.49)						
HOLDER100		0.0227 (0.57)					
NETBUYER			0.00845 (0.22)				
OC_YEARLY4				-0.544*** (-4.15)			
OC_YEARLY5					-1.363*** (-5.47)		
OC_CEOTENURE4						-0.505*** (-3.11)	
OC_CEOTENURE5							-1.457*** (-7.97)

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

4.5. Results: COUNT_RATIO

The COUNT_RATIO proxies are all tested with an ordered logit regression and considering clustering around the firm. The results of the regressions with the COUNT_RATIO proxies can be found in

Table 1 Table 5. The COUNT_RATIO proxies are not used by Kim Wang and Zhang (2016). But the CRASH and COUNT_CRASH proxies can indicate that there has been a crash, while it was just the volatility in a firm's weekly returns. The COUNT_RATIO proxies are adjusted for normal volatility like the NET_COUNT proxies.

In Table 5 the HOLDER67, HOLDER100, NETBUYER, OC_CEOTENURE4 and OC_CEOTENURE5 proxies are all having significant effects on COUNT_RATIO_MEDIUM. The HOLDER67 and OC_CEOTENURE5 proxies are having the lowest level of significance, only 10%. The significant proxies can explain between 3.1% and 23.0% of the standard deviation of COUNT_RATIO_MEDIUM. Adding the control variables did not qualitatively alter the results for the HOLDER67, HOLDER100 and NETBUYER proxies, but OC_CEOTENURE4 and OC_CEO_TENURE5 became insignificant[34]. These results can be seen in Table 27.

The regressions with COUNT_RATIO_SMALL is only having significant coefficients for the NETBUYER, OC_CEOTENURE4 and OC_CEOTENURE5 proxies, this can be seen in Table 5. All the other proxies did not have significant coefficients. The economic significance of these proxies is rather low, between 3.4% and 19.8% of the standard deviation of COUNT_RATIO_SMALL can be explained by the significant proxies for CEO overconfidence. The NETBUYER coefficient did not qualitatively change when the control variables are added to the regressions. The OC_CEOTENURE4 and OC_CEO_TENURE5 became insignificant after adding the control variables, like the regressions containing COUNT_CRASH_MEDIUM. This can be seen in Table 28 in the appendix.

The results of the regressions with the COUNT_RATIO_LARGE can be found in Table 5. Only the NETBUYER proxy is having a significant coefficient. The NETBUYER proxy is significant at the 1% level. The economic significance of this proxy relatively high, 31.2% of the standard deviation of COUNT_RATIO_LARGE can be explained by the NETBUYER proxy. Adding the control variables did not qualitatively alter the results, this can be seen in Table 29.

[34] These results are also not significant when only the control variables used by Kim, Wang and Zhang (2016) are used.

Table 5: Regressions without control variables COUNT_RATIO

	1	2	3	4	5	6	7
COUNT_RATIO_MEDIUM							
HOLDER67	0.0487*						
	(1.65)						
HOLDER100		0.0532**					
		(1.96)					
NETBUYER			0.0836***				
			(3.08)				
OC_YEARLY4				0.00835			
				(1.40)			
OC_YEARLY5					0.00103		
					(0.06)		
OC_CEOTENURE4						0.0112**	
						(2.11)	
OC_CEOTENURE5							0.0227*
							(1.87)
COUNT_RATIO_SMALL							
HOLDER67	0.00279						
	(0.09)						
HOLDER100		0.0124					
		(0.44)					
NETBUYER			0.0668**				
			(2.36)				
OC_YEARLY4				0.00660			
				(1.18)			
OC_YEARLY5					0.00281		
					(0.19)		
OC_CEOTENURE4						0.0116**	
						(2.19)	
OC_CEOTENURE5							0.0205*
							(1.72)
COUNT_RATIO_LARGE							
HOLDER67	0.0479						
	(1.41)						
HOLDER100		0.0433					
		(1.39)					
NETBUYER			0.0915***				
			(2.99)				
OC_YEARLY4				0.00656			
				(1.36)			
OC_YEARLY5					0.0139		
					(0.96)		
OC_CEOTENURE4						0.00361	
						(0.97)	
OC_CEOTENURE5							0.00891
							(1.05)

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

4.6. Results: “Negative Skewness”

The final proxy for stock price crash risk which is tested is negative skewness. This proxy is tested with a normal OLS regression, since it can have all possible values. In the results, which can be seen in Table 6, it becomes clear that most proxies for overconfidence do not have a significant effect on negative skewness. Only the HOLDER67, HOLDER100 and NETBUYER proxies are having a significant and positive effect, the HOLDER67 and HOLDER100 proxies are is significant at the 5% level and the NETBUYER proxy is significant at the 10% level. This means that NCSKEW will increase when someone holds a stock which is 67% or 100% in the money or when a CEO is a net buyer, which implies that stock price crash risk will increase. The economic significance of these coefficients is rather low, between 3.5% and 2.1%.

All the other proxies, except for the OC_YEARLY4 proxy, are having a positive coefficient, but are all not significant. For that reason, it cannot be said that these proxies are related with this measure of stock price crash risk. The fact that there is no significant and positive coefficient with the OC_YEARLY5 and OC_CEOTENURE5 is in contrast with Kim Wang and Zhang (2016). An explanation for that can be that Kim Wang and Zhang (2016) are using other sample years[35].

After that the control variables are added to the regressions, these results can be found in Table 30 in the appendix. By doing this the NETBUYER proxy became insignificant, while the other proxies stay significant at the 5% level. This implies that adding the control variables reduced the explanatory power of the net buyer proxy. All the other results did not qualitatively change by adding the control variables to the regressions with NCSKEW.

[35] I could not test whether I will find the same effect as Kim Wang and Zhang (2016) when I was using the same sample years since the option holding data was nog available before 1996.

Table 6: Regression without control variables NCSKEW

	1	2	3	4	5	6	7
HOLDER67	0.0596**						
	(2.53)						
HOLDER100		0.0455**					
		(2.12)					
NETBUYER			0.0349*				
			(1.68)				
OC_YEARLY4				-0.0165			
				(-0.62)			
OC_YEARLY5					0.0257		
					(0.88)		
OC_CEOTENURE4						0.000431	
						(0.02)	
OC_CEOTENURE5							0.0366
							(1.55)

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

4.6. Results: Industries

The next step in this research was to investigate whether there are differences between the industries. As described before, the industry containing consumer durables, non-durables, wholesale, retail and some services is merged with the “other" industry. Before testing whether there are differences in the effect of CEO overconfidence on stock price crash risk between industries, it is first tested whether there are indeed differences in the means of the proxies for stock price crash risk and CEO overconfidence. This resulted in the finding that there are significant differences between most proxies for stock price crash risk and for CEO overconfidence, except for negative skewness. Therefore, the negative skewness proxy is excluded in the following analysis[36]. A ranking of overconfidence levels in the industries can be found in Table 7.

In Table 7, all proxies for CEO overconfidence indicate the manufacturing industry as least overconfident. The proxies based on CEO-characteristics indicate the business equipment industry as most overconfident, while the healthcare industry is most overconfident for the proxies based on firm characteristics. The industries which are in the middle of the ranking are constantly changing. Hereby, it can be can concluded that the manufacturing industry is least overconfident and the business equipment and healthcare

[36] The NCSKEW proxy can only be used in a regression with two industries, this can be seen in Table 38. Therefore, regressions containing interactions terms with the different industries and the NCSKEW proxy will not give useful results.

industry are most overconfident. If hypothesis 2a holds, it is expected that the effect of CEO overconfidence is bigger in the manufacturing industry and it is smaller in the business equipment and healthcare industries. When hypothesis 2b holds, it is expected that the effect of CEO overconfidence is bigger in the business equipment and healthcare industries and it is smaller in the manufacturing industry.

Table 7: Overconfidence ranking per industry

	Average	HOLDER67	HOLDER100	NETBUYER
Consumer Durables	Rank 3	Rank 3	Rank 2	Rank 2
Manufacturing	Rank 4	Rank 4	Rank 4	Rank 4
Business Equipment	Rank 1/2	Rank 1	Rank 1	Rank 1
Healthcare	Rank 1/2	Rank 2	Rank 3	Rank 3
	OC_YEARLY4	OC_CEOTENURE4	OC_YEARLY5	OC_CEOTENURE5
Consumer Durables	Rank 3	Rank 3	Rank 3	Rank 2
Manufacturing	Rank 4	Rank 4	Rank 4	Rank 4
Business Equipment	Rank 2	Rank 2	Rank 2	Rank 3
Healthcare	Rank 1	Rank 1	Rank 1	Rank 1

After this, all the regressions I have done before, except for the regressions with NCSKEW, are redone including interaction terms between a dummy variable for the industries and the measure for CEO overconfidence. The consumer durables and other industry is the reference category in these regressions. The complete results of these regressions, including the control variables, T-statistics and R-squared can be found in the appendix, Table 40 till Table 54.

CRASH proxies

In Table 8 all the coefficients of the original proxies for the overconfidence proxies are negative, but only the coefficients of HOLDER67 en HOLDER100 proxies are significant. Further, the coefficients of all the interaction terms are significant for the proxies based on CEO-characteristics. Further, the interaction term between the business equipment industry and OC_YEARLY4 proxy, the business equipment industry and OC_CEOTENURE4 proxy, the healthcare industry and OC_CEOTENURE4 proxy, and the interaction term between the health care industry and OC_CEOTENURE5 proxy are also significant.

The results of the regressions with proxies for CEO overconfidence based on firm-characteristics (regression 4 till 6) are in line with the expectations of hypothesis 2b, the effect of CEO overconfidence is smaller when overconfidence is less common in an industry. This finding is opposed by the regressions with proxies for CEO overconfidence based on CEO-characteristics (regression 1 till 3). These regressions show positive and coefficients for all the interaction terms. This means that the effect of CEO overconfidence is bigger than in the reference category for industries where CEO overconfidence is more and in industries where CEO overconfidence is less common. This result does not support hypothesis 2a and 2b.

The results of regression with the CRASH_SMALL proxy can be found in the appendix, Table 41. The only difference between the regressions containing the CRASH_SMALL and the CRASH_MEDIUM proxies is that the interaction term between manufacturing industry and OC_CEOTENURE4 is significant in the regression containing CRASH_SMALL. This indicates that the effect of CEO overconfidence on stock price crash risk does not depend on how common CEO overconfidence is in an industry.

The difference between the regression with the CRASH_LARGE, which can be found in Table 42, and the CRASH_MEDIUM proxy is that the interaction terms between the manufacturing industry and proxies for CEO overconfidence based on CEO-characteristics became insignificant. This supports the idea that the effect of CEO overconfidence is smaller when overconfidence is less common in an industry. Another difference between the CRASH_LARGE and CRASH_MEDIUM proxies is that all the interaction terms containing OC_YEARLY4 became insignificant, which indicates that there is no difference in the effect of CEO overconfidence between the industries.

Table 8: Regression CRASH_MEDIUM incl. industries

	1	2	3	4	5	6	7
HOLDER67	-0.112*						
IND2HOLDER67	0.132**						
IND3HOLDER67	0.279***						
IND4HOLDER67	0.291***						
HOLDER100		-0.132**					
IND2HOLDER100		0.119*					
IND3HOLDER100		0.276***					
IND4HOLDER100		0.288***					
NETBUYER			-0.101				
IND2NETBUYER			0.122*				
IND3NETBUYER			0.274***				
IND4NETBUYER			0.275***				
OC_YEARLY4				-0.168			
IND2OC_YEARLY4				0.0156			
IND3OC_YEARLY4				0.316**			
IND4OC_YEARLY4				0.228			
OC_YEARLY5					-0.279		
IND2OC_YEARLY5					-0.0106		
IND3OC_YEARLY5					0.367		
IND4OC_YEARLY5					0.313		
OC_CEOTENURE4						-0.0961	
IND2OC_CEOTENURE4						0.0423	
IND3OC_CEOTENURE4						0.194**	
IND4OC_CEOTENURE4						0.234**	
OC_CEOTENURE5							-0.194
IND2OC_CEOTENURE5							0.204
IND3OC_CEOTENURE5							0.352
IND4OC_CEOTENURE5							0.492**

* p<.10, ** p<.05, *** p<.01

COUNT_CRASH proxies

The results of the regression containing COUNT_CRASH_MEDIUM can be found in Table 9, the signs and significance levels of the regressions containing COUNT_CRASH_SMALL and COUNT_CRASH_LARGE are equal to these results. Therefore, the results of the regressions containing the other to COUNT_CRASH proxies can be found in the appendix, Table 44 and Table 45.

In Table 9 all the proxies for CEO overconfidence are having a significant and negative effect on COUNT_CRASH_MEDIUM. This indicates that there are less crashes when CEO overconfidence increases. Further, all the interaction terms between the industries and the proxies for CEO overconfidence are significant and positive. This implies that the effect of CEO overconfidence on stock price crash risk is only lower in the consumer durable industry. These results do not support hypothesis 2a or 2b, as the influence of CEO overconfidence is higher for all industries than the reference category. Which shows that the effect of CEO overconfidence on stock price crash risk does not depend on how common CEO overconfidence is in the industry.

