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The use of Contingent Value Rights in M&A

An empirical review

Eivind K. Fosheim & Niklas Olufsen Langerød

Supervisor: Associate Professor Francisco Santos

Master of Science in Economics and Business Administration,

Finance

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

This paper contributes to the literature on payment methods in Mergers and Acquisitions (M&A). It seeks to establish how the use of Contingent Value Rights (CVRs) in M&A affect the probability of deal completion following a bid announcement. Further, the paper provides answers on how the stock market reacts to bidders' issuing CVRs as part of their deal consideration package by estimating the bidders' cumulative abnormal returns (BCAR). It also presents a general definition of a CVR that acknowledges that there exist two main categories of the instrument. Namely, event-driven CVRs and performance CVRs.

By utilizing more than 1,800 U.S. transactions, including 41 observed CVRs, we find robust evidence in favour of that CVRs have a significant positive impact on the probability of deal completion in M&A. More precisely, we run Probit regressions on matched sub-samples and estimate that the marginal probability increase on deal completion when using CVRs are 13.9% to 22.1%. BCAR is estimated using a market model. We find consistent evidence across all our regressions that indicates a negative relationship between BCAR and the use of CVRs. Moreover, the final matched sample regression shows that the issuance of event-driven CVRs have a negative, and statistically significant, effect of 5.08 percentage points on BCAR.

To our knowledge, this paper is the first contribution on both how CVRs affect the deal completion probability, how event-driven CVRs affect BCAR, as well as to be presenting the first general definition of a CVR.

Aknowledgements

This thesis is written as a part of our master's degree in finance at the Norwegian School of Economics (NHH). Our common interest in the field of mergers and acquisitions (M&A) laid the pathway for this thesis. The idea of investigating the use of Contingent Value Rights has its root in the course FIE443 – Mergers & Acquisitions, where one of the authors were first presented with the usage and brief history of the instrument. The writing of this thesis has been a challenging and meaningful experience. We hope that our paper will contribute to the literature on CVRs and that it may inspire other researchers to investigate the instrument further.

There are several people who deserves a special thank you for contributing to our progress. Especially, we wish to thank our supervisor, Associate Professor Francisco Santos, for his thorough feedback and inspiring attitude towards our work. Our supervisor was always available to us and has assisted us through several frustrating phases of this project. We also wish to thank Professor Karin S. Thorburn for sharing her extensive knowledge within the field of M&A with us.

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Eivind K. Fosheim

Niklas Olufsen Langerød

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1. Introduction

In an economic transaction, one party tends to possess more and/or superior information about the goods to be traded than the counterpart. This is commonly referred to as asymmetric information. Akerlof (1970) defines asymmetric information as a market for lemons, and illustrates it by explaining how the seller, and previous owner, in a used car sale normally has greater knowledge than the buyer. This example is transferrable to the mergers and acquisitions (M&A) sphere, where the selling part normally possesses the superior knowledge of its own value compared to the potential buyers. On the other hand, the buyers possess the superior knowledge regarding their value, which can be cause of disagreement in a proposed stock offer. This is also referred to as a two-sided asymmetric information problem. A Contingent Value Right is a financial instrument constructed to reduce the asymmetric information issues in corporate transactions. It was first introduced in the late 1980s (Homburger, 2006) and its key attribute is to shift risk and uncertainty from one party to the other, and at the same time bridge valuation disagreements in M&A. Per 2017, the global M&A market is estimated to have a value of $3.4 trillion (Imaa, 2016). Given this figure, it is no wonder that several researchers have sought to answer how the type of consideration offered in a transaction impacts the probability of success or failure. However, the majority focus solely on the combination of stock and/or cash offers.

This paper is the first to our knowledge to examine and present results on how the use of Contingent Value Rights (CVRs) as part of the bid structure affects the probability of a transaction being consumed. In addition, we build on Chatterjee & Yan (2008) findings on how CVRs affect the bidders cumulative abnormal return (BCAR) following the announcement of a proposed transaction.

Existing literature on CVRs do not provide a clear definition of the instrument. We acknowledge that there are mainly two general CVR structures. Event-driven CVRs and performance CVRs. To our knowledge, we establish the first general definition of a CVR to incorporate both of the two main structures.

Our first hypothesis (H_1) addresses the effect CVRs have on the deal completion probability. Based on the existing literature, we believe that a CVR is a positive driver for a bid being accepted by the target shareholders. The second hypothesis (H_2) is related to how the stock market reacts to the usage of CVRs. Based on Chatterjee & Yan (2008) findings, we expect to identify that CVRs cause positive abnormal stock price reactions in the bidder's stock following the bid announcement.

The CVRs are identified and verified using Thomson Reuters' Securities Data Company (SDC) Platinum, Mergers & Acquisitions database in correspondence with original company filings extracted from the U.S. Securities and Exchange Commission database, EDGAR. We have been successful in constructing a data sample consisting of 41 U.S. CVRs used in M&A transactions for the period 1993-2016. Our control group sample consists of 1,763 company transactions from the U.S. market for the same time span as the CVR sample. Before answering our research questions, we show that comparable descriptive statistics correspond well with previous researchers' data samples.

In order to capture the causal effect of CVRs in our empirical analysis, we ensure that we compare deals that are similar in terms of essential aspects related to the use of CVRs. This is done using a combination of exact- and propensity score matching. The matching covariates are well founded in the literature, which should, according to Stuart (2010), reduce the level of bias. The procedure results in balanced matches and is applied in the analysis of both hypotheses.

We examine H_1 by using a Probit model. It is applied on the complete samples, as well as two matched sub-samples. We find statistically significant and persistent results across all three approaches. For the first matched sample, we found that the use of CVRs in general increases the marginal probability of deal completion by 13.9%. This result is statistically significant at the 10% level. The results from the second matched regression are even more interesting. This regression controls for the different attributes of performance and event-driven CVRs by only including the latter in the estimation of the effect. Our corresponding result is significant at the 5% level and shows that event-driven CVRs, on the margin, increase the probability of deal completion by 22.1%. All of these results are in favour of our first hypothesis, that CVRs have a significant positive impact on the probability of deal completion. We argue that the estimated effects relate to that CVRs diminish the valuation disagreements by reducing the degree of information asymmetries, as well as providing a strong signalling effect to the market that the transaction will be consumed. The latter as a result of the high degree of information and detailed negotiations needed in order to make the CVR attractive to the target shareholders. These results, are to our knowledge, the first empirical assessments of how CVRs influence the probability of deal completion.

The second hypothesis is answered by examining how the bidders' cumulative abnormal returns (BCAR) behave in the event window (-1,1), where day 0 is the bid announcement day. We estimate BCAR by performing an event study using a market model. To estimate the BCAR, we require our data samples to contain stock data for all the bidders in the event window. This constraint reduces the control sample from 1,763 to 1,044 observations and the CVR sample from 41 to 30 deals. To achieve a more comprehensive understanding of the matching covariates as well as the effect of the CVR, we first run an Ordinary Least Squares regression on the BCAR using the whole data sample. The covariates behave as expected and the CVR provides a first indication of its effect in terms of having a negative impact on the BCAR. To further assess this effect, we run matches on the complete CVR sample as well as the event-driven CVR sample. Although we only obtain statistically significant results in the last regression consisting of only event-driven CVRs, we do observe consistent patterns in the first two regressions as well. The final result is also the most interesting as it contributes to a new, more broadened understanding of event-driven CVRs. We find that the bidders issuing an event-driven CVR on average experience a reduction in BCAR of 5.08 percentage points. The finding is statically significant at the 5% level.

We argue that this finding does not contradict the findings of Chatterjee & Yan (2008). They find a positive response on BCAR for bidders that issue performance CVRs. Performance CVRs provide a different signalling effect and function, related to the bidders' confidence in their own stocks. We further argue that event-driven CVRs fuel the level of uncertainty in the investors' assessments of the transaction, mainly because issuing an event-driven CVR highlights that the bidder is increasingly uncertain about the target's true value. In terms of bidder confidence, we argue that event-driven CVRs have an opposite signalling effect compared to performance CVRs.

The proceeding sections of this thesis are structured as follows: Chapter 2 provides a review of the existing literature as well as a definition and description of the key attributes of CVRs. Finally, based on the findings in the literature, we present our two hypotheses. Chapter 3 provides a detailed description on how we construct our dataset. Chapter 4 specifies the methodology we use, the choice of variables and corresponding statistics, before presenting our empirical findings. The chapter covers first the analysis of H_1, then H_2. Finally, chapter 5 concludes this thesis.

2. Literature Review

What is a Contingent Value Right? Academics and finance professionals have different views on this question and the literature is inconclusive. This is why we find it necessary to use the first section of this literature review as a means to define CVRs for the purpose of the thesis. In section 2.2 we present the most common CVR characteristics as well as examples from transactions in where they have been used. Section 2.3 discusses the potential up- and downsides with CVRs, along with empirical findings. Finally, based on the previous sections, we present our research questions in focus and corresponding rationale in section 2.4.

2.1 Definition of Contingent Value Rights

A potential solution to the problems associated with information asymmetry in M&A has been the introduction of more complex instruments. CVRs are examples of such instruments and are offered as an additional consideration to shareholders in M&A. Sometimes they are referred to as "deal sweeteners". The party issuing a CVR ("the issuer") is commonly the bidder. Hausch & Seward (1999) describe the structure of a CVR as a put option that provides the holder with a price protection mechanism against the issuer's stock, by providing an upper and lower bound on the issuer's stock. This protection materializes as a second contingent payment if the underlying stock price (the issuer's stock price) does not meet its pre-specified, post-closing, price level. The payment will often be estimated as the difference between the promised price and the actual price. Moreover, CVRs can be marketable and traded separately from their stock. These descriptions are in line with Willens (1990), Chen (2002)[1] and Caselli et al. (2006). Ritt (2011) underline the CVRs tradability as either non-assignable rights, assignable certificates, or publicly-traded securities.

CVRs can also be structured with a call option like payoff, as mentioned by Chatterjee & Yan (2008) and Gerhard (2006). This structure provides a future contingent payment based on the potential upside value, dependent on a future occurrence or metric. More recent literature

[1] Chen (2002), does not mention the tradability aspect.

emphasizes the earnout structure of the CVR. Wolf & Fox (2010) define event related CVRs as a version of earnouts used in public company sales, tied to a verifiable outcome. Wolf (2011) elaborates on this perspective, and accentuates the event-driven perspective related to milestones as the most common structure in later years.

Investment banks such as Goldman Sachs and Greenhill define CVRs with both perspectives, in which the CVR can be structured either similar to an earnout or as a combination of put options directed at the shareholders (Goldman Sachs & Co, 2008; Greenhill & Co, 2008). The earnout like structure is referred to as an event-driven CVR, while the put structure is referred to as a performance CVR. We argue that a CVR can be either performance-driven or event-driven. Consequently, we agree with the view of Goldman Sachs & Co and Greenhill & Co. However, to our knowledge, there is no commonly used definition of what a CVR is. Thus, we have formulated our own general CVR definition based on the existing empirical literature on the subject. Our definition seeks to capture the common properties of both performance and event-driven CVRs.

