



# Earnouts - Bridging the Gap

*Informational asymmetry and negotiation duration in earnout transactions*

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This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH. Please note that neither the institution nor the examiners are responsible – through the approval of this thesis – for the theories and methods used, or results and conclusions drawn in this work.

# Preface

Writing our thesis has provided us with an inspiring insight into the realm of academic research, for which we are grateful. We have found the opportunity to apply the knowledge and skills attained through relevant courses both challenging and rewarding at the same time. We have gained significant respect for researchers who provide elegant contributions to the understanding of complicated problems.

We would first like to thank our supervisor, Professor Walter Pohl, for offering us his constructive feedback on our work and his contributions to solving several challenging phases along the way. We offer our sincerest gratitude to Professor Karin S. Thorburn, who has not only inspired the topic of our thesis through her M&A course, but graciously engaged in meaningful discussion and offered her take on several issues on the topic of earnouts. Lastly, we would like to thank Ph.D. cand. Trang Quynh Vu, who offered detailed feedback and motivation in the preliminary phase of our thesis work.

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# Abstract

In this thesis, we look into earnout provisions. We contribute to answering two questions: *when earnouts are employed* and *why they are not more common*. By considering asymmetric information in new ways, we augment the understanding of informational asymmetry as an earnout determinant. Our thesis further innovates on existing research by providing evidence on the costs of employing earnouts. The evidence we present is consistent with asymmetric information regarding the target being a primary determinant of earnout employment.

We find that acquirer M&A experience is negatively associated with earnouts, which provides evidence that is consistent with reduced informational asymmetry being associated with a lower probability of including earnout provisions in the consideration. Our thesis contributes to establishing a relationship between investment bank involvement, both on a deal- and firm-level, and the probability of earnout incidence. We find evidence consistent with target investment bank involvement being associated with a lower probability of including earnouts. We find no corresponding evidence on the association between the acquirer's investment bank engagement and earnout provisions. Our findings substantiate previous research on informational asymmetry and provide evidence on the coherence between investment bank involvement and the level of asymmetric information in a deal regarding both target and acquirer. Furthermore, we collect data and provide evidence on the background of public earnout transactions. Our findings suggest that these transactions are associated with a substantially longer private duration and a higher degree of informational asymmetry revolving around the target.

**Keywords** – *Earnout provisions, Informational asymmetry, Private duration, M&A Experience, Investment bank involvement*

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# 1 Introduction

## 1.1 Introduction

M&A is an extensively researched field within corporate finance, where the choice of payment method and the subsequent trade-off between advantages and disadvantages of different payment methods is one of several important aspects of the current research. The most common considerations used are cash and stock. Researchers have empirically proven that the choice of payment method is a strong determinant to the deal dynamics and the value gains for both targets' - and acquirers' shareholders (Eckbo et al., 2018). Our thesis focuses on earnouts, a contingent portion of the consideration acquirers pay to the target shareholder(s) if a predetermined criterion is fulfilled (Barbopoulos and Sudarsanam, 2012). An earnout, unlike cash, can bridge valuation gaps that arise in the light of informational asymmetry by letting the target prove its worth to the acquirer post-acquisition. Similarly, fixed exchange ratio stock offers allow an undervalued target to take part in the potential gains to the acquirer resulting from undervaluation. Still, when offering stock as consideration, the acquirer faces a severe risk of target overvaluation. This risk can be mitigated by employing an earnout instead. This interesting feature of earnouts has caused researchers such as (Kohers and Ang, 2000; Cain et al., 2011) to provide insight into when earnouts are employed. Furthermore, the cumulative abnormal return of acquirers who engage earnouts has been researched in several papers. Results generally indicate that acquirers experience significant positive abnormal returns in earnout deals, compared to deals where cash, stock, or a mix of the two is the payment method (Kohers and Ang, 2000). The desirable incentive-aligning features of earnouts, together with the empirical results showing positive abnormal returns to acquirers, pose questions as to *when earnouts are employed* and *why they are not more common*.

Our paper contributes to the understanding of when and why. We do this by considering a previously established earnout determinant, informational asymmetry, in new ways. We also consider a hitherto neglected aspect of earnout deals - the negotiation phase. We construct a sample of 14 969 U.S. M&A transactions occurring between 1995 and 2020 and research earnout transactions by comparing the deal attributes of these transactions to both an unrestricted- and a self-selection-bias adjusted sample of non-earnout transactions.

We model the likelihood of including earnout provisions in the consideration and provide a nuanced perspective on attributes that are associated with the inclusion of earnout provisions.

Earnouts are commonly employed in transactions with private targets in industries with a high degree of intangible assets, such as healthcare and high-tech (Kohers and Ang, 2000).<sup>1</sup> (Barbopoulos and Sudarsanam, 2012) model the likelihood of earnout provisions on a U.K. sample of M&A transactions to provide an understanding of earnout determinants. They consider target informational asymmetry through the targets public status and industry. (Bates et al., 2018) consider target informational asymmetry on an industry level. While considering the previously researched proxies for target informational asymmetry, we also model the effect of informational asymmetry on earnout employment using observable characteristics on a deal- and firm-level.

Firstly, we consider acquirer M&A experience as a proxy for the level of informational asymmetry associated with the transaction. Experience is, unlike proxies used in previous papers, considered directly. We conjecture that more experienced acquirers are better able to reduce informational asymmetry revolving around the target by leveraging the dos and don'ts from previously completed deals.

Secondly, we introduce investment bank involvement to account for the level of asymmetrical information on a deal- and firm-level. Prior research suggests that investment bank involvement is expected to reduce informational asymmetries.<sup>2</sup> We are able to consider the effect of informational asymmetry on different levels, which provides an increased understanding of when earnouts are employed. Furthermore, by considering investment bank engagement on a firm level, we can differentiate between how informational asymmetry affects the likelihood of earnout inclusion from both the acquirer's and the target's point of view.

Finally, we research the negotiation phase of earnout transactions to better understand why earnouts are not more commonly employed. We do this by considering an alleged cost of earnout employment, timely negotiations. We empirically research whether we

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<sup>1</sup>The limited and unreliable information available on targets in earnout deals complicates the research process. We conjecture this is a fundamental reason for the lack of attention to the private phase of negotiations in the literature.

<sup>2</sup>For a detailed outline on how investment bank involvement relates to informational asymmetry, see section 3.



find evidence consistent with earnouts being associated with timely negotiations by investigating the background of public earnout transactions. This section of our thesis includes event-driven contingent value rights (CVR) in our earnout sample to provide additional data, as the number of public earnout transactions is limited. Event-driven CVRs are reported by (Wolf and Fox, 2010) to be the public equivalent of an earnout, as the properties of these CVR's are close to identical to that of a normal earnout. Due to the similarity in properties, we deem the CVR's effect on timely negotiation to be a worthy proxy of a traditional earnout. They are thus included in our earnout sample for this portion of our thesis.

We believe our contributions to the field consist mainly of three things. Firstly, we contribute to a broader understanding of informational asymmetry as an earnout determinant by adding new dimensions to existing research.<sup>3</sup> We correct for self-selection bias in the sample through propensity score matching and consider informational asymmetry in a (to our awareness) new way. This enhances perspective on the role of informational asymmetry with respect to the choice of consideration. We also investigate the private negotiation phase of earnout transactions which, to our awareness, has yet to be researched in any detail. We do this by considering public earnout transactions. This research provides valuable insight into the characteristics of the background of earnout transactions and provides evidence on the costs of employing earnouts.

## 1.2 Structure of Thesis

In the following section, we present our literature review, which is the foundation of our hypotheses. In section 3, we offer a detailed derivation of our hypotheses. We continue by presenting our data sample in section 4 before we describe the methodology applied to derive our results in section 5. Subsequently, we present our univariate- and multivariate analysis based on our empirical study of the data in section 6. Lastly, we round out our thesis by discussing and concluding our results in section 7.

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<sup>3</sup>The earliest string of research on earnouts fails to apply any matching technique to reduce sample bias. See (Kohers and Ang, 2000; Datar et al., 2001)

## 2 Literature Review

This section presents the literature that forms the foundation of our thesis. We begin the section with a broad perspective by briefly considering payment method determinants in general before looking into earnouts specifically. Next, we define earnout provisions and present literature on how they work. After that, we present determinants and costs of earnout employment. Finally, we present literature related to the private negotiation phase.

### 2.1 Considering Consideration

When an acquirer decides on which form of consideration to offer, there are several essential intricacies to consider, which affect the dynamics of the deal. The most common types of considerations offered are cash and stock. (Faccio and Masulis, 2005) argue that because most firms have limited cash and liquid assets, cash considerations generally require debt financing, leading to increased financial distress costs. Subsequently, they find that an acquirers' choice between cash and stock considerations essentially is a trade-off between increased financial distress costs when paying in cash and weakened corporate control when paying in stock. For the target, (Faccio and Masulis, 2005) highlight a trade-off between the tax benefits of a stock transaction versus the liquidity and risk-minimizing benefits of a cash transaction.

The research of (Fishman, 1989) and (Berkovitch and Narayanan, 1990) find that target-and deal characteristics, such as hostility and competition, also greatly influence the consideration offered. (Eckbo et al., 2018) find capital structure characteristics, external pressure, industry, timing, and informational asymmetry as essential determinants of payment method. (Barbopoulos and Adra, 2016; Datar et al., 2001; Chang, 1998) report that stock has contingent payment properties, so the acquirer and target will share the inherent over-or underpayment risk burden in a stock transaction. In contrast, the potential upside is shared pre-transaction through the premium paid to target shareholders in a cash transaction.

## 2.2 What is an Earnout?

Prior literature points to a difference in opinion regarding the target value as the main reason for the employment of earnouts. (Barbopoulos and Sudarsanam, 2012) define an earnout as a contingent form of payment used to finance an acquisition through a two-stage payment structure. The first payment stage usually represents the portion of the valuation the parties agree upon and is an upfront payment that occurs when the transaction is consummated. The second payment (earnout) occurs at some predetermined later stage and is contingent on the performance of the target measured by one (or more) performance metric(s). In many cases, a difference in opinion regarding target valuation can lead to the cancellation of mutually beneficial deals. (Kohers and Ang, 2000) argue that the use of earnouts facilitates the completion of a deal, even when the parties disagree on valuation.

(Cain et al., 2011) were the first to research earnout contracts by acquiring data directly from targets- and acquirers engaged in earnout deals. They find that earnouts can be structured either as a linear or a step-wise function of target performance, subject to a maximum or not. Convex, concave, or linear functions with no maximums are other possible payoff structures. However, the first two are the most common and contribute to 82% of earnout deals in (Cain et al., 2011)' sample. They find that earnouts contribute to, on average, 33% of the total transaction value. Furthermore, the second payment stage are contingent upon target performance in 90% of cases. In comparison, it is contingent upon the combined performance of the target and acquirer in 9% of the cases. (Cain et al., 2011) also find that the post-merger performance metrics of the target is contingent on sales and cash flows in 63.6% of cases. Their paper also reports that non-financial performance metrics, for instance, achievement of FDA approval for pharmaceutical targets, are used in 12.2% of cases. Cash is most often the consideration offered in the second stage of earnout deals (39%), followed by stock (29%) and mixed consideration (26%). In rare cases, the payment method also involves debt or preferred stock.

Although (Barbopoulos and Sudarsanam, 2012) find that earnouts are primarily observed in private-target acquisitions, (Wolf, 2011) argues that event-driven CVR's are the earnout equivalent for public targets. Similar to an earnout, an event-driven CVR is a contingent second portion of the consideration that is paid at some predetermined later stage,

contingent on target performance. CVR's differ from traditional earnouts in their payoff structure as event-driven CVR's usually have a binomial payoff structure.<sup>4</sup> (Wolf and Fox, 2010) find that CVR's are often used in the pharmaceutical industry, likely because the payoff structure can accommodate the binomial nature of regulatory approval of new drugs. Another difference is that while the second-stage consideration in traditional earnout deals is paid directly to target shareholders when the relevant performance measure is triggered, CVR's can be listed as a derivative, allowing target shareholders to sell the contingent portion of consideration at market price.