Table 9: Regression COUNT_CRASH_MEDIUM incl. industries

	1	2	3	4	5	6	7
HOLDER67	-1.506***						
IND2HOLDER67	1.866***						
IND3HOLDER67	2.019***						
IND4HOLDER67	1.946***						
HOLDER100		-1.520***					
IND2HOLDER100		1.877***					
IND3HOLDER100		2.037***					
IND4HOLDER100		1.966***					
NETBUYER			-1.349***				
IND2NETBUYER			1.721***				
IND3NETBUYER			1.894***				
IND4NETBUYER			1.813***				
OC_YEARLY4				-0.459***			
IND2OC_YEARLY4				0.527***			
IND3OC_YEARLY4				0.673***			
IND4OC_YEARLY4				0.623***			
OC_YEARLY5					-0.489***		
IND2OC_YEARLY5					0.480***		
IND3OC_YEARLY5					0.623***		
IND4OC_YEARLY5					0.563***		
OC_CEOTENURE4						-0.451***	
IND2OC_CEOTENURE4						0.558***	
IND3OC_CEOTENURE4						0.638***	
IND4OC_CEOTENURE4						0.617***	
OC_CEOTENURE5							-0.534***
IND2OC_CEOTENURE5							0.669***
IND3OC_CEOTENURE5							0.763***
IND4OC_CEOTENURE5							0.757***
* p<.10, ** p<.05, *** p<.01							

NET_COUNT proxies

The results of the regression containing NET_COUNT_MEDIUM are very similar to the results of the COUNT_CRASH proxies. The results for the regressions containing NET_COUNT_MEDIUM can be found in Table 46. It is found that all the proxies for CEO overconfidence are having a significant and negative effects on NET_COUNT_MEDIUM, this means that stock price crash risk decreases when CEO overconfidence increases. All the interaction terms between the industries and the proxies for CEO overconfidence are positive and significant, except for the interaction term between the healthcare industry and the

NETBUYER proxy which is not significant. This implies stock price crash risk increases more in all the other industries as the reference category when CEO overconfidence increases, except for the healthcare industry when the NETBUYER proxy is used to measure CEO overconfidence. This shows that the influence CEO overconfidence does not depend on how common CEO overconfidence is in an industry.

The results of the regressions containing the NET_COUNT_SMALL proxy can be found in Table 47. These results are almost similar to the findings of NET_COUNT_MEDIUM and can be found in Table 48. The only difference is that not only the interaction term between the healthcare industry and the NETBUYER proxy is not significant, also the interaction term between the healthcare industry and the HOLDER67 proxy is not significant. Also, these results show that that the influence CEO overconfidence does not depend on how common CEO overconfidence is in an industry.

The signs and significance levels of the regressions containing NET_COUNT_LARGE are qualitatively equal to the results of the regressions with COUNT_CRASH. All the proxies for CEO overconfidence are negative and significant, while all the interactions terms are positive and significant. This means that it does not matter which benchmark for a crash or jump is set, the influence CEO overconfidence does not depend on how common CEO overconfidence is in an industry.

Results of the other proxies

The results of the regressions containing the COUNT_JUMP and COUNT_RATIO proxies are qualitatively equal to the results of the regressions containing COUNT_CRASH. This means that all the proxies for CEO overconfidence are negative and significant, while all the interactions terms are positive and significant. The results of the COUNT_JUMP proxies can be found in Table 49, Table 50 and Table 51. The results of the COUNT_RATIO proxies can be found Table 52, Table 53 and Table 54.

Out of this follows that in the regressions with most of the proxies, it is found that the manufacturing, business equipment and healthcare industry are all more sensitive to CEO overconfidence than the consumer durable and other industry. Further it is found that CEO overconfidence is highest in the business equipment and health care industries, while it is lowest in the manufacturing industry. This implies that the effect of CEO overconfidence on stock price crash risk does not depend on how common overconfidence is in an industry.

5. Conclusion

The goal of this thesis was to investigate whether the Kim, Wang and Zhang (2016) findings that stock price crash risk can be explained by CEO overconfidence are robust. This is tested by including more proxies for CEO overconfidence and stock price crash risk, more control variables and more data. First, a novel mechanism is developed to describe the relationship between CEO overconfidence and stock price crashes. CEOs are said to be overconfident when she is overestimating her own abilities and this is affecting the communication of a CEO to the shareholders. When investors are affected by the CEO's overconfident communication, their estimates of future performance will also be upwardly biased. Therefore, investors will start buying a stock and stock prices will increase. Until some short-term mechanism reveals that prices became too high, and a subsequent crash will occur.

For that reason, the first hypothesis was: *"Firms with a CEO that scores higher on overconfidence measures will have a higher risk of subsequent stock price crashes*". This hypothesis was tested with several proxies for CEO overconfidence and stock price crash risk. By doing this, most of the times we found the same relationship as Kim, Wang and Zhang (2016) when the same proxies for CEO overconfidence and stock price crash risk are used. Only the results of the regression with negative skewness and the OC_YEARLY5 and OC_CEOTENURE5 proxies deviated from the findings of Kim, Wang and Zhang (2016). An explanation for that can be that are using other sample years.

But when other proxies for CEO overconfidence and stock price crash risk are used, it is found that in almost half of the cases there is no significant relationship between CEO overconfidence and stock price crash risk. Therefore, it is concluded that the Kim Wang and Zhang (2016) are not robust. For instance, the CRASH_MEDIUM proxy (which is indicating whether there has been a crash or not for a firm during a year) is having a significant coefficient in the regression with the HOLDER67 proxy, but the CRASH_SMALL and CRASH_LARGE proxies are not and these proxies are just using other benchmarks for a stock price crash. Another example can be the NET_COUNT proxy, this proxy is counting the number of crashes and discounting this with the number of jumps in a firm-year. The NET_COUNT_MEDIUM proxy is having no significant coefficient when the number of crashes in a firm-year are counted and regressed with the HOLDER67 but it is having with all the other proxies. These findings indicate that finding a significant relationship between the proxies for CEO overconfidence and stock price crash risk really depends on the proxies and benchmarks used. Further, it is found that the additional control variables did not have any impact on the robustness of the results.

As mentioned before, investors get influenced by CEO overconfidence due to the communication. In paragraph 2.3.2. it is described that CEO overconfidence is more common in certain industries. When investor know that CEOs in a certain industry are overconfident, then they will till take this into account and they will be less influenced by the overconfident CEO. But the relationship can also be the other way around. When there is less overconfidence in an industry, investors can more easily recognize the overconfident CEO and they will be less influenced by the overconfident CEO. This leaded to two hypotheses: "*The effect of CEO overconfidence is larger when overconfidence is less common in an industry" or "The effect of CEO overconfidence is smaller when overconfidence is less common in an industry".*

By testing these hypotheses, it is found that in most of the regressions all the industries are stronger influenced by CEO overconfidence than the reference industry. The reference industry was always in the middle of the overconfidence ranking. Therefore, it was expected that there was always one industry which is more influence by CEO overconfidence and one industry which was less influenced by CEO overconfidence. But since most of the regressions show positive coefficients for all the regressions, it is concluded that the effect of CEO overconfidence does not depend on how common CEO overconfidence is in an industry.

An important limitation to this research is that it is all based on theoretical constructs. This problem could not have been solved, since it is not possible to measure CEO overconfidence and stock price crash risk directly. I have tried to solve this problem by using 7 different proxies for CEO overconfidence and 16 proxies for stock price crash risk. Not all the proxies had the same results. An explanation for this can be that some proxies are not really measuring CEO overconfidence or stock price crash risk. For further research, it may be interesting to test the relationship of CEO overconfidence and stock price crash risk with other and more proxies for them.

Another limitation to this thesis is that the relationship between stock price crash risk and CEO overconfidence is tested with a sample containing only North-American firms. It would have been better if the sample of firms contained data of companies all around the world. This was not possible for this thesis, since not all the data was available or accessible. The sample with North American firms is used because this data was available and it is most widely used. It can be investigated in a future research whether the found effects are the same in other regions.

The third limitation is about the comparison of the effect of CEO overconfidence on stock price crash risk between industries. Only four industries are used by doing this comparison, which could mean that the industries are defined too general. There could be a difference in the effect of CEO overconfidence on stock price crash risk when the sample is divided in more specified industries. In a future research, it can be investigated whether this is the case by using a bigger sample of firms.

A final limitation that there was data for the control variables was not available for all firms. To solve this, missing values were replaced for the mean of control variable per SIC code and year. But it is not known whether this is a good estimation for the missing values or not. Therefore, the results would have been better when there is data for all the control variables is available for all firms.

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7. Appendix

Table 10: Industries

Industry	SIC codes			
Consumer Durables, NonDurables,	0100-0999,	3940-3989,	3714-3714,	3990-3999,
Wholesale, Retail, and Some	2000-2399,	2500-2519,	3716-3716,	5000-5999,
Services (Laundries, Repair Shops)	2700-2749,	2590-2599,	3750-3751,	7200-7299,
	2770-2799,	3630-3659,	3792-3792,	7600-7699,
	3100-3199,	3710-3711,	3900-3939	
Manufacturing, Energy, and	2520-2589,	3000-3099,	3712-3713,	3860-3899,
Utilities	2600-2699,	3200-3569,	3715-3715,	1200-1399,
	2750-2769,	3580-3621,	3717-3749,	2900-2999,
	2800-2829,	3623-3629,	3752-3791,	4900-4949,
	2840-2899,	3700-3709,	3793-3799	
Business Equipment, Telephone	3570-3579,	3810-3839,	7375-7375,	7379-7379,
and Television Transmission	3622-3622,	7370-7372,	7376-7376,	7391-7391,
	3660-3692,	7373-7373,	7377-7377,	8730-8734,
	3694-3699,	7374-7374,	7378-7378,	4800-4899,
Healthcare, Medical Equipment,	2830-2839,	3693-3693,	3840-3859,	8000-8099
and Drugs				
Other -- Mines, Constr, BldMt,	Others			
Trans, Hotels, Bus Serv,				
Entertainment, Finance				

(French, 2017)

Table 11: Summary statistics

	Count	Mean	SD	P5	P50	P95
HOLDER67	34510	.7552593	.4299396	0	1	1
HOLDER100	34510	.6602144	.4736432	0	1	1
NETBUYER	34510	.5102289	.4999026	0	1	1
OC_YEARLY4	34510	.1100261	.3129268	0	0	1
OC_CEOTENURE4	34510	.3497247	.4768899	0	0	1
OC_YEARLY5	34510	.0120255	.1090011	0	0	0
OC_CEOTENURE5	34510	.0536076	.2252451	0	0	1
CRASH_MEDIUM	27599	.6321968	.4822162	0	1	1
CRASH_SMALL	27599	.8446683	.3622272	0	1	1
CRASH_LARGE	27599	.2706982	.4443285	0	0	1
COUNT_CRASH_MEDIUM	34510	.6827007	.7874006	0	1	2
COUNT_CRASH_SMALL	34510	1.225703	1.096135	0	1	3
COUNT_CRASH_LARGE	34510	.2351492	.4672708	0	0	1
NET_COUNT_MEDIUM	34510	.1331208	1.003781	-2	0	2
NET_COUNT_SMALL	34510	.1018256	1.266191	-2	0	2
NET_COUNT_LARGE	34510	.1197624	.5770245	-1	0	1
COUNT_JUMP_MEDIUM	34510	.5495798	.7267142	0	0	2
COUNT_JUMP_SMALL	34510	1.123877	1.066828	0	1	3
COUNT_JUMP_LARGE	34510	.1153868	.3334288	0	0	1
COUNT_RATIO_MEDIUM	34510	.3017369	.3631413	0	.17322868	1.098612
COUNT_RATIO_SMALL	34510	.3371486	.3367455	0	.34685736	1.098612
COUNT_RATIO_LARGE	34510	.1492066	.2934622	0	0	.6931472
NCSKEW	27493	.4177933	1.700729	-1.756768	.1979666	3.625967
Market-to-book ratio	34397	4224244	50666.2	-9.407846	.5296943	2.847827
Leverage	34389	.375457	15.99355	-.3188645	.1023221	2.384494
Cash reserves	34509	111.1734	519.2932	0	5.626	452.89
R&D expenses	32075	26.4973	79.3469	0	6.745129	86
Present age	34402	66.22859	9.212623	52	66	81
Observations	34510					

Table 12: Test for multicollinearity

Variable	VIF	1/VIF
HOLDER67	1.00	0.999355
Cash reserves	1.15	0.870989
R&D expenses	1.15	0.871000
Present age	1.00	0.999168
Leverage	1.00	0.999826
Market-to-book ratio	1.00	0.999890
Mean VIF	1.05	

Table 13: Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

	Holder67	Holder100	Net buyer
Chi2(1)	2.98		
Prob > chi2	0.0841		
Chi2(1)		2.60	
Prob > chi2		0.1071	
Chi2(1)			3.31
Prob > chi2			0.0690

Table 14: Covariance matrix

e(V)	holder67	Market-to-book ratio	Leverage	Cash reserves	R&D expenses	Present age	Constant
HOLDER67	.00004863						
Market-to-book ratio	-1,37E-09	2,64E-12					
Leverage	4,57E-06	-8,49E-14	3,77E-05				
Cash reserves	-1,51E-07	4,93E-13	-5,09E-09	4,16E-08			
R&D expenses	-3,02E-07	-7,89E-13	-4,88E-08	-1,02E-07	1,94E-06		
Present age	-5,59E-05	1,63E-10	-6,00E-07	1,03E-08	3,59E-08	1,06E-04	
Constant	-.00003283	-1,12E-08	2,81E-05	-2,52E-06	-4,06E-05	-6,98E-03	.00049734