Our proposed general definition of a Contingent Value Right: "A financial instrument, used in public target takeovers, that provides the holder with a post transaction and per share right to receive a future consideration, contingent upon the *fulfilment* or *occurrence* of one or more events"[2].

We follow this definition for the rest of our paper.

2.2 Common Structures of Contingent Value Rights

In this section we seek to assess the simplest and most common structures of the two CVR categories. We also use examples from previous transactions in an effort to try to highlight the key aspects of when and why the instrument is being used. Performance CVRs share common characteristics with event-driven CVRs in terms of their contingent nature and risk shifting attributes. In their purest form, CVRs are constructed to shift risks from one party to another. However, their payoff functions are completely different. It is critical to understand the

[2] "Fulfilment" refers to the event driven CVRs milestone triggers, while "occurrence" refers to the performance CVRs underlying stock or index development. Both words represent the triggering aspects of the contingent payments.

uniqueness of the two structures in order to grasp how they can contribute to adding value in M&A transactions.

Event-driven CVRs

An event-driven CVR is, in its simplest form, a financial contract where the potential future payment has a binomial payoff function. Due to its many shared attributes with regular earnouts, Daniel E. Wolf from Kirkland & Ellis calls event-driven CVRs "the public M&A version of earnouts" (Wolf, 2011). The payoff is a function of one or more milestone events. For instance, a sale threshold or the approval of a new product.

This type of CVR can be an attractive solution when the value of the target is highly dependent upon one single future event – thereby the binomial payoff. In addition, it allows the acquirer to delay a significant amount of the consideration, which can be particularly attractive if the acquirer has limited liquidity at the time of the transaction. However, the consideration that is to be distributed to all the CVR holders, if the milestone event is accomplished, can be either floating or fixed. This implies that the value of an event CVR may change over time unconditional of a change in the probability of the milestone condition being met. An event-driven CVR may also consist of several milestones, with different maturities and payoffs.

In February 2015, Shire Pharmaceuticals International announced that they were acquiring Dyax Corp. in a $6.6 billion deal. The transaction entitled Dyax shareholders to receive $37.30 in cash, plus one CVR, per share. The CVR will pay out a fixed amount of $4.00 per share if Dyax manages to obtain allowance from the U.S. Food and Drug Administration (FDA) to market and sell their hereditary angioedema drug, DX-2930, within five years after the transaction.

The value of the CVR is naturally not the same as the potential $4.00 payoff. To estimate the value of this type of CVR one needs to be able to say something about the probability that the target will trigger the potential payment before the CVR expires. In this case, the probability of Dyax obtaining allowance from the FDA to market and sell DX-2930 within five years. Maximum likelihood estimation is an example of a statistical tool that can be used to solve this type of problem[3]. Furthermore, one needs to make assumptions regarding *when* the payment will be triggered, as this clearly impacts the discount factor. Finally, most investment banks use the target weighted average cost of capital (WACC) as the appropriate risk adjusted discount rate (Goldman Sachs & Co, 2008; Greenhill & Co, 2008).

Centerview Partners, who advised Dyax in the transaction, estimated the probability of achieving the milestone to be 80%. They used a WACC in the range of 10-12% and concluded that the CVRs was worth $2,55 to $2,64 per share (U.S. Securities and Exchange Commission, 2016). This implies that Centerview Partners assumed the *when*, regarding the triggering of the payment, to occur two years after the transaction. The pricing range of the CVR reflects the purpose of the instrument. It is a deal-sweetener that adds ~7% value to the initial $37.30 cash consideration.

Performance CVRs

A performance CVR is a financial contract between two parties that is constructed to fix the value of a stock-consideration. It is designed most often using plain vanilla European puts or European put spread options (Chatterjee, & Yan, 2008). Like collars may be used to hedge the value of the consideration offered pre-transaction, performance CVRs do this post-transaction. In general, a performance CVR will pay out additional cash or securities if the acquirer's stock price (or an agreed upon reference-index) falls below a specified threshold within a certain amount of time after the transaction. A performance CVR can also be constructed in the exact opposite way, i.e. it pays additional cash or securities if the acquirer stock (or a reference index) appreciate above a certain threshold. The properties of performance CVRs vary from transaction to transaction. A performance CVR might have attributes such as a sudden death feature, meaning that the CVR automatically expires valueless if the reference price reaches an upper threshold[4]. It can also have attributes such as that the issuer has the right to call back, or extend the maturity of the CVR, at pre-specified time points.

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[3] The purpose of this paper is not to detail how one should value CVRs. Hence, we will not present in debt details of how one should do this in practice.

[4] The sudden death feature described is for a put option based performance CVR.

During the autumn of 1993 and early 1994, Viacom Inc. and QVC Network Inc. was in a takeover battle for the U.S. entertainment company Paramount Communications Inc. The contest ended on February 15th 1994, when Paramount shareholders accepted a tender offer bid from Viacom that included a performance CVR as part of the consideration. According to the investment bank Lazard, it was actually QVC that offered the superior final bid in terms of per share value for Paramount shareholders[5] (U.S. Securities and Exchange Commission, 1994). Both contestants offered a cash and stock combination in addition to warrants. However, Viacom offered a CVR and QVC did not.

The Performance CVR issued following the acquisition was in the form of an in the money European put option. It would grant the holder an additional payment equal to the difference between $48 and the closing price of Viacom class B shares one year after the transaction, or a maximum payment of $12, given that the Viacom shares traded for less than $48. The CVR had a floor of $36. Meaning that if the Viacom B shares traded for less than $36 at maturity, this would not affect the value of the CVR, as the maximum payment would be $48 - $36 = $12. However, in an effort to try to minimize the risk of short-term disruptive stock price movements, Viacom had several clauses included in the CVR. For instance, one stated that they had the right to delay the maturity date by one year at the end of the first year if they wanted to. This would however increase the maximum potential CVR payoff as the spread between the exercise price and floor of the CVR increased to $14[6]. Finally, Viacom had the right to redeem or call the CVR back, for a premium, at any given time. This would later prove to be an important feature of the CVR.

When valuing a performance CVR, one can use several different techniques depending on the different features of the specific instrument. In the case of the Viacom CVR, Lazard used two of the three main frameworks: Black & Scholes and Monte-Carlo simulation. The third possible framework is the binomial option pricing framework. All the three frameworks have their strengths and weaknesses, and are not conclusive. In this case, the price deviation becomes larger with increased assumed volatility using Black & Scholes compared with

[5] Lazard valued the total and final Viacom offer at $83.35 per share, while QVC's consideration package was valued at $85.91 per Paramount share

[6] If the maturity was delayed by one year, the new exercise price would be $51 and the floor $37.

Monte-Carlo simulation. Hietala, Kaplan, & Robinson (2003) demonstrate this finding in their review of the transaction.

As the value of the CVRs purely depend on the value of the Viacom B shares, arbitrageurs started to trade the two in sophisticated strategies, putting downward pressure on the Viacom stock following the acquisition (Fabrikant, 1995). One week before the expiration of the first maturity Viacom decided to redeem the CVRs for $1.44 per right. Interestingly, the Viacom shares rose $1.75 on the news, most likely due to that the arbitrageurs had to cover their short positions. Following the Viacom/Paramount merger it has been more common to use indexed reference prices to avoid the arbitrageurs to depress the issuers' stock. However, this solution is not optimal and limits the effect of the CVR, as it is the issuers' stock that the instrument is meant to insure, not an only partly corresponding index.

2.3 Advantages and Disadvantages

CVRs can, as previously mentioned, potentially solve problems arising in M&A by bridging valuation gaps trough a strong signalling effect, as well as providing the bidder with a concrete way to ensure that the payment is reflected in the realized value (Chatterjee & Yan, 2008). The potential synergies in a corporate merger or acquisition are often hard to value at the time of the transaction. CVRs can be used to reduce the bidders' potential economic loss if the potential synergies and/or acquired assets fail to meet their excepted value post transaction, by shifting the risk towards the target. This provides the bidder with increased liquidity in the short-term by potentially reducing upfront cash outlays (Goldman Sachs, 2008; Gerhard, 2006). Cash outlays might also be deterred in association with mandatory company tender offers. Typically, one can issue a CVR on the target company's shares to guarantee a minimum price to those shareholders who keep their shares. Thus, it is less likely that the shareholders will sell their positions (Cain et al., 2011).

The backside of the possible short-term liquidity gains from issuing a CVR is that the future payments are potentially large and can sometimes be triggered at an unexpected or unwanted point in time (Cain et al., 2011; Goldman Sachs & Co, 2008). This is one of the major drawbacks associated with CVRs. Another CVR limitation is its complexity. The CVR is for most people an unfamiliar financial product whose purpose to some extent can be contradictive. A CVR can actually increase the level of uncertainty if not constructed correctly and carefully (Gerhard, 2006).

The adoption of FAS (141) R[7], which demands acquirers to record material contingent considerations as liabilities at fair value, has an unknown effect on the usage of CVRs. Wolf (2011) argues that this aspect might be unattractive to the bidders issuing CVRs, as it potentially leads to increased earnings volatility. Bates, Neyland, & Wang (2017) analyse the use of earnouts as a source of financing for bidders, using U.S. transactions. They find that financially constrained bidders attain flexibility on their balance sheet by being able to balance the contingent claim at the lower quantile of the fair value. Hence, given the similar attributes of earnouts and event-driven CVRs, issuing an event-driven CVR in M&A transactions might provide financial flexibility for the bidder as well as solving valuation disagreements.

2.4 Empirical Findings

There is, to our knowledge, only one published empirical article which directly addresses the use of CVRs in mergers and acquisition. It was first published in 2003 as “Contingent Value Rights: Theory and Empirical Evidence”, then later published in 2008 under the title “Using innovative securities under asymmetric information: Why do some firms pay with contingent value rights?”. The paper(s) is written by Sris Chatterjee & An Yan.

They assess the use of performance CVRs using a total sample of 29 observations that consist of 24 CVRs and 5 instruments with put-like structures[8]. The sample is based on U.S. listed companies in the period 1989-2004. The hypotheses are related to capital constraints, asymmetric information and market response. More precisely, they seek to answer if (1) more cash constrained companies are more inclined to offer CVRs, (2) whether CVRs, in combination with stock or cash, will generate larger abnormal announcement returns than pure stock offers. And finally, (3) whether CVR bidders have significantly higher abnormal returns

[7] FAS (141) R is an accounting standard applicable from the fiscal date of 15.12.2008 in an effort to converge U.S. and international accounting standards.

[8] This includes Contingent Value Preferred Shares (CVPS), Common rights and put options (Chatterjee & Yan, 2008).

than all-stock offers. They find significant support for all three hypotheses in addition to not observing any significant differences in the targets abnormal stock returns.

2.5 Resulting Hypothesis

Wolf (2011) emphasizes that the use of CVRs will merely be a part of the discussions in the preliminary steps of the transaction process. Seldom, or never, will they be used as a solution because of their complexity. As he states; "CVRs are a cause to the same troubles that they are structured to solve". Following, we find it essential and interesting to address how the CVRs affect the outcome and response to an offer. Our study is closest to that of Chatterjee & Yan (2008) due to the limited empirical focus on CVRs in the literature. Their focus was primarily on performance CVRs, which is not reflecting the structure of focus in this study. Our study will differ from that of Chatterjee & Yan (2008) both in terms of control variables and to some extent in terms of the questions we want to address.

