University of Zurich[UZH]

M&A Activity and Competition Policy: Anaylsis and Implications for Sales Growth

Bachelor's Thesis

[redacted]

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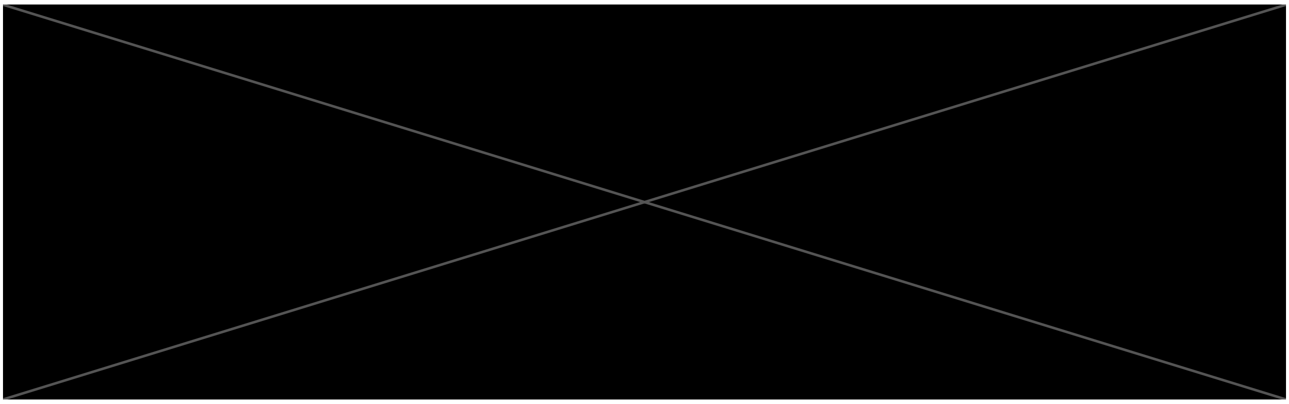
Abstract

Numerous authors quantify firm performance following M&A transactions employing profit-based measures or a financial market approach. This study applies a different method to evaluate performance following such corporate transactions and analyzes acquiror-firms sales figures instead. We measure the significance of sales volumes incorporated from targets to acquiror-sales growth by computing their magnitude as a share of (cumulative) acquiror-sales growth. To accomplish this, we combine large data sets based on Standard & Poor's Compustat and Thomson Reuters' SDC Platinum M&A database to create comprehensive samples of longitudinal data, including acquiror firms' sales, their corporate transactions, and relevant financial data of the targets. In our primary sample, across all firms, the share of sales volumes incorporated from targets in total acquiror-sales growth lies at 227 %. This value drops to 53 % if we compute a weighted mean based on acquiror size. The results suggest that M&A activity may have a detrimental effect on sales development for some firms and that such transactions are less significant to large companies.



1 Introduction

"One of the most important questions in finance is whether managerial actions create shareholders' wealth. M&A performance studies directly examine this issue and, hence, are of substantial importance to shareholders, managers, regulators, and other stakeholders." (Dutta and Saadi, 2011).

This study aims to contribute to the large body of literature that analyses the relationship between mergers and acquisitions and company performance. Some firms seem to apply aggressive acquisition strategies, although, as Section 2 will illustrate, research finds mixed results concerning the implications of such activities. Many studies employ share price-based methods in evaluating the success of a corporate transaction. A smaller body of research analyses this relationship based on accounting data, for example, by computing operating performance measures, such as Healy, Palepu, and Ruback (1992). In this study, we focus directly on sales numbers and thus build our samples using accounting data as well. When a firm is acquired, the new parent company consolidates the targets sales with its own. Generally, this leads to a sales increase for the acquiror at the point of acquisition. We measure the magnitude and significance of sales growth facilitated in this way by computing several summary statistics. An advantage of focusing solely on sales is that these values are affected less by accounting practices and market sentiment compared to, for example, net profits or market capitalization.

To construct a data structure that allows for the computation of the desired statistics, we link companies in an extensive data set of M&A structures (based on SDC Platinum) with their respective entries in a Compustat data set containing financial indicators, including sales. We then use this combination of M&A data and financial characteristics to create a longitudinal data structure, which illustrates an acquirors sales development across a period of several years while also indicating the companies mergers and acquisitions and relevant information about the deals, such as the target's sales in the year of transfer. Section 3 outlines this procedure in detail.

Section 4 explores the data structure obtained in the process and discusses some implications and limitations. We compute and analyze measures to quantify the magnitude of sales growth facilitated through acquisition and their significance as a proportion of total absolute sales. As these figures are crucial, we use several sources to define a target's sales values at acquisition to maximize the number of evaluable observations. To accommodate for differences between these sources, we construct 5 different samples, and derive results accordingly. We find that the sales contribution of acquisitions can be significant, cumulatively making up 227 percent of an average company's total sales growth at the end of the observation period in our primary sample. However, the distribution of this statistic is highly right-tailed, implying that few firms drive this result. Splitting acquirors into groups by firm size shows that this figure is much higher for small firms than for large firms, and hence the sales-weighted mean lies much lower, at 53 percent. Further, these statistics also vary across industries and regions. Section 5 summarizes and reviews the most important results and outlines some supplementary aspects which may be explored in future research employing a similar approach.

2 Review of Existing Literature

According to Dickerson, Gibson, and Tsakalotos (1997), there are two main approaches to research in merger and acquisition activity. Common in the finance literature is the market approach: Assuming efficient markets in the sense of the efficient market hypothesis allows for an analysis of merger activity based on share prices during the event period. The positive or negative economic impact of such transactions is then evaluated based on movements in the stock price of the companies involved, controlling for effects such as systematic risk and general market fluctuations. Some studies of this type date back to the '80s and earlier, such as Halpern (1983). He finds that acquisition behavior is generally consistent with value optimization for bidding firms, and targets also tend to obtain significant abnormal returns near the event period. Especially in tender offers, acquirors tend to earn notable abnormal returns, while he detects mixed effects in the literature for merger activity. Asquith, Bruner, and Mullins (1983) study a 21-day period after a merger event. They control for the success of the merger, target size, and other factors and find that M&A strategies are consistent with value-maximizing behavior and create positive net present value for bidding firms. Slightly more recent studies analyze the longer-run post-merger performance of acquiring firms based on stock price analysis. For example, Agrawal, Jaffe, and Mandelker (1992) find a negative effect of around 10 percent over a five-year post-merger period, confirming similar earlier results, such as Asquith (1983), who finds an abnormal return for the 240-day period after an event of -7.2 percent. Agrawal and Jaffe (2000) research this topic further, calling this phenomenon the "Post-Merger Performance Puzzle." Their extensive literature review finds that, indeed, long-run performance for mergers is negative, but that for tender offers, it is non-negative and potentially even positive. In his essay on the debate about the efficiency effects of corporate transactions, Scherer (1988) summarizes that *"Some takeovers enhance economic efficiency, some degrade it, and the balance of effects, though not fully known, is most likely a close one."*

In a more recent literature review, Yaghoubi, Yaghoubi, Locke, and Gibb (2016) come to similar conclusions: Stock prices at announcement react positively for targets, but slightly negatively for acquirors (other reviews conclude that acquiror returns are on average zero, for example, Bruner (2004)). They note that for several decades, these results have been consistent. While some degree of consensus seems to exist for the short-term impact of M&A activity, results for the analysis of longer-run effects are more controversial, though most studies find significant adverse performance effects for acquirors (Dutta and Saadi, 2011). Evidence against this rather pessimistic outlook for acquiror-performance is a study on the Canadian deals market by Dutta and Jog (2009), which does not find a negative effect.

The results above are mainly based on the market approach. Halpern (1983) notes that his research is focused on such share price-based event studies, as he argues that accounting data, which is the basis for the other approach mentioned, does not yield any insights into the expected long-run consequences of a transaction. Of course, event studies are not without limitations: For stock prices to reflect all available information at any given point in time, markets must be efficient. Hence, as mentioned above, the efficient market hypothesis underlies such merger-event studies as a given axiom. This makes the acceptance of those results dependable on an acceptance of the efficient market hypothesis. Engaging in a more skeptical view of market efficiency, other factors may be elicited as the driving forces of stock price fluctuations in the vicinity of M&A events. Taking up the widespread assumption that stock prices approximate a random walk over time, a random deviation from a share's fair price may become the trigger of a corporate transaction. The market may randomly set prices low enough for a company to become the target of a potentially lucrative takeover. On the other hand, overvaluation may drive companies to take advantage of this situation and engage in a share-exchange acquisition. In this case, price changes during M&A events may not reflect efficiency gains but simply constitute a market correction (Scherer, 1988). Based on the reasoning above, Scherer (1988) highlights the advantages of analyzing firm profits directly. This speaks in favor of the second approach to M&A research, based around the industrial organization literature, where firm performance is determined mainly through analyzing accounting data (Dickerson, Gibson, and Tsakalotos, 1997).

The body of literature exploring accounting data-based approaches is smaller yet growing (Dutta and Saadi, 2011). A variation of operating-performance measures is employed in the research, which finds varying results. Healy, Palepu, and Ruback (1992) investigate post-acquisition performance of U.S. mergers from 1979 to mid-1984, focusing on the 50 largest transactions. They find significantly increased asset productivity relative to industry averages, which results in improved operating cash flow returns. Effects are especially strong if the firms involved have high overlap. Further, they find that mergers do not induce cuts in long-term capital and that there is no downturn in R&D investment. Finally, they also relate these post-merger operating performance improvements with stock returns at the dates of merger announcements and find a strong positive correlation. This yields some evidence that price fluctuations at merger announcements reflect revaluations of equity of the firms involved based on expectations of economic improvement. These findings are consistent with evidence found by Heron and Lie (2002). Their main focus of study is the impact of the payment method on future operating performance. However, results yield insights for post-merger performance in general, based on a large sample of acquisitions from 1985 to 1997. Compared to industry peers, they find that acquiring firms demonstrate above-average operating performance before engaging in any corporate transactions. This superior performance does not cease after an acquisition event. In addition, firms that participate in M&A transactions exhibit significantly higher operating performance levels than peers with similar initial performance but who do not partake in any transactions. They do not find any channels of impact on future performance for the payment method.

On the other hand, some researchers find negative effects on operating performance: Clark and Ofek (1994) analyze takeovers of distressed firms. Their sample involves 38 such events. They find evidence that acquirors do not manage to successfully restructure the distressed firms that they acquire, based on several measures of combined post-merger performance. The success of the undertakings is positively related to the target's financial distress level but negatively related to the premium the acquiror pays in the transaction. Kruse, Park, Park, and Suzuki (2002) base their research on a set of manufacturing firms traded on the Tokyo Stock Exchange between 1969 and 1992. As part of their research, they also measure the post-merger performance of acquisitions where the target firm is distressed. Their results contrast those of Clark and Ofek (1994), as they do not find that rescue mergers lead to a lower level of post-merger performance in the long term. The main subject of Kruse, Park, Park, and Suzuki (2002) is the analysis of diversifying transactions. For mergers in general, they do find an insignificant positive effect on long-run performance. This effect is much stronger and significant if the merger is of a diversifying nature.

Ghosh (2001) notes that results reporting positive impacts on operating performance, compared to industry-medians, may be biased. This bias may stem from acquiring firms primarily engaging in M&A activity after periods of superior performance. Further, he finds that acquiring firms are generally larger than the industry median. Controlling for these circumstances, he finds no evidence of improved operating performance in periods after acquisition events. Additionally, the study investigates the impact of the means of payment on post-merger cash flow and finds a decrease for stock acquisitions. In contrast, cash flow increases if the transaction is executed using cash. This last result contrasts the evidence presented by Heron and Lie (2002). Malmendier, Opp, and Saidi (2016) also analyze outcomes for different payment methods by comparing cash- to stock-financed takeover bids. They focus on unsuccessful takeovers and find that targets of cash offers are subject to a positive revaluation after the failure, whereas for targets in stock offers, the valuation does not change compared to the pre-announcement level. To summarize: It seems that the main research results outlined above do not depend much on the approach employed. Neither accounting-based nor event studies on the financial market suggest a clear consensus on the long-term profitability of M&A activity for acquiring companies. However, event studies overall tend to paint a fairly negative picture. On the other hand, most studies suggest that target-shareholders profit from biddings on their company, while returns for acquirors seem to be somewhere around 0. Aggregate effects on market efficiency are likely balanced, according to Scherer (1988). The ambiguity of the financial profitability of M&A activity begs the question of the economic role of such corporate transactions. A large body of literature concerns this topic and its implications for regulation.

