The Effect of Overconfidence on Stock Market Bubbles, Velocity and Volatility

Luuk van Gasteren

4231287

Financial Economics

Radboud University Nijmegen

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Supervisor: O. Dijk

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Abstract

This study examines the relationship between overconfidence and stock market bubbles, velocity and volatility. Motivated by theoretical evidence, the DHS model and the DSSW model, three hypotheses indicating a positive relationship with overconfidence are formed. Using both Holder 67 and Net Buyer proxies to measure overconfidence, weak evidence is found for the relationship between overconfidence and stock market bubbles proxied by the Bubble Component, no evidence is found for the relationship between overconfidence and velocity and weak evidence is found for the relationship between overconfidence and volatility from the various VAR and VEC models.

Key words: overconfidence, stock market bubble, velocity, volatility

1. Introduction

Behavioral finance is an economic field that attempts to increase the understanding of emotions and mental malfunctioning of investors in their decision making and attracts considerable interest of researchers. Behavioral finance examines financial markets to provide an explanation for stock market anomalies, such as the January Effect, the Equity Premium Puzzle and stock market bubbles. Individuals show many biases, among which are cognitive dissonance, loss aversion, regret aversion and overconfidence, that can lead to these anomalies (Ricciardi and Simon, 2000). Overconfidence is found to be the most widespread, powerful and consistent psychological bias (Johnson and Fowler, 2011). From this can be concluded that overconfidence is among the most important errors in the individual decision making processes. Therefore, it is no surprise that it is found that overconfidence of individuals can be blamed as an important cause of several disasters such as the war in Iraq, the Vietnam war, the First World War, climate change, Hurricane Katrina and even the 2008 Financial Crisis (Johnson and Fowler, 2011). The latter disaster is an interesting topic for a behavioral finance research. This research can examine whether individual overconfidence can be blamed as the cause of the 2008 Financial Crisis or more interestingly as the cause of crises or stock market bubbles in general. This study is very relevant as collapsing stock market bubbles cause enormous distress costs, increased unemployment, lower tax revenues, higher debt, more poverty and inequality among many more (Claessens, Kose and Terrones, 2010).

The experimental paper of Michailova, Julija, Schmidt and Ulrich (2011) is one of the few papers that research the effect of this overconfidence on bubbles. In their research, they simulate a classical Smith, Suchanek and Williams (1988) experimental design to see whether overconfident individuals' behavior causes bubbles. They find that this is the case. This thesis will examine the relationship between individuals' overconfidence and bubbles too. An addition to prior studies is that an empirical approach is chosen while this was previously only done using an experimental approach. Also, the focus is here on both CEOs and individual investors and the stock market as a whole instead of just private investors and one stock. In addition to this, the effect of overconfidence on velocity and volatility is researched. Therefore, the main question this thesis wants to answer is:

"What is the relationship between overconfidence and stock market bubbles, velocity and volatility?"

Existing literature has found that both overconfident CEOs and individual investors trade more (Malmendier and Tate, 2005; Ben-David, Harvey and Graham, 2007; Heaton, 2002; Odean, 1999a; Odean, 1998b; Grinblatt and Keloharju, 2009; Barber and Odean, 2001a), take excessive risks (Gervais, Heaton and Odean, 2011; Chuang and Lee, 2006), take excessive leverage (Barros and Da Silveira, 2007; Hackbarth, 2008; Sullivan, 2009) herd more (Hirshleifer, Subrahmanyam and Titman, 1994), tend to pay too much for their respective investments (Biais, Hilton, Mazurier and Pouget, 2005; Roll, 1986) and suffer more from the self-attribution bias (Barber and Odean, 2001a; Daniel, Hirshleifer and Subrahmanyam, 1998) compared to rational CEOs and individual investors.

Due to this overconfidence, stock market bubble could occur. This is the case because from prior studies it can be concluded that increased trading volume (Scheinkman and Xiong 2003; Minsky, 1966), excessive risk taking behavior (Brunnermeier and Oehmke, 2012), increased leverage taking (Minsky, 1966), overpaying (Barber; Odean, 2001b), feedback trading (Scherbina and Schlusche, 2014; De Long et al, 1990) and the self-attribution bias (Scherbina and Schlusche, 2014; Daniel, Hirshleifer and Subrahmanyam, 1998) are all results of overconfident behavior which also can be causes of stock market bubbles. In conclusion, via these mechanisms, overconfidence causes stock market bubbles. Next to this, other implications of overconfidence are increased velocity and volatility.

To test these theoretical hypotheses, the overconfidence proxies Holder 67 and Net Buyer by Malmendier and Tate (2005) are constructed for the CEOs of most S&P 500 companies during the period 1992-2014. Next to this, a Bubble Component, to proxy stock market bubbles for the S&P 500 index, is constructed according to the Froot and Obstfeld model. The Velocity proxy is based on the measure used by Michailova et al (2011) during 1992-2014 while the Volatility proxy is the annualized daily standard deviation of the S&P 500 index return in each year during the same period. This thesis' empirical findings of the VAR and VEC models do only weakly confirm the hypotheses about stock market bubbles and volatility but do not confirm the hypothesis about velocity with overconfidence.

The definitions, causes and results of overconfidence are discussed in the next chapter. In the following chapter, the definitions and causes of stock market bubbles are

elaborated. In chapter four, the three hypotheses are formed. In the two chapters thereafter the methodology and results are explained. The thesis is finalized by a brief conclusion and discussion.

2. Overconfidence

2.1 Trading Volume, Risk and Leverage Taking, Overpaying, DHS and DSSW

Prior studies find that overconfidence leads to an increased trading volume, increased risk taking, increased leverage taking and overpaying by individuals and CEOs. Also, stock market bubbles are associated with these effects. Thus, this thesis hypothesizes that there is a positive relationship between overconfidence and stock market bubbles. Also, the DHS and DSSW model show this positive relationship between overconfidence and stock market bubbles. Other implications of overconfidence are increased velocity and volatility.

This thesis wants to examine whether these relationships hold. To be able to do this, first an idea about what overconfidence entails and how it could affect behavior should be obtained. Then, the implications for the trading volume, risk taking, leverage taking, overpaying, velocity and volatility of this overconfident behavior in the market are explained. Also, there is need to define stock market bubbles and see what causes these stock market bubbles. Finally, from this theoretical framework the above described relationships are found and tested thereafter.

2.2 Definition of Overconfidence

According to Hackbarth (2008), overconfidence is that investors underestimate the variance of their investments and is often referred to as a miscalibration of beliefs. In addition to this definition, overconfidence is also defined in three other ways. The first additional definition is that overconfidence means that an individual overestimates his or her own ability, performance, level of control and/or probability of success (Moore and Healy, 2008). Another definition of overconfidence is that individuals believe that they perform better than others, the so-called better-than-average effect (Moore and Healy, 2008). An example of this is that 93% of the American drivers and 69% of the Swedish drivers see themselves as more skillful in driving than the median in their country, i.e. respectively 93% and 69% of the drivers paradoxically believe that they belong to the best half of the drivers in their country (Svenson, 1981). The last definition of overconfidence is that individuals have excessive certainty in the accuracy of their beliefs (Moore and Healy, 2008). In other words, an individual's probability distribution or confidence interval of future events is too narrow

(Ben-David, Harvey and Graham, 2007). Therefore, from now on referring to overconfidence relates to one of these four definitions[1].

2.3 Causes of Overconfidence

In the last paragraph, the definition of overconfidence is explained. In this paragraph, various causes of this overconfident behavior will be outlined.

2.3.1 Culture

Stankov and Lee (2014) found that individuals in Anglo-Saxon countries are significantly less confident compared to Asian individuals. Yates et al (1995) has found that individuals in the United States and Japan show significantly lower degrees of overconfidence compared to other Asian individuals. Next to these studies, a lot more research is done on the effect of cultural differences on overconfidence and mainly the findings are the same: Asians (excluding Japanese) exhibit greater overconfidence than Western individuals (Yates, Lee and Bush, 1997; Yates, Lee and Shinotsuka, 1996; Stankov and Lee, 2014). Therefore, cultural difference, which is assumed to be a stable factor over time, can lead to significant differences in overconfident behavior by individuals from different populations.

2.3.2 Individual Constant Factors

Research of Alicke et al (1995) concludes that overconfident behavior is related to selfishness, dominance and/or ambitiousness resulting in maintaining unrealistically positive images of themselves relative to others. Overconfident behavior is also related to narcissism (Campbell and Goodie, 2004). Likewise, researchers have discovered a positive association between individuals having an authoritarian personality and overconfidence (Schaefer et al, 2004). Further, extraverted individuals are often the same individuals as overconfident individuals and there is a positive significant relation between conscientiousness and overconfidence (Schaefer et al, 2004). Next to this, less concessionary individuals are often overconfident (Neal and Bazerman, 1985). Also, Barber and Odean (2001a) find that men are generally more overconfident compared to women.

[1] Overconfidence and optimism in financial studies are often used interchangeably, although they are not entirely the same traits. However, individuals rarely display overconfidence without showing optimistic behavior (Gervais, Heaton and Odean, 2003). Therefore, in this thesis optimism and overconfidence are jointly referred to as overconfidence and measured by a single proxy instead of separating them.

From this it can be concluded that individuals' gender and traits, such as selfishness, dominance, ambitiousness, narcissism, authoritarian, extraversion and/or conscientiousness, can explain the overconfidence by individuals and are stable over time but differs for each individual.[23]

2.3.3 Social Time Varying Factors

Individuals with a good mood, for example caused by sunshine, sports results and/or temperature, tend to be more confident about their investments (Hirshleifer and Shumway, 2003). Hirshleifer and Shumway (2003) find that sunshine positively affects this mood. Also, Edmans, Garcia and Norli (2007) use sport sentiment as an exogenous shock to mood. They find that stock market returns are significantly lower after a loss by the national soccer, basketball, cricket and rugby team at an major international tournament. Cao and Wei (2005) uncover a negative correlation between temperature and mood resulting in lower stock market returns. From these examples can be concluded that there are many forms of investor sentiment that cause a whole population of investors to behave increasingly or decreasingly overconfident over time.

2.3.4 Individual Time Varying Factors

An important individual time varying factor causing overconfidence is also an individual's mood. Joy and thus a good mood leads to overconfidence. Recent research found that an unexpected gift, resulting in a good mood, and no awareness of this good mood results in individuals taking overconfident decisions (Koellinger and Treffers, 2015; Hirshleifer and Shumway, 2003). Also, research by Wolfe and Grosch (1990) has found that individuals with a positive affect, for example happy or enthusiastic individuals, are associated with overconfidence. Contrary to this, individuals that suffer from a depression are linked to lower levels of overconfidence, sometimes even underconfidence (Stone et al, 2001).

In conclusion, during certain periods of time individuals feel more joyful, happy and/or enthusiastic due to some individual specific factor, such as a gift, causing a good

[2] Research using fMRI has found that extravert individuals are more likely to be overconfident and have higher activation of the nucleus accumbens in the brain (Peterson, 2005). Moreover, overconfident individuals have more activation in the medial prefrontal cortex (Peterson, 2005). Thus, individual brain development matters for an individual's overconfidence. However, research on this subject is only in its infancy.

[3] Dalton and Ghosal (2014) find that men that were exposed to higher levels of testosterone in utero are associated with less overconfidence (Dalton and Ghosal, 2014). From this it can be concluded that hormones also play a role in causing overconfidence. However, research on this subject is also still in its infancy.

mood while they might sometimes feel depressed leading to a bad mood. This mood caused by individual specific factors has its effect on an individual's overconfidence and varies from time to time.

2.4 Individual and Population Overconfidence

In the previous paragraph, it is explained that overconfidence is caused by culture, individual constant factors, social time varying factors and individual time varying factors. The individual time varying factors and the individual constant factors are both factors that differ for each individual. Therefore, this part is called the individual component. Social time varying factors and culture are causes for overconfidence that are common for the entire population and thus are called the population component. Then, overconfidence can be modeled as

$$OC_{it} = CC + IC_i + STV_t + ITV_{it} \qquad (1)$$

where OC_{it} is the time varying overconfidence of each individual and $STV_t + CC$ the population component consisting of culture CC and the social time varying factors STV_t while $IC_i + ITV_{it}$ is the individual component including the individual constant factors IC and the individual time varying factors ITV_{it}. This population component implicates that all types of individuals have at least some of their overconfident behavior in common. From this it can be concluded that the measures for CEO overconfidence, which will be elaborated in chapter 5, are good proxies for investor overconfidence in general.

2.5 Implications of Overconfident Behavior

The last paragraph showed that there are individual differences in overconfident behavior. In the financial literature on overconfident behavior, this distinction is mostly based on individual investors versus CEOs. Therefore, in this chapter the implications of overconfident behavior are discussed for both individual investors and CEOs. In the footnotes some other implications of overconfident behavior are mentioned.[4][5][6][7]

[4] Overconfident CEOs are less likely to pay out dividends (Ben-David, Harvey and Graham, 2007). Deshmukh, Goel and Howe (2013) add to this that this relationship is stronger in firms with low growth opportunities, lower cash flows and greater information asymmetry.

2.5.1 Overinvestment

Malmendier and Tate (2005a) state that overconfident CEOs are prone to overinvesting when they have abundant internal fund and thus are not disciplined by the capital market. Ben-David, Harvey and Graham (2007), Gervais, Heaton and Odean (2011) and Heaton (2002) further elaborate on the overinvestment by overconfident CEO. The first authors show that overconfident CEOs observe investment projects as safer than they really are and thus evaluate them with a lower discount rate. As a result of this, CEOs will perceive a greater number of investment projects having a positive net present value leading to overconfident CEOs investing more than rational CEOs (Ben-David, Harvey and Graham, 2007). The latter authors state that overconfident CEOs often are incentivized by highly convex contracts. This inefficient contracting coupled with overconfidence results in overinvesting by the CEO (Gervais, Heaton and Odean, 2011). Heaton (2002) finds that overconfident CEOs also invest in negative net present value projects due to their too optimistic view of the investment opportunities. This also results in overinvestment.

Next to CEO overconfidence leading to overinvestment, this effect holds for individual investors too. When investors are overconfident, trading volume increases (Odean, 1999a; Odean, 1998b; Grinblatt and Keloharju, 2009). Barber and Odean (2001a) find that investors trade more when they are overconfident and add to this that men trade 45% more than women in such a situation.

2.5.2 Excessive Risk Taking

CEOs mostly are incentivized by convex compensation in their contracts. The overconfidence of CEOs in combination with these convex contracts triggers the CEO to take excessive risk (Gervais, Heaton and Odean, 2011). Thus, overconfident CEOs take excessive risks.

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[5] Overconfident investors underreact to information of rational traders leading to positive serially correlated returns of financial securities. Moreover, overconfident investors overreact to salient, anecdotal and less relevant information while they overreact to abstract, statistical and highly relevant information (Odean, 1998b).

[6] Overconfident investors also overestimate the precision of their private signals to (Odean, 1998b). Consequently, investors tend to overreact to their private signals while they underreact to public signals (Chuang and Lee, 2006).

[7] Overconfident CEOs often overestimate their returns on their investment projects (Malmendier and Tate, 2005a).

Additionally, risk taking is found to be more present in more overconfident fund managers relative to less overconfident fund managers (Menkhoff, Schmidt and Brozynski, 2006). Also, overconfident investors underestimate risk and take more risk by trading more in riskier assets (Chuang and Lee, 2006).

2.5.3 Overpayment and Mispricing

In mergers and tender offers, CEOs often pay too much for their targets.[8][9] The hubris hypothesis states that overconfident CEOs pay above the fundamental value of the firm in a merger and tender offer (Roll, 1986).

Another consequence of overconfidence is a worsening of the security's price quality. This means that prices do not properly reflect its fundamental value (Odean, 1998b). Also, overconfident traders often underestimate the conditional uncertainty about the value of a security and are more likely to be vulnerable to the winner's curse (Biais, Hilton, Mazurier and Pouget, 2005). The winner's curse is that the winner of a bid is the investor that (over)pays the most. Therefore, overconfident investors misprice and overpay more.

2.5.4 Excessive Leverage Taking

CEO overconfidence also has implications for the capital structure of the firm. First of all, overconfident CEOs perceive that the market values their firm too low. For this reason, the overconfident CEO is not willing to issue additional equity (Malmendier and Tate, 2005a). Instead of financing by equity, more debt is issued to finance (Barros and Da Silveira, 2007; Hackbarth, 2008). Because of the undervaluation of the firm by the market, as perceived by the overconfident CEO (Heaton, 2002), these borrowing are used to repurchase the firm's shares by the firm (Gervais, Heaton and Odean, 2011). In conclusion, the capital structure gets more debt-intensive as a result of CEO overconfidence.