Table 15: Regression with control variables CRASH_MEDIUM

	1	2	3	4	5	6	7
HOLDER67	0.0869***						
	(2.75)						
HOLDER100		0.0612**					
		(2.12)					
NETBUYER			0.0859***				
			(3.06)				
OC_YEARLY4				0.0693			
				(1.62)			
OC_YEARLY5					0.228*		
					(1.80)		
OC_CEOTENURE4						0.0479	
						(1.62)	
OC_CEOTENURE5							0.0507
							(0.80)
Market-to-book ratio	0.00000373	0.00000362	0.00000364	0.00000347	0.00000343	0.00000347	0.00000346
	(0.63)	(0.61)	(0.61)	(0.73)	(0.72)	(0.73)	(0.73)
Leverage	-0.000513	-0.000534	-0.000539	-0.000562	-0.000563	-0.000566	-0.000566
	(-0.52)	(-0.55)	(-0.55)	(-0.60)	(-0.60)	(-0.60)	(-0.60)
Cash Reserves	0.0000250	0.0000253	0.0000263	0.0000181	0.0000179	0.0000184	0.0000182
	(0.86)	(0.87)	(0.90)	(0.62)	(0.62)	(0.64)	(0.63)
R&D Expense	-0.000431**	-0.000436**	-0.000422*	-0.000360*	-0.000358*	-0.000360*	-0.000360*
	(-1.98)	(-2.00)	(-1.95)	(-1.66)	(-1.65)	(-1.66)	(-1.65)
Present Age	0.000137	0.000151	0.000155	-0.00903***	-0.00906***	-0.00891***	-0.00904***
	(0.09)	(0.10)	(0.10)	(-5.77)	(-5.79)	(-5.68)	(-5.77)
Pseudo R-squared	0.001	0.001	0.001	0.002	0.001	0.002	0.002

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01"

Table 16: Regression with control variables CRASH_SMALL

	1	2	3	4	5	6	7
HOLDER67	0.0186						
	(0.44)						
HOLDER100		0.00552					
		(0.14)					
NETBUYER			0.0895**				
			(2.38)				
OC_YEARLY4				0.0269			
				(0.48)			
OC_YEARLY5					0.0167		
					(0.10)		
OC_CEOTENURE4						0.0349	
						(0.88)	
OC_CEOTENURE5							0.0627
							(0.71)
Market-to-book ratio	0.0000110	0.0000110	0.0000109	0.0000109	0.0000109	0.0000109	0.0000108
	(1.37)	(1.36)	(1.35)	(1.28)	(1.28)	(1.28)	(1.28)
Leverage	-0.00154	-0.00154	-0.00156	-0.00168	-0.00168	-0.00168	-0.00169
	(-1.19)	(-1.19)	(-1.21)	(-1.26)	(-1.26)	(-1.26)	(-1.26)
Cash Reserves	-0.0000163	-0.0000163	-0.0000152	-0.0000131	-0.0000132	-0.0000129	-0.0000130
	(-0.45)	(-0.45)	(-0.42)	(-0.36)	(-0.36)	(-0.36)	(-0.36)
R&D expense	-0.000882***	-0.000882***	-0.000874***	-0.000868***	-0.000869***	-0.000868***	-0.000867***
	(-3.92)	(-3.92)	(-3.88)	(-3.77)	(-3.77)	(-3.77)	(-3.77)
Present Age	-0.000467	-0.000454	-0.000534	-0.0113***	-0.0113***	-0.0111***	-0.0112***
	(-0.22)	(-0.21)	(-0.25)	(-4.87)	(-4.89)	(-4.81)	(-4.84)
Pseudo R-squared	0.001	0.001	0.001	0.002	0.002	0.002	0.002

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01"

Table 17: Regression with control variables CRASH_LARGE

	1	2	3	4	5	6	7
HOLDER67	0.0609*						
	(1.77)						
HOLDER100		0.0437					
		(1.40)					
NETBUYER			0.0900***				
			(2.95)				
OC_YEARLY4				0.0796*			
				(1.73)			
OC_YEARLY5					0.230*		
					(1.80)		
OC_CEOTENURE4						0.0758**	
						(2.36)	
OC_CEOTENURE5							0.112
							(1.63)
Market-to-book ratio	0.00000656	0.00000648	0.00000646	0.00000707	0.00000702	0.00000706	0.00000703
	(1.39)	(1.37)	(1.36)	(1.56)	(1.56)	(1.56)	(1.56)
Leverage	-0.0000483	-0.0000631	-0.0000754	-0.000108	-0.000108	-0.000117	-0.000115
	(-0.07)	(-0.09)	(-0.11)	(-0.15)	(-0.15)	(-0.16)	(-0.16)
Cash Reserves	0.0000481*	0.0000482*	0.0000491*	0.0000449	0.0000447	0.0000454	0.0000452
	(1.67)	(1.67)	(1.70)	(1.52)	(1.51)	(1.53)	(1.53)
R&D Expense	-0.000265	-0.000269	-0.000256	-0.000263	-0.000261	-0.000262	-0.000260
	(-1.13)	(-1.15)	(-1.10)	(-1.20)	(-1.19)	(-1.19)	(-1.19)
Present Age	0.00217	0.00218	0.00216	-0.00617***	-0.00620***	-0.00595***	-0.00608***
	(1.30)	(1.30)	(1.29)	(-3.61)	(-3.63)	(-3.47)	(-3.56)
Pseudo R-squared	0.000	0.000	0.001	0.001	0.001	0.001	0.001

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 18: Regression with control variables COUNT_CRASH_MEDIUM

	1	2	3	4	5	6	7
HOLDER67	0.0519						
	(1.63)						
HOLDER100		0.0524*					
		(1.78)					
NETBUYER			0.0876***				
			(2.99)				
OC_YEARLY4				0.00424			
				(0.29)			
OC_YEARLY5					0.0200		
					(0.48)		
OC_CEOTENURE4						0.00747	
						(0.59)	
OC_CEOTENURE5							-0.0381
							(-1.28)
Market-to-book ratio	8.28e-08***	8.21e-08***	8.88e-08***	3.48e-08***	3.48e-08***	3.50e-08***	3.46e-08***
	(8.35)	(8.22)	(8.83)	(8.08)	(8.08)	(8.09)	(8.02)
Leverage	-0.000412	-0.000425	-0.000441	-0.000121	-0.000121	-0.000121	-0.000118
	(-0.78)	(-0.81)	(-0.84)	(-0.54)	(-0.54)	(-0.54)	(-0.53)
Cash Reserves	0.0000389	0.0000392	0.0000401	0.0000161	0.0000161	0.0000161	0.0000161
	(1.55)	(1.56)	(1.59)	(1.45)	(1.45)	(1.46)	(1.45)
R&D Expense	-0.000574**	-0.000579**	-0.000574**	-0.000173**	-0.000173**	-0.000172**	-0.000174**
	(-2.48)	(-2.50)	(-2.47)	(-2.15)	(-2.15)	(-2.15)	(-2.17)
Present Age	-0.00219	-0.00221	-0.00222	-0.00330***	-0.00330***	-0.00328***	-0.00338***
	(-1.33)	(-1.34)	(-1.35)	(-4.65)	(-4.65)	(-4.59)	(-4.76)
Pseudo R-squared	0.000	0.000	0.001	0.002	0.002	0.002	0.001

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 19: Regression with control variables COUNT_CRASH_SMALL

	1	2	3	4	5	6	7
HOLDER67	0.0200						
	(0.61)						
HOLDER100		0.0373					
		(1.21)					
NETBUYER			0.0669**				
			(2.17)				
OC_YEARLY4				0.0188			
				(0.51)			
OC_YEARLY5					0.106		
					(0.94)		
OC_CEOTENURE4						0.0193	
						(0.61)	
OC_CEOTENURE5							0.000297
							(0.00)
Market-to-book ratio	-0.00000246	-0.00000250	-0.00000260	-0.00000489	0.0000206***	0.0000205***	0.0000207***
	(-0.56)	(-0.57)	(-0.60)	(-0.56)	(8.65)	(8.59)	(8.65)
Leverage	-0.000698	-0.000696	-0.000712	-0.00122	0.000442***	0.000442***	0.000442***
	(-1.20)	(-1.20)	(-1.23)	(-0.85)	(3.78)	(3.82)	(3.77)
Cash Reserves	0.00000606	0.00000606	0.00000740	-0.0000824**	-0.00000291	-0.00000287	-0.00000293
	(0.24)	(0.24)	(0.30)	(-2.56)	(-0.75)	(-0.73)	(-0.75)
R&D Expense	-0.000682***	-0.000683***	-0.000685***	0.00000893	0.00000701	0.00000697	0.00000685
	(-2.92)	(-2.93)	(-2.92)	(0.06)	(0.36)	(0.36)	(0.35)
Present Age	-0.00137	-0.00147	-0.00138	0.146	0.0116	0.0111	0.0116
	(-0.14)	(-0.15)	(-0.14)	(1.58)	(1.23)	(1.18)	(1.23)
Pseudo R-squared	0.000	0.000	0.001	0.002	0.002	0.002	0.001

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 20: Regression with control variables COUNT_CRASH_LARGE

	1	2	3	4	5	6	7
HOLDER67	0.0469						
	(1.33)						
HOLDER100		0.0440					
		(1.35)					
NETBUYER			0.101***				
			(3.16)				
OC_YEARLY4				0.0115			
				(-0.74)			
OC_YEARLY5					0.00377		
					(0.08)		
OC_CEOTENURE4						0.0102	
						(0.91)	
OC_CEOTENURE5							0.0321
							(1.07)
Market-to-book ratio	-0.000000317	-0.000000319	-0.000000325	0.00000509***	0.00000506***	0.00000498***	0.00000502***
	(-1.18)	(-1.17)	(-1.17)	(6.27)	(6.19)	(6.08)	(6.19)
Leverage	-0.000566	-0.000572	-0.000597	0.00000292	0.00000315	0.00000305	0.00000318
	(-0.81)	(-0.82)	(-0.85)	(0.04)	(0.05)	(0.05)	(0.05)
Cash Reserves	0.000000937	0.00000106	0.00000302	-0.00000125	-0.00000122	-0.00000119	-0.00000120
	(0.03)	(0.04)	(0.11)	(-0.82)	(-0.80)	(-0.78)	(-0.78)
R&D Expense	-0.000281	-0.000285	-0.000287	1.81e-08	2.45e-08	8.64e-08	0.000000253
	(-1.23)	(-1.24)	(-1.25)	(0.00)	(0.00)	(0.02)	(0.05)
Present Age	0.00562	0.00561	0.00563	0.00434	0.00430	0.00404	0.00425
	(0.50)	(0.50)	(0.51)	(1.21)	(1.19)	(1.13)	(1.17)
Pseudo R-squared	0.000	0.000	0.001	0.008	0.008	0.002	0.009

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 21: Regression with control variables NET_COUNT_MEDIUM

	1	2	3	4	5	6	7
HOLDER67	0.0411						
	(1.63)						
HOLDER100		0.0429*					
		(1.90)					
NETBUYER			0.0547**				
			(2.54)				
OC_YEARLY4				0.500***			
				(3.69)			
OC_YEARLY5					1.154***		
					(4.06)		
OC_CEOTENURE4						0.361**	
						(2.15)	
OC_CEOTENURE5							1.043***
							(5.26)
Market-to-book ratio	0.000000173***	0.000000172***	0.000000177***	-0.00000163***	-0.00000164***	-0.00000163***	-0.00000163***
	(23.99)	(23.98)	(24.67)	(-19.13)	(-19.27)	(-19.35)	(-19.15)
Leverage	-0.000495	-0.000503	-0.000512	-0.000589	-0.000602	-0.000571	-0.000639
	(-0.73)	(-0.75)	(-0.75)	(-0.62)	(-0.64)	(-0.60)	(-0.68)
Cash Reserves	0.00000434	0.00000449	0.00000508	-0.000251	-0.000250	-0.000249	-0.000247
	(0.19)	(0.20)	(0.23)	(-1.48)	(-1.48)	(-1.47)	(-1.46)
R&D Expense	0.0000665	0.0000633	0.0000647	-0.00589***	-0.00591***	-0.00588***	-0.00588***
	(0.48)	(0.46)	(0.47)	(-4.38)	(-4.39)	(-4.38)	(-4.38)
Present Age	-0.000610	-0.000625	-0.000612	-0.105***	-0.105***	-0.104***	-0.104***
	(-0.53)	(-0.54)	(-0.53)	(-9.80)	(-9.82)	(-9.68)	(-9.69)
Pseudo R-squared	0.000	0.000	0.000	0.009	0.00/8	0.009	0.009

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 22: Regression with control variables NET_COUNT_SMALL

	1	2	3	4	5	6	7
HOLDER67	0.0110						
	(0.45)						
HOLDER100		0.0129					
		(0.59)					
NETBUYER			0.0263				
			(1.26)				
OC_YEARLY4				0.482***			
				(3.53)			
OC_YEARLY5					1.086***		
					(3.75)		
OC_CEOTENURE4						0.360**	
						(2.15)	
OC_CEOTENURE5							1.008***
							(5.13)
Market-to-book ratio	0.000000147***	0.000000147***	0.000000149***	-0.00000163***	-0.00000163***	-0.00000162***	-0.00000163***
	(23.47)	(23.38)	(23.59)	(-18.97)	(-19.10)	(-19.19)	(-18.99)
Leverage	-0.0000480	-0.0000512	-0.0000559	-0.000474	-0.000485	-0.000457	-0.000522
	(-0.09)	(-0.10)	(-0.11)	(-0.50)	(-0.51)	(-0.47)	(-0.55)
Cash Reserves	0.00000533	0.00000537	0.00000574	-0.000248	-0.000247	-0.000245	-0.000243
	(0.25)	(0.25)	(0.27)	(-1.47)	(-1.47)	(-1.46)	(-1.45)
R&D Expense	-0.0000352	-0.0000360	-0.0000362	-0.00601***	-0.00603***	-0.00600***	-0.00600***
	(-0.26)	(-0.27)	(-0.27)	(-4.45)	(-4.46)	(-4.44)	(-4.44)
Present Age	-0.0000966	-0.000102	-0.000107	-0.106***	-0.106***	-0.105***	-0.105***
	(-0.08)	(-0.09)	(-0.09)	(-9.86)	(-9.88)	(-9.74)	(-9.76)
Pseudo R-squared	0.000	0.000	0.000	0.008	0.008	0.008	0.008

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 23: Regression with control variables NET_COUNT_LARGE