Hypothesis 1 (H_1)

In section 2.1 and 2.3, we presented literature that contradicts the opinions of Wolf (2011). Namely, that CVRs are considered a potential solution to disagreements regarding valuation, both by providing a strong signal as well as enabling the payment to reflect the realized value creation. Hence, one could expect that CVRs enhances the probability of completing a deal. On the other hand, we have discussed potential problems related to the complex nature of CVRs. The more advanced structures might cause more bad than good by causing increased management and shareholder uncertainty. One might question if the net effect is actually positive or not. Consequently, we want to assess if the use of CVRs in company transactions influences the outcome with respect to deal completion.

H_1: CVRs increase the probability of deal completion.

Hypothesis 2 (H_2)

Hypothesis 2 is related to how the markets respond to the methods of payment in terms of abnormal stock price reactions in the bidders' stock. The market's response to different payment methods in terms of the bidders' announcement returns is not a clear cut. However, the bidders' announcement returns are rarely positive. From a bidder's perspective there are pros and cons with issuing CVRs. On the positive side is the opportunity of postponing cash payments as well as that the consideration paid better reflects the realized value for both parties. At the same time the risk of possibly large and/or poorly timed cash payments in the future exists. Potential future lawsuits should also be mentioned as a negative factor. Chatterjee & Yan (2008) find significant positive abnormal return for acquirers issuing performance CVRs in M&A. Given the generic option like attributes, and corresponding risk shifting abilities of both the main CVR types, we believe that the bidder stock price reaction should be positive following the issuance of any type of CVR.

H_2: The market reacts positively to the usage of CVRs in terms of CVRs having a positive effect on the bidders' cumulative abnormal returns (BCAR).

3. Dataset construction

Identifying the CVRs

This section provides a comprehensive description of how we build our datasets. We construct two samples based on the Thomson Reuters' Securities Data Company (SDC) Platinum, Mergers & Acquisitions database. Hereafter, the two samples are referred to as "the CVR sample" and "the control group". The software used in this project is a combination of MS Excel, Stata, and R.

Our goal is to identify and sample all bids including contingent value rights (CVRs) as part of the consideration offered. We start by selecting "US Targets". The main reason for choosing U.S. targets is that the American M&A market is considered to be the largest in the world, both in terms of volume and number of transactions. For instance, the U.S. 2016 M&A volume was roughly twice the size of Europe, which is the world's second largest market (Mergermarket, 2017). In addition, we want to avoid regulation differences across nations.

We extract all U.S. bids from 01/01/1993 to 01/01/2017. Our time period starts in 1993 as this was the year the U.S. Securities and Exchange Commission (SEC) started to phase in their Electronic Data Gathering, Analysis, and Retrieval system (EDGAR). The reason for our wide time-horizon is that CVRs are not commonly used. Hence, we want to include as many observations as possible and choose not to restrict our sample-period more than necessary.

Finally, the targets are restricted to be public and U.S. domiciled to ensure data availability. Parts of the consideration has to take the form of either CVR, Contingent Value Preferred Stock (CVPS) or an Earnout. We allow for bids marked with CVPS and/or Earnout in SDC as they are potentially misclassified based on our CVR definition presented in section 2.1. By implementing the above criteria, we end up with a raw sample of 148 bids that potentially include the use of CVRs. For further filtering and identifying, we output the following variables: SDC Deal Number, Date Announced, The firms CUSIP, Nationality and Name, as well as the Deal Status.

At this moment the CVR sample contains unwanted bids including OTC-listed and de-listed targets, wrongly labelled public by SDC, as well as bids that do not include the use of CVRs. We start our cleansing by applying the targets 6-digit CUSIP[9] to identify which of the targets' stocks are listed on either NYSE, Nasdaq or Amex (CGS Identifiers, 2017). In addition to having price information available for at least 100 trading days within the last 297 trading days prior to the announcement date. We do this by using the Center for Research in Security Prices (CRSP) database.

We acknowledge that using CUSIP as a matching criteria has its limitations as it is not a strictly unique identifier for the targets' stock price. A security CUSIP number can change over time due to corporate events (Morris & Goldstein, 2010). Hence, we use the Wharton Research Data Services (WRDS) tool that allows us to match any 6-digit CUSIP towards their PERMNO database. PERMNOs are unique identifiers in the CRSP database. 41 bids were deleted from the CVR sample as they did not have a PERMNO match in WRDS, and an additional 25 are exempt for not meeting the listing requirements and/or the price information criteria described above. To ensure that we do not delete observations due to imprecise data sources, we run manual searches on all the 148 potential CVR targets by their given 6-digit CUSIP and company names in WRDS. No unintentionally deleted bids are identified.

Due to the lack of, or unprecise data regarding CVRs in SDC, we need to rely on original SEC-filings describing the bid-specific considerations offered. We search EDGAR manually, focusing on DEFM14A-, SC 14D9- and 8-K filings to access the data needed. A total of 32 bids are deleted from the CVR sample as the consideration offered did not contain a CVR. Inspired by Betton et al. (2014), we also restrict the sample to meet the general criteria described in table 1. These restrictions are argued to diminish the probability of experiencing extreme outliers in our datasets.

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[9] CUSIP is in its full form a 9-digit identifier, where the 6 first digits identifies the name of the issuer, the next 2 digits identifies the issue within the issuer. The final digit is a "check" digit based on the 8 first digits. SDC only store the first 6 digits in its database.

Table 1: Bid sample criteria

The table describes which general criteria we have restricted our datasets to meet.

Criteria No.:	Criteria Description	Source
1	The deal has to take form of an acquisition or a merger	SDC
2	The total deal value has to be at least $10 million	SDC
3	Acquirers are not allowed to hold more than 49% of target shares prior to the first bid	SDC
4	Stock price 42 days prior to the announcement has to be more than $1.00 for the target	CRSP
5	The initial offer per share and target stock price on day -42 has to be more than $1.00	CRSP
6	The bid outcome status has to be either completed or withdrawn	SDC
7	The target stock exchange code cannot be “NewYorkOTC”, “OTC” or “Pink Sheet”	SDC

9 of the remaining 50 CVR-bids fail to meet all of the criteria listed in table 1 and are removed from the CVR-sample. This leaves us with a validated CVR sample consisting of 41 observations.

Control group construction

The control group sample is built using the same constraints as for the CVR sample, except for the consideration offered restriction. In addition to the above criteria we restrict all bids in the control group to have the same first three Standard Industrial Classification (SIC) digits as those in the CVR-sample. This is done to make sure that our two samples share the same characteristics in terms of industries and sectors. The resulting control group sample consists of 1,763 unique bid observations, excluding the remaining 41 CVR observations.

To finalize our dataset, we use the merged CRSP/Compustat database (CCM) in WRDS to match our sample PERMNOs with their corresponding GVKEY in Compustat[10]. By using GVKEY as our matching key in the Compustat database, we extract income statements, balance sheet and cash flow items for both acquirers and targets for the last fiscal year prior to the announcement date in SDC. We refer to Appendix 1 if the reader wants a more detailed description of our data selection process.

[10] The data gathered from Compustat do not affect our dataset in terms of total bids left in the sample. All remaining targets have data found for the period of interest in Compustat.

4. Empirical Analysis

Chapter 4 is divided into the analysis of our two hypotheses. Section 4.1 address H_1 and section 4.2 addresses H_2. In section 4.1, we briefly present the methodology applied to answer H_1. The model variables are presented with their empirical foundation and rationale. To get a more comprehensive understanding of the variables and data, we further present the variables descriptively. Finally, the analysis and corresponding results are presented. Section 4.2 is structured in a similar manner.

4.1 Deal Completion Probability - H_1

Propensity score matching (PSM)

Our data show clear indications of a non-random selection of CVRs as 56% of the target companies in the CVR sample belong to the pharmaceutical- and biotech industry. Rosenbaum & Rubin (1983) highlight that the treated units often differ systematically from those not exposed to the treatment. This creates a selection bias, making it difficult to estimate the causal effect of CVRs. According to Stuart (2010) matching techniques mitigates the selection bias by creating groups with similar probabilities of using CVRs in the first place.

The use of propensity score matching might be significantly bias-reducing when applied to imbalanced samples (King & Nielsen, 2016). As illustrated in Appendix 2 this is the case in our sample. This imbalance in our sample confirms that the use of propensity score matching is the desired model of choice. Furthermore, we choose to combine exact matching and propensity score matching, as recommended by Stuart (2010), to increase the quality of the matches. The applied method ensures that each CVR deal is matched exactly on industry and then matched in terms of the matching covariates using PSM. We apply a Probit model to estimate our propensity scores.

The choice of covariates to match on is related to the conditional independence assumption[11]. Based on Stuart's (2010) recommendations, we chose empirically established variables in our matching procedure. Given the combination of exact industry matching and a comprehensive set of empirically well-founded variables, we argue that we have fulfilled the conditional independence assumption at a satisfactory level.

To fulfil the common support assumption[12], we ensure that all matches are within the common support area by imposing a common support condition in our matching procedure. This excludes all the observations whose propensity score is of the common support and thereby satisfying this assumption (Caliendo & Kopeinig, 2008).

The Nearest neighbour matching algorithm (NN) is argued to be the easiest to implement and understand when using PSM, as well as being the most conventional method applied (Rubin, 1973). Hence, we go forth with this method and use a 1:1 match, to ensure precise matches as done by Hillion & Vermaelen (2004). This is supplemented with a caliper of 0.2, as recommended by Austin (2011). The 0.2 caliper provides a maximum tolerance level of the propensity score distance.

To mimic a randomized experiment, the covariates of the treated and untreated observations should not be statistically different. We apply the two-sample t-test as we are concerned about the robustness of our results in terms of the samples actually being balanced. This is the preferred test in this case (Caliendo & Kopeinig, 2008).

Dependent variable

To determine the effect CVRs have on the probability of deal completion we construct a binary dependent variable. As done by among others Bates & Lemmon (2003), we use SDC information on whether the transactions are completed or withdrawn. This will be the dependent variable in our test of hypothesis 1. Completed transactions take the value of 1 and

[11] The conditional independence assumption states that the potential outcomes become independent of the treatment status once controlling for the correct set of observable covariates (Caliendo & Kopeinig, 2008).

[12] The common support requirement states that the participants have a probability of both being treated and non-treated (Caliendo & Kopeinig, 2008).

withdrawn deals the value of 0. We use a Probit model to estimate the effect of the CVRs due to the binary dependent variable. The model is presented below, where **x** is a vector consisting of the control variables.

$$P(Completed = 1|x) = G(\beta_0 + \beta_1 DealCVR + \beta\boldsymbol{x}) \quad (1)$$

After the matching process, the Probit model is applied to the matched sample. Given that the matching covariates are well balanced, the effect on the dependent variable of interest can be attributed to the CVR. This is formally expressed in equation (2).

$$P(Completed = 1|x) = G(\beta_0 + \beta_1 DealCVR) \quad (2)$$

Control variables

This section presents the control variables for H_1, as well as their empirical foundation. Appendix 3 consists of a more detailed description of the variable construction and sources.

