Revisiting the Size-Effect in Mergers and Acquisitions:
Four Decades of Evidence on the Underperformance of Large Firms

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Abstract- English

The underperformance of large acquirers compared to smaller ones is well documented in literature. In this study I examine the value-creation of 22,588 acquisitions in the US between 1980 and 2023. I find on average a positive, 0.86% abnormal return for all bidders; however, when considering value-weighted returns, the same average portrays a much more striking value-destruction of -0.45%. I also document a net of 262 billion dollars of aggregate market capitalization being wiped out due to acquisitions in the past four decades. My dissertation corroborates the findings of previous studies on the existence of the so-called size-effect**.** I find a significant, -1.08% difference between the returns of large and small acquirers on announcement. This difference cannot be explained by a wide range of variables used for predicting bidder returns in literature, including target size. My results are also robust to choices made in the research design and hold up to a high statistical standard.

Abstract- Portuguese

O fraco desempenho das grandes empresas adquirentes em comparação com as mais pequenas está bem documentado na literatura. No presente estudo, analiso a criação de valor de 22 588 aquisições efectuadas nos EUA entre 1980 e 2023. Em média, encontro um retorno anormal positivo de 0,86% para todos os licitantes; no entanto, quando se consideram os retornos ponderados pelo valor, a mesma média retrata uma destruição de valor muito mais marcante de -0,45%. Também documentei uma perda líquida de 262 mil milhões de dólares de capitalização de mercado agregada devido a aquisições nas últimas quatro décadas. A minha dissertação corrobora as conclusões de estudos anteriores sobre a existência do chamado efeito de dimensão. Verifico que existe uma diferença significativa, de -1,08%, entre as rendibilidades das grandes e das pequenas empresas adquirentes aquando do anúncio. Esta diferença não pode ser explicada por um vasto leque de variáveis utilizadas na literatura para prever as rendibilidades dos proponentes, incluindo a dimensão do alvo. Os meus resultados também são robustos em relação às escolhas efectuadas no desenho da investigação e resistem a um elevado padrão estatístico.

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1. Introduction

In this dissertation I examine and confirm the existence of the size-effect originally presented by Moeller et al. in 2004. My sample encompasses twice as large of a time period with twice as many acquisitions made from 1980 to 2023. I find that the effect still holds even to an increased scrutiny with additional control factors examined and new robustness measures introduced.

This study was prompted by the paper also by Moeller et al. (2005), titled: *"Wealth Destruction on Massive Scale? A Study of Acquiring-Firm Returns in the Recent Merger Wave"*. The surprising conclusions of this research paper completely jeopardize the notion that M&A activity is a valid strategy to create value. The baseline assumption would be that the combination of firms would usually result in some synergies, yet their results contradicted this. Moeller et al. (2005) show that this value destruction was mostly connected to a merger wave and was committed by large firms.

Based on this paper, I found it important to investigate what makes large firms so incapable of making value-creating acquisitions, when in theory they should have more resources and opportunities to acquire the best targets. Moeller et al. (2004) in a previous paper found that large firms systematically create lower value for their shareholders via acquisitions even when controlling for a range of deal and firm factors. In this dissertation I intend to test whether this effect, that was discovered more than 20 years ago, still stands. Therefore, my analysis mostly follows Moeller et al.'s (2004) methodology to understand this puzzle better.

Moeller et al. (2004) reports a 2.24% difference between the announced abnormal returns of large and small firms. I document a smaller, but significant, 1.08% average difference in my complete sample. While the equal-weighted average cumulative abnormal returns (CAR) show 0.86% return for all firms, the value-weighted average portrays a much more striking value-destruction with -0.45% in total. This means the larger sized acquirors destroy most of the value. I document a net of 262 billion dollars being wiped out from the market capitalization of US firms due to acquisitions during my sample.

Additionally, I find that the size-effect cannot be explained by a large variable set including deal, firm and market characteristics. The findings are also robust to a plethora of discretionary choices made in the research design and sampling and hold up to a higher statistical standard than the original research paper. My results also do not support the conclusion that the target size is the main driver of the size-effect, contrary to Alexandridis et al. (2013).

I do not provide an explanation of why the size-effect exists in this paper, although my findings help in narrowing down the potential underlying drivers. While the size-effect is not a novel concept and there is plenty of research explaining acquisition gains, I believe it is still important to see whether past findings are challengeable. If this phenomenon still exists, besides the research value it could provide a basis for a trading strategy to exploit this consistent difference. This study contributes to the understanding of the puzzle of the size-effect of acquirors and reinforces the phenomenon based on more rigorous testing a larger and fresher dataset.

My research questions and their corresponding hypotheses are the following:

- ***Do acquisitions create value on average?***
  H1*: Acquisitions create significant value on average measured by CAAR-s during the sample period based on t-tests.*
  H0*: Acquisitions either do not create significant*[1] *value or destroy value on average measured by CAAR-s during the sample period based on t-tests.*
- ***Did the size-effect exist, and does it still stand?***
  H2*: the size-effect between small and large firms is significant between both 1980-2001 and 2002-2023 as well as during the combined period across variables based on t-tests.*
  H0*: the size-effect is insignificant for either of the periods across variables based on the t-tests.*
- ***Can the size-effect be explained by other factors?***
  H3*: There is a size-effect proxy that remains statistically significant with the introduction of other variables when considering panel regressions using the complete sample.*
  H0*: all size-effect proxies lose statistical significance by the introduction of other variables in any panel regression models using the complete sample.*
- ***Are all the results robust?***
  H4*: the size-effect remains statistically significant even after altering key choices made in sampling, methodology and applied statistical rigor.*
  H0*: the size-effect loses statistical significance by altering key choices made in sampling, methodology or applying harsher statistical rigor.*

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[1] *Note: statistical significance at the 10% level*

To answer these questions, the study is structured the following way: after this introduction, in **section 2** I present an overview of the literature made on acquisition bidder returns and discuss the methodology, findings and implications of the basal paper of Moeller et al. (2004). Additionally, I present other studies where the size-effect is analyzed or have the potential to explain or isolate the effect. **Section 3** presents how I sampled the data and discusses the properties of the sample. Then, I follow Moeller et al.'s (2004) methodology closely during **section 4.1.-4.2.** and construct cumulative average abnormal returns and other related metrics. I test the differences of large and small firms for these metrics. In **section 4.3.-4.4.** I use an assortment of variables from both the Moeller paper (2004) and other studies to see whether this difference could be explained. To conclude my research, in **section 5** I address some of the statistical issues of the data and tests for the sensitivity of the findings to key inputs where discretion was made**. In the last chapter** I discuss these results, hypothesize about potential explanations, connect my findings to broader literature and outline further research ideas on this topic.

2. Literature review

2.1. Introduction to mergers and acquisitions literature

There has been a wide range of corporate finance research on mergers and acquisitions, ranging from target selection to merger waves. One, if not the most important question is what factors drive the success or failure of these acquisitions. In this literature overview I focus on bidder returns and more specifically, on the importance of the size of the acquirer.

One of the most common ways to measure the performance of acquisitions is to use daily stock data to construct abnormal returns on the announcement of the deal. This method originated from the notion that efficient markets incorporate news into the prices of the stock of the firm following the influential papers of Fama (1970) and Fama, Fisher, Jensen and Roll, (1969). The approach using the semi-strong form of market efficiency assumes the ability of the markets to effectively, accurately and instantly value the synergies resulted by the deal on the day of the announcement. Obviously, there are reservations about how precise this is in practice but using longer return periods introduces the increased problem of confounding events. There is a separate branch of studies and methodologies focusing on the long-term performance on acquisitions.

The paper "*Using Daily Stock Returns: The Case of Event Studies*" by Brown and Warner (1985) highlights the statistical problems surrounding the usage of daily stock data, but still finds it the best for measuring value and establishes that traditional event study methodology can be used on daily stock returns.

Martynova & Renneboog (2008) provides a comparison of M&A literature and used window sizes for short term abnormal returns. It is visible from this comprehensive overview of literature, that the most common way to measure abnormal returns is via cumulative abnormal returns constructed on a 3 day window [-1,+1] surrounding the announcement. This window length is effective at measuring the reaction of the market to specific events, while it keeps the possibility of confounding events to the minimum. Nevertheless, there are alternative ways to measure abnormal returns such as with compounding returns or with different window lengths.

2.2. "Wealth destruction on a massive scale: A Study of Acquiring-Firm Returns in the Recent Merger Wave" (Moeller et al., 2005)

As mentioned in the introduction, this paper served as the main motivation in driving me to conduct this study. The research paper examined and investigated a significant value destruction observable during the late 90-s and early 2000s. Its implications to acquisitive value creation strategies in damning.

It used a sample from the SDC Platinum database of acquisition data between 1980 and 2001, with deals above 1 million and where corporate control was exchanged. Moeller et al. (2005) found that during 1998 to 2001 (which corresponds to the dotcom bubble period) acquisitions destroyed 8 times as more value – 240 billion, than from 1980 to 1997. Besides the aggregate negative dollar values of acquisitions, they identified large loss deals that were the main culprits. These deals were defined as having the acquirer's market value lost more than a billion during the 3-day event window. Large-loss deals are characterized by public targets, high valuations, high deal values, equity used commonly as payment and also longer durations to complete indicating higher complexities and or challenges.

They found that traditional predictors used in explaining abnormal returns could not explain the scale of this destruction. In their findings it is also included that the makers of the large loss deals continue to underperform over a 1-year event window and not recover for a while. The paper concludes that the wealth destruction of the late 90s-early 2000s were driven by these large loss deals. Based on the findings of this paper I intend to examine whether large loss deals drive the size-effect and the negative size-weighted average returns.

2.3. "Firm size and the gains from acquisitions" (Moeller et al., 2004)

This paper forms the baseline of the methodology of my research. Moeller et al. (2004) found a systemic difference between the returns of small and large firms with a consistent underperformance of larger acquirors.

The paper uses the same sample as in "*Wealth destruction on a massive scale*" (Moeller et al., 2005), since it is the precursor of that other study. The authors found that in aggregate, dollar terms acquisitions destroy value, not just during the merger wave.

They constructed cumulative average abnormal returns (CAAR) based on 3-day event window, and other metrics containing value-weights such as dollar abnormal returns. These variables will be discussed more in detail during the methodology part. Moeller et al. (2004) found that although the average CAR-s are positive, any metric using value-weights (of the acquirer's market capitalization) resulted in negative averages.

The paper uses 2 sample t-tests to gauge the significance of the differences in gains of large and small firms. According to the paper, there is a significant size-effect between small and large sized acquirors in terms of abnormal returns from acquisitions. The researchers hypothesized that the size-effect is caused by the hubris of management following Roll's paper (1986).

In later sections of the study, they added other factors that could potentially explain this size-effect which were found in literature to explain announcement abnormal returns well. These key variables that could have potential interactions with size include relative size, time to completion, financing method (cash for small firms is more common, equity vice versa), public status, firm size, cash holdings, leverage and overvaluation.

After analyzing the persistence of the size-effect when segmenting for some of said variables, they also applied panel multiple regressions. The regressions contained a range of control variables that could capture the variation of CAR-s and thus reduce the main size-effect variables that are in the focus. They found that no variable or combinations of variables could fully explain the size-effect, concluding it is not a proxy for acquiror and deal characteristics**.** This size-effect is robust and consistent across categories of firms and variable choice.

More in detail, they suggest that small firms benefit more from transformational deals, deals with larger average relative size, while large firms are more prone to overpay or face integrational challenges. The paper finds no evidence of overvaluation driving the size-effect, supporting the hubris hypothesis and no evidence for equity signaling or growth opportunity signalling hypotheses. I will discuss the underlying theoretical background more in detail later in this section.

Next, they investigated the underlying technical reasons behind the size-effect. They found that large firms do overpay more for their acquisitions, but also achieve a higher success rate. They measured overpayment by analyzing deal premiums. Having a toehold significantly increases the likelihood of deal closure and hostile as well as conglomerate deals are less likely to close. However, overpayment and deal success are not significantly linked.

In terms of synergies, their results show that smaller firms earn higher synergy gains than large firms, the dollar synergy gains being negative on average. These conclusions were reached by constructing portfolios of acquirers and targets (both being only public firms) and measuring their combined value change. There is a question to be raises about the accuracy of these results, since they end up with a biased sample for large firms as they are more likely to be buying public targets.

Lastly, the authors examined whether the difference in gains of small and large firms persist over time via calendar-time post-event monthly abnormal returns. They confirmed this persistence as the returns are negative for large firms and positive / insignificant for small firms. This again shows penalization of deals on average by the market only for large firms.

The paper concludes that the markets efficiently incorporate information from the acquisitions into the stock prices and there is no permanent reversal. I follow mostly the methodology of Moeller et al (2004) in my study to produce results that can be compared side by side to the original paper. My sample size is double that of the original paper with exactly twice as many years.

2.4. "Deal Size, Acquisition Premia and Shareholder Gains" (Alexandridis et al., 2013)

"Deal Size, Acquisition Premia and Shareholder Gains" by Alexandridis et al. (2013) is a later study the re-examines the relationship between acquiror-target size and bidder returns and premia.

Their sample contains 3,691 completed U.S. public acquisitions announced between 1990 and 2007. This sample is significantly smaller than that of the Moeller studies (2004 & 2005), nevertheless it still contains private and public targets. The paper employs similar methodology to Moeller et al. (2004) by using 3-day CAR-s.

They present a robust negative relationship between *target size* and premia, holding up even after controlling for a wide range of factors. This indicates that larger targets tend to be acquired for a lower premium. This may be unexpected in light of Moeller et al. (2004), since they found that larger acquirors buy targets with larger deal values than smaller acquirors and also found that these large firms overpay. Therefore, this implies that large firms should be paying higher premia and not lower comparatively. The Alexandridis (2013) study also confirms that large deals destroy value, but this is not the same as *large sized acquirers* destroying value. They argue that the complexity of integrating large targets might outweigh the benefits of paying lower premiums.

Other findings include that private acquirers pay lower premiums and that lower premiums are associated with cash deals. Lower premiums are also paid during high market valuations. Additionally, they present that the market has positive reactions to withdrawal of large deals.

According to the paper, higher insider ownership is associated with higher premiums due to assumed bargaining power. They also find anchoring behavior to be prevalent of market participants by the measure of reference prices. The closeness of offer prices to their 52-week high prices of target shares was found to have a negative relationship with bidder premiums. The further the actual price is to the anchor, the higher were the premiums. This could indicate that the market is incorporating information inefficiently and is biased in behavioral ways.

In connection to abnormal returns, firstly, they proved that higher premiums and overpayment are associated with lower returns. Secondly, the coefficient for their acquirer size proxy is positive, not negative while including target size as a control variable, indicating that larger acquirers earn better returns ceteris paribus.

They also found that the market reacts worse to large deals than small. When splitting the sample to terciles based on target size they found that the negative relationship between acquirer size and abnormal returns found by Moeller et al. (2004) are only significantly negative within large targets.

They inferred that the impact of the *acquirer size* on bidder returns, and thus the size-effect is actually driven by the *target size*. They attribute the value destruction by large targets to increased complexity, integration challenges and the perception of overpayment by the market (perceived, because according to the paper large targets actually are paid less premiums for).

These results significantly question the findings and conclusions of Moeller et al. (2004). For this reason, I include target size in my analysis to see the relationship and causality between the two variables

2.5. Theoretical background of the size-effect

The Moeller paper (2004) argues that hubris might be the driving factor of the size-effect. This argument originated from Roll's *"The Hubris Hypothesis of Corporate Takeovers"* (1986), where he outlined the CEOs with hubris overpay for their acquisitions.

Jensen (1986)'s findings imply that large firms are also prone to the agency problems of free cash flows. Managers may not act in the best interests of the company or the shareholders if they have too much cash on hand because they invest it in negative NPV projects – often takeovers – due to the desire to empire build or to finance pet projects. The takeover market can actually discipline these managers by initiating a hostile takeover and changing management. However, anti-takeover pills help management to stay entrenched and continue the value destroying behavior.

Malmendier and Tate (2008) showed that on a small, selected sample that overconfident CEO's pay higher premiums for acquisitions, are 65% more likely to make acquisitions with higher likelihood of them being diversification deals and they earn lower announcement abnormal returns. It is important to note that there again might be a bias for large companies in their sample since they only included firms that appeared in the news and additionally the deals had a minimum 5% relative value.

Hubris was proxied by "longholder" dummy variable - a measure of CEO-s leaving their options unexercised, a sign of overconfident behavior. They assumed that the same hubris portrayed in their investment decisions applies to acquisitions as well. Their findings from the variable were confirmed by a text-based measure of CEO overconfidence from Forbes articles as well (Malmendier and Tate, 2008).

Moeller et al. (2004) outlined five possible underlying factors of the size-effect based on previous studies.

1) CEOs of large firms are specifically more prone to hubris because they succeeded growing the firm or feel socially important. Overconfident CEOs were found to overpay for their targets. – hubris hypothesis (Roll, 1986, Malmendier and Tate 2008)
2) Large firms no longer have organic growth opportunities and thus have higher agency costs of free cash flow. Additionally, they are expected to have less alignment of interests between management and ownership due to fragmentation and less overlap - free cash flow hypothesis (Jensen, 1986)
3) Lack of internal growth opportunities drive the managers to be more wasteful with where they invest - growth opportunities signaling hypothesis (McCardle and Viswanathan, 1994 and Jovanovic and Braguinsky, 2004)

4) Price pressure by arbitrageurs is less likely to impact small firms at the announcement, but this should correct over time due to slower information diffusion – arbitrageur hypothesis (Mitchell et al., 2004)
5) Large firms have higher valuations – overvaluation hypothesis (Dong et al. 2006)

They only found solid evidence for the hubris hypothesis proxied by the overpayment by large acquirers.

One important detail seen from the Martynova & Renneboog (2008) study is that most of the evidence from literature and thus the formulated hypotheses are from public-to-public deals. This is due to the fact that in order to allow the measurement of target abnormal returns and synergy gains the researchers need to use public data for the targets. However, from the perspective of the size-effect it introduces a bias in the sample for large and public targets and acquirors, when in reality most of the acquisitions are unlikely to be made this way.

2.6. Other explanatory factors for acquisition gains in literature

In this section I review the literature on other factors that are used to explain abnormal returns on announcement.

Relative size of target and acquirer

The Moeller paper (2004) found that relative size is positively related with abnormal returns for small firms but negatively correlated for large firms, implying that small firms benefit more from larger acquisitions relative to their size, while large firms might struggle with such acquisitions. Asquith et al. (1983) and Schwert (2000) find relative size to have a positive relationship with CAR-s, but Travlos (1987) finds it to be negative. According to Faccio, McConnell, and Stolin (2006), larger relative size of acquisitions is connected to higher abnormal returns for small acquirers. Hackbarth & Morellec (2008) also find a positive connection, they argued that small acquires relative to target integrate better and realize greater synergies. The ambiguity can be explained by the fact that variable might not be linearly related to CAR-s. If the deal is paid with equity, there is a downward sloping demand for the shares of the acquirers due to dilution, and the abnormal return will fall with relative size (Moeller et al., 2004)

Public status of the target

Zingales (1995) presents that the bargaining situation of a public target and private / subsidiary target is different. Fuller et al. (2002) and Chang (1998) showed that bidder returns associated with private firms are higher. In the Moeller paper (2004) private targets and subsidiaries resulted in higher CAR-s, particularly for small firms. Public acquisitions show lower/negative CAR-s, especially for large firms. They found that there is significant interplay with payment type when considering public status. Netter, Stegemoller, and Wintoki (2011) reinforced this evidence of acquisitions of private firms and subsidiaries lead to higher abnormal returns.

Payment type

The authors of the size-effect paper (Moeller et al., 2004) found that equity paid acquisitions are associated with lower abnormal returns, especially for public targets. Cash acquisitions also have significantly lower abnormal returns, claiming that it is due to the high correlation with public acquisitions. The positivity of all-equity and mixed offers can potentially be explained by the insider information of the more highly concentrated ownership of private firms. Thus, they have better information about the true value of the equity payment for their shares (Moeller et al., 2004). Chang (1998) and Fuller et al. (2002) show that private firm owners become large blockholders if paid by equity and thus have incentives to monitor the management. On the contrary, Faccio & Masulis (2005) and Savor and Lu (2009) found that cash-financed deals perform better than equity financed deals due to signalling effect and dilution concerns. Payment type is highly correlated to public status and acquiror size both in literature and in my sample. (see **Table 14** in the appendix)

Competition

It is obvious from intuition that higher competition should lower the returns of the acquiror due to pressure on bid price**.** Schlingemann et al., (2002) presented variable to proxy for competition with a liquidity index of the intermarket competition in order to substitute for the lack of information about number of bidders. Their assumption is that higher liquidity/M&A activity in the industry should result in lower bargaining power (Schlingemann et al., 2002). Boone and Mulherin (2002) demonstrated that in an acquisition where there is only one bidder publicly available, there might have been multiple bidders prior in a private auction. This supports the concerns of lack of information about the true number of bidders. The Moeller paper (2004) confirms this negative relationship with liquidity index and also uses a dummy variable that equals one if the number of bidders is higher than one. Competition is unanimously found to be negatively impacting returns in other literature pieces (Officer, 2003, and Eckbo et al. 2008).

Hostile takeovers, tender offers

The intuition is that hostile takeovers or takeover attempts should result in lower returns and tender offers should yield higher returns due to their direct nature and signalling effect. Small firms, however, are less likely to make tender offers (Moeller et al., 2004). The Moeller study (2004) finds a significant positive relationship with tender offers, but hostile deals are inconclusive and generally more negative for small firms**.** Schwert (2000) suggests that the distinction between hostile and friendly deals is not clear in economic terms and its public distinction is based on negotiation strategies of the parties.

Acquiror leverage

One would anticipate that higher leverage leads to higher returns, however Moeller et al. (2004) finds that the connection is insignificant. From Jensen (1986) and Maloney et al. (1993) a positive relationship could be inferred due to the disciplinary effect of debt on managers. In simpler terms, highly leveraged acquirors would undertake only value-creating acquisitions. Harford, Klasa, and Walcott (2009) find evidence for this disciplinary mechanism working.

Conglomerate deals

Morck et al. (1990) found that diversification deals result in lower abnormal returns for public targets since these are associated with useless, empire building behavior (Jensen 1986). This type of investment could destroy value and has no real synergies, since shareholders can diversify themselves. The Moeller study (2004) confirms conglomerate deals to be significant and negative. Maksimovic and Phillips (2008) also found lower returns for these types of acquisitions.

Overvaluation of acquirer

According to Dong et al. (2006) high Tobin's Q and low book-to-market ratios proxy for overvaluation. Lang et al. (1989) and Servaes (1991) found a positive relation with Tobin's Q and bidder returns. These deals are also more likely to use equity to pay for the acquisition, supporting their misevaluation hypothesis. On the other hand, the Moeller study (2004) presented a very small, but significantly negative result, contradicting the previous findings. According to that paper, it appears that high valuation deals are more penalized, although, book-to-market was insignificant (Moeller et al., 2004).

Excess cash and cash flows

According to Harford (1999), firms with excess cash are more prone to making poor acquisitions. Harford (2005) confirmed these findings when analyzing merger waves. This notion is connected to the free cash flow hypothesis and empire building (Jensen, 1986), but the Moeller study (2004) found no evidence on this.

Days to completion

Moeller et al. (2004) found that large firms take more time to complete deals. This is attributed to bureaucracy and regulatory challenges; however, they are also more likely to complete their deals, possibly indicating managerial hubris (Moeller et al. 2004).

Market sentiment and credit cycle

Shleifer & Vishny (2002), Loughran and Vijh (1997) and Rau and Vermaelen (1998) found that merger waves are mainly driven by stock market overvaluation, categorized by payment with equity and have worse negative long-run returns for the bidders. Danbolt, Siganos, and Vagenas-Nanos (2015) introduced a direct sentiment proxy for the equity market and found a positive relationship with announcement bidder returns.