	1	2	3	4	5	6	7
HOLDER67	0.0344						
	(1.18)						
HOLDER100		0.0129					
		(0.59)					
NETBUYER			0.0770***				
			(2.93)				
OC_YEARLY4				0.507***			
				(3.76)			
OC_YEARLY5					1.130***		
					(4.05)		
OC_CEOTENURE4						0.375**	
						(2.24)	
OC_CEOTENURE5							1.081***
							(5.52)
Market-to-book ratio	0.000000301***	0.000000301***	0.000000306***	-0.00000163***	-0.00000164***	-0.00000163***	-0.00000163***
	(40.86)	(40.77)	(41.11)	(-19.62)	(-19.76)	(-19.86)	(-19.64)
Leverage	0.0000802	0.0000725	0.0000573	-0.000309	-0.000321	-0.000291	-0.000361
	(0.09)	(0.08)	(0.06)	(-0.34)	(-0.36)	(-0.32)	(-0.40)
Cash Reserves	0.0000273	0.0000274	0.0000284	-0.000250	-0.000250	-0.000248	-0.000246
	(1.04)	(1.05)	(1.08)	(-1.48)	(-1.48)	(-1.47)	(-1.46)
R&D Expense	-0.0000741	-0.0000766	-0.0000748	-0.00594***	-0.00595***	-0.00593***	-0.00592***
	(-0.46)	(-0.47)	(-0.46)	(-4.41)	(-4.42)	(-4.40)	(-4.40)
Present Age	0.00253*	0.00252*	0.00251*	-0.104***	-0.104***	-0.103***	-0.103***
	(1.80)	(1.80)	(1.79)	(-9.70)	(-9.72)	(-9.57)	(-9.59)
Pseudo R-squared	0.000	0.000	0.000	0.008	0.007	0.008	0.008

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 24: Regression with control variables COUNT_JUMP_MEDIUM

	1	2	3	4	5	6	7
HOLDER67	-0.00916						
	(-0.29)						
HOLDER100		-0.00807					
		(-0.28)					
NETBUYER			0.0182				
			(0.64)				
OC_YEARLY4				-0.496***			
				(-3.72)			
OC_YEARLY5					-1.134***		
					(-4.06)		
OC_CEOTENURE4						-0.353**	
						(-2.14)	
OC_CEOTENURE5							-1.081***
							(-5.47)
Market-to-book ratio	-0.00000279	-0.00000278	-0.00000278	0.00000167***	0.00000167***	0.00000166***	0.00000167***
	(-0.74)	(-0.73)	(-0.73)	(19.52)	(19.66)	(19.75)	(19.54)
Leverage	0.000264	0.000266	0.000266	0.000468	0.000480	0.000451	0.000520
	(0.31)	(0.31)	(0.31)	(0.48)	(0.50)	(0.46)	(0.54)
Cash Reserves	0.0000393	0.0000393	0.0000393	0.000267	0.000267	0.000265	0.000263
	(1.63)	(1.63)	(1.63)	(1.61)	(1.61)	(1.60)	(1.59)
R&D Expense	-0.000717***	-0.000717***	-0.000717***	0.00572***	0.00573***	0.00571***	0.00570***
	(-3.65)	(-3.65)	(-3.65)	(4.29)	(4.30)	(4.28)	(4.28)
Present Age	-0.00209	-0.00209	-0.00209	0.102***	0.102***	0.101***	0.100***
	(-1.30)	(-1.30)	(-1.30)	(9.65)	(9.67)	(9.53)	(9.53)
Pseudo R-squared	0.000	0.000	0.000	0.018	0.018	0.018	0.019

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 25: Regression with control variables COUNT_JUMP_SMALL

	1	2	3	4	5	6	7
HOLDER67	0.0135						
	(0.41)						
HOLDER100		0.0302					
		(0.98)					
NETBUYER			0.0324				
			(1.08)				
OC_YEARLY4				-0.473***			
				(-3.54)			
OC_YEARLY5					-1.148***		
					(-4.04)		
OC_CEOTENURE4						-0.352**	
						(-2.15)	
OC_CEOTENURE5							-1.098***
							(-5.45)
Market-to-book ratio	-0.00000612	-0.00000616	-0.00000615	0.00000160***	0.00000160***	0.00000159***	0.00000160***
	(-1.44)	(-1.45)	(-1.45)	(17.64)	(17.76)	(17.83)	(17.65)
Leverage	-0.000334	-0.000341	-0.000343	0.000173	0.000187	0.000157	0.000228
	(-0.70)	(-0.71)	(-0.72)	(0.17)	(0.19)	(0.15)	(0.23)
Cash Reserves	0.0000237	0.0000237	0.0000243	0.000264	0.000264	0.000262	0.000260
	(0.93)	(0.93)	(0.95)	(1.62)	(1.62)	(1.61)	(1.60)
R&D Expense	-0.000678***	-0.000680***	-0.000679***	0.00564***	0.00565***	0.00563***	0.00562***
	(-3.12)	(-3.13)	(-3.11)	(4.25)	(4.27)	(4.25)	(4.25)
Present Age	-0.00273	-0.00275	-0.00274	0.101***	0.101***	0.1000***	0.0995***
	(-1.56)	(-1.57)	(-1.56)	(9.65)	(9.67)	(9.52)	(9.52)
Pseudo R-squared	0.000	0.000	0.000	0.008	0.008	0.008	0.008

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 26: Regression with control variables COUNT_JUMP_LARGE

	1	2	3	4	5	6	7
HOLDER67	0.00300						
	(0.07)						
HOLDER100		0.00837					
		(0.20)					
NETBUYER			-0.00216				
			(-0.05)				
OC_YEARLY4				-0.493***			
				(-3.69)			
OC_YEARLY5					-1.087***		
					(-3.94)		
OC_CEOTENURE4						-0.364**	
						(-2.19)	
OC_CEOTENURE5							-1.082***
							(-5.57)
Market-to-book ratio	-0.00000521	-0.00000522	-0.00000521	0.00000171***	0.00000172***	0.00000171***	0.00000171***
	(-0.70)	(-0.70)	(-0.70)	(20.58)	(20.73)	(20.83)	(20.60)
Leverage	-0.000507	-0.000509	-0.000508	0.000314	0.000325	0.000296	0.000366
	(-0.40)	(-0.40)	(-0.40)	(0.34)	(0.35)	(0.32)	(0.40)
Cash Reserves	0.0000281	0.0000281	0.0000281	0.000258	0.000258	0.000256	0.000254
	(0.75)	(0.75)	(0.75)	(1.54)	(1.54)	(1.53)	(1.52)
R&D Expense	-0.000660**	-0.000660**	-0.000660**	0.00588***	0.00590***	0.00587***	0.00587***
	(-2.00)	(-2.00)	(-2.00)	(4.38)	(4.39)	(4.37)	(4.37)
Present Age	-0.00520**	-0.00520**	-0.00519**	0.103***	0.103***	0.102***	0.101***
	(-2.46)	(-2.46)	(-2.46)	(9.65)	(9.67)	(9.53)	(9.53)
Pseudo R-squared	0.001	0.001	0.001	0.008	0.008	0.009	0.009

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 27: Regression with control variables COUNT_RATIO_MEDIUM

	1	2	3	4	5	6	7
HOLDER67	0.0513*						
	(1.68)						
HOLDER100		0.0569**					
		(2.02)					
NETBUYER			0.0865***				
			(3.09)				
OC_YEARLY4				0.00738			
				(1.19)			
OC_YEARLY5					-0.0133		
					(-0.77)		
OC_CEOTENURE4						0.00743	
						(1.34)	
OC_CEOTENURE5							0.00836
							(0.67)
Market-to-book ratio	-0.00000360	-0.00000374	-0.00000365	-2.98e-08***	-2.99e-08***	-2.96e-08***	-2.98e-08***
	(-0.64)	(-0.66)	(-0.66)	(-7.95)	(-8.00)	(-7.92)	(-8.02)
Leverage	-0.00105*	-0.00105*	-0.00108*	-0.000218	-0.000219*	-0.000219	-0.000219*
	(-1.88)	(-1.88)	(-1.90)	(-1.64)	(-1.65)	(-1.64)	(-1.65)
Cash Reserves	-0.0000294	-0.0000294	-0.0000271	-0.00000474	-0.00000469	-0.00000470	-0.00000472
	(-1.21)	(-1.22)	(-1.12)	(-1.28)	(-1.27)	(-1.27)	(-1.27)
R&D Expense	-0.000711***	-0.000716***	-0.000713***	-0.000117***	-0.000118***	-0.000117***	-0.000117***
	(-3.09)	(-3.10)	(-3.08)	(-4.55)	(-4.56)	(-4.55)	(-4.55)
Present Age	-0.00166	-0.00168	-0.00167	-0.00150***	-0.00152***	-0.00148***	-0.00149***
	(-1.05)	(-1.06)	(-1.05)	(-4.60)	(-4.64)	(-4.53)	(-4.56)
Pseudo R-squared	0.000	0.000	0.000	0.003	0.003	0.003	0.003

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 28: Regression with control variables COUNT_RATIO_SMALL

	1	2	3	4	5	6	7
HOLDER67	0.0000885						
	(0.00)						
HOLDER100		0.0140					
		(0.48)					
NETBUYER			0.0661**				
			(2.27)				
OC_YEARLY4				0.00491			
				(0.85)			
OC_YEARLY5					-0.0159		
					(-1.05)		
OC_CEOTENURE4						0.00753	
						(1.37)	
OC_CEOTENURE5							0.00370
							(0.30)
Market-to-book ratio	-0.00000435	-0.00000440	-0.00000446	-3.30e-08***	-3.31e-08***	-3.28e-08***	-3.30e-08***
	(-1.13)	(-1.13)	(-1.16)	(-8.72)	(-8.74)	(-8.69)	(-8.76)
Leverage	-0.000846**	-0.000843**	-0.000864**	-0.000120	-0.000121	-0.000121	-0.000121
	(-2.15)	(-2.14)	(-2.18)	(-1.39)	(-1.40)	(-1.39)	(-1.40)
Cash Reserves	-0.0000254	-0.0000254	-0.0000236	-0.00000469	-0.00000464	-0.00000466	-0.00000467
	(-0.94)	(-0.95)	(-0.88)	(-1.28)	(-1.27)	(-1.27)	(-1.27)
R&D Expense	-0.000722***	-0.000723***	-0.000723***	-0.000119***	-0.000119***	-0.000119***	-0.000119***
	(-3.27)	(-3.28)	(-3.27)	(-4.21)	(-4.21)	(-4.20)	(-4.21)
Present Age	-0.00200	-0.00202	-0.00206	-0.00160***	-0.00161***	-0.00158***	-0.00160***
	(-1.18)	(-1.19)	(-1.21)	(-4.79)	(-4.83)	(-4.71)	(-4.77)
Pseudo R-squared	0.000	0.000	0.000	0.003	0.003	0.003	0.003

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 29: Regression with control variables COUNT_RATIO_LARGE

	1	2	3	4	5	6	7
HOLDER67	0.0505						
	(1.44)						
HOLDER100		0.0449					
		(1.39)					
NETBUYER			0.0996***				
			(3.12)				
OC_YEARLY4				0.00615			
				(1.23)			
OC_YEARLY5					0.00564		
					(0.38)		
OC_CEOTENURE4						0.00234	
						(0.60)	
OC_CEOTENURE5							0.00344
							(0.38)
Market-to-book ratio	-0.000000220	-0.000000222	-0.000000227	-1.27e-08***	-1.27e-08***	-1.27e-08***	-1.27e-08***
	(-1.53)	(-1.54)	(-1.57)	(-5.66)	(-5.68)	(-5.62)	(-5.66)
Leverage	0.000323	0.000323	0.000296	0.00000735	0.00000683	0.00000649	0.00000642
	(0.39)	(0.39)	(0.36)	(0.08)	(0.08)	(0.07)	(0.07)
Cash Reserves	-0.00000551	-0.00000541	-0.00000291	-0.000000381	-0.000000359	-0.000000350	-0.000000356
	(-0.19)	(-0.19)	(-0.10)	(-0.13)	(-0.12)	(-0.12)	(-0.12)
R&D Expense	-0.000516**	-0.000520**	-0.000517**	-0.0000578***	-0.0000579***	-0.0000579***	-0.0000579***
	(-2.08)	(-2.09)	(-2.08)	(-3.18)	(-3.18)	(-3.18)	(-3.18)
Present Age	0.000834	0.000826	0.000809	-0.000874***	-0.000879***	-0.000873***	-0.000875***
	(0.47)	(0.46)	(0.45)	(-4.09)	(-4.10)	(-4.07)	(-4.07)
Pseudo R-squared	0.001	0.000	0.000	0.001	0.003	0.003	0.003

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 30: Regression with control variables NCSKEW

	1	2	3	4	5	6	7
HOLDER67	0.0535**						
	(2.19)						
HOLDER100		0.0444**					
		(1.99)					
NETBUYER			0.0286				
			(1.34)				
OC_YEARLY4				-0.00403			
				(-0.08)			
OC_YEARLY5					-0.00813		
					(-0.16)		
OC_CEOTENURE4						0.0188	
						(0.53)	
OC_CEOTENURE5							0.0491
							(1.17)
Market-to-book ratio	0.000000477***	0.000000477***	0.000000480***	-0.0000368*	-0.0000368*	-0.0000369*	-0.0000370*
	(29.59)	(29.72)	(29.94)	(-1.71)	(-1.71)	(-1.72)	(-1.72)
Leverage	0.000175	0.000161	0.000164	0.000138	0.000139	0.000135	0.000139
	(0.38)	(0.35)	(0.36)	(0.35)	(0.35)	(0.34)	(0.35)
Cash Reserves	0.0000131	0.0000131	0.0000134	-0.00000375	-0.00000375	-0.00000376	-0.00000380
	(0.58)	(0.59)	(0.60)	(-0.54)	(-0.54)	(-0.54)	(-0.55)
R&D Expense	0.0000138	0.0000106	0.0000166	0.0000368	0.0000368	0.0000368	0.0000367
	(0.09)	(0.07)	(0.10)	(1.61)	(1.61)	(1.61)	(1.61)
Present Age	-0.000361	-0.000367	-0.000336	0.00194	0.00194	0.00196	0.00202
	(-0.30)	(-0.31)	(-0.28)	(1.02)	(1.02)	(1.03)	(1.06)
Pseudo R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 31: Frequency industries

