Biased CEOs and the IVOL Effect: An Analysis of the Role of Target Volatility in Takeover Decisions

Author: S. Heijnen (545748)
Supervisor: A. Breaban
Erasmus School of Economics
MSc Financial Economics
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Abstract

Do gambling attitudes play a role within corporate takeover decisions? Based on previous empirical work that links idiosyncratic volatility (IVOL) to gambling, this study tests if IVOL is a determinant in US takeovers. Robust results show that “risky” firms are less likely to be taken over during the years 2007 to 2019. Proxies are conducted to track for overconfidence and gambling preferences among acquiring CEOs. No conclusive evidence is found to support that these biased CEOs prefer “risky” targets.

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Introduction

Mergers and acquisitions are among the most significant events in the lifespan of a firm. They involve the largest corporate investment decisions and have high impact on both sellers and acquirers. Transactions from 2007 to 2020 including public US targets and acquirers had a median transaction value of close to one billion dollars and value on average over two billion[1]. A continuous topic of discussion among economists has been what drives these mergers and acquisitions. Most drivers are derivatives of the pursuit of profit maximization or are categorized among behavioral views examining the managerial role. Examples of these motivations are efficiency, market power, synergies, market timing and managerial entrenchment. While these constructs seem to be 'timeless', much is still unknown about the underlying mechanisms. Perhaps leading this list of unknowns is the following question: which firms are most likely to be involved in M&A activity? This research examines this question and specifically investigates the role of the *riskiness* of takeover targets - measured by idiosyncratic volatility – in explaining variation in merger outcomes.

Idiosyncratic risk, also known as idiosyncratic volatility or IVOL for short, is broadly defined as a stock's residual volatility after controlling for the exposure to systematic risk factors like the stock market's return (Fong, 2014). The traditional notion is that investors can diversify to mitigate this risk and consequently, many pricing models do not account for IVOL. One therefore might expect that low IVOL targets are preferred over high IVOL targets, in order to limit the exposure to negative payoffs. However, Schneider & Spalt (2017) find that "riskier" target firms - firms with high IVOL - are more likely to be taken over. As for the effect this has on shareholder value, they find that deals involving risky targets are worse for both bidders and the combined bidder and target value, and bidders acquiring risky targets have lower future accounting returns. To justify this value destructive behavior of acquiring firms, Schneider & Spalt (2017) examine the role of acquiring CEOs. Specifically, they propose a narrative where biased CEOs are attracted to the IVOL of takeover targets. While excessive risk-taking behavior is often linked to overconfidence, Schneider & Spalt (2017) argue that a different CEO bias functions as central underlying mechanism: a CEOs tendency to gamble.

Gambling is well documented when related to decisions made by individuals (e.g., Friedman & Savage, 1948; Kahneman & Tversky, 1979, 1992; Bailey, Kumar, & Ng, 2011).

[1] Numbers are based on the dataset used in this research

However, in the realm of corporate decision making, the paper of Schneider & Spalt (2017) is the first.

This paper intends to follow-up on these findings. First, the following research question will be analyzed:

Are "risky" US firms, measured by IVOL, more likely to be taken over during the years 2007 – 2019?

By answering this question, important gaps will be filled that currently exist in the literature. First, methodological tradeoffs faced by Schneider & Spalt (2017) will be analyzed and weighed against current statistical developments to validate this new area in behavioral finance. Second, it will fill the time gap that is unexplored after 2008. Third, it provides further research which is needed to achieve conformity about the existence of gambling effects in corporate decision making.

In order to determine whether IVOL influences a firm's takeover probability, an acquisition likelihood model with logistic regressions is conducted. Finding the same positive relationship as Schneider & Spalt (2017) do would be interesting as it is well-documented that for public companies, IVOL negatively correlates with average returns (e.g., Ang, Hodrick, Xing, & Zhang, 2006; Baker & Haugen, 2012).

In the subsequent part of the research, two CEO biases that potentially relate to IVOL are being examined by answering the second research question:

Are biased CEOs, either in the form of overconfidence or gambling attitudes, drawn to target risk?

This section marks a separation in methodology of that of Schneider & Spalt (2017). Specifically, two different approaches are adopted. First, a new model is introduced where IVOL functions as dependent variable and deal characteristics such as proxies for biased managers are directly tested for a relationship with IVOL. To my knowledge, this is the first research that regresses target volatility on deal and acquirer characteristics in order to track for possible effects of behavioral biases. By doing this, my results will provide greater clarity on the economic nature of the relationship between firm riskiness and corporate takeover decisions.

Second, the decision of Schneider & Spalt (2017) to reject overconfidence as a potential CEO bias related to IVOL is reviewed, after an analysis of the relevant literature reveals that overconfidence and gambling attitudes heavily intertwine. This results in an adjustment in methodology, where instead of using gambling as central topic, overconfidence and gambling are equally considered as CEO biases potentially related to IVOL.

The sample period of 2007 – 2019 is deliberately chosen so that, next to filling the time gap in the literature, specific CEO compensation data can be used. This data became public as a result of a change in US reporting requirement from 2006 onwards and allows for the construction of a more accurate proxy for overconfidence.

Literature review

To understand the theories that formed the basis for this research, this section summarizes the literary background of the three main topics: takeovers, gambling, and IVOL. Specifically, the theory on merger motives, developments in takeover prediction models, and the existing literature on IVOL will be discussed. Afterwards, the results, implications, and issues of the research of Schneider & Spalt (2017) are examined. Lastly, the main hypothesis are outlined.

Merger motives

Throughout the decades event studies examining the effects of M&A have been largely elusive in their outcomes: whether value is created, and if so to whom the wealth is distributed. Those trends that are coherent indicate that gains predominantly are accrued by the shareholders of target firms and that the net wealth effect for acquirers, which combines short and long-term returns, is zero or negative (Loughran & Vijh, 1997; Rau & Vermaelen, 1998; Andrade, Mitchell, & Stafford, 2001; Bruner, 2002). With evidence indicating that acquisitions do not create wealth for bidding firms, the question arises what acquirers intend to achieve in merger activity. Despite extensive research, these motivations are still all but conclusive. Yet, for this research it is important to understand what we know about these motives as it provides insights to which characteristics acquirers are looking for in a target. The following section discusses the different existing theories.

Value enhancement

At the most general level, merger motives can be categorized as either value-enhancing or not value-enhancing. In principle, value enhancing mergers are undertaken to benefit from the synergy that arises from combining the physical operations of the two firms (Bradley, Desai, & Kim (1988). Specific considerations include economies of scale, increasing market power, taxes, responses to industry shocks, and exploiting asymmetric information between the acquiring and target firm.

Macroeconomic phenomena such as industry shocks are also responsible for merger waves. Such events increase the general level of uncertainty, subsequently increasing the dispersion of asset valuation. Consequently, this increases the likelihood of a takeover (Gort, 1969). Jovanovic and Rousseau (2002) expand this theory and show that technological shocks trigger asset reallocation from low-growth prospects firms to firms with high-growth prospects. They find that such events have been responsible for all past merger waves except for the 1960s wave, which was driven by consolidation motives.

Market timing

Motives that are not value-enhancing can be divided into three main theories: market timing, agency problems, and hubris. The market timing theory is predominantly driven on the premise that acquisitions are stock market driven. In 2003, Shleifer & Vishny initiated this postulation by showing that overvalued firms use their stock to acquire relatively undervalued targets. Since then, the hypothesis has found empirical support like that of Dong, Hirshleifer, Richardson, & Teoh (2006), who use data on US mergers from 1978 to 2000 to show that on average, acquirers are more overvalued than their targets. Also, these overvalued acquirers are more likely to pay with stock and have lower post-merger abnormal returns.

Agency problems

Agency problems in M&A take place between self-interested managers of both target and acquiring firms, and their shareholders. Instead of maximizing shareholder wealth, managers often are inclined to serve their own interest, sacrificing the long-term horizon cash flows. One category of agency problems is merger-oriented managers who pursue excessive growth and high-risk investments motivated by their limited liability protection and convex compensation scheme (Penrose, 1959; Malatesta, 1983; Morck, Shleifer, & Vishny, 1990). Another category is managers looking to reduce their human capital risk through diversification (Amihud & Lev, 1981), or looking to avoid acquisitions that reduce discretionary compensation (Jensen, 1986; Stulz, 1990). Morck et al. (1990) find that many M&As are driven by managerial objectives where maximizing firm size is preferred over firm value. Harford and Li (2007) find that in general the acquiring CEO benefits from the takeover, even when shareholders value is destroyed. The empirical literature shows consensus in that when mergers are motivated by agency problems, they are generally value decreasing for the acquiring shareholders (e.g., Malatesta, 1983; Alexandridis, Mavrovitis, & Travlos, 2012).

Hubris

Apart from agency problems there is a second merger motive that is managerial related: the exaggerated overconfidence of acquiring CEOs, better known as hubris. Introduced by Roll (1986) as central explanation for corporate takeovers, its biggest differentiator from agency theory is that the manager wrongly believes he or she is maximizing firm value, thus there is no conflict of interest. Roll (1986) states that individual decision makers of bidding firms are often infected with hubris and pay too much for their targets and engage in merger activity even when synergies are absent. This hypothesis is well supported, among others by Berkovitch & Narayanan (1993) and Barnes (1998), who find hubris as the dominant motivation for M&A. Others report that measures of CEO hubris are highly correlated with the premium and profitability of takeovers (e.g., Hayward & Hambrick, 1997; Graham, Harvey, & Puri, 2013; Schneider & Spalt, 2016). Like hubris, gambling attitudes are also a form of a managerial bias and my paper is therefore a product of a research area that started with Roll (1986).

Simultaneous motives

While most research isolates a specific merger motive to find empirical evidence, one motivation does not necessarily have to rule out the other. There is ample evidence suggesting mergers have managerial motivation while simultaneously supporting shareholder goals such as long run survival, a more stable operating performance or long-term growths (Amihud & Lev, 1981; Donaldson & Lorsch, 1983; Shleifer & Vishny, 1989). In some mergers, agency, hubris, and synergistic motivations simultaneously exist (Berkovitch & Narayanan, 1993). In addition, a lack of wealth gains during merger announcements periods in Japan indicates that conflicting merger considerations might be involved (Mehrotra, van Schaik, Spronk, & Steenbeek, 2011).

Predicting targets

This paper will analyze whether "risky" firms are more likely to be taken over. This form of identifying takeover targets on specific characteristics is also used in an area which has triggered considerable theoretical efforts: the prediction of future takeover targets. The statistical procedures this paper will incorporate are therefore for the most part rooted in the literature on predicting takeover targets. The following section will discuss the developments in this area, as well as elaborate on two fundamental characteristics of the data analysis I will conduct in this paper: the state-based sampling procedure and the logistic regression model.

At the root of predicting corporate events lies the assumption that events such as takeovers are not driven by randomness but occur as a consequence of observable factors. The use of this notion in the financial realm was documented as early as 1755, when Alexander Webster laid out a scheme to provide annuities for the widows of Scottish clergymen and ministers (Youngson, 1961). Inspired by the then recent discovery of the Law of Large Numbers by Jacob Bernouilli, and with the help of Colin Maclaurin and Robert Wallace, he used statistics to predict the yearly death rate among clergyman, the average amount of widows left behind, and how many years these widows outlived their husbands. This scheme developed into the Widows' Fund, today known as the life insurance and pensions company Scottish Widows (Ferguson, 2008).

The current literature on predicting takeovers is inspired, perhaps as spill-over effect, by another key corporate restructuring event: bankruptcies. Throughout the 20th century, a growing interest emerged among policy makers, investors and management to understand the determinants of bankruptcy and to quantify the risk that a firm might become insolvent in the future. This attracted the attention of the academic field among which Altman (1968), who constructed the first successful statistical model that accurately predicted the probability of corporate bankruptcy using key accounting variables, such as total assets (TA), earnings before interest and taxes (EBIT), retained earnings (RE) and market value of equity (MV). His model used the Multiple Discriminant Analysis (MDA) technique, which became widely celebrated and is used by many other academics (e.g., Simkowitz & Monroe, 1971; Stevens, 1973; Rege, 1984).

Logit regression

The first papers identifying takeover targets used univariate analyses. These test the relationship between targets and non-target, one independent variable at a time (e.g., Bomford, 1968; Gort, 1969). The introduction of Altman's MDA technique meant a major change in this process, as it enabled to examine all independent variables as well as their interaction, in one go. However useful, the MDA has a number of limitations when applied in an acquisition likelihood model. Ohlson (1980) points out that the MDA assumes absence of multicollinearity, which ignores the fact that firm characteristics frequently interact with each other. Additionally, the MDA has interpretation difficulties. Instead of modelling choice, the test functions as a classification model. This complicates the interpretation of the output as the individual coefficients do not reflect their relative importance for determining the acquisition likelihood.

In his paper, Ohlson (1980) proposes the use of a logistic regression. The logit model solves the violation problem of statistical requirements by not assuming normal distributed errors of the independent variables. It also allows for comparison of the relative contribution of the independent variables in explaining the dependent variable, while taking into account unmeasurable factors. His paper laid the basis for what is still the conventional procedure in analyzing takeover targets. Dietrich & Sorensen (1984) were one of the first to use this method for acquisitions. Their analysis used US data from 1969 to 1973 and reported an overall classification accuracy of 90%. My data analysis will use this logistic regression to establish if a set of variables, among which IVOL, significantly impacts a merger outcome.