Gulen, Jens and Rossi (2022) measure the impact of the cycle of the credit market on acquisition activity and returns. They used CAPE (Shiller and Campbell, 1996), HYS (Greenwood and Hanson, 2013) and SENT (Baker and Wurgler, 2006) indices. HYS is used as a proxy for credit sentiment and the other two are for equity market sentiment. With high credit sentiment, the credit quality issued is low (López-Salido et al., 2017). High sentiment and low credit spreads cause junk bonds to be disproportionately issued, which in turn causes all-cash financed, leveraged takeovers. These conditions drive overconfident CEO-s to engage in acquisitions. In periods of high credit market sentiment, acquisitions tend to yield higher announcement-day returns and better long-term operating performance for acquirers. This relationship is weaker for overconfident CEO-s (proxied by the longholder measure), whose acquisitions tend to underperform compared to the rest. They find less evidence for the stock market sentiment to be driving acquisition waves (Gulen, Jens and Rossi, 2022).

Industry concentration and industry/product relatedness

Hoberg and Phillips (2010) used text-based variables constructed from 10-K report's product section. This approach provides a more refined approach compared to SIC codes or other industry clusters and allows the measure of product or industry fit as a score and not as a binary variable. They found increased stock returns for firms that acquired targets with related products. (Hoberg and Phillips, 2010).

In Offenberg' 2009 paper industry concentration (Herfindahl–Hirschman index) is used as a control variable for the determinants of target selection. They found a negative connection attributed to legislative hurdles with highly concentrated markets. The liquidity index is constructed in a similar way to measure competition.

Relative overvaluation and anchoring effect

Baker et al. (2012) finds that premiums paid for public targets were significantly affected by the 52-week high reference prices of the stock of the targets. Ma (2019) finds that the reference price ratio (pre-announcement stock price to 52-week high price) of the acquirer also significantly negatively influences abnormal returns, suggesting the stock price maximum works like a behavioral anchor and signals perceived overvaluation.

Toehold and serial acquirors

Toehold – a smaller, non-controlling ownership prior to acquisition - is used in the Moeller et al. paper (2004) as a determinant of acquisition success.

Fuller et al. (2002) and other literature (Billet and Quian, 2005 and Aktas 2009) found that serial acquirers tend to underperform compared to single acquirors. Serially acquiring might indicate a situation where the company is not capable of internal growth rates high enough and therefore, they must grow through acquisitions. This would be consistent with the growth signalling hypothesis by Moeller et al. (2004). The same behavior might also indicate that the acquisitions made are not as well founded or crucial for the company as for more cautious acquirers but made in a way to take a gamble on multiple opportunities at once. According to Malmendier and Tate (2008), overconfident CEO-s are also more likely to acquire than non-overconfident CEO-s, logically making them serial acquirors more commonly.

Corporate governance, managerial behavior and ownership

There is extensive literature on less tangible aspects of deal or acquirer characteristics that explain bidder returns, such as governance or culture.

Managerial overconfidence is found to be a driver of the lower abnormal returns in literature (Roll, 1986 and Malmendier & Tate, 2008) as well as the main culprit behind the size-effect according to Moeller et al. (2004). I already discussed this above more in detail.

Acquirors with significant concentrated holdings by independent long-term institutions and earn better abnormal returns which is explained by their monitoring behavior (Chen et al., 2007). Gompers, Ishii, & Metrick (2003) claims that firms with weak stakeholder rights engage in more acquisitions and these are more wasteful.

Mandatory shareholder voting is found to be effective at improving acquisition bidder gains in the UK by Becht, Polo and Rossi (2021).

Acquirers with anti-takeover defense mechanisms in place earn significantly lower return due to insulation from the market for corporate control. Managers protected by anti-takeover pills are more likely to engage in value-destructing behavior, since they are protected from hostile takeovers (Masulis et al., 2007). Harford et al. (2012) found that entrenched managers destroy value via avoiding private targets, avoid shareholder dilution by preferring cash over equity and thus excluding blockholders of the target that could impose discipline.

3. Data

As outlined in the introduction, I follow Moeller et al. (2004) in the compilation of the sample. I use acquisitions made between 1980 and 2023 from the Securities Data Company Platinum (SDC Platinum) database.

The sample only consists of deals made by publicly listed US companies with US targets that have available stock data from Datastream, accounting data from Compustat, available CUSIP, SIC codes and SDC Platinum deal data for all acquirors for the total relevant period. All market value data is from Datastream and all accounting data is retrieved from Compustat.

Deals are also filtered to adhere to the following criteria:

- Announcement date is between 1/1/1980 and 12/31/2023
- Above 1 million USD in deal value reported by SDC Platinum
- Above 1% of the market value of the assets of the acquiror, defined as total book debt plus market value of the shares, for simplicity
- The deal is completed and finished within 1000 days of the announcement
- Only include firms that did not have a controlling interest in the target prior to announcement and gain a controlling stake during the acquisition (from below 50% to above 50% interest)
- Only deals with one acquiror allowed per acquisition, as any consortium deals would be hard to track by the acquirers' stock
- Data split into two samples based on the direct acquiror company and the ultimate parent company of the acquiror: latter intended to filter out shell companies and SPV-s (yielding higher number of observations), but expected to decrease significance due to lower relative size
- Data is subsequently cleaned to only include deals with valid CAR-s

3.1. Merging the datasets

Stock data from Datastream:

Stock and market cap data is retrieved for every acquiror based on 9-digit CUSIP codes for each day available in the sample period plus 1 year before the sample. Market capitalization data is always recorded at the trading day's closing and daily stock returns are recorded from opening to closing. Whenever there is not enough data to form the estimation period later discussed for the market model, the acquiror and corresponding acquisition is dropped. Non-trading days are also cleaned where relevant.

Accounting data from Compustat:

The following data is included for every possible acquiror where it is available: total revenue, book assets, equity, liabilities and total debt. OCF, included in the Moeller et al. sample (2004 and 2005) is unused due to the low frequency of firms with available data. All values for the construction of metrics are used as the year-1 ending data at the time of the acquisition. For instance, for an acquisition made in 5/8/2020, the total value of its assets would be constructed by adding the current market capitalization at 5/8/2020 and the book total debt from 31/12/2019). Total debt is defined as long term debt plus debt in current liabilities, the rest of the variables are used from the source as they are reported in order to achieve cross-consistency between variables.

Market proxy and risk-free return from CRSP and Kenneth French Data library:

The daily market return proxy data is retrieved from Center for Research in Security Prices (CRSP) to be utilized by the market model. Both equal weighted and value weighted indices are used, the same way the original paper does (Moeller, 2004). Additional daily market return is also retrieved from the daily Kenneth-French daily, three factor model (KF 3FF) dataset for added robustness. It is constructed based on value weighted returns of NYSE, AMEX and NASDAQ returns with some adjustment and differs from both indices, although yields close results to value weighted CRSP (Kenneth French Data Library, 2024). Daily risk-free return data is also retrieved from the KF 3FF dataset. Each data element is cleaned from non-trading days and matched to the stock sample by days.

Supplementary data – NYSE 25th:

I use the 25th percentile of the NYSE as a breaking point for the separation of large and small firms as Moeller et al. (2004) did. However, I only was able to retrieve the NYSE total return of the index between 1980 and 2023 and the latest constituents from Datastream. To accurately follow the Moeller et al. paper (2004) I would require the constituents for each year.

However, due to the unavailability of historical constituents for the NYSE composite or any other representative (Russel 3000 or Wilshire 5000) indices from Datastream or CRSP, I make the discretion to reverse engineer the 25th percentile per each year based on the 2023 distribution. I take the current market capitalization of the constituents from 2023 and adjust them by the total return of the index for each year. Finally, I calculate the 25th percentile for this simulated sample of firms for every year. This method assumes that the companies of 2023 are representative of the size and distribution of market caps for every year and the number of constituents is either fixed or adjusted for in the total return.

Some of these assumptions are most likely violated since the official documentation by the index provider, International Exchange Inc. states that all new IPO-s are added and delisted/acquired/merged firms removed, resulting in a fluctuating number and sizes of firms (NYSE, 2024). Nevertheless, the inclusions and delistings are adjusted in the total return of the index, implying that only the distribution and size of the firms in the index are needed to find the 25th percentile. The index contains a diversified sample of around 2000 firms that represent the market and hence a constant distribution (some form of power-law distribution) can be assumed for a "good enough" approximation.

To argue further, Moeller et al.'s (2004) division of large and small firms is quite arbitrary in nature by itself, and that another type of arbitrary split would be just as defendable as the original if it is within reason. The resulting number and distribution of large and small acquirers are comparable to the original paper, reinforcing that this synthetic method is analogous. The synthetic quartiles are displayed by **Figure 2** in the appendix.

Supplementary data – Inflation data

For the construction of inflation adjusted dollar cumulative abnormal return (ANPV) from the Moeller et al. (2004) paper, I use inflation data from Federal Reserve Economic Data (metric: *FPCPITOTLZGUSA*) between 1979 and 2022 (FRED, 2024). At the moment of retrieval and construction of metrics there was no available data for the year 2023 and was substituted by data from Datastream (variable: *US CPI- ALL URBAN SAMPLE: ALL ITEMS - ANNUAL INFLATION RATE NADJ)* for that single year[2]**.**

The inflation data is published at the beginning of each year, I use these values for the reference inflation of the entire year. This creates a lag in inflation to some degree (mostly for deals past

[2] *Note: After the study was completed, inflation for 2023 data was published by FRED with an annual 4.12%. I used 4.14% from Datastream, creating a minor discrepancy. Nevertheless, this should not affect the results in any meaningful way*

the half year mark), however this is mostly irrelevant for the application used later, since the resulting metric does not need to be highly accurate.

From inflation data, a chained inflation index with base of year 2001 and 2023 are constructed to standardize each acquiror's abnormal dollar returns (ANPV) over the estimation period throughout the years. I include the one with base 2001 for side-by-side comparison with the original study. The yearly inflation data and compounded chains are shown in **Figure 3 (appendix).**

Supplementary data for additional variables:

The equity sentiment indicator (Baker and Wurgler, 2006) is retrieved yearly from the Harvard Business School website (Harvard Business School, 2024) and monthly matched to the date of the acquisition. HYS (Greenwood and Hanson, 2013) yearly and quarterly data are also retrieved from the same source and matched to the announcement date of every acquisition. Quarterly and monthly data is assumed to be stock type data at a given date; hence acquisitions are matched to the closest end of quarter/month data to get the variables. Only the quarterly and monthly data is used in the regressions.

The Hoberg-Phillips 10-K Text-based Network Industry Classifications (TNIC) data is retrieved and matched with available acquiror-target GVKEY - year pairs to get a more accurate indicator for industry or product fit. Neither 3-digit nor 2-digit SIC code granularity datasets yield meaningful (both less than 200) matches, so industry closeness is dropped from the variables (Hoberg and Phillips, 2024).

Industry assets and concentration are aggregated per year by 2-digit SIC codes to form variables following the original method (Moeller et al. 2004). As an alternative, I use the Kenneth French 48 industry classification from the Kenneth French Data Library (2024) to reclassify SIC codes and construct industries.

TABLE 1 – Panel A: Yearly aggregate abnormal returns of direct acquirors parents

- *The sample was obtained by the filtration process outlined in the* ***Data section*** *using direct acquirors*
- *Large and small acquiror are split based on the simulated 25th percentile of the NYSE.*
- *The aggregate dollar returns are the cumulative absolute returns earned during the [-1,+1] event window, with market capitalization weights. The Dollar Return = $MC_{+1} - MC_{-2}$., with the market capitalization taken at closing.*
- *Average returns are measured from day-2 to day+1.*
- *CAAR's are constructed over the same event window, using the market model (CAPM) with an estimation window of [-205, -6] for the parameters.*
- *Dollar figures in millions of USD*

Year	All	Large	Small	Aggregate dollar return	Average return [-1, +1]	CAAR [-1, +1]
1980	16	13	3	-634	0.52%	0.47%
1981	131	120	11	-3,910	-0.90%	-0.92%
1982	177	147	30	518	0.88%	0.05%
1983	222	176	46	-496	0.51%	0.39%
1984	277	205	72	1,538	1.06%	0.89%
1985	121	107	14	665	0.48%	0.13%
1986	231	206	25	1,084	1.79%	1.37%
1987	195	161	34	-1,624	0.91%	0.69%
1988	225	152	73	2,336	1.18%	0.30%
1989	292	185	107	-293	0.61%	0.24%
1990	248	154	94	-438	0.89%	0.71%
1991	274	153	121	2,101	6.71%	2.45%
1992	408	229	179	-209	2.85%	2.11%
1993	572	329	243	3,112	1.91%	1.52%
1994	698	401	297	-5,944	1.32%	1.00%
1995	804	443	361	3,398	1.45%	0.83%
1996	967	553	414	16,384	2.28%	1.65%
1997	1326	738	588	-506	1.67%	1.16%
1998	1347	678	669	-3,382	1.68%	-2.76%
1999	988	484	504	-48,045	1.86%	1.06%
2000	828	458	370	-124,408	1.07%	0.66%
2001	638	335	303	-24,287	1.93%	1.27%
2002	613	368	245	-16,155	1.89%	0.84%
2003	618	342	276	-23,033	1.44%	0.59%
2004	684	392	292	-3,186	1.94%	1.25%
2005	748	401	347	-7,258	1.17%	0.98%
2006	744	410	334	2,679	1.30%	0.87%
2007	688	385	303	-1,448	1.16%	0.99%
2008	462	292	170	-23,803	0.67%	1.19%
2009	340	202	138	-3,142	2.67%	1.97%
2010	475	309	166	3,686	1.18%	0.22%
2011	494	323	171	11,369	1.62%	0.96%
2012	531	349	182	16,397	1.94%	1.49%
2013	530	330	200	32,660	3.28%	2.13%
2014	643	389	254	16,534	3.08%	2.22%
2015	593	401	192	11,010	1.09%	0.16%
2016	494	345	149	-34,650	1.85%	0.51%
2017	523	349	174	24,117	1.38%	-0.63%
2018	498	365	133	-43,983	1.40%	0.92%
2019	409	274	135	-22,740	1.29%	0.70%
2020	323	203	120	-19,679	5.01%	2.69%
2021	570	390	180	65,839	3.47%	2.64%
2022	366	227	139	-55,875	0.67%	0.85%
2023	257	158	99	-8,796	2.95%	1.71%
Total	**22588**	**13631**	**8957**	**-262,495**	**1.77%**	**0.86%**

3.2. Discussion of the sample properties

The final sample displayed in **Table 1: Panel A** yields data for 44 years, exactly twice the size of the original paper. Most firms are classified as large in the sample, this is the result of the arbitrary classification, the minimum requirement for size and the fact that data cleaning tend to affect targets with less data which in turn are more likely to be smaller. In reality, most acquisitions would not be made by large firms.

The final sample contains a total of 22558 data points with the direct acquiror approach. See **Table 1: Panel B** in the appendix for the same statistics with ultimate parent approach.

The distribution of small and large firms is comparable to Moeller et al. (55% large firms in their sample for 60% large in my sample), proving my naïve method of generating synthetic NYSE 25^{th} percentiles effective.

Absolute average cumulative return is higher than CAAR, which is also true for most of the years. The cumulative average stock return (non-abnormal) over the event window is 1.77%, indicating that acquirors earn positive returns on average around the announcement days. Acquisitions also yield positive CAR-s on average, consistent with Moeller et al. (2004).

However, there are more years with negative dollar return and negative aggregate dollar returns. This indicates that the acquisitions with higher weights - larger market capitalization - earn negative returns that skew the weighted data to be negative. Stock data can be skewed by design due to the lower bound being 0 for prices but has an uncapped upper bound. The value destruction seems to be driven by larger acquisitions, consistent with Moeller et al. (2005). Wealth destruction is largest around the early 2000-s, but there are more years with negative net aggregate dollar returns than with positive across the sample. On the other hand, the yearly average returns are only once, and average CARs are only three times negative.

As visible from **Table 1: Panel B** in the appendix, the ultimate parent methodology yields more datapoints due to more public acquirors being allowed. This is due to the fact that the end of the corporate chain tends to be public rather than private. The intended effect is to exclude SPV-s in return for less significance. The 23259 observations of the sample are only slightly higher than with the direct acquirors. The method results in very similar returns, with slightly better performance of acquisitions across the board (less negative dollar returns, higher CAAR-s). The proportion of small and large firms is essentially the same as well. This is mostly due to the high overlap of acquirors between the two types of samples.

4. Methodology & results

Purpose of the study is laid out in the introduction section: to examine whether acquisitions create value on average, examine whether the size-effect existed and still stands, test if it is possible to explain it with other factors and check if the results are robust.

4.1. Summary of the methodology

With the data sampled similar to Moeller et al.'s (2004), I follow the paper in methodology for comparable results using standard event study technique. I construct cumulative average abnormal returns for the whole sample, a split sample for the two even time periods and for small and large firms separately. I complement the standard CAAR measure with additional metrics used by Moeller et al. (2004). Then I present the statistical properties of CAAR-s and other metrics and discuss its potential problematic nature. Finally, to conclude the event study part I test for the significance of small and large firms separately and for their differences with t-tests. I evaluate both the direct acquirer and the ultimate parent approach.

In the next section I construct potential explanatory variables from Moeller et al. (2004) and literature to explain the size-effect with OLS regressions. After that I present the summary statistics of these variables for all, large and small firms and split periods. My first regressions imitate Moeller et al.'s (2004) original regressions with minor adjustments. Then, I examine the interactions between the main control variables, such as payment and public status, and size. Subsequently, I introduce new and swap out variables to achieve greater explanatory power. I examine the interactions between target and acquiror size in detail after the findings of the Alexandridis, et al (2013) paper. To conclude this section, I evaluate the models and compare them to literature.

In the original study (Moeller et al. 2004), the authors tested whether the size-effect results from lower synergy gains or overpayment by larger firms. They found that smaller firms do earn higher synergies measured by the combined immediate synergy gain of the two firms on announcement. Note that this methodology inherently disregards private firms, since they do not have returns that could be measured. Public to public transactions could have their own peculiarities and they are also more likely to be done by large firms. This way conclusions cannot be drawn for the whole set of firms due to the bias introduced. For these reasons I do not attempt to retest their findings in this regard. About overpayment, they concluded that large firms overpay for their acquisitions and in turn are more successful as well. These results are in line with the hubris theory, but do not directly support it. My study focuses on the existence and scrutiny of the size-effect and not the hypothetical intangible drivers of it, therefore I skip this part of their analysis.

Moeller et al. (2004) found that small acquirors outperform large acquirors on the long run. Long term underperformance of large firms could signal that at the announcement the market also corrects for the overvaluation of the large acquiror (Moeller et al., 2004). Lack of persistence could suggest arbitrageur activity at the announcement. Including longer horizon testing in this study would require different methods and would be out of scope for the study. Additionally, a large window method (such as calendar-time post-event abnormal returns) would introduce a higher chance endogeneity in the interpretation and would require a more meticulous treatment of confounding events. In my sample I do not control for confounding events directly. From **Figure 4 (appendix)**, the raw and trimmed CAAR figures show that there is a drift of abnormal returns for small acquirors, suggesting the market does not fully incorporate all the information at the time of the announcement into the stock price. In a later part of this study, I will briefly discuss this potential information gap.

In the robustness section, I intend to find if the results hold up to statistical scrutiny. I test for the robustness of the market proxy, the choice of window length and discuss the choice of market model and the division of large and small firms. Additionally, I investigate the issues of outliers and dependency in the sample and introduce remedies. These solutions include trimming the sample, using firm fixed effects or clustered standard errors. I rerun each two-sample t-test and OLS regression where relevant.

To conclude my research, I discuss the results and make reservations about the methodology. Lastly, I connect the findings to the broader literature and outline further research ideas to continue.

4.2. Value creation by acquisitions – event study

4.2.1. Construction of CAAR-s

I follow standard event study methodology; hence the assumptions are that the event is clearly identifiable, the markets are efficient at incorporating information into stock prices, there is a significant impact caused by the event in the event window, the market models adequately capture the normal behavior of stock returns, the underlying stock returns have stationary properties and there are no confounding events within the event window. (MacKinlay, 1997).

By default, I am using a [-1,+1] event window to follow Moeller et al. 's (2004) methodology. Abnormal returns (AR) are defined as: $Abnormal\,return = Return_{actual} - Return_{normal}$, while $CAR_i = \sum_{-1}^{+1} \sum AR_{i,t}$ on the 3-day event window around the announcement day.

Normal returns are forecasted by CAPM: $Expected\,Return_i = R_f + \beta_i(R_m - R_f) + \alpha$. Following Moeller et al. (2004), betas and alphas are estimated over a [-6,-205] range before the announcement for each acquisition based on excess returns. The estimation period in theory ensures that there is no overlap with the event window. I construct normal returns, AR-s and cumulative abnormal returns (CAR) with 3 different market proxies: EW (equal-weighted) from CRSP, VW (value-weighted) from also CRSP and KF (Kenneth French) from the Kenneth French dataset used for additional robustness. The question of choice of variable using VW and KF market proxies instead of EW is reported in the robustness section. In this section all values are using EW-CRSP as the proxy for the market returns.

Table 2 reports cumulative average abnormal returns (CAAR) and the summary statistics of CAR-s in both the direct acquirer and ultimate parent samples. The significance of CAAR-s is tested with cross sectional t-tests and represented by their p-values. The null hypothesis for all t-tests is whether the value or difference equals zero. Cross-sectional t-statistics are constructed the following way:

$$Csect\,T = \sqrt{N}\frac{CAAR}{STDEV_{CAR}}.$$

CAAR-s are positive and visibly different for small and large firms. Every CAAR in the complete sample is significant based on p-values at any level. Median CAR-s are closer to 0 than CAAR-s, as expected, but still positive for every category. The standard deviations of returns are larger for small firms, as intuitively one would expect due to their higher volatility. Both direct acquiror and ultimate parent samples yield similar results.

TABLE 2: Summary statistics of cumulative abnormal returns

- *CAR-s are constructed on a [-1,+1] event window and CAAR is averaged across all observations*
- *Small and large firms are split according to the simulated 25th percentile of the NYSE firms*
- *Normal returns are based on CAPM, betas and alphas are estimated over a [-6, -205] range*
- *Uses Equal Weighted CRSP market proxy*
- *Significance of CAAR-s are based on cross-sectional t-tests and represented by p-values*

ACQUIROR	**DIRECT ACQUIROR**			**ULTIMATE PARENT**		
SAMPLE	ALL	LARGE	SMALL	ALL	LARGE	SMALL
CAAR [-1,+1]	**0.86%**[a]	**0.43%**[a]	**1.51%**[a]	**0.96%**[a]	**0.48%**[a]	**1.71%**[a]
Median CAR	0.3%	0.1%	0.6%	0.4%	0.2%	0.6%
STDEV	28.4%	6.3%	44.4%	30.3%	6.3%	47.6%
Skewness	-57.88	0.69	-38.23	-37.14	0.72	-24.33
Ex. kurtosis	6800.91	12.10	2870.39	5664.93	12.32	2357.59
N	22588	13631	8957	23259	14089	9170
JB test stat	4.35E+10	8.42E+04	3.08E+09	3.11E+10	9.03E+04	2.12E+09
CSect t-stat	4.6	8.0	3.2	4.9	9.0	3.5
p-value	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*	*0.001*

a: *statistical significance at the 1% level*
b: *statistical significance at the 5% level*
c: *statistical significance at the 10% level*

The sample exhibits a very high skewness and excess kurtosis resulting in a right tailed and leptokurtic data. Note **Figure 1** in the appendix for illustration. Extreme outliers reduce the accuracy for the regression fits and the inference testing.

There are also some concerns about dependence in the sample, since firms can be acquirers and targets multiple times and there could be cross-ownership and co-influencing factors (such as industry trends) that are not included in the market proxy. These said problems will also further be discussed in the robustness section.