Industry by			
SIC	Freq.	Percent	Cum.
Consumer	2,587	7.50	7.50
Manufacturing	10,753	31.16	38.66
Business Equipment	9,568	27.73	66.38
Healthcare,	5,621	16.29	82.67
Other	5,981	17.33	100.00
Total	34,51	100.00	

Table 32: Pairwise comparison of means 1

	Holder67			Holder100			Net buyer		
industry	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t
2 vs 1	-.0278022	.0062222	0.000	-.0280998	.0068552	0.000	-.0096599	.0072365	0.541
3 vs 1	.0112227	.0063908	0.295	.0135417	.007041	0.218	-.0313867	.0074325	0.000
4 vs 1	.0011652	.0073751	0.999	-.0074758	.0081253	0.794	.0100246	.0085772	0.647
3 vs 2	.0390249	.0060386	0.000	.0416414	.0066529	0.000	-.0217268	.0070228	0.011
4 vs 2	.0289674	.007072	0.000	.020624	.0077914	0.041	.0196845	.0082247	0.078
4 vs 3	-.0100575	.0072208	0.504	-.0210174	.0079553	0.041	.0414113	.0083977	0.000

Table 33: Pairwise comparison of means 2

	CRASH_MEDIUM			CRASH_SMALL			CRASH_LARGE		
industry	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t
2 vs 1	.0174783	.0105775	0.349	.0297483	.0079446	0.001	-.0159871	.0097337	0.355
3 vs 1	.0519285	.0107153	0.000	.0313393	.0080481	0.001	.0479671	.0098606	0.000
4 vs 1	.0516377	.0115483	0.000	.0329836	.0086738	0.001	.0480404	.0106271	0.000
3 vs 2	.0344503	.0068798	0.000	.001591	.0051673	0.990	.0639542	.006331	0.000
4 vs 2	.0341594	.0081164	0.000	.0032354	.0060961	0.952	.0640275	.007469	0.000
4 vs 3	-.0002908	.0082952	1.000	.0016444	.0062305	0.994	.0000733	.0076335	1.000

Table 34: Pairwise comparison of means 3

	COUNT_CRASH_MEDIUM			COUNT_CRASH_SMALL			COUNT_CRASH_LARGE		
industry	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t
2 vs 1	.5506474	.0107868	0.000	1.047.487	.0144338	0.000	.1636275	.0066287	0.000
3 vs 1	.623788	.0110791	0.000	1.077.642	.0148248	0.000	.2345632	.0068083	0.000
4 vs 1	.5933082	.0127853	0.000	1.027.827	.017108	0.000	.2296332	.0078568	0.000
3 vs 2	.0731406	.0104684	0.000	.030155	.0140077	0.137	.0709357	.006433	0.000
4 vs 2	.0426608	.0122599	0.003	-.0196601	.016405	0.628	.0660056	.0075339	0.000
4 vs 3	-.0304798	.0125178	0.071	-.049815	.0167501	0.016	-.00493	.0076924	0.919

Table 35: Pairwise comparison of means 4

	NET_COUNT_MEDIUM			NET_COUNT_SMALL			NET_COUNT_LARGE		
industry	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t
2 vs 1	-.9450194	.116263	0.000	-.9615443	.1166647	0.000	-.9773369	.1155795	0.000
3 vs 1	-.7118916	.119413	0.000	-.7319632	.1198256	0.000	-.7320874	.118711	0.000
4 vs 1	-.8034691	.1378036	0.000	-.8508235	.1382797	0.000	-.7901818	.1369934	0.000
3 vs 2	.2331277	.1128309	0.164	.2295811	.1132208	0.178	.2452494	.1121676	0.127
4 vs 2	.1415503	.1321408	0.707	.1107209	.1325974	0.838	.1871551	.131364	0.484
4 vs 3	-.0915775	.1349206	0.905	-.1188603	.1353868	0.816	-.0580944	.1341274	0.973

Table 36: Pairwise comparison of means 5

	COUNT_JUMP_MEDIUM			COUNT_JUMP_SMALL			COUNT_JUMP_LARGE		
industry	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t
2 vs 1	.4326664	.0101185	0.000	.9460308	.0142548	0.000	.0779641	.0047852	0.000
3 vs 1	.4586784	.0103926	0.000	.9326038	.014641	0.000	.0896494	.0049148	0.000
4 vs 1	.5124113	.0119932	0.000	.9942842	.0168958	0.000	.135449	.0056718	0.000
3 vs 2	.026012	.0098198	0.040	-.013427	.013834	0.766	.0116853	.0046439	0.057
4 vs 2	.0797448	.0115003	0.000	.0482534	.0162015	0.015	.0574849	.0054387	0.000
4 vs 3	.0537329	.0117423	0.000	.0616804	.0165424	0.001	.0457996	.0055531	0.000

Table 37: Pairwise comparison of means 6

	COUNT_RATIO_MEDIUM			COUNT_RATIO_SMALL			COUNT_RATIO_LARGE		
industry	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t
2 vs 1	.2212558	.0106689	0.000	.197245	.0110132	0.000	.1191455	.0070427	0.000
3 vs 1	.2601583	.010958	0.000	.2313642	.0113116	0.000	.1816184	.0072335	0.000
4 vs 1	.1944375	.0126456	0.000	.1540264	.0130537	0.000	.1465908	.0083475	0.000
3 vs 2	.0389025	.010354	0.001	.0341192	.0106881	0.008	.0624729	.0068348	0.000
4 vs 2	-.0268183	.0121259	0.120	-.0432186	.0125173	0.003	.0274453	.0080045	0.003
4 vs 3	-.0657208	.012381	0.000	-.0773377	.0127806	0.000	-.0350276	.0081729	0.000

Table 38: Pairwise comparison of means 5

	NCSKEW		
industry	Tukey Contrast	Tukey Std. Err.	P>t
2 vs 1	-.1217694	.0182061	0.000

Table 39: Pairwise comparison of means

	OC_YEARLY4			OC_YEARLY5			OC_CEOTENURE4			OC_CEOTENURE5		
industry	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t	Tukey Contrast	Tukey Std. Err.	P>t
2 vs 1	-.0098859	.0050018	0.197	.0013613	.0045449	0.991	-.0135718	.0067327	0.182	.0013613	.0045449	0.991
3 vs 1	-.0188746	.0051373	0.001	-.0012813	.0046681	0.993	-.0350072	.0069151	0.000	-.0012813	.0046681	0.993
4 vs 1	.0016023	.0059285	0.993	.0215431	.005387	0.000	.0032661	.0079801	0.977	.0215431	.005387	0.000
3 vs 2	-.0089886	.0048541	0.249	-.0026426	.0044108	0.932	-.0214354	.0065339	0.006	-.0026426	.0044108	0.932
4 vs 2	.0114882	.0056848	0.180	.0201819	.0051656	0.001	.0168379	.0076522	0.123	.0201819	.0051656	0.001
4 vs 3	.0204769	.0058044	0.002	.0228244	.0052743	0.000	.0382733	.0078131	0.000	.0228244	.0052743	0.000

Table 40: Regressions CRASH_MEDIUM with industries

	1	2	3	4	5	6	7
HOLDER67	-0.112*						
	(-1.84)						
IND2HOLDER67	0.132**						
	(2.19)						
IND3HOLDER67	0.279***						
	(4.58)						
IND4HOLDER67	0.291***						
	(4.38)						
HOLDER100		-0.132**					
		(-2.09)					
IND2HOLDER100		0.119*					
		(1.84)					
IND3HOLDER100		0.276***					
		(4.21)					
IND4HOLDER100		0.288***					
		(4.02)					
NETBUYER			-0.101				
			(-1.58)				
IND2NETBUYER			0.122*				
			(1.77)				
IND3NETBUYER			0.274***				
			(3.89)				
IND4NETBUYER			0.275***				
			(3.67)				
OC_YEARLY4				-0.168			
				(-1.23)			
IND2OC_YEARLY4				0.0156			
				(0.10)			
IND3OC_YEARLY4				0.316**			
				(2.09)			
IND4OC_YEARLY4				0.228			
				(1.41)			
OC_YEARLY5					-0.279		
					(-0.67)		
IND2OC_YEARLY5					-0.0106		
					(-0.02)		
IND3OC_YEARLY5					0.367		
					(0.79)		
IND4OC_YEARLY5					0.313		
					(0.64)		
OC_CEOTENURE4						-0.0961	
						(-1.23)	
IND2OC_CEOTENURE4						0.0423	
						(0.50)	
IND3OC_CEOTENURE4						0.194**	
						(2.27)	
IND4OC_CEOTENURE4						0.234**	
						(2.51)	
OC_CEOTENURE5							-0.194
							(-0.91)
IND2OC_CEOTENURE5							0.204
							(0.86)
IND3OC_CEOTENURE5							0.352
							(1.48)
IND4OC_CEOTENURE5							0.492**
							(1.99)
Market-to-book ratio	0.0000361	0.00000347	0.00000339	0.00000332	0.00000345	0.00000361	0.00000361
	(0.61)	(0.58)	(0.58)	(0.70)	(0.73)	(0.76)	(0.76)
Leverage	-0.000564	-0.000542	-0.000594	-0.000577	-0.000570	-0.000601	-0.000575
	(-0.57)	(-0.54)	(-0.59)	(-0.62)	(-0.60)	(-0.64)	(-0.60)
Cash Reserves	0.0000246	0.0000246	0.0000257	0.0000227	0.0000249	0.0000238	0.0000246
	(0.85)	(0.85)	(0.88)	(0.78)	(0.86)	(0.82)	(0.85)
R&D Expense	-0.000455**	-0.000457**	-0.000440**	-0.000425*	-0.000426*	-0.000425*	-0.000424*
	(-2.09)	(-2.11)	(-2.03)	(-1.92)	(-1.93)	(-1.91)	(-1.92)
Present Age	0.000424	0.000421	0.000231	-0.00906***	-0.00912***	-0.00868***	-0.00889***
	(0.27)	(0.27)	(0.15)	(-5.78)	(-5.82)	(-5.53)	(-5.66)
Pseudo R-squared	0.002	0.002	0.001	0.002	0.001	0.002	0.002

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 41: Regressions CRASH_SMALL with industries

	1	2	3	4	5	6	7
HOLDER67	-0.231***						
	(-2.80)						
IND2HOLDER67	0.264***						
	(3.24)						
IND3HOLDER67	0.271***						
	(3.27)						
IND4HOLDER67	0.316***						
	(3.53)						
HOLDER100		-0.208**					
		(-2.49)					
IND2HOLDER100		0.221**					
		(2.55)					
IND3HOLDER100		0.237***					
		(2.70)					
IND4HOLDER100		0.268***					
		(2.80)					
NETBUYER			-0.115				
			(-1.35)				
IND2NETBUYER			0.240***				
			(2.60)				
IND3NETBUYER			0.230**				
			(2.42)				
IND4NETBUYER			0.212**				
			(2.07)				
OC_YEARLY4				-0.230			
				(-1.49)			
IND2OC_YEARLY4				0.160			
				(0.90)			
IND3OC_YEARLY4				0.357**			
				(1.99)			
IND4OC_YEARLY4				0.160			
				(0.83)			
OC_YEARLY5					-0.145		
					(-0.28)		
IND2OC_YEARLY5					-0.355		
					(-0.61)		
IND3OC_YEARLY5					0.504		
					(0.89)		
IND4OC_YEARLY5					-0.157		
					(-0.25)		
OC_CEOTENURE4						-0.189*	
						(-1.96)	
IND2OC_CEOTENURE4						0.232**	
						(2.18)	
IND3OC_CEOTENURE4						0.315***	
						(2.92)	
IND4OC_CEOTENURE4						0.354***	
						(2.91)	
OC_CEOTENURE5							-0.209
							(-0.88)
IND2OC_CEOTENURE5							0.276
							(0.98)
IND3OC_CEOTENURE5							0.565**
							(2.06)
IND4OC_CEOTENURE5							0.387
							(1.22)
Market-to-book ratio	0.0000107	0.0000108	0.0000109	0.0000108	0.0000109	0.0000112	0.0000111
	(1.34)	(1.34)	(1.35)	(1.27)	(1.28)	(1.31)	(1.31)
Leverage	-0.00162	-0.00159	-0.00163	-0.00168	-0.00173	-0.00171	-0.00172
	(-1.23)	(-1.21)	(-1.25)	(-1.26)	(-1.27)	(-1.28)	(-1.27)
Cash Reserves	-0.0000157	-0.0000163	-0.0000155	-0.0000161	-0.0000147	-0.0000155	-0.0000149
	(-0.43)	(-0.45)	(-0.43)	(-0.45)	(-0.41)	(-0.43)	(-0.42)
R&D Expense	-0.000898***	-0.000893***	-0.000877***	-0.000867***	-0.000867***	-0.000869***	-0.000865***
	(-4.00)	(-3.99)	(-3.91)	(-3.78)	(-3.78)	(-3.78)	(-3.77)
Present Age	-0.000354	-0.000350	-0.000591	-0.0112***	-0.0113***	-0.0107***	-0.0110***
	(-0.16)	(-0.16)	(-0.27)	(-4.86)	(-4.87)	(-4.60)	(-4.77)
Pseudo R-squared	0.002	0.001	0.002	0.003	0.003	0.003	0.003

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 42: Regressions CRASH_LARGE with industries