## 2.3 Earnout Determinants

### 2.3.1 Informational Asymmetry

Difference in valuation opinion is generally the direct cause of earnout employment. Informational asymmetry represents the main reason for these differences in opinion. (Kohers and Ang, 2000) and (Datar et al., 2001) both find that the likelihood of employing an earnout increases with private targets and within high-tech or service industries. For the case of private targets, valuation-relevant information is less accessible as there tends to be little relevant public information available. Information sourced directly from the target largely fails to solve this problem due to the lemon problem (Ragozzino et al., 2007). For the case of high-tech or service industries, these are characterized by lower book values and less tangible assets, making targets within these industries harder to value as they are subject to informational asymmetry. The results of (Kohers and Ang, 2000) also highlight that transactions involving earnouts tend to consist of smaller, privately-held targets and divested subsidiaries in industries such as computer- and biotechnology. (Datar et al., 2001) find that earnouts are more likely to occur for cross-industry deals. Cross-industry deals are associated with more significant informational asymmetries due to the inability of the acquirer to accurately value targets outside their industry. (Datar et al., 2001) go far in suggesting that the employment of earnouts is consistent with solving informational asymmetry issues. They also report that their findings suggest informational asymmetry and agency issues as primary motivations for employing earnouts, as opposed to tax issues and financial reporting concerns, which had previously been suggested.

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<sup>4</sup>Traditional earnouts can share this payoff structure as well, making earnouts and CVR's identical.

(Cain et al., 2011) represents the first of the following sequence of earnout papers, and they further highlight the potential of earnouts to mitigate issues related to moral hazard. Their paper shows that earnouts can be employed as a solution when the net benefits of the acquisition depend on target managers' unobserved efforts. They do this by researching target management retainment by manually collecting data. (Barbopoulos and Sudarsanam, 2012) expand on the existing literature and find informational asymmetry and valuation risk to be the two main motives for employing earnout contracts. However, unlike most previous studies, their results are based on UK corporate acquisitions. Following the informational asymmetry path, (Mantecon, 2009) looks into whether cross-border bidders benefit from employing earnout contracts. Earnouts are employed in cross-border transactions to reduce the informational asymmetries that arise when the target and acquirer are located in different countries, much like those in different industries. Somewhat surprisingly, he finds that cross-border bidders experience negative cumulative abnormal returns (CAR) from employing earnouts compared to the domestic sample where the CAR is positive and significant. Furthermore, (Reuer et al., 2004) argue that inexperience is a source of information asymmetry and find that acquirers lacking M&A- and international experience more often employ contingent consideration methods such as stock- and earnouts.

### 2.3.2 Managerial Retainment

(Kohers and Ang, 2000) were the first to point to managerial retainment as a potential reason for earnout employment, as managements' specialized knowledge about the business can be a source of added value for the acquirer. They suggest that their results indicate management retention as one of two primary motivations for engaging earnouts - together with solving informational asymmetry. Furthermore, they find a strong correlation between actual earnout payment and the retention of target managers beyond the earnout period. The results and indications are based on univariate analysis, making the interpretations less verifiable. (Cain et al., 2011) examine transactions between 1994 and 2003 and find evidence based on multivariate analysis that the relative earnout size to transaction size is positively linked to the importance of target management efforts.

(Cadman et al., 2014) presents new research on managerial retainment as a determinant of earnout inclusion. They find evidence that suggests retainment of target managers is

not a determinant of earnout employment for targets operating in high R&D industries. However, consistent with (Kohers and Ang, 2000), they find that target managers stay longer when earnouts are high.

### 2.3.3 Liquidity and Financial Constraints

(Bates et al., 2018) is the first research we found that ties earnout employment to liquidity by linking earnouts to acquirers with limited access to external capital. They argue that (i) an earnout is an alternative to external funding in transactions, and (ii) the flexibility in estimating the fair value of an earnout provides the possibility of recording a lower liability on their balance sheet. The paper finds a negative relationship between the usage of external funding and the likelihood of employing earnouts, supporting their hypothesis that external funding and earnouts are competing sources of funding in M&A activity.

Prior literature has primarily relied upon the work of (Kaplan and Zingales, 1997) with their KZ index model to proxy for financial constraint at the company level. However, (Hadlock and Pierce, 2010) sheds interesting doubt on the validity of this model, arguing that using explanatory variables such as leverage and cash causes serious endogeneity problems. They find that the company's *size* and *age* are closely related to financial constraints and are much less endogenous than other commonly used variables.

## 2.4 Costs of Employing Earnouts

Researchers investigating earnouts generally find that acquirers employing these contracts experience higher abnormal returns than those who do not. This finding poses the question of why these contracts are not more common. Among several reasons, (Datar et al., 2001) highlight the costs of inefficient risk-sharing, measurement difficulties, litigation risk, and increased deal complexity as factors limiting the use of earnouts.

Firstly, it is worth noting that target owners are generally likely to desire a reduction in business risk when selling their company (Datar et al., 2001). Through an earnout, target owners will still bear the original business risk of the target, as the consideration is contingent on future performance. A further risk is induced to target shareholders through the uncertainty regarding the competency of the acquiring firm in managing the target operations (Datar et al., 2001). The latter risk can be reduced or even mitigated

through retaining original management. Furthermore, (Datar et al., 2001) point out the moral hazard issue of both target and acquirer concerning the performance measure upon which the earnout triggering is contingent. The targets will potentially be incentivized to maximize short-term profits, to the detriment of long-term prospects, in an effort to maximize the size of the earnout (Sudarsanam, 2003). On the other hand, an acquirer may be incentivized to manipulation that causes the opposite effect. Also, the economies of scale an acquirer seeks are best utilized through a high level of integration. This is also a possible source of risk for the target owners, as measurements of target performance, which the earnout payment relies upon, will become increasingly difficult with a higher degree of integration (Datar et al., 2001). (Sudarsanam, 2003) also point out the risk target owners face regarding the acquirer potentially withholding or even renegeing the earnout payments. (Wolf and Fox, 2010) find that disputes regarding earnout payment frequently result in litigation claims. Such claims can be value-destroying and represent a cost to employing earnouts. In their research, (Viarengo et al., 2018) focus on data in numerous legal areas. They find that earnouts are less common in legal jurisdictions tied to poor enforcement quality, while the contrary is the case in jurisdictions with more developed enforcement quality.<sup>5</sup> Both (Kohers and Ang, 2000) and (Cain et al., 2011) point out that the terms of an earnout contract can be hard to negotiate and define. Disagreements regarding earnout terms can lead to timely negotiations, which represent a cost to the transaction.

### 2.4.1 Private Negotiation Phase

The initiation of a deal starts prior to its announcement date (Boone and Mulherin, 2007). The period between the initiation and the announcement of the deal is designated as the private part of the negotiation process. This private phase is initiated either when the target engages an investment bank to initiate a sales process (Boone and Mulherin, 2007) or when the bidder contacts the target to engage in discussions regarding a potential transaction (Eckbo, 2014).

Prior literature covering this topic is scarce, likely because of the difficulty in attaining data from this private phase. (Wolf and Fox, 2010) and (Choi, 2016) both lightly touch upon this topic and highlight the timely aspect of negotiating an earnout. Determining

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<sup>5</sup>It is worth noting that these findings are based on univariate results.

the performance metric(s) and details of these contracts is complicated and can often be the root cause of lengthy negotiations. We leverage literature on deal completion time to provide insight into some of the factors expected to impact the private negotiation phase. (Hunter and Jagtiani, 2003) find that deals that involve top-tier advisors use less time between announcement and completion, supporting their hypothesis that top-tier advisors decrease the deal completion time due to superior skills. As advisors are highly involved in the negotiation phase, a similar effect is expected regarding the negotiation phase. Additionally, (Luypaert and De Maeseneire, 2015) find that deal complexity is positively related to deal duration. They highlight that deals with stock offers, hostile bids, and larger deals take longer to complete. On the other hand, acquirers with prior M&A experience use less time on deal completion.

### 3 Hypotheses

In this section, we present our three main hypotheses, including extensions. We present the derivation of our hypotheses and the literature related to our ideas. Our hypotheses are all founded with a background in the earnout literature covered in the previous section. While our first and second hypotheses relate to *when earnouts are employed*, the last hypothesis relates to *why earnouts are not more commonly employed*.

Section 2.3.1 describes how informational asymmetry is highlighted as the primary determinant of earnout employment in the literature. The findings of (Datar et al., 2001; Cain et al., 2011; Kohers and Ang, 2000) suggest significant relationships between the characteristics of deals associated with a higher degree of informational asymmetry and the inclusion of earnout provisions. However, some newer research fails to find significance in relationships expected to proxy for a higher degree of informational asymmetry. Variables such as cross-industry, international deals, and M&A experience, anticipated to proxy for informational asymmetry, fail to explain earnout employment in some recent papers. Furthermore, due to the problem of acquiring data on private targets, informational asymmetry regarding the target has in previous literature been proxied for at the industry-level. We argue that this further motivates research on the role of informational asymmetry as a determinant of earnouts.



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To better understand how the asymmetric information concerning the acquirer affects the likelihood of including earnout provisions, we consider the acquirer's M&A experience. While *age* has been applied to proxy for reduced informational asymmetry for the acquirer in previous research, we argue that the effect of experience is not accurately captured with this variable, which in turn could be a reason for the inconsistent results of including this variable in previous research. Age is usually measured as the difference in time between the public listing of a firm and the announcement date of the relevant deal. This implies that the actual age of firms is not captured in the variable, as a firm can exist for a long time before going public. Older firms with vast acquisition experience could have recently been listed and are thus recorded with a low age. On the other hand, high age can be recorded for firms that have been public for a long time while relying on organic growth, making age a false representative of M&A experience. Using data from our unrestricted sample to construct an experience variable based on the number of prior recorded deals engaged in by the acquirer, we obtain a variable that we argue can estimate a more direct proxy for M&A experience. In compliance with (Kohers and Ang, 2000; Barbopoulos and Sudarsanam, 2012), we expect that more experienced acquirers are better able to overcome valuation gaps by leveraging M&A experience. Based on this notion, we form the following hypothesis:

**H1:** *More experienced acquirers are less likely to employ earnouts.*

While researchers have previously accounted for informational asymmetries regarding the target, they have primarily done so on an industry level (see (Cain et al., 2011; Bates et al., 2018)).

To enhance the perspective on informational asymmetry further, we want to account for firm-level effects. (Servaes and Zenner, 1996) finds support for their hypothesis that investment banks are engaged to reduce the informational asymmetry between the target and acquirer. We leverage this finding by considering data on financial advisors to account for the level of asymmetric information. By relating earnout provisions to investment bank involvement (IB involvement), we can model the effect on earnouts of reduced informational asymmetry from both the target- and acquirers' point of view.

Based on the findings of (Servaes and Zenner, 1996; Golubov et al., 2012), we conjecture that IB involvement reduces informational asymmetry in several aspects. Firstly, the

payoff structure of investment banks is generally contingent on deal completion (Ma, 2005). Secondly, the reputational risk implied for the investment bank in the deal incentivizes contribution to ensure accurate valuation (Golubov et al., 2012). For investment banks to provide precise valuation, informational asymmetries are implicitly minimized through the due diligence process, which aims to accurately value and understand the business of the target. We further conjecture that the valuation expertise of investment banks leads to more accurate valuations of the target, consequently making the need for an earnout to bridge valuation gaps redundant. We take advantage of the role and incentives of an investment bank to proxy for a reduction in informational asymmetry and form the following hypotheses:

**H2.A:** *Investment bank involvement reduces the likelihood of including an earnout provision.*

(Golubov et al., 2012) find that top-tier IB involvement results in shareholder value enhancement for the acquirer. Their findings support their hypothesis that top-tier investment banks are better at identifying potential synergies and are more skilled negotiators. We leverage this finding by questioning whether higher-tier investment banks are better able to reduce informational asymmetry and thus make earnout inclusion less probable. We form the following hypothesis based on this notion:

**H2.B:** *Top-tier investment banks reduce the likelihood of earnout employment relatively more than lower-tier investment banks.*

To further understand whether reducing the asymmetric information on the targets'- or acquirers' side is more efficient, we consider IB involvement on a firm level. While there are arguments as to why both target- and acquirer IB involvement should reduce informational asymmetry, we conjecture the sell-side advisor, the target IB involvement, should have the most substantial effect on lowering informational asymmetries. The conjecture is based on the logic that the target will have the strongest incentives to reduce informational asymmetries and avoid earnout inclusion as a result of valuation gaps, as the effects of inefficient risk-sharing and litigation risk associated with earnouts is most prominent for the target. We form the following hypothesis:

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**H2.C** *Investment bank engagement for the target reduces the likelihood of earnout employment relatively more than for the acquirer.*

Finally, we seek to better understand *why earnouts are not employed more often*. To do this, we look into an alleged cost of earnout employment - timely negotiations. While previous researchers have highlighted timely negotiation as a potential cost to earnout employment, it has not yet been empirically investigated. Researchers argue that determining performance metrics, length of earnout period, and other contractual terms are relatively more time-consuming than comparable cash- or stock deals (Wolf and Fox, 2010; Choi, 2016). While the intuition is logical, this has to our awareness not yet been empirically investigated. We leverage this notion and research the private negotiation phase of earnout deals. We form the following hypothesis:

**H3:** *Earnout inclusion increases the length of the private negotiation phase.*

## 4 Data

### 4.1 Databases

#### 4.1.1 SDC Platinum

SDC Platinum is our primary source of transaction data and serves as the foundation of our dataset. We retrieve data on transactions from 1995 to 2020 involving U.S. targets classified as either public, private or subsidiary. To avoid noisy deals with inaccurate data, we limit our sample to transactions with a reported deal value over \$1m. Furthermore, we restrict the sample to deals with public acquirers, where the acquirer held less than 50% of target shares before acquisition and above 50% after the transaction is completed. These restrictions are imposed to ensure that financials are available on the acquirer and that the transaction represents a change in control. Lastly, we exclude carveouts, spin-offs, split-offs, recapitalizations, and restructurings as these structures represent transactions that are not deemed comparable in our sample. After our first set of restrictions, SDC returns 41 397 transactions. See table A2.1 for a stepwise rundown of how the restrictions affect deal count.