4.2.2. Construction of additional metrics

I construct additional metrics that better showcase the existence of value creation and destruction on the aggregate. The metrics include value-weighted cumulative average abnormal returns (VWCAAR), average dollar abnormal return (ANPV), inflation average adjusted dollar abnormal return ($ANPV_{year}$) and target relative average dollar return (ANPV/TV). The metrics are constructed the following way:

$\overline{\boldsymbol{VWCAR}}$ is calculated as the value-weighted average of CAR-s instead of the equal weighted as in CAAR. The weights are the market values of the equity measured by the market caps at day t-2 closing. *Formula:* $\overline{VWCAR} = \frac{\sum_{i=1}^{n} MV_i CAR_i}{\sum_{i=1}^{n} MV_i}$

$\overline{\boldsymbol{ANPV}}$ is the average dollar abnormal return. Abnormal dollar returns are defined as $ANPV = CAR * MV_{t-2}$, where MV is the market value of the equity day t-2 closing.

$\frac{\overline{\boldsymbol{ANPV}}}{\boldsymbol{TV}}$ is the average dollar abnormal return divided by the deal value measuring a scaled dollar return per target value. *Formula:* $\frac{\overline{\boldsymbol{ANPV}}}{\boldsymbol{TV}} = \frac{\boldsymbol{1}}{\boldsymbol{n}} \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \frac{\boldsymbol{ANPV_i}}{\boldsymbol{TV_i}}$

$\overline{\boldsymbol{ANPV}}_{\boldsymbol{2001}}$ is the average dollar abnormal return adjusted for inflation, with a base of 2001 (2001 value = 100%), included for comparability with the original study. *Formula:* $\overline{ANPV}_{2001} = \frac{ANPV}{Inflation\ chain}$

$\overline{\boldsymbol{ANPV}}_{\boldsymbol{2023}}$ is the average dollar abnormal return adjusted for inflation with a base of 2023. See **Figure 3** in the appendix for the yearly values for both chained inflation indices.

4.2.3. Discussion of value-creation

For t-testing for the difference between large and small firms I used Welch two-sample t-test (H_0=0), since the two samples have different variances and different number of observations.

Formula: $t = \frac{\mu_1 - \mu_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$

Interestingly, in the first period from **Table 3 - Panel A** - the same period that Moeller et al. (2004) used-, the H_0 cannot be rejected at even a 10% significance level despite an observable, -0.81%, difference between large and small firms. The second sample period (2002-2023) is a lot more conclusive with a -1.38% difference that is significant at the 1% level. The combined sample is also significant at 5%, with a -1.08% difference between large and small firms.

Sample 2002-2023 contains more large firms proportionally than the previous, but the difference is not major, proving again that the arbitrary distinction between small and large firms are relatively stable over a long time (44 years). Both subsamples are similar in size and even in length of timeframe.

TABLE 3 – PANEL A: Abnormal returns per period, based on the direct acquiror

- *CAR-s are constructed the same way as in **Table 2**.*
- *Small and large firms are split according to the simulated 25^{th} percentile of the NYSE firms.*
- *VWCAAR is value weighted CAR, where the weights are MC_{t-2} market capitalizations.*
- *ANPV is the dollar abnormal return with the same weights as above. ANPV/TV is scaled to target size and $ANPV_{year}$ is the dollar abnormal return standardized by inflation.*
- *All metrics are calculated around the [-1,+1] event window.*
- *Significance of CAAR-s are based on Csect t-tests and represented by p-values and the two sample t-tests are based on the Welch t-test.*

PERIOD	**1980-2001**				**2002-2023**				**1980-2023**			
SAMPLE	ALL	LARGE	SMALL	LARGE - SMALL	ALL	LARGE	SMALL	LARGE - SMALL	ALL	LARGE	SMALL	LARGE - SMALL
CAAR	0.60%	**0.26%**[a]	1.07%	-0.81%	**1.11%**[a]	**0.58%**[a]	**1.96%**[a]	**-1.38%**[a]	**0.86%**[a]	**0.43%**[a]	**1.51%**[a]	**-1.08%**[b]
STDEV	38.55%	6.54%	59.33%	0.88%	12.85%	6.18%	19.28%	0.30%	28.41%	6.35%	44.43%	0.47%
N	10985	6427	4558	10985	11603	7204	4399	11603	22588	13631	8957	22588
p-value	*0.103*	*0.001*	*0.222*	*0.359*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.023*
VWCAAR	**-1.15%**[a]	**-1.19%**[a]	0.61%	**-1.80%**[a]	**-0.25%**[a]	**-0.27%**[a]	**0.89%**[a]	**-1.15%**[a]	**-0.45%**[a]	**-0.47%**[a]	**0.80%**[a]	**-1.27%**[a]
WSTDEV	8.70%	6.53%	39.16%	0.59%	4.82%	4.68%	10.78%	0.17%	5.91%	5.15%	23.49%	0.25%
p-value	*0.000*	*0.000*	*0.292*	*0.002*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.000*
ANPV	**-20.85**[a]	**-36.05**[a]	0.59	**-36.65**[a]	**-15.34**[c]	**-25.93**[c]	**2.01**[a]	**-27.95**[c]	**-18.02**[a]	**-30.71**[a]	**1.29**[a]	**-32.00**[a]
STDEV	631.15	824.52	27.26	10.29	966.79	1226.71	25.05	14.46	820.87	1056.31	26.21	9.05
p-value	*0.001*	*0.000*	*0.141*	*0.000*	*0.087*	*0.073*	*0.000*	*0.053*	*0.001*	*0.001*	*0.000*	*0.000*
ANPV/TV	-0.10	0.03	-0.29	0.32	**0.05**[a]	**0.05**[a]	**0.07**[a]	-0.02	-0.02	**0.04**[a]	-0.12	0.15
STDEV	9.93	1.88	15.25	0.23	1.50	1.39	1.66	0.03	7.01	1.64	10.94	0.12
p-value	*0.279*	*0.175*	*0.196*	*0.154*	*0.000*	*0.005*	*0.007*	*0.473*	*0.634*	*0.005*	*0.317*	*0.184*
ANPV (2023)	**-38.08**[a]	**-65.94**[a]	1.20	**-67.15**[a]	**-20.73**[c]	**-34.99**[c]	**2.64**[a]	**-37.64**[b]	**-29.17**[a]	**-49.59**[a]	**1.91**[a]	**-51.50**[a]
STDEV	1138.00	1486.59	50.79	18.56	1208.68	1533.61	31.73	18.08	1174.85	1511.65	42.52	12.96
p-value	*0.000*	*0.000*	*0.109*	*0.000*	*0.065*	*0.053*	*0.000*	*0.037*	*0.000*	*0.000*	*0.000*	*0.000*
ANPV (2001)	**-22.12**[a]	**-38.31**[a]	0.70	**-39.01**[a]	**-12.04**[c]	**-20.33**[c]	**1.53**[a]	**-21.87**[b]	**-16.94**[a]	**-28.81**[a]	**1.11**[a]	**-29.92**[a]
STDEV	661.16	863.68	29.51	10.78	702.22	891.00	18.44	10.50	682.57	878.24	24.70	7.53
p-value	*0.000*	*0.000*	*0.109*	*0.000*	*0.065*	*0.053*	*0.000*	*0.037*	*0.000*	*0.000*	*0.000*	*0.000*

***a**: statistical significance at the 1% level*
***b**: statistical significance at the 5% level*
***c**: statistical significance at the 10% level*

The new period shows higher observable returns across all metrics. The 1980-2001 sample contains lower average returns compared to Moeller et al.'s (2004) findings, who find 1.1% total CAAR-s and -2.2% difference between the firm sizes. My equivalent results show a 0.6% total CAAR and only a -0.8% difference. This inconsistency between findings could be attributed to the sampling. With using ultimate parent as acquirer, the same conclusions can be drawn with slightly different values, -1.24% is size-effect in total. See **Table 3 - Panel B (appendix)** for the results with the ultimate parent method. When considering the weighted metrics there are also observable differences between periods. The underperformance of large firms is consistent throughout the 44 years, which is remarkable.

VWCAAR implies a similar pattern between large and small firms, with a -1.27% (-1.21% for ultimate parent) difference, large than the CAAR. Interestingly, even between subsamples of acquirors of different sizes there is an observable negative bias for higher weights. The CAAR is always higher than the corresponding VWCAAR, implying that the observations with higher weights (sizes) decrease the average CAR within both categories of firms. The total VWCAAR-s are consistently and significantly negative in all periods, but there is an upward trend across the whole sample, consistent with the trend of the equal weighted bidder returns.

Differences between the subgroups in average ANPV and $ANPV_{year}$ metrics are also significant at all levels. The ANPV-s for all samples paint a similar picture as VWCAAR: all significantly negative due to the higher weights for larger, negative gain deals. My results for both the first half of the sample and the total sample are comparable to Moeller et al.'s (2004) findings with slightly lower values. For the ultimate parent sample, the average ANPV metrics exhibit poorer significances for the new period, but in total the differences are still significant at 10%.

ANPV/TV relates the weighted gain/loss of the company at announcement for the amount paid for the target. This metric is less consistent across the board and hence the size-effect gauged by this metric is not significant anywhere. This is unusual compared to looking at the results of the Moeller et al. study (2004), where there is clear significance presented for the differences.

The weighted metrics imply a more drastic value destruction by large firms that is consistent with the aggregate results of **Table 1**. and Moeller et al.'s (2004 and 2005) findings. However, only the abnormal returns without weights contain no information about size in themselves. Its unbiased nature is better suited for explanatory regressions. In total I find that while on average acquisitions do create positive value for the shareholders, in the aggregate they destroy it.

4.3. Explanatory variables of bidder returns

4.3.1. Definition of variables

I follow Moeller et al. (2004) in constructing the variables that are used in both mine and the reference paper for control variables in the explanatory regressions. I add a completely new category of variables: market characteristics. I also introduce new factors from literature and explain their relevance more in detail. For variables I do not elaborate in detail about the variables used in Moeller et al.'s (2004)' regressions, since the theory and findings in literature were already presented in the **2. Literature review** section.

As said before, the OCF data was not available in large enough numbers, so I omitted OCF/assets as a variable from my analysis that was supposed to measure operational efficiency and cash liquidity and instead substituted it with cash/assets. These variables have different information content, but cash/assets also can proxy for the free cash flow hypothesis, since cash on the balance sheet can also be a sign of value-destructive behavior.

Deal characteristics:

- **Deal value:** or target size/ target value (TV) is the total consideration paid by the acquirer excluding fees and expenses. It expresses the scale of acquisition and the size of the target.
- **TV/assets**: the relative size of acquisition, defined as the target value divided by book value of assets.
- **Relative size:** the relative size of the acquisition to the acquirer's equity, defined as the target value divided by acquirer's market capitalization.
- **Days to completion:** proxies for deal complexity, defined as the number of days from announcement to completion.
- **Liquidity index:** proxies for target industry competitiveness, defined as the ratio of the aggregate M&A deal value in a given industry to total combined assets in the industry, with industries grouped by 2-digit SIC codes of the target.
- **Competed deals:** also proxies for bidding competition, defined as a dummy variable, 1 if there is more than one bidder as retrieved from SDC Platinum.
- **%Cash in payment**: proxies for cash financing method, defined as the percentage of transaction value paid in cash by SDC Platinum.
- **%Equity in payment:** proxies for equity financing method, defined as the percentage of transaction value paid in equity by SDC Platinum.

- **%Other in payment**: proxies for any other financing method, defined as the percentage of transaction value paid via other payment methods.
- **All cash:** the deal was only paid by cash, defined as dummy variable, 1 if the deal is 100% financed by cash.
- **All equity:** the deal was only paid by equity, defined as dummy variable, 1 if the deal is 100% financed by equity.
- **Mixed payment:** the deal was paid with a mixture of cash and equity or other, defined as dummy variable, 1 if the deal is not 100% financed by equity or cash
- **Hostile:** proxies for hostile takeover, defined as a dummy variable, 1 if the deal attitude is flagged as hostile by SDC Platinum.
- **Tender offer:** the acquisition is made by a tender offer, defined as a dummy variable, 1 if the acquisition is made with a tender offer.
- **Conglomerate deals**: proxies for a diversification acquisition, defined as a dummy variable, 1 if target's industry differs from acquirer's based on their 2-digit SIC codes
- **Conglomerate deals (Fama-French)** proxies for a diversification acquisition, defined as a dummy variable, 1 if target's industry differs from acquirer's based on the Fama-French 48 industry classification
- **Public target:** the target is a publicly listed firm, defined as a dummy variable, 1 if target is public.
- **Private target**: the target is a privately owned firm, defined as a dummy variable, 1 if target is a private.
- **Subsidiary target:** the target is a subsidiary of another firm, defined as a dummy variable, 1 if target is a subsidiary.
- **Large loss deal:** defined as a deal where the acquiror loses more than a billion dollars during the 3-day event window, defined as MC_{+1}-MC_{-2} >1000 (million dollars), it is included for segmentation purposes to test whether large-loss deals work differently than non-large.
- **Large gain deal:** defined as a deal where the acquiror gains more than a billion dollars during the 3-day event window, defined as MC_{+1}-MC_{-2} >1000 (million dollars), included for the same reason as large loss deals.
- **Non-large loss/gain deal**: defined as a deal where the acquiror does not gain nor loses more than a billion dollars in the 3-day event window, included for segmentation purposes to see if non-extreme deals work differently.

- **Target HHI:** idefined as the Herfindahl-Hirschman index for the same industry where the target operates, the market shares are based on all revenues in the same 2-digit SIC code from the Compustat database. HHI is the squared sum of percentages of market shares (market shares are interpreted as without the percentage sign).
- **Toehold:** proxies for a non-controlling ownership prior to the acquisition, defined as a dummy variable, 1 if there is any prior ownership by the acquiror. Toehold is used in Moeller et al.'s (2004) study as a variable to explain the probability of success for deals. These holdings of acquirers should facilitate closing deals easier, reduce hostility and might imply better information about the target from the perspective of the acquiror (Moeller et al., 2004). I include the variable in the proverbial "kitchen sink" variable set.

Acquiror characteristics

- **Cash/assets (book):** proxies for the liquidity of acquirer, defined as ratio of cash to book value of total assets. As outlined before, it can also proxy for the free-cash flow hypothesis, as firms with high cash reserves might signal for empire building CEO-s.
- **Assets (book):** proxies for the size of acquiror, calculated as the book value of the total assets
- **Assets (market):** proxies for the size of acquiror, calculated as the book value of total the debt plus the market capitalization of the acquirer at the time of the acquisition.
- **Equity (market):** proxies for the size of acquiror, calculated as the market capitalization of the acquiror at the time of the acquisition.
- **Debt/assets (book):** proxies for financial leverage, defined as the total debt divided by the book value of the total assets.
- **Debt/assets (market):** proxies for financial leverage, defined as the total debt divided by the market value of the total assets.
- **Tobin's Q:** proxies for the growth opportunities and overvaluation level of the firm, defined as the market value of the firm's assets divided by the book value of the assets.
- **Book-to-market:** indicator for the valuation level of the acquirer, signaling over/under valuation, defined as the book value of the equity divided by the market value of the equity.
- **RPR ratio:** is another proxy for the market valuation level of the acquirer, but it should capture the perceived overvaluation of the firm by the market as the anchoring effect were found to be prevalent with target firms in literature (discussed in the **Literature**

review section). It is defined as defined as the day-6 market capitalization per 52-week maximum of the market capitalization. I construct RPR ratios based on the market values of the equity instead of the price due to data retrieval limitations, but both ratios should exactly be the same as both the numerator and denominator is multiplied by the number of stocks, equalizing it.

- **Serial acquiror**: proxies for acquirors who made (same as in Moeller et al., 2004) five acquisitions within a 3-year distance from the specific deal, including that deal. Defined as a dummy variable, 1 if the acquirer is a serial acquirer. Serial acquisitive behavior might be connected to hubris.
- **Market share of the acquirer**: represents the market share of the acquirer, defined as the total revenues of the acquirer from the previous year, divided by all revenues in the same year in that 2-digit SIC code. The market share variable should capture the market's evaluation of firms with high market power.
- **Acquirer HHI**: is defined as the Herfindahl-Hirschman index for the same industry where the acquirer operates, the market shares are based on all revenues in the same 2-digit SIC code from the Compustat database. HHI is the squared sum of percentages of market shares (market shares are without the percentage sign).

Market characteristics

- **HYS (Y):** proxies for the cycle of the credit market, defined as the HYS value for the year. The indicator is constructed by Greenwood and Hanson (2013). High HYS indicates that at the time of the deal there is more low-quality debt issued on the market, potentially leading to a higher number of low-quality acquisitions paid by cash financed by cheap debt.
- **HYS (Q):** proxies for the cycle of the credit market, defined as the closest quarterly HYS value (Greenwood and Hanson, 2013).
- **SENT index (Y):** proxies for equity market sentiment, defined as the yearly SENT index Baker and Wurgler (2006). High SENT index indicates high investor enthusiasm, potentially leading to an increased turnover for the takeover and the equity market.
- **SENT index (M):** proxies for equity market sentiment, defined as the monthly SENT index constructed by Baker and Wurgler (2006).

TABLE 4 – PANEL A: Summary statistics of explanatory variables by acquiror size

- *Financial data in millions of USD*
- *Mean values displayed in line with the variable names*
- *Median values below the means in italic when relevant*
- *Small and large firms are split according to the simulated 25th percentile of the NYSE firms*

SAMPLE	ALL	LARGE	SMALL
Number of observations	**22588**	**13631**	**8957**
Deal characteristics			
Deal value	418.51	664.72	43.83
	50.00	*115.00*	*15.15*
TV/assets (mkt)	44.23%	11.91%	93.42%
	6.82%	*4.98%*	*11.03%*
Relative size (TV/equity)	54.75%	16.78%	112.52%
	9.64%	*7.00%*	*16.00%*
Days to completion	71	78	62
	42	*48*	*28*
Liquidity index	0.05	0.05	0.04
	0.013	*0.014*	*0.012*
Competed deals	0.009	0.012	0.004
% Cash in payment	37.96%	39.38%	35.79%
% Equity in payment	23.28%	22.71%	24.13%
% Other in payment	39.01%	38.20%	40.25%
All cash	25.74%	28.80%	21.09%
All equity	15.07%	15.48%	14.44%
Mixed payment	26.32%	22.51%	32.12%
Hostile deal	0.26%	0.38%	0.07%
Tender offer	3.32%	4.55%	1.46%
Conglomerate deal	65.26%	65.12%	65.47%
Conglomerate deal (FF)	39.31%	39.44%	39.10%
Public target	18.95%	22.66%	13.30%
Private target	49.27%	43.47%	58.10%
Subsidiary target	31.78%	33.87%	28.60%
Large loss deal	1.39%	2.31%	0.00%
Large gain deal	1.30%	2.16%	0.00%
Non-large loss/gain deal	97.30%	95.53%	100.00%
HHI of target industry	757.17	751.39	765.95
	462.04	*458.44*	*462.04*
Toehold	1.53%	1.86%	1.03%

TABLE 4 (continued)

Acquiror characteristics			
Cash/assets (book)	0.10	0.09	0.12
	0.04	*0.04*	*0.04*
Assets (book)	6408.41	10256.14	552.83
	568.93	*1509.16*	*109.85*
Assets (market)	5372.33	8724.89	270.31
	726.90	*1931.40*	*151.95*
Equity (market)	4004.54	6529.34	162.24
	505.39	*1362.03*	*111.40*
Debt/assets (book)	0.23	0.24	0.22
	0.18	*0.20*	*0.13*
Debt/assets (market)	0.24	0.23	0.24
	0.17	*0.17*	*0.15*
Tobin's Q	6.13	2.35	11.86
	1.21	*1.35*	*1.05*
Book-to-market ratio	0.75	0.60	0.97
	0.46	*0.41*	*0.57*
RPR ratio	0.71	0.72	0.70
	0.73	*0.72*	*0.70*
%Market share of acquiror	0.93%	1.40%	0.20%
	0.09%	*0.22%*	*0.02%*
HHI of acquirer industry	623.45	598.69	661.81
	388.73	*383.47*	*405.50*
Serial acquirer	22.32%	25.35%	17.71%
Market cycle			
HYS (Yearly)	0.21	0.22	0.19
	0.17	*0.17*	*0.17*
HYS (Quarterly)	0.25	0.26	0.23
	0.13	*0.13*	*0.12*
Sentiment index (Yearly)	0.34	0.34	0.34
	0.34	*0.34*	*0.37*
Sentiment index (Monthly)	0.34	0.34	0.34
	0.34	*0.34*	*0.35*

4.3.2. Discussion of the summary statistics

From the summary statistics (**Table 4 - Panel A**), we can observe that deal values are naturally larger with large firms, with median values being a lot lower than the means for both categories, implying a skewed distribution. Both market and book value based relative size variables have apparent differences between large and small firms, with small firms having a significantly larger relative size. This is in line with Moeller et al.'s (2004) findings and the expectations, since small firms were found to earn more on acquisitions and benefit from large relative sizes. However, the median figures show that the typical differences are less drastic, and averages are skewed by outliers, possibly by some highly leveraged LBO-s. From **Table 4 - Panel B (appendix)** we can observe a radical change between the periods within the group of small firms. This radical increase in relative size could reinforce the LBO theory mainly driven by the peak of the activity in the early 2000-s (Kaplan and Strömberg, 2008).

Large firms also complete deals with increased competition, however the differences are not major. These types of firms take on deals requiring more complexity and thus close longer. Both competition and deal complexity/execution speed decreased in the newer sample according to **Table 4 - Panel B (appendix).**

Payment type variables seem to be relatively similar across firm types, with small firms preferring equity slightly more and cash slightly less than large firms. The percentage of other types of payment seems to be the highest, which is unexpected. The SDC Platinum database calculates this value indirectly from cash and equity payments, therefore this variable might capture some missing data. For these reasons, the mixed payment variable will not be directly used in the explanatory regressions. Between the two subsamples **(Table 4 - Panel B)**, the preference of cash payment seemed to have increased, and equity payment decreased in turn across both firm types. The differences between the subsamples are much greater than the differences within firm types. This questions the accuracy of payment type being a reliable and time-consistent factor.

Small firms do not take on hostile takeovers in line with expectations, and tender offers are also more common with large firms. Hostile takeovers have gone almost entirely out of fashion since the period of Moeller et al.'s (2004) study as shown by the data from **Table 4 - Panel B**.

Conglomerate deals seem to be the same across all firm sizes. This indicates that either both small and large firms take on diversifying acquisitions most of the time, or the metric itself is not working as intended. Hoberg and Phillips (2010) reports that metrics based on SIC codes are unable to measure differences both within and across industries and they are also discrete (they are in the same industry or not). Using raw SIC codes also either makes the defined industries too high level – sectorial level - or omit vertical integration, due to the fact that SIC codes are clustered primarily by activity type and not by product type. An alternative method would be using the Hoberg-Phillips (2010) text-based network industry closeness score. Unfortunately, the number of scores available for the acquirer-target pairs in the sample are too low to take conclusions from. I also test the conglomerate binary variable constructed based on the Fama-French 48 industries (Kenneth French Data Library, 2024). This method clusters two digit SIC codes into broad sectors or industries, allowing vertical integration for the price of decreased granularity. The variable using this classification type yields a sample with lower amounts of conglomerate deals, but again, no major differences between large and small firms. These findings indicate that either firms with different sizes are not different in behavior related to industry fit or these variables do not perfectly define industry boundaries.