	1	2	3	4	5	6	7
HOLDER67	-0.0753						
	(-1.13)						
IND2HOLDER67	-0.0691						
	(-1.03)						
IND3HOLDER67	0.287***						
	(4.25)						
IND4HOLDER67	0.300***						
	(4.20)						
HOLDER100		-0.0824					
		(-1.22)					
IND2HOLDER100		-0.0795					
		(-1.13)					
IND3HOLDER100		0.271***					
		(3.84)					
IND4HOLDER100		0.293***					
		(3.91)					
NETBUYER			-0.00147				
			(-0.02)				
IND2NETBUYER			-0.108				
			(-1.41)				
IND3NETBUYER			0.255***				
			(3.25)				
IND4NETBUYER			0.230***				
			(2.84)				
OC_YEARLY4				-0.0622			
				(-0.42)			
IND2OC_YEARLY4				-0.191			
				(-1.15)			
IND3OC_YEARLY4				0.139			
				(0.86)			
IND4OC_YEARLY4				0.150			
				(0.87)			
OC_YEARLY5					-0.0438		
					(-0.10)		
IND2OC_YEARLY5					-0.248		
					(-0.49)		
IND3OC_YEARLY5					0.0918		
					(0.19)		
IND4OC_YEARLY5					-0.207		
					(-0.39)		
OC_CEOTENURE4						-0.114	
						(-1.30)	
IND2OC_CEOTENURE4						-0.0246	
						(-0.26)	
IND3OC_CEOTENURE4						0.273***	
						(2.84)	
IND4OC_CEOTENURE4						0.273***	
						(2.69)	
OC_CEOTENURE5							-0.278
							(-1.13)
IND2OC_CEOTENURE5							0.155
							(0.55)
IND3OC_CEOTENURE5							0.514*
							(1.85)
IND4OC_CEOTENURE5							0.484*
							(1.73)
Market-to-book ratio	0.00000657	0.00000638	0.00000608	0.00000694	0.00000703	0.00000723	0.00000723
	(1.32)	(1.28)	(1.26)	(1.53)	(1.55)	(1.59)	(1.59)
Leverage	-0.0000913	-0.0000380	-0.000108	-0.000126	-0.000108	-0.000169	-0.000133
	(-0.12)	(-0.05)	(-0.15)	(-0.18)	(-0.15)	(-0.24)	(-0.19)
Cash Reserves	0.0000465	0.0000472	0.0000484*	0.0000382	0.0000397	0.0000383	0.0000394
	(1.61)	(1.63)	(1.67)	(1.28)	(1.34)	(1.29)	(1.33)
R&D Expense	-0.000310	-0.000311	-0.000291	-0.000249	-0.000247	-0.000247	-0.000240
	(-1.33)	(-1.33)	(-1.24)	(-1.14)	(-1.13)	(-1.12)	(-1.10)
Present Age	0.00277*	0.00270	0.00242	-0.00609***	-0.00618***	-0.00556***	-0.00599***
	(1.67)	(1.62)	(1.45)	(-3.58)	(-3.62)	(-3.27)	(-3.51)
Pseudo R-squared	0.004	0.003	0.003	0.002	0.001	0.002	0.001

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 43: Regressions COUNT_CRASH_MEDIUM with industries

	1	2	3	4	5	6	7
HOLDER67	-1.506***						
	(-22.75)						
IND2HOLDER67	1.866***						
	(28.28)						
IND3HOLDER67	2.019***						
	(29.96)						
IND4HOLDER67	1.946***						
	(27.37)						
HOLDER100		-1.520***					
		(-22.37)					
IND2HOLDER100		1.877***					
		(26.93)					
IND3HOLDER100		2.037***					
		(28.78)					
IND4HOLDER100		1.966***					
		(26.25)					
NETBUYER			-1.349***				
			(-18.50)				
IND2NETBUYER			1.721***				
			(22.74)				
IND3NETBUYER			1.894***				
			(24.37)				
IND4NETBUYER			1.813***				
			(22.34)				
OC_YEARLY4				-0.459***			
				(-21.62)			
IND2OC_YEARLY4				0.527***			
				(16.41)			
IND3OC_YEARLY4				0.673***			
				(20.21)			
IND4OC_YEARLY4				0.623***			
				(15.92)			
OC_YEARLY5					-0.489***		
					(-8.28)		
IND2OC_YEARLY5					0.480***		
					(4.99)		
IND3OC_YEARLY5					0.623***		
					(6.74)		
IND4OC_YEARLY5					0.563***		
					(5.22)		
OC_CEOTENURE4						-0.451***	
						(-22.80)	
IND2OC_CEOTENURE4						0.558***	
						(24.02)	
IND3OC_CEOTENURE4						0.638***	
						(26.13)	
IND4OC_CEOTENURE4						0.617***	
						(22.20)	
OC_CEOTENURE5							-0.534***
							(-12.69)
IND2OC_CEOTENURE5							0.669***
							(11.27)
IND3OC_CEOTENURE5							0.763***
							(12.19)
IND4OC_CEOTENURE5							0.757***
							(11.77)
Market-to-book ratio	5.28e-08***	5.22e-08***	9.07e-08***	-0.158***	3.46e-08***	3.54e-08***	3.45e-08***
	(5.14)	(5.10)	(9.19)	(-14.59)	(8.04)	(8.26)	(8.00)
Leverage	-0.000500	-0.000459	-0.000840	0.153***	-0.000127	-0.000188	-0.000111
	(-0.93)	(-0.90)	(-1.48)	(8.68)	(-0.56)	(-0.83)	(-0.49)
Cash Reserves	0.0000299	0.0000280	0.0000319	0.229***	0.0000174	0.0000145	0.0000175
	(1.18)	(1.11)	(1.27)	(11.82)	(1.57)	(1.32)	(1.59)
R&D Expense	-0.000646***	-0.000634***	-0.000556**	0.224***	-0.000183**	-0.000181**	-0.000181**
	(-2.80)	(-2.78)	(-2.49)	(9.78)	(-2.28)	(-2.38)	(-2.27)
Present Age	-0.00148	-0.00155	-0.00216	-0.00331***	-0.00333***	-0.00314***	-0.00323***
	(-0.98)	(-1.03)	(-1.37)	(-4.77)	(-4.70)	(-4.66)	(-4.60)
Pseudo R-squared	0.052	0.046	0.033	0.014	0.003	0.041	0.011

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 44: Regressions COUNT_CRASH_SMALL with industries

	1	2	3	4	5	6	7
HOLDER67	-1.880***						
	(-26.00)						
IND2HOLDER67	2.355***						
	(33.01)						
IND3HOLDER67	2.408***						
	(33.15)						
IND4HOLDER67	2.324***						
	(30.54)						
HOLDER100		-1.866***					
		(-25.37)					
IND2HOLDER100		2.348***					
		(31.64)					
IND3HOLDER100		2.415***					
		(32.14)					
IND4HOLDER100		2.341***					
		(29.61)					
NETBUYER			-1.650***				
			(-20.87)				
IND2NETBUYER			2.140***				
			(26.82)				
IND3NETBUYER			2.195***				
			(26.76)				
IND4NETBUYER			2.099***				
			(24.30)				
OC_YEARLY4				-0.817***			
				(-23.90)			
IND2OC_YEARLY4				1.035***			
				(21.92)			
IND3OC_YEARLY4				1.172***			
				(23.79)			
IND4OC_YEARLY4				1.086***			
				(19.82)			
OC_YEARLY5					-0.889***		
					(-10.46)		
IND2OC_YEARLY5					0.948***		
					(7.00)		
IND3OC_YEARLY5					1.187***		
					(9.46)		
IND4OC_YEARLY5					0.997***		
					(6.51)		
OC_CEOTENURE4						-0.817***	
						(-24.72)	
IND2OC_CEOTENURE4						1.062***	
						(28.89)	
IND3OC_CEOTENURE4						1.127***	
						(30.13)	
IND4OC_CEOTENURE4						1.065***	
						(25.46)	
OC_CEOTENURE5							-0.960***
							(-13.48)
IND2OC_CEOTENURE5							1.228***
							(13.65)
IND3OC_CEOTENURE5							1.312***
							(15.33)
IND4OC_CEOTENURE5							1.228***
							(12.85)
Market-to-book ratio	-7.81e-08***	-7.74e-08***	-2.38e-08**	-2.80e-08***	-2.80e-08***	-2.67e-08***	-2.85e-08***
	(-6.33)	(-6.41)	(-2.10)	(-3.41)	(-3.47)	(-3.60)	(-3.44)
Leverage	-0.000630	-0.000535	-0.000996**	-0.000258	-0.000314	-0.000412	-0.000276
	(-1.35)	(-1.34)	(-2.06)	(-0.88)	(-1.09)	(-1.46)	(-0.98)
Cash Reserves	0.0000169	0.0000143	0.0000184	0.0000110	0.0000157	0.0000108	0.0000162
	(0.65)	(0.56)	(0.74)	(0.74)	(1.05)	(0.73)	(1.08)
R&D Expense	-0.000869***	-0.000843***	-0.000760***	-0.000372***	-0.000373***	-0.000370***	-0.000371***
	(-3.52)	(-3.48)	(-3.27)	(-2.87)	(-2.83)	(-3.00)	(-2.83)
Present Age	-0.00145	-0.00158	-0.00238	-0.00498***	-0.00501***	-0.00480***	-0.00493***
	(-0.90)	(-0.98)	(-1.41)	(-4.56)	(-4.46)	(-4.55)	(-4.44)
Pseudo R-squared	0.065	0.058	0.039	0.023	0.005	0.067	0.016

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 45: Regressions COUNT CRASH_LARGE with industries

	1	2	3	4	5	6	7
HOLDER67	-1.506***						
	-22.75						
IND2HOLDER67	1.866***						
	28.28						
IND3HOLDER67	2.019***						
	29.96						
IND4HOLDER67	1.946***						
	27.37						
HOLDER100		-1.200***					
		(-15.96)					
IND2HOLDER100		1.290***					
		(16.63)					
IND3HOLDER100		1.631***					
		(20.84)					
IND4HOLDER100		1.626***					
		(19.69)					
NETBUYER			-1.007***				
			(-12.52)				
IND2NETBUYER			1.158***				
			(13.69)				
IND3NETBUYER			1.503***				
			(17.42)				
IND4NETBUYER			1.451***				
			(16.22)				
OC_YEARLY4				-0.158***			
				(-14.59)			
IND2OC_YEARLY4				0.153***			
				(8.68)			
IND3OC_YEARLY4				0.229***			
				(11.82)			
IND4OC_YEARLY4				0.224***			
				(9.78)			
OC_YEARLY5					-0.174***		
					(-6.88)		
IND2OC_YEARLY5					0.160***		
					(3.11)		
IND3OC_YEARLY5					0.233***		
					(4.39)		
IND4OC_YEARLY5					0.150***		
					(2.62)		
OC_CEOTENURE4						-0.156***	
						(-18.67)	
IND2OC_CEOTENURE4						0.174***	
						(15.36)	
IND3OC_CEOTENURE4						0.243***	
						(19.20)	
IND4OC_CEOTENURE4						0.235***	
						(15.48)	
OC_CEOTENURE5							-0.190***
							(-12.66)
IND2OC_CEOTENURE5							0.209***
							(7.16)
IND3OC_CEOTENURE5							0.304***
							(8.82)
IND4OC_CEOTENURE5							0.271***
							(8.22)
Market-to-book ratio	0.0000109	0.000000281***	0.000000292***	8.16e-08***	8.18e-08***	8.22e-08***	8.18e-08***
	(1.35)	(35.80)	(37.79)	(38.55)	(38.63)	(39.02)	(38.66)
Leverage	-0.00163	-0.000241	-0.000521	0.0000103	0.00000273	-0.0000235	0.00000463
	(-1.25)	(-0.35)	(-0.75)	(0.08)	(0.02)	(-0.18)	(0.04)
Cash Reserves	-0.0000155	0.0000434	0.0000472*	0.00000632	0.00000733	0.00000622	0.00000735
	(-0.43)	(1.62)	(1.76)	(1.08)	(1.24)	(1.06)	(1.25)
R&D Expense	-0.000877***	-0.000484**	-0.000433*	-0.0000532	-0.0000533	-0.0000526	-0.0000520
	(-3.91)	(-2.01)	(-1.81)	(-1.38)	(-1.38)	(-1.39)	(-1.34)
Present Age	-0.000591	0.00153	0.000963	-0.00131***	-0.00133***	-0.00119***	-0.00129***
	(-0.27)	(0.90)	(0.55)	(-3.76)	(-3.75)	(-3.49)	(-3.67)
Pseudo R-squared	0.002	0.032	0.029	0.020	0.001	0.016	0.004

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 46: Regressions NET_COUNT_MEDIUM with industries