Betton et al. (2014) consider the targets' size when addressing the probability that either the initial bidder or a rival ultimately acquires a target. Their results imply a positive relation between the probability of bid success and the targets size[13]. To control for this, we include a target size variable constructed as the natural logarithm of the targets market value 42 days prior to the announcement, as done by Betton et al. (2014).

The notion that the participants of a deal prefer more liquid assets is also captured by Betton et al. (2014). They find evidence of an increased probability of target acceptance if the acquirer is public. To address this, we include a dummy variable taking the value of 1 if the acquirer is public. We also control for the targets liquidity, estimated as the average daily ratio of trading volume to total shares outstanding over 52 weeks ending on the 42th trading day prior to the announcement.

Baker et al. (2012) assess the use of reference prices from a merger perspective. Their results indicate a positive relationship between offers that exceeds the targets' 52-week high stock

[13] The same result is significant for initial-bidder's success as well (Betton et al., 2014).

price and deal success. To capture this effect, we estimate the change in the target stock price 42 trading days before the announcement relative to the 52-week high.

Bidder shareholder reluctance is especially important if the deal demands financing through the issuance of equity consisting of more than 20% of the bidder's market capitalization. This due to the need of a shareholder vote (Betton et al., 2009). We include a dummy, taking the value of 1 if the issuance exceeds 20% of the bidder's market value. To further control for the effects of the method of payment, we include a cash dummy as Betton et al. (2014) find a positive effect of cash on the probability of success.

We go forth with an exact matching based on the targets 3-first digits of the SIC code, which is the industry code, in all the matched estimates to ensure that we are matching observations from comparable industries (SICCODE.COM, 2017). Further, we also control for time by including a year variable providing the time of the announcement. This is done to reduce the time bias. Bessler & Schneck (2015) emphasize the importance of the impact intra-industry transactions have on the deal completion probability. We go forth with the 3-digit SIC code when assessing if the deal is horizontal, which is consistent with the exact matching criteria. Deals in the same industry should have a positive effect on the deal completion probability, in line with the results of Betton et al. (2014).

The size of the bid premium is a central factor for the deal probability success. This is due to the fact that managers' main objective is to increase shareholder value (Bessler & Schneck, 2015). Betton et al. (2014) provide evidence indicating an increased probability of takeover success with higher premiums. The effect of bid premiums is controlled for by including an estimated premium based on the relative difference between the offer price and targets stock price 42 trading days prior to the announcement.

Higher levels of hostility in the offering process will be associated with a lower probability of deal completion (Schwert, 2000). Flanagan et al. (1998) find evidence that the presence of hostile reactions has a negative impact on the bid success. To control for this, we include a dummy variable for deals involving hostility. We complement this by controlling for the effect a tender offer has on a deal going through, by including a dummy if the bid is a tender offer. Betton et al. (2014) find a positive and significant effect of tender offer bids on the deal completion probability.

Observed trends & Descriptive statistics – H_1

This section provides an overview of our dataset's statistics. It is structured as a comparative analysis of the CVR and control sample throughout the chapter. The first part covers key trends and overall statistics that are independent of the model variables. Finally, we discuss the statistics for the variables used to answer H_1. The intention of this chapter is to ensure that our data corresponds with previous reported statistics from other researchers, and for ourselves, as well as the reader, to better grasp the key findings in our data. Statistics that are attributable to the CVR data sample only can be found in Appendix 4.

Trends & Key findings

Imaa (2016) reports that global M&A activity decreased significantly following the financial crisis, measured by deal frequency. After the 2008 crisis, international deal activity recovered in 2010, before falling back again in the 2011-2013 period. In Appendix 5, we show that we observe the same trends in our control group data. In addition, our control group sample show similar trends before, during and after the dotcom bubble in 2000. Our CVR sample share similar trends compared to the control sample, however with an increased density of bid observations in the later years of the sample period. This could indicate both that CVRs have become an increasingly popular instrument, but also that older data observations in the databases we have used to construct the CVR sample might contain less precise information regarding the identification of potential CVRs.

We have deliberately not controlled for observations with multiple bids for the same target in our data samples. Meaning that we may have contests where we have more than one bid per target. However, we do not have duplicate bids from the same acquirer per unique target in our samples. Table 2 show the number of unique targets and acquirers for our general data sample. Interestingly, we see that the ratio of unique targets in the CVR sample and the control group are almost identical at 90%, indicating that roughly 1 out of 10 targets have more than one bid registered. The same ratio deviates more between the samples when looking at the bidders. It is higher for the CVR sample, which could mean that bidders issuing CVRs are not offering this instrument for every M&A contest they participate in, and that there is a higher degree of serial acquirers present in the control group.

Table 2: Number of unique bidders and targets in the sample

The table illustrates the number of unique bidders and targets in the total CVR and control sample. The samples are over the time period 1993-2016.

	Targets		Acquirers	
Sample	CVR	Control	CVR	Control
No. Of Unique	37	1,565	31	694
No. Of Unique % Total	90.0 %	89.0 %	76.0 %	39.0 %
Total	41	1,763	41	1,763

We have avoided potential issues with the outcome of our bid observation being inconclusive, since we have requested our selected transactions to be either completed or withdrawn[14]. The completion rate, measured as the number of completed transactions divided by the total number of bid observations, is 84.0% and 90.2% in our control and CVR sample respectively. This is shown in table 3. These findings are similar to those of Burch et al. (2012) and Gaspar et al. (2005) which reports completion rates of 82% and 85%.

Table 3: Number of completed and withdrawn bids

The table illustrates the number of Completed and Withdrawn deals in the total CVR and control sample. The samples are over the time period 1993-2016.

	Control sample		CVR sample	
	No. of obs.	Pct. of total	No. of obs.	Pct. of total
Withdrawn	282	16.0 %	4	9.8 %
Completed	1,481	84.0 %	37	90.2 %
Total	1,763	100.0 %	41	100.0 %

[14] By inconclusive we refer to transactions that for instance have status as" announced", "pending" or "unknown" in SDC as the outcome of these bids are not yet known.

Base variables

The variables described in this section are defined as our base variables, as they are present in the analysis of both hypotheses. Table 4 summarizes the average and median statistics for the variables used to answer H_1, across both the CVR and control group sample.

Table 4: Descriptive variable statistics - H_1

The table presents the descriptive statistics for the variables applied in H_1. The statistics are divided into CVR and control sample statistics. Further, the table separates the base variables from the H_1 specific variables. The base variables are the variables used in the analysis of both our hypotheses.

	CVR sample		Control Sample	
	Mean	Median	Mean	Median
Base Variables				
BidPremium	46.7 %	35.9 %	48.6 %	38.9 %
Cash	80.5 %	1	72.8 %	1
Horizontal3	68.3 %	1	53.3 %	1
TargetHostile	12.2 %	0	2.1 %	0
BidTenderOffer	31.7 %	0	25.8 %	0
Year	2009	2011	2005	2005
H_1 Specific Variables				
AcquirerStatusPublic	87.8 %	1	71.5 %	1
Bidder20NewEquity	14.6 %	0	15.0 %	0
Target52WeekHigh	-32.2 %	-25.8 %	-32.1 %	-26.0 %
TargetLNMarketCap42	6.0	5.4	5.7	5.5
TargetTurnover	0.9 %	0.7 %	0.9 %	0.7 %

The *BidPremium* variable is relatively stable between the CVR- and control sample with average values of 46.7% and 48.6%. Furthermore, the median value for our control sample panel is 38.9%. These findings are in line with Betton et al. (2014) who report average and median bid premiums of 45% and 38%, respectively.

Our *Cash* statistic shows that the frequency of bids containing cash is higher for the CVR sample compared to the control sample. An average of 80.5% of the CVR transactions contains cash, while the average cash frequency for the control group is 72.8%. The degree of intra-industry transactions, reported as *Horizontal3,* shows the same trend across our samples. An average of 68.3% of the CVR sample consists of same industry transactions, while the equivalent for the control sample is only 53.3%.

The average amount of hostile transactions (*TargetHostile)* in our CVR sample is 12.2%, compared to 2.1% for the control sample. This is an interesting finding that could indicate that CVRs have a higher probability of being used if the target management has a hostile attitude towards the proposed transaction. Furthermore, the average amount of tender offers (*BidTenderOffer)* is 31.7% for the CVR sample and 25.8% for the control sample. Chatterjee & Yan (2008) reports consistent findings with an average ~ 24% of their CVR transactions being tender offers. The *Year* variable highlights the previously mentioned finding, that we observe more CVRs in the recent years with the median bid occurring in 2011 against 2005 for the control group.

H_1 specific variables

The *AcquirerStatusPublic* variable shows that an average of 88% of the CVR sampled bidders are public, according to SDC[15]. This is a significantly larger fraction than for the control sample, where 71% of the bidders are public. The finding can be explained by the indication that many of the CVR observations can be considered as high-profile transactions between public companies, and that issuers of CVRs normally are publicly listed firms. The "high-profile statement" is to some extent backed by *TargetLNMarketCap42* which shows that the average CVR sample target is larger than the average control sample target.

Both the *Bidder20NewEquity* and the *TargetTurnover* variables are almost constant compared between the CVR and control sample. Around 15% of the bidders issue equity worth more than 20% of their current market capitalization to fund the transactions. This corresponds well with the previous elaborated cash variable findings. The liquidity factor, measured as the daily turnover in the target stock, shows average and median values slightly less than 1% for both samples.

Target52WeekHigh highlights an interesting finding regarding corporate transactions. More precisely, that the bidder management seems to be able to time their bid announcements/ takeover attempts with respect to the target's market value development. We find that 42 days prior to the first bid announcement, the average target stock price is down 32% from the last 52 weeks high. The finding applies for both samples. The median price decline is 26% for the CVR sample, as well as for the control sample.

[15] This finding does not violate our CVR definition, as it is only performance CVRs where it is natural that the bidder is publicly listed. For event-driven CVRs, there are no requirements for the bidders' public status regarding the issuance of the instrument.

Empirical Findings & Analysis of H_1

In this section we present our key results related to our analysis of H_1. Our focus is on the effect attributable to the CVR, but we will also relate our discussion to the control variables in terms of what we can expect of significance and sign. Our sample and control variables might deviate from the compared studies due to different sampling methodology and size, but we should to some extent see the same indications.

The results in table 5 are our preliminary results regarding the effect CVRs have on the probability of deal completion. The table includes the prevailing determinants trough the literature in column 1. Column 2 includes additional important variables that we argue are important to control for. All the variables will be used in the further analysis. Hence, our focus is on the results presented in column 2. The Probit values can be interpreted in a regular manner, both in terms of sign and significance, but their economical relevance must be interpreted as margins. The marginal values are presented in Appendix 6.