As far as known now, this is not researched for individual investors. However, the recent 2008 Financial Crisis showed that overconfident individuals are a major contributor to the increase of 45 billion in credit default swaps (CDS) and a tripling of the residential

[8] The number of merger offers also significantly increases when CEOs become more overconfident (Ferris et al, 2013).

[9] Additionally, Camerer and Lovallo (1999) find that CEO overconfidence leads to excess entry by firms in industries or businesses. Also, it is found that the number of startups increases when the CEOs' overconfidence increases (Koelinger et al, 2007).

mortgages (Sullivan, 2009). This means that it is reasonable to assume that overconfidence plays a role in the excessive leverage taking of individual investors.

2.5.5 Velocity

Ben-David, Harvey and Graham (2007), Gervais, Heaton and Odean (2011), Heaton (2002), Odean (1999a), Odean,(1998b) and Grinblatt and Keloharju (2009) find that overconfidence leads to increased trading. This implicates that as a result of overconfidence, the velocity of trading in the market should increase when the amount of stocks outstanding increases less, decreases or does not change at all. This can be seen in equation in section 5.3.3.

Michailova et al (2011) experimentally find that overconfidence leads to a significant increase in velocity of stocks. As far as currently known, the effect of overconfidence on velocity has not been researched empirically before.[10]

2.5.6 Volatility

Hirshleifer, Low and Teoh (2012) show that firms with overconfident CEOs have excessive return volatility. Also, the excessive trading by overconfident investors leads to excessive volatility of returns in financial markets (Chuang and Lee, 2006). Odean (1998b), Gervais and Odean (2001) and Benos (1998) confirm this by reporting that overconfidence by investors results in an increased volatility of returns.

[10] Scheinkman and Xiong (2003) create a model in which they model the relation between the frequency of trades and asset price bubbles. They find that increasing the frequency of trades, and thus higher velocity when the condition of section 2.5.5 holds, towards infinity compounds to a significant bubble. Therefore, increased overconfidence causing more trading and higher velocity of stocks could also indicate a stock market bubble.

3. Stock Market Bubbles

To examine the relation between overconfidence and stock market bubbles, stock market bubbles should be defined. Also, to be able to research this relation, the causes of stock market bubbles are discussed. This is done in this chapter.

3.1 Definitions of Stock Market Bubbles

Kindleberger (1978) defines a bubble as an increase in price over a certain period of time that then implodes. More precisely, the straightforward definition in financial economics is that a bubble appears when the market value of the asset differs from its fundamental value (Herdegen and Schweizer, 2015). In line with this, a bubble is also seen as a systematic deviation from the asset's fundamental value (Hymøller and Nielsen, 2015). Even more specifically, a positive bubble can be defined as the situation in which the asset's trading price P_t exceeds the discounted value of expected future cash flows CF_τ. Mathematically, this means that:

$$P_t > E_t\left[\sum_{\tau=t+1}^{\infty} \frac{CF_\tau}{(1+r)^{\tau-t}}\right] \qquad (2)$$

where r is the discount rate used and τ is the iterator for time t in the sum function. For investors, it can be difficult to determine the amount of risk compensation that is required or there may be need to use a more conservative discount rate. In these situations, a positive bubble is defined in the same way but then by using the risk-free rate r_f (Scherbina and Schlusche, 2014):

$$P_t > E_t\left[\sum_{\tau=t+1}^{\infty} \frac{CF_\tau}{(1+r_f)^{\tau-t}}\right] \qquad (3)$$

In the stock market, dividends are often used to calculate the fundamental value of an asset since these represent the ultimate cash flow investors receive. Therefore, in inequality (2) and (3) the cash flows CF_τ are replaced by dividends D_τ. Then, the inequality (2) in an efficient market with rational agents implies that:

$$P_t = E_t\left[\sum_{\tau=t+1}^{\infty} \frac{D_\tau}{(1+r)^{\tau-t}}\right] \qquad (4)$$

This equation (4) follows from the definition of returns of a stock or index:

$$R_t = \frac{E_t(P_\tau) - P_t + E_t(D_\tau)}{P_t} \qquad (5)$$

in which P_t and P_{t+1} are the stock or index prices at respectively time t and $t+1$ and D_{t+1} the dividend at time $t+1$. This one period return equation can be rearranged to:

$$P_t = E_t\left[\frac{D_\tau}{(1+r)^{\tau-t}} + \frac{P_\tau}{(1+r)^{\tau-t}}\right] \qquad (6)$$

This function (6) can be aggregated to a multi period model and is equated as follows:

$$P_t = E_t\left[\sum_{\tau=t+1}^{\infty}\left(\frac{D_\tau}{(1+r)^{\tau-t}}\right) + \frac{P_\tau}{(1+r)^{\tau-t}}\right] \qquad (7)$$

Equation (4) then follows from equation (7) and the transversality or non-bubble condition:

$$\lim_{\tau\to\infty}\frac{E_t(P_\tau)}{(1+r)^{\tau-t}} = 0 \qquad (8)$$

where the denominator converges to infinity as the time τ goes to infinity leading to no residual value of the stock or index at period $\tau = \infty$. Thus, the price of the stock or index at time t is equal to:

$$P_t = E_t\left[\sum_{\tau=t+1}^{\infty}\frac{D_\tau}{(1+r)^{\tau-t}}\right] \qquad (9)$$

and thus in case of a positive bubble, equation (9) holds:

$$P_t > E_t\left[\sum_{\tau=t+1}^{\infty}\frac{D_\tau}{(1+r)^{\tau-t}}\right] \qquad (10)$$

This equation (10) basically states that the stock or index price should equal all future expected dividends discounted to the present (Hymøller and Nielsen, 2015). Recall that Hymøller and Nielsen (2015) define a bubble as a systematic deviation from the asset's fundamental value. Thus, next to the mostly observed positive bubbles, a negative bubble is also possible. In this situation, the price of the stock or index is lower than should be based on its fundamental value:

$$P_t < E_t\left[\sum_{\tau=t+1}^{\infty}\frac{D_\tau}{(1+r)^{\tau-t}}\right] \qquad (11)$$

From both equations (10) and (11), this implies that a bubble can be defined as the situation in which the price of an asset systematically differs from its fundamental value:

$$P_t \neq E_t\left[\sum_{\tau=t+1}^{\infty}\frac{D_\tau}{(1+r)^{\tau-t}}\right] \qquad (12)$$

In conclusion, a stock market bubble is defined as the situation in which the price of a stock or index systematically differs from its dividend-based fundamental value and consequently violation of the transversality or non-bubble condition.

3.2 Creation and Causes of Stock Market Bubbles

In the previous paragraph, it is stated that most often a bubble occurs when the price of the stock or index exceeds its fundamental value. In the history of economics, this has been shown several times. A few of the many historical examples of this are the Dutch Tulip Mania (1634-1637), the Mississippi Bubble (1719-1720), the South Sea Bubble (1720), the bubble during 1920's ended by the well-known Black Monday, the recent IT-bubble (1997-2000) and the latest Subprime Crisis in 2008. This paragraph discusses how these kinds of stock market bubbles are created and what the specific causes of these bubbles are.

3.2.1 Minsky Credit Cycles, Overinvestment and Excessive Leverage Taking

Minsky (1966) states that the creation of a bubble follows a specific sequence. First, a certain event causes investor's portfolio preferences to change. Such an event can be seen as an exogenous shock changing the productivity or economic fundamentals, which leads to an increase in expectations of future profitability (Minsky, 1966).[11] This increase makes it attractive to invest thus there is more willingness to borrow money. Banks could thus profit from this by issuing more credit to these investors (Whalen, 2007). This increasing amount of available credit then leads to more investments and thus to more leveraged investors and demand for investments, such as stocks. Consequently, the prices of these investments increase. Therefore, the earlier expected increase in profits is now realized. Following this, the profitability expectation again increases and the positive feedback loop starts over again. This loop feeds optimism and euphoria among investors. This optimism and euphoria leads to another increase in demand for investments because every investor wants to take advantage of the rising investment profits. Also, slower adopting investors see the early investors profit and therefore want to take advantage of the rise of investment profits too. Due to this increasing demand for loans and investments now a bubble is created, where the price of the investment is higher than the fundamental value of the investment (Brunnermeier and Oehmke, 2012). This shows that overinvesting and excessive leverage taking leads to bubbles.

[11] Such an event could also be an exogenous shock in overconfidence itself.

3.2.2 Overpayment and Mispricing

Barber and Odean (2001b) find that bubbles are caused by the winner's curse. This means that the winner of a bid is the bidder which most badly estimates the value of the asset exceeding the true asset value. Therefore, to buy a certain asset, the winning investor has to overpay the most. This overpaying leads to prices which are systematically higher than the fundamental value of the assets and consequently a bubble (Barber and Odean, 2001b). This is also observed in the stock market and thus the winner's curse leading to overpaying by investors causes stock market bubbles.

3.2.3 Excessive Risk Taking

According to Brunnermeier and Oehmke (2012), excessive risk taking also causes bubbles. This is once again illustrated by the recent Subprime Crisis in 2008. In the run up to this crisis, mortgage borrowers with a weak financial position could easily get a mortgage by a so-called subprime mortgage. This means that both the borrower and the bank took high risks because the probability of not repaying was relatively high. Also, these mortgages were based upon the assumption that housing prices would continue to increase as they otherwise were not able to repay these mortgages. These subprime mortgages, in addition to the prime mortgages, led to an increase in demand for houses and therefore a bubble in the housing prices. Consequently, the willingness to take more risk by the subprime borrowers and the banks and the resulting higher demand for houses led to a bubble in the housing market. This illustrates that excessive risk taking could lead to bubbles. Roubini (2006) confirms this statement by arguing that in any asset bubble investors take excessive risk. Carmassi, Gros and Micossi (2009) state that excessive risk taking is an important ingredient in every bubble as there is a constant game of circumventing regulation by innovations and regulators preventing this. When this risk taking accelerates, then stock market bubbles grow rapidly (Carmassi, Gros and Micossi, 2009).

4. Overconfidence and Stock Market Bubbles, Velocity and Volatility

The last chapter of the theoretical framework links the distinctively outlined concepts overconfidence and stock market bubbles. After outlining 3 mechanisms showing the relationship between overconfidence and stock market bubbles, a hypothesis is formed. Finally, also the hypotheses about the relationship between overconfidence and respectively velocity and volatility can be formed.

4.1 Overconfidence and Self-Attribution Bias Causing Stock Market Bubbles and Increased Volatility

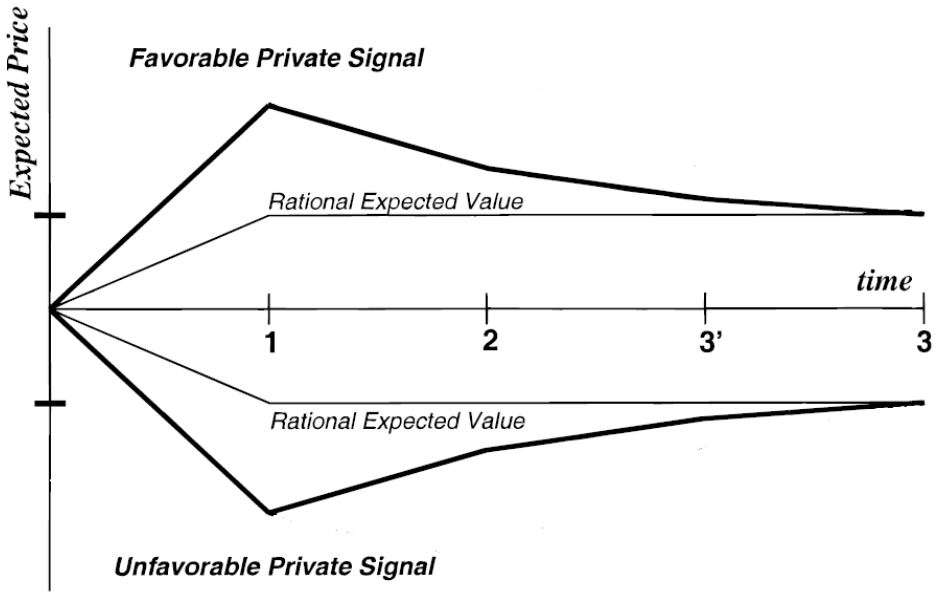
The Daniel, Hirshleifer and Subrahmanyam (DHS) model shows the relationship of overconfidence with stock market bubbles and volatility and is explained in the next three sections. In appendix C, the derivation of this model is further elaborated.

4.1.1 Overconfidence and Stock Market Bubbles

During period 1, an informed investor *I* receives a private signal about the value of a stock. Due to the fact that the investor is overconfident, the informed investor *I* overreacts to this signal. This too strong reaction to the favorable (unfavorable) signal leads to a too strong increase (decrease) of the price of the share as the informed investor *I* acts on this private signal in an overconfident way.

At date 2, the noisy public signal arrives. Then, the initial overreaction is partially corrected on average. This correction goes on after date 2 until it reaches the rational expected value. From this, it can be concluded that in the short run there is bubble creation as a consequence of overconfidence because the price moves above (below) the rational expected value of the share in case of a favorable (unfavorable) private signal but in the long run this bubble bursts and the price move is reversed. This can also be seen in figure 1 (Daniel et al, 1998).

Figure 1: DHS model effect of overconfidence on share price

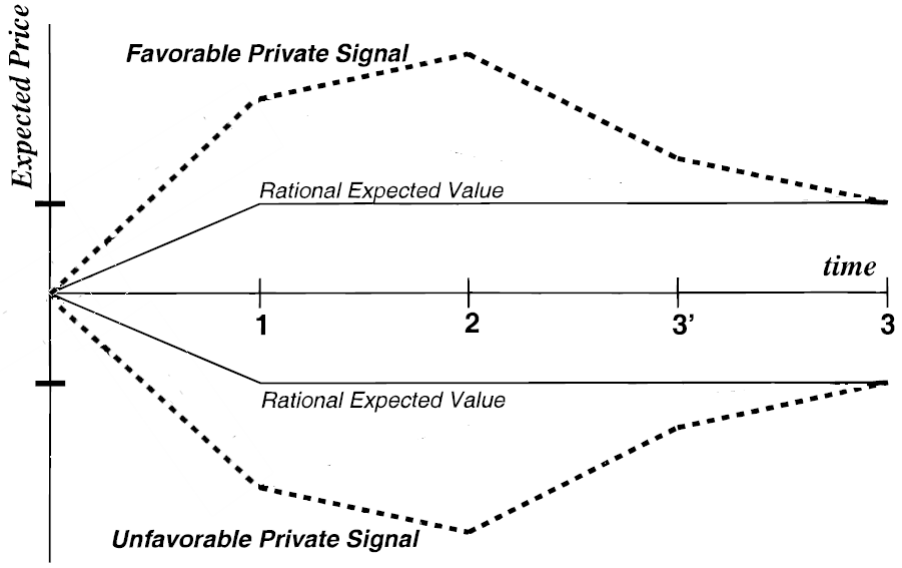


4.1.2 The Self-Attribution Bias

The informed investor *I* receives a private signal about the value of a stock in period 1. The overconfident informed investor *I* overreacts to this signal. The consequence of this is a too strong reaction to the favorable (unfavorable) signal leading to a too strong increase (decrease) of the price of the share, as the informed investor *I* acts overconfident when he or she deals with this private signal. Until here, this is just the same as in 4.1.1.

An additional result of overconfidence is the so-called self-attribution bias. This self-attribution bias increases the confidence about the private signal when the public signal confirms the private signal at date 2. When the public signal differs from the private signal, the confidence does not change. Therefore, in case of a favorable (unfavorable) signal the stock price increases (decreases) on top of the initial price increase (decrease) at date 2, as was outlined in section 4.1.1. It is further shown by Daniel et al (1998) that as more public signals are revealed at date '3, the share price converges towards the rational expected value (Daniel et al, 1998). In conclusion, a stock market bubble is caused by overconfidence itself and the self-attribution bias resulting from overconfidence. This is summarized in figure 2 (Daniel et al, 1998)

Figure 2: DHS model effect of overconfidence and self-attribution bias on share price



4.1.3 Overconfidence and Volatility

The DHS model finds that in period 1, overconfidence results in wider swings away from the rational expected value of the stock and thus an increased volatility around the private signal. Next to this, higher overconfidence leads to a relative underweighting of the public signal causing a decrease in volatility. However, because the wide swings in period 1 need to be corrected and thus an increased need for corrective price movements at dates 2 and 3, higher overconfidence can both increase or decrease the volatility of the public signals. Under the condition that there is no distinction made between private and public signals, then volatility can be calculated as the volatility's equal average of all periods. Now, an increase in the unconditional volatility is found. Therefore, the DHS model confirms the positive relation between overconfidence and volatility explained in section 2.5.6.