	1	2	3	4	5	6	7
HOLDER67	-0.150***						
	(-5.80)						
IND2HOLDER67	0.263***						
	(9.12)						
IND3HOLDER67	0.337***						
	(10.82)						
IND4HOLDER67	0.172***						
	(4.56)						
HOLDER100		-0.151***					
		(-6.47)					
IND2HOLDER100		0.275***					
		(8.99)					
IND3HOLDER100		0.334***					
		(10.03)					
IND4HOLDER100		0.170***					
		(4.14)					
NETBUYER			-1.046***				
			(-4.59)				
IND2NETBUYER			1.063***				
			(3.16)				
IND3NETBUYER			0.645**				
			(1.96)				
IND4NETBUYER			0.259				
			(0.76)				
OC_YEARLY4				-1.565***			
				(-17.44)			
IND2OC_YEARLY4				2.186***			
				(18.32)			
IND3OC_YEARLY4				2.109***			
				(17.82)			
IND4OC_YEARLY4				1.984***			
				(15.43)			
OC_YEARLY5					-1.995***		
					(-7.32)		
IND2OC_YEARLY5					2.636***		
					(7.37)		
IND3OC_YEARLY5					2.404***		
					(7.07)		
IND4OC_YEARLY5					2.518***		
					(6.27)		
OC_CEOTENURE4						-1.618***	
						(-18.15)	
IND2OC_CEOTENURE4						2.193***	
						(21.84)	
IND3OC_CEOTENURE4						2.168***	
						(21.84)	
IND4OC_CEOTENURE4						2.047***	
						(19.36)	
OC_CEOTENURE5							-2.114***
							(-9.42)
IND2OC_CEOTENURE5							2.676***
							(10.02)
IND3OC_CEOTENURE5							2.725***
							(10.58)
IND4OC_CEOTENURE5							2.587***
							(9.83)
Market-to-book ratio	0.000000166***	0.000000165***	0.000000177***	0.000000264**	0.000000267**	0.000000296**	0.000000260**
	(22.13)	(21.80)	(24.65)	(2.06)	(2.06)	(2.29)	(2.02)
Leverage	-0.000508	-0.000506	-0.000584	-0.000291	-0.000321	-0.000450	-0.000356
	(-0.78)	(-0.78)	(-0.88)	(-0.40)	(-0.44)	(-0.63)	(-0.49)
Cash Reserves	0.00000136	0.000000897	0.00000326	0.0000532*	0.0000547*	0.0000485	0.0000522*
	(0.06)	(0.04)	(0.15)	(1.85)	(1.95)	(1.64)	(1.87)
R&D Expense	0.0000695	0.0000693	0.0000735	-0.000137	-0.000128	-0.000126	-0.000133
	(0.52)	(0.52)	(0.55)	(-0.59)	(-0.54)	(-0.57)	(-0.57)
Present Age	-0.000448	-0.000492	-0.000542	0.00166	0.00136	0.00187	0.000843
	(-0.39)	(-0.43)	(-0.47)	(0.82)	(0.65)	(0.93)	(0.41)
Pseudo R-squared	0.001	0.001	0.001	0.015	0.003	0.049	0.011

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 47: Regressions NET_COUNT_SMALL with industries

	1	2	3	4	5	6	7
HOLDER67	-0.105***						
	(-4.22)						
IND2HOLDER67	0.159***						
	(5.38)						
IND3HOLDER67	0.234***						
	(7.89)						
IND4HOLDER67	0.0599						
	(1.64)						
HOLDER100		-0.0996***					
		(-4.40)					
IND2HOLDER100		0.150***					
		(4.72)					
IND3HOLDER100		0.223***					
		(7.07)					
IND4HOLDER100		0.0756*					
		(1.93)					
NETBUYER			-0.0800***				
			(-3.68)				
IND2NETBUYER			0.119***				
			(3.35)				
IND3NETBUYER			0.251***				
			(6.84)				
IND4NETBUYER			0.0609				
			(1.37)				
OC_YEARLY4				-1.782***			
				(-19.82)			
IND2OC_YEARLY4				2.477***			
				(20.46)			
IND3OC_YEARLY4				2.428***			
				(20.25)			
IND4OC_YEARLY4				2.256***			
				(16.26)			
OC_YEARLY5					-2.144***		
					(-7.86)		
IND2OC_YEARLY5					2.995***		
					(8.03)		
IND3OC_YEARLY5					2.852***		
					(7.72)		
IND4OC_YEARLY5					3.301***		
					(7.43)		
OC_CEOTENURE4						-1.765***	
						(-19.55)	
IND2OC_CEOTENURE4						2.462***	
						(24.08)	
IND3OC_CEOTENURE4						2.403***	
						(23.49)	
IND4OC_CEOTENURE4						2.151***	
						(19.31)	
OC_CEOTENURE5							-2.255***
							(-9.87)
IND2OC_CEOTENURE5							3.041***
							(10.83)
IND3OC_CEOTENURE5							3.076***
							(11.64)
IND4OC_CEOTENURE5							2.761***
							(9.91)
Market-to-book ratio	0.000000143***	0.000000144***	0.000000149***	0.000000268*	0.000000272*	0.000000309**	0.000000261*
	(21.26)	(21.05)	(23.43)	(1.94)	(1.94)	(2.17)	(1.92)
Leverage	-0.0000452	-0.0000448	-0.0000835	-0.000710	-0.000746	-0.000929	-0.000801
	(-0.09)	(-0.09)	(-0.16)	(-0.88)	(-0.92)	(-1.17)	(-0.97)
Cash Reserves	0.00000287	0.00000279	0.00000437	0.0000329	0.0000345	0.0000267	0.0000320
	(0.13)	(0.13)	(0.21)	(1.12)	(1.22)	(0.88)	(1.13)
R&D Expense	-0.0000313	-0.0000321	-0.0000321	-0.000248	-0.000234	-0.000240	-0.000243
	(-0.23)	(-0.24)	(-0.24)	(-1.08)	(-1.01)	(-1.09)	(-1.05)
Present Age	0.0000357	0.0000253	-0.0000509	-0.000105	-0.000351	-0.000110	-0.000970
	(0.03)	(0.02)	(-0.04)	(-0.05)	(-0.16)	(-0.05)	(-0.44)
Pseudo R-squared	0.001	0.001	0.000	0.020	0.004	0.061	0.014

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 48: Regressions NET_COUNT_LARGE with industries

	1	2	3	4	5	6	7
HOLDER67	-0.301***						
	(-9.54)						
IND2HOLDER67	0.346***						
	(10.54)						
IND3HOLDER67	0.598***						
	(15.47)						
IND4HOLDER67	0.411***						
	(8.37)						
HOLDER100		-0.307***					
		(-10.57)					
IND2HOLDER100		0.348***					
		(9.97)					
IND3HOLDER100		0.592***					
		(14.52)					
IND4HOLDER100		0.415***					
		(7.91)					
NETBUYER			-0.254***				
			(-8.39)				
IND2NETBUYER			0.344***				
			(8.44)				
IND3NETBUYER			0.603***				
			(12.59)				
IND4NETBUYER			0.410***				
			(7.16)				
OC_YEARLY4				-1.271***			
				(-13.61)			
IND2OC_YEARLY4				1.492***			
				(12.84)			
IND3OC_YEARLY4				1.793***			
				(15.46)			
IND4OC_YEARLY4				1.586***			
				(12.76)			
OC_YEARLY5					-1.817***		
					(-5.84)		
IND2OC_YEARLY5					1.954***		
					(5.18)		
IND3OC_YEARLY5					2.299***		
					(6.38)		
IND4OC_YEARLY5					2.383***		
					(6.04)		
OC_CEOTENURE4						-1.255***	
						(-14.31)	
IND2OC_CEOTENURE4						1.470***	
						(15.02)	
IND3OC_CEOTENURE4						1.685***	
						(17.49)	
IND4OC_CEOTENURE4						1.592***	
						(15.72)	
OC_CEOTENURE5							-1.779***
							(-7.89)
IND2OC_CEOTENURE5							1.978***
							(7.59)
IND3OC_CEOTENURE5							2.086***
							(8.56)
IND4OC_CEOTENURE5							2.174***
							(8.34)
Market-to-book ratio	0.000000302***	0.000000301***	0.000000307***	0.000000334**	0.000000336***	0.000000358***	0.000000331**
	(39.80)	(39.36)	(41.75)	(2.57)	(2.58)	(2.72)	(2.57)
Leverage	0.0000714	0.0000966	-0.0000396	-0.000286	-0.000297	-0.000395	-0.000323
	(0.08)	(0.11)	(-0.04)	(-0.38)	(-0.40)	(-0.54)	(-0.44)
Cash Reserves	0.0000222	0.0000214	0.0000252	0.0000544**	0.0000558**	0.0000505**	0.0000543**
	(0.85)	(0.82)	(0.97)	(2.18)	(2.25)	(2.00)	(2.19)
R&D Expense	-0.0000786	-0.0000768	-0.0000646	0.0000637	0.0000713	0.0000767	0.0000648
	(-0.50)	(-0.49)	(-0.41)	(0.31)	(0.34)	(0.39)	(0.31)
Present Age	0.00299**	0.00292**	0.00268*	0.00289	0.00261	0.00312*	0.00224
	(2.18)	(2.13)	(1.94)	(1.52)	(1.37)	(1.65)	(1.18)
Pseudo R-squared	0.005	0.005	0.004	0.003	0.002	0.025	0.006

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 49: Regressions COUNT_JUMP_MEDIUM with industries

	1	2	3	4	5	6	7
HOLDER67	-1.384***						
	(-21.65)						
IND2HOLDER67	1.633***						
	(25.55)						
IND3HOLDER67	1.697***						
	(26.33)						
IND4HOLDER67	1.836***						
	(26.67)						
HOLDER100		-1.400***					
		(-21.43)					
IND2HOLDER100		1.637***					
		(24.33)					
IND3HOLDER100		1.726***					
		(25.45)					
IND4HOLDER100		1.865***					
		(25.58)					
NETBUYER			-1.233***				
			(-18.04)				
IND2NETBUYER			1.515***				
			(20.91)				
IND3NETBUYER			1.553***				
			(20.86)				
IND4NETBUYER			1.670***				
			(21.13)				
OC_YEARLY4				-1.508***			
				(-16.30)			
IND2OC_YEARLY4				1.906***			
				(16.36)			
IND3OC_YEARLY4				1.969***			
				(16.99)			
IND4OC_YEARLY4				2.088***			
				(16.08)			
OC_YEARLY5					-1.961***		
					(-6.95)		
IND2OC_YEARLY5					1.965***		
					(5.56)		
IND3OC_YEARLY5					2.386***		
					(6.91)		
IND4OC_YEARLY5					2.718***		
					(6.96)		
OC_CEOTENURE4						-1.455***	
						(-16.55)	
IND2OC_CEOTENURE4						1.826***	
						(18.72)	
IND3OC_CEOTENURE4						1.914***	
						(19.59)	
IND4OC_CEOTENURE4						1.974***	
						(18.58)	
OC_CEOTENURE5							-1.977***
							(-8.64)
IND2OC_CEOTENURE5							2.219***
							(8.27)
IND3OC_CEOTENURE5							2.396***
							(9.49)
IND4OC_CEOTENURE5							2.624***
							(10.03)
Market-to-book ratio	-0.00000377	-0.00000370	-0.00000330	0.000000344**	0.000000348**	0.000000395**	0.000000341**
	(-1.04)	(-1.02)	(-0.86)	(2.24)	(2.23)	(2.24)	(2.25)
Leverage	0.000104	0.000171	-0.000121	-0.000453	-0.000470	-0.000595	-0.000506
	(0.12)	(0.20)	(-0.13)	(-0.64)	(-0.66)	(-0.85)	(-0.71)
Cash Reserves	0.0000344	0.0000326	0.0000335	0.0000476*	0.0000487*	0.0000433	0.0000469*
	(1.38)	(1.31)	(1.41)	(1.80)	(1.87)	(1.60)	(1.81)
R&D Expense	-0.000794***	-0.000779***	-0.000719***	-0.0000286	-0.0000196	-0.0000171	-0.0000246
	(-3.94)	(-3.92)	(-3.69)	(-0.13)	(-0.09)	(-0.09)	(-0.12)
Present Age	-0.00142	-0.00153	-0.00203	0.00162	0.00128	0.00194	0.000920
	(-0.95)	(-1.02)	(-1.32)	(0.84)	(0.65)	(1.00)	(0.48)
Pseudo R-squared	0.041	0.037	0.025	0.019	0.019	0.020	0.019

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 50: Regressions COUNT_JUMP_SMALL with industries

	1	2	3	4	5	6	7
HOLDER67	-1.772***						
	(-25.07)						
IND2HOLDER67	2.220***						
	(31.73)						
IND3HOLDER67	2.188***						
	(30.90)						
IND4HOLDER67	2.291***						
	(30.25)						
HOLDER100		-1.769***					
		(-24.64)					
IND2HOLDER100		2.233***					
		(30.74)					
IND3HOLDER100		2.213***					
		(30.22)					
IND4HOLDER100		2.297***					
		(29.27)					
NETBUYER			-1.578***				
			(-20.65)				
IND2NETBUYER			2.049***				
			(26.02)				
IND3NETBUYER			1.960***				
			(24.35)				
IND4NETBUYER			2.058***				
			(24.09)				
OC_YEARLY4				-1.929***			
				(-21.45)			
IND2OC_YEARLY4				2.886***			
				(21.51)			
IND3OC_YEARLY4				2.811***			
				(21.19)			
IND4OC_YEARLY4				2.903***			
				(18.16)			
OC_YEARLY5					-2.446***		
					(-9.40)		
IND2OC_YEARLY5					2.743***		
					(7.69)		
IND3OC_YEARLY5					3.310***		
					(8.81)		
IND4OC_YEARLY5					4.192***		
					(7.39)		
OC_CEOTENURE4						-1.903***	
						(-20.71)	
IND2OC_CEOTENURE4						2.759***	
						(25.24)	
IND3OC_CEOTENURE4						2.770***	
						(25.23)	
IND4OC_CEOTENURE4						2.739***	
						(21.11)	
OC_CEOTENURE5							-2.473***
							(-10.39)
IND2OC_CEOTENURE5							2.991***
							(10.20)
IND3OC_CEOTENURE5							3.441***
							(12.03)
IND4OC_CEOTENURE5							3.519***
							(11.41)
Market-to-book ratio	-0.00000796*	-0.00000778*	-0.00000678	0.000000201	0.000000204	0.000000233*	0.000000197
	(-1.92)	(-1.89)	(-1.56)	(1.56)	(1.57)	(1.83)	(1.53)
Leverage	-0.000537	-0.000450	-0.000800	-0.00148	-0.00151	-0.00179*	-0.00160
	(-1.06)	(-0.90)	(-1.46)	(-1.54)	(-1.57)	(-1.94)	(-1.61)
Cash Reserves	0.0000111	0.00000843	0.0000180	0.0000582*	0.0000592*	0.0000527	0.0000562*
	(0.42)	(0.32)	(0.71)	(1.65)	(1.74)	(1.42)	(1.66)
R&D Expense	-0.000754***	-0.000728***	-0.000666***	-0.000407	-0.000388	-0.000413*	-0.000398
	(-3.47)	(-3.41)	(-3.20)	(-1.57)	(-1.49)	(-1.67)	(-1.54)
Present Age	-0.00206	-0.00220	-0.00277*	-0.000566	-0.00102	-0.000310	-0.00174
	(-1.30)	(-1.38)	(-1.68)	(-0.22)	(-0.40)	(-0.12)	(-0.68)
Pseudo R-squared	0.059	0.052	0.035	0.019	0.018	0.021	0.019