According to **Table 4 - Panel A**, small firms are less likely to acquire a public target than large firms, however the difference is less drastic compared to Moeller et al.'s (2004) sample. Deals with private targets work the other way. Subsidiaries are more likely to be acquired by large firms, which theory does not suggest, nor does the original study. Moeller et al., 2004 reports acquisitions of subsidiaries yielding the highest returns of all target types. Naturally large loss or gain deals are exclusive to large firms. The HHI of targets seems to not differ greatly between firms of different sizes. Both the means and medians are unusually low compared to expectations, as HHI-s around 400-800 would imply a very unconcentrated industry. The fact that typical scores are around that range is not impossible, but I would expect higher averages due to the exponential nature of this metric (U.S. Department of Justice, 2010). For context, Offenberg (2009) reports HHI indicators around 700-900 on average based on Fama-French 48 industries.

The existence of toeholds is associated with higher acquiror size. The number of firms with toeholds is unusually low, only in the hundreds. Calculating the percentages of ownership indirectly from other SDC variables yields a slightly higher number but within the same magnitude. It is also claimed to be potentially endogenous in nature by Moeller et al. (2004).

In terms of acquiror characteristics, cash-to-assets are similar across firm sizes, but smaller ones seem to have more cash on hand proportionately. This is in line with Moeller et al.'s (2004) data, but contrary to expectations. It is not a perfect equivalent for OCF/assets, but it can substitute in proxying for the free cash flow hypothesis. The free cash flow theory suggests that cash-rich firms should be more prone to empire building, associated with larger firms in theory.

Leverage levels are essentially the same across all firm sizes. Tobin's Q is a lot higher for smaller firms, although it is potentially skewed by outliers as indicated by the median values. The original paper's summary statistics (Moeller et al., 2004) contain significantly lower Tobin's Q values for small firms. If we compare the two periods (original and new), there is an apparent difference. From **Table 4 - Panel B** it is visible that the values of the first sample are very similar to Moeller et al.'s (2004) findings, while the same variable for small firms in the new sample is extremely high (22.18 versus the 1.9 of the old). The median values, that are not reported in this study per period, are both actually around 1, indicating a similar phenomenon as with the relative sizes. The book-to-market ratio is higher for smaller firms, indicating less overvaluation with no radical change over time, in line with intuition. The RPR ratio uses a different approach for overvaluation (perceived), the average shows no major difference between large and small companies.

The market share of large acquirers is naturally higher than smaller ones, yet it is still quite low numerically. This could indicate that the definition of markets is too high level. The relationship of market share-based variables to returns can be double-edged since the existence of a higher market share is preferred, but hypothetically additional market power can have diminishing returns. This is due to the fact that new market power after a certain point does not allow to set prices better, regulatory hurdles are more common due to anti-monopoly laws and the maintenance of high market shares could be linked to more overpriced preventative takeovers. On the one hand, market participants might deem further acquisitions unnecessary or wasteful for monopolistic firms, but on the other hand consolidation of the market could be interpreted positively for firms in competitive industries.

The acquiror HHI displays similar characteristics to target HHI. With this variable there is a more significant difference between the HHI of small and large acquirors, but still within statistical margins. The ranges of acquiror HHI is lower than target HHI, indicating that targets are more likely to be acquired from competitive markets relative to the acquiror's market. The best way to capture the change in market concentration is via the change in HHI scores resulted by the acquisition. This can be calculated by subtracting the squared revenues of the two firms and adding back the squared combined revenues. Unfortunately, due to sparce data of the target firms in the Compustat database, this approach could not be adopted. Both HHI and market share possess the same theoretical problem with the 2-digit SIC code classification as the conglomerate variable.

Serial acquirors are more likely to be large firms, with around 1 in 5 acquisitions having an acquirer that made 5 deals within a 3-year range just in the sample, excluding filtered out acquisitions.

Market sentiment is similar across large and small firms and all metrics, which falls in line with logic as it is an outside factor commonly influencing all companies. However, there could be small a difference between the two subgroups, if for example, large firms are more likely to be influenced by market valuations or credit spreads to take on additional acquisitions than small firms. Nevertheless, only HYS exhibits a minor preference by large firms.

4.4. Explanatory regressions

My next step in this dissertation is to test whether the size-effect can be explained by the other factors described above.

For that purpose, I use panel data OLS regression with pooled panels, following Moeller et al.'s (2004) methodology. I use one dependent variable; the abnormal returns, and multiple dependents with one key variable; the size proxy, and others for control. The goal is to see if the significance or the power of the size-effect could be alleviated by introducing other variables that explain the abnormal returns in literature.

By using OLS regressions, I make the standard underlying assumptions. Some variables might have a non-linear relationship with the dependent, such as market share as described before, but this possibility will remain unaddressed, and linearity is assumed. I make transformations of certain variables to standardize their scale and mitigate the strength of outliers. The independence required for the implicit IID assumption is also potentially an issue since firms are included multiple times in the sample as both acquirers and targets. This will be addressed in the robustness section of the study. To account for potential heteroscedasticity or non-normal distributions of the residuals, I use White-robust standard errors following the original paper (Moeller et al., 2004). The dependence of residuals is also tested, but not indicated by the Durbin-Watson tests. Exogeneity is assumed due to short event windows, but simultaneity still could exist (other announcements). Multicollinearity is mitigated by the exclusion of highly correlated variables (**Table 14** in the appendix), but for the purposes of this testing, the issue of multicollinearity is less important, since the point is not to fit a perfect model but find if any combination of control variables can explain the size variable.

Firstly, I run individual univariate regressions explaining [-1,+1] event window CAR-s by each variable, the resulting coefficients and p-values are displayed in **Table 13 (appendix)**.

The (in)significance of variables might not mean that they will be a (in)significant explanatory variable in a multiple regression including other regressors. Nevertheless, it indicates which variables might perform better in proxying for the same effect. There are also reasons to include non-significant variables in the final regressions due to potential interactions that are not shown in the univariate regressions on CAR-s.

4.4.1. Repetition of Moeller et al. (2004) regressions with new data

As the next step, I repeat the original paper's (Moeller et al., 2004) *Table 5* panel regressions with slight adjustments and I also include the first variable set used on the new sample only for comparison. I use the same dependent and explanatory variables with one exception: instead of OCF/assets, I use cash/assets(market). I ignore multicollinearity issues for now to maintain comparability with the original paper (Moeller et al., 2004). I report these regressions in **Table 5**.

All size-effect proxies still retain their negative sign and significance for the coefficients even after including this specific set of control variables. *Ln(A)* seems to be weakest of them based on the coefficient, but it is still significant at 10%, while the strongest is the *LS dummy* (large dummy), similarly to the Moeller paper (2004). *Ln(MC)* and *LS dummy* are both significant at all levels. From the control variables, *relative size* is only significant in the new sample. Its dubious nature was discussed before. *The liquidity index* is only significant for small firms. Implying that for small firms, higher competition lowers returns. *Public* status is significantly negative across all regressions at least on the 5% level. *Private target* also has a negative sign in all cases, but only significantly negative for large firms and the new sample (at 1%). We can observe the same for *all equity* deals, just with a positive sign. *All cash* deals have a significantly negative coefficient only for large firms, otherwise the variable is insignificant. In contrast, Moeller et al. (2004) reports negative coefficients for both payment types.

Hostility is significantly negative in some of the regressions (at 10%) while *tender offer* is significantly positive, except with large firms where the p-value is 11%. *Conglomerate* is significantly negative at the 10% level for most of the regression. *Tobin's Q* still has high significance but has a completely negligible coefficient. *Debt/assets (market)* is significantly negative (10%) with the **Moeller (2)** regression containing *ln(MC)* and if controlled for large firms (5%). *Cash/assets (book)* only becomes significant in the new sample.

Overall, in the new sample a lot of variables lose significance, but the large dummy *(LS dummy)* still retains it even at 1%. In the overwhelming majority of cases these findings fall in line with the original study (Moeller et al., 2004), based on the same set of variables, the size-effect is still unexplained by other factors.

TABLE 5: Explanatory regressions using the variables of Moeller et al. (2004)

- *The dependent variable is the [-1,+1] window CAR-s everywhere*
- *Regressions Moeller **(1)-(5)** contain the original regressors from the Moeller study (2004) except instead of OCF/assets, I use cash/assets(market). I use the complete sample from 1980-2023 on regressions **(1)-(5)***
- *Regressions Moeller **(4)-(5)** does not contain the size-effect, but splits the sample by controlling for the ls_dummy*
- *Regression Moeller **(1*)** is exactly regression **(1)** with only the new sample (2002-2023)*
- *ls_dummy takes the values of 0 if small, 1 if large, the firms are split based on the simulated 25th percentile of the NYSE. In the original study, the size dummy took the value of 1 if small.*
- *ln_mc, ln_assets are the natural logarithms of the size proxies. Please refer to **Table 13 (appendix)** for clarifications of variable names*
- *P-values are displayed in italic below the coefficients based on t-tests and using White-standard errors*
- *The number of observations and adjusted r-squared of the regressions are reported below*

SAMPLE	**ALL**	**ALL**	**ALL**	**LARGE**	**SMALL**	**2002-2023**
	Moeller (1)	Moeller (2)	Moeller (3)	Moeller (4)	Moeller (5)	Moeller (1*)
intercept	**0.0284**[a]	**0.0538**[a]	**0.0375**[a]	**0.0147**[a]	**0.0317**[a]	**0.0212**[a]
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
ls_dummy	**-0.0106**[a]					**-0.0094**[a]
	0.008					*0.001*
ln_mc		**-0.0050**[a]				
		0.000				
ln_a			**-0.0029**[c]			
			0.082			
rel_size	0.0011	0.0009	0.0010	-0.0003	0.0010	**0.0189**[a]
	0.256	*0.306*	*0.265*	*0.907*	*0.260*	*0.000*
competed	-0.0027	-0.0015	-0.0027	0.0065	**-0.0374**[c]	0.0099
	0.641	*0.801*	*0.637*	*0.229*	*0.057*	*0.224*
liq_index	-0.0003	-0.0002	-0.0003	0.0002	**-0.0009**[a]	-0.0003
	0.509	*0.672*	*0.529*	*0.452*	*0.000*	*0.574*
pub_target	**-0.0244**[a]	**-0.0214**[a]	**-0.0218**[a]	**-0.0230**[a]	**-0.0246**[b]	**-0.0296**[a]
	0.000	*0.000*	*0.000*	*0.000*	*0.043*	*0.000*
priv_target	-0.0024	-0.0032	-0.0023	**-0.0033**[a]	-0.0021	**-0.0061**[a]
	0.704	*0.617*	*0.728*	*0.007*	*0.894*	*0.009*
all_eq	0.0022	0.0043	0.0033	**0.0043**[a]	-0.0043	**0.0033**[c]
	0.611	*0.317*	*0.417*	*0.001*	*0.698*	*0.062*
all_cash	0.0013	0.0003	0.0008	**-0.0063**[a]	0.0119	-0.0021
	0.716	*0.930*	*0.841*	*0.002*	*0.129*	*0.750*
hostile_dummy	-0.0144	**-0.0178**[c]	**-0.0164**[c]	-0.0117	0.0139	-0.0177
	0.149	*0.068*	*0.095*	*0.201*	*0.724*	*0.458*
tender	**0.0188**[a]	**0.0182**[a]	**0.0171**[a]	0.0048	**0.0787**[a]	**0.0140**[b]
	0.000	*0.000*	*0.000*	*0.109*	*0.000*	*0.013*
congolmerate	**-0.0069**[c]	**-0.0068**[c]	**-0.0069**[c]	**-0.0044**[a]	-0.0098	-0.0029
	0.090	*0.091*	*0.087*	*0.000*	*0.340*	*0.184*
tobin	**0.0000**[a]	**0.0000**[a]	**0.0000**[a]	**0.0002**[b]	**0.0000**[a]	**0.0000**[a]
	0.000	*0.000*	*0.000*	*0.024*	*0.000*	*0.000*
debt_assets_m	-0.003	**-0.0061**[c]	0.0078	**-0.0062**[b]	0.0017	-0.0071
	0.370	*0.070*	*0.219*	*0.021*	*0.793*	0.165
cash_assets_b	-0.0368	-0.0389	-0.0384	-0.0022	-0.0642	**0.0170**[c]
	0.314	*0.288*	*0.268*	*0.749*	*0.320*	*0.075*
No. Observations:	21700	21700	21700	13272	8428	11150
Adj. R-squared:	0.004	0.005	0.004	0.026	0.003	0.06

***a**: statistical significance at the 1% level*
***b**: statistical significance at the 5% level*
***c**: statistical significance at the 10% level*

4.4.2. Interaction of size and main explanatory variables

In this section I examine the interaction between the size-effect and other variables by segmenting the sample via controlling for key variables. It is not the exact same type of methodology that is used in the Moeller study (2004) in their *Table 4*. Theirs did not include size proxies, and only used t-tests for the segmented groups, which do not include other variables and are not explanatory in nature. All regressions have the same set of variables as the ones used in **Table 5** with the following aspects controlled for: 1) large or small acquirers, 2) all cash or equity financing, 3) public, private or subsidiary targets, 4) large loss, gain, non-large loss/gain deals. The point of the last split is to see whether the sample behaves differently when trimmed of large loss(gain) deals defined by Moeller et al. (2005).

TABLE 6: Explanatory regressions split by main regressors

- *The dependent variable is the [-1,+1] window CAR-s everywhere.*
- *The regressions contain the ones from **Table 5** with the variables that are controlled for removed.*
- *The power of the coefficient is added up to condense the information of the table, but it is not a combined variable and therefore cannot be tested for significance just based on their combined individual significance.*
- *In the first regression, Moeller **(2)** and **(3)** regressions are segment by size, in the second Moeller **(2)** is segmented for payment type, in the third the same regression is segmented for public status and in the last it is for large loss/gain.*
- *P-values are displayed in italic below the coefficients based on t-tests and using White-standard errors*
- *The number of observations and adjusted r-squared of the regressions are reported below.*

SPLIT (1) - Size	Large	Small	Large	Small
intercept	**0.0394**[a]	**0.0908**[a]	**0.0297**[a]	0.0355
	0.000	*0.000*	*0.000*	*0.133*
ln_mc	**-0.0033**[a]	**-0.0130**[a]		
	0.000	*0.000*		
ln_a			**-0.0022**[a]	-0.0009
			0.000	*0.852*
Control variables	-0.0450	-0.0440	-0.0366	-0.0337
No. Observations:	13251	8413	13251	8413
Adj. R-squared:	0.028	0.003	0.03	0.004
SPLIT (2) - Payment		Cash	Equity	Mixed
intercept		**0.0389**[a]	**0.0882**[a]	**0.0600**[a]
		0.000	*0.000*	*0.000*
ln_mc		-0.0021	**-0.0097**[a]	**-0.0036**[b]
		0.342	*0.000*	*0.025*
Control variables		-0.1061	-0.0659	-0.1102
No. Observations:		5554	3283	5803
Adj. R-squared:		0.0040	0.1280	0.0140
SPLIT (3) - Public status		Public	Private	Subsidiary
intercept		**0.0483**[a]	**0.0432**[a]	**0.0544**[a]
		0.001	*0.001*	*0.000*
ln_mc		**-0.0073**[a]	**-0.0042**[b]	-0.0039
		0.000	*0.030*	*0.136*
Control variables		-0.0494	-0.0484	-0.0797
No. Observations:		4110	10744	6846
Adj. R-squared:		0.041	0.008	0

TABLE 6 (continued)

SPLIT (4) - Large loss/gain deals	Large loss	Large gain	Non-large gain/loss
intercept	**-0.3871**[a]	**0.5610**[a]	**0.0560**[a]
	0.000	*0.000*	*0.000*
ln_mc	**0.0316**[a]	**-0.0489**[a]	**-0.0054**[a]
	0.000	*0.000*	*0.000*
Control variables	-0.0626	0.2146	-0.0728
No. Observations:	313	294	21057
Adj. R-squared:	0.423	0.468	0.005

***a**: statistical significance at the 1% level*
***b**: statistical significance at the 5% level*
***c**: statistical significance at the 10% level*

The first regression in **Table 6** tests whether the size-effect works within the groups of small and large firms. These are essentially the same regressions as **Moeller (4) and (5)** from **Table 5**, but I added back the other non-dummy size proxies. The size-effect is still negative and significant in 3 out of 4 of the splits, with *Ln(A) – small* being the only non-significant. The whole variable set including *ln(A)* also has a poorer explanatory power than the others. The type of regression and the maintained significance of *ln(MC*) proves that the size-effect exists even within small and large firms after controlling for a range of other factors. This also implies that the size-effect is robust to the choice of separation small and large firms. The adjusted R-squared of the regressions signal that the specific selection of variables is much poorer for small firms than large, which was the same case as with the **Moeller regression (4) and (5)** in **Table 5**. This could be attributed to a higher variance of CAR-s within small firms, with higher relative size and therefore a more drastic impact on the value of the company.

To examine the interaction between the size-effect and payment, I control for the payment type and split the sample into three. I proxy size only with *ln(MC)* because it has proved to be the best variable within size proxies that are also not arbitrarily split. Additionally, market capitalization is a more accurate proxy for the true size of the firm on the stock market than the assets and could be more closely related to managerial hubris (Roll, 1986). With *all equity* and *mixed payment*, *ln(MC)* is still significantly negative at 5%. Within *all cash* deals, the significance of the size-effect disappears, but still retains a negative coefficient. In contrast, Moeller et al. (2004) found that equity financed, large acquirer deals perform especially poorly, with negative average returns. They also report that cash deals perform better than equity deals for both firm types.

In the third regressions I examine the interaction between the size-effect and public status. I proxy the size-effect with *ln(MC)* for the same reasons mentioned above. Within *public* and *private* groups, the variable retains its negative significance. For *subsidiary* targets it loses it with 13% p-value and a -0.0039 coefficient, but the whole regression has very low adjusted R-squared, indicating that the loss of explanatory power cannot be attributed to the other variables. Based on this, there might be a specificity with the nature of subsidiary acquisitions, since according to the summary statistics larger firms are associated more with these targets, yet large acquirers are associated with lower returns. Moeller et al. (2004) reported higher than average returns for both firm types when acquiring subsidiaries as well.

Finally, to test whether *large loss deals* – outliers, which could be peculiar in nature - or more specifically, the removal of these deals, could explain some of the size-effect. I find significantly positive coefficient for large firms, indicating that within *large loss deals*, large acquirers lose less in terms of percentage. This is expected as bad deals should impact them less, due to the scale of the acquirer. Nevertheless, if this effect had all resulted by relative size, then it should be explained by that exact variable as it is included as control variable. The inverse of this is also true: with *large gain deals*, acquiror size is significantly negatively explains the variation of CAR-s, meaning smaller firms earn more than large firms with large gain deals. These relationships might be more due to how the stock market views the impact of these events rather than actual relative size. Without these extreme impact deals on the acquiror, the size-effect does not change compared to **Table 5, regression (2).**

4.4.3. Regressions with new variables introduced

The next step of my study is to examine if other variables could be introduced in order to explain the size-effect. The research on mergers and acquisitions has progressed significantly since the time of the original study, and it is quite possible that other researchers have come up with variables that explain CAR-s and were omitted prior. All variables used in the original study (Moeller et al., 2004) are quite conservative, strictly related to basic deal attributes or accounting/market data of the acquirors. Thus, other, new variables could explain the size-effect and prove that acquirer size was just a proxy for something or some things else.

TABLE 7: Explanatory regressions with new variables

- *The dependent variable is the [-1,+1] window CAR-s everywhere*
- *The size-effect is represented by ln(MC) as it performed the best previously and not discretionary in nature*
- *Variables from the previous regressions that had low significance or are explained by another variable were removed. Some variables are included due to the fact that they proxy for a unique factor or reduce significance of the size-effect*
- *Multicollinearity is kept low by including variables that are relatively uncorrelated, see* ***Table 14 (appendix).***
- *Introduced serial dummy and toehold dummy for all regressions, and changed a set of other variables incrementally*
- *In regression* ***(1)*** *I introduced sent_m, the monthly equity market sentiment indicator (Baker and Wurgler, 2006) and mktsh, the market share of the acquiror in percentage terms*
- *Compared to regression* ***(1)****, in regression* ***(2)*** *I removed tobin for overvaluation and introduced rpr, a measure for the anchoring effect of the price maximum in the past year*
- *In regression* ***(3)****, the difference to regression (1 I swapped hys_q for sent_m, the quarterly HYS index (Greenwood and Hanson, 2013) as a proxy for credit market conditions*
- *In regression* ***(4)*** *I also used the variables from regression* ***(1)****, but changed mktsh to ln_ahhi: nature logarithm of the concentration measured by the HHI of the industry of the acquirer*
- *From the previous set of variables, in regression* ***(5)*** *I changed ln_ahhi to ln_thhi, the natural logarithm of the HHI of the target's industry*
- *Lastly, in regression* ***(6)*** *I take the variables from regression* ***(4)*** *and used conglomerate_ff, the Fama French 48 industry version instead of the SIC based conglomerate variables.*
- *P-values are displayed in italic below the coefficients based on t-tests and using White-standard errors*
- *The number of observations and adjusted r-squared of the regressions are reported below*

SAMPLE	**ALL** (1)	**ALL** (2)	**ALL** (3)	**ALL** (4)	**ALL** (5)	**ALL** (6)
intercept	**0.0521[a]**	**0.0504[b]**	**0.0499[a]**	**0.0203[c]**	**0.0272[c]**	**0.0342[a]**
	0.000	*0.029*	*0.000*	*0.050*	*0.058*	*0.001*
ln_mc	**-0.0042[b]**	**-0.0042[a]**	**-0.0039[b]**	**-0.0039[b]**	**-0.0041[b]**	**-0.0134[a]**
	0.015	*0.007*	*the*	*0.014*	*0.010*	*0.000*
tv_assets	0.0044	0.0043	0.0045	0.0044	0.0044	0.0009
	0.149	*0.149*	*0.148*	*0.148*	*0.150*	*0.266*
pub_target	**-0.0211[a]**	**-0.0212[a]**	**-0.0226[a]**	**-0.0208[a]**	**-0.0197[a]**	**-0.0309[a]**
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
all_eq	0.0039	0.0039	0.0038	0.0039	0.0044	0.0057
	0.412	*0.401*	*0.376*	*0.412*	*0.358*	*0.233*
all_cash	0.0034	0.0032	0.0026	0.0038	0.0039	0.0060
	0.548	*0.649*	*0.628*	*0.510*	*0.507*	*0.314*
hostile_dummy	**-0.0177[c]**	-0.0146	-0.0130	**-0.0180[c]**	**-0.0181[c]**	**-0.0313[a]**
	0.079	*0.108*	*0.151*	*0.074*	*0.073*	*0.003*
tender	**0.0181[a]**	**0.0179[a]**	**0.0187[a]**	**0.0175[a]**	**0.0175[a]**	**0.0155[a]**
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*
congolmerate	-0.0068	-0.0072	**-0.0073[c]**	-0.0062	-0.0072	
	0.129	*0.128*	*0.087*	*0.173*	*0.113*	
conglomerate_ff						-0.0051
						0.328
tobin	-0.0001		-0.0001	-0.0001	**0.0000[a]**	-0.0001
	0.457		*0.459*	*0.434*	*0.000*	*0.405*
rpr		0.0042				
		0.881				
debt_assets_m	-0.0031	-0.0038	-0.0032	0.0004	-0.0021	**-0.0131[a]**
	0.419	*0.432*	*0.386*	*0.929*	*0.591*	*0.001*
cash_assets_b	-0.0633	-0.0690	-0.0585	-0.0611	-0.0632	-0.0596
	0.176	*0.150*	*0.187*	*0.189*	*0.172*	*0.198*
sent_m	**-0.0024[c]**	**-0.0027[c]**		**-0.0026[c]**	**-0.0024[c]**	-0.0021
	0.084	*0.059*		*0.071*	*0.089*	*0.145*

***TABLE** 7 (continued)*

SAMPLE	**ALL** (1)	**ALL** (2)	**ALL** (3)	**ALL** (4)	**ALL** (5)	**ALL** (6)
hys_q			0.0020			
			0.829			
mktsh	0.0059	0.0039	0.0076			
	0.844	*0.904*	*0.796*			
ln_ahhi				**0.0046**[a]		**0.0041**[a]
				0.000		*0.000*
ln_thhi					**0.0038**[b]	
					0.014	
serial	**-0.0189**[c]	**-0.0191**[c]	**-0.0200**[c]	-0.0181	**-0.0193**[c]	-0.0144
	0.092	*0.068*	*0.055*	*0.100*	*0.082*	*0.173*
toehold	-0.0034	-0.0041	-0.0023	-0.0039	-0.0039	-0.0028
	0.352	*0.273*	*0.520*	*0.283*	*0.278*	*0.459*
No. Observations:	18275	17905	19449	18275	18282	18275
Adj. R-squared:	0.002	0.002	0.002	0.002	0.005	0.004

***a**: statistical significance at the 1% level*
***b**: statistical significance at the 5% level*
***c**: statistical significance at the 10% level*

Ln(MC) as the size-proxy remains significant at least at the 5% level for all regressions despite the introduction of the new variables. Its explanatory power slightly decreases compared to the adjusted **Moeller regressions** (**Table 5**). The *RPR* does not explain CAR well, nor it is a good replacement for *Tobin's Q*. *SENT monthly* variable operates the best as the market sentiment proxy, it is significant at 10% for most regressions, and close to significance in **regression (6)**. However, the size-effect does not lose significance with the inclusion of this variable. *Yearly SENT* and *HYS* variables are not displayed, but neither of them performs significantly better than the more frequent variations. *Toehold dummy* is not significant in any case, but *serial dummy* is for most of the regressions at the 10% level. It displays a negative coefficient confirming the findings of the wider literature.