### 4.1.2 CRSP

We retrieve acquirer market data from CRSP to control for acquirer size as the book value of equity recorded in SDC Platinum tends to differ substantially from the actual market value of equity pre-transaction. CRSP is matched to our dataset using CUSIP<sup>6</sup> and PERMNO<sup>7</sup> as identifiers. After attaining market-value data from CRSP, our sample is reduced from 41 397 to 24 387 observations.<sup>8</sup> The CRSP data is based on values one month prior to the deal announcement. We lag these values to avoid run-up effects on the acquirer share price. This approach is consistent with most previous research requiring information about acquirer market value.<sup>9</sup>

### 4.1.3 Compustat

We engage Compustat as a source of financial information about the acquirer. The financial information is required to control for several crucial acquirer characteristics.<sup>10</sup> We retrieve financial data from the last quarter prior to deal announcement, which essentially lags all our financial variables.<sup>11</sup> We merge using GVKEY<sup>12</sup>, which serves as our primary matching identifier. Our sample size is reduced from 24 387 to 21 613 after matching Compustat data to SDC.

### 4.1.4 SEC-Data

The purpose of extracting data from SEC filings is to record information about the background of the merger. In our unrestricted sample, we record 58 public earnout transactions. Because earnouts are, as previously highlighted, very rare in public transactions, we also include event-driven CVR's. (Wolf and Fox, 2010) describes event-driven CVR's as the public version of an earnout. Thus, we include the 24 event-driven

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<sup>6</sup>CUSIP is a unique identifier assigned to stocks- and bonds in North America.

<sup>7</sup>PERMNO is CRSP's permanent security identifier. Each security will only have one PERMNO.

<sup>8</sup>The relatively substantial loss of observations when matching CRSP and SDC is consistent with prior research. We lose 41% of our observations, while (Kohers and Ang, 2000) lose 52% of theirs.

<sup>9</sup>The bias effect of run-ups on market value is likely to be minimal on our market values when using the 1-month lagged share price data. (Kohers and Ang, 2000) used a 10 day lag in their paper.

<sup>10</sup>Our multivariate analysis highlights how we leverage financial information to control for acquirer characteristics.

<sup>11</sup>We justify this as our model(s) seek to determine what affects the likelihood of earnout provisions. The acquirer attributes *prior* to engaging in the deal will be a relevant determinant.

<sup>12</sup>GVKEY is a unique six-digit key assigned in the Capital IQ Compustat Database to all companies.

CVR's in our sample of public earnouts as these structures are close to identical to that of a normal earnout. To our awareness, we will be the first to examine the background of public earnout deals specifically in greater detail.<sup>13</sup>

To record the private negotiation phase, we follow the approach of (Aktas et al., 2016), which relies on extracting data from SEC filings through EDGAR.<sup>14</sup> Deal initiation is reported in the "Merger Background" section of DEFM14A or PREM14A.<sup>15</sup> We apply this approach to our 82 public earnout/CVR transactions. The filings necessary to identify the background of the merger are only available for a minority of public earnout transactions. After gathering data from SEC, we are left with 28 public earnout deals. The public earnout transactions with initiation data available and a matched control group of 33 transactions make up our subsample of 61 transactions, representing the dataset for our third and final hypothesis, H3.

## 4.2 Restrictions and Transformations

To achieve a comparable sample, we exclude transactions from the financial- and utility industry.<sup>16</sup> The regulatory situation in the financial- and utility industries imposes potential strong bias effects to our sample. Our decision to exclude these industries is consistent with previous earnout research.<sup>17</sup> To reduce the effect of potential misreported values, we winsorize continuous variables at the 1%- and 99% levels. A selection of variables is also log-transformed for the purpose of our regressions.<sup>18</sup> The rationale is twofold: Ensuring a more normal distribution of our variables; It can serve as a tool to achieve more economically sensible interpretations of coefficients.

Our final unrestricted sample contains 14 969 transactions. See table 4.1 for an overview of how the sourcing and restricting of data affects our sample creation.

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<sup>13</sup>See (Wolf and Fox, 2010; Wolf, 2011) for more on CVR's and how they relate to earnouts.

<sup>14</sup>Edgar is a publicly available search tool developed by SEC.

<sup>15</sup>See A4 for examples on data extraction from SEC filings.

<sup>16</sup>We do so by dropping acquirer- and targets with SIC codes of [6000,6999] and [4900,4999].

<sup>17</sup>See (Bates et al., 2018).

<sup>18</sup>See table A1.1 for a full overview of variable definition.

**Table 4.1:** Deal count by step

<b>Step</b>	<b>Description</b>	<b># of deals</b>
1	Initial data retrieval from SDC Platinum	41 397
2	Merging with CRSP market data	24 387
3	Merging with Compustat financial data	21 613
4	Dropped financial- & utility industry deals	14 969
<b>Subsample</b>		
1	Earnout & CVR deals with SEC data available	28
2	Matched control sample	33
3	Total subsample	61

## 4.3 Variables

For a selection of our variables, we present a detailed description of variable construction. For the remaining variables, which are more intuitive, we refer to table A1.1 for details on variable construction- and definitions.

### 4.3.1 Dependent Variables

#### 4.3.1.1 Earnout

Earnout occurrence is the dependent variable for hypothesis H1-H2.C. To construct a variable representing earnout occurrence, we employ SDC data to create an indicator variable, which equals one if an earnout was employed in a transaction and 0 if not. We define earnout occurrence by whether or not an earnout was included in the offered consideration or if the value of the earnout is greater than 0. This leaves us with 1369 earnout transactions out of the 14 969 in our unrestricted sample.

#### 4.3.1.2 Private-phase Duration

To record the duration of the negotiation phase (the private duration), we record initiation and the signing of the merger agreement as reported in SEC-filings.<sup>19</sup> The variable is constructed as the number of days between “Date initiated” and “Merger Agreement” from SEC-filings.

<sup>19</sup>For an overview of how we record initiation, please see A4.

## 4.3.2 Deal Characteristics

### 4.3.2.1 Advisors

To account for investment bank involvement, we retrieve data from SDC on the reported financial advisor(s) for both the target and the acquirer. First, we manually classify each financial advisor represented in our dataset as either investment bank, commercial bank, or private equity firm. This classification is essential to provide validity to our analysis, as our hypotheses are based on research on investment banks specifically. Subsequently, we classify each advisor in a categorical variable, which takes the value of 1 if at least one financial advisor(s) is an investment bank, 0 if-else.

We rank the investment banks based on the total dollar value of advised transactions and the aggregate number of deals advised in our unrestricted sample. The final rank is based on a weighted average of the two parameters. We apply this ranking technique to investment banks, both company- and deal-level. Tier-1 is defined as the top 10 advisors, while the remaining investment banks are captured in the intercept. Our approach is based on that of (Golubov et al., 2012). Goldman Sachs, JP Morgan, Morgan Stanley, and Merrill Lynch are among the top five advisors in both categories. The categorical ranking of investment banking firms is favoured over a continuous approach as a continuous approach would likely induce inefficiency to our multivariate analysis.<sup>20</sup>

**Table 4.2:** Top five advisors by both number of deals advised (left) and total dollar amount (mill) of advised deals (right).

RANK	COMPANY	# of deals	Rank	COMPANY	\$-amount
1	Goldman Sachs	2 181	1	Goldman Sachs	13 017,120
2	JP Morgan	1 386	2	JP Morgan	6 036,694
3	Merrill Lynch	1 037	3	Morgan Stanley	5 941,418
4	Morgan Stanley	1 011	4	Centerview	3 205,480
5	Houlihan Lokey	785	5	Merrill Lynch	3 159,097

## 4.3.3 Target Characteristics

### 4.3.3.1 Volatility and Research & Development

For our public earnout subsample, we account for observable target characteristics which are associated with informational asymmetry - volatility and R&D cost. *Target Volatility*

<sup>20</sup>(Golubov et al., 2012) highlights a similar rationale for applying this approach.

is computed as the annualized standard deviation of the return of the target's share price, measured over the last 100 days prior to the announcement date. Furthermore, we construct *relative R&D cost* - which is computed as the ratio of R&D cost over the target value (proxied by transaction value).<sup>21</sup>

### 4.3.4 Acquirer Characteristics

#### 4.3.4.1 Market Value of Equity

Market data from CRSP is utilized to determine the market value of the acquirer. The market value of the acquirer's equity is constructed as the product of the share price and the total number of shares outstanding.

$$MV\ Acquirer = Shares\ outstanding * Share\ price \quad (4.1)$$

#### 4.3.4.2 Capital Structure

The market value of equity and the total liabilities, reported in CRSP and Compustat, respectively, are used to create our D/E-ratio.

$$Debt / MVEquity = Total\ Liabilities / MV\ Equity \quad (4.2)$$

#### 4.3.4.3 Financial Constraint

We employ data from Compustat and CRSP to construct an SA-Index<sup>22</sup> that proxies for an acquirer's level of financial constraint (Hadlock and Pierce, 2010). *Age* is defined as the number of years the acquirer has been listed in the CRSP database. We winsorize the variable above at 37 years. *Size* is defined as the log of the inflation-adjusted total assets of the acquirer.<sup>23</sup> This variable is winsorized above at \$4,5 billion.

$$SA - Index = (-0.737 * \log(Size)) + (0.043 * \log(Size)^2) - (0.040 * Age) \quad (4.3)$$

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<sup>21</sup>R&D costs are retrieved from the last quarter prior to the announcement date. Our approach is based on that of (Bates et al., 2018).

<sup>22</sup>The SA-Index is described under Section 2.3.3

<sup>23</sup>We adjust the value of total assets for inflation by transforming them into their 2004 value. The index used for this adjustment is the U.S. CPI for all urban consumers, gathered from Federal Reserve Economic Data (FRED).



#### 4.3.4.4 M&A Experience

One of the variables used as a proxy for the acquirer's M&A experience is age. We define age as the difference between the first time the acquirer was recorded in CRSP (after 1965) and the announcement date of the deal the acquirer is partaking in.

$$Age = Date\ announced - First\ recorded\ stock\ price\ date \quad (4.4)$$

In addition to *age*, we also use the cumulative number of deals previously executed by an acquirer in our dataset as a proxy for M&A experience. To our awareness, we are the first to utilize this variable to proxy for experience with this variable in earnout literature.

## 4.4 Descriptive Statistics

In this section, we present descriptive statistics on deal-, acquirer- and target level. We compare the transactions involving an earnout agreement to those without and to the unrestricted population in our sample. Table 4.3 displays highlighted descriptive statistics for our unrestricted sample, grouped by earnout vs. non-earnout transactions. Our unrestricted sample consists of 1 369 earnout deals and 13 630 non-earnout deals, meaning earnout provisions are included in 9.1% of our sample. We comment on the mean and median of key characteristics. For a more detailed composition of descriptive statistics, we refer to table A7.2 in the appendix.