Andrade and Stafford (2004) investigate the economic role of mergers at the firm and industry level, by comparing mergers to internal corporate investment. They find that mergers can have an expansionary and a contractive effect in industry restructuring and that mergers often appear in clusters (on the industry level). Firms seem to use mergers to increase their capital base when growth prospects are good. Consequently, merger (and non-merger) investment is positively related to sales growth. A more challenging industry environment (often induced by shocks), leading to excess capacities, also creates increased within-industry merger activity, as this facilitates an overall capacity reduction. Further, they find that acquirers in these contracting industries are, on average, firms with lower capacity utilization and superior performance, apparent in their lower leverage and potentially better management. This yields some evidence that asset reallocation resulting from such mergers leads to increased industry efficiency. Andrade and Stafford (2004) observe such contractions through merger activity, especially in the '70s and '80s. At the same time, improved growth prospects in the '90s reverse this phenomenon, implying that mainly firms with high capacity utilization and profitability engaged in merger activity during this period. Mitchell and Mulherin (1996) specifically analyze takeovers in the context of industry restructurings in the '80s takeover wave. They find that industry shocks lead to subsequent restructuring activity and that, as Andrade and Stafford (2004) note, industry merger activity is often clustered in the domain of shocks. They infer that increased takeover activity during such periods may be a least-cost means of achieving such a restructuring. Specifically, they mention and collect evidence for shocks such as deregulation, financing innovations, and input cost changes. In response to some of the literature above finding zero- or even negative acquiror-returns in corporate takeovers, Mitchell and Mulherin (1996) note that if industry shocks induce takeover activity, acquisitions completed in this context should not necessarily be expected to increase post-merger performance. This argument seems reasonable, as some of the literature on post-merger performance may imply inconsistencies in managerial actions based on the premise that M&A activity is driven exclusively by value-maximizing behavior.

Regulatory changes do not only affect M&A activity in the sense of Mitchell and Mulherin (1996). Regulation in the form of competition policy may also determine the success of such transactions, i.e., based on antitrust laws. Aktas, Bodt, and Roll (2007) explore this field and ask why M&A transactions are subject to thorough regulation. Important regulators such as U.S. Federal Trade Commission members often highlight the potential risk of an increase in anti-competitive practices stemming from large mergers. Certainly, these authorities also acknowledge that potential efficiency gains from M&A may benefit consumers as well (Aktas, Bodt, and Roll, 2007). These potentially competition-decreasing effects of mergers and acquisitions are analyzed in M&A literature under the term *market power hypothesis*. As is outlined in Stigler (1964), horizontal mergers may lead to price hikes at a cost to consumers, as this may facilitate collusion with rival firms. However, a more recent study finds little empirical evidence of this: Fee and Thomas (2004) analyze horizontal mergers based on a large sample from 1980 to 1997. The resulting evidence does not imply increased monopolistic collusion of the firms involved. Eckbo and Wier (1985) and Pesendorfer (2003) note similar results. The study of 290 proposed acquisitions investigated by European regulators during the '90s by Aktas, Bodt, and Roll (2007) may even imply that European antitrust decisions have been focused on deterring foreign competitive pressure instead of protecting consumers during this period. Bradford (2020) notes that European regulatory practices in some areas, including antitrust policy, also tend to externalize to a global level.

Bansal, Finck, Hofmann, and Miller (2022) report 349 failed-deals with a value above USD 1 billion between 2013 and 2020 (based on the announcement date). Of those, 47 were unsuccessful due to antitrust or other regulatory reasons. However, the most frequent reason for failure in the sample is price disagreements (40 percent of the 349 failed deals, followed by 14 percent due to regulatory reasons). Overall, about 10 percent of large transactions are terminated in any given year. Note that failure in this context corresponds to deals that were never completed. Other literature determining the average success rate of M&A investments may rather be concerned with success in a financial or strategic sense. For example Hunt (1990) finds that 45 percent of mergers in his sample were deemed disappointing or even very unsuccessful, based on evaluations some years after the event.

The literature above primarily concerns corporate transactions' outcomes and consequences. The economic impact of M&A activity may empirically be less harmful to competition than theory might suggest, and it seems that such transactions might indeed increase industry efficiency under certain circumstances. Still, corporate transactions, especially from the point of view of acquirors, do not have an easy standing: Results for long-run financial profitability tend to be rather negative, and scrutiny from regulators is high. Nonetheless, according to Nishant (2021) the global volume of M&A transactions has reached a new record high of USD 5.8 trillion in 2021, topping the previous record of USD 4.55 trillion, dating back to 2007, which corresponds to a 64 percent increase compared to 2020. The evidence outlined above begs the question of why M&A activity is so widespread. Several researchers have been exploring this question, listing various motives. Of relevance in this context is the "hubris hypothesis of corporate takeovers" under which Roll (1986) explains the phenomenon of corporate takeovers in an environment where this does often not pay off financially. He argues that hubris is necessary for managers to engage continuously in bidding under such circumstances. Another frequent term is "synergy". Sirower (1997) defines synergy as *"increases in competitiveness and resulting cash flows beyond what the two companies are expected to accomplish independently"*. In their study, Bradley, Desai, and Kim (1988) analyze gains from corporate acquisitions in the context of synergy. They assume that a bidding firm that engages in a tender offer wants to utilize a profit opportunity resulting from changes in economic conditions. Under these new conditions, the combination with the target may create value through economies of scale, efficiency gains in management, exploitation of market power, and other mechanisms often summarized under synergy. Bradley, Desai, and Kim (1988) attribute wealth increases of the combined entity after a successful tender offer to synergy gains. Berkovitch and Narayanan (1993) show that in takeovers with positive gains, synergy is the primary motive for the transaction (using a sample of U.S. firms). At the same time, there is evidence of consistency with the hubris hypothesis. Similarly, Hodgkinson and Partington (2008) find evidence of bids being motivated by synergy in a U.K. sample while noting the existence of hubris as well. In a study of the determinants of merger success, Epstein (2005) notes that cost-cutting synergies and revenue growth synergies must be paid attention to in a merging process. However, Houston, James, and Ryngaert (2001) study bank mergers and suggest that the possibility of cutting costs is far more important than the opportunity of increasing revenues in the typical bank merger.

This Study's Approach and Objective Our analysis focuses explicitly on the implications of M&A activity on the sales figures of acquiror companies. Engaging in an accounting data-based approach, we study to what degree firms depend on sales incorporated from targets through M&A ventures. For inter-corporate equity transactions, which are not purely security-trading related, an acquiror firm, in principle, obtains a share of the target's revenues (and resulting incomes). As our data will show, most corporate transactions involve the entire stake of a target and, therefore, often result in the complete consolidation of the target with the acquiror. Therefore, the remaining entity's total sales are a combination of the sales stream of the companies involved. By linking financial data with M&A data, it is possible to split an acquiror's sales into acquisition-related- and remaining sales. This separation allows for the computation of several interesting statistics. Namely, we measure the cumulative share of sales from acquisition in an acquirors total sales growth and absolute sales. Based on these results, we can evaluate whether acquirors, on average, manage to sustain the (usually) increased sales level, which results from the incorporation of the target's sales. This approach allows us to assess the effects of M&A activity on corporate performance with respect to sales development.

3 Data and Methodology

To allow for a thorough empirical analysis, we gather a large sample, mainly using two data sources. On one side, we use the Securities Data Corporation (hereinafter "SDC ") Platinum Mergers & Acquisitions database hosted by Thomson Reuters. This database contains extensive information on M&A transactions in the United States and internationally. Naturally, this data source supplies mainly information on merger and acquisition events, listing the companies involved and the total value of the transaction, including a large number of relevant identifiers. On the other side, we use Standard and Poor's Compustat database, which provides financial information for the companies involved in relevant transactions. We mainly use the time series of those companies' sales, as this is the primary interest of study. Using comprehensive methods for merging, we link the data provided by the two sources. We describe below the databases and the methods used to match firms between the sources.

3.1 Thomson Reuters SDC Platinum Database

Thomson Reuters provides some insight into the scope and the contents of its SDC Platinum deals database in a factsheet published in 2015. The database contains more than 950'000 transaction events, including deals from 225 nations. The date range for US transactions begins in 1979, while the first international event is recorded for 1985. The data includes more than 282'000 transactions with targets located in the United States and more than 660'000 transactions involving non-US-targets. Thomson Reuters lists several data sources, including regulatory filings, corporate statements, and media outlets (Thomson Reuters, 2015). In a similar factsheet published in 1999, Thomson Reuters states that it uses *"Over 200 English and foreign language news sources, SEC filings and their international counterparts, trade publications, wires and proprietary surveys of investment banks, law firms and other advisors"* (Thomson Reuters, 1999). According to the document, all corporate transactions concerning a minimum of 5% of ownership of a company are included. Before 1992, only deals with a transaction value of $ 1 million or more are covered (and transactions that have their transaction value undisclosed). Both public and private transactions are covered. Among regular M&A activity, the database also includes leveraged buyouts, stake purchases, stock swaps, privatizations, bankruptcy liquidations, and other types of asset sales. In the same 1999 publication, Thomson Reuters states that the database contains more than 1400 "data elements," including target and acquiror profiles, financial advisor assignments and fees, synopsis and event history, deal status, and deal value. A 2017 publication (Thomson Reuters, 2017) lists all data identifiers available for transactions in the database and presents descriptions of those variables.

Thomson Reuters (2015) reports that at the point of data entry, more than 2'500 "pre-product quality control validations" take place and that the data is validated continuously. Although we found some inaccuracies during the data analysis, widespread usage and popularity of the data support the claim of a high level of quality: Bollaert and Delanghe (2015) find that more than 75 percent of papers published in the top four finance journals between 2000 and 2012 base their M&A data on SDC Platinum. Barrios and Wollmann (2022) note that the "league tables" (tables containing legal and advisory fees to measure performance in the investment banking sector) published by Thomson Reuters are the most widely cited in the industry. A comprehensive evaluation by Barnes, L. Harp, and Oler (2014) finds that SDC is less accurate than hand-collected samples but that accuracy improves over time. Nonetheless, they conclude that the data provided by SDC is reasonably accurate and complete and that biases (e.g., better coverage of firms that receive a lot of media attention) in the SDC database are not a major concern for academic research. Additionally, they note that M&A data acquisition through SDC is less costly than hand-collection, which also cannot ensure the total correctness of the information obtained.

SDC Dataset and Collection Workflow This paragraph outlines the SDC Platinum dataset used in this analysis and describes the workflow used to acquire the data. We select a total of 77 transaction identifiers from the database. The names of the identifiers collected are listed in Table 1. We select the full range of transactions that have their value disclosed and which have been completed. The sample contains the entire date range available in the database, up to the end of 2019 (earliest observations in 1979) (based on the identifier *DateAnnounced*). No geographical restrictions or restrictions on specific industries are imposed on the selection. The dataset contains a total of 406'890 observations concerning 172'550 distinct acquiror firms (identifier *AcquirorName*) and 334'594 distinct

Table 1: SDC Data Identifiers Collected from SDC Platinum Database

AcquirorHighTechIndustry	FirmValueMil	TargetCUSIP
AcquirorAdvisors	EquityValueMil	TargetEarningsPerShareLTMUS
AcquirorClosingPrice10DaysAfterAnnDate	FirmValueMil	TargetEBITDALTMMil
AcquirorClosingPrice180DaysAfterAnnDate	HistoryFileEvent	TargetImmediateParentCUSIP
AcquirorClosingPrice1DayAfterAnnDate	NetIncomeLastTwelveMonthsMil	TargetIndustrySector
AcquirorClosingPrice1WeekAfterAnnDate	PreTaxIncomeLastTwelveMonthsMil	TargetName
AcquirorCUSIP	PricePerShare	TargetNation
AcquirorImmediateParentCUSIP	RankDate	TargetNetAssetsMil
AcquirorIndustrySector	RankingValueincNetDebtofTargetMil	TargetNetSalesLTMMil
AcquirorName	RatioofOfferPricetoEPS	TargetPrimarySICCode
AcquirorNation	ReasonRelatedDescription	TargetPrimaryTickerSymbol
AcquirorPrimarySICCode	Status	TargetSharePrice1DayPriortoAnnouncement
AcquirorPrimaryTickerSymbol	Synopsis	TargetSharePrice1WeekPriortoAnnouncement
AcquirorShortBusinessDescription	TargetHighTechIndustry	TargetSharePrice4WeeksPriortoAnnouncement
AcquirorState	TargetAdvisors	TargetShortBusinessDescription
AcquirorTickerSymbol	TargetandAcquirorAdvisorFeesTotalMil	TargetState
AcquirorTotalFeesMil	TargetBookValuePerShareLTMUS	TargetTickerSymbol
AcquirorUltimateParentCUSIP	TargetClosingPrice180DaysAfterAnnDate	TargetTotalAssetsMil
AcquirorUltimateParentPrimaryTickerSymbol	TargetClosingPrice1DayAfterAnnDate	TargetUltimateParentCUSIP
AcquirorUltimateParentTickerSymbol	TargetClosingPrice1WeekAfterAnnDate	TargetUltimateParentPrimaryTickerSymbol
DateAnnounced	TargetCommonDividendsFourYearsPriorMil	TargetUltimateParentTickerSymbol
DateEffective	TargetCommonDividendsOneYearPriorMil	ValueofTransactionMil
DateEffectiveUnconditional	TargetCommonDividendsThreeYearsPriorMil	XofSharesAcq
DateWithdrawn	TargetCommonDividendsTwoYearsPriorMil	XownedAfterTransaction
EBITLastTwelveMonthsMil	TargetCommonEquityMil	Xsought
EnterpriseValueMil	TargetCompanyDateofFin	

targets (*TargetName*). 42'842 acquirors are located in the United States. For the targets, this number is 99'854. Based on four-digit SIC-codes, the acquirors in the sample are active in 1'011 distinct primary industries, whereas targets are active in 1014 distinct primary industries (identifiers *AcquirorPrimarySICCode* and *TargetPrimarySICCode* in Table 1). The sample includes acquisitions where less than 100 percent of the shares are transferred, which is the case for at least 46 percent of the total observations (for 9.7 percent of the total observations, the value for shares transferred is missing). Figure 1 shows the distribution of this identifier, denoted *XofSharesAcq* in Table 1. Evidently, in most transactions, 100 percent of the target shares are acquired, followed by minimal stakes below 50 percent and transactions which transfer around 50 percent of the shares. The mean is 64.5 percent, and the median is 95 percent. Another key identifier for our analysis is the value of transaction (*ValueofTransactionMil* in Table 1), which attributes a value in million USD to each transaction. This value is independent of the method of payment, which is not relevant to this analysis. As the sample only contains transactions where the value is disclosed and known, there are no missing values. Transaction values range from as little as USD 1000, up to USD 210 billion, with a mean of USD 180.3 million and a median of USD 13 million.[1] As can be seen in Figure 1, the logarithmic value of transaction is approximately normally distributed. 14'530 deals have a transaction value of USD 1 billion or more, while 58'575

[1]Note that throughout this analysis, we make use of nominal values exclusively.

have a transaction value below USD 1 million. For analysis purposes, we assign every transaction in the dataset an ID (see *Aggregating Matches* in Section 3.3 for details on their use).