Both *acquiror and target HHI* have a positive and significant coefficient on at least 5% level. The former is even significant at 1%, both implying that higher market concentrations are associated with better abnormal returns. This finding might seem counter intuitive at first glance, however due to the dual nature of the variable this result might be reasonable. The efficiency benefits of consolidation activity on markets with moderately high, but not too high concentration might compensate in the aggregate for the potential value loss due to regulatory hurdles encountered on highly concentrated markets. The pre-acquisition market share of the acquirer on the other hand is not significant, which might be resulted by the low granularity of the market definitions. In regression **(6)**, the coefficient for the *Fama-French industry-based conglomerate* is still negative, but has higher p-value, indicating that this variable is less accurate in measuring the conglomerate effect than simpler SIC code-based measures. The lower significance might be resulted by the overly high-level definition of industries. Going forward, I use the normal, 2-digit SIC code based conglomerate variable.

4.4.4. Interaction of acquiror size and target size

In this section I examine the findings of Alexandridis et al. (2013) about how target size explains the size-effect. I facilitate this by adding the natural logarithm of the target size to the regression, measured by the deal value paid by the acquirer. The expectation is from Alexandridis et al. (2013), that after having controlled for target size, the size dummy should lose its significance. In other words, the target size should explain the variation of the acquiror size, and therefore replace its power in the bidder regression. In this section I provide incremental changes to the best performing regression (that has the lowest explanatory power for *ln(MC)* so far). My results are displayed in **Table 8**, below:

TABLE 8: Explanatory regressions with target size

- *The dependent variable is the [-1,+1] window CAR-s*
- *All regressor sets are based on regression (6) from **Table 7***
- *In regression (7) ln_tv added instead to see if target size reduces significance of ln_mc*
- *Regression (8) is Regression (7) controlled for size to include only large firms, while (9) is the same for small firms*
- *In regression (10) I an interaction term is added for ln_tv and ln_mc and both variables are standardized reduce scale of the interaction variable (ln_tv*ln_mc)*
- *In regression (11) and (12) ln_mc and ln_tv is represented by residuals acquired by regressing on the other*
- *P-values are displayed in italic below the coefficients based on t-tests and using White-standard errors*
- *The number of observations and adjusted r-squared of the regressions are reported below*

SAMPLE	ALL (7)	LARGE (8)	SMALL (9)	ALL (10)	ALL (11)	ALL (12)
intercept	**0.0342**[a]	**0.0284**[a]	**0.0634**[b]	0.0045	-0.0053	**0.0270**[a]
	0.001	*0.000*	*0.022*	*0.704*	*0.536*	*0.009*
ln_mc	**-0.0134**[a]	**-0.0102**[a]	**-0.0228**[a]			**-0.0039**[b]
	0.000	*0.000*	*0.000*			*0.013*
std_ln_mc				**-0.0264**[a]		
				0.000		
ln_mc_res					**-0.0134**[a]	
					0.000	
ln_tv	**0.0129**[a]	**0.0082**[a]	**0.0244**[a]		0.0019	
	0.000	*0.000*	*0.000*		*0.312*	
std_ln_tv				**0.0244**[a]		
				0.000		
ln_tv_res						**0.0129**[a]
						0.000
std(ln_mc*ln_tv)				-0.0042		
				0.226		
tv_assets	0.0009	**-0.0267**[a]	-0.0003	0.0007	0.0009	0.0009
	0.266	*0.000*	*0.687*	*0.353*	*0.266*	*0.266*

***TABLE 8** (continued)*

SAMPLE	**ALL** (7)	**LARGE** (8)	**SMALL** (8)	**ALL** (8)	**ALL** (8)	**ALL** (8)
pub_target	**-0.0309**[a]	**-0.0203**[a]	**-0.0426**[a]	**-0.0296**[a]	**-0.0309**[a]	**-0.0309**[a]
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
all_eq	0.0057	**0.0059**[a]	0.0015	0.0055	0.0057	0.0057
	0.233	*0.000*	*0.899*	*0.246*	*0.233*	*0.233*
all_cash	0.0060	**-0.0059**[a]	0.0148	0.0059	0.0060	0.0060
	0.314	*0.005*	*0.156*	*0.317*	*0.314*	*0.314*
hostile_dummy	**-0.0313**[a]	-0.0151	-0.0088	**-0.0310**[a]	**-0.0313**[a]	**-0.0313**[a]
	0.003	*0.106*	*0.793*	*0.003*	*0.003*	*0.003*
tender	**0.0155**[a]	0.0038	**0.0596**[a]	**0.0159**[a]	**0.0155**[a]	**0.0155**[a]
	0.001	*0.234*	*0.002*	*0.000*	*0.001*	*0.001*
congolmerate	-0.0043	**-0.0039**[a]	-0.0060	-0.0043	-0.0043	-0.0043
	0.328	*0.004*	*0.578*	*0.327*	*0.328*	*0.328*
tobin	-0.0001	**0.0002**[b]	**-0.0004**[a]	-0.0001	-0.0001	-0.0001
	0.405	*0.017*	*0.003*	*0.406*	*0.405*	*0.405*
debt_assets_m	**-0.0131**[a]	**-0.0168**[a]	**-0.0165**[b]	**-0.0140**[a]	**-0.0131**[a]	**-0.0131**[a]
	0.001	*0.000*	*0.026*	*0.000*	*0.001*	*0.001*
cash_assets_b	-0.0596	**-0.0142**[c]	-0.0962	-0.0595	-0.0596	-0.0596
	0.198	*0.068*	*0.242*	*0.198*	*0.198*	*0.198*
sent_m	-0.0021	**-0.0027**[b]	-0.0014	-0.0021	-0.0021	-0.0021
	0.145	*0.013*	*0.645*	*0.140*	*0.145*	*0.145*
ln_ahhi	**0.0041**[a]	**0.0044**[a]	0.0031	**0.0043**[a]	**0.0041**[a]	**0.0041**[a]
	0.000	*0.000*	*0.176*	*0.000*	*0.000*	*0.000*
serial	-0.0144	0.0002	-0.0433	-0.0156	-0.0144	-0.0144
	0.173	*0.870*	*0.178*	*0.175*	*0.173*	*0.173*
toehold	-0.0028	0.0011	-0.0149	-0.0031	-0.0028	-0.0028
	0.459	*0.730*	*0.188*	*0.416*	*0.459*	*0.459*
No. Observations:	18275	10920	7355	18275	18275	18275
Adj. R-squared:	0.004	0.042	0.005	0.004	0.004	0.004

***a**: statistical significance at the 1% level*
***b**: statistical significance at the 5% level*
***c**: statistical significance at the 10% level*

In regression **(7),** *ln(TV),* the proxy for target size is significantly positive with a very low p-value. *Ln(TV)* seems to be associated with higher returns, while acquirer size is still with lower. In itself this might be aligned with some of the conclusions from the relative size variable: when small firms acquire larger targets, the market rewards them, while this may not be the case for large firms. Another interesting detail of this regression is that the coefficient of *ln(MC)* significantly decreased (meaning a higher strength with negative sign) implying an interaction between the variables. So far these results would indicate conclusions opposite to Alexandridis et al. 's (2013) findings. Additionally, from **Table 14** it is clearly visible that *ln(MC)* and *ln(TV)* have a high correlation – almost 80%. *Ln(TV)* also explains most of the variation in ln(MC) when regressing on it, which could be caused by multicollinearity. However, *ln(TV)* does not have significant explanatory power in itself for CAR, unlike *ln(MC)* which has, as demonstrated. Since the peculiar interrelation of *ln(TV)* and *ln(MC)* I analyze the interaction of these variables more in detail.

Next, I split my sample to large and small to analyze the effect of the target size. In regression **(8)** I include large firms only by controlling for size. Here both *ln(MC)* and *ln(TV)* stay significant with the same sign for the coefficients. *TV/assets*, the proxy for the relative size gains significance with a negative coefficient. *Ln(TV)*, as well as *ln(MC)* loses power when considering large firms and relative size is significantly negative, which was not the case with the **Moeller-large only <u>(Table 5)</u>** regression. This could indicate that "larger" targets are only deemed favorable for large acquirers if the targets are not large comparatively to them.

For regression **(9)** I apply the same set of variables for small firms only. By controlling for small firms, both *ln(MC)* and *ln(TV)* stay significant with the same signed coefficients again. As a results, the coefficient for *ln(MC)* becomes even stronger (negative) for small firms. Additionally, the significance of *relative size* decreases and has a close to 0 coefficient which could provide support for the arguments for small firms being rewarded if they acquire larger targets. However, to contextualize, these results could be just the product of multicollinearity at play, since some of these variables have high correlation with each other. Nevertheless, we can state that there is a complex relationship between acquirer and target size since they are so highly correlated yet explain the dependent the opposite way.

In regression **(10)** I standardize the scale of *ln(MC)* and *ln(TV)* (*formula:* $\frac{X_i - \overline{X}}{STDEV}$), so that I can include an interaction term on the same scale: *std-ln(MC)*std-ln(TV)*. The interaction term is also insignificant and negative. With the standardization and interaction term, the coefficient of the size proxy is even higher, while *ln(TV)* stays positive with both remaining significant. We cannot say that the interaction between the variables drives the unusual results.

To further analyze the relationship, I regress *ln(MC)* on *ln(TV)* and substitute *ln(MC)* with its residuals in regression **(11)**. As residuals represent the part of acquiror size that deal size cannot explain, I use these residuals in the place of the actual *ln(MC)* variable. The resulting residuals are the completely uncorrelated part of *ln(MC)* to *ln(TV),* therefore this should completely eliminate the interplay. The coefficient of *ln(MC)* variable is naturally the same, while the *ln(TV)* variable loses power and significance at 10%.

Finally, I also try the inverse of this method to try to explain this unusual behavior in regression **(12)**. *Ln(MC)* loses some significance and explanatory power and the residual *ln(TV)* stays the same as in **(7)**. However, *ln(MC)* stays significantly negative at the 5% level even after accounting for the for the portion of *ln(TV)* that is explained by *ln(MC)*.

For most of the regressions *acquiror HHI* significantly explains abnormal returns. Interestingly the *SENT index* seems to be only penalizing for large firms, which could indicate the less attention paid to small firms outlined by the arbitrageur hypothesis (Moeller et al., 2004). Alternatively, large firms could utilize the better market conditions to acquire more or that acquisitions made by large firms during high sentiment could be more wasteful.

As a conclusion for this analysis we can firstly infer that all regressions across the board show that *ln(TV)* cannot fully substitute *ln(MC)* in the regressions. Secondly, all results suggest that the effect of *ln(MC)* on CAR-s is somewhat independent of *ln(TV)*, and vice versa. Therefore, larger acquirers tend to have lower abnormal returns, even when the influence of the target is controlled for. Finally, while holding the acquirer size constant, larger targets tend to be associated with higher CARs, not lower.

These findings go directly against the suggestions of Alexandridis et al. (2013)**.** A potential explanation for this contradiction is that they use a short and specific dataset around both the dotcom bubble and global financial crisis. In comparison, my dataset is a lot larger and encompasses a longer time frame, where factors are smoothed out. Additionally, the authors used *ln(market relative sizes)* and not *ln(actual sizes)* (Alexandridis et al. (2013). These are not the same as the *relative size* variable from Moeller et al. (2004), which represents acquirer-target relativity and not market-target relativity. However, I argue that their findings purely from a statistical point of view should still hold if using transformed absolute values as well, since the non-standardized values are still relatively low scale with ln-transformation. Market relativity should not matter because they are standardized by the median of the market (proxied by all market caps of all Compustat firms) and both target and acquiror are thus divided by the same number.

4.4.5. Evaluation of models

Both the adjusted Moeller regression models and my modified version with market sentiment proxy and other variables cannot fully explain the size-effect. Significance of size is only lost **1)** when already controlling for size (with small firms) or using *ln(A)* that has less clear relation to the underlying factors, **2)** when we consider cash only deals, **3)** when looking at only sales of subsidiaries and **4)** when looking at extreme cases, such as large loss deals.

In none of the models with a full range of control variables the size proxy loses significance at the 10% level and all non-segmented regressions that contain *ln(MC)* as size proxy are significant at 5%. Additionally, the inclusion of any market sentiment proxy only marginally affects the model fit compared to the adjusted Moeller regressions **(Table 5)**. Nevertheless, its coefficient is significantly negative. This is in line with intuition since deals made in increased market sentiment might be considered more wasteful and prone to overpayment.

With the addition of target size, I examined if it could substitute acquirer size or if there is any causality between them. Its relation to the acquirer size and returns is puzzling, however it cannot explain or proxy for the acquirer size-effect, even when including a plethora of control variables. Moreover, when controlling for the size of the target, the power of the size-effect seems to increase.

To connect back to our initial research questions and hypotheses, with these tests it is established that the size-effect cannot fully be explained by a range of variables, the size-effect still exists even within groups of large and small firms separated and it is not just a proxy for target size.

5. Robustness

In this last section I analyze if the results are sensitive to inputs chosen at the study design level and if they hold up to statistical scrutiny. These tests are necessary, because there were discretionary choices made during the study which could potentially alter the results. The existence of the size-effect should not depend on any of these decisions.

5.1. Time-consistency of the size-effect

In terms of the time-consistency of the size-effect, in the previous sections it was already established that the original findings of Moeller et al. (2004) have not deteriorated since then, moreover they gained significance in the new sample. Both the paired t-tests and the new sample regression confirm this. However, the two sample t-test for the first period yield insignificant differences due to the high standard deviation of small firms.

5.2. Sensitivity to separation of large and small

To see if the results are sensitive to the choice of what firm is considered large or small I employed multiple methods. Firstly, to see whether the size-effect still stands within both the large and small groups of firms I used segmented regressions by size while including another size-effect variable, displayed in **Table 6**. I only find contradictory evidence when looking at small firms and when using the *ln(A)* size variable. However, since *ln(MC)* was significant within both categories of acquirers, we can conclude that the arbitrary choice of what is large and small (25^{th} of NYSE – which was reverse engineered) does not influence the results. Clearly larger "small" firms earn less than smaller "small" firms. The later results are reinforced by the usage of the continuous *ln(MC)* instead of the binary *LS dummy* when testing new variables. In those regressions, *ln(MC)* was also significantly negative, confirming the robustness to the choice of separation of large and small firm size.

5.3. Robustness to market model choice

The question of definition of normal returns is a key input in constructing CAR-s, therefore the sensitivity to the market model will be discussed. I use CAPM-based normal returns, predicted on a [-205, -6] estimation period. I use this method primarily to be consistent with Moeller et al.'s (2004) methodology. Abnormal returns in the estimation period are 0 for all firms, proving that there is no bias in the estimation.

CAPM is widely disputed in literature in its ability to predict returns well. It yields an incorrect fit in the event period when there are confounding events in the event window or the relationship of the stock and the market changes in the event period unrelated to the acquisition. This is due to the fact that the CAPM assumes stationary alpha and beta.

Alternatively, using a simple market-adjusted model would not be able to provide additional information compared to the CAPM and assumes the return of the market to be the norm. Nonetheless, in a test directly not reported in detail here, CAAR-s are constructed based on the adjusted market model ($AR = R_i - R_m$) with the same event window, the resulting difference between small and large firms is even greater than with the CAPM.

The 3FF (Fama and French, 1992) or other factor models would also be an unsuitable fit since they already contain the size-effect as a factor, therefore there is a credible concern that it might completely alleviate the equivalent size-effect observed by acquisitions[3]. Nevertheless, it would be an interesting research topic for a future study to examine whether the size-effect of both studies is the same.

However, the choice of the market proxy is not of high importance, since the average daily normal returns should be relatively close to the average daily market returns, a really small number. The reason is that annual stock returns are usually at the single-double digit percentage range which divided by the number of trading days in a year (around 250) would result in a number close to 0. In contrast, the total returns resulted by acquisition announcement will probably be larger at least by one magnitude if not more, and the contribution of the normal return in this equation is dwarfed by the abnormal return. Hence, the choice of the market will not significantly impact the results from the size-effect.

5.4. Robustness to market proxy

The choice of market proxy is a more important factor (all market models use some form of a market proxy), and its robustness will be addressed by testing it with 2 additional proxies besides the equal-weighted CRSP market index. Moeller et al. (2004) found that their results

[3] *Note: The 3FF (Fama and French, 1992) uses the 50th percentile of NYSE for the divider of small and large firms*

are robust with both equal-weighted and value-weighted CRSP market indices. Added to these two, I also test a third proxy being the "Mkt" variable from the 3FF daily dataset, which is defined as the value-weighted market return of all NYSE, AMEX, and NASDAQ stocks (Kenneth French Data Library, 2024).

The resulting market returns of the value-weighted CRSP and value-weighted KF are very similar. I re-test the initial two sample t-tests for all metrics displayed in **Table 3-Panel C (appendix)** with the additional two methods and compare it side by side to the original **Table 3- Panel A.** The results are essentially the same across all metrics with the two-sample t-tests. I also repeat the same Moeller regressions **(1)-(3)** that contain the size dummies one by one with only using the VW CRSP market proxy. For that purpose, I drop the KF market proxy, since it is both similar in methodology and in result to VW CRSP. According to **Table 9 (appendix)** the regression results are very similar, *ln(A)* even gains significance from 10% to 5%. Based on these tests it is inferable that the size-effect is robust to the choice of market proxy.

5.5. Robustness to window length

There is extensive discussion on the choice of event windows in literature (McKinlay 1996 and Brown and Warner, 1985). Generally, there is a tradeoff between using short and long event windows. Long event windows allow slower information diffusion and leakage before deals to be included, while short windows significantly reduce the chance of confounding events. In my robustness testing I use window lengths falling on the shorter side due to the fact that I do not specifically control for confounding events. I will examine 3 different additional event windows, [-3,+3] and [-5,+5] besides the standard [-1,+1] window. In literature [-1,+1] window seems to be preferred due to the low likelihood of incorporating confounding effects during the 3-day window while at the same time including post-announcement correction and pre-announcement information leakage. There are studies that showed that information of small firms diffuses slower than large firms, therefore longer event windows are worth considering. (Hong, 2000)

In Table 3-Panel D in the appendix, I present the same two-sample t-test with multiple window lengths. It appears that the strength of the size-effect decreases with window length. The differences are [-1,+1]: -1.08% , [-3,+3]: -0.40% and [-5,+5]: +1.04% respectively. The large-small differences and total CAAR-s for all other window lengths besides the [-1,+1] are not even significant at 10%. This is caused by the increase in the differences of CAAR-s (closer to 0) and their higher standard deviations. Comparatively, the difference is less drastic with value-weighted CAAR-s as they remain significantly negative. Same with ANPV-s, except with ANPV/TV that was already non-significant. However, all of the value-weighted metrics have sizes incorporated in the weights and therefore biased towards large firms. These findings raise a question about how much of the size-effect is due to size or to the different speed of information diffusion or leakage.

I further examine the robustness of window length through rerunning the large dummy regressions the same way as with the market proxy, using the regressor set from **Moeller (1), Table 5.** The results are displayed by **Table 11- Panel A (appendix)**. We can observe the same effect with the t-tests: none of the other window lengths are significant and for [-5,+5] the coefficient is even positive with a 0.0037 coefficient. The results using *ln(MC)* as proxy for size are not reported here, but are less drastic, albeit still none of the other window lengths are significant at the 10% level. These findings seriously question the legitimacy of the results for [-1,+1] and also the original paper's findings. This concern will be further discussed in the next section.

5.6. Sensitivity to event window length

To further analyze the issue of sensitivity to window length, I examine the average daily AAR-s, and their cumulative versions display in **Figure 4**. The AAR spikes from day -1 to day +2, with day -1 being the opening value for day 0. The AAR graph visually confirms that large firms earn less than small firms around the announcement. However, while the abnormal returns of large firms start from about the 0% mark on day -1 and completely reverse to the mean by day +5, the same thing cannot be said about small firms. Small firms seem to exhibit volatility even well before and after the announcement. This behavior would be highly unusual for acquisition announcement, since we could maybe expect a gradual drift before the announcement due to information leakage (which might be the movement noticeable from day -3 to day -1), but the pattern does not follow this behavior. Following higher positive abnormal returns around the announcement day, small firms earn negative AR-s after day +3. This could be genuine due to a slower correction or just noise in the data.

This negative CAAR for small firms seems to be persistent, however in order to state anything conclusive, we would need a larger window size, which has its own problems. Additionally, using event windows that overlap with the [-205, -6] estimation period is also problematic. For large firms, the CAAR on day +5 seems to be persistent after a small correction from the announcement. Based on this we can infer that the data of small firms are very volatile and could skew the results and conclusions presented so far about the size-effect. I already discussed this problem when analyzing the sample properties.

From the median figures **in Figure 4**, firms seem to be earning negative abnormal returns before the acquisition, a sign for pre-announcement anticipation perhaps. This is followed by a positive spike from the announcement day and then a wave shaped correction to finally converge to a steady state reached on day +5 or later. The cumulative median AR seems to be slightly negative in total for all firm types (around -0.4%) through the whole 11 days. The difference between small and large firms is less drastic.

The unstable nature of window length raises a question for the sample distribution and problems about the outliers. In the data section I already highlighted this issue about the high skewness and fat tails of the sample. **Figure 1** shows that the distribution of [-1,+1] CAR-s is skewed to the right and leptokurtic. Thus, the sample might benefit from directly cutting outliers, resulting in decreased noise and increased significance.

5.7. Trimmed CAR-s

By trimming the extreme values, the data is closer to normal, but still retains negative skewness and some positive excess kurtosis. I apply a combined 5% trim from each side for the extreme values. This way the sample uses less datapoints, but the fat tails are mostly removed. **Figure 4** also shows the 5% trimmed AAR-s and CAAR-s below the means and medians. The reduction of the noise in the data is drastic, in the resulting sample there is less drift in AAR-s of small firms. There still seems to be a minor, positive drift for small firms before the announcement with some fluctuation after the announcement, but these essentially could be assumed to be zero. Both large and small firms show signs of a positive reaction to the announcement, and some leakage with negative CAAR before day 0. Subsequently, the AAR-s infer a market correction with a negative sign, followed by a reversion to the mean. Small firms still earn higher returns than large firms. The CAAR-s of both firm types reverse after the 2nd day. The CAAR of large firms seems to be persistent, but a lot lower than small firms by end of day +5. On the other hand, the day +5 CAAR belonging to small firms might not imply a full stabilization at a steady state. These could be only examined with larger event windows, which have their own problems as mentioned before. Moeller et al. (2004) found that these gains are persistent on longer horizons.