4.2 Would Rational Arbitrageurs Undo the Effect of Overconfidence on Stock Market Bubbles?

Hirshleifer, Subrahmanyam and Titman (1994) find that overconfident individuals have a stronger tendency to herd. Overconfidence thus can promote herding behavior by investors. De Long et al (1990) model the effect of this herding behavior on stock markets in their famous De Long, Shleifer, Summers and Waldmann (DSSW) model. Next to this, they explain

in their model that rational arbitrageurs cannot undo the bubble. The derivation of this model is explained in appendix D.

4.2.1 The DSSW Model Implications

According to Friedman (1953), rational speculators should stabilize stock prices in the market. Rational speculators could do this by buying underpriced stocks and selling overpriced stocks. Contrary, speculators destabilize stock prices when they buy high priced stocks and sell low priced stocks.

When goods news arrives, rational speculators logically will buy stocks. This actually stimulates feedback traders tomorrow to buy additional stocks driving up the prices even more and so prices move above the fundamental value. The key point is here that, although part of the price increase is fully rational, a bubble can emerge due to the feedback traders' reaction to these rational trades. Trading by rational speculators destabilizes stock price because it triggers positive feedback trading by feedback traders. In conclusion, the DSSW model shows positive correlation of stock returns in the short term resulting in a bubble when positive feedback traders react on the previous price increase and negative correlation of stock return in the long term as stock prices convert to the fundamental value (De Long et al, 1990). As was stated before, Hirshleifer, Subrahmanyam and Titman (1994) found that overconfident investors have a strong tendency to behave like these feedback traders that can cause a stock market bubble as explained by the DSSW model. This effect of investors' overconfidence cannot be undone by rational speculators.

4.3 Linking the Implications of Overconfidence and Causes of Stock Market Bubbles

In paragraph 2.5 and 3.2 respectively the results of overconfident behavior and the causes of stock market bubbles are explained. In this paragraph, these different results and causes are linked to each other to see the relation between overconfidence and stock market bubbles

4.3.1 The Overinvestment Channel

Section 2.5.1 shows that overconfident CEOs overinvest due to lower discount rates and therefore perceiving too high present values of projects (Ben-David, Harvey and Graham, 2007), convex contracts incentivizing to invest (Gervais, Heaton and Odean, 2011) and the tendency to also invest in negative present value projects (Heaton, 2002). Also, individual investors tend to trade more when they are overconfident (Odean, 1999a, Odean, 1998b,

Grinblatt and Keloharju, 2009, Barber and Odean, 2001a). Minsky (1966) finds that increased demand due to euphoria and optimism in the market leads to bubble creation. Thus, an increased trading volume resulting from this higher demand causes a bubble to emerge. This leads to the conclusion that overconfidence can results in more trading, which can lead to stock market bubbles.

4.3.2 The Excessive Leverage Channel

According to overconfident CEOs, the market values their firm too low (Heaton, 2002) and they are thus not willing to issue additional equity (Malmendier and Tate, 2005a). Instead of financing by equity, overconfident CEOs decide to increase the leverage of the firm (Barros and Da Silveira, 2007, Hackbarth, 2008). These borrowings are used to repurchase the firm's shares (Gervais, Heaton and Odean, 2011). Therefore, CEO overconfidence leads to more leverage taking. Also, the recent Subprime Crisis has shown that overconfident individual investors excessively accumulate debt (Sullivan, 2009). This increased leverage taking is the root of a stock market bubble according to Minsky (1966). Consequently, overconfidence can cause stock market bubbles via increased leverage taking.

4.3.3 The Excessive Risk Taking Channel

CEOs are incentivized by convex contracts leading them to take excessive risks. In addition to this, overconfident investors underestimate risk (Gervais, Heaton and Odean, 2011) and take more risk by trading more in riskier assets (Chuang and Lee, 2006). Excessive risk taking is also an important cause of bubble creation (Brunnermeier and Oehmke, 2012). For example, this was an important cause of the Subprime Crisis. As a result of this, it can be concluded that overconfident investors are excessively risk taking causing them to create a stock market bubble.

4.3.4 The Overpaying and Mispricing Channel

Following the well-known research of Roll (1986), overconfident CEOs tend to pay too much for their target in merger and tender offers. Thus, the hubris hypothesis states that overconfident CEOs pay more than they actually should according to the fundamental value, i.e. they overpay. Next to this, overconfident individual investors underestimate the conditional uncertainty about the value of the share and are more vulnerable to the winner’s curse (Biais, Hilton, Mazurier and Pouget, 2005). Therefore, the overconfident investor that wins the bid pays too much for the stock. In conclusion, investor

overconfidence leads to overpaying of stocks and can therefore cause a bubble in the stock market.

4.4 Formation of the Hypotheses

In this chapter, the relation between overconfidence and stock market bubbles is examined. From the DHS model, it is found that overconfidence causes a stock market bubble due to the biased reaction to signals as a result of this overconfidence and the resulting self-attribution bias. Next to this, from connecting chapter 2 and 3, it can be concluded that overconfidence resulting in an increase in trading volume, excessive risk taking behavior, increased leverage taking and overpaying can cause stock market bubbles to emerge. Finally, overconfident investors are likely to trade as feedback traders. This feedback trading leads, according to the DSSW model, to stock prices to diverge from the fundamental value in reaction to either a noisy or a noiseless signal.[12] Therefore, taking this together, investor overconfidence leads to herding behavior which can cause stock market bubbles. The hypothesis that now can be formed is:

<u>Hypothesis 1:</u> *"Investor overconfidence can cause stock market bubbles"*

Section 2.5.5 shows that overconfidence is related to an increase of velocity of the stock market. Therefore, the second hypothesis that can be formed is:

<u>Hypothesis 2:</u> *"Investor overconfidence can cause increased velocity on the stock market"*

Hirshleifer, Low and Teoh (2012) state that firms with overconfident CEOs suffer from excessive volatility. Also, Chuang and Lee (2006), Odean (1998b), Gervais and Odean (2001) and Benos (1998) confirm this relation for overconfident investors. Also, the DHS model finds this relationship between overconfident investors and increased volatility (Daniel et al, 1998). Therefore, the third hypothesis that can be formed is:

<u>Hypothesis 3:</u> *"Investor overconfidence can cause increased volatility of returns"*

These hypotheses are now statistically tested in the following chapters. First, the method to do this is outlined in the next chapter. Moreover, the chapter thereafter shows the results of this method to test the hypothesis.

[12] See appendix D for an explanation of this.

5. Methodology

This chapter outlines the method used to examine the relationship between overconfidence and stock price bubbles, velocity and volatility. First, there will be a short elaboration on the data and sample. After this, the proxies of overconfidence will be discussed followed by the proxies of stock price bubbles. Finally, the regression specification is discussed.

5.1 Data and Sample

In this research, the data is acquired from two different data sources. The first data source is Wharton Research Data Services' (WRDS) Compustat and more specifically Execucomp. From this, the value of the exercisable unexercised options and the number of exercisable unexercised options of CEOs for each company and year can be retrieved. Also, the fiscal year end stock prices are collected from the Fundamentals Annual from the Compustat database. This data is necessary to construct the proxies of overconfidence, which will be outlined later. The second source of data is Datastream. The data that is retrieved from Datastream in this thesis are the index prices, dividend payments on the 31st of December, inflation rates and the daily returns of the index for each year. The time period this thesis will examine is from 1992 until 2014. This time period is chosen this way because only from this period of time, the annual compensation of the CEOs is collected by Execucomp. This data is retrieved once for each of the two overconfidence proxies that will be used. From now on, this thesis will refer to these respective datasets as the Holder 67 dataset and the Net Buyer dataset. To research the effect of overconfidence on bubbles in the stock market, this thesis examines almost all companies that are listed in the S&P500 index. Some companies are excluded from the analysis because, for example Blizzard and Allergian amongst others, did not make the relevant data available via Execucomp. This means that the Holder 67 dataset includes 486 firms, implying an omission percentage of 2.8% while the Net Buyer dataset consists of 487 firms, meaning an omission percentage of 2.6%.

5.2 Proxies of Overconfidence

The following sections in this paragraph describe the way overconfidence is measured. Also, the use of these measures as proxies of investor overconfidence is justified and the logic behind the proxies is outlined.

5.2.1 Different Proxies of Overconfidence

Baker and Wurgler (2011) among many other authors state that obtaining a direct proxy of overconfidence is difficult. This difficulty comes from the fact that biased beliefs are hard to measure directly and precisely (Malmendier and Tate, 2005b). Nevertheless, there are a lot of rough proxies for overconfidence. These proxies can be categorized in a few different groups.

The first group of proxies uses firm characteristics to construct a proxy for overconfidence. An example of this is Doukas and Petmezas (2007) which examine the degree of overconfidence by the number of acquisitions overconfident CEOs do, following the Hubris hypothesis of Roll (1986). Overconfident CEOs engage in multiple acquisitions because they believe this can lead to abnormal returns for the company. Therefore, the firm's acquiring behavior is used as proxy for overconfidence (Doukas and Petmezas, 2007).

A second group of proxies uses questionnaires to survey overconfidence. Ben-David et al (2007) uses surveys containing eight questions regarding the confidence intervals of questions about their own company or the economy in general. Then, a too tight confidence interval implicates overconfidence. Other examples include Oliver (2005) which measures overconfidence using the Consumer Sentiment Index (CSI) and Puri and Robinson (2007) which measure overconfidence by using data from the Survey of Consumer Finances (SCF). The advantage of this method is the fact that the researcher can measure general overconfidence instead of CEO or managerial overconfidence. As this thesis is interested in the first, this could be an interesting way of measuring overconfidence. The drawback of this method is that it is very time consuming and costly to do. Also, these proxies measure the overconfidence of all kinds of individuals and not only of investors. Due to these constraints, this is also not the desirable proxy of overconfidence.

The third group of proxies measuring overconfidence uses the role that an individual occupies within an organization. An example of this is the examination of overconfidence by Barros and Silveira (2007). They use manager's status in the firm as a proxy of overconfidence because entrepreneurs tend to show more overconfidence than the employees of companies.

Finally, probably the most influential proxies of individual overconfidence are constructed first by Malmendier and Tate (2002). In their paper, they construct three different proxies for CEO overconfidence which are all based on the idea that an

overconfident CEO will voluntary expose himself or herself to firm-specific risk.[13] In the opposite situation when the CEO is not overconfident, this exposure along with his or her risk aversion should lead to exercising the stock option as soon as possible and minimizing the stock holdings in their own firm. The overconfidence proxies are called Holder 67, Longholder and Net Buyer. The *Holder 67* stands for holding onto an option even when the option is at least 67% in the money. The *Longholder* stands for holding options all the way to the expiration date. The third and last proxy of overconfidence is *Net Buyer* which includes the tendency to buy additional shares in the CEO's own company (Malmendier and Tate, 2002).

These proxies can be simply calculated using the data sources mentioned before and therefore the costs and time of acquiring the data is relatively low. Another advantage of using Malmendier and Tate's (2002) proxies is that they measure the overconfidence of individuals that are focused on investing in the stock market instead of proxies based on the role of individuals within an organization or using all kind of surveys to proxy overconfidence of individuals which mostly are not investing on the stock market. A further advantage of using the Malmendier and Tate (2002) proxies is that these are behavioral measures as they measure the actual decision making of the CEOs while surveys cannot measure the actual behavior of individuals and CEOs but only how they say they behave. A disadvantage of using the Malmendier and Tate (2002) proxies is that they are based upon options paid out to CEOs to give incentives to increase firm performances while the other proxies, such as the surveys, are unincentivized proxies. This means that the Malmendier and Tate (2002) proxies could endogenously measure these incentive effects while the unincentivized proxies do not do this. However, these proxies of Malmendier and Tate (2002) are frequently used in the past and therefore seem to be very robust as a proxy of overconfidence (Malmendier and Tate, 2002; Yan, 2007; Hirshleifer, Low and Teoh, 2012; Campbell et al, 2010; Galasso and Simcoe, 2011; Bressane and Maia, 2010). Therefore, the latter disadvantage should not be a problem. Another drawback of these proxies is that the Malmendier and Tate (2002) proxies

[13] Malmendier and Tate (2002) state that CEOs are mostly compensated by large quantities of stocks and option grants of their own company. Because of so-called incentive effects, these stocks and options cannot be traded during a certain period, the vesting period. Also, CEOs cannot hedge against the risks of holding these options and stocks by short selling because this is prohibited. CEOs also have large amounts of human capital invested in the firm and therefore possible future bad performances of the company reduce their future employment opportunities. In conclusion, these effects leave CEOs to be exposed to significant amounts of idiosyncratic risk of their firm (Malmendier and Tate, 2002).

measure CEO overconfidence rather than general investor overconfidence which is the point of interest here. This topic is further elaborated in the next paragraph.

5.2.2 Proxies of General Investor Overconfidence

In paragraph 2.4, it is argued that CEO overconfidence measures are good proxies for general investor overconfidence. However, psychological studies have found that there are significant individual differences in the expression of overconfidence (Klayman, Soll and González-Vallejo, 1999). From this, Malmendier and Tate (2005b) conclude that CEOs appear to be particularly prone to show overconfidence. They support this assumption by the findings of Weinstein (1980) and Langer (1975) that individuals are particularly prone to overconfidence when they believe outcomes are under their control and when they are highly committed to the outcomes, which is certainly the case for CEOs. Malmendier and Tate (2005b) thus state that this overconfidence is on average consistently higher for CEOs than for other individuals.

Following this reasoning, supported by Weinstein (1980) and Langer (1975), it is also reasonable to assume that individuals investing in the stock market should also be particularly prone to overconfidence because their individual wealth highly depends upon their investments. Individuals investing in the stock market also believe that outcomes are under their control and are highly committed to the outcomes as the investment is an important part of their individual wealth and consequently are also particularly prone to overconfidence. Therefore, it is reasonable to assume that CEOs share both constant and time varying causes of overconfidence which are the same for investors and CEOs, as also stated in paragraph 2.4.

5.2.3 Constructing Holder 67 and Net Buyer using Hirshleifer et al (2012)

In this paragraph, the different proxies to measure overconfidence are explained. A relevant problem in this context is that Malmendier and Tate (2002) were able to use a private dataset. This dataset relates to option exercising and is very detailed data. However, this research does not have the possibility to construct the exact same measures as this dataset is not publically available. In the first paragraph of this chapter, it was already stated that using data gathered from the Compustat Executive Compensation (Execucomp) database, it actually is possible to construct somewhat adjusted proxies (Hirshleifer, Low and Teoh, 2012). Using the method from Hirshleifer, Low and Teoh (2012), there is now a way to

construct the proxies Holder 67 and Net Buyer. Due to a lack of data on the exercise date of the specific options by CEOs, constructing the Longholder proxy is still not possible and thus is not done in this thesis.

The Holder 67 proxy requires calculating the moneyness of the options. To do this, the option grant specific exercise price is needed. As Execucomp does not provide this data, instead the average exercise price is estimated using the approximation method of Core and Guay (2002). First of all, the value of the exercisable unexercised options θ should be divided by the number of exercisable unexercised options η. This results in an estimate of how far these options are in the money on average and can be seen as average "profits" per option α. After this, the approximation is completed by subtracting this average value per option α from the stock price at the fiscal year end ρ[14] (Core and Guay, 2002). Therefore, the average exercise price per option ε according to Core and Guay's (2002) approximation method equals $\varepsilon = \rho - \alpha$ using $\alpha = \frac{\theta}{\eta}$. With this data[15], the average moneyness of the option β can be calculated by dividing the average value per option by the average exercise price per option. Thus, substituting the formulas of the average value per option and the average exercise price per option in $\beta = \frac{\alpha}{\varepsilon}$ leads to the final formula $\beta = \frac{\alpha}{\rho - \alpha}$ (Campbell et al, 2011). This formula is the adjusted form of the Holder 67 proxy as derived by Malmendier and Tate (2002). Malmendier and Tate (2002) define CEOs as overconfident when they hold options that are more than 67% in the money, meaning the stock price exceeds the exercise price by more than 67%.[16]

Malmendier and Tate (2002) require this to happen at least twice but Hirshleifer, Low and Teoh (2012) find that there is no statistical difference between the two methods and thus for consistency reasons Hirshleifer, Low and Teoh's (2012) requirement is followed.

[14] Stock price at fiscal year-end is PRCCF in Compustat.