An illustrative selection of observations in the SDC dataset is depicted in Table 2. In addition to the value of transactions, Table 2 shows the data identifiers *AcquirorName, TargetName, AcquirorCUSIP, TargetCUSIP, DateEffective, XofSharesAcq* (see Table 1), for the highest value transactions. The ranking in Table 2 excludes stock buybacks, spin-offs, and special purpose entities.

Table 2: SDC Highest Value Transactions

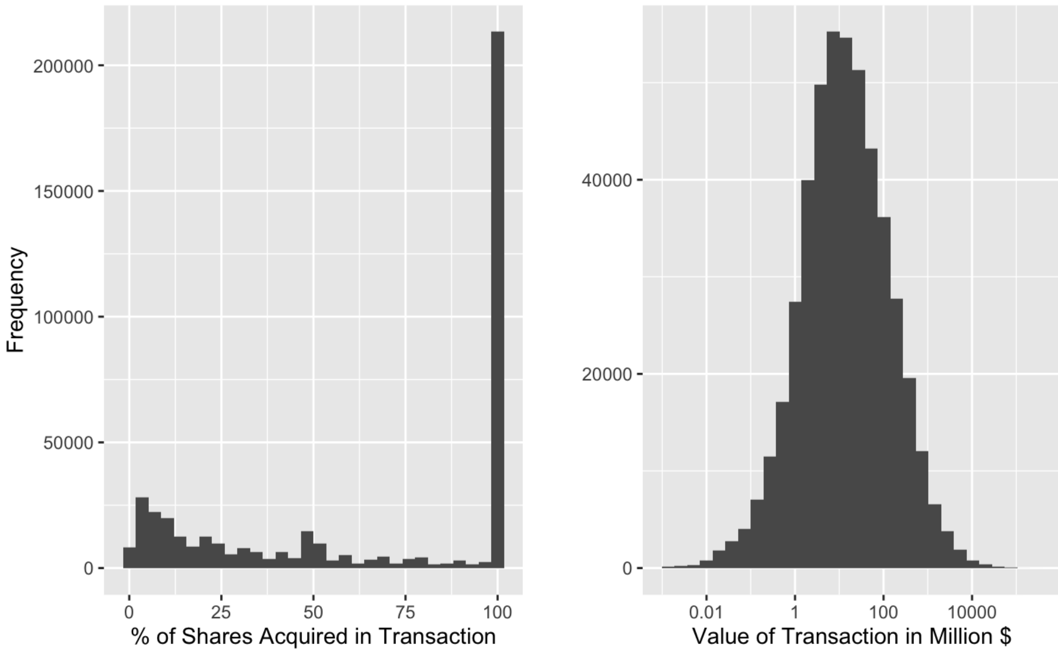
AcquirorName	TargetName	DateEffective	Value Mil.$	%SharesAcq	AcquirorCUSIP	TargetCUSIP
Vodafone AirTouch PLC	Mannesmann AG	2000-06-19	202'785	100	92857T	563775
America Online Inc	Time Warner	2001-01-12	164'747	100	02364J	887315
Anheuser-Busch Inbev SA/NV	SABMiller PLC	2016-10-04	101'475	100	03500W	78572M
Pfizer Inc	Warner-Lambert Co	2000-06-19	89'555	100	717081	934488
United Technologies Corp	Raytheon Co	2020-04-03	86'831	100	913017	755111

For the purpose of data exploration, it is also interesting to look at deal volume over time. Figure 2 shows the development of yearly transaction volumes. An upward trend is visible, with steep drops in the wake of financial crises, namely during the early 2000s recession and the great recession after 2007. After this second more significant recession, the recovery of transaction volume seems slower and less stable. However, the decline in the most recent year (2019) might also derive from missing observations, as new transactions may not be entered into the database immediately or have not been finalized. As Barnes, L. Harp, and Oler (2014) note in their study of SDC Platinum, data for the eighties may also lack completeness, which may be partially responsible for the low figures during this time.

3.2 Standard and Poor's Compustat Database

Our second data source is Compustat. It covers all publicly traded firms across all sectors of the U.S. economy between 1955 and 2016. This data set provides the necessary financial information, namely sales figures, which we will later use to analyze sales development for those companies involved in M&A transactions. Compustat is a comprehensive database covering market and corporate financial data published by Standard and Poor's. The date range begins in 1950, and several thousand firms, both US-based and international,

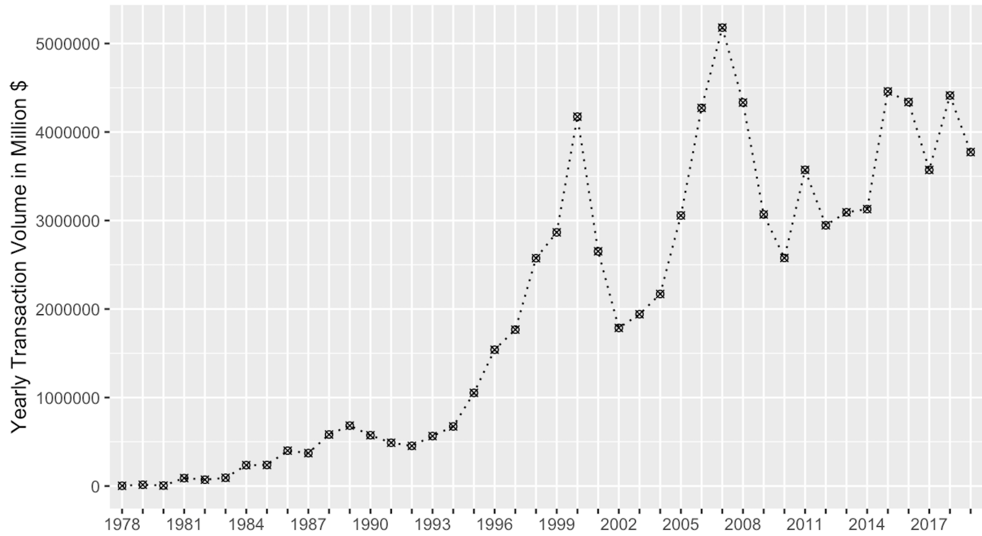
Figure 1: Histograms of % Shares Acquired and Logarithm of Value of Transactions in Mil. USD



are covered (Refinitv, 2022). Compustat is widely used in academic research: Ulbricht and Weiner (2005) find that 95 percent of published papers that require accounting data base their research on Compustat (based on publications in five journals between 1995 and 2004). Only 5 percent depend on a competitor, even though their study finds few differences between Compustat and one of its competitors, Worldscope. In their analysis Ulbricht and Weiner (2005) report that Compustat offers 1'307 data identifiers (descriptive variables).

Compustat Dataset and Collection Workflow This paragraph briefly outlines the specific Compustat datasets used in this analysis. We mainly use two datasets from Compustat. One set has financial information on a large set of companies, while the other only contains companies that no longer exist, where some disappearances could be due to M&A transactions. The datasets consist of 10 data identifiers, which are listed in Table 3. Figure 3 shows the number of observations for each year in the dataset containing firm-level financial information. The data set approximately replicates the one used in De Loecker, Eeckhout, and Unger (2020). It covers all publicly traded firms across all sectors of the U.S. economy between 1955 and 2016. They note that publicly traded firms are only a small sample of the total number of firms in the economy, although, according to Davis,

Figure 2: SDC Aggregated Transaction Volume by Year in Million USD

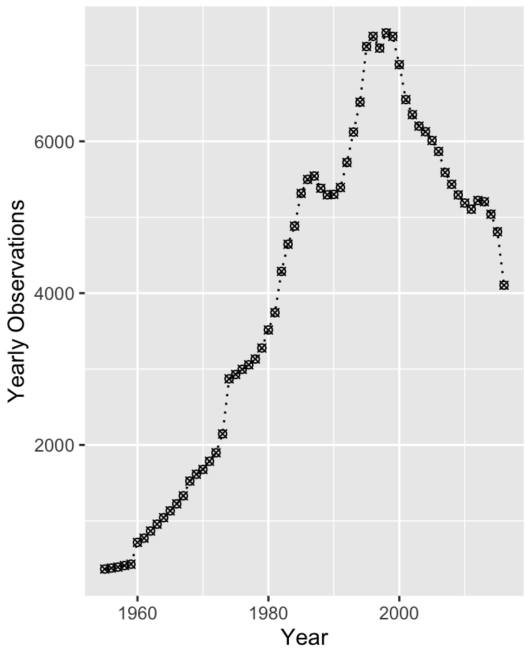


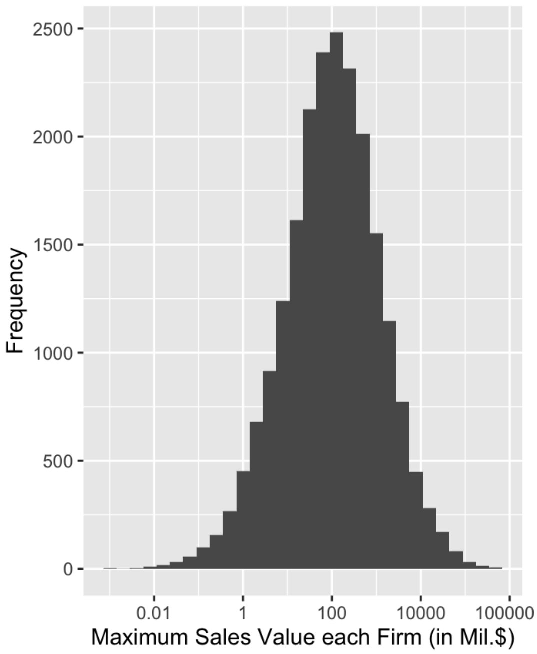
Haltiwanger, Jarmin, Miranda, Foote, and Nagypal (2006), in the year 2000, they account for 29 percent of private (non-farm) employment in the U.S. De Loecker, Eeckhout, and Unger (2020) further observe that listed firms are not only older and bigger but that they also tend to be more capital- and skill-intensive, and represent an industry mix which differs from the economy as a whole. In conclusion, the Compustat data set does not fully represent the entire private sector. Implications of selection biases for the results of this analysis are discussed in Section 4.1. The second data set, based on Compustat, identifies delisted firms. It covers the same date range but only includes firms that disappear during the period (i.e., the time series of their observations ends before the last period). In consequence, the last year with observations is 2015.

Table 3: Compustat Data Identifiers

conm	Company name (capitalized)	*conml*	Company name
cusip	6 digit CUSIP	*gvkey*	Global company key
ind2d	2 digit industry code	*ind3d*	3 digit industry code
ind4d	4 digit industry code	*naics*	NAICS industry code
sale	Total sales	*year*	Year of observation

Figure 3: Number of Observations in the Compustat-Dataset per Year (Left), Distribution of the Maximum Value for Sales Reported per Firm (Right)





The first Compustat-data set contains financial data of 21'367 distinct firms (247'845 total observations). Based on the industry code identifier *ind4d* in Table 3, those are active in 409 different industries (compared to 1'011 industries in SDC). All 62 years of the date range are reflected in the data, with the minimum being 365 observations in 1955 and the maximum being 7429 observations in 1998 (see Figure 3). The largest value for *sale* in the data is recorded in 2014 for "Walmart Inc," reporting sales of USD 483.521 billion. Figure 3 illustrates the distribution of the highest value for sales which the firms in the sample report. The mean of all sales observations is USD 1.537 billion, while the median is much lower at USD 92.751 million. The second Compustat-data set describes 27'013 delisted firms. For these companies, the identifiers *year* references the last year data for the company was observed before its delisting. The most common years for delisting in the sample are 1997 to 2001, with each around 1'000 such events (for a complete histogram, see Figure 9 in Appendix B).