**Table 4.3:** Descriptive statistics four our earnout- non-earnout and unrestricted sample

	Unrestricted Sample		Earnout Deals		Non-Earnout Deals	
	Mean	Median	Mean	Median	Mean	Median
<i>Independent variables</i>						
Age Acquirer	13.52	9.02	12.79	8.97	13.59	9.03
Nr. of deals Acquirer	4.97	3.00	4.41	3.00	5.03	3.00
IB engaged	0.48	0.00	0.41	0.00	0.49	0.00
Target IB	0.40	0.00	0.31	0.00	0.41	0.00
Acquirer IB	0.29	0.00	0.24	0.00	0.29	0.00
<i>Acquirer Characteristics</i>						
D/E (MV) Acquirer	0.74	0.36	0.60	0.30	0.75	0.37
High SA Index	0.50	1.00	0.58	1.00	0.49	0.00
Assets Acquirer	4,757.28	586.31	3,957.03	306.22	4,837.83	629.66
Liabilities Acquirer	2,600.97	265.30	2,107.61	112.27	2,650.63	287.37
MV Equity	7,614.25	719.11	5,960.26	448.19	7,780.74	755.85
M/B multiple Acquirer	3.57	2.46	3.23	2.36	3.60	2.47
<i>Deal Characteristics</i>						
Deal Value	299.70	40.30	177.94	33.00	311.96	41.70
DV/MV Acquirer	0.26	0.06	0.18	0.08	0.27	0.06
perc. Cash as consideration	44.64	30.39	45.79	50.00	44.52	19.93
perc. Stock as consideration	20.47	0.00	10.15	0.00	21.51	0.00
perc. Other as consideration	11.20	0.00	35.89	30.36	8.71	0.00
Cross Industry	0.28	0.00	0.30	0.00	0.28	0.00
Earnout Value	5.52	0.00	60.37	8.00	0.00	0.00
<i>Target characteristics</i>						
Private target	0.54	1.00	0.76	1.00	0.52	1.00
Subsidiary target	0.32	0.00	0.21	0.00	0.33	0.00
Public target	0.14	0.00	0.03	0.00	0.15	0.00

Monetary values are reported in millions. Age reported in years. See table A1.1 for variable definitions.

### 4.4.1 Independent Variables

The average acquirer in our sample has an age of 13.5 and has been involved in 5 prior deals. In comparison, acquirers engaging in earnout deals are slightly lower, both in age and the number of deals completed. This provides weak evidence of any substantial difference in experience across earnout vs. non-earnout deals. We note that there is a substantial difference between the mean and median of our experience proxies, indicating that the distribution of our variables is skewed.<sup>24</sup>

We observe investment bank involvement in 48% of the observations of our unrestricted sample. Earnout deals have a slightly lower mean and median of investment bank engagement, both on a deal level and for the case of the acquirer. There is a significant difference between the mean of our restricted- and unrestricted sample for *Target IB*, which is consistent with what we would expect to see under H2.C.

### 4.4.2 Acquirer

Acquirers engaging in earnout deals in our sample are characterized by some key differences to our unrestricted- and non-earnout sample. The average D/E ratio of acquirers in our full sample is 0.74. There is a severe deviation between mean and median, indicating a highly skewed variable. Interestingly, the acquirers engaging in earnout deals have lower debt-to-equity levels compared to non-earnout acquirers. This finding is surprising, considering (Bates et al., 2018) find acquirers with restricted access to external capital to be associated with earnout engagement. Simultaneously, the descriptive statistics reveal that a larger share of earnout(non-earnout) acquirers have a high *SA-Index*, which proxies for financial constraint, implying dislocation between capital structure and the level of financial constraint. The higher level of financial constraint in earnout acquirers is consistent with the findings of (Bates et al., 2018). We observe that the average size of acquirers, measured by the equity value, is lower for our earnout (non-earnout) observations.

Acquirers engaging in earnout transactions are generally priced similarly to acquirers engaging in non-earnout deals with regards to the M/B multiple. (Barbopoulos and Sudarsanam, 2012) argue that high M/B acquirers face higher business risk and will

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<sup>24</sup>See table A7.2, which highlights this further by showcasing more detailed descriptive statistics.

therefore seek to mitigate acquisition risk through the use of earnouts. We observe a slightly higher M/B multiple for non-earnout acquirers, which is inconsistent with this notion. Furthermore, acquirers engaging in earnout (non-earnout) deals have lower assets-and liabilities on their balance sheet. While this has not previously been highlighted, the notion of smaller acquirers engaging earnout provisions is consistent with this observation.

### 4.4.3 Deal

Table 4.3 highlights that deal value relative to the acquirer's market value is smaller for earnout deals (18% compared to 27%), consistent with a higher share of private targets and lower deal value for earnout deals. As for consideration, the upfront portion consists of a lower(higher) portion of stock for earnout(non-earnout) deals. (Barbopoulos and Adra, 2016) highlight that stock, much like earnouts, contains contingency properties. If one considers earnout provisions and stock to be competing forms of consideration, seeing a lower share of stock as consideration is sensible as earnout- and stock considerations possess many of the same features. We note that the mean reported earnout value is \$60m, contributing to, on average, 33.9% of the total transaction value. The average relative size of earnouts in our sample is consistent with that reported by (Cain et al., 2011). Lastly, we would expect to see a relatively higher(lower) proportion of earnout(non-earnout) deals being cross-industry, seeing as these deals are associated with a higher(lower) degree of informational asymmetry in the literature.<sup>25</sup> Instead, our sample shows no statistical difference in the means of cross-industry for the two subgroups.<sup>26</sup>

### 4.4.4 Target

Table 4.3 also highlights the difference in targets engaged between deals where earnouts are typically employed versus avoided. In our sample, earnouts are more common for private targets operating in industries with a higher proportion of intangible assets, such as high-tech and healthcare, and are rarely employed in public targets (2.6%). This is all consistent with the findings of previous research.<sup>25</sup>

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<sup>25</sup>See (Kohers and Ang, 2000; Datar et al., 2001).

<sup>26</sup>A formal test of the difference between the two subgroups is presented in table 5.2.

## 5 Methodology

In this section, we present the methodology we apply to derive our results. Earnout incidence is modeled as the dependent variable using POLS- and logit models. We apply various model specifications to our unrestricted and matched samples to test H1 and H2. For H3, we apply a model based on the negative binomial distribution to model the coherence between earnout incidence and private duration.

### 5.1 Modelling Earnout Incidence

#### 5.1.1 Logit Model

H1 - H2 covers the relationship between informational asymmetry and earnout incidence. The logit model offers an intuitive and economically rational way of investigating our hypotheses which relate to earnout determinants (Aldrich and Nelson, 1984; McFadden et al., 1973). Probit and logit models have been popular in former earnout research for these reasons, among others.<sup>27</sup> We choose to apply logit over probit due to the intuitive interpretation of coefficients (odds-ratios) and the applicability of the model in our software of choice.<sup>28</sup>

We note that the probit and logit approach generally provide similar results. The dependent variable in our logit models is an earnout dummy, which is restricted by the logistic distribution. The predicted values of the dependent variable vary in the interval  $[0,1]$ .

To account for the year- and time effects in our logit models, we apply a fixed effects estimator, using year as our panel variable.<sup>29</sup> In our logit models, we control for industries by including indicator variables. By grouping industries on a macro-level, we achieve a large number of observations within each industry, reducing the potential inefficiency-inducing effect of including a large number of industry indicators.

Our logit-model is displayed in equation 5.1 on a general form:

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<sup>27</sup>(Barbopoulos and Sudarsanam, 2012) apply a logit model to predict earnout employment.

<sup>28</sup>We use Stata for most of our data processing and subsequently for all of our analysis.

<sup>29</sup>We do not go into detail on the estimation technique in this thesis. For a detailed derivation of our logit model, we refer to (Stata, 2021).

$$Pr(y_{it} = 1|x_{it}) = F(\alpha_i + X_{it}\beta) \quad (5.1)$$

where F follows the cumulative logistic distribution:

$$F(z) = \frac{\exp(z)}{1 + \exp(z)} \quad (5.2)$$

### 5.1.2 OLS Model

In addition to logit models, we apply an ordinary least squared (OLS) model to model earnout incidence. The OLS coefficients can be directly interpreted as marginal probabilities. A high(low) positive(negative) coefficient is interpreted as a high(low) increase(decrease) in the probability of earnout inclusion. The economic intuition behind this interpretation is essential for providing magnitude to our results. We motivate the use of OLS further by its commonality in earnout literature, the easy implementation, and the opportunity it provides to cross-check and provide validity to our logit models. The model which we apply is displayed, in its general form, in equation 5.3:

$$Y_i = \beta_0 + \sum_{i=1}^n \beta_i X_i + \epsilon_i \quad (5.3)$$

## 5.2 Negative Binomial Model

For H3, our dependent variable is *Private Duration*. The distribution of the dependent variable is most consistent with that of a Poisson distribution. To account for overdispersion, we employ the negative binomial model, which does not assume a mean equal to the variance.<sup>30</sup> Our choice of model is consistent with (Aktas et al., 2016), which, to our awareness, is the only published paper that utilizes private duration as their dependent variable.

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<sup>30</sup>This is in contrast to the Poisson model.

### 5.2.1 Propensity Score Matching

To mitigate potential self-selection bias induced by employing earnouts, we use the method of propensity score matching (PSM) to create a comparable sample of earnout- and non-earnout transactions. We motivate applying PSM by the strong results in reducing sample bias in previous research.<sup>31</sup> By applying PSM, we obtain a comparable matched sample, allowing us to be more confident in the sign and magnitude of our estimated coefficients (Leuven and Sianesi, 2003). We combine this approach with unrestricted sample OLS and logit models that control for a wider variety of variables to provide additional validity to our results.

#### 5.2.1.1 Applying PSM

We introduce a probit-model that predicts earnout employment to estimate a propensity score for each transaction in our sample.

The model is based on (Bates et al., 2018) and includes deal characteristics such as *target termination fee*, *deal value*, and *target public status*. By matching our transactions on propensity scores based on the estimated coefficients of the model covariates, we seek to obtain a comparable sample of earnout and non-earnout transactions.<sup>32</sup>

The model's ability to construct a matched sample that reduces the self-selection bias observed in our unrestricted sample is emphasized. We consider its ability to do so through comparing the means of deal characteristics of interest in the earnout- and matched sample with t-tests. T-tests, displayed in table 5.2, indicate no difference in mean across most of our observed characteristics. We match the estimated propensity scores of our earnout sample to its nearest non-earnout neighbor in the following way:

$$\text{Min } | (Pscore_i | Earnout_i = 1) - (Pscore_i | Earnout_i = 0) | \quad (5.4)$$

We apply the Nearest-Neighbor (NN) matching approach, matching on a 1:1 basis. We motivate using NN as opposed to other matching techniques by the intuitive implementation of NN and the opportunity to verify matching accuracy. We verify

<sup>31</sup>See (Bates et al., 2018; Stuart, 2010)

<sup>32</sup>Table A7.4 showcases the comparability of our matched sample

matching accuracy by considering the distance measured in propensity score between matched observations. While our earnout sample contains 1 369 earnout transactions, our unrestricted sample consists of 14 969 observations. The large pool of potential matching transactions significantly reduces the sampling bias by achieving close matches.<sup>33</sup>

**Table 5.1:** Probit model predicting earnout employment

	(1)
Deal Value	0.028*** (0.009)
Lockup	-0.236 (0.253)
Toehold	-0.178 (0.164)
Tender Offer	-0.457*** (0.152)
Cash only	0.257*** (0.031)
Private target	0.462*** (0.036)
Target Term. fee	-0.489*** (0.079)
Constant	-2.539*** (0.175)
Observations	14969
Acquirer Industry Effects	Yes
Pseudo R2	0.075

The dependent variable is earnout incidence

Robust standard errors in parantheses

Deal Value is log-transformed.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

See table A1.1 for variable definitions.

Table 5.1 displays the estimated coefficients of our earnout-prediction model. Coefficients' signs and significance are largely consistent with the findings of (Bates et al., 2018).

Table 5.2 highlights the difference in means of our independent variables of interest, our matching covariates, and other control variables. T-tests indicate no difference in mean for most of our matching covariates, indicating that the matching quality is high. We still observe significant difference in mean across the matched groups of the SA-index that proxies for financial constraint.

<sup>33</sup>See table A7.4 for matching quality.



**Table 5.2:** T-test for all characteristics comparing the mean of earnout- and non-earnout transactions for our matched sample

	Mean No EA	Mean EA	No EA - EA
<i>Independent variables</i>			
Acquirer nr. of deals	4.936	4.405	0.531**
IB engaged	0.455	0.415	0.040**
Acquirer IB	0.250	0.235	0.015
Target IB	0.370	0.312	0.058***
Tier 1 IB-firm	0.161	0.139	0.023*
<i>Matching covariates</i>			
Deal Value	189.818	177.938	11.880
Target Term. fee	0.020	0.028	-0.008
Lockup	0.004	0.002	0.001
Toehold	0.004	0.007	-0.003
Tender Offer	0.003	0.006	-0.003
Cash only	0.558	0.523	0.035*
Private target	0.743	0.760	-0.018
<i>Control variables</i>			
MV Equity	6941.176	5960.256	980.920
Cross Industry	0.291	0.302	-0.010
High SA-Index	0.533	0.584	-0.051***
<i>Target characteristics</i>			
Subsidiary Target	0.221	0.213	0.008
Public Target	0.036	0.026	0.009

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

See table A1.1 for variable definitions.