[15] Value of exercisable unexercised options is in Compustat (ExecuComp) OPT_UNEX_EXER_EST_VAL and the number of exercisable unexercised options is in Compustat (ExecuComp) OPT_UNEX_EXER_NUM.

[16] This benchmark is derived from Hall and Murphy's (2002) calibrating model, in which they use a dataset about exercise decisions and executive stock holdings. They find that risk averse CEOs often hold undiversified portfolios and should exercise their options early when they maximize expected utility rationally. This specific 67% benchmark is chosen according to Hall and Murphy (2002) corresponding to an individual with a risk aversion of three, a constant relative risk-aversion (CRRA) utility and a percentage of wealth in the company's equity of 66%. Because Hall and Murphy (2002) use a detailed dataset which is not available and therefore doing a similar calibration is not possible, the same benchmark of 67% for the entire sample is assumed (Campbell et al, 2011). Therefore, a CEO holding options that are more than 67% in the money is seen as an overconfident CEO.

Therefore, the ratio of the number of times a CEO is denoted as overconfident relative to the total observations in a given year is used as the Holder 67 proxy in that year, i.e. the fraction of the CEOs that hold options that are more than 67% in the money in a year is the value of Holder 67 in that year.

The second proxy for CEO overconfidence is the Net Buyer measure. This proxy indicates the number of own company stocks the CEO buys and sells and is similar to the Net Buyer measure of Malmendier and Tate (2002). First, for each CEO the percentage increase or decrease in shares owned is calculated. When this percentage is positive, the CEO is denoted as a net buyer. Also, there are no restrictions made on the minimum length of tenure. The ratio of the number of times CEOs are denoted as net buyers to the total observations in that year is used as the Net Buyer proxy in that year, i.e. the fraction of the CEOs that is net buyer in that year.

5.3 Proxies of Stock Market Bubbles

The next three sections explain the two different proxies of stock market bubbles and the data sources used.

5.3.1 Froot and Obstfeld Model

In the model of Froot and Obstfeld (1989) stock market bubbles are seen as intrinsic bubbles depending on dividends only.[17] This model of intrinsic bubbles delivers a suitable proxy for stock market bubbles.

In this model, the price of a share is defined as $P_t = P_t^{PV} + B_t$ in which P_t^{PV} is the fundamental value of the stock determined by dividends and B_t is called the *Bubble Component*. Froot and Obstfeld (1989) further specify these two components of the stock price. In the next section, the Froot and Obstfeld model of stock market bubbles is further elaborated.

5.3.2 Specification of the Froot and Obstfeld Model

The model of Froot and Obstfeld (1989) starts on the assumption that a time series of dividends is linked to the same time series of stock prices, or in this case index prices, when the real rate of return r is constant. In addition to this, P_t is the price of the index and D_t is

[17] Contrary to intrinsic bubbles, rational bubbles are characterized as driven by the rational believe that fundamentals depend on rumors, extraneous events or self-fulfilling expectations instead of only fundamentals itself (Froot and Obstfeld, 1989).

the dividend paid over period t. The price of the index then can be described by the following basic finance equation:

$$P_t = \frac{E_t(D_t + P_{t+1})}{e^{rt}} \qquad (13)$$

where E_t shows the expectations of the dividend and the index price based on information known at the beginning of period t. Next to this, the present value equation of the index:

$$P_t^{PV} = \sum_{t=0}^{\infty} \frac{E_t(D_t)}{e^{rt}} \qquad (14)$$

where the present value of all expected dividends in the future equals the fundamental value of the index. This equation (14) can be derived from (13) using the assumption known as the transversality condition:

$$\lim_{t\to\infty} \frac{E_t(P_t)}{e^{rt}} = 0 \qquad (15)$$

where the denominator converges to infinity as the time t goes to infinity leading to approximately no residual value of the index at period $t = \infty$. When this transversality condition holds equation (13) and (14) should be equal. However, often equation (13) seems to have other solutions than equation (14). Therefore, there is some other component in addition to equation (14) that explains the index price. This component is called the Bubble Component and is denoted as:

$$B_t = \frac{E_t(B_{t+1})}{e^{r}} \qquad (16)$$

Then, the adjusted equation (14) looks like:

$$P_t = P_t^{PV} + B_t \qquad (17)$$

where the transversality condition is violated when $B_t \neq 0$ and therefore the price of the index differs from the fundamental value of the index.

As stated before, intrinsic bubbles depend entirely on dividends. From rewriting equation (17) and using this information, the following equation can be denoted:

$$P_t = P_t^{PV} + B_t(D_t) = kD_t + cD_t^{\lambda} \qquad (18)$$

Therefore, the fundamental value of the index is equal to $P_t^{PV} = kD_t$ where $k = (e^r - e^{\mu + \frac{\sigma^2}{2}})^{-1}$.[18] Similarily, $B_t(D_t) = cD_t^{\lambda}$ where λ is the positive root of the quadratic function:

$$\frac{\lambda^2\sigma^2}{2} + \lambda\mu - r = 0 \qquad (19)$$

and the constant coefficient c. λ then can be calculated using the quadratic formula:

[18] This is a stochastic version of Gordon's (1962) model describing stock prices under certainty.

$$\lambda = \frac{-\mu+\sqrt{\mu^2+2\sigma^2 r}}{\sigma^2} \qquad (20)$$

where μ is the trend growth rate of the dividend, σ^2 is the variance of a random variable ε_{t+1} with mean zero. This ε_{t+1} can be estimated using the equation:

$$d_{t+1} = \mu + d_t + \varepsilon_{t+1} \quad (21)$$

where d_t is the log of the dividend in period t and d_{t+1} for one period later. Then, the average variance can be calculated. To be able to calculate the Bubble Component in the Froot and Obstfeld model, the coefficient c_1 can be determined by using an OLS regression of the function $P_t = c_0 D_t + c_1 D_t^{\lambda} + \varepsilon$ written differently as $\frac{P_t}{D_t} = c_0 + c_1 D_t^{\lambda-1} + \eta$ where the null hypothesis of no stock market bubble is that $c_0 = k$ and $c_1 = 0$. The Bubble Component $B_t(D_t)$ then is calculated by multiplying this coefficient and the dividend by D_t^{λ}. This Bubble Component measure is used as a proxy for stock market bubbles.

5.3.3 Velocity

Similar to Michailova et al (2011), *Velocity* can be calculated by dividing the total number of stocks traded in the company's stock by the total number of stocks outstanding by the company in a given year times the fraction of the number of stocks outstanding for each company in a given year. The velocity of the index thus is defined as:

$$Velocity_t = \sum_{i=0}^{k} \frac{Number\ of\ Stocks\ Traded_{it}}{Total\ Number\ of\ Outstanding\ Stocks_{it}} \cdot \frac{Number\ of\ Stocks\ Outstanding_{it}}{Total\ Number\ of\ Outstanding\ Stocks_t} \qquad (22)$$

where *k* is equal to the number of companies is both data sets, so *k* equals 486 and 487. The data on the number of stocks traded and the number of outstanding stocks are retrieved from Compustat Fundamentals Annual. However, Compustat only reports the common shares outstanding and the common shares traded in each year but it does not report this for all kinds of shares. Therefore, the velocity of the common shares of each company included in the S&P500 index in its respective year is used as a proxy of stock market bubbles in the S&P500 index.

5.3.4 Volatility

To calculate the *Volatility* of the S&P 500 index, first the daily returns of the index are retrieved from Datastream. Now, the volatility of each year can be calculated using the following equation:

$$Volatility_t = \sqrt{\frac{\sum_t^n (R_t - R_{Average})^2}{n-1} \cdot n} \qquad (23)$$

where R is the daily return, $R_{average}$ the average daily return during that year, t the trading day in a given year and n the number of trading days in that year (Daly, 2011). Thus, for each year the daily variance is calculated. After this, the annualized variance of a year is calculated by multiplying by the number of trading days to the daily variance in that year. Finally, the annual variance is square rooted to receive the annual volatility of the S&P 500 index for each year.

5.4 Regression Specification

To examine the effect of overconfidence on stock market bubbles, a regression analysis should be done. The first step towards the correct model to perform a regression analysis is specifying the properties of the data. The data used in this thesis is time series data and therefore analyzed by VAR or VEC models.

5.4.1 Dealing with Time Series Data

A well-known method of dealing with time series data is the so-called Vector Autoregressive (VAR) model or Vector Error Correction (VEC) model. Using a VAR model is only possible when the variables are not cointegrated in the first order. Contrary to this, using a VEC model is only necessary when the variables are cointegrated in the first order. The first thing to do is thus testing whether the variables are cointegrated or not. This will be done by the Dickey-Fuller Test. When it turns out the stock market bubble (SMB) variable and the overconfidence (OC) proxy are nonstationary variables in the first order 1 and thus not cointegrated, then the VAR model should be specified as denoted in equation 24:

$$SMB_t = \beta_{11}OC_{t-1} + \beta_{12}SMB_{t-1} + \sum_{p=2}^{\infty}\beta_{1t}OC_{t-p} + \sum_{p=2}^{\infty}\beta_{2t}SMB_{t-p} + \varepsilon_t \qquad (24)$$

in which this thesis' interest is on the β_{1t} coefficients and where OC_{t-p} are the lagged variables of the overconfidence proxy and SMB_{t-p} the (lagged) variables of the stock market bubble proxy. When there is cointegration, a VEC model should be implemented and is equal to the following equation 25:

$$\Delta SMB_t = \beta_{11}\Delta OC_{t-1} + \beta_{12}\Delta SMB_{t-1} + \sum_{p=2}^{\infty}\beta_{1t}\Delta OC_{t-p} + \sum_{p=2}^{\infty}\beta_{2t}\Delta SMB_{t-p} - \lambda(SMB_{t-1} - \alpha_0 - \alpha_1 OC_{t-1}) + \varepsilon_t \qquad (25)$$

in which this thesis' interest is on the β_{1t} coefficients and where ΔOC_{t-p} are the lagged variables of the overconfidence proxy in first differences, ΔSMB_{t-p} the (lagged) variables of the stock market bubble proxy in first differences and $\lambda(SMB_{t-1} - \alpha_0 - \alpha_1 OC_{t-1})$ is the

error correction term showing the long run cointegration relation between the two variables.

6. Results

In this chapter the results of the method used to examine the relationship between overconfidence and stock market bubbles, velocity and volatility will be discussed. First, this chapter starts with some descriptive statistics. This is followed by the Bubble Component, correlations between the variables, graphical analysis, stationarity, cointegration and lag selection, the results from the regressions, Granger Causality and Impulse Response Functions. Most tables are reported in appendix A.

6.1 Descriptive Statistics

The summary statistics for both datasets are reported in table 1 and 2 on the next page. In the Holder 67 dataset, there are 486 S&P 500 companies included from which 90, 170, 86, 66, 48 and 53 firms[19] operate respectively in the financial, technical, manufacturing, transportation, trade and services industry. The additional company in the Net Buyer dataset summing up to 487 S&P 500 companies is located in the technical industry. These industry groups are classified into six broad categories according to the specification of Malmendier and Tate (2005a) based on the SIC code of each company. In appendix B, it can be seen which companies are allocated to what kind of industry category. In only 1.92% of reported years, the CEO of a company in the S&P500 index was female. The Holder 67 proxy defines the CEO in almost 61% of the years as overconfident.[20] Malmendier and Tate (2005a) find that 58 of the 113 or 51% of the CEOs are overconfident according to the Holder 67 proxy. However, Hirshleifer, Low and Teoh (2012) conclude that 61% of the CEOs are overconfident according to their adjusted Holder 67 proxy and thus both are comparable to this thesis's sample findings. According to the Net Buyer proxy, in almost 47% of the years the CEO is labeled as overconfident.[20] Malmendier and Tate (2005a) find that 97 of the 158 CEOs are overconfident according to the Net Buyer proxy which is 61%.

[19] Does not add up to 486 because some firms belong to multiple industries.

[20] Note that the percentage of overconfident CEOs is somewhat different than the percentage of the years a CEO is overconfident. This results from the specification in section 5.2.3 and the fact that the number of reported years are different per CEO.

Table 1: Summary Statistics Holder67 Dataset

Variable	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Holder 67	23	.6023696	.0954777	.3455	.7509
Bubble Component	23	572.2675	100.5276	447.9843	858.1823
Velocity	23	1.585236	.7623203	.5410705	3.338841
Volatility	23	.1666172	.0787394	.07813	.4105031

Table 1 shows that the overconfidence proxy Holder 67 strongly deviates in different years as the values vary from 0.3455 to 0.7509. It can also be seen that the Bubble Component, Velocity an Volatility vary sufficiently during the period 1992-2014. Another important fact is that all the variables report positive values only, which is in line with the theory and methods.

Table 2: Summary Statistics Net Buyer Dataset

Variable	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Net Buyer	23	.7177762	.0535065	.5	.7640187
Bubble Component	23	572.2675	100.5276	447.9843	858.1823
Velocity	23	1.570248	.7771788	.5375429	3.337323
Volatility	23	.1666172	.0787394	.07813	.4105031

From table 2 it can be seen that the overconfidence proxy Net Buyer deviates in various years as the values vary from 0.5 to 0.7640187. However, these deviations are less strong compared to the Holder 67 proxy. The Bubble Component, Velocity an Volatility vary sufficiently during the period 1992-2014. Another important fact is that all the variables only show positive values, which corresponds to the theory and methods.

From table 3 until 6, a first indication can be provided about the relationship between overconfidence and stock market bubbles, velocity and volatility. In these tables, the mean and median of the variables 3 years before and 3 years after two important crises affecting the United States are reported. From both table 3 and 4, it can be seen that there is a significant decrease in the mean or median of overconfidence proxied by Holder 67 comparing before versus after both crisis periods. This is in line with the theory. Next to this in table 3 and 4, the Bubble Component is consistently higher before the crises compared to after the crises which is in line with the theory too. Therefore, this is a first indication of a relationship between overconfidence measured by Holder 67 and stock market bubbles proxied by the Bubble Component. Table 5 and 6 show the same but now for the Net Buyer

proxy. These tables display that, although the Net Buyer proxy is always lower after the crises, that there is no significant decrease in overconfidence measured by the Net Buyer proxy after the crises. Therefore, this indicates the hypothesized relationship between overconfidence and stock market bubbles albeit somewhat weaker.

The Velocity variables do not show evidence of the hypothesized relationship between overconfidence and velocity. This is because the median and mean are always higher after the crisis relative to before while the overconfidence proxies' mean and median are lower after a crisis compared to before.

Moreover, the hypothesized relationship between overconfidence and volatility is also not confirmed by the median and mean comparisons before and after both crises. This can be concluded because the median and mean of the volatility are always higher after the crisis in both crises, but not significant, while the overconfidence proxies' mean and median are lower after a crisis compared to before.

6.2 Bubble Component

Section 5.3.2 shows how the Bubble Component is derived from the data. To be able to do this, first the λ is calculated using the explained method. This λ is found to be equal to 1.4522174. Then, using data about the dividends and the index prices, the function $P_t = c_0 D_t + c_1 D_t^{\lambda} + \varepsilon$ could be regressed by an OLS regression. The problem of this equation is that the explanatory variables both contain D_t and thus there can be a collinearity problem. Therefore, the function $\frac{P_t}{D_t} = c_0 + c_1 D_t^{\lambda-1} + \varepsilon$ is regressed by using an OLS regression. The coefficients c_0 and c_1 are respectively equal to 10.22647 and 7.034219 in this regression equation. The Bubble Component of each year is calculated by multiplying the dividend of the index to the power $\lambda - 1$ by $c_1 D_t$. Furthermore, the calculated Bubble Component is corrected for inflation with 1992 as the base year.

6.3 Correlations

In this paragraph, the correlations between the different dependent and independent variables are examined to see how the variables are related to each other. In table 4, the correlations between the variables are displayed.

6.3.1 Correlations Overconfidence and Stock Market Bubbles

The correlation between the Holder 67 proxy and Bubble Component is equal to 0.3492 and not significant. Also, the first lag of Holder 67 is positively correlated with the Bubble Component while the second and third lags are negatively correlated with the Bubble Component. These lags have respectively a coefficient of 0.1798, -0.1955 and -0.4182 and are all not significant with 5% significance. This indicates that there is a semi-strong but non-significant and ambiguous relationship between overconfidence measured by Holder 67 and stock market bubbles as proxied by Bubble Component. The correlations between the Net Buyer proxy and the Bubble Component, however, show more consistent evidence of overconfidence leading to stock market bubbles. The correlation between Net Buyer and Bubble Component is positive but not significant. Also, the lags show positive coefficients and no significance

6.3.2 Correlations Overconfidence and Velocity

The correlation of around -0.12 between the Holder 67 proxy and Velocity is, contrary to the theory, negative. Additionally, this correlation is not significant. Also, there is no consistency in the sign of the correlation coefficients of the lagged variables for the Holder 67 proxy with the velocity proxy and no significance. The correlation between Net Buyer and Velocity is about 0.47 and significant. The lagged Net Buyer proxies are positive and significant too, which is consistent with the theory.