3.3 Linking SDC-Acquirors to Compustat-Companies

We identify which merger transactions concern companies included in the Compustat data. For that, we merge the SDC dataset with the Compustat datasets. Several methods were used to match firms between the datasets outlined above. While the source datasets are extensive, it was challenging to find a large enough number of matches to achieve an adequate sample size for the final analysis. This process aims to find as many companies as possible which are present in both datasets, to merge the data identifiers available in each set. Fortunately, all of our data sets have unique CUSIP identifiers,[2] which are suitable for matching and which form the main approach in the linking process. However, due to missing CUSIP identifiers and other potential inconsistencies, some companies were also matched by names, by ticker symbols, and by comparing URL results from web searches using company names. The procedures were executed using the statistical-computing language *R*. The codes used are in Appendix C.1, *Matching SDC and Compustat*. We describe the methods outlined above concerning the matching of SDC-acquirors (see *AcquirorName* in Table 1) to Compustat-companies (see *conml* in Table 3).

Matching Using CUSIP-Identifiers The CUSIP is an American standardized identifier assigned to firms and their financial securities. The name derives from the "Committee on Uniform Security Identification Procedures." A CUSIP is a six-, eight-, or nine-character identification code. The first six digits serve as a unique identifier, sufficient for the identification of a specific company. Digits seven and eight identify different security issues of the company defined by digits one to six, while digit nine is computed as a checksum from digits one to eight, yielding information about the CUSIPs "correctness" (CUSIP Global Services, 2022). In the SDC dataset, both the acquiror and the target are assigned a CUSIP. Additionally, CUSIPs for their immediate- and ultimate parents are also available. Compustat also has CUSIPs for almost all observations. In a first step, the SDC acquiror company's primary CUSIP was matched to CUSIPs in the Compustat financial dataset. As SDC uses only 6-digit CUSIPs and Compustat uses the full 9-digits, we trim the identifiers in Compustat by selecting only the first six digits. A data frame that holds all SDC data identifiers and the identifiers *conm, conml, gvkey,* and *year* from Compustat (see Table 3) results, containing 45'756 deals of 10'256 distinct acquirors. This means that 10'256 firms from Compustat were assigned at least one of their transactions in SDC, on the basis that the acquiror firm in SDC has the same (primary) CUSIP as the respective

[2] CUSIP is an abbreviation for the Committee on Uniform Security Identification Procedures, which is the issuer of the identifiers. See *Matching Using CUSIP-Identifiers* for details.

firm in Compustat (hence they are the same entity). The same procedure is repeated using SDC's *ImmediateParentCUSIP* and *UltimateParentCUSIP*, matching to the same single CUSIP item in Compustat both times. This results in 9'877 distinct acquirors in the new data frame for *ImmediateParentCUSIP* and 9'612 for *UltimateParentCUSIP* (see Table 4 for an overview of the numbers).[3] Note that we do not remove matched companies from the source data after each dataset merger. Most of the matches above overlap. Repeated entries are removed in a later step. Checking the merged data frames mentioned above, it turns out that some matches are missing, even though CUSIPs concerning the same entity are available in both datasets. The root of the problem is found in the updating of CUSIPs over time: While CUSIPs change over time, especially due to merger activity, SDC uses CUSIPs at the time of the transaction, while Compustat uses current, updated CUSIPs for prior years. Fortunately, this problem can be solved by using a linking table on the SDC-CUSIPs, which can assign corresponding updated CUSIPs to some of the outdated ones. The linking table has data identifiers containing old CUSIPs and an identifier with the updated CUSIP; hence, assigning updated identifiers to SDC works similarly to merging the two data sources outlined above. Finally, the merging process between SDC and Compustat is repeated using the updated CUSIPs in SDC, yielding 9'428 distinct acquirors in the new data frame. The following methods attempt to match acquirors for cases where CUSIP matching does not work. For example, this is the case when entries do not have a CUSIP assigned at all; or when the CUSIP has changed, but the relevant, updated CUSIP is missing.

Matching Using Company Names While names between SDC and Compustat are not standardized, for many firms, the names correspond and are identical. This method simply creates a merged data frame by matching the SDC identifier *AcquirorName* with the Compustat identifier *conml*. To avoid missing matches due to minor differences in the names, special characters and spaces are removed, and all strings are converted to a capitalized format (this is especially useful for endings, as dots after abbreviations, such as *Inc.* are used inconsistently). This method yields 39'685 observations of 9'057 distinct acquirors in the merged data frame (again noting that firms matched through CUSIP are

[3] Cowgill, Prat, and Valletti (2022) merge Compustat and SDC data based on CUSIP identifiers as well. Though their objective is different, comparing the approaches shows that they yield a similar number of matches.

not removed). An example where name-matching yields a result but CUSIPs do not is the case of “Vodafone Group PLC.“ As can be seen in Table 6, the SDC acquiror “Vodafone AirTouch PLC“ (*AcquirorName*) is correctly linked to the Compustat company “Vodafone Group PLC.“ However, SDC also lists many of the company’s transactions with “Vodafone Group Plc“ for the acquiror name. No CUSIP data is available for “Vodafone Group Plc“ in SDC. Tough, if we convert the *conml* and the *AcquirorName* with the simple steps above, both strings read “VODAFONEGROUPPLC,“ and the two entries match by name. We also considered merging the data using “fuzzy strings,“ i.e., not only matching names which were precisely the same but all names which are sufficiently similar, where string similarity is defined as the Levenshtein distance. This approach was unsuccessful mainly because it is difficult to define a clear cut-off distance that would yield a reasonable amount of matches without including large numbers of false positives.

Matching Using Ticker Symbols Since ticker symbols are available in SDC and Compustat, these provide another possibility to merge the datasets. Compustat has just one identifier for the ticker (see *tic* in Table 3), whereas SDC also provides the ultimate parent’s ticker (see *AcquirorPrimaryTickerSymbol* and *AcquirorUltimateParentPrimaryTickerSymbol* in Table 1). Similarly to the CUSIP approach, it turns out that SDC ticker symbols are not updated. However, with the same linking table used in the CUSIP approach, it is easily possible to assign updated tickers to the SDC data as well. Once all data identifiers are up to date, the procedure works just as in the CUSIP case: Three merged data frames are created, one using *AcquirorPrimaryTickerSymbol*, one using *AcquirorUltimateParentPrimaryTickerSymbol* and one using the updated ticker created with the linking table. Table 4 summarises the resulting numbers of matches in the merged data set. Again, matched firms are not removed from the datasets before the next approach. Unfortunately, ticker symbols are only unique to the exchange where the security is traded. A surprisingly large amount of identical ticker symbols are associated with different firms on different exchanges. For example, “AO Smith Corp“ and “Advanced Ocular Systems Ltd“ both use the ticker “AOS.“ While “Advanced Ocular Systems Ltd“ is traded on the Australian Securities Exchange ASX, “AO Smith Corp“ is traded on the New York Stock Exchange NYSE. With the procedure described above, the two companies are incorrectly matched.

To distinguish between correct and incorrect matches, further selection is needed. We use an URL-scraping approach to select correct matches. This approach is explained in more detail in the next paragraph.

Matching Using URL-Results To remove false positives created through merging approaches that do not necessarily yield only correct results (namely matching with ticker symbols) and to find potential matches missed by all previous methods, we use URL results comparison as a final attempt to maximize the sample size. This works as follows: Using a script, we engage in web searches using a search engine for all companies in all available data sets. The search results for each company are stored as a list of URLs. The next step counts the number of common URLs between the two company names. Based on this number, we can later evaluate whether both names apply to the same entity or not. This approach exploits the powerful search algorithms modern search engines apply to identify similar expressions. For example, URL comparison also recognizes name changes and is hence able to match companies with completely different names, even when other identifiers, such as CUSIPs, are missing. Specifically, we use a Python script and the Selenium package (Baiju Muthukadan, 2018) to use Chromedriver (Chromium Project, 2022) to scrape URL results for each company using the Microsoft Bing search engine. The procedure follows the matching approach implemented in Autor, Dorn, Hanson, Pisano, and Shu (2020). The full code is available in Appendix C.2, *URL-Scraping*. Once every company is assigned a set of search-result-URLs (usually between 5 and 10 URLs), those can be used in two ways: For companies that already have a potential match, e.g., from matching with tickers, the URLs can be used to determine, whether this assignment is correct, or a false positive. On the other side, the URL results can also be used to find new matches which have potentially not been detected in any of the steps above.

To use the URLs to control for false positives in existing matches, the results for both companies are compared by counting the common URLs. As the search results are stored in lists, the common URLs can be found by simply intersecting the two companies' result lists and counting the new list's length. This length describes the URL-similarity and is assigned to each pair of a *conml* and *AcquirorName*. This step takes place in R and is computed for all matches. The code can be found in Appendix C.1, *Aggregating Matches*.

To find new matches, an additional step is necessary. Although this is computationally intensive, we do this by creating a matrix that has the lists of all Compustat URL results in the rows and the lists of all SDC URL results in the columns. Through iteration, list intersections for all the elements in the matrix are computed. Matrix elements are then assigned the lengths of the intersected list (URL similarity). In a second iteration, company names that have at least one URL in common are paired together. It is now an easy task to assign the relevant data identifiers from both SDC and Compustat to each pair. Together with matches from all methods that may contain false positives, we filter these potential matches by imposing an appropriate threshold for minimum URL similarity in a subsequent step. This process is outlined in *Aggregating Matches.* Matrix-iteration steps are executed using Python (see Appendix C.2, *Matrix Iterations (URL-Matching)* for the full codes).

The following example illustrates the functionality of this URL-scraping procedure: In 2001, "AmeriSource Corp" and "Bergen Brunswig Corp"completed their merger and formed the new entity "AmerisourceBergen Corporation" (AmerisourceBergen, 2001), which, in our data, engages in more than 20 acquisitions after its conception (the data also contains the initial merger). SDC's *AcquirorName* shows this name change resulting from the merger: After the deal, the acquiror name changes to "AmerisourceBergen Corp," whereas Compustat's entry for the company reads "AmeriSource Corp" (*conml*). While some CUSIPs are available, none of them match in this case. All transactions concerning this entity are exclusively assigned using URLs. The search engine that the URL-scraper utilizes yields similar results for both company names, as they are connected and reference similar information. To be specific, 4 URLs appear both in the search for "AmeriSource Corp" and for "AmerisourceBergen Corp." Hence, URL similarity is 4, and a match results.

The top row of Table 4 shows the number of (non-exclusive) transactions each matching method yields, with the number of distinct firms in these matches below. The third row of Table 4 shows the number of new, exclusive transactions per method (transactions which are not matched by any other method) and how many distinct acquiror firms these transactions concern. Note that these firms are not mutually exclusive: Not all of a Compustat acquiror's transactions are necessarily assigned to them with the same method. Consequently, the sum of the firm counts in the bottom column of Table 4 exceeds the total number of firms matched across all methods (23'310 vs. 14'291). In Table 4, the codes *CUS*, and *Tic* abbreviate CUSIP- and ticker-matches. The prefix *P* stands for *Primary*, while *IP* and *UP* denote *Immediate Parent* and *Ultimate Parent* methods. *N* marks methods based on updated identifiers from the linking table, such as *New CUSIP*. Note also that the resulting matches from the ticker- and URL methods naturally still contain many false positives at this point, as ticker symbols are not unique, and because at this point, any two companies with at least one URL result in common are considered a match. The next paragraph concerns the aggregation of the matches resulting from the methods outlined above and the removal of such false positives.

Table 4: Number of Distinct Firm and Matched Transactions by Matching-Method

	P CUS	**N CUS**	**IP CUS**	**UP CUS**	**Name**	**P Tic**	**UP Tic**	**N Tic**	**URLs**
Deals	45'756	50'459	51'243	52'432	39'685	45'360	52'261	29'293	46'489
Firms	10'256	9'428	9'877	9'612	9'057	6'237	6'046	4'997	7'374
New Deals	45'756	10'101	8'189	1'863	3'048	14'144	4'479	586	17'351
Firms	10'256	2'120	2'791	486	972	2'291	1'038	147	3'209

Aggregating Matches All of the methods described above yield a merged data frame, matching acquiror names from the SDC dataset to acquiror names in the Compustat dataset. The succeeding step is to consolidate those data frames. By design, all of the data frames created in the procedures above, have exactly the same columns. Hence, to attain the consolidated data frame we simply stack the data frames on top of each other, in the order they were created. This order corresponds to the columns of Table 4 from left to right, beginning with the matches based on primary CUSIPs. As mentioned above, we do not delete any firms from the dataset after each procedure, hence, the consolidated dataset contains several duplicated entries. We remove those by using the IDs assigned to each transaction in Section 3.1 and deleting repeated IDs, starting at the top. This way, if a transaction is matched to a Compustat firm in more than one procedure, methods using identifiers such as CUSIP and tickers are preferred, before depending on URL matches.[4]
Next to removing duplicates, it is also necessary to set a threshold based on the URL-similarity, in order to omit false positives. So far, all potential matches based on tickers or

[4]Specifically, following the columns of Table 4, the order will be: Primary CUSIPs, updated CUSIPs, immediate parent CUSIPs, ultimate parent CUSIPs, exact names, primary tickers, parent tickers, updated tickers, URL matches.