### 5.2.1.2 Public Earnout Subsample

To account for self-selection in our public earnout subsample, we apply a similar PSM methodology to create a matched sample. As these observations differ substantially from our general earnout population, we introduce a second PSM model, which utilizes our public earnout subsample as the dependent variable. We combine PSM with an exact matching approach as we require matched observations to include public targets.<sup>34</sup>

We match, using NN, on a 1:5 basis. Thereafter, we include the matched transaction(s) that have a DEFM-14 or PREFM14 filing available in our matched sample. We motivate matching on a 1:N as opposed to a 1:1 basis for two main reasons. Firstly, by matching on a 1:N basis, we increase the likelihood of including matches that have SEC-filings containing the background of the merger available. Secondly, we are in some cases able to include several matches with correct filing available, which is favourable to increase our limited sample size. For a display of our matching model and a comparison of covariates between our public earnout- and matched sample, we refer to table A7.5 in the appendix.

## 5.3 Model Selection

To select model specifications, we consider a variety of measures. Most important is statistical and economic intuition. R<sup>2</sup> and Pseudo R<sup>2</sup> are considered as measures of the explanatory power of our POLS and logit models, respectively, where we prefer higher(lower) R<sup>2</sup>. We account for year- and industry effects through indicator variables in our POLS models and through a combination of indicators and a fixed effect estimator in our logit specifications. In our logit specifications, we use *Year* as our grouped time variable while controlling for industry-effects through indicators.

We apply VIF-tests to account for potential multicollinearity. We follow the recommendation of (Wooldridge, 2015) by rejecting models with a VIF score greater than 10 as standard errors are likely to be significantly inflated in these cases. RESET tests for our OLS models are also considered to account for potential under-specification. Finally, for our logit models, we consider log-likelihood to compare model fit across specifications. For an elaborated discussion of robustness, please see section 6.3.

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<sup>34</sup>This requirement is set to ensure we can collect data on the background of the transaction from the SEC. Only public targets will be available to collect data on.

## 6 Analysis

We begin our analysis by considering our independent variables of interest and key characteristics univariately. Subsequently, we present our multivariate analysis before we round out this section by presenting our concerns regarding the robustness of our estimated results.

### 6.1 Univariate Analysis

In this section, we will present our univariate analysis of our independent variables of interest over time. We motivate this analysis by two main points. Firstly, analyzing the variables relevant to our hypotheses univariately adds a foundation to the analysis and gives an initial prospect to our hypotheses. Secondly, univariate analysis allows us to better understand considerations that can be important to implement when we consider the multivariate analysis of our hypotheses. Furthermore, table 6.2 allows us to better observe any potential trends or anomalies in our data. By interpreting the means of our observations over time, we can cross-check whether the results are consistent with known market-impacting events such as the dot-com bubble and the financial crisis.

**Table 6.1:** Acquirer industry by Earnout employment

	Earnout	No Earnout
Consumer Products	0.11	0.07
Consumer Staples	0.03	0.04
Healthcare	0.25	0.14
High-tech	0.33	0.29
Industrials	0.12	0.14
Materials	0.03	0.07
Media & Entertainment	0.04	0.07
Retail	0.02	0.04
Telecom	0.04	0.05
Energy & Power	0.03	0.08
Observations	1369	13600

**Table 6.2:** M&A experience and investment bank involvement over time.

	Non-Earnout Deals				Earnout Deals			
	Age	Nr. of Deals	T_IB	A_IB	Age	Nr. of Deals	T_IB	A_IB
1995	9.70	1.54	0.25	0.24	7.05	1.47	0.18	0.24
1996	8.63	2.27	0.28	0.24	9.28	1.57	0.21	0.25
1997	8.25	2.99	0.28	0.23	6.45	2.00	0.17	0.11
1998	8.88	3.27	0.30	0.25	5.98	2.33	0.13	0.18
1999	9.94	3.27	0.37	0.28	7.34	2.65	0.17	0.19
2000	8.81	3.68	0.39	0.32	6.44	3.39	0.25	0.22
2001	10.92	3.96	0.48	0.32	9.92	3.10	0.25	0.31
2002	12.67	4.32	0.42	0.28	8.60	3.44	0.29	0.29
2003	13.31	4.66	0.45	0.28	10.44	3.29	0.35	0.27
2004	14.12	5.46	0.41	0.29	10.49	5.06	0.24	0.22
2005	13.17	6.19	0.41	0.31	11.62	5.19	0.23	0.23
2006	14.44	6.57	0.38	0.27	10.18	3.40	0.35	0.24
2007	14.91	5.81	0.42	0.32	11.74	3.94	0.27	0.22
2008	15.94	5.77	0.41	0.23	11.96	3.60	0.35	0.15
2009	17.60	7.28	0.41	0.23	15.14	4.41	0.35	0.14
2010	17.62	6.07	0.50	0.31	13.73	5.31	0.43	0.33
2011	18.83	7.23	0.45	0.23	18.18	4.78	0.34	0.20
2012	19.13	7.56	0.51	0.32	16.63	5.70	0.35	0.24
2013	17.51	8.16	0.50	0.29	16.60	6.54	0.38	0.33
2014	19.08	6.28	0.54	0.34	15.96	5.29	0.36	0.17
2015	19.20	6.93	0.55	0.38	16.45	4.58	0.49	0.31
2016	20.06	6.95	0.57	0.37	19.87	5.09	0.50	0.25
2017	25.12	9.35	0.60	0.39	21.74	8.91	0.45	0.33
2018	24.22	9.93	0.61	0.43	21.32	11.06	0.53	0.28
2019	26.93	9.72	0.59	0.47	26.92	6.67	0.36	0.21
2020	27.24	8.12	0.61	0.44	25.53	7.28	0.44	0.40
Total	13.59	5.03	0.41	0.29	12.79	4.41	0.31	0.24
Observations	13600				1369			

See table A1.1 for variable definitions.

Table 6.1 highlights that earnout provisions are significantly more likely to be employed by acquirers operating in the healthcare- or high-tech industry. These industries are characterized by a high degree of informational asymmetry. The bias towards the healthcare- and high-tech industries illustrates the need to control for industry-effects in our multivariate analysis of earnout incidence.

Both proxies for M&A experience, *Age* and *Avg. Nr of Deals* are trending positively over the time dimension in our sample. We note that the average age of earnout(non-earnout) acquirers is lower(higher), however, this is not consistent over time. The same differences

are observed across groups for *Avg. Nr of Deals*. As both IB involvement and experience (which proxy for a reduction in informational asymmetry) are growing over time, according to H1 & H2, we would expect to see a lower share of earnout deals over time as well. As shown in table A7.1 in the appendix, the relative share of earnouts is substantially higher for the second half of our observed years, relative to the first half. Meanwhile, the share of private targets and high-tech- and healthcare acquirers show no clear trends over time. IB involvement is also trending positively over time in our sample. Where only 25% of targets- and 24% acquirers in non-earnout deals engaged an investment bank in 1995, the mean has increased to 61% and 44%, respectively, in 2020. For earnout deals, we observe a similar increase in IB involvement, however, on consistently lower levels than for non-earnout deals. We note that the share of earnout-targets engaging an investment bank as their financial advisor is consistently lower relative to targets in non-earnout deals.

### 6.1.1 Private Duration

Table 6.3 highlights descriptive statistics on characteristics that are expected to be associated with private duration, grouped by the public earnout deals and their matched sample. The mean across groups provides evidence that earnout deals are, on average, associated with significantly longer private durations. The same notion applies when considering median - where the private duration of our public earnout transactions is over twice as long as that of our matched sample.

The mean deal value for our earnout(non-earnout) sample is slightly higher(lower). While target value is negatively associated with informational asymmetry, higher deal value is expected to be associated with longer deals, as the relative importance to acquirers of larger deals is greater. Interestingly, the earnout deals are relatively more often initiated by the target. We find this coherence logical, as target initiation is associated with the lemon problem that the use of contingent consideration provides a solution to (Akerlof, 1978; Ragozzino and Reuer, 2009).

While auction incidence is slightly higher for our earnout sample and the average number of bidders is slightly higher for or non-earnout sample, the means of both variables are

statistically indifferent across the subgroups of our subsample.<sup>35</sup>

Finally, we consider asymmetric information regarding targets through stock-price volatility and R&D expense. While R&D expense is statistically indifferent across the subgroups, we see significantly higher volatility for public earnout-targets. This is consistent with the well-established notion of informational asymmetry being an earnout determinant. While the higher average private duration of earnout deals compared to non-earnout deals is consistent with what we would expect to find under H3, we are unable to determine whether earnout incidence is the cause of the longer private duration. There could be other unobserved characteristics of our public earnout deals that represent the true cause of the significant difference in private duration. The difference in private duration could be explained by earnouts being employed in deals with more uncertainty, which the target volatility provides evidence on.

**Table 6.3:** Descriptives for our subsample

	<b>Earnout Deals</b>		<b>Non-Earnout Deals</b>	
	Mean	Median	Mean	Median
Private Duration	267.82	252.50	113.82	105.00
Acquirer prior deals	3.57	2.00	5.27	3.00
MV Equity	19,776.32	1,478.31	16,313.06	3,755.80
Earnout Value	44.29	1.25		
Deal Value	1,217.36	206.01	1,022.91	365.60
Target Initiated	0.43	0.00	0.36	0.00
Nr of Bidders	1.64	1.00	2.18	2.00
Auction incidence	0.71	1.00	0.67	1.00
Target R&D expense / DV	0.04	0.01	0.04	0.01
Target volatility	0.82	0.69	0.60	0.45
Observations	28		33	

## 6.2 Multivariate Analysis

### 6.2.1 Control Variables

We begin our multivariate analysis by commenting on the estimations of our control variables for H1-H2.C. H3 is subsequently considered separately. Earnout incidence is the dependent variable across specifications for H1-H2.C.

<sup>35</sup>See table A7.5 for t-tests comparing the means of our public earnout vs. matched non-earnout sample.

Deal value, which proxies for target value, has a significant and positive coefficient across specifications on our unrestricted sample in POLS- and logit models, in line with the findings of (Barbopoulos and Sudarsanam, 2012; Kohers and Ang, 2000). While larger targets are associated with a lower degree of informational asymmetry, researchers have generally found that earnout provisions are associated with larger targets. The market value of acquirer equity is significant and negative across specifications. This finding is consistent with previous earnout research. Market value of acquirer proxies for lower informational asymmetry regarding the acquirer for several reasons. Firstly, larger acquirers tend to have more in-house resources to spend on M&A activity. Secondly, acquirer size could also proxy for experience, arguably more so than *age*.<sup>36</sup> For our unrestricted sample, private- and subsidiary targets are also included as proxies for informational asymmetry regarding the target. The coefficients of the two indicators are positive and significant across specifications. We would expect to estimate economically and statistically significant coefficients of the private- and subsidiary target variables, seeing as earnouts are vastly more common in deals including unlisted targets. Our findings are consistent with this expectation.

*Cross-Industry* is included as prior researchers have found that it is associated with a higher degree of informational asymmetry (Cain et al., 2011). *Cross-Industry* is positive across specifications, but the magnitude and significance of the coefficient is varying. While former research has established cross-industry transactions as a source of informational asymmetry, results have proven inconsistent. Similarly, we find varying degrees of significance and magnitude for the coefficient of cross-industry. We include the *SA-Index* to proxy for acquirer financial constraint based on the findings of (Bates et al., 2018). In line with our expectation, the coefficient is positive and significant across specifications. Finally, in our investment banking related models, we include experience as a proxy in our unrestricted sample POLS model. The coefficient is negative, significant, and similar in magnitude to what we find in our experience model.

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<sup>36</sup>Section 3, paragraph 3 provides an explanation as to why age could potentially be a poor proxy for M&A experience.

### 6.2.2 H1: M&A Experience

Our desired proxy for M&A experience, *Acquirer Nr. of deals*, has a negative and significant coefficient both in our unrestricted and matched sample. We conjecture that our desired proxy, *Acquirer Nr. of deals*, is a superior proxy for experience as it directly measures experience, in contrast to *age*. The estimated results of *Acquirer Nr. of deals* yield unambiguous results, suggesting that acquirers with more M&A experience are associated with a lower probability of employing earnouts, consistent with what we would expect to see under hypothesis H1. Interestingly, the coefficient of *MV Equity* is slightly higher in our experience models, compared to those related to investment bank involvement, displayed in table 6.4 and 6.5. We conjecture that acquirer market value is positively related to M&A experience. Accordingly, we would expect *MV Equity* to pick up some of the effect of experience when not controlling for it directly, as we do when including *Acquirer nr. of deals*, highlighted in table 6.4. While the estimated coefficient of experience is significant on 5%- and 1%-levels across specifications, the magnitude of the coefficient is modest in economic terms.