6.3.3 Correlations Overconfidence and Volatility

The correlation between the Holder 67 proxy and Volatility is, according to the theory, positive and significant for most lags. The correlation between the Net Buyer proxy and Volatility still shows a positive relation between overconfidence and volatility for all lags but there is no significance.

6.4 Graphical Analysis

6.4.1 Graphical Analysis Overconfidence and Stock Market Bubbles

In figure 3, the relationship between overconfidence proxied by Holder 67 and stock market bubbles measured by the Bubble Component is shown. From this figure, it can be seen that the Holder 67 proxy frequency ratio increase or decrease corresponds to a respective increase or decrease in the Bubble Component during almost all periods albeit in some

periods with higher peaks and troughs than others. Figure 4 presents the relationship between overconfidence proxied by Net Buyer and stock market bubbles measured by the Bubble Component. Figure 4, again, shows that an increase or decrease in the Net Buyer proxy frequency ratio corresponds to a respective increase or decrease in the Bubble Component during most periods. The implication of this is that these figures show graphical evidence of the hypothesized relationship between overconfidence and stock market bubbles.

Figure 3: Holder 67 vs. Bubble Component

The relationship between the fraction of the number of times a CEO is categorized as overconfident for the Holder 67 proxy is shown by the bars and the first y-axis. Also, the Bubble Component is shown in this figure by the lines and the second y-axis.

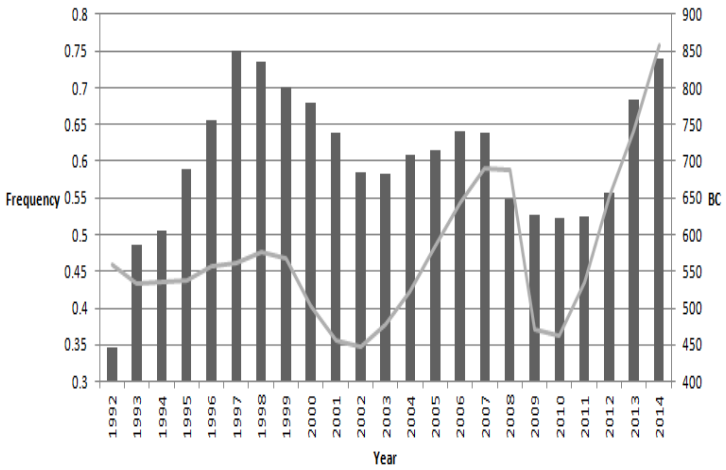
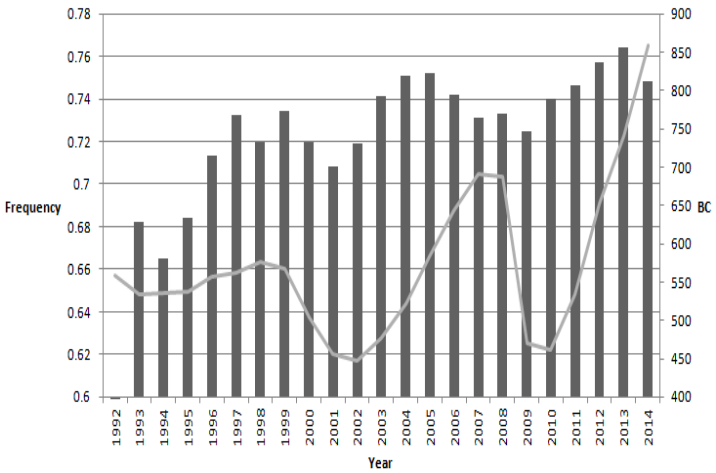


Figure 4: Net Buyer vs. Bubble Component

The relationship between the fraction of the number of times a CEO is categorized as overconfident for the Net Buyer proxy is shown by the bars and the first y-axis. Also, the Bubble Component is shown in this figure by the lines and the second y-axis.



6.4.2 Graphical Analysis Overconfidence and Velocity

The relation between overconfidence and velocity is displayed in figure 5 and 6. The Holder 67 proxy frequency ratio increase or decrease corresponds to a respective increase or decrease of Velocity during 1994-1997, 2002-2003 and 2004-2007 in figure 5. Figure 6 shows the relation between overconfidence proxied by Net Buyer and Velocity. From this figure it can be seen that the Net Buyer proxy frequency ratio increase or decrease corresponds to a respective increase or decrease of Velocity during 1994-1997, 1998-1999 and 2001-2002. In conclusion, Velocity seems to show a weaker relation with overconfidence compared to with

the Bubble Component because it does not properly show the historical crises in the time period 1992-2014, such as the Dot Com Crisis in 2000 and the 2008 Financial Crisis.

Figure 5: Holder 67 vs. Velocity

The relationship between the fraction of the number of times a CEO is categorized as overconfident for the Holder 67 proxy is shown by the bars and the first y-axis. Also, the Velocity is shown in this figure by the lines and the second y-axis.

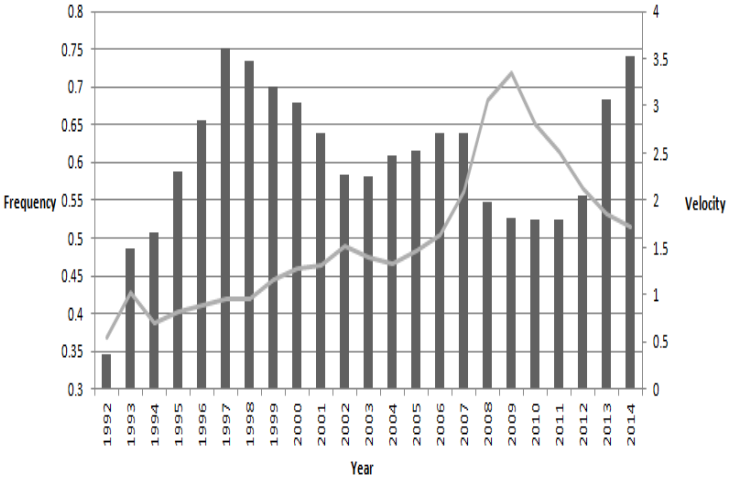
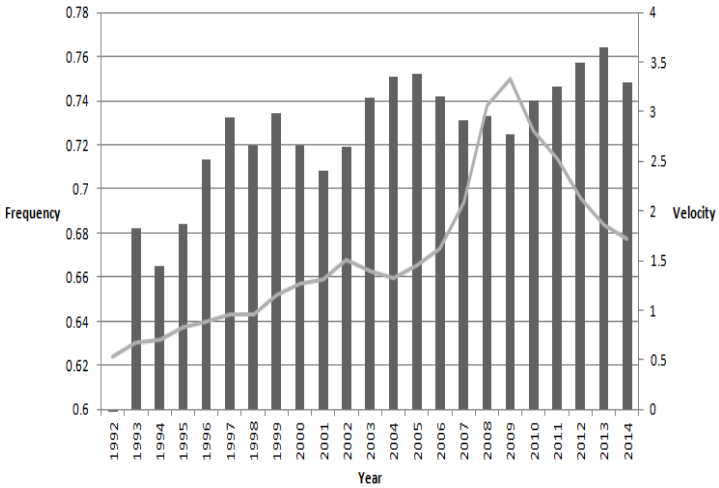


Figure 6: Net Buyer vs. Velocity

The relationship between the fraction of the number of times a CEO is categorized as overconfident for the Net Buyer proxy is shown by the bars and the first y-axis. Also, the Velocity is shown in this figure by the lines and the second y-axis.



6.4.3 Graphical Analysis Overconfidence and Volatility

Figure 7 and 8 display the relationship between overconfidence and volatility. The Holder 67 proxy frequency ratio increase or decrease corresponds to a respective increase or decrease of Volatility during 1994-1997, 1998-1999, 2000-2001 and 2008-2010 as shown by figure 7. In figure 8, the same can be seen only now for the Net Buyer proxy of overconfidence. The Net Buyer proxy frequency ratio increase or decrease corresponds to a respective increase or decrease of Volatility during 1994-1997, 2000-2002, 2005-2006 and 2008-2010. Also here, the relation between overconfidence and volatility seems to be weaker than the relation between overconfidence and stock market bubbles but stronger than the relation with velocity.

Figure 7: Holder 67 vs. Volatility

The relationship between the fraction of the number of times a CEO is categorized as overconfident for the Holder 67 proxy is shown by the bars and the first x-axis. Also, the Volatility is shown in this figure by the lines and the second x-axis.

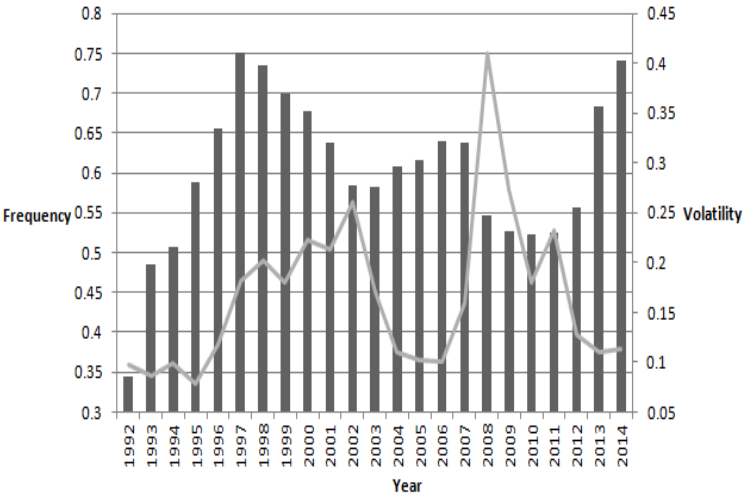
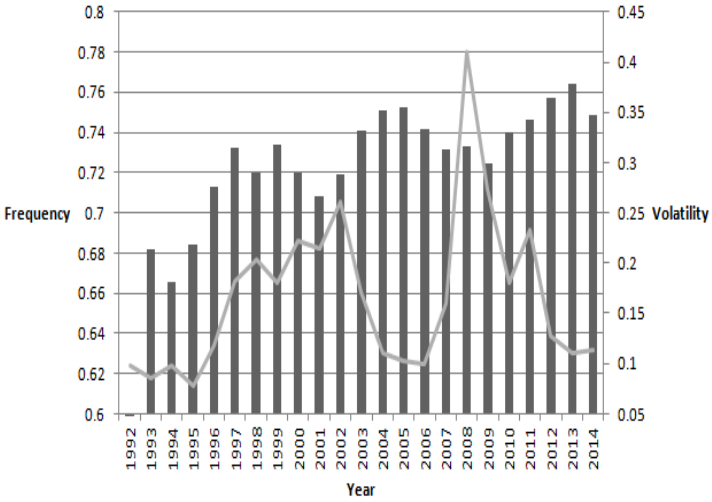


Figure 8: Net Buyer vs. Volatility

The relationship between the fraction of the number of times a CEO is categorized as overconfident for the Net Buyer proxy is shown by the bars and the first x-axis. Also, the Volatility is shown in this figure by the lines and the second x-axis.



6.5 Stationarity, Cointegration and Lag Selection

In the methodology chapter, it was explained that the relationship between stock market bubbles, velocity and volatility with overconfidence is statistically tested using a VAR or a VEC model. An important assumption of this VAR model is that the variables should be stationary at level, i.e. integrated of order 0. This then means that the variables should not be cointegrated. Therefore, first it is tested whether the relevant variables are (non)stationary at different levels. This can be done by the Dickey-Fuller Test using the variables' appropriate form, constant, trend or constant and trend. These tests are reported in table 8 until 13 in the appendix. For each table in the first test, it is checked whether the third lag is significant, in the second test whether the second lag is significant and in the third test whether the first lag is significant. The tables show that for all but the Volatility variable only the first lag in the third test is significant while there is no significance of the third and second lag in respectively the first and second test. Therefore, from these Dickey-Fuller Tests done for the variables Bubble Component, Velocity of the Holder 67 dataset, Velocity of the Net Buyer dataset, Holder 67 and Net Buyer, it is found that all these variables are integrated of order 1. As a consequence of this stationarity, the variables could

be cointegrated and then the VAR model is not appropriate to use. In that scenario, the error term should be corrected by using a VEC model. However, the Volatility variable is the only variable that differs in this respect. From the Dickey-Fuller Test it is found that there is no stationarity because the first difference is not significant in the third test and the test statistic is lower than the critical value. From this, non-stationarity can be concluded. Now, because of this non-stationarity, there cannot be cointegration and thus the VAR model should be used.

To see whether the other variables are cointegrated, Johansen Cointegration Tests are performed. These Johansen Cointegration Tests are reported in table 14 until 17. From these tests' trace statistic and/or max statistic, evidence is found that there is no cointegration between Bubble Component and Holder 67 and Velocity and Net Buyer. However, the max and trace statistics report cointegration between the Velocity and Holder 67 and Bubble Component and Net Buyer. Therefore, the first two relationships should be tested using a VAR model as the assumption of no cointegration holds and the last two relationships should be tested using a VEC model as the assumption of no cointegration does not hold.

Before the VAR and VEC models can be used, the number of lags that is appropriate to use, should be determined. This can be done by obtaining the lag-order selection statistics for VAR and VEC models. These are reported in table 18 until 23 in the appendix. From this, it can be concluded that the models for the Bubble Component and Holder 67, the Bubble Component and Net Buyer and Velocity of the Holder 67 dataset and Holder 67 should respectively have lag 2, 1 and 4 while the model for Velocity Net Buyer and Net Buyer should have lag 2. The Holder 67 and Net Buyer proxies with Volatility should both have lag 1. Using these lags, now the actual statistical testing of the relation between overconfidence and stock market bubbles can be done using the VAR and VEC models.

6.6 Regression Results

In this paragraph, the results of the five different regressions are explained. These results are displayed in table 24 until 29. In this table, the bold vertical axes are the lagged independent variables in the VAR and VEC regressions while the bold horizontal axes are the dependent

variables. In both VEC regression tables 25 and 26, 'D' denotes that variable is in its first differences which is done because of the cointegration concerns.

6.6.1 Regression Results Holder 67 and Bubble Component

The VAR regression between overconfidence proxied by Holder 67 and stock market bubbles proxied by the Bubble Component, as shown in table 24, displays a positive significant relationship between the first lag of Holder 67 and the Bubble Component. Also, the second lag of Holder 67 with the Bubble Component is significantly negative. This indicates a short run relationship between overconfidence and stock market bubbles. However, the sign of the short run relationship is ambiguous. Next to this, postestimation tests are performed to see whether there is autocorrelation and/or whether the residuals are normally distributed and are displayed in table 30. From the Lagrange multiplier test, it can be concluded that there is autocorrelation in the first lag while there is no autocorrelation in the second lag. The Jarque-Bera test finds that the residuals are normally distributed.

6.6.2 Regression Results Net Buyer and Bubble Component

The VEC regression between overconfidence proxied by Net Buyer and the Bubble Component which measures stock market bubbles shows a positive but not significant relationship between both variables in table 25. This indicates that there is no significant short run relationship between overconfidence and stock market bubble as proxied by these variables. The cointegration equation coefficient is negative but not significant. This means that there is no long run relation between both variables. Just as before, postestimation tests are performed to see whether there is autocorrelation and/or whether the residuals are normally distributed and are displayed in table 31. These tests find that there is no serial correlation and the residuals are not normally distributed for the relationship between the lagged Net Buyer variable and the Bubble Component in first differences.

6.6.3 Regression Results Holder 67 and Velocity

The third regression uses a VAR to estimate the relationship between Velocity and overconfidence proxied by Holder 67. Contrary to the theorized relationship between overconfidence and velocity, positive non-significant coefficients are found for the second and fourth lag while negative non-significant coefficients are found for the first and third lag as reported in table 26. Moreover, from table 32, it can be concluded that there is no autocorrelation and the residuals are normally distributed.

6.6.4 Regression Results Net Buyer and Velocity

The VAR regression between overconfidence proxied by Net Buyer and Velocity shows for both lags a positive but not significant relationship between both variables in table 27. This is in line with the theory and means that there is no significant positive relation between overconfidence and velocity. Next to this, the Lagrange and the Jarque-Bera test show that there is no autocorrelation and residuals are not normally distributed in table 33.