State based sampling

As acquisitions are rare events, predicting a target is like 'searching for a needle in a haystack' (Palepu, 1986). Consequently, random samples of these populations lead to a few target firms against a very high percentage of non-target firms. Such models have low 'information content' and their parameters are relatively imprecise (Simkowitz & Monroe, 1971). To solve this issue, most studies use state-based sampling[2], a procedure where an equal number of targets and non-targets is selected. Cosslett (1981) shows through an extensive simulation analysis that this sample design usually is close-to-optimum.

For the sake of completeness, I should mention that the last major shift in the literature on predicting corporate events was introduced by Palepu (1986), which provides a comprehensive critique of the preceding articles which he argues use '...inconsistent and asymptotically biased estimates of the model parameters and hence biased estimates of the acquisition probability' (p. 7). In his seminal paper he argues that many studies use state-based sampling while simultaneously using procedures that assume random sampling. He proposes modified estimators that recognize the non-random characteristic of the sample. These estimators and thus his criticism are irrelevant to my data analysis, as my interest is to find characteristics on

[2] Also referred to in literature as choice-based sampling / hold-out sampling / matched-sampling / matching criterion approach

which target firms significantly differ from non-targets, as opposed to developing a classification model that can predict M&A target firms.

Table 1 provides an overview of the most notable studies throughout the years, performed in the US.

TABLE 1
Key studies

This table represents the key studies in predicting takeover targets, performed in the US. The study of Schneider and Spalt (2017) is included for comparison.

No	Year	Study	Time window	Analysis	Dataset
1	(1971)	Simkowitz & Monroe	1968	MDA, State-based sample	23 targets and 25 non-targets [Listed at: NYSE]
2	(1973)	Stevens	1966 - 1968	MDA, State-based sample	40 targets and 40 non-targets [Listed at: NYSE or AMEX]
3	(1982)	Harris, Steward, Guilkey & Carleton	1974 - 1977	Univariate Probit regression	106 targets and 1200 non-targets [Listed at: NYSE or AMEX]
4	(1984)	Dietrich & Sorensen	1969 - 1973	Logit regression, State-based sample	30 targets and 60 non-targets [Listed at: NYSE or AMEX]
5	(1985)	Hasbrouck	1976 - 1982	Logit regression (matched on SIC codes)	86 targets and 172 non-targets [Listed at: NYSE or AMEX]
6	(1986)	Palepu	1971 - 1979	Logit regression , State-based sample	163 targets and 256 non-targets [Listed at: NYSE or AMEX]
7	(1992)	Ambrose & Megginson	1981 - 1986	Logit regression , State-based sample	169 targets and 267 non-targets [Listed at: NYSE or AMEX]
8	(2000)	Sorensen	1996	Logit regression, Factor Analysis	286 targets, 217 non-targets [Listed at: NYSE or AMEX]
9	(2003)	Espahbodi & Espahbodi	1993 - 1997	Logit regression, MDA	133 targets and 385 non-targets [Listed at: NYSE or AMEX]
10	(2009)	Cremers, Nair & John	1981 - 2004	Logit regression	2,813 targets, 80,939 non-targets
11	(2011)	Sokolyk	1990 - 2004	Logit regression	558 targets and 2,231 non-targets [Listed at: NYSE or AMEX]
12	(2012)	Shafer	1996 - 2010	Logit regression	824 targets, 5,539,654 non-target-days [Listed at: NYSE or AMEX]
13	(2017)	Scheider & Spalt	1987 - 2008	Linear regression	3,538 targets and 73,911 non-target

IVOL

IVOL as predictor

Over the years, many key financial ratios have been used when predicting acquisition likelihood. The most established ratios are age, growth, leverage, momentum, industry and takeover defenses. The recent paper of Schneider & Spalt (2017) adds idiosyncratic volatility

(IVOL) to that list. While the relation between IVOL and M&A activity is fairly new, the research on IVOL's nature and predictive ability has received considerable attention.

In financial economics it is common understanding that investors seek reward for bearing risk. Pricing models try to decompose the returns of securities into underlying risk factors. As groundwork in this field, the CAPM, or Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965) postulates that risk is solely reflected through beta, and the trade-off between risk and expected return follows a linear relationship. Being the first to test CAPM, Douglas (1969) already rejects the model by showing that the average returns of individual stocks are positively correlated with the residual variance of the model. Later, Fama & French (1993, 1996) developed a three-factor alternative to the CAPM, which significantly reduced the portion of return that could not be explained by the model's risk-factors. Since, many academics have studied the residual variance that is the IVOL, in search for factors that might (partially) explain it.

Studies focusing on the US market find a correlation between idiosyncratic risk and stock market characteristics. Durnev, Morck, Yeung, & Zarowin (2003) find that stock price informativeness, a measure for the ability of financial markets to aggregate information, positively correlates with idiosyncratic risk. Durnev, Morck, & Yeung (2004) further show that high IVOL will lead to efficient capital allocation and increased external financing. They argue that idiosyncratic risk attracts informed arbitrageurs looking to trade on their private information, leading to prices that follow fundamental value more accurately. The removed discrepancy between fundamental value and the market cap reduces information asymmetry problems that hinder external financing and capital spending decisions. Ferreira and Laux (2007) find evidence that governance mechanisms designed to limit the openness to takeover offers are correlated with idiosyncratic risk. They argue that these mechanisms stimulate the accumulation of, and trading on, private information which results in more firm-specific information being processed into the stock price. From an international perspective it is found that idiosyncratic volatility varies by country depending on their governing mechanisms. Also, evidence exists that relates property rights protection and accounting transparency to increased idiosyncratic risk on domestic stock returns (Morck et al. 2000; Jin & Myers, 2006; Wurgler, 2000).

Merton (1987) predicts a positive relation between IVOL and realized returns, following the intuitive reasoning that investors should be rewarded for risk. However, Ang et al. (2006) show that IVOL is priced in the "wrong way". Their study on IVOL examines stocks traded on AMEX, NASDAQ, and NYSE from 1963 to 2001. They use a two-factor pricing model with market return and stochastic volatility and subsequently create quintile portfolios sorted on IVOL. They document that high IVOL portfolios have a lower average return (of around 12% per year), than low quintile portfolios. The results remain significant after controlling for relevant firm-specific variables including book-to-market ratio, firm size, leverage, and trading volume. Using the three-factor model of Fama & French worsens the underperformance to around 16%. Evidence in support of the IVOL anomaly is found by various studies, including for time periods up until 2011 (Baker & Haugen, 2012; Fong, 2013; Conrad, Kapadia, & Xing, 2014).

IVOL, gambling, and merger outcome

Schneider & Spalt (2017) are the first to centralize IVOL in the realm of acquisitions. They find that the idiosyncratic volatility of a target functions as a central variable explaining variation in merger outcomes in the period 1987 to 2008. Using a sample of nearly 74,000 US companies and IVOL as proxy for firm riskiness, they find that targets categorized as riskier have a higher likelihood of being taken over. They also find that deals involving "risky" targets are worse for both bidders and the combined bidder and target value, and bidders acquiring risky targets have lower future accounting returns.

These results of underperforming "risky" takeovers are in line with the IVOL anomaly found by Ang et al. (2006). In fact, Schneider and Spalt (2017) use a similar behavioral narrative as proposed by Kumar (2009) to explain the IVOL anomaly.

Baker and Wurgler (2007) write that investors overvalue speculative stocks as a result of investor sentiment. They use volatility as a proxy for a stock's degree of speculation, which includes both market- and idiosyncratic volatility. Evidence shows that this sentiment strongly relates to gambling. Barber, Lee, Liu, & Odean (2009) document the introduction of a government sponsored lottery in Taiwan and find that it reduced stock trading activity with about a quarter. Kumar (2009) is the first to use this gambling tendency among investors as explanation for the IVOL anomaly. Like low prices and high idiosyncratic skewness, high IVOL is a driving characteristic of stocks that have lottery-like payoffs (Kumar, 2009). Analogous to real lotteries, these stocks provide potentially enormous rewards while having negative average returns. Kumar (2009) shows that investors with a tendency to gamble are more likely to hold, and are willing to pay a premium for, high IVOL stocks.

Schneider and Spalt (2017) extend this theory by shifting the focus from individual investors to bidding CEOs. In their argumentation, biased managers perceive high IVOL targets as investment options with lottery-like payoffs. To managers who focus too much on upside potential a higher volatility means a more attractive bet. As a result, Schneider and Spalt (2017) find that "risky" targets have a higher likelihood of being taken over and are more likely to destroy value. These findings provide the basis for my research and lead to the formation of the following two hypothesis:

Hypothesis 1: IVOL is a positive determinant of acquisition likelihood.
Hypothesis 2: CEO gambling attitudes positively impact the IVOL of takeover targets.

Gambling versus overconfidence

A skewed focus on upside potential is reminiscent of another CEO bias: overconfidence. Corporate overconfidence is one of the well documented motives for mergers, and is attributed to CEOs, because they widely dominate the M&A decisions (Graham, Harvey, & Puri, 2015). The evidence on the effect of overconfidence is overwhelming; overconfident managers tend to do more takeovers, which are on average more value destructing (Malmendier & Tate, 2008). Schneider & Spalt (2017) find similar results; gambling-oriented managers do more *risky* takeovers, which are on average more value destructing. Schneider and Spalt (2017) confirm the "similar flavors" between the two, however emphasize that overconfidence and gambling differ in their implications on corporate behavior through the following example: "under the overconfidence story, a CEO would place too high a probability on the best-case scenario in a DCF spreadsheet because she believes she has special skill in making the firm reach that state. Under the gambling story, a CEO would place too high a probability on that scenario because the payoff associated with the best-case is a particularly attractive prize to win" (p. 24).
They isolate the gambling effect by constructing an overconfidence proxy and multiple proxies for a CEO's propensity to gamble, among which his age, religious background, and the firm's recent performance. They conclude that only gambling can be responsible for the relationship between IVOL and variation in merger activity. However, their proxies are not yet recognized in the literature and an analysis of all other literature on this topic lead to the conclusion that overconfidence and the tendency to gamble intimately relate.

Both seem to find common ground in risk-taking behavior. Gambling is defined as taking a risky action in the hope of a desired outcome. One of the main associations of overconfidence is excessive risk taking, corresponding to a higher likeliness to accept risk for which there is no apparent reward (Dorn & Huberman, 2005; Nosic & Weber, 2010). In fact, individuals showing a tendency towards lottery-type stocks are the same people who exhibit a high propensity to trade (Bailey et al. 2011). The latter is widely known as the main characteristic of overconfidence among investors (e.g., Barber & Odean, 2001; Glaser & Weber, 2007; Daniel & Hirschleifer, 2015). Therefore, if a high IVOL investment would represent risk-taking behavior, theory predicts a positive relationship between IVOL and both overconfidence and gambling behavior.

Not only the theoretical literature supports a positive relationship between overconfidence and risky takeovers, the argumentation of Schneider & Spalt (2017) also includes a flaw that tightens the connection between overconfidence and gambling. In their paper, they conclude/ with the implications of the gambling hypothesis: "[Well-meaning CEOs] go with their guts which leads them to focus too much on upside potential." (p. 34). Their choice of words is derived from a previous section where they state: "almost 50% of CEOs in a survey [of the working paper] by Graham, Harvey, and Puri (2010) say that "gut feeling" is either important or very important for their M&A decisions" (p. 3). However, the concerned paper of Graham et al. (2010) makes no mentioning of this statement in any way. Instead, "gut feeling" is used in a different paper by Graham, Harvey, and Puri (2015) about capital allocation decisions of CEOs and CFOs. Here, gut feeling is not explained as a central identifier for M&A decisions, but as an important factor affecting the allocation of capital throughout divisions. In fact, the article which Schneider & Spalt (2017) refer to is about CEO attitudes and corporate actions, and links CEO behavior with optimism. And based on the self-serving attribution literature of the renowned paper of Malmendier & Tate (2005), optimism is also referred to as overconfidence.

Lacking sufficient empirical evidence, the distinction between overconfidence and gambling in the corporate atmosphere currently seems to be based on semantics. As attempt to provide some clarity in this discussion, the distinction between overconfident behavior and gambling behavior might be best described by dividing them into two different forms of optimism: (1) overconfidence as internal optimism regarding personal skills, and (2) gambling as external optimism regarding the future states of the world.

In conclusion, it is clear that overconfidence and the tendency to gamble heavily relate. For Schneider and Spalt (2017) the distinction is quite important as it determines the narrative of their paper. However, one could argue that establishing consensus about whether any bias can cause CEOs to be attracted towards risky takeover targets should be the first concern. This paper therefore equally considers overconfidence and gambling as potential CEO biases that can explain risky takeover behavior among CEOs. Taking the evidence into account, the final hypothesis is formed.

Hypothesis 3: CEO overconfidence positively impacts the IVOL of takeover targets.

Methodology

This study has two goals. Firstly, it examines if the idiosyncratic volatility of targets defers from non-targets and how this influences acquisition likelihood. Secondly, it aims to provide clarity on the economic nature of the relationship where specifically, CEO overconfidence and CEO gambling propensity are being examined.

This section discusses the analysis and data used in the empirical research. The rationale behind the use of a multivariate regression in the acquisition likelihood model is discussed. Afterwards, the data collection and sample construction process is described for the different sample strategies. The different samples consist of the sample of the target population, the sample of the entire US public firm population needed for the yearly takeover probabilities, and the state-based sample, which is needed to perform the multivariate regression on the differences between targets and non-targets. Lastly, the used variables are discussed, which include IVOL, firm characteristics and the proxies for overconfidence and gambling.