**Table 6.4:** POLS models relating acquirer's M&A experience to earnout incidence.

	Full sample, POLS & Logit		Matched sample, POLS & Logit	
	(1)	(2)	(3)	(4)
Acquirer nr. of deals	-0.012*** (0.003)	-0.117*** (0.034)	-0.028** (0.012)	-0.120** (0.053)
Deal Value	0.012*** (0.002)	0.170*** (0.018)		
MV Equity	-0.012*** (0.002)	-0.164*** (0.019)	-0.032*** (0.006)	-0.145*** (0.027)
Cross Industry	0.013** (0.005)	0.188** (0.086)	0.032 (0.022)	0.143 (0.107)
High SA-Index	0.019*** (0.006)	0.320*** (0.080)	0.069*** (0.024)	0.311*** (0.119)
Subsidiary target	0.054*** (0.008)	1.500*** (0.196)		
Private target	0.116*** (0.008)	2.290*** (0.193)		
Constant	-0.078** (0.039)		0.770*** (0.146)	
Year Effects	Yes		Yes	
Year Fixed Effects		Yes		Yes
Target Industry Effects	No	No	Yes	Yes
Acquirer Industry Effects	Yes	Yes	No	No
Adj. R2	0.059		0.099	
Pseudo R2		0.089		0.034
N	14,969	14,969	2,738	2,738

Earnout incidence is the dependent variable across all specifications.

Robust standard errors in parantheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

See table A1.1 for variable definitions.

Acquirer nr. of deals, Deal value, and MV equity are log-transformed for the purpose of regressions.

Column (1) and (2) represent POLS- and Logit models on our unrestricted sample.

Column (3) and (4) are POLS- and Logit models, respectively, on our matched sample.

Year effects are represented by indicator variables for our POLS models.

For the logit specifications, a fixed-effects estimator is applied, with time as our panel variable.

Industry effects are represented by indicators variables representing SDC's macroindustries

## 6.2.3 H2: Investment Bank Engagement

### 6.2.3.1 Deal Level

Under H2.A, we would expect to see a negative coefficient of IB involvement. On a deal level, the coefficient of IB is negative and significant for all reported specifications. The magnitude of the coefficient, *Deal IB*, is modest in the POLS model on our unrestricted sample. However, for our matched sample estimations, the magnitude of the coefficient is significantly higher. The POLS model on our matched sample suggests that investment bank involvement is associated with a 5.5% lower probability of including earnout in the consideration. The logit model on the matched sample suggests a 24.6% decrease in the odds-ratio of the consideration including an earnout when an investment bank is engaged in the deal. Generally, the estimated coefficients of *Deal IB* suggests that the probability of including an earnout in the consideration is lower when an investment bank is engaged as a financial advisor on the deal. These findings provide evidence that is consistent with H2.A.

The estimated coefficients of *Tier 1 IB-firm* yield ambiguous results. While it is negative and insignificant for our unrestricted sample, the coefficient is positive and insignificant when applied to the matched sample. The estimated coefficient is also of low economic magnitude. We find no evidence, on a deal level, that Tier 1 IB involvement is associated with a lower probability of earnout inclusion. This is inconsistent with what we would expect to find under H2.B.

**Table 6.5:** POLS & Logit models relating investment banking involvement to earnouts on deal level.

	Full sample, POLS & Logit		Matched sample POLS & Logit	
	(1)	(2)	(3)	(4)
Deal IB	-0.014** (0.006)	-0.204*** (0.074)	-0.055** (0.021)	-0.246*** (0.081)
Tier 1 IB-firm	-0.008 (0.007)	-0.083 (0.119)	0.017 (0.032)	0.078 (0.135)
Deal Value	0.015*** (0.002)	0.220*** (0.024)		
MV Equity	-0.012*** (0.002)	-0.188*** (0.020)	-0.035*** (0.006)	-0.155*** (0.030)
Cross Industry	0.014*** (0.005)	0.203** (0.085)	0.032 (0.022)	0.143 (0.109)
High SA-Index	0.018*** (0.006)	0.370*** (0.084)	0.072*** (0.023)	0.328*** (0.121)
Acquirer nr. of deals	-0.013*** (0.003)			
Private target	0.112*** (0.006)	2.234*** (0.199)		
Subsidiary target	0.051*** (0.006)	1.461*** (0.199)		
Constant	-0.117*** (0.040)		0.817*** (0.146)	
Year Effects	Yes	No	Yes	No
Year Fixed effects		Yes		Yes
Target Industry Effects	No	No	Yes	Yes
Acquirer Industry Effects	Yes	Yes	No	No
Log-likelihood	-2,143	-3,997	-1,825	-1,672
Adj. R2	0.059		0.099	
Pseudo R2		0.089		0.034
N	14,969	14,969	2,738	2,738

Earnout incidence is the dependent variable across all specifications.

Robust standard errors in parantheses.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

See table A1.1 for variable definitions

Deal value and MV equity are log-transformed in all regressions.

Column (1) and (2) represent POLS- and Logit models on our unrestricted sample.

Column (3) and (4) are POLS- and Logit models, respectively, on our matched sample.

Year effects are represented by indicator variables for our POLS models.

For the logit specifications, a fixed-effects estimator is applied, with time as our panel variable.

Industry effects are represented by indicators variables representing SDC's macroindustries

Investment bank involvement and tier are considered at deal level across specifications.

### 6.2.3.2 Firm Level

In table 6.6, we present the results related to H2 at a company level. Columns (1) and (2) represent POLS models on how acquirer- and target IB involvement relate to the probability of including earnout provisions. In column (1), we consider acquirer- and target investment bank involvement separately. The coefficient of acquirer investment bank involvement is statistically insignificant and close to zero in magnitude. Target investment bank involvement has a significant and negative coefficient, in line with what we expect to find under H2.C. The magnitude of the *Target IB* coefficient is also economically significant, suggesting (on our matched sample) that target investment bank involvement is associated with a 7.2% lower probability of earnout inclusion. In column (2), we introduce an interaction variable of target- and acquirer investment bank engagement to account for potential synergistic effects of investment bank involvement. We include a similar interaction variable for Tier 1 IB involvement as well. POLS- and Logit models on the matched sample estimate negative coefficients for both interaction variables, consistent with what we would expect to estimate if H2 was true. *Acq. IB x Trg. IB* is significant on a 10%-level, while Tier 1 involvement is insignificant. The magnitudes of the coefficients for both estimated interaction variables are modest relative to that observed for target IB-involvement, separately. These findings provide weak evidence of any synergistic association between the likelihood of earnout engagement and both parties engaging an investment bank.

In our logit specifications, displayed in columns (3) and (4) of table 6.6, we estimate results that are consistent with those found in our POLS models. The coefficient of Target IB involvement is significant on 1% level and suggests that targets with an IB engaged corresponds to a 32.5% decrease in the odds-ratio of earnout incidence. Acquirer investment bank involvement is statistically indifferent from zero. Column (4) yields a statistically significant negative coefficient of our interaction variable, which provides some evidence of potential synergistic effects of IB involvement for both parties. While the interaction variable of Tier 1 involvement, *Tier 1 IB, Acquirer x Target*, is insignificant, the magnitude of the coefficient is relatively high compared to other estimated coefficients and could be of economic significance.

**Table 6.6:** POLS & logit models on our matched sample with various specifications with respect to target- and acquirer investment bank involvement

	POLS		Logit	
	(1)	(2)	(3)	(4)
Acquirer IB	-0.002 (0.023)		-0.011 (0.095)	
Target IB	-0.072*** (0.022)		-0.325*** (0.103)	
Acq. IB x Trg. IB		-0.051* (0.028)		-0.231** (0.099)
Tier 1 IB, Acquirer x Target		-0.086 (0.069)		-0.355 (0.273)
MV Equity	-0.033*** (0.006)	-0.034*** (0.006)	-0.146*** (0.028)	-0.152*** (0.028)
Cross Industry	0.031 (0.022)	0.032 (0.022)	0.141 (0.108)	0.144 (0.108)
High SA-Index	0.068*** (0.023)	0.075*** (0.023)	0.310** (0.124)	0.341*** (0.123)
Constant	0.777*** (0.145)	0.792*** (0.145)		
Year Effects	Yes	Yes		
Year Fixed Effects			Yes	Yes
Target Industry Effects	Yes	Yes	Yes	Yes
Acquirer Industry Effects	No	No	No	No
Adj. R2	0.101	0.099		
Pseudo R2			0.036	0.034
N	2,738	2,738	2,738	2,738

Earnout incidence is the dependent variable across all specifications.

Robust standard errors in parentheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

See table A1.1 for variable definitions.

MV equity is log-transformed across specifications

Column (1) and (3) include specifications of acquirer- and target investment bank involvement separately. Column (2) and (4) considers an interaction variable which represents the effect of both deal parties engaging an investment bank as a financial advisor. Column (2) and (4) also includes an interaction effect of both parties engaging Tier 1 investment banks.

Year effects are represented by indicator variables for our POLS models.

For the logit specifications, a fixed-effects estimator is applied, with time as our panel variable.

Industry effects are represented by indicators variables representing SDC's macroindustries

### 6.2.4 H3: Private Duration

Earnout incidence has a positive and statistically significant coefficient (1% level) in both our POLS and Negative Binomial models. Our results are indicative of earnout deals being associated with a longer private phase, which is the relationship we would expect to estimate if H3 was true. Target initiation has a positive and significant coefficient in our restricted OLS model, however, it is insignificant in our expanded OLS model and for both of our negative binomial models. The sign of the coefficient is consistent with that found by (Aktas et al., 2013). We include acquirer prior deals to proxy for experience as more experienced acquirers are expected to negatively impact the private duration (Aktas et al., 2013). To account for a higher degree of asymmetric information regarding the target, we include target volatility as a proxy for this. The estimated coefficients are positive but insignificant across specifications.

Both our POLS and negative binomial model indicate that earnout inclusion is significantly positively associated with a longer private duration.

**Table 6.7:** POLS & Negative binomial models relating earnout employment to private duration.

	POLS		Negative Binomial	
	(1)	(2)	(3)	(4)
Earnout incidence	0.780*** (0.128)	0.806*** (0.152)	0.813*** (0.138)	0.797*** (0.151)
Target Initiated	0.092 (0.113)	0.257** (0.126)	0.043 (0.119)	0.186 (0.130)
Nr of Bidders	0.033 (0.043)		0.044 (0.049)	
Auction incidence	0.561*** (0.167)		0.473*** (0.160)	
Acquirer prior deals	-0.008 (0.014)	-0.013 (0.021)	-0.006 (0.014)	-0.009 (0.016)
Cross Industry		0.013 (0.165)	-0.111 (0.128)	
Target volatility		0.142 (0.146)	0.145 (0.144)	0.127 (0.143)
Constant	4.218*** (0.146)	4.533*** (0.223)	4.280*** (0.187)	4.677*** (0.166)
Pseudo R2			0.073	0.053
Adj. R2	0.553	0.425		
Log-likelihood	-34	-40	-321	-328
Alpha			0.173	0.219
N	60	57	57	57

The dependent variable is private duration across specifications

Robust standard errors in parantheses

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

See table A1.1 for variable definitions.

Columns (1) and (2) represent POLS models, while (3) and (4) are negative binomial models.

## 6.3 Robustness

### 6.3.1 Sampling

We recognize that the restrictions- and transformations performed to obtain our unrestricted sample may induce bias and cause our estimated results to be specific to our sample. By engaging CRSP and Compustat to retrieve market- and financial data about acquirers causes a severe loss in our number of observations, inducing a bias towards larger acquirers, as these are more likely to have financial information available.

For our public earnout subsample, related to H3, the requirement of available SEC-filings could potentially further bias our sample, reducing the validity of our estimated results. Secondly, the severe size limitation of our public-earnout sample poses further concerns regarding the validity of estimated results.

Overall, the potential bias(es) related to our sample creation favors caution in extrapolating our results.

### 6.3.2 H1 & H2 Model Fit

Both in our logit- and POLS models, we consider multicollinearity and potential underfitting. We do this through VIF-scores and RESET tests, respectively. Taking (Wooldridge, 2015)' suggested thresh-hold VIF-score of 10 into account, multicollinearity is deemed un concerning for models related to H1 and H2. RESET-tests on our POLS specifications reveal a rejection of the null hypothesis of no omitted variables for our unrestricted sample. We suspect a potential cause of the results could be simultaneity issues in these models as we control for a broad set of variables in our unrestricted sample to account for the vast differences in characteristics of our earnout- and non-earnout transactions in the unrestricted sample.

For the matched sample, RESET-tests fail to reject the null hypothesis of no model misspecification with respect to both our acquirer experience and investment bank involvement models (see table A8.1). Residuals generally reveal heteroskedasticity across specifications. To account for this, we employ robust standard errors for all our estimated models (Wooldridge, 2015; Long and Ervin, 2000).