6.6.5 Regression Results Holder 67 and Volatility

In the fifth equation, the relation between overconfidence proxied by Holder 67 and Volatility is examined. This is done in table 28. From this table it can be seen that the lagged Holder 67 proxy shows a positive relation, as the theory suggests, and is significant with 10% confidence. Therefore, this implicates a weak short run positive relation between overconfidence and volatility. Another finding from the Lagrange and the Jarque-Bera test is that the residuals are not normally distributed and there is no autocorrelation as displayed in table 34.

6.6.6 Regression Results Net Buyer and Volatility

The final VAR regression for the relationship of overconfidence measured by Net Buyer and Volatility is stated in table 29. A positive relationship is found between the Net Buyer proxy and Volatility. However, this relation is not significant. Thus, there is no short run relationship between overconfidence and volatility. The Lagrange and Jarque-Bera test show that there is no autocorrelation and also the residuals are not normally distributed as can be seen from table 35.

6.7 Granger Causality

Granger Causality tests whether the cause, which is overconfidence, happens prior to its effect, namely stock market bubbles, velocity and volatility. When this is the case, overconfidence Granger causes stock market bubbles, velocity and volatility.[21] From table 36, it can be seen that Holder 67 at a 5% significance level Granger causes the Bubble Component. Therefore, it can be concluded that overconfidence proxied by Holder 67 happens prior to the stock market bubbles as proxied by the Bubble Component. Both

[21] This, however, does not necessarily mean that overconfidence indeed causes stock market bubbles, velocity and volatility.

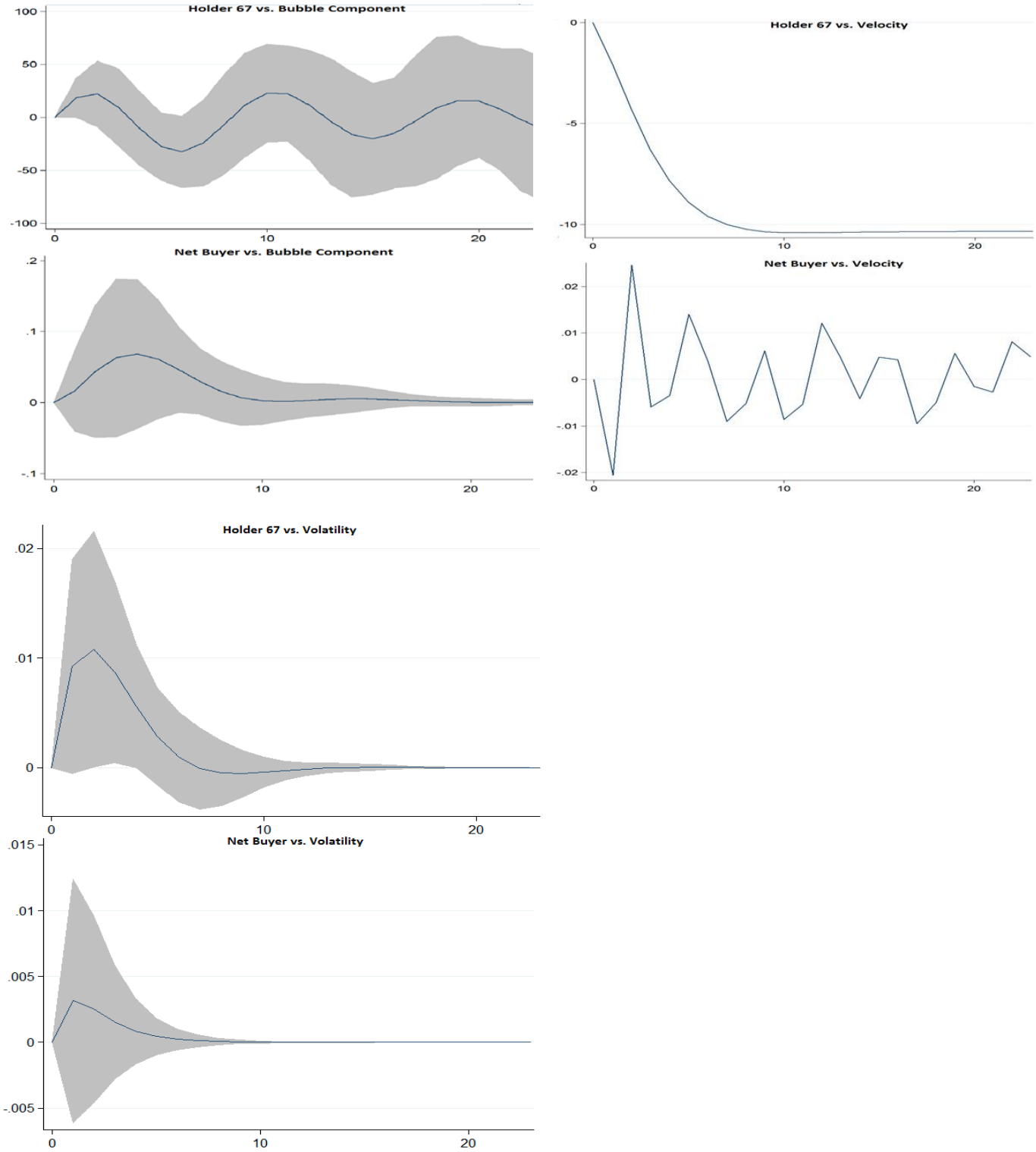
overconfidence proxies do not granger cause Velocity. Finally, only overconfidence proxied by Holder 67 granger causes Volatility with 10% significance. This does not hold for overconfidence measured by Net Buyer.

6.8 Impulse Response Function

Impulse Response Functions (IRFs) provide a useful insight in the dynamic effects of overconfidence on stock market bubbles. These IRFs show the impact of a shock in overconfidence on the Bubble Component and Velocity at time period 0. These results are displayed in figure 9. The grey area displays the 95% confidence interval for the VAR estimations[22] and the line shows the orthogonalized impulse response function for the VAR and VEC estimations. This line thus shows how the respective stock market bubble proxy, velocity proxy or volatility proxy reacts to a shock in the overconfidence proxy at time 0 over the years. From the panel at the left top, it is displayed that a shock in overconfidence measured by Holder 67 leads to a sine wave like movement in the Bubble Component in the following years, but is slowly fading out. In the same panel, a shock in overconfidence proxied by Net Buyer shows an increase in the Bubble Component over the years but fades out within about the first ten years after the shock. The top right panel shows a rigorous decrease in Velocity as a consequence of a shock in overconfidence proxied by Holder 67 in the first ten years after the shock. The same panel shows that a shock in overconfidence measured by Net Buyer leads to a cyclical movement in Velocity for almost all years after the shock. The bottom panel shows the effect of a shock in the overconfidence proxies on Volatility. For both proxies, it holds that there is a positive effect over the first few years after a shock in overconfidence. However, the shock in Holder 67 stabilizes somewhat slower compared to the shock in the Net Buyer proxy.

[22] Using this procedure confidence intervals for VEC models cannot be estimated.

Figure 9: Impulse Response Functions



6.9 Testing the Hypotheses

The empirical findings of this thesis show only weak confirmation of a positive relationship between overconfidence and stock market bubbles. *Hypothesis 1* is tested by a VAR and VEC model using respectively Holder 67 and Net Buyer as overconfidence proxies and the stock market bubble proxy Bubble Component. The VAR model of Holder 67 and the Bubble Component does not reject hypothesis 1 for the one period lag but does due to a change in the coefficients' sign for the two period lag. Thus, a one-year lagged significant effect of overconfidence on stock market bubbles is found. Also, it is found that in this relationship overconfidence significantly granger causes stock market bubbles and that there is a cyclical movement by the Bubble Component due to a shock in overconfidence. The VEC model testing Net Buyer and the Bubble Component reports a positive relationship between overconfidence and stock market bubbles but hypothesis 1 has to be reject due to no significance of this relationship. Moreover, there is no granger causality found. However, from the impulse response functions it can be seen that there is a positive reaction of the Bubble Component due to a shock in overconfidence proxied by Net Buyer. Taking these two relationships together, hypothesis 1 can only be weakly confirmed.

The results of the VEC and VAR models testing the relationship between overconfidence and velocity show no significant relationship. *Hypothesis 2* thus cannot be confirmed by the empirical finding in this thesis as the lags of the Holder 67 and Net Buyer proxies are mostly positive but not significant. Another finding is that both Holder 67 and Net Buyer do not granger cause Velocity. According to the impulse response functions, Velocity suffers from a negative shock due to overconfidence proxied by Holder 67 while a more cyclical movement is found for the relation between Velocity and Net Buyer. In conclusion, hypothesis 2 is not accepted.

The VAR models examining the relationship between overconfidence and volatility do find a positive relation but it is only 10% significant for the Holder 67 proxy. *Hypothesis 3* therefore is only weakly confirmed as it cannot be rejected with 10% significance for the Holder 67 proxy. Also, overconfidence in this relation 10% significantly granger causes Volatility. The hypothesis should be rejected according to the VAR model of the Net Buyer proxy. There is no granger causality found in this relation. Finally, for both overconfidence proxies the impulse response functions show a positive shock in the Bubble Component in

response to a shock in overconfidence that fades away within ten years. All in all, hypothesis 3 can only be weakly confirmed.

7. Conclusion and Discussion

7.1 Summary of the Results and Conclusion

The goal of this thesis is to research and explain the relationship between overconfidence and stock market bubbles, velocity and volatility. This thesis outlines that overconfidence causes increased trading volume, excessive risk taking behavior, increased leverage taking and overpaying. Consequently, via these channels stock market bubbles are caused. Next to this, the DHS model finds that overconfidence and the resulting self-attribution bias can cause stock market bubbles while the DSSW model explains that herding leads to stock market bubbles which is behavior associated with overconfidence according to Hirshleifer, Subrahmanyam and Titman (1994) and is not arbitraged away by rational speculators. Therefore, a positive relation between overconfidence and stock market bubbles is hypothesized. Another theoretical finding is that overconfidence can cause increased velocity and volatility.

The theoretical findings for the relationship between overconfidence and stock market bubbles, velocity and volatility are not convincingly found in the empirical tests. Using our previously described methods, there is no relationship found for overconfidence and velocity. Moreover, this thesis reports a weak positive relationship between overconfidence and stock market bubbles and overconfidence and volatility. Therefore, it can be concluded that overconfidence can at least in some situations cause stock market bubbles and increased volatility while it cannot cause increased velocity.

7.2 Discussion and Suggestions for Further Research

A research often has its limitations and drawbacks. Obviously, this holds for this thesis too. Some of these limitations are outlined in this chapter. Finally, suggestions for further research are put forth.

A first important limitation is that for some theoretical results, there is not always consensus among economist that this relation always should hold. An example of this is the relation found between overconfidence and trading volume. Malmendier and Tate (2005), Ben-David, Harvey and Graham (2007), Heaton (2002), Odean (1999a), Odean (1998b), Grinblatt and Keloharju (2009) and Barber and Odean (2001a) among others find that overconfidence leads to higher trading volume. In this thesis, it is stated that this causes stock market bubbles to occur. However, Glaser and Weber (2007) find the opposite of this.

They researched the effect of overconfidence on trading volume and found that overconfidence does not lead to higher trading volume and thus overconfidence causing stock market bubbles via higher trading volume can be doubted. Also, the theoretical relation between overconfidence and velocity is weakened by this finding. Another example of this limitation is that Ko and Huang (2007) find that overconfidence improves pricing. This is contrary to this thesis' theoretical result that overconfidence causes mispricing which can be responsible for stock market bubbles. Also, they find that the volatility of returns does not increase as a consequence of overconfidence which contradicts this thesis' theoretical conclusion.

A methodological limitation is that the Holder 67 proxy depends upon fiscal year end stock prices of the company. This is not a problem when it is used in relation to velocity but could be a problem when it is used to examine the relationship between overconfidence and stock market bubbles and overconfidence and volatility. This is because a stock market bubble also depends upon the stock prices of the company in the index and volatility is the variation in the daily returns of the index and thus also depends upon stock prices. Therefore, some endogeneity in the relationship between the Holder 67 proxy and stock market bubbles and volatility can be found.

Other methodological limitations are that there might be some seasonality in the Bubble Component and that the Bubble Component is biased upwards. Hymøller and Nielsen (2015) state that choosing to change dividends is often done in certain months of the year, mostly because of the announcement of annual reports. This results in aggregate dividend showing seasonality. Also, because lowering the dividends by managers of the firm is often seen as a very bad signal, managers tend to slowly adjust the dividends upwards and even more slowly downwards (Hymøller and Nielsen, 2015). This means that the Bubble Component could be biased.

A last limitation can be extracted from paragraph 2.4, where the graphical analysis of Velocity is displayed in figure 5 and 6. It is clearly visible that there is some trend visible. To detrend, there should be some variable that causes this trend. However, prior research does not provide information about what this variable could be so it is not known whether this trend and how this trend can be corrected. Intuitively, the positive trend could be caused by technology improvements but this is not confirmed in the theory.

Therefore, the cause of a positive trend in trading velocity and how this can be detrended is an interesting topic to research. Another suggestion for further related research is to see whether there are other psychological biases that can cause stock market bubbles, velocity or volatility. Also, researching the effect of endogeneity in the Holder 67 proxy, seasonality in the Bubble Component and the upward bias in the Bubble Component in explaining stock market bubbles is an interesting topic to research.

Appendix A: Results

Table 1: Summary Statistics Holder67 Dataset

Variable	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Holder 67	23	.6023696	.0954777	.3455	.7509
Bubble Component	23	572.2675	100.5276	447.9843	858.1823
Velocity Holder67	23	1.585236	.7623203	.5410705	3.338841
Volatility	23	.1666172	.0787394	.07813	.4105031

Table 2: Summary Statistics Net Buyer Dataset

Variable	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Net Buyer	23	.7177762	.0535065	.5	.7640187
Bubble Component	23	572.2675	100.5276	447.9843	858.1823
Velocity Net Buyer	23	1.570248	.7771788	.5375429	3.337323
Volatility	23	.1666172	.0787394	.07813	.4105031

Table 3: Difference Analysis Holder 67 Dataset Before and After Dot Com Bubble

Variable	**Mean Before**	**Median Before**	**Mean After**	**Median After**	**Difference Mean**	**Difference Median**
Holder 67	.7046333	.7003	.6012667	.5838	-0.10337**	-.1165***
Bubble Component	549.4069	567.4796	460.7366	456.6968	-88.6703**	-110.783***
Velocity Holder67	1.128012	1.152836	1.408397	1.395002	.280385*	.242166*
Volatility	.1884297	.1816844	.2321126	.2222155	.0436829*	.0405311*

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 4: Difference Analysis Holder 67 Dataset Before and After 2008 Financial Crisis

Variable	**Mean Before**	**Median Before**	**Mean After**	**Median After**	**Difference Mean**	**Difference Median**
Holder 67	.6312	.6379	.5323667	.5264	-.0988333***	-.1115***
Bubble Component	639.3273	643.2422	539.9551	470.3992	-99.37218	-172.843
Velocity Holder67	2.257616	2.089911	2.888504	2.805133	.630888	.715222
Volatility	.2233971	.1595261	.2286941	.2327248	.0052969	0.073199*

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 5: Difference Analysis Net Buyer Dataset Before and After Dot Com Bubble

Variable	**Mean Before**	**Median Before**	**Mean After**	**Median After**	**Difference Mean**	**Difference Median**
Net Buyer	.7245326	.7198582	.7228597	.7190332	-.0016728	-.000825
Bubble Component	549.4069	567.4796	460.7366	456.6968	-88.6703**	-110.783***
Velocity Net Buyer	1.127873	1.152678	1.409056	1.396939	.281183*	.244261*
Volatility	.1884297	.1816844	.2321126	.2222155	.0436829*	.0405311*

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 6: Difference Analysis Net Buyer Dataset Before and After 2008 Financial Crisis

Variable	**Mean Before**	**Median Before**	**Mean After**	**Median After**	**Difference Mean**	**Difference Median**
Net Buyer	.7245326	.7198582	.7228597	.7190332	-.0016728	-.000825
Bubble Component	639.3273	643.2422	539.9551	470.3992	-99.37218	-172.843
Velocity Net Buyer	2.256667	2.08948	2.888596	2.805652	.631929	.716172
Volatility	.2233971	.1595261	.2286941	.2327248	.0052969	0.073199*

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 7: Correlations Between Variables