URL-comparisons, are included. Now we impose stricter restrictions on this similarity, to remove false positives. We decide to select only matches with 3 or more identical URLs.[5] A dataset results, which contains 12'410 distinct acquirors (based on *conml*) engaged in 70'280 unique transactions (based on transaction IDs assigned to SDC).

At this point, we also remove buybacks and other within-company transactions, as those are not relevant to the analysis. Such transactions do not lead to the incorporation of any new sales streams for the acquiror firm. This is accomplished by removing any entries from the matched data frame, where one of the acquiror's CUSIPs is identical to one of the target's CUSIPs. Further we delete entries where both of the firms involved have the exact same name. The remaining matched data frame holds 61'452 transactions, concerning 11'711 distinct acquirors. To recap on the different matching methods, Table 5 shows the results of Table 4 for the filtered data frame.

Table 5: Distinct Firms and New Transactions By Matching-Method

	P CUS	**N CUS**	**IP CUS**	**UP CUS**	**Name**	**P Tic**	**UP Tic**	**N Tic**	**URLs**
New Deals	39'889	8'699	7'370	1654	2'686	340	48	17	749
Firms	9'543	1'958	2'663	448	905	70	28	6	298

Table 6 and Table 7 illustrate the contents of this data frame containing the cleaned aggregate of all matches. Table 6, recreates the ranking in Table 2, by sorting the data frame by *Value Mil.$* and adding some relevant identifiers resulting from the matching process. If we instead sort the acquisitions of a given acquiror by *DateEffective*, we can look at a time line of this companies M&A activity. Table 7 shows the acquisitions of "Advanced Micro Devices Inc" (abbreviated to AMD Inc for readability), using the same identifiers as in Table 6. The dataset records 6 acquisitions for AMD.

With the current dataset, we are able to keep track of an acquirors acquisitions. Having linked the acquirors to companies in Compustat, we are also able to assign them relevant financial information, namely their sales figures through the years (see Section 3.5). However, one variable which is crucial to the analysis is missing still: Only few targets have data concerning their own sales numbers available in the data set. Although SDC offers a data identifier specifically for the targets sales, for 298'808 of 406'890 total transactions,

[5] Autor, Dorn, Hanson, Pisano, and Shu (2020) set this threshold at 2. However, they only scrape the top five URL-results per name, while we do not restrict this number and save all top results. Therefore we have more results per name on average and set this threshold slightly higher.

these values are missing. In the merged dataset, this translates to 40'938 out of 61'452 missing (67 percent). One approach to decreasing this number, is to link the targets with the Compustat dataset as well. This process is outlined in Section 3.4.

Table 6: Highest Value Transactions in the Merged Dataset

gvkey	conml	Method	AcquirorName	TargetName	DateEffective	Value Mil.$	%SharesAcq
14894	Vodafone Group PLC	NewCUSIP	Vodafone AirTouch PLC	Mannesmann AG	2000-06-19	202'785	100
25056	Time Warner Inc	NewCUSIP	America Online Inc	Time Warner	2001-01-12	164'747	100
241637	Anheuser-Busch InBev SA/NV	Name	Anheuser-Busch Inbev SA/NV	SABMiller PLC	2016-10-04	101'475	100
8530	Pfizer Inc	CUSIP	Pfizer Inc	Warner-Lambert Co	2000-06-19	89'555	100
10983	Raytheon Technologies Corp	NewCUSIP	United Technologies Corp	Raytheon Co	2020-04-03	86'831	100

Table 7: Acquisitions of "Advanced Micro Devices Inc"

gvkey	conml	Method	AcquirorName	TargetName	DateEffective	Value Mil.$	%SharesAcq
1161	AMD Inc	CUSIP	AMD Inc	Monolithic Memories Inc	1987-08-13	441	100
1161	AMD Inc	CUSIP	AMD Inc	NexGen Inc	1996-01-17	756	100
1161	AMD Inc	CUSIP	AMD Inc	Alchemy Semiconductor Inc	2002-02-19	50	100
1161	AMD Inc	ImmediateParentCUSIP	AMD Inc	Fujitsu Ltd-Flash Memory Bus	2003-07-14	1'200	100
1161	AMD Inc	CUSIP	AMD Inc	ATI Technologies Inc	2006-10-25	4'836	100
1161	AMD Inc	CUSIP	AMD Inc	SeaMicro Inc	2012-03-23	334	100

3.4 Linking SDC-Targets to Compustat-Companies

In order to assign sales values from Compustat to SDC-target-companies, we use the same procedure outlined above. Like the acquirors, we merge Compustat- and SDC-data using the following sequence of attributes: Primary CUSIPs, updated CUSIPs, immediate parent CUSIPs, ultimate parent CUSIPs, exact names, primary tickers, parent tickers, updated tickers, URL results. Here, we use the second Compustat dataset, containing only delisted firms. Many of those ceased due to corporate takeovers. For this reason, we match SDC targets to this set of exited firms in the first step. This Compustat dataset is similar to the one introduced for the methods above but contains only company names and other relevant firm identifiers instead of financial data. This matching sequence aims to attribute gvkeys and Compustat company names to SDC targets. This way, it is easy to assign additional information from Compustat to those targets in subsequent procedures. We use the same methods as in Section 3.3 and create an aggregated, matched data frame by stacking the resulting matches in the same manner. Instead of an acquiror and its acquisitions, this data frame yields targets and companies they were bought by. While many targets disappear after one transaction (as they are incorporated fully into the acquiror), the dataset also records smaller-stake transactions, and other types of transactions, where the target remains as an entity. This data frame contains 19'932 distinct targets (based on *conml*) appearing in 41'322 distinct deals.[6] We briefly illustrate the contents of this data frame using transactions involving "3Com Corp" (3Com). Table 8 shows the recorded transactions for the company. We see that "Hewlett-Packard Co" (HP) acquired a small stake of 5 percent of the company in 1989. In 1990, 3Com bought back some of its outstanding stock,[7] before HP acquired all of 3Com in 2010. Consequently, 3Com disappears as an entity, and there are no further records for this target.

Table 8: Acquirors of "3Com Corp"

gvkey	conml	Method	TargetName	AcquirorName	DateEffective	Value Mil.$	%SharesAcq
10553	3Com Corp	CUSIP	3Com Corp	Hewlett-Packard Co	1989-12-07	27	5.00
10553	3Com Corp	CUSIP	3Com Corp	3Com Corp	1990-04-09	60	11.49
10553	3Com Corp	CUSIP	3Com Corp	Hewlett-Packard Co	2010-04-12	3183	100.00

While this data frame yields some interesting insights, the purpose of the merging steps outlined above is mainly to pair SDC-targets with their gvkey. Using only the data identifiers *TargetName* and *gvkey* of this data frame, we join it with the final merged data frame containing the acquiror-matches. Specifically, we use a merging algorithm, which adds the identifiers, namely the gvkeys in the target data frame, to the corresponding entry in the acquiror data frame (acquiror matches), based on the common identifier *TargetName*. Instead of deleting entries with no match, this algorithm simply assigns a missing value for this target's gvkey. Consequently, the number of entries in the acquiror data frame remains unchanged, but 7'428 of the targets are now assigned a gvkey. We focus on this new data frame, resulting from adding the target gvkeys to the acquiror data frame. Unchanged in size, it contains 11'711 distinct acquirors (based on *conml*) engaged in 61'452 unique transactions. For 8'608 transactions, in addition to the acquiror, the target is now also assigned a gvkey. At this point, we can assign sales observations from Compustat to each acquiror in this M&A dataset, which is the main interest of study. Additionally, it is possible to assign such sales values to those targets which have been attributed a gvkey. The procedure employed to assign these values is the topic of Section 3.5.

[6] For comparison: The SDC data lists 334'594 unique targets, and our data frame of linked acquirors contains transactions concerning 58'022 distinct targets.

[7] Buybacks and similar transactions are not excluded in this data frame containing matched targets. At this point, it is enough to do this for the acquirors, which constitute the primary data set.

3.5 Assigning Sales Figures to Acquirors and Targets

As mentioned earlier, we need a dataset that tracks the sales of acquiring companies over time and assigns them their targets. For the target, we also need sales information, though only for the year it is acquired. This will allow for a split of acquiror revenues into internal growth and growth through acquisitions.

We begin by assigning targets a sales value for the year in which they are acquired. Some companies already have this information (see *TargetNetSalesLTMMil* in SDC); however, as mentioned above, for 67 percent of transactions, this value is missing. There are two approaches to fill this gap. If the target is listed in our Compustat financial data, it is possible to assign a sales value from there, using the gvkey assigned in Section 3.4. The other option is to predict missing sales values based on a statistical model fitted to the known values, either in SDC or Compustat. Consequently, we continue by selecting only transactions from our data frame containing the matched acquirors, where it is possible to assign a sales value from one of the above sources. Hence, targets must either have a non-missing gvkey, a non-missing sales value from SDC (*TargetNetSalesLTMMil*), or they must allow for the prediction of a sales value.

In the first step, we assign a Compustat-sales observation to the targets with a gvkey by joining this data frame with the Compustat data set containing sales values. For each of those targets, this new data frame now contains all corresponding sales observations from Compustat once for every transaction this company is involved in. Naturally, this data frame is large, with more than 200'000 rows. To illustrate the contents of this data frame, Table 9 shows a selection of its identifiers for the target "3Com Corp" (3Com). To avoid confusion, some identifiers were renamed from their original names in SDC and Compustat, and some new identifiers were created in the procedure of compiling this set. Specifically: *gvkeyT* is the targets gvkey, *YEARan* is the year in which the transaction was announced, based on SDC's *DateAnnounced*, *yearS* is the year of the sales observation based on Compustat, *saleMil$* are the target's sales in million USD based on Compustat's *sale* and, most importantly, *yearDiff* is the (absolute) year-difference between the year before *YEARan* (year of announcement -1) and *yearS* (year of the sales observation from Compustat). In this case, SDC also lists a sales value in the column *S.saleMil$*.

In 2009, 3Com was acquired by "HP Inc" for 3182.65 billion USD. Before 3Com delists

Table 9: Joint Data Frame: "3Com Corp" with assigned Compustat Sales Observations

gvkey	conml	Method	AcquirorName	TargetName	gvkeyT	yearS	saleMil$	YEARan	yearDiff	Val Mil.$	S.saleMil$
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	1982	4.75	2009	26	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	1983	16.65	2009	25	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	1984	46.32	2009	24	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	1985	63.99	2009	23	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	1986	110.38	2009	22	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	1987	251.95	2009	21	3182.65	1264.83
	...		...		...		...		...		...
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	2003	698.88	2009	5	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	2004	651.24	2009	4	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	2005	794.81	2009	3	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	2006	1267.48	2009	2	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	2007	1294.88	2009	1	3182.65	1264.83
5606	HP Inc	NewCUSIP	Hewlett Packard Co	3Com Corp	10553	2008	1316.98	2009	0	3182.65	1264.83

following its acquisition, we see one last observation of its sales in 2008 (USD 1316.98 billion), while the first observation is from 1982 (USD 4.75 million). Since the development of the target's sales before the transaction is not relevant to this analysis, we need to select only the value of its sales for the year of the deal. For this purpose, we use *yearDiff*. In a subsequent step, we select only one observation for the target's sales, namely the one closest to the transaction's announcement year. We choose *YearAnnounced -1* to compute this difference, as from the investigation of several examples, it seems that SDC tends to note target net sales at the announcement date. We speculate that at this point, the available sales data (e.g., in firm reports and media outlets) most likely stems from the target's business report of the year prior to the announcement.[8] The minimum value for *yearDiff* is not always 0 as there may be delays between the year of the announcement and the year of the acquisition, where Compustat observations usually end if the target is fully consolidated with its new parent. To accommodate such variability, we select the lowest values of *yearDiff* not exceeding 2. If the difference in years between the SDC event and the Compustat observations is 3 or larger, we do not assign a Compustat value. To summarize: After assigning Compustat sales values where possible, each target in our dataset is now either assigned a relevant sales value for the year of the transaction from Compustat, a *TargetNetSalesLTMMil* value from SDC, or it has the necessary characteristics for a sales value to be estimated.[9] Of course, a target may also be assigned a value from each of the

[8] Table 9 shows that in this case, there are no Compustat sales observations, which exactly match the figure noted by SDC. We discuss such discrepancies in detail in the paragraph *Inconsistencies and Discrepancies in the Sales Data*.