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 51: Regressions COUNT_JUMP_LARGE with industries

	1	2	3	4	5	6	7
HOLDER67	-1.021***						
	(-11.79)						
IND2HOLDER67	1.090***						
	(12.51)						
IND3HOLDER67	1.186***						
	(13.46)						
IND4HOLDER67	1.530***						
	(16.78)						
HOLDER100		-1.030***					
		(-11.51)					
IND2HOLDER100		1.101***					
		(11.73)					
IND3HOLDER100		1.207***					
		(12.77)					
IND4HOLDER100		1.551***					
		(15.80)					
NETBUYER			-0.923***				
			(-10.03)				
IND2NETBUYER			0.992***				
			(9.91)				
IND3NETBUYER			1.074***				
			(10.56)				
IND4NETBUYER			1.389***				
			(13.29)				
OC_YEARLY4				-1.508***			
				(-16.30)			
IND2OC_YEARLY4				1.906***			
				(16.36)			
IND3OC_YEARLY4				1.969***			
				(16.99)			
IND4OC_YEARLY4				2.088***			
				(16.08)			
OC_YEARLY5					-1.354***		
					(-4.22)		
IND2OC_YEARLY5					1.390***		
					(3.61)		
IND3OC_YEARLY5					1.417***		
					(3.76)		
IND4OC_YEARLY5					1.609***		
					(3.95)		
OC_CEOTENURE4						-0.956***	
						(-10.16)	
IND2OC_CEOTENURE4						1.108***	
						(10.43)	
IND3OC_CEOTENURE4						1.139***	
						(10.93)	
IND4OC_CEOTENURE4						1.199***	
						(10.76)	
OC_CEOTENURE5							-1.338***
							(-5.86)
IND2OC_CEOTENURE5							1.465***
							(5.47)
IND3OC_CEOTENURE5							1.390***
							(5.33)
IND4OC_CEOTENURE5							1.588***
							(5.90)
Market-to-book ratio	-0.00000651	-0.00000654	-0.00000625	0.000000422***	0.000000424***	0.000000442***	0.000000419***
	(-0.85)	(-0.85)	(-0.82)	(3.03)	(3.03)	(3.02)	(3.03)
Leverage	-0.000615	-0.000565	-0.000731	-0.000149	-0.000161	-0.000216	-0.000177
	(-0.50)	(-0.46)	(-0.60)	(-0.16)	(-0.17)	(-0.23)	(-0.19)
Cash Reserves	0.0000248	0.0000246	0.0000234	0.0000398	0.0000406*	0.0000372	0.0000395
	(0.66)	(0.65)	(0.63)	(1.64)	(1.67)	(1.54)	(1.63)
R&D Expense	-0.000740**	-0.000729**	-0.000683**	0.000331*	0.000337*	0.000339*	0.000331*
	(-2.19)	(-2.17)	(-2.00)	(1.67)	(1.69)	(1.77)	(1.67)
Present Age	-0.00454**	-0.00468**	-0.00498**	0.00553***	0.00534**	0.00559***	0.00504**
	(-2.20)	(-2.26)	(-2.40)	(2.60)	(2.51)	(2.61)	(2.36)
Pseudo R-squared	0.023	0.020	0.014	0.019	0.019	0.020	0.020

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 52: Regressions COUNT_RATIO_MEDIUM with industries

	1	2	3	4	5	6	7
HOLDER67	-1.500***						
	(-22.58)						
IND2HOLDER67	1.875***						
	(28.20)						
IND3HOLDER67	1.971***						
	(29.31)						
IND4HOLDER67	1.857***						
	(26.61)						
HOLDER100		-1.507***					
		(-22.12)					
IND2HOLDER100		1.888***					
		(26.97)					
IND3HOLDER100		1.989***					
		(28.23)					
IND4HOLDER100		1.876***					
		(25.61)					
NETBUYER			-1.341***				
			(-18.30)				
IND2NETBUYER			1.738***				
			(22.85)				
IND3NETBUYER			1.842***				
			(23.94)				
IND4NETBUYER			1.726***				
			(21.56)				
OC_YEARLY4				-0.176***			
				(-20.76)			
IND2OC_YEARLY4				0.240***			
				(17.61)			
IND3OC_YEARLY4				0.237***			
				(16.75)			
IND4OC_YEARLY4				0.235***			
				(13.61)			
OC_YEARLY5					-0.164***		
					(-7.25)		
IND2OC_YEARLY5					0.263***		
					(6.06)		
IND3OC_YEARLY5					0.192***		
					(4.95)		
IND4OC_YEARLY5					0.109***		
					(2.67)		
OC_CEOTENURE4						-0.169***	
						(-21.63)	
IND2OC_CEOTENURE4						0.227***	
						(21.92)	
IND3OC_CEOTENURE4						0.242***	
						(22.41)	
IND4OC_CEOTENURE4						0.230***	
						(19.17)	
OC_CEOTENURE5							-0.184***
							(-11.39)
IND2OC_CEOTENURE5							0.270***
							(10.19)
IND3OC_CEOTENURE5							0.255***
							(10.50)
IND4OC_CEOTENURE5							0.248***
							(9.60)
Market-to-book ratio	-0.00000519	-0.00000515	-0.00000458	-2.95e-08***	-2.99e-08***	-2.88e-08***	-2.99e-08***
	(-1.35)	(-1.34)	(-1.14)	(-8.48)	(-8.00)	(-9.69)	(-7.99)
Leverage	-0.000657	-0.000717	-0.000451	-0.000205	-0.000218	-0.000196	-0.000195
	(-0.69)	(-0.75)	(-0.53)	(-1.51)	(-1.64)	(-1.46)	(-1.46)
Cash Reserves	-0.0000148	-0.0000150	-0.00000873	-0.00000458	-0.00000483	-0.00000437	-0.00000512
	(-0.59)	(-0.60)	(-0.35)	(-1.25)	(-1.30)	(-1.20)	(-1.39)
R&D Expense	-0.000603***	-0.000592***	-0.000501**	-0.000117***	-0.000116***	-0.000120***	-0.000117***
	(-2.80)	(-2.76)	(-2.45)	(-4.63)	(-4.51)	(-4.73)	(-4.53)
Present Age	-0.00106	-0.00112	-0.00160	-0.00150***	-0.00152***	-0.00154***	-0.00151***
	(-0.74)	(-0.78)	(-1.06)	(-4.69)	(-4.66)	(-4.96)	(-4.64)
Pseudo R-squared	0.035	0.031	0.022	0.012	0.004	0.034	0.008

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 53: Regressions COUNT_RATIO_SMALL with industries

	1	2	3	4	5	6	7
HOLDER67	-1.868***						
	(-25.86)						
IND2HOLDER67	2.317***						
	(32.59)						
IND3HOLDER67	2.341***						
	(32.37)						
IND4HOLDER67	2.190***						
	(29.42)						
HOLDER100		-1.852***					
		(-25.20)					
IND2HOLDER100		2.309***					
		(31.26)					
IND3HOLDER100		2.339***					
		(31.25)					
IND4HOLDER100		2.204***					
		(28.53)					
NETBUYER			-1.617***				
			(-20.47)				
IND2NETBUYER			2.099***				
			(26.34)				
IND3NETBUYER			2.157***				
			(26.53)				
IND4NETBUYER			1.983***				
			(23.39)				
OC_YEARLY4				-0.197***			
				(-24.29)			
IND2OC_YEARLY4				0.274***			
				(20.94)			
IND3OC_YEARLY4				0.253***			
				(19.83)			
IND4OC_YEARLY4				0.254***			
				(17.21)			
OC_YEARLY5					-0.182***		
					(-7.21)		
IND2OC_YEARLY5					0.251***		
					(6.38)		
IND3OC_YEARLY5					0.206***		
					(5.75)		
IND4OC_YEARLY5					0.202***		
					(4.79)		
OC_CEOTENURE4						-0.189***	
						(-24.11)	
IND2OC_CEOTENURE4						0.262***	
						(25.92)	
IND3OC_CEOTENURE4						0.265***	
						(24.99)	
IND4OC_CEOTENURE4						0.243***	
						(21.83)	
OC_CEOTENURE5							-0.206***
							(-12.41)
IND2OC_CEOTENURE5							0.280***
							(12.15)
IND3OC_CEOTENURE5							0.279***
							(12.00)
IND4OC_CEOTENURE5							0.288***
							(11.22)
Market-to-book ratio	-0.00000274	-0.00000256	-0.00000185	-3.27e-08***	-3.31e-08***	-3.18e-08***	-3.31e-08***
	(-0.94)	(-0.89)	(-0.64)	(-9.42)	(-8.74)	(-11.20)	(-8.71)
Leverage	-0.00117	-0.00124	-0.000903	-0.000108	-0.000120	-0.0000952	-0.0000940
	(-1.38)	(-1.46)	(-1.28)	(-1.24)	(-1.39)	(-1.13)	(-1.11)
Cash Reserves	-0.0000332	-0.0000327	-0.0000269	-0.00000452	-0.00000484	-0.00000433	-0.00000514
	(-1.29)	(-1.28)	(-1.06)	(-1.25)	(-1.32)	(-1.21)	(-1.41)
R&D Expense	-0.000742***	-0.000718***	-0.000622***	-0.000119***	-0.000118***	-0.000121***	-0.000119***
	(-3.21)	(-3.15)	(-2.93)	(-4.29)	(-4.17)	(-4.37)	(-4.23)
Present Age	-0.00114	-0.00118	-0.00209	-0.00160***	-0.00161***	-0.00167***	-0.00161***
	(-0.75)	(-0.77)	(-1.30)	(-4.92)	(-4.83)	(-5.30)	(-4.84)
Pseudo R-squared	0.039	0.035	0.024	0.017	0.004	0.048	0.011

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01

Table 54: Regressions COUNT_RATIO_LARGE with industries

	1	2	3	4	5	6	7
HOLDER67	-1.188***						
	(-16.27)						
IND2HOLDER67	1.289***						
	(17.47)						
IND3HOLDER67	1.631***						
	(21.86)						
IND4HOLDER67	1.598***						
	(20.43)						
HOLDER100		-1.199***					
		(-15.96)					
IND2HOLDER100		1.296***					
		(16.70)					
IND3HOLDER100		1.634***					
		(20.90)					
IND4HOLDER100		1.612***					
		(19.64)					
NETBUYER			-1.007***				
			(-12.52)				
IND2NETBUYER			1.160***				
			(13.70)				
IND3NETBUYER			1.504***				
			(17.46)				
IND4NETBUYER			1.437***				
			(16.14)				
OC_YEARLY4				-0.0928***			
				(-15.90)			
IND2OC_YEARLY4				0.112***			
				(10.90)			
IND3OC_YEARLY4				0.141***			
				(12.33)			
IND4OC_YEARLY4				0.137***			
				(9.79)			
OC_YEARLY5					-0.0919***		
					(-5.41)		
IND2OC_YEARLY5					0.135***		
					(3.99)		
IND3OC_YEARLY5					0.114***		
					(3.40)		
IND4OC_YEARLY5					0.153***		
					(3.75)		
OC_CEOTENURE4						-0.0892***	
						(-18.88)	
IND2OC_CEOTENURE4						0.0978***	
						(14.98)	
IND3OC_CEOTENURE4						0.137***	
						(17.86)	
IND4OC_CEOTENURE4						0.137***	
						(15.51)	
OC_CEOTENURE5							-0.0983***
							(-9.99)
IND2OC_CEOTENURE5							0.120***
							(6.88)
IND3OC_CEOTENURE5							0.141***
							(7.12)
IND4OC_CEOTENURE5							0.154***
							(7.35)
Market-to-book ratio	-0.000000321*	-0.000000322*	-0.000000213	-1.26e-08***	-1.27e-08***	-1.23e-08***	-1.28e-08***
	(-1.76)	(-1.76)	(-1.12)	(-5.54)	(-5.68)	(-5.22)	(-5.70)
Leverage	0.0000999	0.0000856	0.000260	0.0000173	0.00000719	0.0000203	0.0000200
	(0.16)	(0.13)	(0.40)	(0.19)	(0.08)	(0.24)	(0.24)
Cash Reserves	0.00000609	0.00000645	0.0000143	-0.000000275	-0.000000479	-0.000000128	-0.000000632
	(0.20)	(0.21)	(0.47)	(-0.09)	(-0.16)	(-0.04)	(-0.21)
R&D Expense	-0.000624**	-0.000611**	-0.000533**	-0.0000588***	-0.0000571***	-0.0000606***	-0.0000580***
	(-2.51)	(-2.47)	(-2.18)	(-3.27)	(-3.15)	(-3.39)	(-3.21)
Present Age	0.00193	0.00177	0.00124	-0.000860***	-0.000875***	-0.000860***	-0.000876***
	(1.14)	(1.04)	(0.72)	(-4.08)	(-4.09)	(-4.17)	(-4.10)
Pseudo R-squared	0.029	0.025	0.018	0.006	0.002	0.016	0.004

T-statistics in parentheses
* p<.10, ** p<.05, *** p<.01