Variable	**Holder 67**	**Holder 67 L1**	**Holder 67 L2**	**Holder 67 L3**	**Net Buyer**	**Net Buyer L1**	**Net Buyer L2**
Holder 67	1.0000						
Holder 67 L1	0.7851***	1.0000					
Holder 67 L2	0.3764*	0.7770***	1.0000				
Holder 67 L3	-0.0998	0.4393**	0.8218***	1.0000			
Net Buyer	0.6373***	0.3292	0.2608	0.0890	1.0000		
Net Buyer L1	0.4197**	0.6351***	0.3025	0.2817	0.7074***	1.0000	
Net Buyer L2	0.2684	0.3819*	0.6195***	0.3533	0.7605***	0.6967***	1.0000
Net Buyer L3	-0.0853	0.2213	0.3556	0.6482***	0.6441***	0.7525***	0.6865***
Bubble Component	0.3492	0.1798	-0.1955	-0.4182*	0.2109	0.3137	0.2874
Velocity Holder 67	-0.1271	-0.0857	0.1116	0.1818	0.4731**	0.3768*	0.4906**
Velocity Net Buyer	-0.0997	-0.0262	0.1110	0.1818	0.4783**	0.4542**	0.4904**
Volatility	0.0198	0.3636*	0.5188***	0.4866***	0.2202	0.2415	0.2446

Variable	**Net Buyer L3**	**Bubble Component**	**Velocity Holder 67**	**Velocity Net Buyer**
Net Buyer L3	1.0000			
Bubble Component	0.2101	1.0000		
Velocity Holder	0.5344**	0.1268	1.0000	

67				
Velocity Net Buyer	0.5345**	0.1318	0.9958***	1.0000
Volatility	0.3683	-0.1670	0.6063***	0.6148***

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 8: Stationarity Tests

Bubble Component	**Test 1**	**Test 2**	**Test 3**
L1.	-.4801393	-.5225295	-.4138167
	(.40876)	(.2994138)	(.1992589)
LD.	.7220628*	.7561293**	.7452445***
	(.3462902)	(.256828)	(.2422982)
L2D.	.156133	.1720211	
	(.3657251)	(.3381657)	
L3D.	-.05897		
	(.3639228)		
Constant	277.8054	300.3909*	240.4163**
	(226.5732)	(166.1495)	(111.0641)

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 9: Stationarity Tests

Velocity Holder 67	**Test 1**	**Test 2**	**Test 3**
L1.	-.7972408***	-.52498**	-.4312392**
	(.2630126)	(.2058879)	(.1619525)
LD.	.9799248***	.7103731***	.6618662***
	(.2321482)	(.1970757)	(.2133444)
L2D.	.2136339	.2426261	
	(.2613008)	(.2532873)	
L3D.	.4104533		
	(.2489244)		
Trend	.0848381**	.0483182*	.0432997**
	(.0319974)	(.0257095)	(.0201786)
Constant	.1921389	.2689782*	.1747676
	(.1472736)	(.1381162)	(.1430579)

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 10: Stationarity Tests

Velocity Net Buyer	**Test 1**	**Test 2**	**Test 3**
L1.	-.8911363***	-.5111577**	-.4329667***
	(.2672841)	(.2173932)	(.1401422)
LD.	1.088567***	.7926469***	.8175643***
	(.236531)	(.2088188)	(.1942527)
L2D.	.1578303	.1576189	
	(.2813294)	(.3048558)	
L3D.	.6046232		
	(.2856149)		
Trend	.0969299**	.0505345*	.0422898**
	(.0330587)	(.0270972)	(.0179223)
Constant	.1689362	.2078707	.1891104
	(.1371335)	(.1349399)	(.1181796)

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 11: Stationarity Tests

Holder 67	**Test 1**	**Test 2**	**Test 3**
L1.	-.5016457**	-	-.2610926*
	(.1767555)	.4399278***	(.1293225)
		(.1261193)	
LD.	.6118562***	.6290703***	.4431965**
	(.199383)	(.1857426)	(.1673172)
L2D.	.2086148	.1796639	
	(.2086148)	(.1791054)	
L3D.	.1153199		
	(.1153199)		
Constant	.3113381**	.273737***	.1637224*
	(.1088832)	(.0772428)	(.0790926)

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 12: Stationarity Tests

Net Buyer	**Test 1**	**Test 2**	**Test 3**
L1.	-.4412656**	-.4199151***	-.2968286**
	(.1776832)	(.1237209)	(.1130062)
LD.	.2479874	.2440028	-.1505938**
	(.2185427)	(.1941104)	(.06991)
L2D.	-.026194	-.0394329	
	(.2174702)	(.0713225)	
L3D.	-.0126406		
	(.0780353)		
Constant	.3254867**	.309746***	.2207435**
	(.1302943)	(.0905557)	(.0824376)

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 13: Stationarity Tests

Volatility	**Test 1**	**Test 2**	**Test 3**
L1.	-1.079162***	-.7119868**	-.6316558**
	(.317376)	(.2928131)	(.2292905)
LD.	.5566991*	.2502088	.2083213
	(.2779272)	(.2587887)	(.2267129)
L2D.	.2764164	.0655163	
	(.2454036)	(.2435024)	
L3D.	.4206079*		
	(.2318372)		
Constant	.193112	.1262056**	.1101007***
	(.0584088)	(.0540075)	(.0424093)

[1]Meaning of asterisks: * trace/max statistic is lower than critical value indicating at maximum rank 0 no cointegration and at maximum rank 1 cointegration

Test Statistic: -2.755
5% Critical Value: -3.000

Table 14: Johansen Cointegration Test Bubble Component and Holder 67

Maximum Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**Critical Value**
0	-78.147873	.	12.7152*	15.41
1	-73.593073	0.35195	3.6056	3.76
2	-71.790249	0.15777		
Maximum Rank	**LL**	**Eigenvalue**	**Max Statistic**	**Critical Value**
0	-78.147873	.	9.1096*	14.07
1	-73.593073	0.35195	3.6056	3.76
2	-71.790249	0.15777		

[1]Meaning of asterisks: * trace/max statistic is lower than critical value indicating at maximum rank 0 no cointegration and at maximum rank 1 cointegration

Table 15: Johansen Cointegration Test Bubble Component and Net Buyer

Maximum Rank	**LL**	**Eigenvalue**	**Trace Statistic**	**Critical Value**
0	-84.439773	.	41.7836	15.41
1	-63.713801	0.84805	0.3317*	3.76
2	-63.54797	0.01496		
Maximum Rank	**LL**	**Eigenvalue**	**Max Statistic**	**Critical Value**
0	-84.439773	.	41.4519	14.07
1	-63.713801	0.84805	0.3317*	3.76
2	-63.54797	0.01496		

[1]Meaning of asterisks: * trace/max statistic is lower than critical value indicating at maximum rank 0 no cointegration and at maximum rank 1 cointegration

Table 16: Johansen Cointegration Test Velocity and Holder 67

Maximum Rank	LL	Eigenvalue	Trace Statistic	Critical Value
0	41.179396	.	39.1524	15.41
1	59.681617	0.85738	2.1480*	3.76
2	60.755599	0.10689		
Maximum Rank	**LL**	**Eigenvalue**	**Max Statistic**	**Critical Value**
0	41.179396	.	37.0044	14.07
1	59.681617	0.85738	2.1480*	3.76
2	60.755599	0.10689		

[1]Meaning of asterisks: * trace/max statistic is lower than critical value indicating at maximum rank 0 no cointegration and at maximum rank 1 cointegration

Table 17: Johansen Cointegration Test Velocity and Net Buyer

Maximum Rank	LL	Eigenvalue	Trace Statistic	Critical Value
0	60.432443	.	18.2019	15.41
1	66.395774	0.43331	6.2753	3.76
2	69.533402	0.25831		
Maximum Rank	**LL**	**Eigenvalue**	**Max Statistic**	**Critical Value**
0	60.432443	.	11.9267*	14.07
1	66.395774	0.43331	6.2753	3.76
2	127.00119	0.25742		

[1]Meaning of asterisks: * trace/max statistic is lower than critical value indicating at maximum rank 0 no cointegration and at maximum rank 1 cointegration

Table 18: Lag Selection Bubble Component and Holder 67

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	-91.11		61.8982	9.80105	9.81788	9.90047
1	-75.1463	31.927	17.6599	8.54172	8.59219	8.83996
2	-59.8345	30.624*	5.47727*	7.351*	7.43512*	7.84807*
3	-57.3113	5.0463	6.70865	7.50646	7.62423	8.20236
4	54.7686	5.0855	8.57284	7.65985	7.81128	8.55458

[1]Meaning of asterisks: * appropriate lag to use according to test

Table 19: Lag Selection Bubble Component and Net Buyer

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	-60.1668		2.3829	6.54388	6.5607	6.64329
1	-42.6593	35.015*	.577878*	5.12203*	5.17251*	5.42028*
2	-39.5121	6.2944	.644945	5.2118	5.29593	5.70887
3	-38.9761	1.072	.973724	5.57643	5.69421	6.27233
4	-35.9018	6.1486	1.17659	5.67387	5.8253	6.56861

[1]Meaning of asterisks: * appropriate lag to use according to test

Table 20: Lag Selection Velocity and Holder 67

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	10.1882			.001448	-.861915	-.84509
1	31.3632	42.35	0.000	.000239	-2.66981	-2.61934
2	40.5953	18.464	0.001	.00014	-3.22056	-3.13644
3	43.842	6.4933	0.165	.000159	-3.14126	-3.02349
4	60.7556	33.827*	0.000	.000045*	-4.50059*	-4.34917*

[1]Meaning of asterisks: * appropriate lag to use according to test

Table 21: Lag Selection Velocity and Net Buyer

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	32.9557			.000132	-3.25849	-3.24167
1	57.0462	48.181	4 0.000	.000016	-5.37329	-5.32281
2	66.3164	18.54*	4 0.001	9.4e-06*	-5.92804*	-5.84392*
3	68.3004	3.9679	4 0.410	.000012	-5.71583	-5.59805
4	69.9334	3.2661	4 0.514	.000017	-5.46667	-5.31525

[1]Meaning of asterisks: * appropriate lag to use according to test

Table 22: Lag Selection Volatility and Holder 67

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	46.6494		.000031	-4.69994	-4.68311	-4.60052
1	63.3193	33.34*	8.3e-06*	-6.03361*	-5.98313*	-5.73536*
2	67.2251	7.8118	8.5e-06	-6.0237	-5.93957	-5.52663
3	69.0608	3.6713	.000011	-5.79587	-5.6781	-5.09997
4	72.1196	6.1176	.000014	-5.6968	-5.54538	-4.80207

[1]Meaning of asterisks: * appropriate lag to use according to test

Table 23: Lag Selection Volatility and Net Buyer

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	77.0532		1.3e-06	-7.90033	-7.88351	-7.80092
1	85.2731	16.44	8.2e-07*	-8.34454*	-8.29406*	-8.04629*
2	89.2148	7.8835	8.4e-07	-8.3384	-8.25428	-7.84133
3	90.7769	3.1242	1.1e-06	-8.08178	-7.96401	-7.38588
4	96.9878	12.422*	9.9e-07	-8.3145	-8.16308	-7.41977

[1]Meaning of asterisks: * appropriate lag to use according to test

Table 24: VAR Bubble Component and Holder 67

	Coefficient (Standard Error) **Bubble Component**		*Coefficient* (Standard Error) **Holder 67**
Bubble Component		**Bubble Component**	
L1.	1.199078***	**L1.**	.0002088
	(.1759747)		(.0001379)
L2.	-.6451685***	**L2.**	-.0002785**
	(.1936248)		(.0001518)

Holder 67		**Holder 67**	
L1.	492.4899**	**L1.**	1.099455***
	(240.5036)		(.188492)
L2.	-541.77***	**L2.**	-.3770158**
	(190.8488)		(.1495756)
Constant	280.5634**	**Constant**	.2113689**
	(111.9477)		(.0877378)
R^2	0.7827	**R^2**	0.7425

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 25: VEC Bubble Component and Net Buyer

	Coefficient (Standard Error) **D.Bubble Component**		*Coefficient* (Standard Error) **D.Net Buyer**
Cointegration Equation	-.0521999	**Cointegration Equation**	-.000074***
	(.1301978)		(.0000207)
Bubble Component		**Bubble Component**	
LD.	.530538*	**LD.**	.0000602
	(.2852127)		(.0000453)
Net Buyer		**Net Buyer**	
LD.	19.51078	**LD.**	-.1635924***
	(395.1793)		(.0627291)
Constant	.0000146	**Constant**	-.0103303**
	(30.86321)		(.0048991)
R^2	0.2387	**R^2**	0.5155

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 26: VEC Velocity and Holder 67

	Coefficient (Standard Error) **D.Velocity**		*Coefficient* (Standard Error) **D.Holder 67**
Cointegration Equation	.0015808	**Cointegration Equation**	-.0473697***
	(.1848527)		(.0138583)
Velocity		**Velocity**	
LD.	.5866489	**LD.**	-.0641357**
	(.4026716)		(.030188)
L2D.	-.3506791	**L2D.**	-.013153
	(.5388576)		(.0403977)
L3D.	.0421436	**L3D.**	-.0487368
	(.4283887)		(.032116)

L4D.	-.4616991	**L4D.**	-.046973
	(.6102276)		(.0457483)
Holder 67		**Holder 67**	
LD.	-2.225572	**LD.**	.3886232
	(2.503701)		(.1877004)
L2D.	3.83096	**L2D.**	.1665371
	(2.757095)		(.2066973)
L3D.	-2.901942	**L3D.**	.6444538**
	(3.382437)		(.2535786)
L4D.	1.036968	**L4D.**	.3336806
	(2.873161)		(.2153986)
Constant	.0928123	**Constant**	.0030973*
	(.0956523)		(.007171)
R^2	0.6443	**R^2**	0.9128

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 27: VAR Velocity and Net Buyer

	Coefficient		*Coefficient*
	(Standard Error)		(Standard Error)
	Velocity		**Net Buyer**
Velocity		**Velocity**	
L1.	1.430317***	**L1.**	-.0129642*
	(.1669003)		(.0075792)
L2.	-.6453527***	**L2.**	.0181498**
	(.168626)		(.0076576)
Net Buyer		**Net Buyer**	
L1.	1.718468	**L1.**	.4131956***
	(2.955688)		(.1342223)
L2.	1.356446	**L2.**	.1533377***
	(1.268698)		(.0576135)
Constant	-1.86136	**Constant**	.3128565***
	(1.707221)		(.0775275)
R^2	0.9111	**R^2**	0.8165

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Table 28: VAR Volatility and Holder 67

	Coefficient		*Coefficient*
	(Standard Error)		(Standard Error)
	Volatility		**Holder 67**
Volatility		**Volatility**	
L1.	.4784148***	**L1.**	-.3325372***
	(.1691487)		(.1106823)

Holder 67		**Holder 67**	
L1.	.2811176*	**L1.**	.6898257***
	(.145353)		(.0951116)
Constant	-.0786688**	**Constant**	.2590371***
	(.0902802)		(.0590748)
R^2	0.3636	**R^2**	0.7279

Table 29: VAR Volatility and Net Buyer

	Coefficient		*Coefficient*
	(Standard Error)		(Standard Error)
	Volatility		**Net Buyer**
Volatility		**Volatility**	
L1.	.4709282**	**L1.**	.0197277
	(.1862427)		(.0490475)
Net Buyer		**Net Buyer**	
L1.	.1837398	**L1.**	.3218214***
	(.145353)		(.0719552)
Constant	-.041455	**Constant**	.4937905
	(.1910743)		(.0503199)
R^2	0.2704	**R^2**	0.5040

Table 30: Postestimation Tests P-Values Bubble Component and Holder 67

	Lagrange-Multiplier Test		**Jarque-Bera Test**
Lag		**Bubble Component**	0.93235
1	0.01161	**Holder 67**	0.87061
2	0.42798	**All**	0.98104

Table 31: Postestimation Tests Bubble P-Values Bubble Component and Net Buyer

	Lagrange-Multiplier Test		**Jarque-Bera Test**
Lag		**D.Bubble Component**	0.00000
1	0.84083	**D.Net Buyer**	0.58796
		All	0.00000

Table 32: Postestimation Tests Bubble P-Values Velocity and Holder 67

	Lagrange-Multiplier Test		**Jarque-Bera Test**
Lag		**Velocity**	0.18084
1	0.73679	**Holder 67**	0.88439
2	0.42725	**All**	0.45309
3	0.22697		

4	0.90409

Table 33: Postestimation Tests Bubble P-Values Velocity and Net Buyer

	Lagrange-Multiplier Test		**Jarque-Bera Test**
Lag		**D.Velocity**	0.00021
1	0.70143	**D.Holder 67**	0.70357
2	0.42493	**All**	0.00147

Table 34: Postestimation Tests Bubble P-Values Volatility and Holder 67

	Lagrange-Multiplier Test		**Jarque-Bera Test**
Lag		**Volatility**	0.00000
1	0.15676	**Holder 67**	0.03962
		All	0.00000

Table 35: Postestimation Tests Bubble P-Values Volatility and Holder 67

	Lagrange-Multiplier Test		**Jarque-Bera Test**
Lag		**Volatility**	0.00000
1	0.77004	**Net Buyer**	0.11776
		All	0.00000

Table 36: Granger Causality

	Bubble Component	**Velocity**	**Volatility**
Holder 67	Yes**	No	Yes*
Net Buyer	No	No	No

[1]Meaning of asterisks: * significance at 10% level, ** significance at 5% level, *** significance at 1% level

Appendix B: Industry Categorization

Industry	SIC codes
1. Technical	*1000-1799* (mining, construction), *2800-2999* (chemicals, petroleum, coal), *3300-3699* (metal, machinery), *4900-4999* (electric, gas services), *8711* (engineering services)
2. Financial	*6000-6799* (financial, insurance, and real estate industries), *8721* (accounting, auditing, and bookkeeping)
3. Manufacturing	*2000-2799* (food, tobacco, textile, wood, printing), *3000-3299* (plastics, leather, glass), *3700-3999* (vehicles, miscellaneous)
4. Transportation	*4100-4599*, *4700-4799* (passenger & freight transportation), *4600-4699*, *4900-4999*, (pipelines, energy distribution), *4800-4899* (communications)
5. Trade	*5000-5199* (wholesale trade), *5200-5999* (retail trade)
6. Services	*7000-8699* (hotels, repair, recreation, legal, educational, social), *8712-8713* (architectural, surveying), *8730-8999* (R&D, PR, miscellaneous)

Appendix C: Derivation of the DHS Model

C1 Set-Up of the DHS Model

The Daniel, Hirshleifer and Subrahmanyam (DHS) model is able to explain how overconfidence leads to stock market bubbles. The model consists of two different investors: uninformed investors *U* and informed investors *I*. There are four different time periods starting at period 0 where the investors are endowed with a basket of shares and risk free assets. At this date, the investors start with their prior beliefs. In period 1, the informed investors *I* receives a private signal about the price of the shares and trade with uninformed investors *U*. The next period, a noisy public signal arrives and trade goes on. In the last period, conclusive public information arrives and the true, terminal value of the shares θ gets revealed. This terminal value θ has a mean of zero and a variance σ_θ.