[9] These characteristics are outlined in subsequent paragraphs of this subsection, see *Predicting Sales Values: SDC Based*, and *Predicting Sales Values: Compustat Based*.

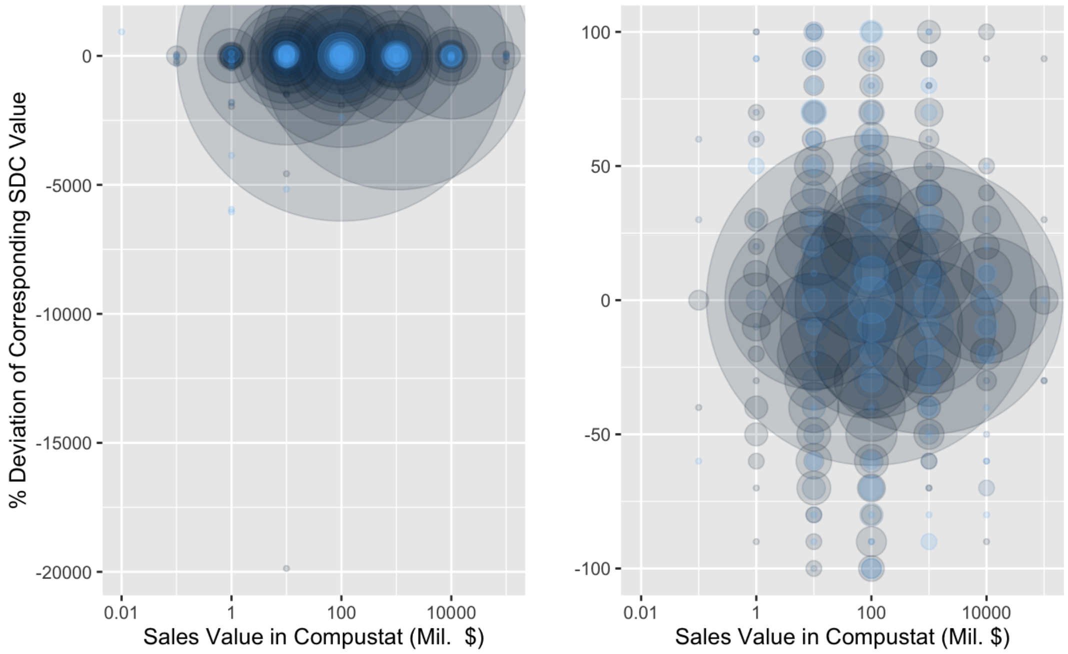
sources mentioned or a specific combination of them. In the further course of the analysis, we compute results for different sales-data sources distinctively. We ultimately create five different samples based on the given sales data sources: The first sample consists only of transactions where the target's sales are assigned from Compustat. The second sample supplements those with SDC values if Compustat data is not available. The third sample supplements the second sample with predicted values (based on known SDC values) when the other two sources are unavailable. The fourth sample supplements Compustat data with predicted values based on known Compustat values, while the fifth sample exclusively uses predicted values based on SDC. Naturally, sample size increases when using SDC and/ or predicted values, as can be seen in table Table 10 (*Observed Firms* is based on Compustat's firm identifier *gvkey*).[10] The advantage of combining the sources of sales values is an increase in observations; however, doing so is not unproblematic. Not only are there cases where discrepancies between SDC and Compustat values for the same year and target are large, SDC values clearly contain some inconsistencies. The paragraph *Inconsistencies and Discrepancies in the Sales Data* explains the problems with the sales data on hand in more detail.

Table 10: Final Matched Samples Based on Different Sources of Sales Values

Sample	**Sales Data Source**	**Observed Transactions**	**Observed Firms**
Sample 1	Compustat	5'448	2'895
Sample 2	Compustat + SDC	19'445	6'948
Sample 3	Compustat + SDC + SDC Prediction	57'683	11'603
Sample 4	Compustat + Compustat Prediction	57'507	11'570
Sample 5	SDC Prediction	57'681	11'603

[10]Note the maximum number of observations of 57'683. This implies that of the 61'452 initially matched transactions, in 3'769 cases, it is not possible to assign a sales value to the target from any source.

Figure 4: Discrepancies in Sales Figures and Difference in the Years of Observation: Darker colors correspond to a shorter time-difference between the observation years of the two values (Compustat and SDC). Circle size represents the number of observations in the immediate area.



Inconsistencies and Discrepancies in the Sales Data Using Compustat data or SDC data, when the former is unavailable, requires some degree of consistency between the two data sources. We analyze cases where values from both sources are available. One source of inconsistency may result from different definitions of the variables. SDC's target-sales item is *TargetNetSalesLTMMil* and hence contains net sale values in the 12 months prior to the transaction (though, as indicated in the previous paragraph, at least for some cases, it seems that this value may correspond to the reported sales value in the year before the announcement of the deal). SDC defines this target-sales identifier as follows: *"Target Net Sales Last 12 Months: Primary source of revenue after taking into account returned goods and allowances for price reductions for the last 12 months ending on the date of the most recent financial information prior to the announcement of the transaction ($mil). If not available, total revenues are used. For banks, net sales equal interest income plus non-interest income "* (Thomson Reuters, 2017). The Compustat User Guide states: *"(SALE) represents gross sales (the amount of actual billings to customers for regular sales completed during the period) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers "* (Standard & Poor's, 2011). Both definitions of sales values seem to cover the same types of revenues. What may differ is the period over which this value is recorded.

Comparing the actual numbers, we find an extremely skewed distribution for the difference in sales. The mean relative difference in sales between Compustat and SDC is -579.5 percent (implying that, on average, SDC values are larger than Compustat values), while the median is 0 percent. Potentially, the discrepancies could increase with the distance between the SDC and the Compustat observation, as we allow for a difference (*yearDiff*) in those years of up to two years. However, this does not seem to be the case, as can be seen in Figure 4. Darker colors imply a lower value of *yearDiff*. As the coloring does not show a specific pattern, the discrepancies most likely do not depend on this difference in the year of observation. The left- and right-hand plots only differ in the limits of the y-axis. The left-hand plot illustrates the extreme outlier driving the high mean of the distribution. This point is among the cases of problematic SDC sales values. For some observations, SDC clearly used the wrong format upon entry: While target sales in SDC are measured in millions of USD, some values are entered in another format. We suspect that thousands of USD is accidentally used for most such cases, resulting in implausibly high sales numbers. Identifying some of those irregularities is possible by ranking the SDC data set by target net sales. A selection of the results is presented in Table 11.

Table 11: SDC Targets Ranked by their Net Sales in Mil. $

Rank	**TargetName**	**Year**	**Value SDC in Mil. $**	**Implied Net Sales in Bil. $**
1	Fiat SpA	1991	52'019'000	52'019
2	Turcas Petrolculuk	1996	31'339'047	31'339
3	Istituto Bancario San Paolo di	1995	16'297'210	16'297
...	...	...	...	...
37	Exxon Mobil Corp	2012	433'526	434
38	Wal-Mart Stores Inc	2013	426'190	426

To put some of these high numbers into context: According to Fortune (2021), "Walmart Inc." regularly ranks among the highest revenue companies worldwide, reporting total revenues slightly above USD 570 billion in 2021, which is in line with the USD 426 billion net sales reported in Table 11 for the year 2013. Clearly, the top-ranking sales in SDC are wrongfully inflated, most likely by some constant. According to Cowell (1992), "Fiat SpA" reported revenues of USD 48 billion in 1991, implying that this constant may be 1'000 for some of these cases. Unfortunately, except for the firms topping the ranking in Table 11, it is not possible to thoroughly identify all incorrect sales values based on the data we have and correct them. As mentioned, in an attempt to mitigate this problem, we primarily use Compustat data when several sources are available.

Predicting Sales Values: SDC Based To increase the maximum sample size, we estimate missing sales values in SDC using linear regression. For 132'377 transactions in SDC, we know the target's sales from a non-missing *TargetEBITDALTMMil* value. We select several predictors suitable to fit a model on these known values. As SDC offers a large number of data identifiers, a variety of possible predictors is available. A reasonable approach may be to use additional financial data of the target, such as *EnterpriseValueMil*. Unfortunately, these identifiers have far too many missing values. Large numbers of missing values in an identifier decrease the size of the training set we can create and also limit the number of transactions for which we can subsequently estimate a sales value. Hence, we choose predictors with few missing values, specifically *ValueofTransactionMil*, and *XofSharesAcq*. Additionally, we implement fixed effects, using *AcquirorIndustrySector*, *AcquirorNation*, *AcquirorState*, *TargetIndustrySector*, *TargetNation* , *TargetState* , and *YEARef*, which is derived from *DateEffective*, and describes the year in which the transaction officially takes effect. Of the 406'890 transactions in our SDC dataset, 376'556 do not have any missing values in any of the chosen identifiers listed above. 122'381 of those also have a non-missing value for the target's net sales, while for the rest of those (244'179), this value is absent. Consequently, we can use 122'381 observations to estimate a model based on the predictors outlined above and use it to predict sales values for the 244'179 transactions, which have all the necessary predictors but do not have a known sales value.

We train the model as follows: Of the 122'381 transactions with a known sales value and the necessary predictors, we randomly assign 100'000 observations to a training set, while we set the remaining observations aside to a test set. The formal model is noted in Equation (1). We transform the dependent variable and the predictor *ValueofTransactionMil* using the natural logarithm to linearize the relationship. This improves the model fit in our case. Further, Figure 5 illustrates the regression's diagnostic plots (the plotted model omits fixed-effect variables), implying that the approach is reasonable. There are no signs of non-linearity or heteroscedasticity, though normality of the error terms is compromised in the distribution's tails.

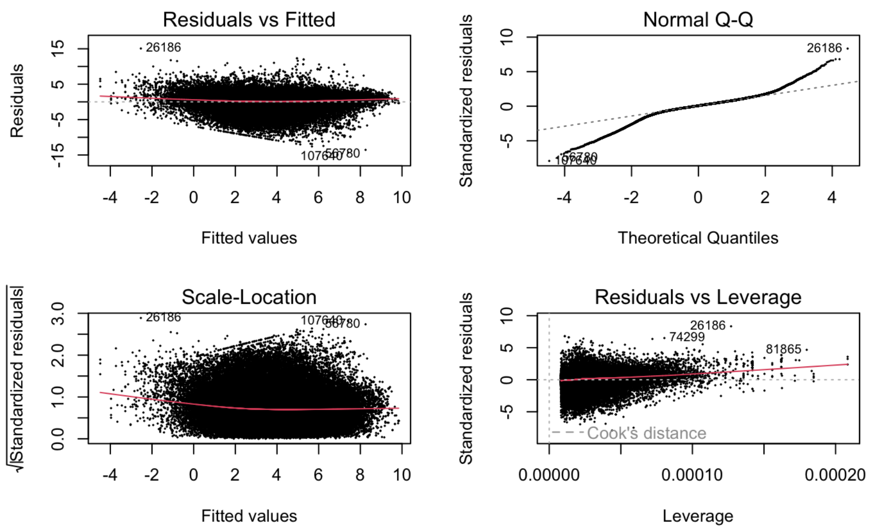
$$ln(Sales) = \beta_1 ln(TransactionValue) + \beta_2 SharesAcquired + FixedEffects + \varepsilon \quad (1)$$

Table 12 shows the resulting coefficients. Particularly the coefficient of *ln(Transaction Value)* is very robust. The driver behind this estimation is the relatively stable relationship between logarithmic sales and the logarithmic transaction value. Changes in the composition of fixed-effect variables or their removal do not affect this value by a significant magnitude. Adjusted R-squared is 0.616805.

Table 12: Regression Coefficients: Estimation Using SDC Values

Predictor	**Estimate**	**Std. Error**	**t-Value**	**p-Value**
ln(Transaction Value)	0.723627	0.013341	54.2414	2.2e-16
Shares Acquired	-0.022217	0.000223	-99.5475	2.2e-16

Figure 5: Diagnostic Plots of Model Used to Estimate Sales Values



In the first step, we predict sales values in the test set and compute the difference to the known values. The mean difference between the predicted logarithm and the known logarithm of the target-sales value is 0.0024. This translates to a mean difference of USD 1.0026 million, while the transformed median is USD 1.0665 million. Another measure of prediction accuracy can be obtained from the training set: We transform the predicted log values by applying the exponential function and find a median deviation between transformed fitted values and known values of USD 1.0521 million. This corresponds to a median relative deviation of 4.96 percent from the known value. In a final step, sales values are estimated for all possible entries (deals that do not have missing values in any of the variables used in the estimation), and the transformed predicted values are added to the SDC data frame.