Table 5: Probit model with two specifications

In both Probit models the dependent variable takes the value of 1 if the deal is registered as completed in SDC, and 0 if withdrawn. Both regressions consist of the full sample of CVR and control deals. The standard errors are based on QML (Huber/White) heteroscedasticity robust standard errors. This means that the significance tests based on the z-statistics are also heteroscedasticity robust. Specification 1 consists of the most prominent determinants while specification 2 includes additional well-established variables.

	Specification 1	Specification 2
DealCVR	0.652**	0.674**
	(0.325)	(0.330)
AcquirorStatusPublic	0.326***	0.347***
	(0.0888)	(0.0899)
Acquiror20NewEquity	-0.150	-0.130
	(0.115)	(0.115)
BidTenderOffer	0.671***	0.691***
	(0.113)	(0.113)
Cash	0.0433	-0.000784
	(0.0981)	(0.100)
TargetHostile	-2.047***	-2.032***
	(0.229)	(0.231)
BidPremium	0.319***	0.390***
	(0.0971)	(0.101)
Horizontal3	0.201**	0.193**
	(0.0784)	(0.0794)
TargetLNMarketCap42	0.0417*	0.0228
	(0.0229)	(0.0256)
Target52WeekHigh		0.527***
		(0.141)
TargetTurnover		-3.922
		(3.965)
_cons	0.225	0.526***
	(0.175)	(0.194)
N	1,804	1,804
Pseudo R^2	0.1090	0.1188

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

We find that the hostility variable (*TargetHostile*) indicates a negative and significant relationship between completion and hostility. This is in line with the expected behaviour elaborated in the variables section, in which increased resistance from the target management reduces the probability of the deal going through. Further we see that the *BidPremium* is significant at a 1% level and positive. This is similar to the results provided in the variable section and implicates the importance of the price level in the offer. The horizontal variable

(*Horizontal3*) is positive and significant at a 5% level. This finding is close to the results of Betton et al. (2014) although they use a more restrictive measure[16].

The target size variable (*TargetLNMarketCap42*) goes from being significant at a 10% level to insignificant when including the *Target52WeekHigh* and *TargetTurnover*. However, in terms of sign it behaves as expected. The variable for the target 52-week high and turnover also behaves in accordance with what we expected in the variable section. Although only the former is as significant as other studies. This might be due to differences in the respective samples as well as the composition of variables. The rest of the control variables behaves as expected, except *cash*, which changes sign from positive to negative, although it is insignificant in both specifications

Both the sign and significance of the CVR dummy (*DealCVR*) are in favour of H_1. This is persistent in both regressions and provides a first indication of the effect of the CVR in relation to deal completion. The positive effect can be related to the potential positive attributes of the CVR elaborated in the literature review. In terms of economic relevance, we assess the margins of the Probit estimates[17]. Our results provide a marginal value of 0.141 in specification 1 and 0.144 in specification 2. This indicates that the marginal effect of including a CVR, provided that all other variables are at their means, increase the probability of observing a completed deal by 14.1% or 14.4%. In which the latter is the most prominent result. This is a rather substantial size and economically relevant.

A reason for the sizable and positive effect is the reduction of informational problems as discussed by among others Chatterjee & Yan (2008). The CVR provides the bidder with more time to assess the potential value of the target as well as ensuring that the payment reflects the realized value. Hence, the probability of completion should increase. Further, the target might face substantial difficulties of signalling and ensuring a price that reflects their potential value. Especially event-driven CVRs addresses this problem by providing the target with a value contingent on their achievements, by alleviating the uncertainty regarding the true value of the target firm. The CVR should reduce the potential obstacles in the negotiations and hence

[16] Betton et al. (2014) uses a 4-digit SIC code while we use a 3-digit SIC code to be consistent with our exact matching on industry.

[17] The regressions are tested for multicollinearity using a vif model. There are no signs of multicollinearity. See Appendix 7.

increase the probability of completion. These arguments and implications correspond well with our results.

To further address the effect of using a CVR, we ensure that we compare similar transactions across our sample by applying matching techniques. Table 6 shows that our sample is well balanced. Two observations are removed via the common support enforcement, ensuring that the common support assumption is satisfied. Hence, we can attribute any remaining effects to the CVR, provided that we have controlled for a sufficient number of variables. The latter issue was discussed in the methodology section and we argued it is fulfilled.

Table 6: Matching quality for the CVR samples

The table provides a comparison of the matched sample in relation to its control group. The matching procedure was conducted using one-to-one nearest neighbour matching with replacement, common support and a caliper of 0.2 to ensure precise matches. Note that in addition to the matched covariates, exact matching on target industry using the 3-digit SIC code has been performed to avoid any sector bias. The "t-value" as well as the "p-value" is assigned to asses matching quality. A low "t-value" and a high "p-value" indicates higher matching quality.

	Full CVR sample		Event-driven CVR sample	
Matching variables	t-value	p>|t|	t-value	p>|t|
AcquirorStatusPublic	-0.35	0.727	-0.35	0.726
Acquiror20NewEquity	-1.52	0.132	0.00	1.000
BidTenderOffer	-0.70	0.489	1.08	0.283
Cash	0.27	0.787	1.13	0.263
TargetHostile	0.46	0.649	0.00	1.000
BidPremium	0.02	0.987	0.13	0.900
Horizontal3	0.24	0.815	-0.82	0.412
TargetLNMarketCap42	-1.47	0.146	-1.21	0.231
Target52WeekHigh	-0.73	0.470	0.19	0.852
TargetTurnover	0.05	0.961	-0.81	0.423
Year	-0.44	0.661	0.45	0.651
No. of CVRs in sample	41		36	
No. of CVRs on support	39		36	

The results from the Probit regression on the matched samples is presented in table 7.

Table 7: Probit – The effect of CVRs on deal completion

In the Probit model the dependent variable takes the value of 1 if the deal is registered as completed in SDC, and 0 if withdrawn. The regression consists of the CVR sample and the matched control sample deals. The standard errors are based on QML (Huber/White) heteroscedasticity robust standard errors. This means that the significance tests based on the z-statistics are also heteroscedasticity robust.

	Complete CVR sample	Event-driven CVR sample
DealCVR	0.641*	1.014**
	(0.377)	(0.417)
No. of CVRs in sample	39	36

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The estimated effect from the complete CVR sample is very close to the pre-matching results both in terms of significance and sign. This adds to the support of hypothesis 1. Further we find an economical effect of 0.139 which is quite like the second specification in table 5. The value implies that the marginal effect of the CVR, all other variables at their mean values, provide a 13.9% higher probability of the deal becoming completed.

One problem with the results so far is that they do not distinguish between event-driven and performance CVRs. The differences between these two structures where elaborated in section 2.2. This issue is addressed in the second regression of table 7. The result from the regression indicates that the event-driven CVRs have a stronger positive effect on the deal completion probability than the complete sample with an estimated marginal effect of 22.1%. The result is significant at a 5% significance level.

The increased economical relevance can be attributed to the event-driven CVRs strong signal in terms of the target being able to gain more of their true value contingent on their performance. Further, the bidder will be able to pay for "what they get". As Wolf (2011) stated, the event-driven is the prevailing CVR structure today, which is to a large extent due to its less complex structure. Hence, it reduces the level of uncertainty relative to the performance CVRs. Considering this, the qualitative considerations of the different CVR structures are consistent with the presented results.

We have provided several results with and without matching. The results are rather stable both in terms of significance and economical relevance. In which the economical relevance ranges from 13.9-22.1%. Although the effect is limited to the sample characteristics, we provide a clear indication of the scope of the effect CVRs have on deal completion. The results are all in favour of H_1 and to our knowledge, the first results providing empirical evidence on how CVRs affect the probability of deal completion.

4.2 Bidder Cumulative Abnormal Return - H_2

Estimating the Bidder Cumulative Abnormal Return (BCAR)

The estimation of the abnormal returns and cumulative abnormal returns are formally expressed in Appendix 8.

In our study, the period of interest is the announcement date for the observed transactions. The event window for the abnormal return is according to Mackinlay (1997) customary to be larger than the period of interest. We focus on the event window consisting of the day prior to the announcement as well as the succeeding day (-1,1), to reduce noise from other takeover or non-takeover related factors.

We use an estimation window equal to Betton et al. (2014), and in line with Mackinlay (1997), by using a window starting 297 days prior to announcement and ending 43 days prior to the announcement date.

The use of the market model captures most of the explanatory power provided by more complex models (Mackinlay, 1997). The market model is also the prevailing model in the event study methodology, used by among other Betton et al. (2014). Given our short event-window, the market model should be a sufficient model to estimate BCAR. Thus, we find it appropriate to proceed with the market model in our study. Mackinlay (1997) mentions the use of broad based indexes such as the S&P 500 index, the CRSP value weighted index and the CRSP equal weighted index as common proxies for the market when using the market model. Event Study Metrics (2015) emphasizes the use of the broadest indexes in the country of interest. We choose to use the S&P composite index as a proxy for the market, due to its substantial scope.

One issue that arises when estimating the abnormal returns is that some deals are announced during holidays and weekends, i.e. points of time where the stock markets are closed. We solve this issue by adjusting the time window. More precisely, we move the announcement date forward to the closest weekday. The resulting average bidder cumulative abnormal returns (BCAR) are presented in table 8. We further assess if the average BCARs are significantly different from zero by assessing their p-value with robust standard errors, as recommended by Princeton University (2008). We find that both samples are significantly different from zero.

Table 8: Average bidder cumulative abnormal return

The table presents the average bidder cumulative abnormal returns for the CVR sample and the control sample. The abnormal returns are estimated using a market model then cumulated for the window (-1,1) and averaged for the control and CVR sample. The average bidder cumulative abnormal returns are tested for being significantly different from zero using p-values with robust standard errors.

	N	Mean	Median	Event Window
Control sample	1,044	-0.02**	-0.011	(-1,1)
CVR sample	30	-0.03*	-0.014	(-1,1)

Standard errors in parentheses
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

To assess how CVRs influence BCAR, we find it necessary to use an approach like that of Servaes (1991). We run an Ordinary Least Squares (OLS) model on the determinants of the BCAR. This is expressed below where **x** is a vector consisting of the control variables.

$$\widehat{BCAR}_i(-1,1) = \alpha_0 + \beta_1 DealCVR_{1,i} + \beta\boldsymbol{x} + \varepsilon_{i,}\ i = 1, \dots, N \quad (3)$$

After controlling for the variable covariates through matching, as well as assuring that the matches are well balanced, we estimate the effect of the CVR by applying the following regression on the matched sample.

$$\widehat{BCAR}_i(-1,1) = \alpha_0 + \beta_1 DealCVR_{1,i} + \varepsilon_{i,}\ i = 1, \dots, N \quad (4)$$

Control Variables

To control for the potential detrimental effects a large premium can have on the bidders' returns, we include the bid premium variable (Bessler & Schneck, 2015). The potential negative impact of hostility is also controlled for when assessing the bidders' returns (Betton et al. 2014). Barbopoulos & Sudarsanam (2012) find a negative relationship between bidders' gains and investments in unfamiliar industries. To control for this, we include the horizontal variable.

The effect of a cash payment on the bidder's announcement return is not a clear cut. However, more recent studies such as Betton et al. (2014) do find a positive effect. We find it necessary to include a cash variable to control for this.