The private information that arrives at date 1 is equal to:

$$s_1 = \theta + \epsilon \qquad (1)$$

where the error variance of the signal is normally distributed with mean zero. The uninformed investors *U* correctly determine the error variance while the informed investors *I* underestimate it: $\sigma_C^2 < \sigma_\varepsilon^2$

In line with this, the public signal that arrives at date 2 is equal to:

$$s_1 = \theta + \eta \qquad (2)$$

where the noise term of the signal is normally distributed with mean zero and correctly determined by both investor groups.

Following this, the prices can be calculated as follows because the informed investors *I* is risk neutral so the variance does not play a role:

$$P_1 = E_c[\theta|\theta + \epsilon] \qquad (3)$$

$$P_1 = E_c[\theta|\theta + \epsilon, \theta + \eta] \qquad (4)$$

$$P_1 = \theta \qquad (5)$$

where the *C* operator means that informed investors calculate these price based on their (over)confident beliefs. From this, it can be concluded that prices at date 1 depend upon the terminal value and the private signal while the prices at date 2 are dependent on the terminal value and both the private and the public signals. Then by the property of normal variables it follows that:

$$P_1 = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_C^2}(\theta + \epsilon) \qquad (6)$$

$$P_2 = \frac{\sigma_\theta^2(\sigma_p^2+\sigma_C^2)}{D}\theta + \frac{\sigma_p^2\sigma_\theta^2}{D}\varepsilon + \frac{\sigma_C^2\sigma_\theta^2}{D}\eta \quad (7)$$

where the denominator D is equal to $D \equiv \sigma_\theta^2\left(\sigma_p^2 + \sigma_C^2\right) + \sigma_p^2\sigma_C^2$ (Daniel et al, 1998).

C2 The Self-Attribution Bias

Barber and Odean (2001a) explain that overconfident investors suffer from the self-attribution bias and that especially men affected by this. Also, Scherbina and Schlusche (2014) confirm that the self-attribution bias can lead to bubbles as put forward by Daniel et al (1998). Therefore, the DHS model is extended by investors that suffer from the self-attribution bias. The self-attribution is a cognitive bias in which individuals only consider signals that confirm their beliefs and ignore signals contradicting their beliefs. Thus, the overconfidence of individuals resulting in the self-attribution bias causes them to accept the public signal only if it confirms their private signal but do ignore it when it contradicts the private signal and the public signal is only considered when $sign\ (\theta + \epsilon) = sign\ (s_2)$ and not when $sign\ (\theta + \epsilon) \neq sign\ (s_2)$. The private signal arrives in period 1 and the public signal in period 2. When the public signal confirms the private signal, the overconfident investor gets even more confident about the private signal and when it does not confirm the private signal nothing happens to the initial overconfidence of the investor. Therefore, when $sign\ (\theta + \epsilon) = sign\ (s_2)$ then the informed investor's overconfidence converges to $\sigma_C^2 - k$ with $k > 0$. Consequently following from equation (6), when the public signal contradicts the private signal, the price at date 2 is as follows:

$$P_{2C} = \frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_C^2}(\theta + \epsilon) \qquad (8)$$

and when the public signal confirms the private signal

$$P_{2C} = \frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_C^2-k}(\theta + \epsilon) \qquad (9)$$

Next to this, when there is an additional date '3 where again a public signal is released, the price of the share is according to equation (7):

$$P_{3C} = \frac{\sigma_\theta^2(\sigma_p^2+\sigma_C^2-k)}{D}\theta + \frac{\sigma_p^2\sigma_\theta^2}{D}\varepsilon + \frac{(\sigma_C^2-k)\sigma_\theta^2}{D}\eta \qquad (10)$$

when the public signal confirms the private signal and

$$P_{3C} = \frac{\sigma_\theta^2(\sigma_p^2+\sigma_C^2)}{D}\theta + \frac{\sigma_p^2\sigma_\theta^2}{D}\varepsilon + \frac{\sigma_C^2\sigma_\theta^2}{D}\eta \qquad (11)$$

when the public signal contradicts the private signal with respectively $D \equiv \sigma_\theta^2\left(\sigma_p^2 + \sigma_C^2 - k\right.$ $+\sigma p2(\sigma C2-k)$ and $D\equiv\sigma\theta2\sigma p2+\sigma C2+\sigma p2\sigma C2$ in equation (10) and (11).

Using these formulas, overconfidence at date 1 leads to an overreaction to the private signal just as before. The difference however now is that the self-attribution bias resulting from overconfidence comes into play. This self-attribution bias increases the confidence about the private signal when the public signal confirms the private signal at date 2. Therefore, the share price increases again additional to the initial price increase at date 1. Also, as more public signals are revealed at date '3, the share price converges towards the rational expected value again (Daniel et al, 1998). In conclusion, a stock market bubble is caused by overconfidence itself and the self-attribution bias resulting from overconfidence.

Appendix D: Derivation of the DSSW Model

D1 The DSSW Model Assumptions

The model starts on the assumption that there are three types of investors, two assets and four different time periods. The first type of investors is the informed rational speculator. Rational speculators are present in a fraction of μ and trade based on private information. Next to this, passive investors are present in a fraction $1-\mu$ and buy undervalued stocks and sell overvalued stocks. The total of these two investor groups is assumed to be constant to hold the risk bearing capacity of the market the same. The last group of investors is the feedback traders. This group of investor demands stocks based on the price change of the past period. When the price has increased, they buy and when it has decreased, they sell the stock. Also, there are two assets: stocks and cash. A stock pays a dividend of $\Phi+\theta$ in period 3. No information is released about θ before period 3 and Φ can have three values $-\phi$, 0 and $+\phi$. The value of Φ is revealed in period 2 to the public and a signal about this value is given in period 1. Now, the four different time periods will be backwardly discussed in the following sections (De Long et al, 1990).

D2 Period 3

In period 3, the trades of the prior periods are settled and there is no additional trading anymore. The investors holding the stocks receive the dividends $\Phi+\theta$. Because the dividends are known in this period, the rational investors find the price of the stock to be equal to its fundamental value $\Phi+\theta$ (De Long et al, 1990).

D3 Period 2

In period 2, the value of Φ is revealed to the passive traders and the informed rational speculators. The positive feedback traders' demand for stock in this period is equal to:

$$D_2^f = \beta(p_1 - p_0) = \beta p_1 \qquad (1)$$

where p_1 is the price in period 1 and p_0 is the price in period 0 which is set to be equal to zero and β is the positive feedback coefficient. From this formula, it can be seen that feedback traders indeed trade on past price changes and that the β-coefficient is positive. Informed rational speculators choose their period 2 demand as follows:

$$D_2^r = \frac{(\Phi - p_2)}{2\gamma\sigma_\theta^2} = \alpha(\Phi - p_2) \qquad (2)$$

where α is set $\frac{1}{2\gamma\sigma_\theta^2}$, γ is the risk aversion coefficient and σ_θ^2 is the variance of θ. Contrary to feedback traders but in line with informed rational speculators, a passive investor's demand is negatively related to the stock price:

$D_2^e = \alpha(\Phi = p_2)$ (3)

where α is the same as in equation (2) (De Long et al, 1990).

D4 Period 1

In period 1, informed rational speculators receive a signal ε, which gives information about the value of Φ to be $-\phi$, 0 or $+\phi$. There are two possible situations: a noiseless signal or a noisy signal. In case of a noiseless signal, there is no doubt about the value of Φ: $\varepsilon = \Phi$. When the signal is noisy and, for example, the signal ε is $+\phi$ there is a 50% probability that the value is $+\Phi$ and a 50% probability that is shows $+\phi$ but it actually is 0. Therefore, the expected value of Φ is $\frac{\phi}{2}$. The demand function of the informed rational speculator is the same as in period 2 and is equal to equation (2). The demand function of passive investors is:

$D_1^e = -\alpha p_1$ (4)

and for positive feedback traders the demand function is zero:

$D_1^f = 0$ (5)

since there is no past price change in this period to react on (De Long et al, 1990).

D5 Period 0

Period 0 is the reference period and no signal is received by the investors resulting in a price set at its fundamental value of 0. Also, there is no trading in this period and this period gives a benchmark to the positive feedback traders, so they can see the increase or decrease in prices from period 0 to 1 and from period 1 to 2 to be able to form their demand in periods 1 and 2. In period 0 and 3 there is no trading, so market clearing conditions are not necessary. For period 1 and 2, the market clearing conditions are respectively (De Long et al, 1990):

$D_1^f + \mu D_1^r + (1-\mu)D_1^e = 0$ (6)

and

$D_2^f + \mu D_2^r + (1-\mu)D_2^e = 0.$ (7)

In the next two sections, the results of a noiseless and a noisy signal are explained.

D6 Noiseless and Noisy Signals

In this section, the case of a positive demand shock $\Phi = +\phi$ is discussed only because the argument is symmetric when the demand shock is negative. When the period 2 demand shock is exactly the same as the noisy signal retrieved in period 1, i.e. a noiseless signal, then there is no uncertainty about the period 2 stock price in period 1. When there are informed rational speculators, $\mu > 0$, arbitrage leads to equal prices in both periods:

$p_1 = p_2$ (8)

and when there are no informed rational speculators, $\mu = 0$, the period 1 stock price equals 0 as the signal is ε now received by no one and thus there is no information about the value of the stock $\Phi + \theta$ in period 3 and thus:

$p_1 = 0$ (9)

Including equation (1), (2) and (3) in equation (7) yields the period 2 equilibrium equation:

$\beta p_1 + \alpha(\phi - p_2) = 0$ (10)

and combining equation (8), (9) and 10) gives:

$p_1 = p_2 = \frac{\alpha\phi}{\alpha-\beta}$ (11)

when $\mu > 0$

and

$p_1 = 0$ and $p_2 = \phi$ (12)

when $\mu = 0$.

In the situation that $\beta > \frac{\alpha}{2}$, then the stock price is further away from the fundamental value in all four periods when rational informed speculators are present compared to when they are not present.

Informed rational speculators also could receive a noisy signal. In this case the signal ε can be either $\Phi = +\phi$ or $\Phi = 0$ with equal probability. The first situation is called 2a while the second situation is called 2b. Then the market clearing conditions for period 2 are:

$\beta p_1 + \alpha(\phi - p_{2a}) = 0$ (13)

and

$\beta p_1 + \alpha(\phi - p_{2b}) = 0$ (14)

while the condition for period 1 is just:

$\mu D_2^r - \alpha(1-\mu)p_1 = 0$ (15)

with $D_2^r = \frac{p_{2a}+p_{2b}-2p_1}{\gamma(p_{2a}-p_{2b})^2}$

From equation (13), (14) and (15), the solution for the stock price in period 1 is:

$$p_1 = \frac{\phi}{2}\frac{\alpha}{\alpha-\beta}\frac{1}{1+\frac{\phi^2}{4\sigma_\theta^2}\frac{\alpha}{\alpha-\beta}\frac{1-\mu}{\mu}} \qquad (16)$$

In the special case that $\mu = 1$ or $\mu = 0$, the expression is respectively:

$$p_1 = \frac{\phi}{2}\frac{\alpha}{\alpha-\beta} \qquad (17)$$

and

$$p_1 = 0. \qquad (18)$$

When equation (13) and (14) are rewritten, the prices in period 2 are derived:

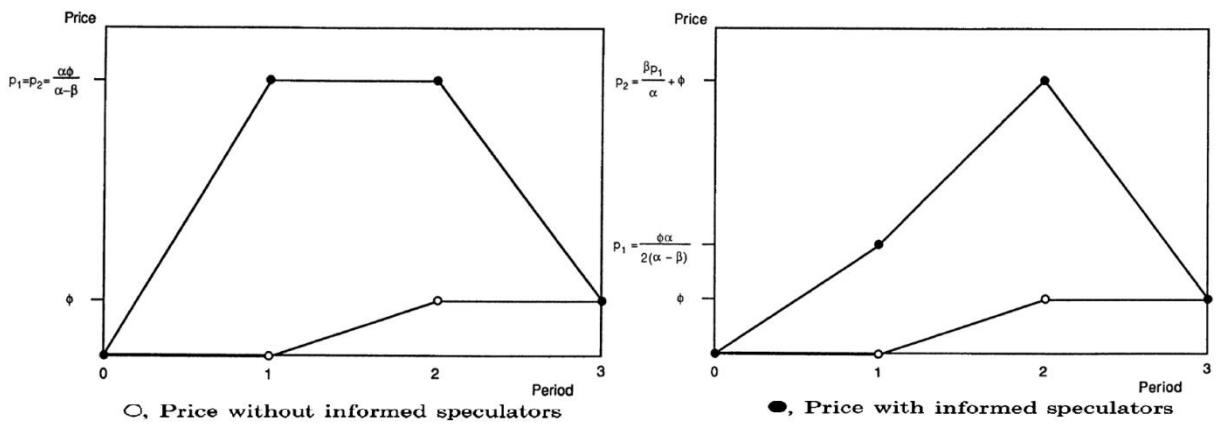
$$p_{2a} = \frac{\beta}{\alpha}p_1 + \phi \qquad (19)$$

and

$$p_{2b} = \frac{\beta}{\alpha}p_1. \qquad (20)$$

From, these equations (19) and (20) it can be seen that the period 2 deviations from the fundamental value increase consistently from period 1 as long as β is non-negative. The prices in period 1, 2 and 3 are just the same as in the noiseless case when there are no informed rational speculators, $\mu = 0$.

Figure 3: Graphical Representation of Prices vs. Periods (Left Noiseless and Right Noisy)



The equations (11), (12) and (16) until (20) show that both in the case of a noisy and noiseless signal, there is bubble creation and is, contrary to the prior literature, even more present when there are rational speculators in the market. Therefore, the area below the functions of figure 3 is higher in the case of presence of informal rational speculators. This bubble creation is due to the fact that these informal rational speculators' Φ being high in period 2 and thus demanding stock in period 1 driving up the prices above 0. This then leads to positive feedback traders raising their demand in period 2 in both a noisy and noiseless

situation. This drives up the price above its fundamental value $\frac{\phi}{2}$. In period 2, informed rational speculators short sell their stock while positive feedback traders are still demanding the stock and therefore keeping the stock price above its fundamental value. In last period, the stock price returns to its fundamental value (De Long et al, 1990).

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