Acquisition likelihood model

This research will use the logistic probability model as applied by Ohlson (1980). It is preferred over the MDA and as Table 1 shows, in line with the methodological trends in the literature. In this regard, this study deviates from the methodology of Schneider & Spalt (2017). They use a linear probability model which is similar to an ordinary linear regression, but with a discrete dependent variable. It closely relates to the MDA. As Ladd (1966) puts it: “[they] start from quite different places, but end up at nearly the same place” (p. 875). The literature deems the linear probability model inferior to the MDA, mainly because it heavily depends on the false assumption that residuals are approximately normally distributed. Instead of a normal distribution, the error term follows the same distribution as the dependent variable: a binary one (either a firm is acquired, or it is not). Schneider & Spalt’s choice is therefore rather noticeable. For reasons of comparability, Appendix A includes a regression estimated by a linear probability model.

Unlike the linear probability model, the logistic probability model transforms the regression so that the fitted probabilities fall within the logical bounds of 0 and 1. Two major reasons for its dominant use in the literature are: (1) the regression is not required to meet statistical assumptions; (2) the statistical tests are straightforward and include non-linear effects (Hair, Black, Babin, Anderson, & Tatham, 2006). The relationship between a firm's characteristics and its takeover probability is specified by the following cumulative logistic function:

$$Logit(P_{it}) = Ln\left(\frac{P_{it}}{1-P_{it}}\right) = \beta x_{it} \tag{1}$$

P_{it} represents the probability that the firm *i* will be acquired at time *t*, x_{it} is a vector of pre-specified variables. This vector consists a chosen combination of independent variables, which are displayed in Table 4 and further discussed in the section Variables. From the data, the unknown coefficients β_i are estimated using the maximum log-likelihood method:

$$l(\beta) = \sum_{i=1}^{N}\{y_i \ln(P_{it}) + (1 - y_i)\ln(1 - P_{it})\} \tag{2}$$

The division $\frac{P_{it}}{1-P_{it}}$ is referred to as the odds ratio, where ln implies the logit transformation. P_{it} can be computed as the inverse of the logistical function:

$$P_{it} = Logit(\beta x_{it}) = \frac{1}{1+e^{-\beta x_{it}}} \tag{3}$$

Sample construction

Target sample

The initial sample contains the entire population of acquisitions involving public targets and acquirers from the United States listed in the ThomsonOne database between January 1, 2007 and 31 December 2019. Following the requirements of Baker, Pan, & Wurgler (2012) deals are included if the offer price is mentioned and at least 85% of the target firm is acquired. Deals are excluded if they are classified as repurchases, rumors, recapitalizations, white-knight or target solicitations. Also, penny stocks and deals that have a deal value smaller than $1 million are excluded. This resulted in an initial sample of 1,280 firms.

Stock price data was collected via Datastream, after a comparison with CRSP showed its superior integration with ThomsonOne in this area. Stock price data and deal data were merged by generating a unique code for each firm. Around 60 observations had announcement dates in the weekend, which were moved to the nearest following trading day to ensure alignment across variables. Appendix B provides an overview of the sample amount after each restriction is applied.

Takeover population sample

The first basic indicator of the takeover probability follows Schneider & Spalt (2017) by measuring the yearly percentage of firms that is acquired. For this, the sample needs to include both the target sample described in the prior section, as well as all public US firms that have not been acquired during the time period. Collecting these 'non-target' firms has historically proved to be the source of a significant survivorship bias.

Prior research typically only collects the firms that are still operating at the end of the study period, also referred as 'live' firms (e.g., Palepu, 1986; Brar, Giamouridis, & Liodakis, 2009). As no evidence exists that delisted (liquidated/privatized/bankrupt) firms are not a potential target in the years prior to their termination, this process causes a survivorship bias that can be quite substantial[3]. This bias is problematic as this pool of 'non-target' firms is used to draw the control sample from for the acquisition likelihood model. By using the database Compustat, this research corrects for this bias. Compustat lists both live and dead firms.

For the period 01/01/2007 – 31/12/2019, all firms listed on Compustat are added to the initial sample of target firms. Again, stock pennies as well as companies with a total value of less than $1 million are excluded. Besides the targets identified by ThomsonOne, a firm from the Compustat database is classified as a target if its reason for deletion is classified as "Acquisition or Merger" (Compustat: DLRSN = 1). In such cases, the last present fiscal year is marked as a target while previous years are dropped. This is done to keep the set of control firms free from future target firms. Also, the last fiscal year of a delisted firm is dropped if Compustat reports a reason for deletion other than "Acquisition of Merger", like bankruptcy (Compustat: DLRSN = 2 / 14). Next, targets from ThomsonOne are cross-checked with the targets and non-targets of Compustat to make sure that there are no duplicates or misclassified control firms. Lastly, stocks primarily traded in countries other than the US are dropped.

To evaluate the industry division of the sample, 12 industry groupings are created for both target and non-target sample. This scheme is based on that of the North American Industry Classification System (NAICS) and the 2020 US Securities and Exchange Commission (SEC).

[3] The final dataset used in this research shows that 33% of all non-target firms is delisted during the period 01/01/2007 – 31/12/2018.

Table 2 shows a summary. It is noted that the distribution of target and non-target firms seems to follow the expected trends. For targets, financial intermediation is well overrepresented which is in line with general knowledge of the industry being one of the most common to experience takeovers. This trend started in the 1980s and was motivated by an increasingly favorable regulatory environment and technological advancements, among others (Rezaee, 2011).

Later on, in the statistical analysis, financial intermediaries (SIC code 6000-6999) are excluded. This follows the developments in the literature where most papers support exclusion because financial firms: (1) have significant different capital structures, liquidity and operations which makes them incomparable to others (Ambrose & Megginson, 1992), (2) are regulated and follow unique reporting standards which causes the interpretation of their financial ratios to differ from other firms (discussion provided by e.g., Renneboog & Trojanowski, 2007; Brar et al., 2009). In order to preserve the power of generalizability, no other industry restrictions are applied.

TABLE 2

Industry division

Table 2 shows the industry division of public US target and non-target firms during 2007 - 2019. The sample intends to follow the actual population. Non-target firms are represented by the fiscal years that they are publicly listed. For target firms, only the last fiscal year prior to the takeover is retained in the sample. Groupings are based on the North American Industry Classification System (NAICS) and the 2020 US Securities and Exchange Commission (SEC).

#	SIC Code	Industry	Targets	%	Non-target years	%
1	0100 - 0999	Agriculture, Forestry & Fishing	6	0.18	195	0.25
2	1000 - 1499	Mining & Quarrying	147	4.58	3,331	4.32
3	1500 - 3999	Manufacturing	930	31.27	21,278	27.61
4	4000 - 4499	Electricity, Gas & Water	22	0.72	1,125	1.46
5	4500 - 4999	Construction	204	6.43	5,662	7.35
6	5000 - 5499	Wholesale & Retail	76	2.39	1,989	2.58
7	5500 - 5999	Hotels & Restaurants	90	2.60	2,219	2.88
8	6000 - 6999	Financial Intermediation	1,009	33.66	32,318	41.93
9	7000 - 7499	Real Estate & Business Services	414	12.94	5,942	7.71
10	7500 - 7999	Public admin. & Defence	28	0.95	735	0.95
11	8000 - 8499	Education & Training	66	2.11	1,084	1.41
12	8500 - 9999	Social work, Health & Other Services	75	2.16	1,201	1.56
Total			3,067	100.00	77,079	100.00

Sample robustness test

The Compustat database is compared with that of Reuters Datastream to evaluate which one resembles the true firm population more accurately. Standard & Poor's Compustat North America claims to have the most complete database of US firms. However, research indicates that after the year 1998, Datastream covers more US firms than Compustat (Ulbricht & Weiner, 2005). Public US firms are collected through the Datastream constituent lists FAMERA – FAMERZ (a list for each letter of the alphabet) and DEADUS1 – DEADUS12. These lists provide all 'live' equities currently trading and all equities that are no longer traded in the US, respectively. First, the live firms are compared. After controlling for our sample period, the lists shows 10,646 active firms, which is slightly higher than the 9,024 active US firms collected from Compustat. However, closer inspection shows that the list of Datastream also includes firms registered in Mexico or Canada.

The constituent dead list resulted in 8,142 dead firms previously trading on the US market in the sample period, significantly higher than the final 4,443 dead US firms collected from Compustat. This time, analysis of the list shows that many observations consist of different asset classes of the same firm, as well as companies traded in the US but headquartered somewhere else. After the appropriate adjustments Datastream no longer shows superior data availability, which justifies the use of Compustat as database for the acquisition likelihood model.

State-based sample

The unbiased approach to analyze characteristics on which targets differ from non-targets would be to use a sample that comprises the total population. This is what Schneider & Spalt (2017) aim for in their study. Their efforts to follow the actual population as closely as possible results in a sample of 74,000 firm years over the years 1987 – 2007. Analyzing similar amounts of firms including the calculation of their respective IVOL is outside the scope of this research. Instead, this paper uses state-based sampling. This is a sample process that results in a target group and a non-target group of a similar size by reducing the non-targets to approximately level the number of targets. It is the leading sampling method among papers in this field (see Table 1). While the target group comprises the total population of target firms in the sample period, reducing the non-targets can be done in various ways. Some papers draw non-target firms randomly (Palepu, 1986; Brar et al., 2009). This research will apply a process where individual target firm are matched with a non-target firm based on year, industry, and size.

Matching on size controls for the consistently observed fact that small firms are more likely than large firms to be taken over (Bartley & Boardman, 1986). Matching on industry controls for merger waves. Finally, years controls for periods of heightened takeover activity. Bartley & Boardman (1990) support this method, although they argue that matching in any form is arbitrary when predicting targets, because there is no theoretical justification for the matching criterion. However, the objective of this paper is to examine the statistical significance of causal variables instead of creating a classification model that predicts targets. For this purpose, Bartley & Boardman (1990) argue the proposed matching approach is appropriate.

The takeover population sample is used as initial pool. SIC codes are used to match for industry. Fiscal years of non-target firms are matched on the last fiscal year prior to the target's announcement date. Total assets are used to match on size, with the smallest difference being chosen and with maximum bounds set on 75% to 125% of total assets of the target. Initially, for every target the five best fitting non-targets are kept, which are checked for accounting and three-year stock price data availability.

The literature deals with outliers in different ways. Powel (2001) removes them, while others modify them through a process called winsorizing (e.g., Baker et al., 2012; Schneider & Spalt, 2017). These methods are criticized, perhaps most famously by Tukey (1960) who says such methods are: "forgetting that the distribution relevant to statistical practice is that of the values actually provided and not of the values which ought to have been provided" (p. 478). To avoid using these "inappropriate" (Tukey, 1960) actions, while ascertaining that the tests are reliable, robust regression will be performed in Stata. In addition, tests are run with removed and winsorized outliers. The results are similar and provided in Table 4 and Appendix A.

Variables

IVOL

Like Schneider & Spalt (2017), I use the riskiness of a target firm as the central variable of this paper, proxied by the idiosyncratic volatility or IVOL for short. Throughout the research it is interchangeably referred to as "target risk" or "target volatility". Following Ang et al. (2011) and Schneider & Spalt (2017), IVOL is defined on the basis of the standard deviation of the unexplained portion of the Fama & French (1993) three-factor model. For each target firm i, residuals are estimated using a three-year period of daily data ending in month $t-2$ for an announcement in month t. The regression is:

$$R_{i,d} - rf_d = \alpha_i + \beta_i MKT_d + \gamma_i SMB_d + \theta_i HML_d + \varepsilon_{i,d} \quad (4)$$

R represents the return of stock i, and subscript d denotes a particular day. The risk-free rate r_f (one-month T-bill rate), the market's excess return index MKT, and the factors Small-minus-Big (SMB) and High-minus-Low (MKT) are obtained from Kenneth French's website. The estimate of the IVOL of firm *i* is then defined as the square root of the variance of the regression residual:

$$IVOL_{i,t} = \sqrt{\frac{\sum_{k=1}^{n}(\varepsilon_{k,i,d}^{2})}{n}} \tag{5}$$

Later in this research the annualized IVOL will be used, which is computed by multiplying IVOL with the square root of 250, a proxy for the amount of yearly trading days.

$$Annual\ IVOL_i = \sqrt{250} \times IVOL_{i,t} \tag{6}$$

To check if the results are method dependent, additional regressions are run using a one-year window and using the Fama & French (2015) five-factor model, which adds the factors Robust-minus-Weak (RMW) and Conservative-minus-Aggressive (CMA) and looks as follows:

$$R_{i,d} - rf_d = \alpha_i + \beta_i MKT_d + \gamma_i SMB_d + \theta_i HML_d + \lambda_i RMW_{i,d} + \delta_i CMA_{i,d} + \varepsilon_{i,d} \tag{7}$$

Firm characteristics

In determining which firm characteristics contribute to the selection of takeover targets, the conventional method (pre-Palepu, 1986) was to start with a large number of financial-ratios and let the statistical significance of the regression decide which variables make the final cut (Simkowitz & Monroe, 1971). As Palepu (1986) points out, this arbitrary selection process leads to an overfitted model. So, even though a well-fitting regression model is important for controlling purposes and to comprehend the factors that determine a takeover, the variables I select to be included in the model are based on theoretical reasons exclusively. Apart from the IVOL hypothesis, five commonly suggested theories from the literature determine the remaining variables of the acquisition likelihood model which are discussed below. For a comprehensive description of how the variables are collected and computed, see Appendix C and Appendix D.