Dong et al. (2006) indicate significant differences between tender and non-tender bids. They find that tender offers are less likely to occur by high valuation bidders, and further indicate that higher value bidders are associated with lower bidder abnormal returns. To control for potential effects related to this difference, we include the tender offer variable.

We also perform exact matching on industry as well as include a time variable for the announcement date to reduce the industry and time bias. The base model variables are further detailed in Appendix 2. In addition to the above base model variables, we introduce the H_2 model specific variables in the following section.

A potential determinant of the announcement return is the degree of asymmetric information in the deal. To control for this, we apply an age variable as a proxy for the potential differences in information held by the target and bidder as used by Barbopoulos & Sudarsanam (2012). We choose to include the variable for both the target and the bidder to ensure that we control for the potential two-way asymmetry. The variable proxies age as the difference between the announcement date and the initial public offering date for each observation.

The bidder's price-to-book ratio have proven to influence its announcement returns (Barbopoulos & Sudarsanam, 2012) We choose to control for this effect by including the price-to-book ratios for the bidders' in our samples. The target's price-to-book ratio is associated with an increasing degree of asymmetric information according to Officer (2003). This may have detrimental effects on the BCAR. Hence, we also include the targets' price-to-book ratios as an independent variable. We estimate the variable as the market value of equity to the book value of equity 42 trading days prior to the announcement date.

The relative deal value size, measured as deal value to bidder market capitalization, has proven to affect the bidder returns in a positive manner. Barpopoleus & Sudarsanam (2012) find evidence indicating positive return effects when analysing the determinants of UK bidder returns. The latter effect is consistent with the results of Fuller et al. (2002). Bessler & Schneck (2015) on the other hand, argue that larger deals will return in lower bidder returns due to increased complexity and risk. We chose to include this variable in our model and estimate it by dividing the deal value by the market capitalization of the bidder 42 trading days prior to the announcement.

Descriptive statistics - H_2

This section provides insight on how our samples change from answering our first hypothesis to our second one. Furthermore, it highlights the different statistical findings in our previously discussed base variables as well as findings in our H_2 specific variables.

Reasoning for the sample differences between H_1 and H_2

Our two hypotheses both seek to capture how CVRs impact M&A transactions. However, the data we use to examine them are somewhat different between the two. Appendix 1 shows the specific step-by-step difference. Moving from H_1 to H_2, we are dependent upon stock price information for the bidders in the period previous to the announcement dates. Hence, we omit 719 control sample- and 11 CVR sample observations. This is described in table 9. We could have done this at once before answering H_1, however, we argue that this is the preferred approach as we want to include as many CVR observations as possible when answering either hypothesis.

Table 9: How the dataset changes from H_1 to H_2

The table illustrates how the sample size changes when changing from the dataset used in H_1, which did not require stock data for the acquirer, to the dataset for H_2 which does.

	H_1	H_2	Absolute Change
Control sample size	1,763	1,044	719
CVR sample size	41	30	11
Total	1,804	1,074	730

Base variable differences

All the base variables presented in section 4.1 are used in our analysis of H_2. Table 10 describes the average and median statistics for both the base variables and our H_2 specific variables. We focus our discussion on how the sample reduction has affected the statistics for the base variables, and do not repeat what is already presented in section 4.1. In addition, the model specific variables for H_2 are thoroughly described in the next chapter.

Table 10: Descriptive statistics – H_2

The table presents the descriptive statistics for the variables applied in H_2. The statistics are divided into CVR and control sample statistics. Further, the table separates the base variables from the H_2 specific variables. The base variables are the variables used in the analysis of both our hypotheses.

	CVR sample		Control Sample	
	Mean	Median	Mean	Median
Base Variables				
BidPremium	51.90 %	44.50 %	49.70 %	41.20 %
Cash	80.00 %	1	62.00 %	1
Horizontal3	70.00 %	1	64.10 %	1
TargetHostile	3.30 %	0	2.80 %	0
BidTenderOffer	30.00 %	0	24.90 %	0
Year	2009	2010	2004	2003
H2 Specific Variables				
Acquirer P/B	3.5	2.5	5.7	3.4
AcquirerAge	19.2	16	21.7	16
Relative deal size	57.20 %	21.10 %	56.70 %	17.20 %
Target P/B	7.7	2.4	11.4	2.4
TargetAge	10.5	6.5	10.6	6.0

Our CVR sample is relatively small, hence the change in the data panels from H_1 to H_2 impact our variable statistics significantly in some cases. We do see an example of this in the median bid premiums (*BidPremium*) for our CVR sample, which increases to 44.5% when moving from the H_1 data panel to the H_2 data panel. Generally, the bid premiums are larger for our H_2 samples, both in median and average values. This could be evidence of that publicly listed bidders are willing, and able, to pay larger premiums than private bidders. The *Cash* variable reports an average of 80% for the CVR sample, and 62% for the control group sample. The reduction in the magnitude of the *Cash* variable with respect to the control group makes sense, as public firms have improved opportunities of paying with shares than private firms.

The average values for *Horizontal3* is 70.0% and 64.1% for the CVR and control group sample respectively. This represents a minor increase in the CVR sample, but a more than 10 percentage point increase in the control group compared to H_1. However, it is in our opinion meaningful, and could indicate that public bidders to a larger extent seek intra-industry transactions. *TargetHostile* is, measured in averages, reduced from 12.2% to 3.3% in our current CVR panel. This finding could indicate that non-listed bidders in CVR transactions tend to face more hostile management reactions compared to public ones. The same reported statistic for the control group sample is 2.8%. The ratio of tender offers (*BidTenderOffer)* is similar for our H_2 and H_1 samples. The current CVR sample has an average value of 30%, while the control group sample equivalent is 24.9%. Finally, the *Year* variable shows that the median CVR bid occurred in 2010, while the median control sample bid occurred in 2003. This finding is similar to the one discussed in section 4.1.

H_2 specific variables

When comparing median statistics in table 10 for *Acquirer P/B* and *Target P/B*, we find that the bidders have the highest price to book ratios. Due to our sample characteristics, we argue that it makes more sense to compare the median statistic, at the aggregate level, and not average values for this variable. The acquirer P/B for the CVR sample and control sample is 2.5 and 3.4 respectively, while the coherent target statistic is 2.4 for both samples. When comparing the target and acquirer P/B for each bid, we find that the target P/B on average is 34% less than the acquiring firm. This points towards that bidders are buying "cheaper" firms compared to themselves. We also argue that it makes sense to compare the P/B ratios in a target/bidder perspective for our sample, as most of the contests are intra-industry transactions.

Relative deal size, which measures the ratio between the total deal value and the bidder's market capitalization, is quite stable across the samples and show an average value of 57% and median value of 21% for the CVR sample. In general, we have larger relative deal relationships in our sample than that of Faccio & Masulis (2005) who report an average relative deal size statistic of only 9%. This can, to some extent, be explained by that we have a high degree of mergers in our sample, implying more evenly sized targets and bidders compared to pure acquisitions.

The age of a company seems to be a determinant of whether the firm is the target or bidder. *AcquirerAge* is on average roughly 20 years for both samples, while *TargetAge* on average is only 10 years. In other words, the bidders are on average twice as old as the targets. The age difference relationship between bidders and targets only becomes larger when comparing the median statistics relative to the average statistics in table 10.

Empirical findings & Analysis of H_2

We run our first regressions on the complete CVR and control sample for H_2. The regressions are tested for multicollinearity using a VIF model. There are no signs of multicollinearity. See Appendix 9. The results are presented in table 11 and consist of two specifications. The first specification does not control for the age variables while the latter does.

Table 11: OLS regression on the cumulative abnormal return

In the OLS model the dependent variable is the cumulative abnormal return of the bidder in the window of one day prior, to one day post the announcement. The regression consists of the full CVR and control sample. The standard errors are based on QML (Huber/White) heteroscedasticity robust standard errors. This means that the significance tests based on the t-statistics are heteroscedasticity robust.

	Specification 1	Specification 2
DealCVR	-0.00920	-0.00744
	(0.0146)	(0.0145)
Cash	0.0459***	0.0408***
	(0.00635)	(0.00631)
TargetHostile	-0.0162	-0.0180
	(0.0114)	(0.0115)
BidPremium	-0.00996*	-0.00993*
	(0.00599)	(0.00595)
Horizontal3	-0.000876	0.00114
	(0.00515)	(0.00517)
AcquirerRelativeSize	-0.000191***	-0.000173***
	(0.0000273)	(0.0000246)
BidTenderOffer	-0.000308	-0.000529
	(0.00538)	(0.00540)
TargetPB	-0.0000231***	-0.0000212***
	(0.00000475)	(0.00000432)
AcquirerPB	0.00000748**	0.00000928**
	(0.00000378)	(0.00000382)
AcquirerAge		0.000349***
		(0.000106)
TargetAge		0.000328*
		(0.000173)
_cons	-0.0463***	-0.0555***
	(0.00682)	(0.00759)
N	1,074	1,074
adj. R^2	0.060	0.067

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Cash is positive and significant at a 1% level. This is consistent with some of the empirical results from the literature review and the variable section, indicating that the market responds well to the use of cash. The effect of hostile management reactions from the target (*TargetHostile*) has, as expected, a negative effect although it is insignificant. The effect of a horizontal deal (*Horizontal3*) changes from negative to positive when we include the age variables. The latter is consistent with the empirical foundation in terms of that same industry firms involved in M&A tend to receive a more positive market response, as the expected synergies usually are larger. Further, the *BidPremium* has a negative and significant effect in the second regression. The negative effect of the bid premium can be related to the risk of overpaying, which results in a negative market response in terms of the bidders' returns.

The relative deal size (*AcquirerRelativeSize*) is negative and significant, which is consistent with Bessler & Schneck (2015) reasoning. Acquirer market-to-book (*AcquirerPB*) is also consistent with what we expected in the variable section, having a positive impact on BCAR. The target market-to-book (*TargetPB*) variable is significantly negative which is in line with the findings of Officer (2003). He reasons that a higher target market-to-book implies a larger degree of uncertainty. The tender offer variable (*BidTenderOffer*) has a negative, but not significant, impact on the BCAR. This effect is as expected with respect to the sign, given Dong, Hirshleifer, Richardson, & Teoh (2006) results.

The *AcquirerAge* and *TargetAge* variables both show a positive impact on BCAR, although only acquirer age is significant at a 1% level. This finding makes sense as the information available to investors increase with the age of a company.

The effect of the CVR (*DealCVR*) on BCAR is insignificant and economically modest, giving an effect of -0.74 percentage points in the second specification. Although it is not significant, the sign indicates that the market has an increased negative response when including a CVR. This is not consistent with the results of Chatterjee & Yan (2008), who found a positive effect. The result is also a first indication of a different response than the positive reaction expected in hypothesis 2. This might be due to differences in the control variables as well as the time-period, size, and other characteristics of the sample. Further, we have not yet assured that we compare transactions that are similar to each other. This is done in the following section using the same model variables as described in table 10, in addition to that we require exact matching on industry. Table 12 presents the matching quality for the CVR sample.