With these findings, I recalculate the CAAR-s for the two-sample t-tests for every window length and period. The results are presented in **Table 10** in the appendix. With this change, the size-effect with a [-3,+3] window and also a [-5,+5] window gained significance at 1% and 5% respectively. Post-announcement drift would be especially relevant for small firms. With this modification the size-effect for both periods using a [-1,+1] window become statistically significant at the 1% level. In contrast, in **Table 3-Panel A** 1980-2001 the period the two sample t-test yielded no significance at 10%. This change is mainly due to the reduction of noise and variance in the sample of small firms.

Table 11- Panel B in the appendix presents the **Moeller (1)** regression with the different event windows calculated on the 5% trimmed sample. With this change, regressions are significant at 1% throughout every window length. The strength of the coefficient even increases with lengthening the event window from -0.0072 at [-1,+1] to -0.0106 at [-5,+5].

The explanatory strength of other variables changes with this modification too. With the trimmed averages, *relative size* loses significance, *public* and *private target* variables gain significance on at least a 5% level while retaining their negative coefficients. *All equity* dummy is significantly negative except when using the [-3,+3] window, *tender offer* remains significantly positive at 1% and *Tobin's Q* loses its significance. The coefficients of *conglomerate* deals are still negative at the 10% level. *Debt-to-assets (market)* also becomes significant for every event window at the 1% level with a negative sign. We can conclude that the trimming substantially improved the quality of the sample and increased the significance of the size-effect across every window length choice.

5.8. The issue of dependence

As with the issue of outliers, the problems from potential dependence in the sample were first raised in the **data section**. Dependence could violate the IID assumption needed for the central limit theory to be applicable to large samples. This implies that standard errors and therefore inference testing (such as t-tests) may not be accurate.

The IID properties of the error term in OLS regressions were so far partially ensured via using heteroscedasticity robust standard errors (White-standard errors) and no major autocorrelation were indicated by the Durbin-Watson tests. However, this leads within-group correlation to be unaddressed, which is the main concern with repeated acquirers in panel data.

As the next step, I apply methods that help alleviate the dependence problem with a more direct approach. One solution for dealing with within-group correlation is using firm fixed effects. With firm fixed effect I control for the variation within deals made by the same acquirors, and therefore the main source of dependence of the sample is solved.

However, applying firm fixed effects for the regressions are flagged for multicollinearity problems by Python due to perfect multicollinearity of dummies resulted by insufficient variation (no full column ranks). There are simply too many unique firms for the sample size.

An alternative way to deal with dependence is using clustered standard errors. Liang-Zeger standard errors (Liang and Zeger, 1986) also inherently account for heteroscedasticity across clusters and therefore it also addresses the same issue as the White-standard errors, besides the within-group dependence.

Table 12 in the appendix contains the resulting regressions with clustered standard errors for the trimmed CAR-s using the **Moeller variables (1)-(3**) from **Table 5** and regression **(1)** and **(7)** of my model from **Table 7-8**. All of the size proxies are still significantly negative. Variables for *all cash*, *all equity*, *private*, *public*, *conglomerate*, *debt/assets* and *Tobin's Q* are significant. With this change, both all equity and all cash are significant at any level and have opposing signed coefficients, with cash being negative and equity being positive. This falls in line with literature. In my new variable sets, and **(7)**, *SENT indicator* is significantly negative at 10% in variable set **(1)** and close to significance in **(7)**, the *acquiror market share* is insignificant, while *acquiror HHI* is significantly positive. *Serial dummy* interestingly is only significant in set **(1)** and not in set **(2)** indicating some interplay between the variables. Finally, *target size* remains significantly positive at the 1% level where it is included.

The overall significances increased for all relevant variables, while the size-effect did not lose much power nor significance. These are better regression fits than in **Tables 5 and 7-8**, however note the twofold difference (trimming and standard errors) between those and **Table 12**. To conclude, after accounting for potential dependence and outlier issues in the sample, the size-effect remains still significant and unexplained by other factors.

6. Conclusions

6.1. Discussion of results

My results confirm the existence of the size-effect and the findings of Moeller et al. (2004) by using a much longer sample of acquisitions, added control variables and increased robustness testing. Acquisitions do create value on the average but destroy in the aggregate. The size-effect is significant across a variety of metrics, sample splits and the specification of the acquiror. The only time the size-effect is insignificant when looking at a complete sample of firms is in the first subperiod (1980-2001), when considering only untrimmed CAAR-s. The results become significant after getting rid of the outliers.

The size-effect is robust to the choice of market proxy and market model. It also persists within small and large firms, equity and cash payment, public and private firms, samples split in time periods and a sample using only non-extreme deals. The acquiror size-effect cannot be explained by any combination of explanatory variables used in my analysis. I find no evidence that the effect is caused by target size or relative size of the target to acquiror. It also cannot be explained by firm specific variations of acquirors. The results are robust to the choice of event window if outliers are removed. The size-effect is significant while using proxies based on market value but retains less significance and power if it is based on book assets across all regressions. All of my initial research questions have been answered. The null hypothesis can be rejected in *Hypotheses 1, 3* and *4*. In *Hypothesis 2* the null can be rejected if using a trimmed sample. These findings contradict the remarks of remarks of Alexandridis et al. (2013) on the size actually being driven by target size. Nevertheless, my findings do not provide an additional or alternative explanation for the size-effect but help contextualize it across the literature. Hubris, organizational specificities of size and price pressure could still explain the phenomenon.

6.2. Methodological reservations

To contextualize the results, there are reservations to be made about the methodology and statistical rigor. Firstly, regarding sampling I only included acquisitions of a certain size and certain relative size which introduces a bias for larger targets and larger acquirors. Additionally, my sample is narrowed to acquisitions with change in corporate control and a single acquirer. In the raw sample, a substantial number of deals were made by a consortium of investors, which would be hard to disentangle by traditional CAR methodology. These deals are more common in the newer part of the sample and by excluding them we do not factor in deals made by a group of smaller firms (since they have more incentive to pool up money to acquire).

I also exclusively include takeovers that are successfully completed, which use hindsight and exclude some deals. Moeller et al. (2004) found that larger firms complete deals more successfully than small firms but did not find it to be the cause of the size-effect. Therefore, the possibility of the size-effect at least partially being driven by the exclusion of unsuccessful acquisitions that are in turn more likely to be made by small firms cannot be entirely ruled out as an explanation.

My sample only includes acquisitions with public acquirors and where proper stock and accounting data is available. This again makes the data more biased towards large acquirers and large targets. Additionally similar sized private firms as acquirors could have their own specificities and the size-effect dynamic might not be the same for them. In their case, using CAR methodology and stock return data is not possible.

As discussed in the robustness section, I only include short event windows to filter out confounding effects. However, small firms might have longer information diffusion and post-announcement drift that are not captured here and thus we have to rely on Moeller et al.'s (2004) findings on post-event performance. Synergy gains are not tested either since it would only measure public to public deals and introduce bias, excluding a valuable dimension. Other categories of explanatory variables are also untested such as the longholder measure (Malmendier and Tate, 2008) or other governance-based metrics. These could potentially explain the size-effect directly but are publicly unavailable for smaller, less known firms in detail.

During the use of OLS regressions besides the other assumptions that I directly address, I also take linearity of relationships and lack of errors in the sample as granted. If the relation between the variables is non-linear in nature, the power and significance of some control variables or the size itself is not accurate.

Regarding confounding events, they are assumed to be filtered out by the short event windows. However, in reality firms can announce the acquisitions with or on the same day as other reports such as quarterly earnings and in that case the reaction of the market to other information about the firm is blended together with the news of the deal. This way the effects of the acquisition are confounded by the simultaneity. Hence there is a high probability that at least some of the announcements are confounded in the sample.

6.3. Connection to literature

Since my results do not explain the driver of the size-effect, there are potential explanations left open. Mainly, hubris cannot be ruled out to explain the size-effect, but there is no direct evidence for it in this dissertation as corporate governance variables were not included. The arbitrageur theory about market pressuring only large firms also remains untested here.

The variables used to represent market concentration did not seem to explain the size-effect. However, there was no effective way to test the actual change of the HHI variables and the HHI measures seemed to not accurately represent the actual concentration of the industries. Concentration might be too conditional or non-linear in nature to directly explain why large firms, ceteris paribus, earn less.

Whether and why large firms pay more for targets is not investigated by this study, but there are potential answers for it in literature, such as to increase probability of success (Moeller et al., 2004). The Moeller paper (2004) establishes that a diversified investor should not be affected (holds the buyer and the seller too), because the premium is just redistributed between the two investments. However, the claim was not directly tested on seller returns and whether it explains the negative synergies (Moeller et al., 2004). The finding that larger firms earn lower synergy gains is also not tested by my analysis and the causality behind the lower returns for large firms and synergy is not investigated. Therefore, simply size imposed bureaucracy and higher integration costs for targets remain a valid possible explanation for the lower synergy gains and the size-effect as well.

6.4. Further research ideas

As an ending note, in this last section I outline further research ideas based on my findings and analysis.

A study with a focused effort to compile a representative sample across all acquisition types, including both small and private firms with their corresponding accounting and corporate governance data would help alleviate some of the concerns about the generality of the conclusions of the literature. This way, the hubris hypothesis could accurately be tested whether it is the main driving factor behind the size-effect.

Another research idea is to test the bidder premia by also including returns of the seller on announcement. This would significantly shorten the sample to only include targets with public sellers and buyers but would directly confirm whether large firms earn lower bidder returns because of this redistribution effect and not due to the synergies. Synergies might be wiped out explicitly for large firms because of the overpayment compared to small firms.

Investigating the issue of synergy gains more in detail and finding a way to test for private firms via alternative methods (not *CARC* or $*CARC* used in the 2004 Moeller paper) would help clarify the connection of size and synergies. Lower synergy gains might be the actual reason behind the size-effect, but what drives these lower synergy gains/ negative synergies and why exactly larger firms have lower still needs to be investigated in detail.

Finally, a long-short trading strategy utilizing difference between large and small firms could be constructed using a sample including failed deals to exclude hindsight. Identifying aspects of deals that could skew results and control measures could be key to improving the strategy. Another important aspect is to find the optimal split of large and small firms. For how long to keep the acquirers in the portfolio also needs to be determined. In order to evaluate this strategy, it needs to be viable real-time on a larger, but simpler sample containing only stock and accounting information.

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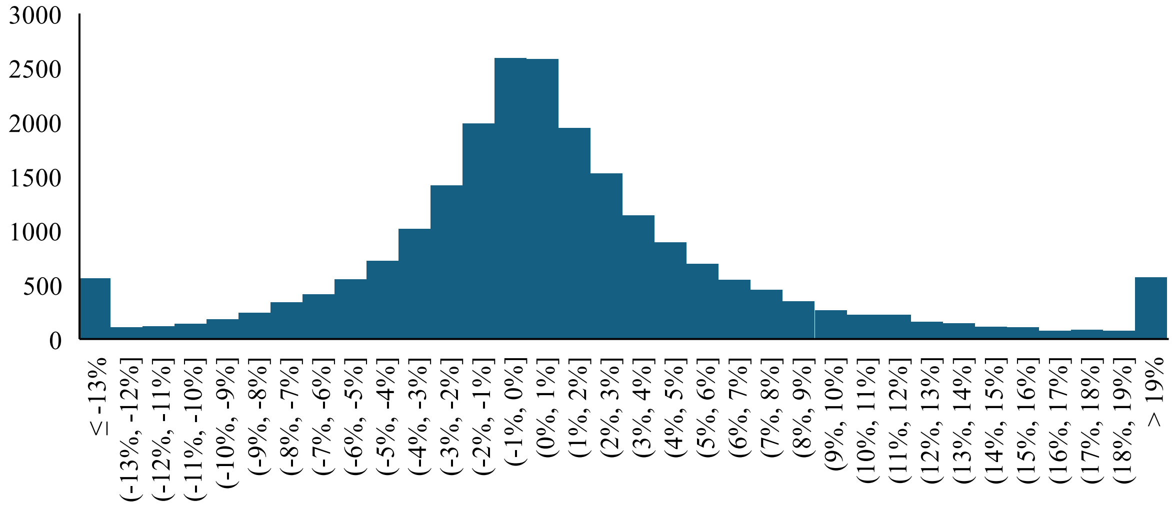
8. Appendix

8.1. Figures

FIGURE 1: CAR histograms

- *Bin boundaries are displayed in percentages on the horizontal axis*
- *Number of observations is displayed on the vertical axis*

CAR-s, non-trimmed



CAR-s, trimmed (5%)

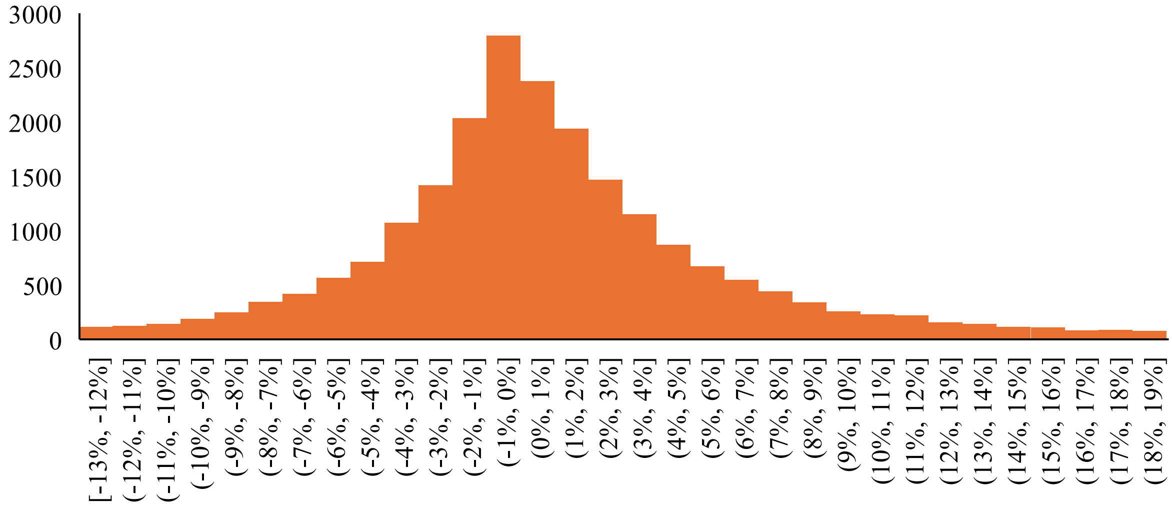


FIGURE 2: NYSE synthetic percentiles

- *NYSE synthetic quartiles acquired by dividing the market capitalizations of the 2023 NYSE constituents by the cumulative total return of the index and finding their respective percentiles for each year*
- *Market capitalization is displayed on the left vertical axis and total index returns on the right*

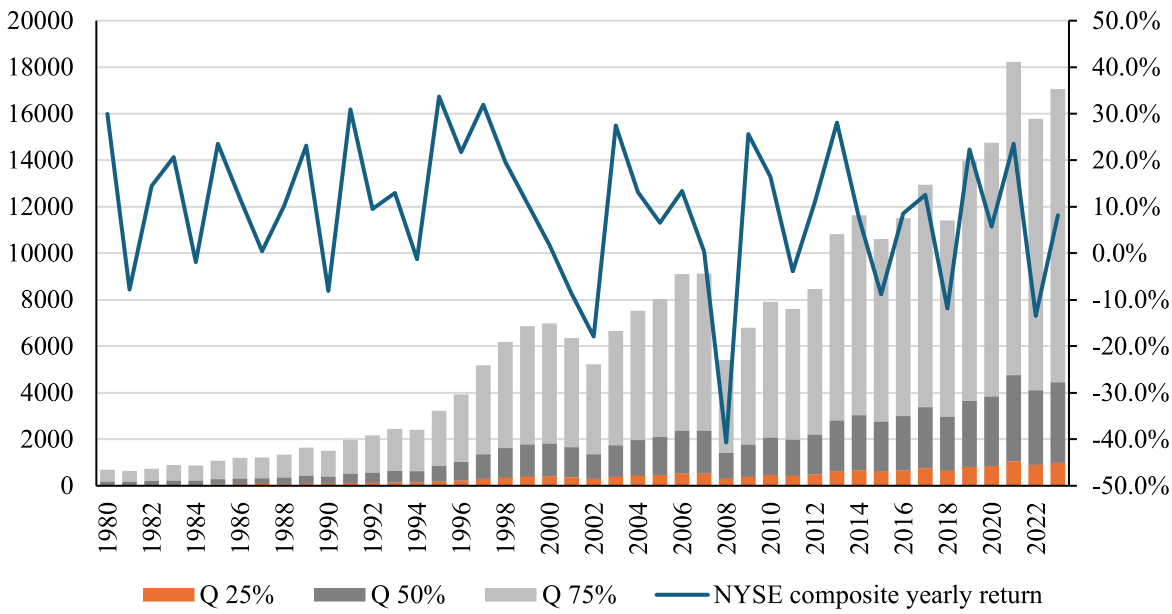


FIGURE 3: Inflation data

- *Chained inflation indices are displayed on the left vertical axis and yearly inflation on the right*
- *Chained inflation indices are constructed as a compounded index of yearly inflation data with a base of 2001 or 2023*

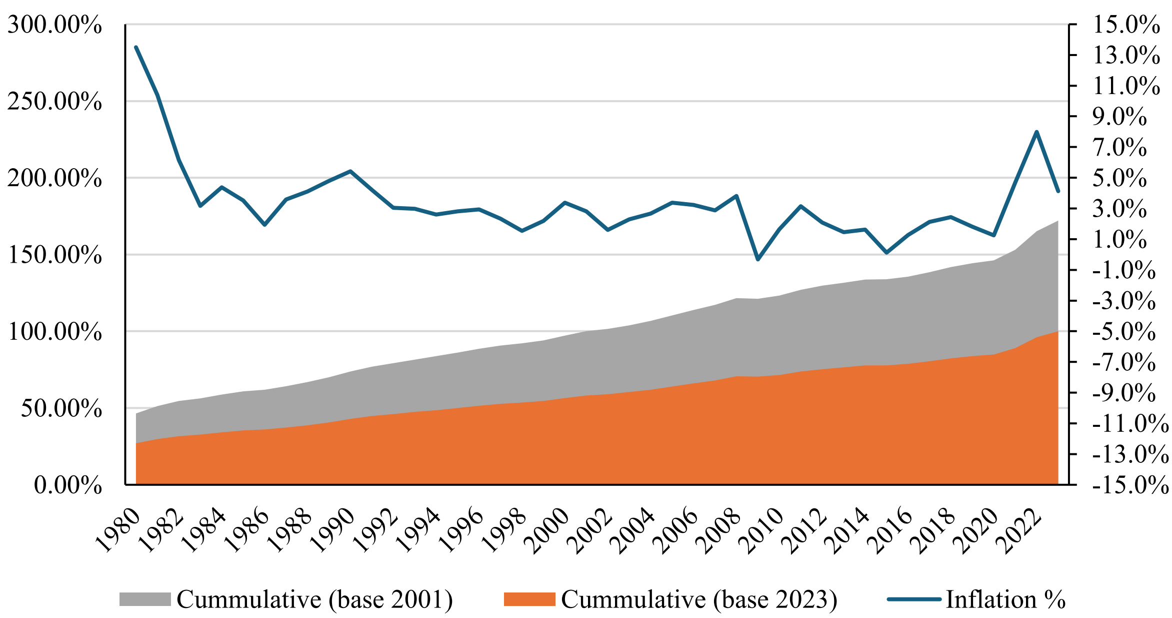
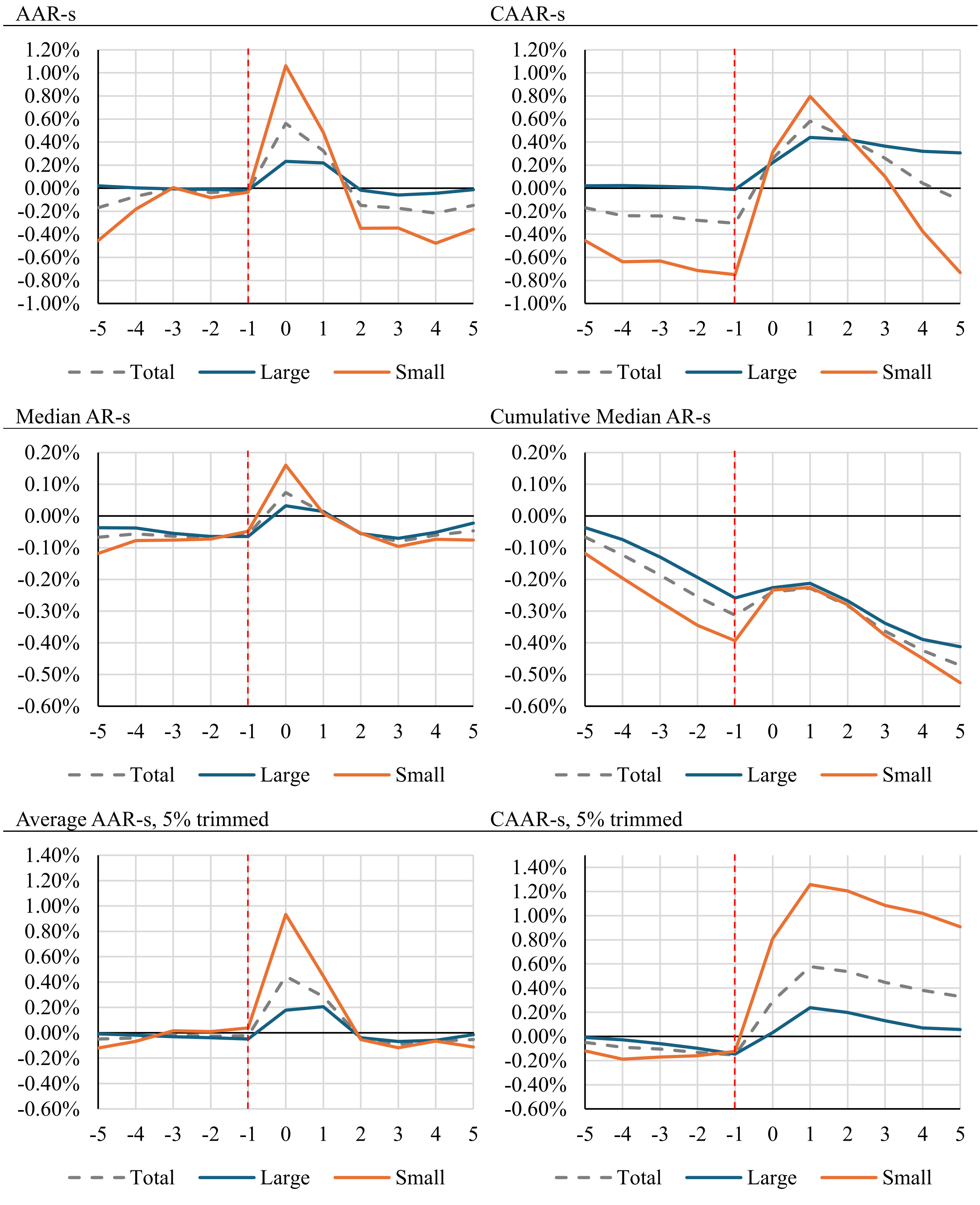


FIGURE 4: Average and median metrics for AR-s and CAR-s

- *Average and cumulative return metrics are calculated along the full [-5,+5] event window*
- *The values of the horizontal axis are end of the days. For instance, the return from -1 to 0 is the return for day 0.*
- *The metrics are displayed on the vertical axes by acquiror size*
- *Large and small acquiror are split based on the simulated 25th percentile of the NYSE.*