Inefficient management

The inefficient management theory is based on the idea that acquisitions are a means to replace managers incapable of maximizing firm value. Firms with inefficient managers are therefore likely targets (e.g., Grossman & Hart, 1980; Jensen & Ruback, 1983). Return on equity is used as a proxy for management performance.

Growth-resource mismatch

This theory proposes that firms with a mismatch between their financial resources and their growth provide opportunities for potential acquirers, making them likely target candidates. This mismatch comes in two forms: high growth, resource-poor firms and low-growth, resource rich firms. The first causes underinvestment in available growth opportunities, while the latter descends from the agency theory and predicts that the abundant free cash flows are used to fund negative NPV projects, rather than being distributed to shareholders. A dummy variable, denoted as the Growth-Resource Dummy, is constructed to account for this mismatch. It is based on the three variables sales growth, liquidity, and leverage. The dummy is one if the firm has a combination of either high sales growth-low liquidity-high leverage, or low sales growth-high liquidity-low leverage. Following Palepu (1986), the separate three variables sales growth, liquidity, and leverage are also included to find out which of the two mismatches is more dominant.

Industry disturbance

Gort (1969) argues that mergers cluster by industry as a result of economic shocks like technological advancements. Following this theory, a firm is more likely to be taken over if there has been takeover activity in its industry. A dummy variable, denoted as Industry Takeover Activity, is assigned a value of one if at least one takeover occurred in the same four-digit SIC industry in the year prior to the year of announcement.

Market-to-book

Palepu (1986) writes that firms with low market-to-book ratios are viewed as 'cheap' buys and are therefore likely takeover targets. The ratio is constructed as market value of equity over the book value of equity.

Price-earnings

Another theory based on valuation is the claim that firms with low price-earnings ratios are likely takeover candidates. This is based on the premise that the market uses the P/E ratio of the acquirer to value the earnings of the target once the takeover is finalized. This provides the opportunity to realize instant capital gains to bidders with a superior P/E ratio. The ratio is computed by dividing a firm's stock price per share at fiscal year-end with the earnings per share.

Additionally, the variables firm size and tangible assets are included to mimic the research of Schneider & Spalt (2017) for reasons of comparability. Firm size is represented by total assets, and tangible assets is measured by the book value of property, plant, and equipment over total assets.

IVOL model

The second part of this research aims to provide clarity on the economic nature of the proposed relationship. By analyzing IVOL, the goal is to find out if biased CEOs, either in the form of gambling or overconfidence, are attracted to the riskiness of target firms. This part deviates from the methodology that Schneider & Spalt (2017) use to analyze the role of gambling in takeovers. The section will look as follows. First, I will outline my critique on the methodology of Schneider & Spalt (2017) and the implemented adjustments. Thereafter, data collection and the used variables are discussed.

Critique Schneider & Spalt (2017)

The test of Schneider & Spalt (2017) to track for the existence of a gambling bias among acquiring CEOs broadly consists of two steps. First, they create proxies for gambling, among which the central ones are CEO age and religious background. Next, they measure the impact of these proxies on the "target risk effect", which is the effect IVOL has on the average cumulative abnormal return (ACAR) of the target and acquiror surrounding the takeover day. For example, they test the target risk effect of CEO age and show that the negative effect IVOL has on ACAR is stronger if a CEO is relatively young. They use this as evidence that gambling attitudes relate to IVOL.

But, as markets determine the stock price of the merging companies, the ACAR tracks for market perception. Therefore, assuming that the proxies are reliable, the test does not measure if the high IVOL takeovers are caused by gambling, but how these gambling attitudes of acquiring CEOs are valued by the market.

As this research tries to determine if CEO biases can explain the possible IVOL effect on takeovers, I propose a different test. A linear multivariate analysis will be conducted with IVOL as dependent variable and proxies for overconfidence and for gambling propensity as central explanatory variables. Provided that the proxies are reliable, the model should reveal if overconfidence or gambling contributes to the volatility of takeover targets.

Data collection

Compensation data of the acquiring CEO is needed, which is collected through Compustat ExecuComp using the CUSIP and TICKER identifier codes of the acquirer provided by ThomsonOne. These databases are not perfectly integrated, as ExecuComp requires 8-digit CUSIP codes as firm identifiers, while ThomsonOne provides 6-digit CUSIP codes. Database CRSP provides a tool to convert the CUSIP codes, however this method resulted in significant data loss. Instead, the Datastream Codes of acquiring firms provided by ThomsonOne are used to obtain 9-digit CUSIP codes from Datastream. Subsequently, the last digit of each string is removed to obtain the necessary 8-digit code. Variables containing executive/company combination identifiers, the date a CEO started, and the date a CEO left, provide the possibility to drop the CEOs that are not employed at the year of announcement. Also, CEOs are dropped if their start date is unknown. The remaining CEO compensation data from ExecuComp is merged with the ThomsonOne deal and IVOL data. Of the initial sample of 606 takeovers, acquirer CEO data is collected of 165.

Variables

Overconfidence

Overconfidence is the prominent alternative CEO-based bias that has a potential role in the relationship between takeovers and target risk. In contrast to gambling, it has methods of measuring its existence that are widely accepted in the literature. A proxy for overconfidence will therefore be one of the central variables in the regression. Like Schneider & Spalt (2017), the Holder67 measure is constructed, which is one of the most renowned quantitative proxies for overconfidence and was introduced by Malmendier & Tate (2005, 2008). It defines CEOs as overconfident if they hold vested options in their company that are at least 67% in the money. In their paper, Malmendier & Tate (2008) present the theoretical reasoning behind it. Unlike regular option-holders, CEOs have a great exposure to idiosyncratic risk of their own firm in the form of their allocated human capital. Therefore, the marginal costs of idiosyncratic risk from holding the compensational options exceeds the value of the option, if it is vested and sufficiently in the money. In such a case, a rational risk-averse manager would exercise his or her stock options. Malmendier & Tate (2008) argue that CEOs who retain their options do this because they overestimate the future performance of the firm, a bias they ascribe to overconfidence.

A problem in the CEO overconfidence literature has been the lack of data. Malmendier & Tate (2005, 2008) possessed private detailed option information from 1980 to 1994. Data on expiration dates, grant dates, and exercise prices allowed them to calculate the "moneyness" of an option which is necessary for the Holder67 measure. In order to compensate for the lack of publicly available data, many scholars calculated this "moneyness" by estimating the average exercise price of the aggregated option portfolios of CEOs (Campbell et al., 2011; Hirschleifer et al., 2012; Schneider & Spalt, 2017). Not only do these estimations misrepresent the actual moneyness, Malmendier & Tate (2015) also argue that estimating the average moneyness leads to confounding factors.

A change in reporting requirements (specifically, account rule FAS 123R in form DEF 14A) that took effect in 2006 obliged firms to include individual option package data on CEO option holdings in their financial statements. The time period of this research is therefore deliberately chosen so that this new data can be fully utilized resulting in a proxy for overconfidence that is more accurate than that of most prior research (e.g., Campbell, Gallmeyer, Johnson, Rutherford, & Stanley, 2011; Hirschleifer et al., 2012; Schneider & Spalt, 2017). If a CEO holds different vested option packages the fiscal year prior to the announcement date, he or she is labelled a Holder67 if at least one option package satisfies the following criteria:

$$\frac{p}{k_j} - 1 < 0.67 \tag{8}$$

Here, the left side of the equation represents the moneyness of an option where p represents the stock price at year end, and k_j the strike price. The right side of the equation represents the moneyness of an option.

Gambling

The proxies for gambling-prone CEOs used in this research are based on the three main proxies used by Schneider & Spalt (2017): CPRATIO, CEO age, and prior losses. Other variables are included based on additional literature that mostly examines gambling behavior among individual investors. All variables are discussed below.

Catholic vs Protestants

Schneider & Spalt (2017) use the variable CPRATIO as main proxy for gambling. CPRATIO represents the local proportional differences between the Catholic and Protestant population and is based on a body of literature proposing the variable captures gambling propensity (Kumar, Page, & Spalt, 2011; Benjamin, Choi, & Fisher, 2013). A dummy variable is created representing the value one for the states with the highest CPRATIO[4].

Prior losses

The second proxy is predicated on the test of Schneider & Spalt (2017) that links prior losses to gambling. Their reasoning is based two theories: (1) the prospect theory of Kahneman & Tversky (1979) that predicts risk-seeking behavior when losses have moderate probabilities, (2) the "break-even effect" of Thaler & Johnson (1990), which postulates individuals seek outcomes that offer a chance to break even in the presence of prior losses. Moreover, Schneider & Spalt (2017) indicate that prior performance also functions as discriminator between gambling and overconfidence. They argue that where losses indicate possible future gambling behavior, prior success is documented to boost overconfidence (Gervais, Heaton, & Odean, 2011). Following Schneider & Spalt (2017), a dummy variable is created that equals one if the net income of the fiscal year prior to the announcement date is negative. Following this theory, a positive correlation with IVOL would support a possible relationship with gambling, while a negative correlation supports the overconfidence narrative.

[4] Because Schneider & Spalt do not provide the CPRATIO per county, the paper of Abakah (2020) is used.

CEO age

Lastly, Schneider & Spalt (2017) use the age of acquiring CEOs as proxy for gambling. They base this on the paper of Goetzmann & Kumar (2008) and Kumar (2009) who show that a preference for lottery tickets tends to be negatively correlated with age among individual investors. However, it is noted that the average age of an acquiring CEO in our sample is 56, while it is common knowledge that the average age of a retail investor is much lower.

Jackpot returns

Schneider & Spalt (2017) refer to high IVOL targets as "lottery" targets because IVOL is one of the stock characteristics that predicts enormous "jackpot" returns (Kumar, 2009). It is checked if the data in this study is consistent with this prediction by adding the variable MAX that tracks the maximum daily return in the estimation period of the IVOL. If IVOL makes a stock an "attractive bet", the data will show a strong relationship.

Overpaying

Schneider & Spalt (2017) propose that acquiring CEOs overpay for targets that are attractive as a bet because they focus too much on upside potential. The variable premium paid is therefore included, representing the percentage of premium paid relative to the pre-announcement stock price. A positive coefficient would support the reasoning of Schneider & Spalt (2017).

Additional variables

Price informativeness

As elaborated on in the literature review, Durnev et al. (2004) find evidence that high IVOL firms use more external financing. They argue that idiosyncratic risk attracts informed arbitrageurs looking to trade on their private information, which subsequently results in more external financing within the firm. A variable is included which represents the total liabilities of a target firm. The theory of Durnev et al. (2004) predicts a positive relation with IVOL. In addition, Chava & Purnanandam (2010) find a positive relation between a CEO's risk-preference and the firm's leverage policy.

Payment method, gender, and financial crisis

Rhodes-Kropf & Viswanathan (2004) find that cash targets are idiosyncratically undervalued while stock targets experience idiosyncratic overvaluation. Although the regression's error used to calculate IVOL does not distinguish between positive and negative misvaluation, the dummy variables stock and cash are included to check for a possible relationship. The dummies indicate if a deal is financed exclusively by one of these payment methods. Additionally, a male dummy is added as various research shows females to be less risk seeking than their male counterparts (Beckmann, Lütje, & Rebeggiani, 2007; Mallin & Farag, 2017). Lastly, a financial crisis dummy is added. This is based on literature of another area within behavioral finance where new results indicate that risk preference of CEOs changes during the financial crisis (Ho, Huang, Lin & Yen, 2016). Prominent research on the relationship between managerial biases and recession periods has not yet been published, but general trends seem to indicate that overconfidence deteriorates during bust periods (Jlassi, Naoui, & Mansour, 2014; Gupta, Goyal, Kalakbandi, & Basu, 2018). The crisis dummy represents the value of one if the takeover was announced in the period August 2007 – December 2011.

Results and discussion

This section discusses the empirical findings of the research. Throughout the research process, two models are estimated. The first is an acquisition likelihood model which tests whether a pre-defined set of variables bears a significant statistical relationship to the takeover probability of a firm. The model is estimated using a logit regression and special attention is given to the effect of the independent variable IVOL. The second model aims to establish clarity on the possible relation between firm riskiness and a CEO's gambling propensity or overconfidence. This time, IVOL is used as the dependent variable and estimated using an OLS regression. Independent variables include, but are not limited to, proxies for overconfidence and the propensity to gamble.

Descriptive statistics and preliminary results

Table 3 presents summary statistics for the main variables used in this study.

TABLE 3

Summary statistics

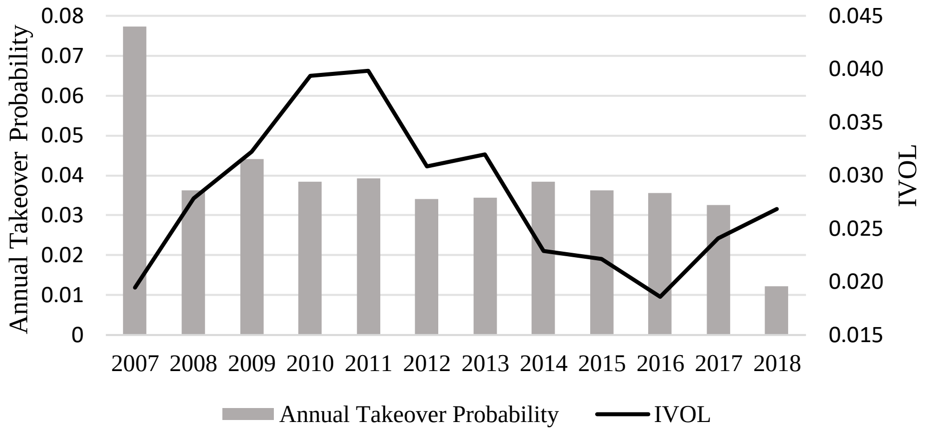
This table shows descriptive statistics for the variables used throughout the research. The Takeover Population Sample shows observations as firm years. Takeover dummy indicates if a firm originated from the ThomsonOne database, or if a firm's last present fiscal year is classified as target by Compustat. Inactive dummy is equal to one in the year a firm is delisted. Takeover probability is computed as the percentage of firms that is acquired, during each fiscal year. The descriptive statistics of the variables used in model (4) of the acquisition likelihood model are shown. The sample consists of 110 targets individually matched to a non-target. IVOL is calculated by taking the residual from the Fama & French three-factor model using daily returns over a course of three years ending at two months prior to the announcement date. All other variables are measured as of the end of the fiscal year prior to the year of announcement. Some variables are based on a three-year average. If data is insufficient, an average of two years is used. See appendix C for a comprehensive description of how these are computed.