Table 12: Matching quality for the CVR sample

The table provides a comparison of the matched sample in relation to its control group. The matching procedure was conducted using one-to-one nearest neighbour matching with replacement, common support and a caliper of 0.2 to ensure quality matches. Note that in addition to the matched covariates, exact matching on industry using the 3-digit SIC code has been performed to avoid any sector bias. The "t-value" as well as the "p-value" is assigned to assess matching quality. A low "t-value" and a high "p-value" indicates higher matching quality.

	Full CVR sample		Event-driven CVR sample	
Matching variables	t-value	p>|t|	t-value	p>|t|
Cash	0.31	0.759	0.00	1.000
TargetHostile	1.00	0.321	-0.58	0.561
BidPremium	-0.59	0.558	-0.38	0.706
Horizontal3	0.80	0.425	-0.31	0.757
AcquirerRelativeSize	0.69	0.492	0.32	0.753
BidTenderOffer	-0.80	0.425	-0.55	0.585
Year	-0.32	0.749	-0.25	0.800
TargetPB	0.73	0.471	0.54	0.589
AcquirerPB	-1.27	0.209	-1.00	0.320
AcquirerAge	-1.26	0.211	-1.29	0.201
TargetAge	0.09	0.929	-0.31	0.760
No. of CVRs in sample	30		28	
No. of CVRs on support	30		28	

The t-tests in table 12 indicate that the matching is balanced in terms of the transactions not being significantly different from each other. Thus, we can estimate the CVRs effect on BCAR. These results are presented in the below table.

Table 13: OLS – All CVR deals and matched control sample

In the OLS model the dependent variable is the bidder cumulative abnormal return over the window of one day prior, to one day post the announcement. The regression consists of the full CVR sample and the matched control sample. The standard errors are based on QML (Huber/White) heteroscedasticity robust standard errors. This means that the significance tests based on the t-statistics are heteroscedasticity robust.

	Full CVR sample	Event-driven CVR sample
DealCVR	-0.0333	-0.0508^{**}
	(0.0201)	(0.0231)
No. of CVRs in sample	30	28

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

The result is still insignificant but more economically relevant indicating that including a CVR results in a 3.33 percentage points lower BCAR when comparing similar deals on all other controlled aspects. Chatterjee & Yan (2008) assessed the use of performance CVRs and found a positive relation between CVRs and BCAR. An important reason why performance CVRs might induce a positive effect on the BCAR is that they reflect significant confidence in the bidder stock due to the potential payments the bidder faces if the stock does not perform well. Our sample consists mainly of event-driven CVRs which implies a quite different signal than that of the performance CVRs. To further assess this, we move to the second regression of table 13.

The effect is significant at a 5% level and negative. Further on, the economical relevance of -5.08 percentage points, which is a relatively substantial increase. One possible reason for the negative response to event-driven CVRs is that the CVR deals might induce more perceived uncertainty in certain cases. This because of the future payment being contingent on some occurrence. Although the second payment is contingent on the event, the upfront payment might be of no value if the event does not occur. This might be the case in pharmaceutical and biotech deals where the value of the target is highly dependent on e.g. an FDA approval. Providing a full upfront payment in these cases might represent a stronger signal of the bidder believing that the occurrence will happen. Hence, it might receive a more positive response from the market. Creating more uncertainty regarding the future value causes the market to respond in a more negative manner.

Regarding the results of hypothesis 2, the evidence is not very persistent, neither in terms of economical relevance nor significance, but this can be related to the different signals of event-driven and performance CVRs. What is evident, is the indication of a negative market response. Which is, considering the last result, related to the use of event-driven CVRs. We provide a first indication that the market does not respond positively to the usage of event-driven CVRs in terms of BCAR. The effect is significant and economically relevant, indicating an effect of -5.08 percentage points on BCAR. This finding contradicts $H_{2,}$ which expected a positive market reaction to the usage of all types CVRs. As a result, we cannot conclude with a positive market response to all CVR structures.

5. Conclusion

This paper has explored the use of CVRs in the U.S. M&A market. This has been done descriptively through a thorough review of financial instruments registered in SDC and verified with EDGAR. The descriptive process has been performed in line with this papers definition of CVRs. The definition has been developed based on the available CVR literature, and provides a more comprehensive understanding of a CVR in our opinion.

The review of SDC and EDGAR resulted in a unique dataset consisting of 41 CVRs, which provides a clear indication of whom of the CVR types that have been the most common in recent years. The dataset also provides a more concrete understanding of the different structural elements used when constructing a CVR. We used CRSP and Compustat to complement our data, enabling us to construct additional variables and conducting a more comprehensive analysis.

The empirical study has been limited due to the low level of CVRs in the sample. This has been overcome through a combination of exact and propensity score matching. The matching procedure, based on empirically and theoretically well-founded covariates, has provided significant and persistently positive results. Our results show that using a CVR as part of the bid consideration improves the probability of deal completion by 13.9% to 22.1%. This is robust evidence in favour of H_1. However, the results are largely linked to our sample and more specifically the matched sample. Hence, one should be careful when interpreting our results with respect to extrapolation, but the results provide an indication that can, and should, be tested further.

When answering our second hypothesis, we used the same matching procedure as in hypothesis 1. The dependent variable was estimated following the standard event study literature, by applying a market model to attain a measure of the markets response to the announcement. This measure was named the bidder cumulative abnormal return (BCAR). The CVRs effect on BCAR where estimated using OLS. This resulted in persistently negative results, although only significant in the last regression using the event-driven CVR sample. More specifically, the final result showed that the usage of event-driven CVRs have a significant negative impact of 5.08 percentage points on BCAR. This finding resulted in a rejection of H_2, but we argued that the latter result is consistent with the results of Chatterjee & Yan (2008) due to the substantial differences between performance and event-driven CVRs.

The results from H_1 and H_2 are in our opinion, not contradictive. In terms of deal completion, the use of CVRs enhance the probability of the deal going through due to strong signalling effects as well as solving valuation disagreements. This effect is, to a large extent, related to the event-driven CVRs. The market's response to the use of CVRs is on the other side highly negative relative to a non-CVR deal, which is also related to the event-driven structure. This because the markets might perceive more uncertainty regarding the deal value combined with an increased probability of the deal going through. Consequently, the observed BCAR for bidders' issuing event-driven CVRs are significantly lower relative to bidders in non-CVR deals.

The results in this paper are, to our knowledge, the first empirical evidence of the effect CVRs have on deal completion as well as of how the market responds to event-driven CVRs. Due to the, currently, limited set of data available, we have not been able to further assess the effect of the different structural elements in the different CVRs. This is in our opinion an important aspect, and should be addressed in the further research concerning CVRs.

This study has focused on the U.S. M&A market. An interesting topic could be to investigate if one finds similar effects in other markets. This applies, among others, to the European market, which also constitutes a central M&A market.

An essential aspect of the CVRs are the differences in terms of characteristics related to the maturity, number of triggers and payoff. Assessing these elements might be feasible if the use of CVRs increases. Further analysis of the effect the different elements of a CVR have on the topics of this paper can help to better understand how to apply CVRs more effectively.

Finally, to investigate how a CVR transaction performs post-merger could be interesting. This can be assessed by analysing the retention of essential human capital. This is a feature of earnouts and one could expect event-driven CVRs to provide a similar function. The post-merger performance in relation to the event-driven CVRs fulfilment might also be of interest, this due to the potential motivational effects provided by the CVR in terms of payments contingent on the target company's efforts and results.

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Appendix

A.1 Data sample development – By request description

The table describe the development of our data samples in terms of bid observations per continuously fulfilled request description. Ex. 1804 bids fulfil all the previous request descriptions incl. deal outcome being either completed or withdrawn. Furthermore, the "Hypothesis" column indicate how the dataset develop from H_1 to H_2.

Total Bids	Control Sample	CVR	Request Description (Source in parentheses if not described)	Hypothesis
-	-	-	DATABASES: Domestic Mergers, 1979-Present (SDC)	
-	-	-	Date Announced: 01/01/1993 to 01/01/2017 (SDC)	
259 615	259 565	50	Target Nation = US (SDC)	
45 192	45 142	50	Target Public Status = Public (SDC)	
12 446	12 396	50	Form of the Deal: Acquisition and/or Merger (SDC)	
9 426	9 378	48	Deal Value: More than $10 million (SDC)	
9 421	9 373	48	Percent of Shares Held at Announcement: Less than 49% (SDC)	
7 758	7 710	48	Target Stock Exchange in SDC cannot be NewYorkOTC, OTC or Pink Sheet	
2 534	2 486	48	Target Primary SIC = First 3 SIC digits as in CVR sample (SDC)	
2 146	2 102	44	Initial Offer Per Share variable present in SDC	
1 937	1 893	44	Target has at least 100 days of common stock returns in CRSP over the estimation period (day -297 to -43) and is listed on NYSE, Amex or Nasdaq	
1 842	1 801	41	Target stock price on day -42 >$1,00 (CRSP)	
1 832	1 791	41	Initial Offer Per Share > $1,00 (SDC)	
1 804	1 763	41	Deal outcome is either Completed or Withdrawn (SDC)	H_1
1074	1044	30	Bidder has at least 100 days of common stock returns in CRSP over the estimation period (day -297 to -43) and is listed on NYSE, Amex or Nasdaq	H_2

A.2 Bias reduction – Match on full CVR sample

The table illustrates the reduced level of bias in the sample after matching. "U" denotes the sample pre-matching and "M" denotes the sample post matching. The "t" as well as the "$p>|t|$" is assigned to asses matching quality. A low "t-value" and a high "p-value" indicates higher matching quality. A t-value below 1.645 indicates that the samples are not statistically different from each other. The MeanBias indicates the average bias in the sample and the MedBias indicates the median bias in the sample.

Variable		t-value	$p>\|t\|$
AcquirorStatusPublic	U	2.30	0.021
	M	-0.35	0.727
Acquiror20NewEquity	U	-0.07	0.944
	M	-1.52	0.132
BidTenderOffer	U	0.86	0.390
	M	-0.70	0.489
Cash	U	1.09	0.275
	M	0.27	0.787
TargetHostile	U	4.26	0.000
	M	0.46	0.649
BidPremium	U	-0.24	0.808
	M	0.02	0.987
Horizontal3	U	1.91	0.056
	M	0.24	0.815
TargetLNMarketCap42	U	1.13	0.258
	M	-1.47	0.146
Target52WeekHigh	U	-0.02	0.985
	M	-0.73	0.470
TargetTurnover	U	-0.30	0.767
	M	0.05	0.961
Year	U	4.10	0.000
	M	-0.44	0.661

	MeanBias	MedBias
Unmatched	21.1	17.6
Matched	12.9	10.0

A.3 Variable specification

The table describes all the variables used in our different models. It also lists the sources for our variable constructions.