8.2. Tables

TABLE 1 – Panel B: Yearly aggregate abnormal returns of ultimate parents

- *The sample was obtained by the filtration process outlined in the Data section using the ultimate parent companies of acquirors*
- *Large and small acquiror are split based on the simulated 25th percentile of the NYSE.*
- *The aggregate dollar returns are the cumulative absolute returns earned during the [-1,+1] event window, with market capitalization weights. The Dollar Return = MC+1 – MC-2., with the market capitalization taken at closing. Average returns are measured from day-2 to day+1.*
- *CAAR's are constructed over the same event window, using the market model (CAPM) with an estimation window of [-205, -6] for the parameters.*
- *Dollar figures in millions of USD*

Year	All	Large	Small	Aggregate Dollar return	Average return [-1, +1]	CAAR [-1, +1]
1980	16	13	3	-638	-1.34%	-1.39%
1981	120	109	11	-3,027	-0.82%	-0.74%
1982	175	146	29	333	0.95%	0.03%
1983	213	167	46	-197	0.63%	0.55%
1984	268	202	66	1,686	1.01%	0.85%
1985	128	111	17	356	0.53%	0.08%
1986	244	220	24	3,160	1.94%	1.44%
1987	206	175	31	-805	0.87%	0.74%
1988	222	152	70	1,475	1.48%	0.52%
1989	298	185	113	2,338	0.61%	0.08%
1990	251	158	93	-1,227	0.49%	0.34%
1991	302	164	138	3,105	6.24%	2.29%
1992	422	236	186	81	2.77%	2.05%
1993	590	341	249	5,263	1.96%	1.56%
1994	715	414	301	-5,817	1.28%	0.98%
1995	807	435	372	3,720	1.50%	0.90%
1996	968	553	415	17,688	2.31%	1.67%
1997	1315	727	588	760	1.63%	1.10%
1998	1348	674	674	-6,805	1.78%	-2.66%
1999	981	481	500	-50,422	1.91%	1.11%
2000	835	457	378	-119,333	0.98%	0.70%
2001	618	326	292	-21,807	1.49%	0.95%
2002	627	372	255	-10,596	1.90%	1.82%
2003	632	357	275	-27,288	1.40%	3.44%
2004	693	399	294	804	1.68%	0.98%
2005	782	422	360	-7,451	1.22%	1.01%
2006	765	422	343	1,809	1.29%	0.86%
2007	712	402	310	-10,284	1.11%	0.94%
2008	481	310	171	-25,439	0.88%	1.30%
2009	360	218	142	-4,440	2.39%	0.71%
2010	545	351	194	8,498	1.40%	0.40%
2011	597	395	202	25,202	1.61%	0.85%
2012	603	399	204	20,195	1.92%	1.45%
2013	576	369	207	40,892	3.27%	2.19%
2014	664	409	255	12,595	3.05%	2.16%
2015	621	419	202	18,846	1.16%	0.30%
2016	533	376	157	-11,962	2.36%	1.02%
2017	553	374	179	23,007	1.36%	-0.65%
2018	525	383	142	-40,596	1.24%	1.00%
2019	438	286	152	-18,140	1.36%	0.79%
2020	342	218	124	-13,277	4.83%	2.69%
2021	614	431	183	88,849	3.41%	2.59%
2022	305	178	127	-63,640	0.17%	0.78%
2023	249	153	96	-6,404	3.41%	2.18%
Total	**23259**	**14089**	**9170**	**-168,933**	**1.77%**	**0.96%**

TABLE 3 – PANEL B: Abnormal returns per period, based on the ultimate parent of the acquiror

- *CAR-s are constructed the same way as in **Table 2**. All metrics are calculated around the [-1,+1] event window*
- *Small and large firms are split according to the simulated 25th percentile of the NYSE firms*
- *VWCAAR is value weighted CAR, where the weights are MC_{t-2} market capitalizations.*
- *ANPV is the dollar abnormal return with the same weights as above. ANPV/TV is scaled to target size and $ANPV_{year}$ is the dollar AR standardized by inflation*
- *Significance of CAAR-s are based on Csect t-tests and represented by p-values and the two sample t-tests are based on the Welch t-test.*

PERIOD	**1980-2001**				**2002-2023**				**1980-2023**			
SAMPLE	ALL	LARGE	SMALL	LARGE - SMALL	ALL	LARGE	SMALL	LARGE - SMALL	ALL	LARGE	SMALL	LARGE - SMALL
CAAR	**0.60%**[c]	**0.30%**[a]	1.02%	-0.73%	**1.29%**[a]	**0.63%**[a]	**2.41%**[a]	**-1.78%**[a]	**0.96%**[a]	**0.48%**[a]	**1.71%**[a]	**-1.24%**[b]
STDEV	38.42%	6.46%	59.05%	0.87%	20.26%	6.15%	32.13%	0.48%	30.27%	6.30%	47.57%	0.50%
N	12870	6446	4596	11042	12217	7643	4574	12217	23259	14089	9170	23259
p-value	*0.077*	*0.000*	*0.240*	*0.405*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.013*
VWCAAR	**-0.98%**[a]	**-1.01%**[a]	0.61%	**-1.62%**[a]	**-0.16%**[a]	**-0.18%**[a]	**0.95%**[a]	**-1.13%**[a]	**-0.34%**[a]	**-0.36%**[a]	**0.85%**[a]	**-1.21%**[a]
WSTDEV	8.45%	6.33%	39.15%	0.58%	4.71%	4.57%	10.68%	0.17%	5.72%	5.02%	23.21%	0.25%
p-value	*0.000*	*0.000*	*0.102*	*0.005*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
ANPV	**-19.43**[a]	**-33.70**[a]	0.59	**-34.28**[a]	**-10.42**	**-17.94**	**2.16**[a]	**-20.10**	**-14.69**[a]	**-25.15**[a]	**1.37**[a]	**-26.52**[a]
STDEV	653.28	854.45	27.15	10.65	972.60	1229.48	25.02	14.07	836.34	1074.26	26.12	9.05
p-value	*0.001*	*0.002*	*0.142*	*0.001*	*0.236*	*0.202*	*0.000*	*0.153*	*0.007*	*0.005*	*0.000*	*0.003*
ANPV/TV	-0.11	0.03	-0.29	0.32	**0.06**[a]	**0.05**[a]	**0.06**[b]	-0.01	-0.02	**0.04**[a]	-0.12	0.16
STDEV	9.90	1.85	15.19	0.23	1.49	1.38	1.66	0.03	6.91	1.61	10.82	0.11
p-value	*0.228*	*0.255*	*0.196*	*0.160*	*0.000*	*0.001*	*0.015*	*0.859*	*0.655*	*0.002*	*0.307*	*0.167*
ANPV (2023)	**-35.01**[a]	**-60.81**[a]	1.18	**-61.99**[a]	**-15.01**	**-25.65**	**2.78**[a]	**-28.42**	**-24.50**[a]	**-41.73**[a]	**1.98**[a]	**-43.71**[a]
STDEV	1175.54	1537.50	50.60	19.16	1222.93	1545.89	31.64	17.69	1200.68	1542.10	42.22	13.00
p-value	*0.001*	*0.002*	*0.114*	*0.001*	*0.175*	*0.147*	*0.000*	*0.108*	*0.002*	*0.001*	*0.000*	*0.001*
ANPV (2001)	**-20.34**[a]	**-35.33**[a]	0.69	**-36.01**[a]	**-8.72**	**-14.90**	**1.61**[a]	**-16.51**	**-14.23**[a]	**-24.25**[a]	**1.15**[a]	**-25.40**[a]
STDEV	682.97	893.26	29.40	11.13	710.50	898.14	18.38	10.28	697.57	895.94	24.53	7.55
p-value	*0.001*	*0.002*	*0.114*	*0.001*	*0.175*	*0.147*	*0.000*	*0.108*	*0.002*	*0.001*	*0.000*	*0.001*

***a**: statistical significance at the 1% level*
***b**: statistical significance at the 5% level*
***c**: statistical significance at the 10% level*

TABLE 3 – PANEL C: Abnormal returns of small and large firms per market proxy

- *CAR-s are based on the CAPM using EW- CRSP, VW-CRSP and KF market proxies*
- *Additional metrics are constructed according to Table 3: Panel A-B*
- *All metrics are calculated around the [-1,+1] event window*
- *Small and large firms are split according to the simulated 25th percentile of the NYSE firms*
- *Significance of CAAR-s are based on Csect t-tests and represented by p-values*
- *Two sample t-tests are based on the Welch t-test.*

SAMPLE		**ALL**			**LARGE**			**SMALL**			**LARGE - SMALL**	
MARKET PROXY	EW	VW	KF	EW	VW	KF	EW	VW	KF	EW	VW	KF
CAAR	**0.86%**[a]	**0.81%**[a]	**0.82%**[a]	**0.43%**[a]	**0.38%**[a]	**0.38%**[a]	**1.51%**[a]	**1.47%**[a]	**1.48%**[a]	**-1.08%**[b]	**-1.08%**[a]	**-1.10%**[a]
STDEV (CAAR)	28.41%	23.97%	23.54%	6.35%	6.37%	6.37%	44.43%	37.24%	36.54%	0.47%	0.40%	0.39%
N	22588	22588	22588	13631	13631	13631	8957	8957	8957	22588	22588	22588
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*	*0.023*	*0.006*	*0.005*
VWCAAR	**-0.45%**[a]	**-0.43%**[a]	**-0.43%**[a]	**-0.47%**[a]	**-0.45%**[a]	**-0.45%**[a]	**0.80%**[a]	**0.73%**[a]	**0.74%**[a]	**-1.27%**[a]	**-1.18%**[a]	**-1.19%**[a]
STDEV	5.91%	5.64%	5.62%	5.15%	5.07%	5.07%	23.49%	20.25%	19.87%	0.25%	0.22%	0.21%
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.001*	*0.000*	*0.000*	*0.000*	*0.000*
ANPV	**-18.02**[a]	**-17.15**[a]	**-17.17**[a]	**-30.71**[a]	**-29.20**[a]	**-29.24**[a]	**1.29**[a]	**1.18**[a]	**1.19**[a]	**-32.00**[a]	**-30.38**[a]	**-30.42**[a]
STDEV	820.87	873.63	884.20	1056.31	1124.29	1137.90	26.21	24.54	24.20	9.05	9.63	9.75
P-value	*0.001*	*0.003*	*0.004*	*0.001*	*0.002*	*0.003*	*0.000*	*0.000*	*0.000*	*0.000*	*0.002*	*0.002*
ANPV /TV	-0.02	-0.03	-0.03	**0.04**[a]	**0.03**[c]	**0.03**[c]	-0.12	-0.12	-0.11	0.15	0.14	0.14
STDEV	7.01	6.38	6.28	1.64	1.60	1.60	10.94	9.93	9.77	0.12	0.11	0.10
p-value	*0.634*	*0.472*	*0.481*	*0.005*	*0.060*	*0.063*	*0.317*	*0.268*	*0.273*	*0.184*	*0.179*	*0.183*
ANPV (2023)	**-29.17**[a]	**-29.21**[a]	**-29.33**[a]	**-49.59**[a]	**-49.54**[a]	**-49.74**[a]	**1.91**[a]	**1.73**[a]	**1.75**[a]	**-51.50**[a]	**-51.27**[a]	**-51.49**[a]
STDEV	1174.85	1180.19	1188.91	1511.65	1518.60	1529.83	42.52	38.88	38.37	12.96	13.01	13.11
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
ANPV (2001)	**-16.94**[a]	**-16.97**[a]	**-17.04**[a]	**-28.81**[a]	**-28.78**[a]	**-28.90**[a]	**1.11**[a]	**1.01**[a]	**1.02**[a]	**-29.92**[a]	**-29.79**[a]	**-29.92**[a]
STDEV	682.57	685.67	690.74	878.24	882.28	888.80	24.70	22.59	22.29	7.53	7.56	7.62
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

a*: statistical significance at the 1% level*
b*: statistical significance at the 5% level*
c*: statistical significance at the 10% level*

TABLE 3 – PANEL D: Abnormal returns per period by different event windows

- *CAR-s are based on the CAPM using EW- CRSP, with different event window*
- *Additional metrics are constructed according to Table 3: Panel A-B*
- *All metrics are calculated around the [-1,+1], [-3,+3] and [-5,+5] event windows, using the same estimation period as in Table 2*
- *Small and large firms are split according to the simulated 25th percentile of the NYSE firms*
- *Significance of CAAR-s are based on Csect t-tests and represented by p-values*
- *Two sample t-tests are based on the Welch t-test.*

EVENT WINDOW	**[-1,+1]**				**[-3,+3]**				**[-5,+5]**			
SAMPLE	ALL	LARGE	SMALL	LARGE-SMALL	ALL	LARGE	SMALL	LARGE-SMALL	ALL	LARGE	SMALL	LARGE-SMALL
CAAR	**0.86%[a]**	**0.43%[a]**	**1.51%[a]**	**-1.08%[b]**	0.50%	**0.34%[a]**	0.74%	-0.40%	-0.11%	**0.31%[a]**	-0.73%	1.04%
STDEV	28.41%	6.35%	44.43%	0.47%	47.15%	7.87%	74.24%	0.79%	78.04%	9.96%	123.30%	1.31%
N	22588	13631	8957	22588	22584	13627	8957	22584	22581	13624	8957	22581
p-value	*0.000*	*0.000*	*0.001*	*0.023*	*0.112*	*0.000*	*0.346*	*0.614*	*0.839*	*0.000*	*0.575*	*0.427*
VWCAAR	**-0.45%[a]**	**-0.47%[a]**	**0.80%[a]**	**-1.27%[a]**	**-0.62%[a]**	**-0.64%[a]**	0.58%	**-1.22%[a]**	**-0.90%[a]**	**-0.91%[a]**	-0.06%	-0.86%
STDEV	5.91%	5.15%	23.49%	0.25%	8.15%	6.65%	38.00%	0.41%	11.75%	8.63%	63.81%	0.68%
p-value	*0.000*	*0.000*	*0.001*	*0.000*	*0.000*	*0.000*	*0.150*	*0.003*	*0.000*	*0.000*	*0.933*	*0.206*
ANPV	**-18.02[a]**	**-30.71[a]**	**1.29[a]**	**-32.00[a]**	**-25.04[a]**	**-42.12[a]**	**0.93[b]**	**-43.05[a]**	**-36.09[a]**	**-59.77[a]**	-0.09	**-59.68[a]**
STDEV	820.87	1056.31	26.21	9.05	1264.96	1627.60	39.59	13.95	1799.42	2315.20	61.42	19.85
p-value	*0.001*	*0.001*	*0.000*	*0.000*	*0.003*	*0.003*	*0.026*	*0.002*	*0.003*	*0.003*	*0.889*	*0.003*
ANPV /TV	-0.02	**0.04[a]**	-0.12	0.15	-0.12	-0.01	-0.27	0.26	**-0.27[b]**	-0.04	**-0.63[c]**	**0.59[c]**
STDEV	7.01	1.64	10.94	0.12	11.67	2.26	18.32	0.19	20.32	3.07	32.04	0.34
p-value	*0.634*	*0.005*	*0.317*	*0.184*	*0.137*	*0.520*	*0.159*	*0.181*	*0.043*	*0.130*	*0.063*	*0.082*
ANPV (2023)	**-29.17[a]**	**-49.59[a]**	**1.91[a]**	**-51.50[a]**	**-38.93[a]**	**-65.34[a]**	**1.25[c]**	**-66.59[a]**	**-53.48[a]**	**-88.33[a]**	-0.44	**-87.89[a]**
STDEV	1174.85	1511.65	42.52	12.96	1807.82	2326.21	66.97	19.94	2570.04	3306.83	106.93	28.35
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.001*	*0.077*	*0.001*	*0.002*	*0.002*	*0.695*	*0.002*
ANPV (2001)	**-16.94[a]**	**-28.81[a]**	**1.11[a]**	**-29.92[a]**	**-22.62[a]**	**-37.96[a]**	**0.73[c]**	**-38.69[a]**	**-31.07[a]**	**-51.32[a]**	-0.26	**-51.06[a]**
STDEV	682.57	878.24	24.70	7.53	1050.31	1351.49	37.58	11.58	1493.15	1921.21	64.14	16.47
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.001*	*0.067*	*0.001*	*0.002*	*0.002*	*0.704*	*0.002*

a*: statistical significance at the 1% level*
b*: statistical significance at the 5% level*
c*: statistical significance at the 10% level*

TABLE 4 – PANEL B: Summary statistics of explanatory variables by period and size

- *Financial data in millions of USD*
- *Mean values displayed*
- *Small and large firms are split according to the simulated 25th percentile of the NYSE firms*
- *Samples split to 2002-2023 and 1980-2001*

	2002-2023			1980-2001		
SAMPLE	ALL	LARGE	SMALL	ALL	LARGE	SMALL
Number of observations	**11603**	**7204**	**4399**	**10985**	**6427**	**4558**
Deal characteristics						
Deal value	611.34	947.69	60.51	214.84	347.54	27.73
TV/assets (market)	64.93%	10.85%	153.48%	22.38%	13.10%	35.46%
Relative size (TV/equity)	72.63%	15.37%	166.42%	35.85%	18.37%	60.50%
Days to completion	61	65	53	82	91	70
Liquidity index	0.03	0.03	0.03	0.05	0.07	0.04
Competed deals	0.63%	0.85%	0.27%	1.21%	1.63%	0.61%
%Cash in payment	47.16%	50.49%	41.71%	28.23%	26.93%	30.07%
%Equity in payment	15.86%	13.72%	19.38%	31.11%	32.80%	28.73%
%Other in payment	37.45%	36.35%	39.27%	40.66%	40.28%	41.20%
All cash	31.89%	36.94%	23.62%	19.25%	19.68%	18.65%
All equity	6.88%	6.01%	8.30%	23.71%	26.09%	20.36%
Mixed payment	30.07%	25.86%	36.96%	22.36%	18.75%	27.45%
Hostile	0.05%	0.07%	0.02%	0.47%	0.73%	0.11%
Tender offer	2.41%	3.26%	1.02%	4.29%	5.99%	1.89%
Conglomerate deal	65.01%	65.10%	64.86%	65.53%	65.15%	66.06%
Conglomerate deal (FF)	39.62%	40.51%	38.16%	38.98%	38.26%	40.00%
Public target	17.23%	19.75%	13.09%	20.76%	25.92%	13.49%
Private target	50.12%	44.74%	58.95%	48.37%	42.04%	57.28%
Subsidiary target	32.65%	35.51%	27.96%	30.87%	32.04%	29.22%
Large loss deal	1.99%	3.21%	0.00%	0.76%	1.31%	0.00%
Large gain deal	1.97%	3.16%	0.00%	0.60%	1.03%	0.00%
Non-large loss/gain deal	96.04%	93.63%	100.00%	98.63%	97.67%	100.00%
HHI of target industry	740.61	741.73	738.77	774.66	762.22	792.19
Toehold dummy	1.15%	1.30%	0.89%	1.93%	2.47%	1.16%
Acquiror characteristics						
Cash/assets (book)	0.12	0.10	0.14	0.09	0.08	0.10
Assets (book)	9321.11	14508.56	825.91	3331.84	5489.62	289.27
Assets (market)	8145.40	12882.87	387.12	2443.24	4064.22	157.58
Equity (market)	6089.02	9667.52	228.71	1802.80	3011.77	98.09
Debt/assets (book)	0.24	0.25	0.21	0.22	0.21	0.23
Debt/assets (market)	0.24	0.24	0.24	0.23	0.23	0.24
Tobin's Q	9.52	1.79	22.18	2.54	2.99	1.90
Book-to-market ratio	0.68	0.58	0.84	0.82	0.63	1.10
RPR Ratio	0.73	0.74	0.72	0.69	0.70	0.69
%Market share of acquiror	1.03%	1.56%	0.15%	0.83%	1.23%	0.25%

***TABLE 4 – PANEL B** (continued)*

HHI of acquirer industry	584.55	582.02	588.84	664.09	617.38	730.23
Serial acquirer	19.2%	20.8%	16.7%	25.6%	30.5%	18.7%
Market characteristics						
HYS (Y)	-0.23	-0.24	-0.22	0.51	0.54	0.47
HYS (M)	-0.16	-0.17	-0.16	0.55	0.58	0.51
Sentiment index (Q)	0.35	0.35	0.36	0.33	0.33	0.33
Sentiment index (Q)	0.34	0.34	0.34	0.34	0.34	0.33

TABLE 9: Regression robustness to choice of market proxy

- *The dependent variable is the [-1,+1] window CAR-s using the VW-CRSP market proxy in the prediction of normal returns*
- *All regressions use the same variable set as the **Moeller regression (1)-(3)** in **Table 5***
- *ls_dummy takes the values of 0 if small, 1 if large, the firms are split based on the simulated 25th percentile of the NYSE*
- *ln_mc, ln_assets are the natural logarithms of the corresponding size proxies*
- *P-values are displayed in italic below the coefficients based on t-tests and using White-standard errors*
- *The number of observations and adjusted r-squared of the regressions are reported below*

SAMPLE	**ALL -VW** Moeller (1)	**ALL -VW** Moeller (1)	**ALL -VW** Moeller (3)
intercept	**0.0288**[a]	**0.0547**[a]	**0.0378**[a]
	0.000	*0.000*	*0.000*
ls_dummy	**-0.0110**[a]		
	0.001		
ln_mc		**-0.0051**[a]	
		0.000	
ln_a			**-0.0029**[b]
			0.034
rel_size	0.0011	0.0009	0.0010
	0.258	*0.310*	*0.266*
competed	-0.0041	-0.0028	-0.0041
	0.485	*0.629*	*0.480*
liq_index	-0.0004	-0.0003	-0.0004
	0.407	*0.529*	*0.417*
pub_target	**-0.0258**[a]	**-0.0227**[a]	**-0.0232**[a]
	0.000	*0.000*	*0.000*
priv_target	-0.0045	-0.0053	-0.0043
	0.366	*0.289*	*0.393*
all_eq	0.0028	0.0049	0.0039
	0.441	*0.176*	*0.266*
all_cash	0.0018	0.0007	0.0012
	0.600	*0.833*	*0.734*
hostile_dummy	-0.0144	**-0.0180**[c]	**-0.0165**[c]
	0.145	*0.066*	*0.093*
tender	**0.0198**[a]	**0.0192**[a]	**0.0180**[a]
	0.000	*0.000*	*0.000*
congolmerate	**-0.0057**[c]	**-0.0057**[c]	**-0.0058**[c]
	0.081	*0.083*	*0.078*
tobin	**0.0000**[a]	**0.0000**[a]	**0.0000**[a]
	0.000	*0.000*	*0.000*
debt_assets_m	-0.0031	**-0.0062**[c]	0.0079
	0.351	*0.061*	*0.160*
cash_assets_b	-0.0398	-0.0419	-0.0413
	0.183	*0.162*	*0.146*
No. Observations:	21700	21700	21700
Adj. R-squared:	0.006	0.007	0.006

a: statistical significance at the 1% level
b: statistical significance at the 5% level
c: statistical significance at the 10% level

TABLE 10: Summary statistics of 5% trimmed cumulative abnormal returns

- *CAR-s are constructed on a [-1,+1] event window and CAAR is averaged across all observations*
- *Maximum and minimum 2.5% removed from the CAR-s*
- *Small and large firms are split according to the simulated 25th percentile of the NYSE firms*
- *Normal returns are based on CAPM, betas and alphas are estimated over a [-6, -205] range*
- *Uses EW CRSP market proxy*
- *Significance of CAAR-s are based on cross-sectional t-tests and represented by p-values*

PANEL A – 5% trimmed CAAR-s by event window

SAMPLE	ALL (-5%)	LARGE (-5%)	SMALL (-5%)	LARGE-SMALL (-5%)
EVENT WINDOW		[-1,+1]		
CAAR	**0.84%**[a]	**0.54%**[a]	**1.32%**[a]	**-0.78%**[a]
p-value	*0.000*	*0.000*	*0.000*	*0.000*
EVENT WINDOW		[-3,+3]		
CAAR	**0.90%**[a]	**0.51%**[a]	**1.51%**[a]	**-1.00%**[a]
p-value	*0.000*	*0.000*	*0.000*	*0.000*
EVENT WINDOW		[-5,+5]		
CAAR	**0.89%**[a]	**0.47%**[a]	**0.72%**[a]	**-0.25%**[b]
p-value	*0.000*	*0.000*	*0.000*	*0.048*