Variable	Mean	Median	SD	25th pctl	75th pctl	N
Takeover Population sample						
Takeover dummy	0.048	0.000	0.214	0.000	0.000	80,965
Inactive dummy	0.110	0.000	0.313	0.000	0.000	80,965
Takeover probability	0.048	0.046	0.027	0.043	0.049	80,965
Acquisition Likelihood Model						
Takeover dummy	0.500	0.500	0.501	0.000	1.000	220
IVOL	0.037	0.022	0.059	0.016	0.031	220
Return on Equity	-0.011	0.062	0.721	-0.056	0.138	220
Growth-Resource dummy	0.273	0.000	0.446	0.000	1.000	220
Sales Growth	0.124	0.057	0.310	-0.021	0.172	210
Liquidity	0.357	0.302	0.239	0.182	0.490	220
Leverage	0.642	0.410	2.044	0.012	0.867	220
Market-to-book ratio	2.847	1.898	6.439	1.298	3.137	220
PE ratio	8.646	14.830	81.840	-6.012	25.222	220
Firm size	4469.286	1162.561	8526.996	339.731	3528.672	220
Tangible Assets	0.249	0.149	0.253	0.069	0.340	220
Industry Takeover Activity dummy	0.373	0.000	0.485	0.000	1.000	220
Overconfidence Sample						
IVOL (Annualized)	0.448	0.394	0.264	0.275	0.541	165
Overconfidence Dummy	0.636	1.000	0.483	0.000	1.000	165
CPRATIO	0.485	0.000	0.501	0.000	1.000	165
Underperformance Dummy	0.303	0.000	0.461	0.000	1.000	165
MAX	0.217	0.178	0.167	0.115	0.265	165
Age	55.448	55.000	6.978	51.000	60.000	165
Female Dummy	0.018	0.000	0.134	0.000	0.000	165
Liabilities	1356.510	176.421	3738.807	33.539	796.272	165
Size	2131.368	459.043	5409.118	138.634	1380.921	165
Transaction Value	2394.184	890.287	5372.814	323.323	1963.650	165
Premium	1.418	1.359	0.349	1.217	1.529	165
Cash Dummy	0.388	0.000	0.489	0.000	1.000	165
Stock Dummy	0.267	0.000	0.444	0.000	1.000	165

Examination of Figure 1 below indicates some interesting preliminary results. The figure shows the annual average takeover probability as well as the annual average IVOL of takeover targets. Looking at the takeover probabilities, the year 2007 stands out. The relative high number corresponds with the literature, as it is well known that the boom period prior to the financial crisis resulted in a larger fraction of acquired US firms. Examining IVOL it is noticed that there are no abrupt fluctuations, but the trend rather follows a cyclical pattern. These clusters indicate that either (1) IVOL fluctuates over time across the entire market, or (2) specifically the IVOL of takeover targets changes, providing the possibility that acquirers' preferences for target volatility changes over time.

FIGURE 1
Annual takeover probabilities & IVOL

Figure 1 shows the average annual takeover probability (bars) and IVOL (line). For each year the takeover probability is computed by dividing the target firms by the entire population sample from Compustat, where a firm is marked as a target when it originates from the ThomsonOne database or if the reason for delisting from Compustat is "Acquisition or Merger" (DLRSN = 1). For IVOL the yearly average is taken from the ThomsonOne sample.



Acquisition likelihood model

Table 4 reports the acquisition likelihood model, estimated using a logit regression. For the detailed construction of the variables used in the regression, see Appendix C. Note that interpreting the estimated coefficients differs from linear regression models. In linear regressions a change in the independent variable of one unit corresponds to a unit 'x' change in the predicted variable. Instead, in logit regressions, a one-unit change in the independent variable implies an 'x' unit change in the log odds of event probability. In this research, the log odds is the acquisition likelihood (equation 3).

The first and most important independent variable of the regression is IVOL, as described estimated for each target using the Fama & French 3-factor model, daily data, and a three-year estimation period. Hypothesis 1 states that IVOL positively impacts acquisition likelihood, following the rationale that acquirers are prone to gamble and a firm's attractiveness as a gamble is represented by IVOL. The results in Table 4 document the opposite. All models show a strong negative relationship between firm volatility and acquisition likelihood at the 1% significance level. The results remain largely unchanged when different samples are used and when controlling for year and industry fixed effects. Appendix A presents results using different methodologies based on previous literature. The Models (1) to (4) show that target volatility remains a strong negative significant predictor of takeover probability when other methods are used in calculating IVOL and processing outliers. All logit models document sufficient explanatory power. The McFadden R^2, an analog to the R^2 reported in linear regression models, shows similar numbers to that of Palepu (1986). Model 5 from Appendix A presents results using a linear probability model and the exact same set of variables as that of Schneider & Spalt (2017), thus allowing for a reliable comparison of the results. Like the other models, it shows a negative relationship between IVOL and takeover probability. In terms of overall explanatory power, it outperforms the model of Schneider & Spalt (2017), with an R^2 of 0.191, relative to 0.012.

The results lead to the rejection of hypothesis 1 and indicate that acquiring firms are less inclined to buy risky firms. This surprising outcome is in strong contrast with the findings of Schneider & Spalt (2017). They document the opposite during the period 1987 – 2008.

Three theories are discussed that might explain the obtained results. The first two are predicated on rational, instead of gambling behavior, among CEOs.

(1) *CEOs are aware of the IVOL anomaly.* The IVOL anomaly implies that low IVOL firms outperform high IVOL firms (Ang et al., 2006; Baker & Haugen, 2012; Fong, 2013; Conrad et al., 2014; Schneider & Spalt, 2017). In this light, the results support a narrative of rational acquirers who are aware of the anomaly and subsequently are less inclined to acquire 'overpriced' high IVOL targets.

(2) *CEOs use IVOL as risk measure.* As the unexplained portion of an asset pricing model, IVOL lowers a model's precision and increases uncertainty. Rational CEOs would therefore dislike high IVOL targets.

Both theories are based on the assumption that CEOs use asset pricing models - and specifically IVOL – in valuation techniques and takeover decisions. However, evidence shows that managers mainly rely on discounted cash flow (DCF) valuations in takeover decisions (e.g., Bruner, Eades, Harris, & Higgins, 1998; Graham & Harvey, 2001; Mukherjee, Kiymar & Baker, 2004). In fact, Mukherjee et al. (2004) show that only 5% of CFOs use valuation methods other than the DCF and market multiple analysis. It is therefore unlikely that CEOs use asset pricing models like the Fama & French models as separate instruments for valuation purposes. The most plausible influence IVOL might have is therefore its impact on the cost of equity capital that is used to discount the cash flows in a DCF valuation. If IVOL was to be accounted for, it would increase the cost of capital, thus increasing the discount rate and decreasing the value of the investment. In theory, this mechanism could explain the documented inverse relationship between IVOL and takeover probability. Yet, processing the unsystematic risk in the cost of capital is not part of the standard procedure and any trace of its use is not documented. Bruner, Eades, Harris & Higgins (1998) report that 41% of surveyed CEOs do not adjust for the risk of individual investment opportunities once the cost of capital is estimated. Mukherjee et al. (2004) even find that 61.3% of the management they surveyed use their own WACC as the discount rate instead of the cost of capital of the target. Reviewing the evidence, it is unlikely that IVOL has a significant role within takeover decisions. Although this limits the plausibility of both theories, it could still be the case that IVOL reflects actual risks within a potential takeover target. So even if CEOs would not use IVOL directly, these risks could still be exposed throughout the due diligence process preceding a takeover, and subsequently scare off risk-averse managers.

The abovementioned theories also face another complication: they are unable to explain the results of Schneider & Spalt (2017). Combining the results of this paper with theirs suggests that the relationship between IVOL and merger outcomes changes over time. Finding different outcomes on variables in different time periods is not uncommon in the literature. Harris, Stewart, Guilkey, & Carleton (1982) document the same and conclude that it is crucial to realize that as mergers combine two separate entities, a few common factors of takeover targets are just a small fraction of all factors contributing to takeover decisions (Harris et al., 1982). However, in understanding the economical drivers, it does push the narrative away from the behavioral perspective. Instead, it forces to evaluate IVOL more closely. Brandt, Brav, Graham, & Kumar (2010) study the time-series behavior of IVOL and find that its fluctuation does not represent a time trend. Instead, it reflects episodic phenomena like an economic event. These findings lead to the creation of a third theory:

(3) *Certain economic events correlate with IVOL and merger activity, at the same time*. As we know from the economic disturbance theory of Gort (1969), mergers cluster by industry as a result of economic shocks like technological advancements. If these same shocks would cause fluctuation in IVOL, it could explain why the relationship between IVOL and merger outcomes varies over time. The idea that economic shocks influence the correctness of asset pricing model and thus also IVOL is not difficult to imagine. Pastor & Veronesi (2005) examine the effect of technological revolutions on asset prices and find that it changes the nature of uncertainty for both idiosyncratic to systematic risk. This expansion of Gort's theory could explain both the results of this paper as the ones of Schneider & Spalt (2017). It does however suggest that not biased managers, but economical episodes are responsible for the fluctuation in IVOL.

The remaining variables of the model mainly explore the established theories on takeover determinants. The growth-resource dummy shows a positive significant relationship at the 5% level, which is in line with Palepu's (1986) results and supports the theory that companies with a mismatch between their financial resources and their growth make up for likely targets. When examining the dummy's individual variables, negative significant results are found for the variable sales growth for all models except Model 4. This suggests that out of the two possible growth-resource mismatches, low-sales growth, high-liquidity, and low-leverage is more present. Palepu (1986) finds similar results using a sample period from 1971 to 1979. Model 1 also documents statistically significant results for size, year, and industry. This makes sense as they are not completely controlled for in the sample due to the disparity in the amount of target and non-target firms, and studies have repeatedly shown that these variables influence acquisition likelihood (e.g., Palepu, 1986; Powel, 1997). Model 2 and 3 show that the results are not driven by year and industry fixed effects. In Model 4 the perfect matched sample completely controls for these variables, and thus as expected, their effects disappear. Further results show evidence of a negative relationship between the price-earnings ratio and acquisition likelihood, although significance decreases when controlling for fixed effects and disappears when the variables are winsorized at the 1% and 99% level. Palmer, Barber, Zhou, & Soysal (1995) find a similar, economically minor, relationship during the 1960s at the 5% level for friendly acquisitions.

TABLE 4

Acquisition likelihood model

This table represents results for the logit regressions. The dependant variable is a dummy that takes the value 1 for a target firm and 0 for a non-target firm. Model 1, 2, and 3 are estimated using the full sample of targets and their five best fitting non-targets that had data availability. This resulted in 639 firms, from which 498 target firms. Model 2 controls for fixed year and industy effects. Industry dummies are based on 2-digit SIC codes. Model 3 uses winsorized variables at the 1% and 99% level. Model 4 is estimated using a sample that only consists of matched targets, consisting of 110 firms (55 targets and their 55 matched non-targets). The McFadden R2 is an analog to the R2 reported in linear regression models and provides an indication of the logit model's explanatory power. *, ** and *** specify the significance of the p-value at the 10%, 5% and 1% levels, respectively.

Estimates of logit acquisition likelihood models				
	Models			
	(1)	(2)	(3)	(4)
IVOL	-10.064	-11.829	-14.685	-7.474
	[-5.05]***	[-5.36]***	[-4.27]***	[-3.71]***
Return on Equity	-0.008	-0.008	-0.080	-0.013
	[-0.11]	[-0.12]	[-0.47]	[-0.11]
Growth-Resource Dummy	0.602	0.526	0.518	0.561
	[2.44]**	[2.07]**	[2.07]**	[1.72]**
Sales Growth	-0.093	-0.114	-0.192	-0.317
	[-1.99]**	[-2.17]**	[-1.08]	[-0.65]
Liquid Assets	0.479	0.438	0.383	0.826
	[0.80]	[0.72]	[0.60]	[1.08]
Leverage	0.042	0.034	0.060	0.060
	[1.54]	[1.45]	[0.96]	[1.24]
Market-to-book	-0.014	-0.011	-0.024	-0.007
	[-0.86]	[-0.81]	[-1.16]	[-0.40]
PE Ratio	-0.001	-0.001	-0.001	-0.001
	[-2.04]**	[-1.92]*	[-0.47]	[-0.87]
Tangible Assets	0.648	0.680	0.630	0.560
	[1.19]	[0.93]	[0.86]	[0.77]
Industry Takeover Activity	0.252	0.242	0.229	-0.093
	[1.02]	[0.96]	[0.92]	[-0.30]
Size	-4.15E-05	-4.39E-05	-4.39E-05	-2.05E-06
	[-2.33]**	[-2.27]**	[-3.41]***	[-0.16]
Year	-0.204			-0.023
	[-6.48]***			[-0.59]
Industry	0.095			0.026
	[2.33]**			[0.41]
Year Dummies	No	Yes	Yes	No
Industry Dummies	No	Yes	Yes	No
McFadden R^2	0.076	0.174	0.169	0.055
Number of observations	639	639	620	220

IVOL and CEO biases

Table 5 shows the Ordinary Least Squares (OLS) regressions that are conducted to examine the relationship between IVOL and a CEO's gambling propensity or overconfidence. For the detailed construction of the variables used in the regression, see Appendix C. Note that if the proxies for gambling used in this research are a valid measure for a CEO's propensity to gamble, and if IVOL represents the riskiness of a firm and its value as a bet, these proxies should positively impact IVOL and support the gambling narrative provided by Schneider & Spalt (2017). Similarly, if Holder67 would accurately track CEO overconfidence, a positive relation between Holder67 and IVOL would suggest that overconfident CEOs are attracted to target risk.