Predicting Sales Values: Compustat Based We do not know how many of the sales values in SDC may be inflated. If this number is large, it may negatively influence the estimation above. Hence, we repeat the estimation using Compustat data, where we are not aware of any similar problems. Using matched transactions with an attributed Compustat-sales value, we repeat the estimation outlined above, using a similar model (Equation (1)). Fewer observations are available for this type of estimation: We create a training set with 5'000 entries and attribute 1'219 entries to the test set. We omit the fixed effect variable *TargetNation* and *AcquirorNation*. In this smaller sample, for *TargetNation*, more than half of the factor-levels have two or fewer observations, and for *AcquirorNation*, around half have 5 or fewer observations. Further, we reduce the number of factor-levels for for *TargetIndustrySector* and *AcquirorIndustrySector*, by cutting them to 2-digit codes. Besides preventing potential over-fitting, these measures increase the number of predictable values in the full data (as they decrease the probability that the training set is missing factor levels observed in the full data). An advantage of using this smaller matched sample is the availability of other Compustat identifiers besides the target's sale: We are able to use the acquirors sales as an additional predictor. Creating the same diagnostic plots as for the previous model yields similar results and implies that this approach is reasonable as well (see Figure 10 in Appendix B). Table 13 shows the resulting coefficients. Adjusted R-squared is 0.576636.

$$
\begin{aligned}
ln(Sales) = \beta_1 ln(TransactionValue) + \beta_2 ln(AcquirorSales) + \beta_3 SharesAcquired \\
+ FixedEffects + \varepsilon \qquad (2)
\end{aligned}
$$

Table 13: Regression Coefficients: Estimation Using Compustat Values

Predictor	Estimate	Std. Error	t-Value	p-Value
ln(Transaction Value)	0.635432	0.012434	51.10543	2.2e-16
ln(Acquiror Sales)	0.055851	0.009711	5.75147	4.3e-07
Shares Acquired	-0.014338	0.000616	-23.27319	2.2e-16

Employing the test set for an evaluation of the prediction yields that the mean difference between the predicted logarithm and the known logarithm of the target-sales value is 0.0391, which translates to a mean difference of USD 1.039898 million, while the transformed median is USD 1.0546 million. Based on these statistics, it seems that the models perform quite similarly for both data sources. In a final step, we apply the prediction to all matched transactions. Although both models are quite similar, a quick comparison yields a median difference in their predictions of USD 9.0431 million.

3.6 Assigning Acquisitions and Revenues Involved on a Timeline

Having matched companies between SDC and Compustat and assigned necessary sales values to the targets, we can now compute the volumes of the sales streams an acquiror obtains in each deal. For this, it is necessary to know what portion of the target's total outstanding shares is transferred in the transaction. Hence, entries with missing values for *XofSharesAcq* are dropped. By multiplying the share acquired (*XofSharesAcq*) with the targets sales in the corresponding year (depending on the sample, this sales value may stem from varying sources, see Table 10). Using these computed values, which represent the sales acquired from the target, it is easy to aggregate the sales obtained by each acquiror by year. If an acquiror is involved in acquiring several targets in one year, they are summarized into a list. In a subsequent step, we create a new data frame containing all matched acquiror firms and their sales observations from our Compustat data. Using a method conceptually similar to the one used in assigning each matched target their Compustat sales value, we allocate the yearly aggregated acquired revenues to the corresponding year in the data frame containing the acquirors sales observations. For each observed year, it is now possible to compare the sales figure of the acquiror to the sales that were "acquired" during this year (if any). The desired longitudinal structure of sales values and transaction data results. Overall, we managed to attribute SDC transaction data to their time series of sales observations for about half of the firms in our Compustat samples. Before being able to do the final computations of interest, it is necessary to consider the possibility of acquirors selling previously acquired shares or entire firms. Approximately 25 percent (5'710 of 19'978) of matched targets appear in more than one transaction.

Tracking Targets Involved in Several Transactions Since no direct data on acquiror divestment is available, approximating their asset sales involving matched targets is quite challenging. However, not accounting for divestiture would lead to overestimating the sales share obtained from merger and acquisition activity, as some revenues would be assigned to several companies. For example: Company A buys 100 percent of company B in 1990 and sells the entire firm to Company C in 1995. Unless divestment is considered, Company B's sales streams incorrectly remain with company A for the rest of the observation period while also being assigned to Company C from 1995 on. The procedure outlined in this paragraph aims to obtain a data frame which, for each acquiror affected, lists sales of a specific target's shares by each year. For each target sold, an acquiror will have an entry for each year in which some of this target's shares were sold. Such a structure can be constructed from the data frame containing the matched delisted firms (targets). This data frame is the result of merging the SDC data with the Compustat data of those delisted firms (the counterpart for the acquirors has been discussed extensively in the paragraphs above). To create the desired structure outlined above, we assume that an acquiror may be involved in any future transactions of the targets previously acquired (in future transactions, the acquiror acts as a seller). Once this is achieved, the challenge becomes to populate the data frame with appropriate values for the amount sold in each potential selling instance. The year of selling (denoted by *YearSold* from now on) corresponds to the year the subsequent transaction takes effect. Of more importance is the size of the stake sold: Unless the subsequent acquiror buys 100 percent of the outstanding stock, it is impossible to compute the exact volume of this selling stake, as this would require knowledge of specific divestment transactions. As an approximation, we assume that a previous acquiror will sell the maximum of the stock owned to the subsequent acquiror. Hence, either the entire stake owned is sold or as much as the subsequent acquiror obtains. This is subject to one exception: If the bidding firms in our sample, which are at one point involved in a target, own and trade an aggregated amount of less than 100 percent of this target's shares, we assume that previous acquirors do not sell their stock to subsequent acquirors (as in that case this stock may just as well originate from firms outside of the sample). Once information on the volumes and dates of shares sold is allocated, only the target's sales values for the years of divestment (*YearSold*) are missing for the computation of sales "sold." Using procedures outlined in Section 3.5, these values are assigned. Again, we differentiate between sales-data sources and create the same types of samples as in Section 3.5. An excerpt of the resulting data frame based on Sample 2 sales data is depicted in Table 14 and concerns the transactions of the target "Continental AG." Three acquirors sell a stake of this company in our sample. The first one to sell is "Elektrowatt AG." In 1990, the company sold 5 percent of its stake in "Continental AG." To compute the volume of the sales streams the company loses through this divestment, we need the target's sales in 1990. Apparently, for "Continental AG," both Compustat and SDC values are available. However, the Compustat observation is 12 years apart from the relevant year; hence it is not considered. Consequently, the source of the relevant sales of USD 8.382 billion is SDC. Multiplying these sales with the stake sold, the value of USD 419 million for *SalesSold* is obtained. The last acquiror to sell a "Continental AG" stake is a group of non-specified investors. Such entries are also included in this data frame in order to get a comprehensive view of a target's share trades. For the final results, such entries do not matter: This transaction disappears once we assign the acquirors in our matched data set their divestments, as this data set does not contain unspecified investors. Overall, considering divestment does not significantly impact the final results. As mentioned, 25 percent of targets are involved in several acquisitions, though the median stake involved in these divestments is only 10 percent. Further, in the largest sample, we only record 6'179 such transactions, compared to 57'683 acquisitions.

Table 14: Divestment Transactions Concerning "Continental AG"

AcquirorName	TargetName	YearSold	YearDiff	VolumeS	Sales(C)	Sales(S)	SalesRelevant	Source	SalesSold
Elektrowatt AG	Continental AG	1990	12	5.00	11961.60	8381.86	8381.86	S	419.09
Fintitoli SpA	Continental AG	1991	11	5.00	11961.60	5721.48	5721.48	S	286.07
Investors	Continental AG	1993	9	5.00	11961.60	5985.43	5985.43	S	299.27

3.7 Computing Acquisition Shares of Sales Growth

For all matched acquirors in our sample, it is now known for each year which targets they acquired and which targets they sold off. Using this information, it is possible to compute the total yearly net sales deriving from M&A activity. This data structure allows for the computation of the statistics of interest. Before taking into account acquisitions, we compute the (absolute) growth of sales and the accumulated (absolute) growth of sales for each acquiror for each year with a sales observation. These values describe an acquirors total sales and their growth. We are interested in the share of acquisition-related sales in these values. To compute such statistics, in the first step, we compute the cumulative sales volume acquired by each acquiror over the years. Subtracting these values from total sales yields "internal" sales, which are not generated through acquisition. To find the share which acquisitions have in sales growth, we divide cumulative sales from acquisitions by cumulative sales growth. This yields the aggregated share of sales growth for a given year, which stems solely from acquisition activity. Similarly, we compute the aggregated sales volume from acquisition as a fraction of the total absolute sales in each year. This yields the share of absolute sales for a given year, which stems from acquisitions. Another approach to computing shares of acquisitions in sales growth is simply dividing the sales from transactions by the growth in sales for that year. Instead of yielding the aggregated share of acquired revenues in total sales growth at a given point in time, this describes the share of acquired revenues in sales growth for single years. Note that during the computations, resulting negative values are transformed into missing values. Conceptually, negative shares are not interpretable in a meaningful manner in this analysis (this does not remove the entire observation but simply assigns NAs to some values). Most negative values result when an acquiror has negative sales growth. For a handful of cases, the reason is negative net sales from acquisition. For the primary sample, consisting only of target-sales values obtained from Compustat or SDC (no predictions), this results in the creation of 2'939 missing values for the cumulative acquisition share of sales growth out of 105'671 total observations across all firms and years. This value is lower for the other share statistics, such as the yearly acquisition share of sales growth.

Table 15 shows an excerpt of this final data frame for the acquiror "Advanced Micro Devices Inc".[11] See Appendix A for the full table.

Table 15: Final Data Structure with Computed Results for "Advanced Micro Devices Inc"

conml	Year	Sales	SalG	CuSalG	TarAcq	SalAcq	TarSo	SalSo	NSalAc	CuSalAcq	IntRev	CASS	YASSG	CASSG	Src
AMD	1972	11.20		0.00		0.00		0.00	0.00	0.00	11.20	0.00			
AMD	1973	26.43	15.23	15.23		0.00		0.00	0.00	0.00	26.43	0.00	0.00	0.00	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
AMD	1985	576.12	-354.95	564.92		0.00		0.00	0.00	0.00	576.12	0.00	0.00	0.00	
AMD	1986	631.98	55.86	620.78		0.00		0.00	0.00	0.00	631.98	0.00	0.00	0.00	
AMD	1987	997.08	365.10	985.88	MM Inc	204.88		0.00	204.88	204.88	792.20	0.20	0.56	0.21	C
AMD	1988	1125.86	128.77	1114.66		0.00		0.00	0.00	204.88	920.98	0.18	0.00	0.18	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
AMD	1995	2429.72	295.07	2418.53		0.00		0.00	0.00	204.88	2224.84	0.08	0.00	0.09	
AMD	1996	1953.02	-476.71	1941.82	NG Inc	20.79		0.00	20.79	225.67	1727.35	0.12		0.12	C
AMD	1997	2356.38	403.36	2345.18		0.00		0.00	0.00	225.67	2130.70	0.10	0.00	0.10	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
AMD	2005	5847.58	846.14	5836.38		0.00		0.00	0.00	225.67	5621.90	0.04	0.00	0.04	
AMD	2006	5649.00	-198.58	5637.80	ATI Inc	2222.51		0.00	2222.51	2448.18	3200.82	0.43		0.43	C
AMD	2007	6013.00	364.00	6001.80		0.00		0.00	0.00	2448.18	3564.82	0.41	0.00	0.41	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
AMD	2015	3991.00	-1515.00	3979.80		0.00		0.00	0.00	2448.18	1542.82	0.61	-0.00	0.61	
AMD	2016	4272.00	281.00	4260.80		0.00		0.00	0.00	2448.18	1823.82	0.57	0.00	0.57	

Reading example for Table 15: In the year 1987, "Advanced Micro Devices Inc" reported sales of USD 997.08 million, which is USD 365.1 million more than in the previous year (*SalG*). Since 1972, "Advanced Micro Devices Inc" sales have grown by USD 985.88 million (*CuSalG*). Through the acquisition of "Monolithic Memories Inc", "Advanced Micro Devices Inc" incorporates sales of USD 204.88 million (*SalAcq*), which corresponds to the net sales from acquisitions (*NSalAc*), as no divestments took place. It's the first acquisition in the sample; hence the USD 204.88 million also correspond to the cumulative sales from acquisition (*CuSalAcq*). Subtracting these acquired sales from "Advanced Micro Devices Inc's" total sales results in USD 792.2 million of internal sales, which stem from internal growth (*IntSale*). In 1987, the USD 204.88 million accumulated sales from acquisition correspond to 20 percent of "Advanced Micro Devices Inc's" sales (*CASS*). Further, the USD 204.88 million contributed 56 percent of the absolute sales growth in 1986 (*YASS*), and they correspond to 21 percent of cumulative sales growth since the beginning of the observation period (*CASSG*). In other words, focusing on the computed columns: In 1987, "Advanced Micro Devices Inc's" sales grew by USD 365.1 million, of which 56 percent was due to ac-

[11]For readability, Table 15 shows abbreviated company names and column names. "Advanced Micro Devices Inc" is abbreviated to "AMD Inc," Monolithic Memories Inc "to "MM Inc," NexGen Inc" to "NG Inc," and "ATI Technologies Inc" to "ATI Inc."

quisition activity. Since the beginning of the observation period, 21 percent of "Advanced Micro Devices Inc's" sales growth stems from acquisition activity, which corresponds to 20 percent of its absolute sales in 1987.