Our models all have significant explanatory power, measured by R2 and Pseudo R2 for our POLS and logit-models, respectively. The values of the R2 and Pseudo R2 are in the range of what we would expect, given R2's and Pseudo R2's reported in previous research.

#### 6.3.2.1 Omitted Variable Bias

While we have considered previous research and accounted for potential endogeneity issues to the best of our abilities, we recognize that we were not able to control for all potential control variables that can be related to both our dependent and independent variables of interest. While we engage propensity score matching to reduce the sampling bias and we



control for industry effects, the unavailability of data on private targets limits our ability to control for target characteristics. Unobserved target characteristics could be related to both earnout incidence and our independent variables of interest, inducing omitted variable bias to our estimated coefficients. We acknowledge these potential issues and advocate discretion when interpreting results.

## 6.4 Model Fit: H3

While our models of private duration highlight the strong positive correlation between earnout deals and private duration, the model is likely to suffer from simultaneity issues. As the earnout is offered *during* the private negotiation, there exists simultaneity between the negotiation of the earnout and the private duration. This could induce bias to our estimated coefficients, making our estimated coefficients inaccurate. Taking this into consideration, we interpret our estimations on the relationship between the private duration and earnouts as a strong positive correlation. Furthermore, we make our conclusions based mainly on our univariate findings with respect to H3.

# 7 Conclusion

In this last section of our thesis, we contextualize and conclude our results before sharing our thoughts regarding potential avenues for future research on the topic of earnouts.

## 7.1 Conclusion

In our thesis, we consider two aspects of earnout provisions - when are they employed, and why are they not more common? First, we consider an established determinant of earnout employment, informational asymmetry, on a target- and deal-level. We find that a lower degree of informational asymmetry is associated with a lower probability of earnout inclusion on both levels. This finding strengthens the evidence in favor of informational asymmetry as a determinant for employing earnout provisions, consistent with (Kohers and Ang, 2000) and (Barbopoulos and Sudarsanam, 2012). Our findings highlight that earnouts are more likely to be engaged in transactions with private- or subsidiary targets within intangible asset-rich industries such as high-tech- or healthcare. Consistent with

(Bates et al., 2018), our findings show that financially constrained acquirers are more likely to employ earnout provisions.

On a deal level, we find that investment bank involvement is associated with a lower probability of the consideration including an earnout. This provides evidence in favour of our second hypothesis; that investment bank involvement is associated with a reduced likelihood of including earnout provision. When considering investment bank ranking, the evidence is inconclusive. We find no unambiguous evidence on the association between top-tier investment and the probability of earnout provisions. The evidence disfavors the notion that top-tier investment banks have a superior effect on reducing informational asymmetry.

Our results suggest that more experienced acquirers are associated with a lower probability of earnout inclusion. This evidence is consistent with the notion that more experienced acquirers can better reduce informational asymmetry and ultimately avoid the need for an earnout to bridge valuation gaps. On the contrary, we find no evidence of a similar effect concerning the acquirer when using acquirer investment bank involvement to proxy for a reduction in informational asymmetry. We conjecture that this could follow from the asymmetry in risk-sharing associated with earnout employment (Datar et al., 2001), which favors the acquirer. Consequently, the insignificant association between acquirer investment bank involvement and the likelihood of including an earnout provision could result from relatively more favorable terms of including an earnout for the acquirer. Overall, the evidence we provide on asymmetric information regarding the acquirer is inconclusive in its association with the likelihood of including earnout provisions.

For the target, our findings provide evidence that engaging an investment bank as a financial advisor is associated with a lower probability of the deal including an earnout provision. These findings are highly significant and unambiguous. Furthermore, the evidence is consistent with previous findings of target informational asymmetry, based on industry-level target characteristics (e.g., (Bates et al., 2018)). Our findings provide additional evidence on the relationship between asymmetric information and earnout provisions by accounting for target informational asymmetry on firm-level as opposed to industry characteristics. The evidence on target investment bank involvement is consistent with the notion that asymmetric information regarding the target is a primary determinant

to earnout employment.

Lastly, we collect and present data on the background of public earnout transactions. We find that target initiation and auction incidence are slightly more common in public transactions that contain contingent consideration. We also find significantly higher volatility prior to the deal announcement for targets in public earnout deals compared to our matched non-earnout sample. We find a strong positive correlation between the private duration of a transaction and a contingent payment structure of the consideration. This correlation is consistent with what we would expect to find under our hypothesis that earnout inclusion increases the length of the private duration. Overall, the findings on the background of public earnouts provide evidence that public earnout transactions are characterized by a high degree of informational asymmetry and long negotiation processes.

## 7.2 Avenues for future research

There is still much to understand about the effect of contingent consideration on the dynamics of M&A transactions. We will highlight two aspects that we came across during our research which we find especially interesting to consider for future researchers.

While we have looked into and provided analysis on the private phase of contingent payment transactions, we found the multivariate analysis challenging, as there are several econometric intricacies in modelling the relationship between private phase characteristics and earnout provisions. We believe future researchers could leverage our findings on the background of public earnout transactions and provide stronger evidence on determinants of the private duration of M&A transactions.

Lastly, we would like to highlight the relationship between earnout provisions and the likelihood of deal completion as a potential avenue for future researchers. While ensuring deal completion is highlighted as a benefit of earnout provisions in the literature, there is no empiric evidence on it's ability to do so. Through modelling the relationship between deal completion, and earnout provisions, researchers could contribute to the understanding of whether or not earnout provisions really serve to ensure the consummation of deals that would have otherwise not gone through.

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# Appendix

## A1 Variable definitions

**Table A1.1:** Variables: description and source

<b>Name</b>	<b>Description</b>	<b>Source</b>
<i>Deal Characteristics</i>		
Deal Value	Value of the deal in USD	SDC Platinum
perc. Cash	Percentage of cash used as consideration in the deal	SDC Platinum
perc. Stock	Percentage of acquirer stock used as consideration in the deal	SDC Platinum
perc. Other	Percentage of other consideration used in the deal. Includes debt and earnout	SDC Platinum
Cash Only	Takes the value of 1 if the consideration consisted of 100% cash.	SDC Platinum
Earnout Value	Value of the earnout in USD	SDC Platinum
Cross Industry	Takes the value of 1 when acquirer and target are based in different industries. 0 otherwise.	SDC Platinum
Earnout	Takes the value of 1 if earnout is employed. 0 otherwise.	SDC Platinum
DV/MV Acquirer	Ratio of deal value to market value of acquirer.	SDC & CRSP
Tier 1	Takes the value of 1 when a tier 1 investment bank is involved in the deal. 0 otherwise.	SDC Platinum
IB engaged	Takes the value of 1 when an investment bank is involved in the deal. 0 otherwise.	SDC Platinum
Acquirer IB	Takes the value of 1 when an investment bank is engaged by the acquirer. 0 otherwise.	SDC Platinum
Target IB	Takes the value of 1 when an investment bank is engaged by the target. 0 otherwise.	SDC Platinum

*Continued from previous page*

<b>Name</b>	<b>Description</b>	<b>Source</b>
Lockup	Takes the value of 1 if lockup provision is included. 0 otherwise.	SDC Platinum
Toehold	Takes the value of 1 if acquirer executed toehold purchase, 0 otherwise.	SDC Platinum
Tender offer	Takes the value of 1 if the acquirer made a tender offer. 0 otherwise.	SDC Platinum
<i>Target Characteristics</i>		
High-tech	Takes on value 1 if the target operates in a high-tech industry, 0 if not.	SDC Platinum
Consumer Products	Takes on value 1 if the target operates in the consumer products industry, 0 if not.	SDC Platinum
Consumer Staples	Takes on value 1 if the target operates in the consumer staples industry, 0 if not.	SDC Platinum
Healthcare	Takes on value 1 if the target operates in the healthcare industry, 0 if not.	SDC Platinum
Industrials	Takes on value 1 if the target operates in the industrials industry, 0 if not.	SDC Platinum
Media&E.	Takes on value 1 if the target operates in the media and entertainment industry, 0 if not.	SDC Platinum
Retail	Takes on value 1 if the target operates in the retail industry, 0 if not.	SDC Platinum
Materials	Takes on value 1 if the target operates in the materials industry, 0 if not.	SDC Platinum
Telecom	Takes on value 1 if the target operates in the telecom industry, 0 if not.	SDC Platinum
Energy & Power	Takes on value 1 if the target operates in the energy and power industry, 0 if not.	SDC Platinum



*Continued from previous page*

<b>Name</b>	<b>Description</b>	<b>Source</b>
Public Target	Takes on value 1 if the target is a public company, 0 if not.	SDC Platinum
Private Target	Takes on value 1 if the target is a private company, 0 if not.	SDC Platinum
Subsidiary Target	Takes on value 1 if the target is a subsidiary, 0 if not.	SDC Platinum
R&D	Targets research and development expenses in quarter prior to announcement date	Compustat
Termination Fee	Takes the value of 1 target faces termination fees, 0 if not.	SDC Platinum
Target volatility	Annualized volatility of the stock price, 100 days prior to announcement date	CRSP
Auction	Takes the value of 1 if an action occurred during negotiation phase, 0 if not (subsample)	SEC-filings
Nr of Bidders	Number of bidders during negotiation phase (subsample)	SEC-filings
Target Initiated	Takes value of 1 if target initiated the process, 0 if not (subsample)	SEC-filings
Private Duration	Number of days between initiation- and announcement date (subsample)	SEC-filings
<b><i>Acquirer Characteristics</i></b>		
MV Equity	Market value of acquirer is the product of shares outstanding and share price	CRSP
D/E (MV) Acquirer	Ratio of debt over market value of acquirer.	CRSP&Compustat
D/BV Equity	Ratio of debt over book value of acquirer.	Compustat
Assets	Book value of assets in USD	Compustat
Liabilities	Book value of liabilities in USD	Compustat

*Continued from previous page*

Name	Description	Source
M/B Multiple	Ratio of market value of equity over book value of equity.	CRSP&Compustat
AGE	Number of years between when the acquirer is first recorded on CRSP and acquisition's announcement day.	CRSP
NumberOfDeals	The cumulative number of deals for the acquirer up until announcement date.	SDC Platinum
High SA-Index	Takes the value of 1 if the acquirer has a SA-Index value higher than the median for the sample.	CRSP&Compustat

*Monetary values are reported in millions.*

## A2 Sample Construction

**Table A2.1:** SDC deal count by step

Step	Restrictions	# of deals
1	Date announced: 01.01.1995 to 31.12.2020	-
2	Deal value: >1 (\$ Mil)	117 194
3	Exclude carveouts, spinoffs, splitoffs, recapitalizations and restructurings	77 803
4	Deal must be completed	69 140
5	Percent of shares owned after transaction must be >50%	67 274
6	Percent of shares held at announcement must be <49%	67 207
7	Acquirer must be public	41 681
8	Exclude all splitoffs	41 673
9	Target must be private, subsidiary or public	41 397

## A3 SEC data retrieval

### A3.1 Initiation date

**Example** Target: Abaxis Inc Ann. date: 16/05/2018 CIK: 881890

*Excerpt from DEFM14A:* On October 30, 2017, Juan Ramon Alaix, chief executive officer of Zoetis, contacted Clinton H. Severson, Abaxis' chief executive officer, by telephone to express interest on behalf of Zoetis in pursuing a possible acquisition of Abaxis for

\$65.00 per share of Abaxis common stock. Messrs. Alaix and Severson discussed their shared views that a potential acquisition could create significant value for each company and their respective shareholders. Later that day, Mr. Alaix sent Mr. Severson a letter setting forth the non-binding proposal (the “Zoetis \$65.00 per share proposal”).

**Conclusion: The transaction was initiated on October 30, 2017.**

### A3.2 Merger agreement date

**Example** Target: Talarian Corp. Ann. date: 05/01/2002 CIK: 857914

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*Excerpt from DEFM14A:* Late in the evening of January 4, 2002, the transaction documents were executed by the parties to such agreements.

**Conclusion: The merger agreement was executed on January 04, 2002.**

### A3.3 Initiated by target

**Example** Target: Aronex Pharma. Inc Ann. date: 24/04/2001 CIK: 854691

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*Excerpt from DEFM14A:* For some time, the board of directors and management of Aronex Pharmaceuticals has believed that beneficial alliances or other partnership arrangements with significant partners would provide it with important support and leverage in its research and development efforts, including increased financial and personnel resources with which to develop its product portfolio. With this in mind, in March 2000, Aronex Pharmaceuticals entered into an agreement with Robertson Stephens, Inc. pursuant to which Robertson Stephens was engaged to provide Aronex Pharmaceuticals with financial advisory and investment banking services in connection with Aronex Pharmaceuticals’s exploration of various strategic alternatives, including potentially the identification and review of possible merger candidates for, and/or acquirers of, Aronex Pharmaceuticals.