To see to it that the results are robust, the OLS assumptions are tested. Scatterplots are used to check for linearity between the independent and dependent variables. Variation inflation factors (VIF) of all independent variable are below 4 with an average of 1.64 implying little multicollinearity with no cause for concern (Brigida & Madura, 2012). Normality of residuals is checked with the Jarque-Bera test, which showed significant results causing the null hypothesis of normality among residuals to be rejected. However, this assumption can be relaxed by the law of large numbers which applies for this model (e.g., Jaccard & Becker, 2009; Pek, Wong, & Wong, 2018). Finally, the Breush-Pagan / Cook-Weisberg test for heteroskedasticity showed significant results indicating that for at least one variable the variance of the residual increases. In order to correct for this heteroskedasticity, all regression models are estimated using robust standard errors (Croux, Dhaene, & Hoorelbeke, 2004; King & Roberts, 2015).

Gambling

I hypothesized that gambling CEOs undertake riskier takeovers, however, the three proxies for gambling show disappointing results. The age of a CEO, being marked an "underperformer", and religious background (CPRATIO) show no statistical relationship with target riskiness in the basic model. Model 2, which controls for year and industry fixed effects, also lacks promising result. Model 3 and 4 expand the regression by examining the gambling and overconfidence effect more closely. Specifically, interaction terms are introduced between the most valid proxies of each bias. For gambling, CPRATIO and underperformance are combined. This is predicated on the idea that, if CPRATIO accurately measures the religious background of the CEO, a CEO that is (1) catholic and (2) underperforming, will be more inclined to gamble than if he was only one out of the two.

In line with hypothesis 2 that predicts a positive impact of gambling on IVOL, a minor positive relationship of 0.042 is documented between CPRATIO and IVOL in Model 4 where year and industry fixed effects are controlled for. To gauge the economic significance of this effect, note that it is around 10% of the average IVOL (see Table 3). However, this effect disappears when the interaction term of -0.065 between CPRATIO and underperformance is taken into consideration. This interaction term provides the cleanest measure to capture gambling as it combines both proxies and although the results are not significant, the negative sign indicates that the model is unable to provide reasonable support for hypothesis 2.

Relative to the acquisition likelihood model - which showed high IVOL firms are not more, but less preferred by acquirers - the results of Table 5 show no support for IVOL being determined by the gambling attitudes of acquiring CEOs. The significant results of industry on the model show that IVOL fluctuates across industries and functions as support for the earlier proposed theory that suggests economic phenomena simultaneously influence merger clusters and IVOL.

Although the results do not favor hypothesis 2, it could still be that gambling attitudes among CEOs during takeover decision do exist and the IVOL model failed to detect it. For example, the following proxies incorporated in the model carry the risk of not accurately representing their variable of interest.

(1) IVOL does not track for lottery acquisitions. Previously I questioned the use of IVOL as valuation technique, but one can also question its ability to detect lottery acquisitions. Following the gambling narrative initiated by Kumar (2009) and expanded by Schneider & Spalt (2017) to the CEO level, a gambler is attracted to the potential for extreme lottery returns. Their claim that this characteristic is captured by IVOL finds support in my data. Table 5 shows a strong economic and statistical relationship between the highest daily returns (MAX) and IVOL, for all models. With the model confirming that IVOL accurately tracks for lottery returns, but not displaying support for hypothesis 2, it is sensible to question whether the attractiveness of lottery stocks among retail traders as demonstrated by Kumar (2009) is equal to the lottery acquisitions as proposed by Schneider & Spalt (2017). For a retail investor the attraction is sensible; they can benefit instantaneously from a spike in the stock price ("hitting the jackpot") by selling the stocks. However, the success of an acquisition depends on many facets. It is therefore reasonable to argue that CEOs will benefit to a much smaller extent from

a sudden spike in the stock price and one could therefore question if a CEO would use IVOL as benchmark if he is looking for a gamble. While Schneider & Spalt (2017) do consider idiosyncratic skewness as alternative proxy for lottery returns, they do not consider the possibility that lottery returns differ from lottery acquisitions. Therefore, if takeovers do present gambling opportunities, further research could find out which instrument CEOs use to detect these.

(2) The proxies for CEO gambling attitudes are incorrect. An alternative explanation for the lack of support of hypothesis 2, is that IVOL does proxy for lottery acquisitions, but the proxies for a CEOs proneness to gamble are inaccurate. Unlike the overconfidence proxy, the recently introduced gambling proxies are not yet widely accepted and even Schneider & Spalt (2017) recognize that their indirect nature calls for additional evidence.

Overconfidence

The third and last hypothesis predicts that IVOL is positively impacted by overconfidence among acquiring CEOs. Model 1 of Table 5 shows the basic model and opposing the hypothesis, Holder67 is negative and statistically significant at the 10% level. Significance disappears when controlling for industry effects in Model 2. Adding the interaction term does not change the outcome. Model 3 shows that the IVOL of a target is 0.03 lower when the acquiring CEO is overconfident and male. But the statistical significance disappears again when controlling for industry effects. With regard to the remaining variables, all show no significance, except for the positive coefficient for cash only transactions in Model 1 and CPRATIO in Model 4 (both with $P<0.10$).

The results function as weak support that overconfident CEOs are not more, but less likely to acquire high IVOL targets.

Many papers demonstrate that overconfidence leads to excessive risk taking (e.g., Barber & Odean, 2001; Niu, 2010). The documented results are therefore quite noticeable. According to my findings, papers that connect overconfidence to less risk-taking behavior do not exist. It is therefore more likely that IVOL might be unrepresentative of risk-taking behavior. For example, it could be that the IVOL model suffers from the “bad model” problem (Kapadia, 2006). It is assumed that high IVOL implies high idiosyncratic risk. However, if the model is incorrectly specified, IVOL could also represent a missing factor. If this was the case, the obtained results could imply that overconfidence is not linked to less risk-taking behavior, but to an unknown missing factor.

An alternative explanation for the obtained results finds their origin in the paper of Durnev et al. (2004), who argue that high idiosyncratic risk attracts the attention of informed arbitrageurs who trade on the private information they possess. As acquirers often possess private information, their information would be more valuable with high IVOL firms. Following this reasoning, overconfident managers who might prefer “gut” feeling over the value of their private information, could be more drawn to low-IVOL targets. The problem of this reasoning is that it predicts a positive relationship between IVOL and acquisition likelihood. And as we know from the results of Table 4, this is not the case.

The last possible explanation is based on the paper of Ferreira and Laux (2007) who find that IVOL is associated with openness to takeover offers. In this light, low IVOL could imply low openness to takeover offers which would scare off many acquirers, except for the overconfident ones.

In conclusion, it must be noted that while the results hint that there might be a negative relationship between overconfidence and IVOL, there is not enough credible evidence to reject hypothesis 3 or even to tell with certainty that a relationship between IVOL and overconfidence exists.

Limitations

There are limitations to the interpretation of the presented results. The state-based sample used for the acquisition likelihood model limits the generalizability to other samples with the same artificial composition (Bartley & Boartman, 1990). And as it is known that IVOL and behavioral traits such as risk-taking behavior varies across countries (Jin & Myers, 2006), generalizability of the results are assumably limited to the US. Also, this research makes use of multiple proxies which carry the risk of not accurately representing the variable of interest.

TABLE 5

IVOL & CEO bias

Table 5 represents results for the OLS regressions. The dependant variable is the annualized IVOL (equation 6). All models use a sample of 163 target firms that were acquired during the period 2007 - 2019. All the firms originate from the ThomsonOne sample and have data availability on Datastream, Compustat, and Execucomp. The variables are adjusted for the different notation styles between the databases. For more details on the sampIe see Appendix B. Model 1 represents the basic model. Model 2 controls for year and industry effect. Model 3 and 4 emphasize the gambling and overconfidence effect through interacted proxies. All models are regressed using robust standard errors. *, ** and *** specify the significance of the p-value at the 10%, 5% and 1% levels, respectively.

Estimates of OLS models				
	Models			
	(1)	(2)	(3)	(4)
Holder67	-0.034	-0.032	0.074	0.065
	[-1.72]*	[-1.37]	[1.77]*	[0.77]
Male	0.039	0.042	0.105	0.095
	[1.2]	[1.18]	[3.13]***	[1.48]
CPRATIO	0.015	0.023	0.028	0.042
	[0.88]	[1.34]	[1.31]	[1.88]*
Underperformance	0.015	0.007	0.042	0.042
	[0.72]	[0.34]	[1.46]	[1.34]
CEO age	0.002	0.001	0.002	0.001
	[1.39]	[0.66]	[1.54]	[0.88]
MAX	1.419	1.352	1.427	1.359
	[18.38]***	[20.02]***	[18.02]***	[19.83]***
Liabilities	-0.002	-0.004	-0.002	-0.005
	[-0.24]	[-0.47]	[-0.27]	[-0.48]
Acquisition value	0.000	0.005	0.001	0.005
	[0.01]	[0.51]	[0.08]	[0.47]
Premium paid	-0.011	-0.037	-0.010	-0.037
	[-0.41]	[-1.29]	[-0.38]	[-1.30]
Stock	-0.028	-0.035	-0.032	-0.037
	[-1.10]	[-1.28]	[-1.24]	[-1.36]
Cash	0.035	0.015	0.015	0.014
	[1.76]*	[0.68]	[1.66]	[0.64]
Crisis	0.023	0.022	0.021	0.018
	[1.06]	[0.59]	[0.95]	[0.50]
Holder67 x Male			-0.104	-0.089
			[-2.28]**	[-1.11]
CPRATIO x Underperformance			-0.050	-0.065
			[-1.16]	[-1.44]
Year Dummies	No	Yes	No	Yes
Industry Dummies	No	Yes***	No	Yes***
R^2	0.840	0.872	0.842	0.056
Number of observations	163	163	163	163

Conclusion

Literature on the origin of idiosyncratic volatility and the way it is valued and used by investors has taken a turn in recent times. Evidence seems to indicate that markets do price IVOL and that IVOL functions as predictor of “jackpot” returns. These lottery-like stocks in turn attract retail traders who have a tendency to gamble (Kumar, 2009). Schneider & Spalt (2017) introduce this subject to the realm of acquisitions, by proposing that gambling attitudes among acquiring CEOs might explain the positive relation they document between IVOL and the acquisition likelihood of a firm. This research further explores this novel area by initially focusing on the question: *Are “risky” US firms, measured by IVOL, more likely to be taken over during the years 2007 – 2019?*

Results show that IVOL negatively correlates with acquisition likelihood. Results are economically and significantly strong, and robust to different statistical approaches adopted from prior literature. They are in direct opposition to the findings of Schneider & Spalt (2017).

The second part of the research explores whether irrational behavior of acquiring CEOs functions as the causal mechanism of the influence of IVOL on takeover probabilities. While the results confirm that IVOL represents characteristics of “jackpot” returns, evidence on a relationship with CEO gambling attitudes or overconfidence is marginal and disappears when controlling for industry fixed effects. These results call into question the ability of IVOL to detect lottery acquisitions or represent risk-taking behavior.

Taken the evidence together, I conclude that the narrative provided by Schneider & Spalt (2017) in which CEOs are drawn to the IVOL of targets as a consequence of their proneness to gamble, is not supported by this research. Instead, my data of the years 2007 – 2019 support a narrative of rational CEOs who acquire low IVOL firms that are expected to perform better, as is in line with the IVOL anomaly (Baker & Haugen, 2012; Fong, 2013; Conrad, Kapadia, & Xing, 2014). However, this explanation becomes implausible when the results of Schneider & Spalt (2017) are considered, as well as the fact that the literature indicates that the role IVOL plays within the valuation process and final takeover decision, is limited. This paper therefore proposes a new theory that suggests economic events, like the technological advancements which cause merger clusters, might influence IVOL and merger activity simultaneously. This theory combines the results of Brandt et al. (2010) who find that IVOL reflects economical episodes, with the economical disturbance theory of Gort (1969). Results in this study showing IVOL fluctuates across industries support this theory but considering its novel nature it presents a fruitful subject for future research.

Prior literature undeniably shows that an inflated belief about the probability of winning can lead to bad betting decisions. But as this research does not find conclusive evidence, future research should provide consensus about the existence of a CEO based preference for “risky” takeovers, being it in the form of overconfidence, gambling attitudes, or any other bias.

Another area of interest is idiosyncratic skewness. Evidence suggest that it is not IVOL, but idiosyncratic skewness that explains the “lottery” returns that appeal to gamblers (Garreth & Sobel, 1999; Walker & Young, 2001). Boyer, Mitton & Vorkink (2010) even show that IVOL strongly predicts idiosyncratic skewness.