Variable	Formula/Comment	Source
Deal Completion (H_1)		
TargetLNMarketCap42	Natural logarithm of the target market capitalization in $ billion on day -42	CRSP
AcquirorStatusPublic	The acquirer is publicly traded (dummy)	SDC
Acquiror20NewEquity	The consideration includes a stock portion that exceeds 20% of the acquirers shares outstanding (dummy)	SDC
Target52WeekHigh	Change in the targets stock price over the 52-weeks ending on day-43 ($Price_{-42}/Price_{high}$)-1	CRSP
TargetTurnover	The Average daily ratio of trading volume to total shares outstanding over the 52 weeks ending on day -43	CRSP
Announcement return (H_2)		
AcquirorRelativeSize	Ratio of target market capitalization to bidder market capitalization on day -42	CRSP, Compustat
TargetPB	Market value of equity to book value of equity on day -42	CRSP, Compustat
AcquirerPB	Market value of equity to book value of equity on day -42	CRSP, Compustat
AcquirerAge	The difference between the date of the announcement and the first day recorded in CRSP	CRSP, SDC
TargetAge	The difference between the date of the announcement and the first day recorded in CRSP	CRSP, SDC
Base variables		
BidTenderOffer	The bid is a tender offer (Dummy)	SDC
Cash	There is cash in the offer (Dummy)	SDC
TargetHostile	The targets management is hostile (Dummy)	SDC
BidPremium	Offer price relative to the target price at day -42 ($Offerprice/Price_{-42}$)-1	CRSP, SDC
Horizontal3	The target and bidder have the same 3-digit SIC code (dummy)	SDC

A.4 CVR specific descriptive statistics

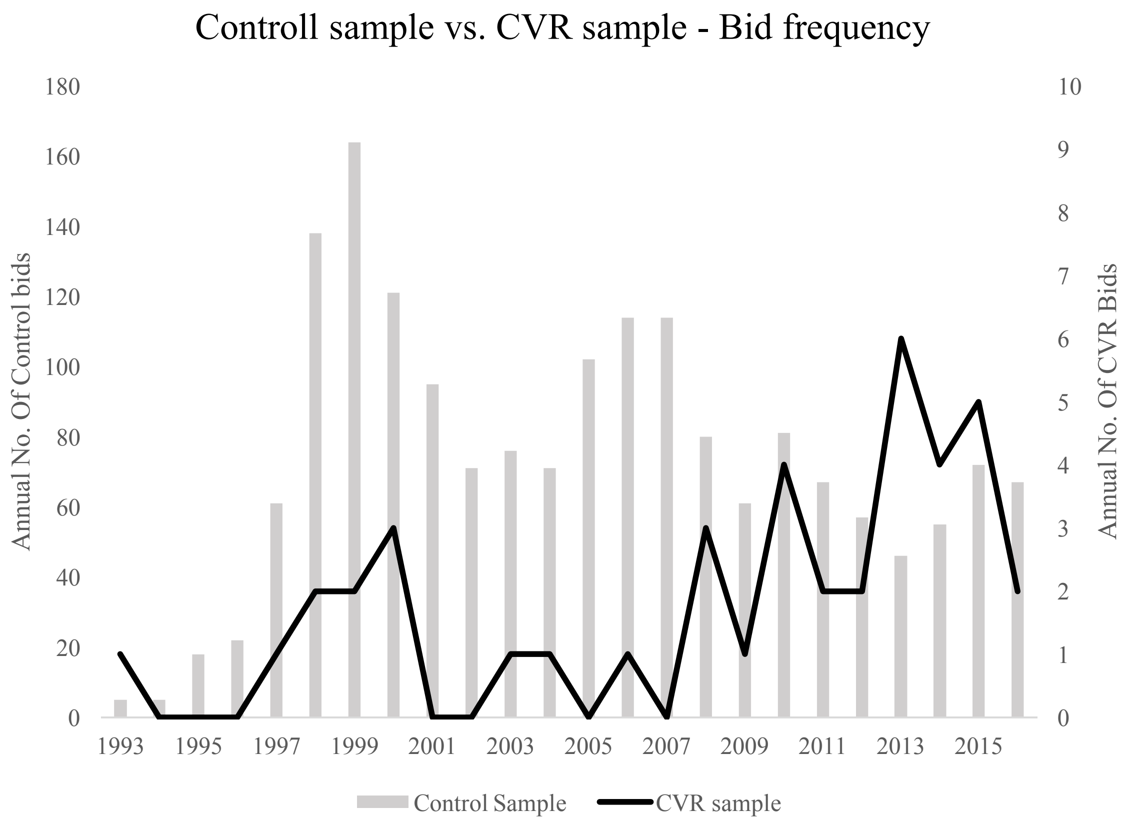
The following table summarizes the different characteristics of the CVRs in our sample at a general level. The CVRs are not a homogenous instrument. Thus, the table is an attempt to tabulate some of the attributes that are generic across our sample. For instance, all CVRs have one or more triggers, hence, "trigger" is used as a descriptor. In terms of better understanding how large of a deal sweetener the CVRs on average are, we have used a proxy, consisting of the average maximum CVR payment to the total deal value.

CVR feature	Average	Median
Extendable	4.9 %	0.0
Fixed Consideration	49.0 %	0.0
Listed	32.0 %	0.0
Maturity (Years)	3.7	3.0
Max CVR Payment to Deal Value	23.0 %	17.0 %
No. Of Triggers	2.2	2.0
Number of Cash Payment CVR's	80.0 %	1.0
Product Approval Milestone	34.0 %	0.0
Sales figure Milestone	59.0 %	1.0

CVR feature	Description
Extendable	The maturity of the CVR can be extended.
Fixed Consideration	The consideration is a fixed value.
Listed	The CVR is listed on an exchange.
Maturity (Years)	The maturity of the CVR.
Max CVR Payment to Deal Value	The maximum CVR payment relative to the deal value.
No. Of Triggers	Number of occurrences or fulfilments which can activate the CVR.
Number of Cash Payment CVR's	The number of CVRs paying the contingent consideration in cash.
Product Approval Milestone	The consideration is contingent on a product approval.
Sales figure Milestone	The consideration is contingent on a sales figure threshold.

A.5 Historic bid frequency

The graph illustrates the bid frequency for the control sample of 1,763 deals and the CVR sample of 41 deals. The time spans from 1993-2017.



A.6 Estimated marginal effects of the Probit model

The table gives the partial effects dy/dx. For the Probit y = P(Completed). x is one explanatory variable. The partial effects in the tables above are dependent on the values of all explanatory variables. We have given the partial effects at the average. The CVR deals marginal effect is the change when x goes from 0 to 1.

	Specification 1	Specification 2
DealCVR	0.141**	0.144**
	(0.0699)	(0.0701)
N	1,804	1,804

	Full CVR sample	Event-driven CVR sample
DealCVR	0.139*	0.221***
	(0.0804)	(0.0849)
No. of CVR Deals	39	36

Standard errors in parentheses
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

A.7 VIF test after preliminary Probit regression

A VIF statistic above 10 is according to O'Brien (2007) perceived as problematic. We have very low VIF values in our sample, hence we do not further investigate the variable with respect to multicollinearity.

Specification 1			Specification 2		
Variable	VIF	1/VIF	Variable	VIF	1/VIF
Cash	1.47	0.681474	Cash	1.50	0.668879
Acquiror20NewEquity	1.34	0.744549	TargetLNMarketCap42	1.38	0.722697
AcquirorStatusPublic	1.28	0.781720	Acquiror20NewEquity	1.35	0.742705
BidTenderOffer	1.17	0.854709	AcquirorStatusPublic	1.28	0.779708
Horizontal3	1.11	0.899551	Target52WeekHigh	1.27	0.785833
TargetLNMarketCap42	1.11	0.903424	TargetTurnover	1.19	0.838237
BidPremium	1.08	0.929889	BidTenderOffer	1.18	0.851018
TargetHostile	1.04	0.963778	BidPremium	1.13	0.885486
DealCVR	1.02	0.984600	Horizontal3	1.12	0.896828
			TargetHostile	1.04	0.962649
			DealCVR	1.02	0.984122
Mean VIF	1.18		Mean VIF	1.22	

A.8 Formal event study expressions.

Formally the abnormal return can be expressed as:

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_t) \quad (1)$$

Where i denotes firm and the event date is denoted as τ. $AR_{i\tau}$ is the abnormal return, $R_{i\tau}$actual return and $E(R_{i\tau}|X_t)$is the normal return for time period τ. The conditioning of information for the normal return is denoted X_t (Mackinlay, 1997).

The market model expressed formally:

$$R_{i\tau} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{it} \quad (2)$$

$$E(\varepsilon_{i,t}) = 0 \quad (3)$$

$$var(\varepsilon_{i,t}) = \sigma^2{}_{\varepsilon i} \quad (4)$$

The model illustrates the assumed linear relationship between the security return i and the market portfolio. $R_{i\tau}$ is the return of security i and R_{mt} is the return of the market portfolio over time *t*, $\varepsilon_{i,t}$ is the zero-mean error term, and α_i, β_i and $\sigma^2{}_{\varepsilon i}$ are parameters estimated with the model.

The first step in the estimation process is to estimate the daily returns for each stock i at time t where $R_{i,t}$ is the stock return and $P_{i,t}$ and $P_{i,t-1}$are the closing prices for stock i.

$$R_{i,t} = \ln (P_{i,t}/P_{i,t-1}) \quad (5)$$

To estimate the market model, we need the daily returns for our chosen market proxy. This is expressed in the same manner as the stock returns. The only difference is the use of the S&P composite index instead of a stock sample.

$$R_{m,t} = \ln\,(P_{m,t}/P_{m,t-1}) \tag{6}$$

With these inputs we can estimate the normal return by regressing the stock returns against the market returns using ordinary least squares estimation. This provides the necessary alphas and betas used in establishing the stock individual normal return. The abnormal return for a one day can then be estimated using the following model:

$$\widehat{AR}_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t}) \tag{7}$$

In our study we accumulate the return over a specified time post and prior to the event date. The cumulative abnormal return (CAR) is determined by the following equation for stock i:

$$\widehat{CAR}_i(T_{1,}T_2) = \sum_{t=T_i}^{T_2} AR_{i,t} \tag{8}$$

Where T_1 and T_2 expresses the given time for the CAR estimation.

A.9 VIF test after preliminary OLS regression

A VIF statistic above 10 is according to O'Brien (2007) perceived as problematic. We have very low VIF values in our sample, hence we do not further investigate the variable with respect to multicollinearity.

Specification 1			Specification 2		
Variable	VIF	1/VIF	Variable	VIF	1/VIF
AcquirerPB	1.00	0.996570	AcquirerPB	1.00	0.995995
AcquirerRelativeSize	1.01	0.994888	AcquirerRelativeSize	1.01	0.993858
BidPremium	1.01	0.987783	BidPremium	1.02	0.984640
BidTenderOffer	1.20	0.831152	BidTenderOffer	1.20	0.830960
Cash	1.18	0.850635	Cash	1.27	0.790424
DealCVR	1.00	0.995694	DealCVR	1.01	0.994396
Horizontal3	1.00	0.996446	Horizontal3	1.03	0.975053
TargetHostile	1.03	0.973961	TargetHostile	1.03	0.972557
TargetPB	1.01	0.993791	TargetPB	1.01	0.993384
			AcquirerAge	1.10	0.907422
			TargetAge	1.06	0.940044
Mean VIF	1.05		Mean VIF	1.07	