[...] In line with this strategy, Geoffrey F. Cox, Ph.D., Aronex Pharmaceuticals’s Chairman and Chief Executive Officer, met with Garo H. Armen, Ph.D., Antigenics’s President, Chief Executive Officer and Chairman, in July 2000 as a result of an introduction by Robertson Stephens. Drs. Cox and Armen discussed possible transactions between Aronex Pharmaceuticals and Antigenics.

**Conclusion:** The transaction was initiated by the target.

### A3.4 Initiated by acquirer

**Example** Target: Benthos Inc Ann. date: 02/11/2005 CIK: 11390

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*Excerpt from DEFM14A:* On July 6, 2005, Ronald L. Marsiglio, Chief Executive Officer and President of Benthos, telephoned Al Pichelli, Teledyne's Senior Vice President and Chief Operating Officer, Electronics and Communications Segment. Mr. Pichelli asked Mr. Marsiglio if Benthos had any interest in being acquired. Mr. Marsiglio and Mr. Pichelli agreed that they would meet at Benthos in early August.

**Conclusion:** The transaction was initiated by the acquirer.

### A3.5 Auction

**Example** Target: Aptimus Inc Ann. date: 08/08/2007 CIK: 1087277

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*Excerpt from DEFM14A:* On March 23, 2007, we notified JMP Securities that we had selected such firm to act as our financial advisor. JMP Securities, in its role as financial advisor, then began assisting with our market check in respect of the proposed business combination with Company A by contacting 15 potential buyers.

[...] our board of directors held a special meeting to discuss potential candidates to acquire Aptimus, including Apollo and Company A, Company B, Company C and Company D, including the timing and likelihood of reaching a definitive agreement with such companies. The board also compared these options with the possible business models for Aptimus as an independent company.

**Conclusion:** The target initiated an auction through its financial advisor.

## A4 Earnout example

Target: Advanced Bionics Corp Acquirer: Boston Scient. Corp Ann. date: 06/01/2004

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*Excerpt from 8K of acquirer* Pursuant to the Agreement, the Registrant acquired 100 percent of the fully diluted equity of Advanced Bionics for an initial payment of approximately \$740 million in cash, plus earn out payments tied to future performance milestones. The initial purchase price was funded by the issuance of commercial paper.

The acquisition has been structured to include a substantial earnout mechanism. Performance milestones are primarily based on the achievement of net sales, with certain milestone payments also tied to profitability.

The performance milestones are segmented by the four principal technology platforms (cochlear implants, implantable pulse generators, drug pumps and bion microstimulators), each with a 72-month earnout horizon. Base earnout payments on these performance milestones approximate two and a quarter times incremental sales for each annual period. There are also bonus earnout payments available based on the attainment of certain aggregate sales performance targets and a certain gross margin level.

## A5 Psmatch, H3

**Table A5.1:** Probit model predicting public earnout employment, public sample

	(1)
Deal Value	0.131*** (0.031)
Cross Industry	0.036 (0.158)
Acquirer Healthcare	0.809*** (0.126)
Constant	-5.605*** (0.601)
Observations	14969
Pseudo R2	0.141

The dependent variable is a dummy variable representing our subsample of public earnouts.

Robust standard errors in parantheses

Deal Value is log-transformed.

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

See table A1.1 for variable definitions.

## A6 Correlation matrix

**Table A6.1:** Correlation matrix for key variables

(1)

	Earnout	Age Acquirer	Number of prior deals	IB engaged	Deal Value	MV Acquirer	Cross Industry	Private target	Subsidiary target	Public Target	High SA Index	Tier 1 IB-firm
Earnout	1.000											
Age Acquirer	-0.018*	1.000										
Number of prior deals	-0.024**	0.200***	1.000									
IB engaged	-0.043***	0.188***	0.040***	1.000								
Deal Value	-0.028***	0.138***	0.056***	0.150***	1.000							
MV Acquirer	-0.021*	0.221***	0.365***	0.105***	0.220***	1.000						
Cross Industry	0.016*	0.054***	-0.032***	-0.011	-0.027**	-0.018*	1.000					
Private target	0.140***	-0.145***	0.014	-0.263***	-0.129***	-0.046***	0.044***	1.000				
Subsidiary target	-0.073***	0.053***	-0.030***	0.011	-0.036***	-0.045***	-0.015	-0.743***	1.000			
Public target	-0.104***	0.136***	0.020*	0.363***	0.235***	0.125***	-0.042***	-0.437***	-0.277***	1.000		
High SA Index	0.052***	-0.687***	-0.271***	-0.246***	-0.113***	-0.199***	-0.021*	0.178***	-0.078***	-0.151***	1.000	
Tier 1 IB-firm	-0.042***	0.212***	0.076***	0.504***	0.251***	0.157***	-0.024**	-0.266***	0.035***	0.334***	-0.252***	1.000

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

## A7 Descriptive statistics

### A7.1 Unrestricted Sample

**Table A7.1:** Percentage of deals including earnouts, private targets, and Healthcare- and High-tech acquirers over time.

	Earnout	Private Target	Healthcare	High-tech
1995	0.04	0.53	0.13	0.24
1996	0.03	0.55	0.16	0.23
1997	0.05	0.58	0.13	0.23
1998	0.06	0.58	0.09	0.27
1999	0.07	0.58	0.08	0.37
2000	0.06	0.59	0.08	0.47
2001	0.08	0.47	0.12	0.41
2002	0.07	0.48	0.12	0.36
2003	0.11	0.47	0.16	0.34
2004	0.10	0.55	0.16	0.34
2005	0.10	0.56	0.18	0.33
2006	0.11	0.56	0.16	0.30
2007	0.13	0.55	0.17	0.26
2008	0.11	0.52	0.19	0.28
2009	0.16	0.53	0.23	0.31
2010	0.14	0.52	0.19	0.29
2011	0.14	0.57	0.17	0.24
2012	0.14	0.55	0.16	0.26
2013	0.14	0.52	0.16	0.21
2014	0.13	0.57	0.15	0.24
2015	0.12	0.52	0.22	0.22
2016	0.09	0.44	0.21	0.21
2017	0.11	0.45	0.16	0.23
2018	0.11	0.47	0.15	0.25
2019	0.15	0.48	0.22	0.28
2020	0.13	0.54	0.21	0.21
2021	0.00	0.30	0.13	0.17
Total	0.09	0.54	0.15	0.30

**Table A7.2:** Expanded descriptives for earnout vs. non-earnout deals, unrestricted sample

	<b>No Earnout Deals</b>				<b>Earnout Deals</b>			
	Mean	Median	Min	Max	Mean	Median	Min	Max
<i>Independent variables</i>								
Nr. of deals Acquirer	4.41	3.00	1.00	80.00	5.03	3.00	1.00	122.00
IB engaged	0.41	0.00	0.00	1.00	0.49	0.00	0.00	1.00
Target IB	0.31	0.00	0.00	1.00	0.41	0.00	0.00	1.00
Acquirer IB	0.24	0.00	0.00	1.00	0.29	0.00	0.00	1.00
<i>Acquirer Characteristics</i>								
D/E (MV) Acquirer	0.60	0.30	0.01	8.44	0.75	0.37	0.01	8.44
High SA Index	0.58	1.00	0.00	1.00	0.49	0.00	0.00	1.00
Assets Acquirer	3,957.03	306.22	8.83	104,155.00	4,837.83	629.66	8.83	104,155.00
Liabilities Acquirer	2,107.61	112.27	1.82	56,755.00	2,650.63	287.37	1.82	56,755.00
MV Equity	5,960.26	448.19	6.40	173,987.11	7,780.74	755.85	6.40	173,987.11
M/B multiple Acquirer	3.23	2.36	-4.95	29.69	3.60	2.47	-4.95	29.69
<i>Deal Characteristics</i>								
Deal Value	177.94	33.00	1.30	7,000.00	311.96	41.70	1.30	7,000.00
DV/MV Acquirer	0.18	0.08	0.00	8.51	0.27	0.06	0.00	309.13
perc. Cash as consideration	45.79	50.00	0.00	99.91	44.52	19.93	0.00	100.00
perc. Stock as consideration	10.15	0.00	0.00	98.40	21.51	0.00	0.00	100.00
perc. Other as consideration	35.89	30.36	0.09	100.00	8.71	0.00	0.00	100.00
Cross Industry	0.30	0.00	0.00	1.00	0.28	0.00	0.00	1.00
Earnout Value	60.37	8.00	0.02	5,900.00	0.00	0.00	0.00	0.00
<i>Target characteristics</i>								
Private target	0.76	1.00	0.00	1.00	0.52	1.00	0.00	1.00
Subsidiary target	0.21	0.00	0.00	1.00	0.33	0.00	0.00	1.00
Public target	0.03	0.00	0.00	1.00	0.15	0.00	0.00	1.00

Monetary values in millions \$.

See appendix A1.1 for variable definitions.

The unrestricted sample contains 14 969 observations.



## A7.2 Matched Sample

**Table A7.3:** Comparing the means of characteristics for earnout vs. non-earnout transactions on the unrestricted sample

	Mean No EA	Mean EA	No EA - EA	S.E.
Number of prior deals	4.028	3.405	0.623***	(0.162)
Deal IB	0.488	0.415	0.073***	(0.014)
Target IB	0.410	0.312	0.099***	(0.013)
Acquirer IB	0.292	0.235	0.057***	(0.012)
<i>Matching covariates</i>				
Deal Value	311.961	177.938	134.023***	(17.105)
Target Term. fee	0.127	0.028	0.099***	(0.005)
Lockup	0.012	0.002	0.010***	(0.002)
Toehold	0.010	0.007	0.003	(0.002)
Tender Offer	0.036	0.006	0.031***	(0.003)
Cash Only	0.415	0.523	-0.108***	(0.014)
<i>Control variables</i>				
MV Equity	7780.742	5960.256	1820.486***	(628.331)
Cross Industry	0.276	0.302	-0.025*	(0.013)
High SA-Index	0.495	0.584	-0.089***	(0.014)
<i>Target characteristics</i>				
Subsidiary target	0.331	0.213	0.117***	(0.012)
Public target	0.151	0.026	0.125***	(0.005)
Private target	0.518	0.760	-0.242***	(0.012)
Observations	14969			

See table A1.1 for variable definitions

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table A7.4:** Difference in propensity score for earnout vs. non-earnout transactions in the matched sample

	Mean	Median	Min	Max
$\Delta Pscore$	0.00028	0.00000	0.000	0.034

### A7.3 Public Earnout Subsample

**Table A7.5:** Comparing the means of our public earnouts and the matched sample

	Mean No EA	Mean EA	No EA - EA
Private Duration	113.818	267.821	-154.003***
Acquirer prior deals	5.273	3.571	1.701
MV Equity	16313.064	19776.325	-3463.260
Earnout Value	0.000	44.292	-44.292*
Deal Value	1022.908	1217.356	-194.449
Target Initiated	0.364	0.429	-0.065
Nr of Bidders	2.182	1.643	0.539
Auction incidence	0.667	0.714	-0.048
Target R&D expense / DV	0.035	0.043	-0.007
Target volatility	0.601	0.817	-0.216**

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

See table A1.1 for variable definitions.

## A8 Robustness

**Table A8.1:** VIF scores and RESET-test p-values for all POLS models

	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer nr. of deals	1.48				1.47	1.48
Deal IB	1.69	1.37				
Acquirer IB			1.14			
Target IB			1.28			
Tier 1 IB-firm	1.65	1.43				
Acq. IB x Trg. IB				1.20		
Tier 1 IB, Acquirer x Target				1.19		
High SA-Index	1.67	1.58	1.58	1.56	1.67	1.60
Subsidiary target	2.63				2.57	
Private target	2.92				2.80	
MV Equity	2.28	1.68	1.62	1.60	2.27	1.71
Deal Value	2.81				2.05	
Cross Industry	1.06	1.16	1.16	1.16	1.06	1.16
Constant						
Sample	Unrestricted	Matched	Matched	Matched	Unrestricted	Matched
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects						
Target Industry Effects	No	Yes	Yes	Yes	No	Yes
Acquirer Industry Effects	Yes	No	No	No	Yes	No
RESET p-value	0.00	0.24	0.14	0.32	0.00	0.56
N	14,969	2,738	2,738	2,738	14,969	2,738

VIF-scores for coefficients are displayed in the table.

See table A1.1 for variable definitions.

Acquirer nr. of deals, Deal value, and MV equity are log-transformed for the purpose of regressions.

Column (1) - (4) represent our IB models in chronological order, based on table 6.5 and 6.6, respectively.

Column (5) and (6) represent our experience models, highlighted in table 6.4