In all, this research contributes to the takeover modelling literature by finding further evidence that IVOL is a significant determinant in acquisition likelihood. Moreover, the paper contributes to the novel academic area on the role of gambling and overconfidence on taking risky takeover decisions. The presented results reveal that the behavioral narrative provided by Schneider & Spalt (2017) is disputed and calls for further research.

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References

Abakah, A. A. (2020). Local religious beliefs and municipal bond market outcomes. *Financial Management, 49*(2), 447-471.

Alexandridis, G., Mavrovitis, C. F., & Travlos, N. G. (2012). How have M&As changed? Evidence from the sixth merger wave. *The European Journal of Finance, 18(*8), 663-688.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance, 23(*4), 589-609.

Ambrose, B. W., & Megginson, W. L. (1992). The role of asset structure, ownership structure, and takeover defenses in determining acquisition likelihood. *Journal of Financial and Quantitative Analysis*, 575-589.

Amihud, Y., & Lev, B. (1981). Risk reduction as a managerial motive for conglomerate mergers. *The bell journal of economics*, 605-617.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *Journal of Finance 61,* 259-299.

Andrade, G., Mitchell, M., & Stafford, E. (2001). New evidence and perspectives on mergers. *Journal of economic perspectives, 15*(2), 103-120.

Bailey, W., Kumar, A., & Ng, D. (2011). Behavioral biases of mutual fund investors. *Journal of Financial Economics, 102*(1), 1-27.

Barber, B. M., Lee, Y. T., Liu, Y. J., & Odean, T. (2009). Just how much do individual investors lose by trading? *The Review of Financial Studies, 22*(2), 609-632.

Baker, N. L., & Haugen, R. A. (2012). Low risk stocks outperform within all observable markets of the world. *Available at SSRN 2055431.*

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*, *21*(2), 129-152.

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The quarterly journal of economics*, *116(*1), 261-292.

Bartley, J. W., & Boardman, C. M. (1986). Replacement-cost-adjusted valuation ratio as a discriminator among takeover target and nontarget firms. *Journal of Economics and Business*, *38*(1), 41-55.

Bartley, J. W., & Boardman, C. M. (1990). The relevance of inflation adjusted accounting data to the prediction of corporate takeovers. *Journal of Business Finance & Accounting, 17*(1), 53-72.

Barnes, P. (1998). Why do bidders do badly out of mergers? Some UK evidence. *Journal of Business Finance & Accounting, 25*(5-6), 571-594.

Beckmann, D., Lütje, T., & Rebeggiani, L. (2007). Italian Asset Managers?. *Behavior: Evidence on Overconfidence, Risk Taking and Gender* (No. 358). Diskussionsbeitrag.

Benjamin, D. J., Choi, J. J., & Fisher, G. (2016). Religious identity and economic behavior. *Review of Economics and Statistics, 98*(4), 617-637.

Berkovitch, E., & Narayanan, M. P. (1993). Motives for takeovers: An empirical investigation. *Journal of Financial and Quantitative analysis*, 347-362.

Bomford, M. (1968). Changes in the evaluation of equities'. The Investment analyst, 22, 3-12.

Boyer, B., Mitton, T., & Vorkink, K. (2010). Expected idiosyncratic skewness. *The Review of Financial Studies*, *23*(1), 169-202.

Bradley, M., Desai, A., & Kim, E. H. (1988). Synergistic gains from corporate acquisitions and their division between the stockholders of target and acquiring firms. *Journal of financial Economics, 21*(1), 3-40.

Brar, G., Giamouridis, D., & Liodakis, M. (2009). Predicting European takeover targets. *European Financial Management*, *15*(2), 430-450.

Bruner, R. F., Eades, K. M., Harris, R. S., & Higgins, R. C. (1998). Best practices in estimating the cost of capital: survey and synthesis. *Financial practice and education, 8*, 13-28.

Bruner, R. F. (2002). Does M&A pay? A survey of evidence for the decision-maker. *Journal of applied Finance, 12*(1), 48-68.

Campbell, T. C., Gallmeyer, M., Johnson, S. A., Rutherford, J., & Stanley, B. W. (2011). CEO optimism and forced turnover. *Journal of Financial Economics*, *101*(3), 695-712.

Chava, S., & Purnanandam, A. (2010). CEOs versus CFOs: Incentives and corporate policies. *Journal of financial Economics, 97*(2), 263-278.

Conrad, J., Kapadia, N., & Xing, Y. (2014). Death and jackpot: Why do individual investors hold overpriced stocks?. *Journal of Financial Economics, 113*(3), 455-475.

Cosslett, S. R. (1981). Efficient estimation of discrete-choice models. *Structural analysis of discrete data with econometric applications, 3,* 51-111.

Cremers, K. M., Nair, V. B., & John, K. (2009). Takeovers and the cross-section of returns. *The Review of Financial Studies, 22*(4), 1409-1445.

Croux, C., Dhaene, G., & Hoorelbeke, D. (2004). Robust standard errors for robust estimators. *CES-Discussion paper series (DPS) 03.16*, 1-20.

Daniel, K., & Hirshleifer, D. (2015). Overconfident investors, predictable returns, and excessive trading. *Journal of Economic Perspectives, 29*(4), 61-88.

Dietrich, J. K., & Sorensen, E. (1984). An application of logit analysis to prediction of merger targets. *Journal of Business Research, 12*(3), 393-402.

Donaldson, G., & Lorsch, J. W. (1983). Decision making at the top: The shaping of strategic direction.

Dong, M., Hirshleifer, D., Richardson, S., & Teoh, S. H. (2006). Does investor misvaluation drive the takeover market?. *The Journal of Finance*, *61*(2), 725-762.

Dorn, D., & Huberman, G. (2005). Talk and action: What individual investors say and what they do. *Review of Finance, 9*(4), 437-481.

Douglas, G. (1969). Risk in the Equity Markets: An Empirical Appraisal of Market Efficiency. *Yale Economic Essays, 9*, 3–45

Durnev, A., Morck, R., Yeung, B., & Zarowin, P. 2003. Does greater firm-specific return variation mean more or less informed stock pricing?. *Journal of Accounting Research, 41*(5), 797-836.

Durnev, A., Morck, R., & Yeung, B. 2004. Value-enhancing capital budgeting and firm-specific stock return variation. *The Journal of Finance*, *59*(1), 65-105.

Espahbodi, H., & Espahbodi, P. (2003). Binary choice models and corporate takeover. *Journal of Banking & Finance, 27*(4), 549-574.

Farag, H., & Mallin, C. (2017). Board diversity and financial fragility: Evidence from European banks. *International Review of Financial Analysis*, *49*, 98-112.

Ferguson, N., 2008. The Ascent Of Money. [Old Saybrook, Conn.]: Tantor Media, pp.185-198.

Ferreira, M. A., & Laux, P. A. (2007). Corporate governance, idiosyncratic risk, and information flow. *The Journal of Finance*, *62*(2), 951-989.

Fong, W.M. (2013). Risk Preferences, Investor Sentiment and Lottery Stocks: A Stochastic Dominance Approach. *Journal of Behavioral Finance, 14,* 42–52.

Fong, W. M. (2014). The IVOL Puzzle. *The Lottery Mindset: Investors, Gambling and the Stock Market* (pp. 122-137). Palgrave Pivot, London.

Garrett, T. A., & Sobel, R. S. (1999). Gamblers favor skewness, not risk: Further evidence from United States' lottery games. *Economics Letters*, *63*(1), 85-90.

Gervais, S., Heaton, J. B., & Odean, T. (2011). Overconfidence, compensation contracts, and capital budgeting. *The Journal of Finance*, *66*(5), 1735-1777.

Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. *The Geneva Risk and Insurance Review, 32*(1), 1-36.

Gort, M. (1969). An economic disturbance theory of mergers. *The Quarterly Journal of Economics*, 624-642.

Goetzmann, W. N., & Kumar, A. (2008). Equity portfolio diversification. *Review of Finance, 12*(3), 433-463.

Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of financial economics, 60*(2-3), 187-243.

Graham, J. R., Harvey, C. R., & Puri, M. (2010). Managerial attitudes and corporate actions. *Working Paper*, Duke University

Graham, J. R., Harvey, C. R., & Puri, M. (2013). Managerial attitudes and corporate actions. *Journal of financial economics, 109*(1), 103-121.

Graham, J. R., Harvey, C. R., & Puri, M. (2015). Capital allocation and delegation of decision-making authority within firms. *Journal of financial economics, 115*(3), 449-470.

Grossman, S. J. & Hart, O. D. (1980) Takeover bids, the free-rider problem and the theory of the corporation. *The Bell Journal of Economics*, 42-64.

Gupta, S., Goyal, V., Kalakbandi, V. K., & Basu, S. (2018). Overconfidence, trading volume and liquidity effect in Asia's Giants: evidence from pre-, during-and post-global recession. *Decision, 45*(3), 235-257.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. (2006). *Multivariate data analysis*. Uppersaddle River.

Hasbrouck, J. (1985). The characteristics of takeover targets q and other measures. *Journal of Banking & Finance, 9*(3), 351-362.

Harris, R. S., Stewart, J. F., Guilkey, D. K., & Carleton, W. T. (1982). Characteristics of acquired firms: fixed and random coefficients probit analyses. *Southern Economic Journal*, 164-184.

Hayward, M. L., & Hambrick, D. C. (1997). Explaining the premiums paid for large acquisitions: Evidence of CEO hubris. *Administrative science quarterly*, 103-127.

Harford, J. & Li, K. (2007) Decoupling CEO wealth and firm performance: The case of acquiring CEOs. *The Journal of Finance, 62*(2), 917-949.

Hirshleifer, D., Low, A., & Teoh, S. H. (2012). Are overconfident CEOs better innovators?. *The journal of finance, 67*(4), 1457-1498.

Ho, P. H., Huang, C. W., Lin, C. Y., & Yen, J. F. (2016). CEO overconfidence and financial crisis: Evidence from bank lending and leverage. *Journal of Financial Economics*, *120*(1), 194-209.

Jensen, M.C. & Ruback, R.S. (1983) The market for corporate control: The scientific evidence. *Journal of Financial economics, 11*(1), 5-50.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American economic review, 76*(2), 323-329.

Jin, L., & Myers, S. C. (2006). R2 around the world: New theory and new tests. *Journal of financial Economics*, *79*(2), 257-292.

Jlassi, M., Naoui, K., & Mansour, W. (2014). Overconfidence behavior and dynamic market volatility: evidence from international data. *Procedia Economics and Finance*, *13*, 128-142.

Jovanovic, B., & Rousseau, P. L. (2002). The Q-theory of mergers. *American Economic Review, 92*(2), 198-204.

Kahneman, D., & Tversky, A. (1979). On the interpretation of intuitive probability: A reply to Jonathan Cohen.

Kapadia, N. (2006). The next Microsoft? Skewness, idiosyncratic volatility, and expected returns. *Skewness, Idiosyncratic Volatility, and Expected Returns (November 2006).*

Kaplan, S. (1989). The effects of management buyouts on operating performance and value. *Journal of financial economics*, *24*(2), 217-254.

Kumar, A. (2009). Who gambles in the stock market?. *The Journal of Finance*, *64*(4), 1889-1933.

Kumar, A., Page, J. K., & Spalt, O. G. (2011). Religious beliefs, gambling attitudes, and financial market outcomes. *Journal of Financial Economics*, *102(*3), 671-708.

Ladd, G. W. (1966). Linear probability functions and discriminant functions. *Econometrica: Journal of the Econometric Society*, 873-885.

Lintner, J. (1965). The Valuation of risk asset and the selection of risk investments in stock portfolios and capital budgets. *Review of Economics and Statistics 47*, 13-37.

Loughran, T., & Vijh, A. M. (1997). Do long-term shareholders benefit from corporate acquisitions?. *The Journal of Finance*, *52*(5), 1765-1790.

Malatesta, P. H. (1983). The wealth effect of merger activity and the objective functions of merging firms. *Journal of financial economics, 11*(1-4), 155-181.

Malmendier, U., & Tate, G. (2005). CEO overconfidence and corporate investment. *The journal of finance, 60*(6), 2661-2700.

Malmendier, U., & Tate, G. (2008). Who makes acquisitions? CEO overconfidence and the market's reaction. *Journal of financial Economics, 89*(1), 20-43.

Markowtiz, H. (1952). Portfolio selection. *Journal of Finance, 7*, 77-91.

Mehrotra, V., van Schaik, D., Spronk, J., & Steenbeek, O. (2011). Creditor-focused corporate governance: evidence from mergers and acquisitions in Japan. *Journal of Financial and Quantitative Analysis*, 1051-1072.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information.

Morck, R., Shleifer, A., & Vishny, R. W. (1990). Do managerial objectives drive bad acquisitions?. *The Journal of Finance, 45*(1), 31-48.

Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements?. *Journal of financial economics, 58*(1-2), 215-260.

Mukherjee, T. K., Kiymaz, H., & Baker, H. K. (2004). Merger motives and target valuation: A survey of evidence from CFOs. *Journal of Applied Finance, 14(*2).

Niu, J. (2010). The effect of CEO overconfidence on bank risk taking. *Economics Bulletin, 30*(4), 3288-3299.

Nosić, A., & Weber, M. (2010). How riskily do I invest? The role of risk attitudes, risk perceptions, and overconfidence. *Decision Analysis, 7*(3), 282-301.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of accounting research*, 109-131.