PANEL B – 5% trimmed [-1,+1]CAAR-s by period

SAMPLE	ALL (-5%)	LARGE (-5%)	SMALL (-5%)	LARGE-SMALL (-5%)
PERIOD		1980-2001		
CAAR	**0.80%**[a]	**0.42%**[a]	**1.36%**[a]	**-0.94%**[a]
p-value	*0.000*	*0.000*	*0.000*	*0.000*
PERIOD		2002-2023		
CAAR	**0.88%**[a]	**0.64%**[a]	**1.28%**[a]	**-0.64%**[a]
p-value	*0.000*	*0.000*	*0.000*	*0.000*

a*: statistical significance at the 1% level*
b*: statistical significance at the 5% level*
c*: statistical significance at the 10% level*

TABLE 11: Regression robustness to event windows

- *For **PANEL A,** the dependent variable is the [-1,+1], [-3,+3]and [-5,+5] CAR-s. For **PANEL B**, the same dependents were trimmed of outliers by 2.5% from each end of the sample. Everything else about the CAR-s is calculated according to **Table 2***
- *All regressions use the same variable set as the Moeller regression **(1)** in Table 5*
- *ls_dummy takes the values of 0 if small, 1 if large, the firms are split based on the simulated 25th percentile of the NYSE.*
- *P-values are displayed in italic below the coefficients based on t-tests and using White-standard errors*
- *The number of observations and adjusted r-squared of the regressions are reported below*

	PANEL A: CAR by event window			**PANEL B: 5% trimmed CAR by event window**		
SAMPLE	**ALL**	**ALL**	**ALL**	**ALL -5%**	**ALL -5%**	**ALL -5%**
EVENT WINDOW	[-1,+1]	[-3,+3]	[-5,+5]	[-1,+1]	[-3,+3]	[-5,+5]
intercept	**0.0284**[a]	**0.0295**[a]	**0.0240**[b]	**0.0222**[a]	**0.0266**[a]	**0.0273**[a]
	0.000	*0.000*	*0.026*	*0.000*	*0.000*	*0.000*
ls_dummy	**-0.0106**[a]	-0.0071	0.0037	**-0.0072**[a]	**-0.0095**[a]	**-0.0106**[a]
	0.008	*0.280*	*0.729*	*0.000*	*0.000*	*0.000*
rel_size	0.0011	0.0015	0.0018	0.0002	0.0001	4.57E-05
	0.256	*0.243*	*0.238*	*0.315*	*0.447*	*0.742*
competed	-0.0027	-0.0086	-0.0073	0.0000	-0.0054	-0.0053
	0.641	0.259	0.439	0.991	0.31	0.415
liq_index	-0.0003	-0.0004	-0.0010	-0.0003	-0.0004	-0.0009
	0.509	*0.366*	*0.242*	*0.470*	*0.323*	*0.196*
pub_target	**-0.0244**[a]	**-0.0292**[a]	**-0.0270**[b]	**-0.0194**[a]	**-0.0230**[a]	**-0.0220**[a]
	0.000	*0.000*	*0.010*	*0.000*	*0.000*	*0.000*
priv_target	-0.0024	-0.0050	-0.0039	**-0.0035**[a]	**-0.0051**[a]	**-0.0048**[a]
	0.704	*0.641*	*0.825*	*0.000*	*0.000*	*0.001*
all_eq	0.0022	0.0016	0.0035	**0.0017**[b]	0.0014	0.0007
	0.611	*0.845*	*0.792*	*0.043*	*0.196*	*0.601*
all_cash	0.0013	**0.0096**[c]	**0.0154**[c]	**-0.0049**[a]	-0.0023	**-0.0060**[a]
	0.716	*0.066*	*0.059*	*0.000*	*0.137*	*0.002*
hostile_dummy	-0.0144	**-0.0269**[b]	**-0.0384**[a]	-0.0046	-0.0129	-0.0159
	0.149	*0.020*	*0.006*	*0.512*	*0.167*	*0.188*
tender	**0.0188**[a]	**0.0277**[a]	**0.0323**[a]	**0.0085**[a]	**0.0101**[a]	**0.0105**[a]
	0.000	*0.000*	*0.000*	*0.000*	*0.001*	*0.004*
congolmerate	**-0.0069**[c]	-0.0047	-0.0031	**-0.0019**[b]	**-0.0033**[a]	**-0.0026**[b]
	0.090	*0.467*	*0.779*	*0.011*	*0.001*	*0.046*
tobin	**0.0000**[a]	**0.0000**[a]	**0.0000**[a]	0.0001	0.0000	0.0001
	0.000	*0.000*	*0.000*	*0.309*	*0.154*	*0.586*
debt_assets_m	-0.0030	-0.0003	-0.0013	**-0.0108**[a]	**-0.0113**[a]	**-0.0123**[a]
	0.370	*0.941*	*0.823*	*0.000*	*0.000*	*0.000*
cash_assets_b	-0.0368	**-0.1108**[c]	**-0.2077**[b]	-0.0002	-0.0009	0.0014
	0.314	*0.072*	*0.045*	*0.945*	*0.834*	*0.807*
No. Observations:	21700	21696	21693	20613	20613	20621
Adj. R-squared:	0.004	0.0020	0.0010	0.031	0.0220	0.0150

***a**: statistical significance at the 1% level*
***b**: statistical significance at the 5% level*
***c**: statistical significance at the 10% level*

TABLE 12: Regressions with clustered standard errors

- *The dependent variable is the [-1,+1] 5%-trimmed CAR-s used in* ***Table 11*** *in both panels*
- *The regressor set Moeller (1)-(3) is from* ***Table 5****, (1) is from* ***Table 6*** *and (7) is from* ***Table 8***
- *ls_dummy takes the values of 0 if small, 1 if large, the firms are split based on the simulated 25th percentile of the NYSE. Ln_mc, ln_assets are the natural logarithms of the corresponding size proxies*
- *P-values are displayed in italic below the coefficients based on z-tests using clustered standard errors*
- *The number of observations and adjusted r-squared of the regressions are reported below*

SAMPLE	ALL Moeller (1) - CSE	ALL Moeller (2) - CSE	ALL Moeller (3) - CSE	ALL (1) - CSE	ALL (7) - CSE
intercept	**0.0222**[a]	**0.0360**[a]	**0.0325**[a]	**0.0336**[a]	**0.0084**[b]
	0.000	*0.000*	*0.000*	*0.000*	*0.043*
ls_dummy	**-0.0072**[a]				
	0.000				
ln_mc		**-0.0029**[a]		**-0.0027**[a]	**-0.0063**[a]
		0.000		*0.000*	*0.000*
ln_a			**-0.0026**[a]		
			0.000		
rel_size	0.0002	0.0001	0.0002		
	0.316	*0.494*	*0.371*		
tv_assets				**0.0016**[a]	0.0003
				0.001	*0.501*
competed	0.0000	0.0005	0.0001		
	0.991	*0.896*	*0.979*		
liq_index	-0.0003	-0.0002	-0.0003		
	0.470	*0.549*	*0.499*		
pub_target	**-0.0194**[a]	**-0.0177**[a]	**-0.0168**[a]	**-0.0141**[a]	**-0.0177**[a]
	0.000	*0.000*	*0.000*	*0.000*	*0.000*
priv_target	**-0.0035**[a]	**-0.0038**[a]	**-0.0036**[a]		
	0.000	*0.000*	*0.000*		
all_eq	**0.0017**[b]	**0.0028**[a]	**0.0028**[a]	**0.0027**[a]	**0.0034**[a]
	0.045	*0.001*	*0.001*	*0.003*	*0.000*
all_cash	**-0.0049**[a]	**-0.0055**[a]	**-0.0051**[a]	**-0.0053**[a]	**-0.0039**[a]
	0.000	*0.000*	*0.000*	*0.000*	*0.001*
hostile_dummy	-0.0046	-0.0067	-0.0061	-0.0074	**-0.0131**[c]
	0.504	*0.320*	*0.358*	*0.274*	*0.055*
tender	**0.0085**[a]	**0.0082**[a]	**0.0073**[a]	**0.0081**[a]	**0.0068**[a]
	0.000	*0.001*	*0.002*	*0.002*	*0.008*
congolmerate	**-0.0019**[b]	**-0.0019**[b]	**-0.0020**[b]	**-0.0027**[a]	-0.0013
	0.013	*0.014*	*0.012*	*0.001*	*0.113*
tobin	**0.0001**[b]	**0.0001**[b]	0.0000	**0.0001**[b]	**0.0001**[c]
	0.045	*0.042*	*0.362*	*0.036*	*0.060*
debt_assets_m	**-0.0108**[a]	**-0.0122**[a]	-0.0017	**-0.0123**[a]	**-0.0141**[a]
	0.000	*0.000*	*0.364*	*0.000*	*0.000*
cash_assets_b	-0.0002	-0.0009	-0.0024	-0.0058	-0.0026
	0.946	*0.787*	*0.471*	*0.114*	*0.483*
sent_m				**-0.0012**[c]	-0.0011
				0.080	*0.105*
mktsh				0.0065	
				0.476	
ln_ahhi					**0.0043**[a]
					0.000
serial				**-0.0021**[b]	0.0001
				0.029	*0.918*
toehold				-0.0007	-0.0009
				0.814	*0.756*
ln_tv					**0.0052**[a]
					0.000
No. Observations:	20613	20613	20613	17374	17374
Adj. R-squared:	0.031	0.036	0.035	0.033	0.047

TABLE 13: Individual explanatory strength of regressors

- *All variables are regressed on [-1,+1] CAR-s with univariate OLS regression*
- *The natural logarithm was taken of Acquiror and target size proxies and HHI scores*

Variable name	Regressor name	Separate coefficient	p-value
Large-small dummy	ls_dummy	**-0.0108**[a]	*0.5%*
ln(Market cap)	ln_mc	**-0.0045**[a]	*0.0%*
ln(Assets)	ln_a	**-0.0029**[a]	*0.1%*
ln(Target size)	ln_tv	0.000	*95.8%*
TV/assets (market)	tv_assets	**-0.0006**[a]	*0.0%*
Relative size (TV/equity)	rel_size	**-0.0005**[a]	*0.0%*
Days to completion	days_complete	0.000	*90.2%*
Liquidity index	liq_index	0.000	*87.1%*
Competed deals	compated	-0.012	*54.6%*
%Cash in payment	cash_pch	0.004	*31.0%*
%Equity in payment	eq_pch	-0.006	*27.5%*
%Other in payment	other_pch	0.000	*55.3%*
All cash	all_cash	0.001	*77.9%*
All equity	all_eq	**-0.0083**[c]	*9.2%*
Mixed payment	mixed_payment	0.004	*34.0%*
Hostile	hostile_dummy	-0.013	*73.2%*
Tender offer	tender	-0.001	*93.2%*
Conglomerate deal	conglomerate	-0.005	*17.5%*
Conglomerate deal (Fama French)	conglomerate_ff	-0.004	*31.8%*
Public target	pub_target	**-0.0187**[a]	*0.0%*
Private target	priv_target	0.006	*12.2%*
Subsidiary target	sub_target	0.006	*11.1%*
Large loss deal	large_loss	**-0.0838**[a]	*0.0%*
Large gain deal	large_gain	**0.0661**[a]	*0.0%*
Non-large loss/gain deal	non_large_lossgain	0.012	*32.1%*
ln(HHI) of target industry	ln_thhi	0.004	*10.7%*
Toehold	toehold	-0.008	*60.8%*
Cash/assets (book)	cash_assets_b	**-0.0252**[c]	*5.8%*
Debt/assets (book)	debt_assets_b	**0.0102**[b]	*4.6%*
Debt/assets (market)	debt_assets_m	0.002	*82.7%*
Tobin's Q	tobin	**0.0000**[a]	*0.0%*
Book-to-market ratio	b2m	0.000	*96.0%*
RPR ratio	RPR	-0.004	*64.8%*
%Market share of acquiror	mktsh	-0.033	*54.5%*
ln(HHI) of acquirer industry	ln_ahhi	**0.0085**[a]	*0.1%*
Serial acquirer	serial	**-0.0183**[a]	*0.0%*
Sentiment index (Y)	sent_y	0.003	*48.2%*
Sentiment index (M)	sent_m	-0.002	*64.3%*
HYS (Y)	hys_y	-0.013	*53.3%*
HYS (Q)	hys_q	-0.001	*96.9%*

a*: statistical significance at the 1% level*
b*: statistical significance at the 5% level*
c*: statistical significance at the 10% level*

TABLE 14: Correlations of variables

VARIABLES	ls_dummy	ln_mc	ln_a	ln_tv	tv_assets	rel_size	days_complete	liq_index	competed	cash_pch	eq_pch	other_pch	all_cash	all_eq	mixed_payment	hostile_dummy	tender	conglomerate	conglomerate_ff	pub_target	priv_target	sub_target	large_loss	large_gain	non_large_lossga…	ln_thhi	toehold	cash_assets_b	debt_assets_b	debt_assets_m	tobin	b2m	RPR	mktsh	ln_ahhi	serial	sent_y	sent_m	hys_y	hys_q
ls_dummy	**1.00**																																							
ln_mc	0.72	**1.00**																																						
ln_a	0.57	0.80	**1.00**																																					
ln_tv	0.55	0.78	0.71	**1.00**																																				
tv_assets	-0.02	-0.07	-0.10	0.01	**1.00**																																			
rel_size	-0.03	-0.08	-0.04	0.01	0.98	**1.00**																																		
days_complete	0.08	0.07	0.27	0.24	0.00	0.00	**1.00**																																	
liq_index	0.01	0.01	0.01	0.02	0.00	0.00	0.00	**1.00**																																
competed	0.04	0.05	0.05	0.11	0.00	0.00	0.08	0.01	**1.00**																															
cash_pch	0.04	0.14	0.08	0.13	0.01	0.01	-0.07	0.01	0.04	**1.00**																														
eq_pch	-0.02	-0.03	0.01	0.03	-0.01	-0.01	0.28	-0.01	0.01	-0.39	**1.00**																													
other_pch	-0.02	-0.10	-0.08	-0.15	-0.01	-0.01	-0.16	0.00	-0.05	-0.63	-0.46	**1.00**																												
all_cash	0.09	0.16	0.12	0.10	0.01	0.01	-0.05	-0.01	0.04	0.83	-0.36	-0.49	**1.00**																											
all_eq	0.01	-0.02	0.02	0.01	0.00	0.00	0.23	-0.01	0.00	-0.36	0.84	-0.36	-0.25	**1.00**																										
mixed_payment	-0.11	-0.06	-0.09	0.05	0.00	0.00	0.02	0.01	0.02	0.11	0.12	-0.21	-0.35	-0.25	**1.00**																									
hostile_dummy	0.03	0.01	0.02	0.05	0.00	0.00	0.06	0.06	0.10	0.02	-0.02	-0.01	0.02	-0.01	0.00	**1.00**																								
tender	0.08	0.09	0.08	0.15	0.03	0.03	0.03	0.01	0.19	0.16	-0.08	-0.08	0.16	-0.06	-0.03	0.24	**1.00**																							
conglomerate	0.00	-0.01	-0.01	-0.06	0.01	0.01	-0.10	0.02	-0.01	-0.01	-0.07	0.07	0.00	-0.05	-0.03	0.00	-0.02	**1.00**																						
conglomerate_ff	0.00	-0.01	-0.05	-0.05	0.00	0.00	-0.16	0.03	-0.02	-0.02	-0.15	0.14	0.00	-0.11	-0.05	0.01	-0.01	0.56	**1.00**																					
pub_target	0.12	0.18	0.28	0.32	0.01	0.01	0.37	-0.01	0.15	0.00	0.33	-0.28	0.02	0.28	0.02	0.08	0.35	-0.08	-0.14	**1.00**																				
priv_target	-0.14	-0.17	-0.23	-0.31	-0.02	-0.02	-0.22	0.00	-0.08	-0.07	0.00	0.07	-0.11	-0.02	0.08	-0.04	-0.17	0.07	0.07	-0.48	**1.00**																			
sub_target	0.06	0.04	0.01	0.06	0.01	0.01	-0.08	0.00	-0.04	0.07	-0.27	0.16	0.10	-0.22	-0.10	-0.02	-0.12	0.00	0.04	-0.33	-0.67	**1.00**																		
large_loss	0.10	0.26	0.20	0.25	0.00	0.00	0.06	0.00	0.03	0.04	0.03	-0.06	0.03	0.03	0.00	0.02	0.06	-0.02	-0.02	0.12	-0.07	-0.03	**1.00**																	
large_gain	0.09	0.25	0.18	0.22	0.00	0.00	0.06	0.00	0.01	0.05	0.00	-0.05	0.04	0.00	0.01	0.00	0.04	-0.01	-0.01	0.05	-0.05	0.01	-0.01	**1.00**																
nonlarge_lossgain	-0.13	-0.36	-0.27	-0.34	0.00	0.00	-0.09	0.00	-0.02	-0.06	-0.03	0.08	-0.06	-0.02	0.00	-0.01	-0.08	0.02	0.02	-0.12	0.08	0.02	-0.71	-0.69	**1.00**															
ln_thhi	-0.01	-0.08	-0.15	-0.09	0.00	0.00	-0.20	0.07	-0.01	-0.05	-0.19	0.21	-0.04	-0.15	-0.06	0.01	-0.01	0.10	0.23	-0.19	0.07	0.09	-0.04	-0.03	0.05	**1.00**														
toehold	0.03	0.02	0.03	0.04	0.01	0.01	0.07	0.00	0.04	0.00	0.01	-0.01	0.01	0.01	-0.01	0.18	0.13	0.00	0.01	0.11	-0.05	-0.04	0.03	0.00	-0.02	0.01	**1.00**													
cash_assets_b	-0.11	-0.08	-0.30	-0.12	0.02	0.00	-0.13	0.00	-0.01	0.05	0.06	-0.11	0.01	0.04	0.09	-0.02	-0.01	-0.03	-0.04	-0.07	0.12	-0.07	0.01	0.00	-0.01	-0.06	-0.03	**1.00**												
debt_assets_b	0.01	-0.01	0.01	0.06	0.00	0.02	-0.02	0.01	0.00	-0.03	-0.11	0.12	-0.02	-0.09	-0.02	0.00	-0.01	0.01	0.07	-0.05	-0.03	0.08	0.00	0.00	0.00	0.10	0.01	-0.16	**1.00**											
debt_assets_m	-0.04	-0.07	0.40	0.09	-0.02	0.05	0.22	0.00	0.01	-0.12	0.01	0.12	-0.09	0.01	-0.05	0.01	-0.03	0.01	0.01	0.12	-0.12	0.03	-0.04	-0.04	0.06	-0.01	0.02	-0.40	0.33	**1.00**										
tobin	-0.01	0.00	-0.04	0.00	0.00	0.00	-0.01	0.00	0.00	-0.01	0.01	-0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.01	-0.01	0.00	0.00	0.00	-0.01	0.00	0.01	0.00	-0.01	**1.00**									
b2m	-0.02	-0.05	0.01	-0.01	0.01	0.90	0.01	0.00	0.00	-0.01	0.00	0.02	-0.01	0.00	-0.01	0.00	0.00	0.01	0.00	0.00	-0.01	0.01	-0.01	0.00	0.01	0.00	0.00	-0.01	-0.01	0.05	0.00	**1.00**								
RPR	0.03	0.05	0.26	0.08	0.02	0.02	0.04	0.02	0.01	0.05	-0.13	0.07	0.07	-0.09	-0.07	0.00	0.03	0.04	0.03	0.05	-0.07	0.03	0.02	-0.03	0.01	-0.01	0.03	-0.14	-0.02	0.20	-0.02	0.03	**1.00**							
mktsh	0.17	0.26	0.23	0.23	-0.02	-0.01	0.04	0.01	0.04	0.06	-0.07	0.00	0.07	-0.05	-0.03	0.02	0.07	0.02	0.04	0.06	-0.08	0.03	0.09	0.11	-0.14	0.13	0.02	-0.08	0.04	0.01	-0.02	-0.01	0.05	**1.00**						
ln_ahhi	-0.05	-0.11	-0.23	-0.09	0.03	0.01	-0.08	-0.01	0.00	0.06	-0.06	-0.01	0.03	-0.06	0.04	0.01	0.02	-0.07	-0.07	-0.07	0.00	0.06	-0.01	0.00	0.01	0.39	0.01	0.03	-0.02	-0.20	0.02	-0.01	-0.11	0.28	**1.00**					
serial	0.09	0.05	0.05	-0.04	-0.01	-0.01	-0.05	0.01	-0.02	-0.08	0.02	0.05	-0.06	0.04	-0.05	0.00	-0.05	0.04	0.07	-0.05	0.07	-0.03	-0.03	-0.03	0.05	0.07	-0.01	-0.10	0.07	0.10	0.00	0.00	-0.05	-0.06	-0.13	**1.00**				
sent_y	0.02	-0.09	-0.11	-0.08	-0.01	-0.01	0.08	0.01	0.00	-0.19	0.10	0.09	-0.14	0.11	-0.06	0.03	0.04	0.02	0.01	0.03	0.00	-0.03	0.02	0.01	-0.02	0.01	0.03	-0.06	0.00	0.01	0.00	0.00	-0.07	-0.01	0.03	0.01	**1.00**			
sent_m	0.02	-0.10	-0.09	-0.08	0.00	0.00	0.06	0.02	0.00	-0.16	0.08	0.09	-0.12	0.09	-0.04	0.02	0.05	0.01	0.00	0.03	0.00	-0.02	0.01	-0.02	0.00	0.00	0.02	-0.06	0.00	0.00	-0.01	0.00	0.01	-0.01	0.03	0.01	0.75	**1.00**		
hys_y	-0.03	0.05	0.01	0.03	-0.01	-0.01	-0.05	0.03	0.00	0.05	0.01	-0.06	0.04	0.01	0.02	-0.01	-0.04	0.01	0.01	-0.01	0.02	-0.01	-0.03	-0.02	0.04	0.00	-0.03	-0.01	0.02	-0.01	0.00	0.00	-0.03	-0.02	-0.06	0.10	-0.28	-0.22	**1.00**	
hys_q	-0.01	0.01	0.00	0.00	-0.01	0.00	-0.03	0.01	-0.01	0.02	-0.01	-0.02	0.02	0.00	0.00	0.00	-0.02	0.01	0.01	-0.01	0.02	-0.01	-0.03	-0.02	0.04	0.01	-0.01	-0.02	0.01	-0.01	0.00	0.02	-0.03	-0.01	-0.03	0.07	-0.21	-0.15	0.72	**1.00**

8.3. Glossary of abbreviations

ANPV	Abnormal Dollar Return
AR	Abnormal Return
CAAR	Cumulative Average Abnormal Return
CAPE	Cyclically Adjusted Price-to-Earnings Ratio
CAR	Cumulative Abnormal Return
CARC	Cumulative Abnormal Return of Target-acquirer Portfolio
DW	Durbin-Watson Test Statistic
EW	Equal-weighted
HHI	Herfindahl–Hirschman Index
HYS	High Yield Share
IID	Independent and Identically Distributed Random Variables
JB	Jarque–Bera Test Statistic
KF	Kenneth French
MC	Market Capitalization
MV	Market Value
OCF	Operating Cash Flow
RPR	Reference Price Ratio
SENT	Equity Sentiment Index
TNIC	Text-based Network Industry Classifications
TV	Target Value
VW	Value-weighted
VWCAR	Value-weighted CAR
VWCAAR	Value-weighted CAAR
3FF	3 Fama-French Factors
$CARC	Dollar CAR of Target-acquirer Portfolio

Link to Dataset