Palepu, K. G. (1986). Predicting takeover targets: A methodological and empirical analysis. *Journal of accounting and economics, 8*(1), 3-35.

Palmer, D., Barber, B. M., Zhou, X., & Soysal, Y. (1995). The friendly and predatory acquisition of large US corporations in the 1960s: The other contested terrain. *American Sociological Review*, 469-499.

Pek, J., Wong, O., & Wong, A. (2018). How to address non-normality: A taxonomy of approaches, reviewed, and illustrated. *Frontiers in psychology, 9*, 2104.

Penrose, E. (1959). The Theory of the Growth of the Firm. (Oxford: Basil Blackwell).

Powell, R. G. (2001). Takeover prediction and portfolio performance: A note. *Journal of Business Finance & Accounting, 28*(7-8), 993-1011.

Rege, U. P. (1984). Accounting ratios to locate take-over targets. *Journal of Business Finance & Accounting, 11*(3), 301-311.

Renneboog, L., & Trojanowski, G. (2007). Control structures and payout policy. *Managerial Finance*.

Rezaee, Z. (2011). *Financial Services Firms: Governance, Regulations, Valuations, Mergers, and Acquisitions* (Vol. 14). John Wiley & Sons. Page 181

Rhodes-Kropf, M., & Viswanathan, S. (2004). Market valuation and merger waves. *The Journal of Finance*, *59*(6), 2685-2718.

Roll, R. (1986). The hubris hypothesis of corporate takeovers. *Journal of business*, 197-216.

Schneider, C., & Spalt, O. G. (2016). Conglomerate investment, skewness, and the ceo long-shot bias. *The Journal of Finance*, *71*(2), 635-672.

Schneider, C., & Spalt, O. G. (2017). Acquisitions as lotteries? The selection of target-firm risk and its impact on merger outcomes. The Selection of Target-Firm Risk and its Impact on Merger Outcomes (January 9, 2015). *Critical Finance Review*, *6*(1), 77-132.

Shleifer, A., & Vishny, R. W. (1989). Management entrenchment: The case of manager-specific investments. *Journal of financial economics*, *25*(1), 123-139.

Sharpe, W. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance 19*, 425-442.

Simkowitz, M., & Monroe, R. J. (1971). A discriminant analysis function for conglomerate targets. *Southern Journal of Business*, *6*(1), 1-15.

Sorensen, D. E. (2000). Characteristics of merging firms. *Journal of economics and business*, *52*(5), 423-433.

Stevens, D. L. (1973). Financial characteristics of merged firms: A multivariate analysis. *Journal of Financial and Quantitative analysis*, 149-158.

Sokolyk, T. (2011). The effects of antitakeover provisions on acquisition targets. *Journal of Corporate Finance*, *17*(3), 612-627.

Stulz, R. (1990). Managerial discretion and optimal financing policies. *Journal of financial Economics*, *26(*1), 3-27.

Rau, P. R., & Vermaelen, T. (1998). Glamour, value and the post-acquisition performance of acquiring firms. *Journal of financial economics*, *49*(2), 223-253.

Thaler, R. H., & Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management science*, *36*(6), 643-660.

Tukey, J. W. (1960). A survey of sampling from contaminated distributions. *Contributions to probability and statistics*, 448-485.

Ulbricht, N., & Weiner, C. (2005). Worldscope meets Compustat: A comparison of financial databases. *Available at SSRN 871169*.

Walker, I., Young, J., 2001. An economist's guide to lottery design. *Economic Journal 111*, F700–F722.

Wurgler, J. (2000). Financial markets and the allocation of capital. *Journal of financial economics*, *58*(1-2), 187-214.

Youngson, A. J. (1961). Alexander Webster and his "Account of the Number of People in Scotland in the Year 1755". *Population Studies, 15*(2), 198-200.

Appendices

Appendix A

Acquisition likelihood model: alternative regressions

This table represents results for the OLS regressions. The dependant variable is a dummy that takes the value 1 for a target firm and 0 for a non-target firm. All models are estimated using the full sample of targets and their five best fitting non-targets that had data availability. This resulted in 639 firms, from which 498 target firms. Model 1 shows the logit regression results using the Fama-French 5 factor to estimate IVOL. Model 2 estimates IVOL using the Fama-French 3 factor model and a one-year estimation period. Model 3 uses the Fama-French 5 factor model and a one-year estimation period. Model 4 shows the logit regression with outliers removed. Model 5 represents results for the linear OLS regression. All models control for fixed year and industy effects. Industry dummies are based on 2-digit SIC codes. *, ** and *** specify the significance of the p-value at the 10%, 5% and 1% levels, respectively.

Estimates of logit acquisition likelihood models					
	Estimates				
	(1)	(2)	(3)	(4)	(5)
IVOL	-11.779	-11.156	-11.098	-8.542	-1.629
	[-5.37]***	[-5.80]***	[-5.79]***	[-1.98]**	[-11.88]***
Return on Equity	-0.008	-0.027	-0.027	0.038	-0.001
	[-0.12]	[-0.38]	[-0.38]	[-0.45]	[-0.14]
Growth-Resource Dummy	0.525	0.549	0.549	0.426	0.072
	[2.07]**	[2.14]**	[2.14]**	[1.66]*	[2.21]**
Sales Growth	-0.114	-0.110	-0.110	-0.166	-0.019
	[-2.17]**	[-2.17]**	[-2.17]**	[-0.47]	[-3.23]***
Liquid Assets	0.433	0.500	0.495	0.543	0.048
	[0.71]	[0.82]	[0.81]	[0.77]	[0.53]
Leverage	0.034	0.042	0.042	0.244	0.005
	[1.45]	[1.63]	[1.63]	[2.60]***	[2.00]**
Market-to-book	-0.011	-0.013	-0.013	-0.048	-0.001
	[-0.81]	[-0.89]	[-0.90]	[-1.67]*	[-0.86]
PE Ratio	-7.38E-04	-7.42E-04	-7.42E-04	-1.70E-04	-1.28E-04
	[-1.92]*	[-1.91]*	[-1.91]*	[-0.09]	[-2.59]**
Tangible Assets	0.677	0.702	0.699	0.367	0.090
	[0.92]	[0.96]	[0.96]	[0.46]	[0.85]
Industry Takeover Activity	0.242	0.188	0.188	0.242	0.037
	[0.96]	[0.75]	[0.75]	[0.90]	[0.98]
Size	1.94E-05	-4.28E-05	-4.28E-05	-5.80E-05	-8.09E-06
	[-2.27]**	[-2.23]**	[-2.23]**	[-3.17]***	[-2.62]***
Year Dummies	Yes***	Yes***	Yes***	Yes***	Yes***
Industry Dummies	Yes***	Yes***	Yes***	Yes	Yes***
(McFadden) R^2	0.174	0.173	0.173	0.169	0.191
Number of observations	639	639	639	639	639

APPENDIX B

Target sample creation

Appendix B reports the amount of deals following each restriction in the ThomsonOne database. Additionally, the amount of observations are mentioned after data collection from the other databases.

Request		Description	Deals
Acquirer Nation	=	US	363.038
Target Nation	=	US	310,299
Acquirer Status	=	Public	143,740
Target Status	=	Public	42,518
Time period	=	2007 - 2019	11,844
% of Shares Acquired	≥	85%	1,737
Deal Status	=	Completed or Unconditional	1,737
Deal Value	≥	1 million USD	1,649
Rumored Deals	=	No	1,494
Target Solicited Deals	=	No	1,458
Deal type	≠	Repurchase or Recapitalization	1,456
Acquirer is a White Knight	=	No	1,456
Target Share Price (1 Day Prior to Announcement)	≥	1 USD	1,280
Total deals initial sample			1,280
Datastream	=	3-year daily stock prices prior to announcement date	1,107
Financial firms	=	No	606
Datastream	=	Accounting data	536
Execucomp	=	Acquirer CEO compensation data	165

Appendix C

Definitions and computations of variables.

Target accounting data is retrieved from Datastream, non-target accounting data from Compustat, and CEO compensation data from ExecuComp. For some variables, the three-year average is used consisting of the year of observation and the two preceding years. If data is insufficient, a two-year average is taken. Datastream frequently denotes their units in millions, where Compustat uses thousands. This denotational disparity has been corrected for. For the specific data items used from Compustat and Datastream, see Appendix D.

(1) *Return on equity*: Return on Equity is computed by the three-year average of net income divided by shareholder's equity. If data is insufficient, an average of two years is used.

(2) *Sales growth*: The three-year average of the annual rate of change in the firm's net sales.

(3) *Liquidity*: The three-year average of cash and equivalents plus receivables, over total assets.

(4) *Leverage*: The three-year average of long-term debt over the book value of equity. The book value of equity is computed by the subtracting total liabilities from total assets.

(5) *Growth-resource dummy*: A 0/1 variable computed on the basis of the three variables sales growth, liquidity, and leverage, as defined above. Growth-resource dummy is one if the firm has a combination of either high sales growth-low liquidity-high leverage, or low sales growth-high liquidity-low leverage. The dummy is given a value of zero for all other combinations. The median is used to distinct between 'high' and 'low'.

(6) *Market-to-book ratio*: The ratio of the market value of equity to the book value of equity. From Compustat the data items Market Value Of Equity [MKVALT] and Book Value Total Assets [AT] are collected. From Datastream the items Market Value (Capital) [MV] and Total Assets [WC02999].

(7) *Price-earnings ratio*: The price per share over the earnings per share. Price per share is measured by the market value of equity divided by the shares outstanding. Earnings per share is calculated by the three-year average of net income, divided by the shares outstanding.

(8) *Firm size*: Measured by the total net book value of a firm's assets. In line with Palepu (1986) and Powel (1997) the log value is used.

(9) *Tangible assets*: Measured by the book value of property, plant, and equipment divided by total assets.

(10) *Industry takeover dummy*: A 0/1 variable with the value of one if at least one takeover occurred in the same four-digit SIC industry in the year prior to the observation year; otherwise, the dummy is assigned a value of zero.

(11) *Overconfidence*: From ExecuComp the variables containing executive/company combination identifiers, the date a CEO started, and the date a CEO allowed to determine which CEO was active at the time of the acquisition. For these CEOs the moneyness of each compensation package the fiscal year prior to the announcement date was determined by dividing the stock's year-end close price (ExecuComp: PRCCF) with the option exercise price (ExecuComp: EXPRIC) and subtracting one. Finally, the dummy variable overconfidence is created. If at least one of the compensation packages has a moneyness higher than 0.67, the dummy variable is appointed the value of one. In all other cases the dummy has the value of zero.

(12) *CPRATIO*: A 0/1 variable indicating the states with the highest ratio of catholic to protestant population. The top percentile of states is used based on the ratios provide by Abakah (2020). States instead of counties are used for brevity. The dummy represents the value of one if the headquarter of the acquirer is located in one of the following states: Rhode Island, Massachusetts, New Jersey, Connecticut, New Mexico, New York, New Hampshire, California, Vermont, Louisiana, Nevada, Utah, Arizona, Hawaii, Maine, and Colorado. For all other states, a value of zero is assigned.

(13) *CEO age*: ExecuComp provides the current age of all the CEOs listed in their database. The difference between the current year and the year of the takeover was subtracted from the current age of the CEO to determine his age when the takeover took place.

(14) *Prior losses*: A 0/1 variable that equals one if the net income of the fiscal year prior to the announcement date is negative; otherwise, the dummy is assigned a value of zero.

(15) *MAX*: Represents the highest daily return achieved during the estimation period that is used for calculating IVOL.

(16) *Premium paid*: Calculated by dividing the offer price per share with the target stock price thirty days prior to the announcement date.

(17) *Price informativeness*: Represented by the total liabilities of a target firm. In line with Brigida and Madura (2012), the log value is used.

(18) *Cash (Stock):* A 0/1 variable indicating that the takeover is financed exclusively with cash (stock)

APPENDIX D

Data items used from Compustat and Datastream

This table represents the retrieved accounting data items. Datastream was used for the target firms and Compustat for the non-target firms.

		Data items	
		Compustat	Datastream
(1)	*Return on equity*	Common Equity [CEQ]	Common Equity [WC03501]
		Preferred Equity [PSTK]	Preferred Stock [WC03451]
		Net income [NI]	Net Income Available To Common [WC01751]
(2)	*Growth-resource dummy*		
	- *Sales growth*	Sales/Turnover (net) [SALES]	Net Sales [WC01001]
	- *Liquidity*	Cash and Short Term Investments [CHE]	Cash and Equivalents Generic [WC02005]
		Receivables Total [RECT]	Receivables [WC02051]
		Book Value Total Assets [AT]	Total Assets [WC02999]
	- *Leverage*	Long-term Debt Total [DLTT]	Long Term Debt [WC03251]
		Book Value Total Assets [AT]	Total Assets [WC02999]
		Book value Total liabilities [LT]	Total liabilities [WC03351]
(3)	*Market-to-book ratio*	Market Value Of Equity [MKVALT]	Market Value (Capital) [MV]
		Book Value Total Assets [AT]	Total Assets [WC02999]
		Book value Total liabilities [LT]	Total liabilities [WC03351]
(4)	*Price-earnings ratio*	Market Value Of Equity [MKVALT]	Market Value (Capital) [MV]
		Common Shares Used To Calculate Earnings per Share – Fully Diluted [CSHFD]	Common Shares Used To Calculate Fully Diluted EPS [WC05194]
		Net Income [NI]	Net Income Available To Common [WC01751]
(5)	*Tangible assets*	Property, Plant And Equipment [PPENT]	Property, Plant And Equipment Net [WC02501]