Table 16 holds more detailed descriptions of the columns in Table 15. Of the most interest are the three computed share statistics *CASS*, *YASS*, and *CASSG*.

Table 16: Identifiers of the Final Data Structure in Table 15

conml	Acquiror's name according to the Compustat identifier
Year	Year of observation for the acquiror
Sales	Acquiror's sales in the year of observation based on Compustat
SalG	Absolute growth of acquiror's sales compared to previous year
CuSalG	Cumulative absolute growth of acquiror's sales since the beginning of the observation period
TarAcq	Names of the targets acquired, based on SDC
SalAcq	Sales acquired from the target corresponds to the share acquired multiplied by the target's sales
TarSo	Names of the targets sold, based on SDC
SalSo	Sales lost through divestment corresponds to the share sold multiplied by the target's sales
NSalAc	Sales acquired net of sales sold, across all transactions of the year
CuSalAcq	Cumulative sales acquired since the beginning of the observation period
IntSale	Acquiror's sales net of cumulative sales acquired since the beginning of the observation period
CASS	Cumulative acquisition share of sales, Corresponds to the ratio of cumulative sales acquired to sales in the year of observation
YASSG	Yearly acquisition share of sales growth corresponds to the ratio of sales acquired to absolute sales growth in the year of observation
CASSG	Cumulative acquisition share of sales growth corresponds to cumulative sales acquired divided by cumulative absolute growth
Src	Source of the target's sales value, "C" for Compustat an "S" for SDC

4 Results

Using the data structure outlined in Section 3.7, we compute our main results based on the samples introduced in Table 10. Output mainly concerns the three values for acquisition shares in sales growth and absolute sales value, introduced in Table 16:

Cumulative Acquisition Share of Sales: Corresponds to the ratio of cumulative sales acquired to sales in the year of observation. We attribute the abbreviation ***CASS***.

Yearly Acquisition Share of Sales Growth: Corresponds to the ratio of sales acquired to absolute sales growth in the year of observation. Abbreviation: ***YASSG***.

Cumulative Acquisition Share of Sales Growth: Corresponds to cumulative sales acquired divided by cumulative absolute growth. We attribute the abbreviation ***CASSG***.

Specifically, we are interested in the means and medians of these variables across all firms and all observations in our sample. For the cumulative acquisition share of sales growth, an additional value is of relevance: The final cumulative acquisition share of sales growth corresponds to the cumulative share of acquisition activity in the sales growth of a company at the end of the observation period, i.e., in the last year where a sales value for the company is available. We use the abbreviation ***FCASSG***. Similarly, we compute the final cumulative acquisition share of growth, ***FCASS***, representing the ratio between cumulative sales from acquisition and absolute sales at the end of the observation period.
Table 17 shows the resulting summary values when computing statistics across all firms. In the third to last row of Table 17, *Weighted Mean FCASSG* is weighted with the acquirors sales in the final observation period. Samples correspond to those introduced in Table 10 in Section 3.5. Sample 1 only uses target-sales values from Compustat (N = 2'895), while Sample 2 supplements those values with figures from SDC (N = 6'948). Sample 3 further adds predicted sales figures to Sample 2 (N = 11'603), whereas Sample 4 supplements Compustat values with predicted values (N = 11'570). Finally, Sample 5 uses predicted values exclusively (N = 11'603). Note that the numbers of observed firms reported in the bottom row of Table 17 are lower than the sample sizes introduced in Table 10. For the firms missing, the dates of their transactions did not match any year in the corresponding Compustat sales observations; hence they were lost in the compilation of the final results.

Table 17: Main Results: Summarizing Across All Firms

	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**
Mean *CASS* %	53.05	53.75	83.94	111.44	68.52
Median *CASS* %	6.78	9.17	13.67	19.57	11.90
Mean *FCASS*	61.03	99.23	171.82	236.36	142.76
Mean *YASSG* %	46.62	72.83	85.39	99.40	56.50
Median *YASSG* %	4.09	6.64	11.37	16.84	10.32
Mean *CASSG* %	122.69	226.99	269.63	283.36	186.33
Median *CASSG* %	9.33	13.70	22.92	32.77	20.26
Mean *FCASSG* %	152.62	206.65	271.00	411.07	209.16
Weighted Mean *FCASSG* %	31.29	52.98	65.38	62.09	39.86
Median *FCASSG* %	18.30	22.30	35.40	51.30	30.80
Number of Firms	2'379	5'717	9'539	9'503	9'539

Instead of computing statistics across all of the firms in the sample, another approach is to take measures across all observations, which applies equal weights to all entries. The final cumulative acquisition share of sales growth is omitted in the resulting table (Table 18), as this statistic is firm based (and hence would be identical to the previous case, despite summarizing across all observations).

Table 18: Main Results: Summarizing Across All Observations

	Sample 1	**Sample 2**	**Sample 3**	**Sample 4**	**Sample 5**
Mean *CASS* %	32.34	40.89	64.71	80.83	52.46
Median *CASS* %	0.00	0.00	3.60	5.60	3.60
Mean *YASSG* %	26.67	47.66	64.93	74.33	43.61
Median *YASSG* %	0.00	0.00	0.00	0.00	0.00
Mean *CASSG* %	50.00	82.86	120.84	139.14	91.49
Median *CASSG* %	0.00	0.60	6.20	8.70	5.90
Total Observations	52'546	105'671	150'952	150'530	150'952

4.1 Implications

Focusing again on the main results illustrated in Table 17, we are presented with various values for each summary statistic, depending on the sample. Still, the results across samples in this table are comparable: The highest values lie in the statistics for *CASSG* and *CASSG*, whereas the lowest value is the median of *YASSG*, and so forth - the summary statistics are evidently correlated across samples. Hence, we analyze the results for Sample 2 in more detail, noting that these reflections also translate to the other samples. Starting at the top of Table 17, we find a mean cumulative acquisition share of sales of 54.75 percent. This indicates that in any given year, a company has accumulated slightly more than 50 percent of its current sales in acquisition sales on average. As for all statistics in Table 17, the median is much lower (9.19 percent in this case), implying a heavily skewed distribution. The values are driven by a smaller number of firms with extremely high shares. Next, the value for mean *YASSG* lies at 72.94 percent, with a very low median of 6.66 percent. This is to be expected due to the definition of this statistic: It is the yearly acquisition share of sales growth, meaning that no cumulative variables are involved and that in any year without acquisitions, this value is 0. In most years, firms do not make any acquisitions; hence the many zeros also drive down the mean, and if we were to consider only years with acquisitions, this share would naturally be significantly higher (474.88 percent).

Moving on to cumulative share statistics, we see a general increase in the figures: Mean *CASSG* is 228.62 percent. This implies that in a given year, on average, the accumulated sales acquired from incorporating targets (since the beginning of the observation period) are more than twice as high as the cumulative sales growth of the acquiror (since the beginning of the observation period). All values above 100 percent imply that acquirors do not manage to "keep" the sales that they acquire. For example, assume that in year 1, Company A has sales of 100 and buys Company B and consequently incorporates all of the target's total sales of 50. Assuming that Company A does not grow organically, growth for year 1 will be 50, resulting in a total of 150 in sales. If, in year 2, Company A's *CASSG* is above 100 percent, it must be the case that its sales have decreased below 150 and below 125 if *CASSG* is above 200 percent. Therefore, on average, if two companies "combine" their sales, this results in an aggregated sales value below the sum of the combined values. This result agrees with the significant number of authors who find negative effects of M&A activity on firm performance, such as Dickerson, Gibson, and Tsakalotos (1997), who also use accounting data. They base their findings on a panel of firm data from the UK, which our study, in fact, finds to be the country with the highest mean *CASSG* in Sample 2, as we will show in Section 4.2, *Results by Geographical Regions*. The UK also ranks in the top ten in all other samples, with a minimum mean *CASSG* across samples of 127.15 percent in Sample 1, which is consistent with the poor performance of acquiring companies. Though, a detrimental impact on combined sales is not necessarily a sufficient indicator of post-acquisition performance. Efficiency gains in the sense of Sirower (1997), Bradley, Desai, and Kim (1988), or Berkovitch and Narayanan (1993) may counteract these effects.

Mean *FCASSG* has a very similar interpretation to *CASSG*: It is the last (most recent) value for *CASSG* in the observation period. Hence, mean *FCASSG* and mean *CASSG* tend to be close together, with mean *FCASSG* usually exceeding mean *CASSG*, as it weighs the early years of a companies observation period, where acquisition shares tend to be lower, less. Table 17 supports this argument across all samples (in Sample 2, mean *CASSG* is slightly higher than its final year counterpart). The lowest mean of the cumulative acquisition statistics lies in the weighted mean of the final cumulative acquisition share of sales growth (*FCASSG*), where the acquiror's sales of the same year set the weights. The difference compared to the other two cumulative mean values is striking. It is evidence of the strong negative correlation between this statistic and firm size, which we outline in Section 4.2, *Results by Firm Size*. For the cumulative share statistics, medians are also much lower, though this difference is smaller for the weighted *FCASSG*. Still, these results too describe a skewed distribution, where few high-activity firms drive the high means.

Except for categorization into values below and above 100 percent, a meaningful interpretation of the summary statistics based on their value alone is difficult. Comparisons between subgroups yield more purposeful results. Section 4.2 analyses summary statistics in more detail for a number of subgroups of our samples.

4.2 Summary Statistics for a Number of Subgroups

Results by Industry In addition to these general summarizing statistics, the data structure created in Section 3.7 allows for more detailed analyses, for example, based on industry sectors. Computing the results across all industry observations yields the results in table Table 19, which is based on Sample 2 (Compustat values + SDC values). Again this is our primary sample, as it has a reasonable amount of observations but does not depend on predicted values. Industries are ranked by *CASSG*. Only industries with at least 50 obser-

Table 19: Summarizing Across All Observations by Industry - SAMPLE 2

Rank	SIC (2D)	Industry Description	Obs.	Mean *CASSG*	Mean *YASSG*
1	30	Rubber and Misc. Plastic Products	56	270.64	184.26
2	73	Business Services	870	215.41	38.51
3	10	Metal Mining	112	205.54	16.46
4	50	Wholesale Trade - Durable Goods	144	161.42	34.40
5	67	Holding and Other Investment Offices	134	133.54	10.92
...	...	...	...	...	...
21	34	Fabricated Metal Products	82	29.45	14.07
22	26	Paper and Allied Products	78	28.95	15.45
23	59	Miscellaneous Retail	89	27.77	22.48
24	80	Health Services	147	24.48	22.18
25	20	Food and Kindred Products	132	19.89	49.11

Table 20: Summarizing Across All Observations by Industry - SAMPLE 1

Rank	SIC (2D)	Industry Description	Obs.	Mean *CASSG*	Mean *YASSG*
1	10	Metal Mining	60	186.36	13.58
2	38	Photo., Medical, & Optic. Gds, & Clocks	147	76.86	64.32
3	36	Electrical Equipment & Components	213	63.92	18.56
4	37	Transportation Equipment	52	62.02	41.22
5	73	Business Services	318	48.30	22.81
...	...	...	...	...	...
8	35	Machinery & Computer Equip.	159	26.66	9.84
9	48	Communications	118	20.73	8.60
10	28	Chemicals and Allied Products	163	19.97	16.50
11	87	Engineer., Accnt., R&D, and Mgmt Svcs	50	16.20	15.11
12	20	Food and Kindred Products	58	8.94	57.92

vations (*Obs.*) are included in the ranking. The two-digit SIC industry with the highest mean cumulative acquisition share of sales growth is “Rubber and Miscellaneous Plastic Products,“ with a mean *CASSG* of 270.64 percent. This industry also has the highest, *YASSG*, although it is not always the case that the rank of *CASSG* corresponds to the rank of *YASSG*. To check whether the findings in Table 19 are robust, we create Table 20 with the results for Sample 1 (only Compustat values). Due to the significantly smaller number of observations, the obtained ranking does not list some of the industries of Table 19. Therefore, as the second option of comparison, we create an industry-ranking table from Sample 4 (Compustat + predictions based on Compustat) as well (see Appendix A.2). This sample does also not depend on SDC values and is much larger. Generally, the rankings have a reasonable degree of similarity. “Rubber and Miscellaneous Plastic Products“ does not appear in the results based on Sample 1 but is in 2nd place in the results based on

Sample 4. "Business services" appears in 5th place in the Sample 1 results, while "Metal Mining" ranks first. "Wholesale Trade - Durable Goods" does not appear in Table 20, but is in first place in the results for Sample 4. "Holding and Other Investment Offices" is ranked 7th in the Sample 1 results and 3rd in the ranking obtained from Sample 4. Except for "Food and Kindred Products," which is in last place both in Table 19, and Table 20, none of the bottom five industries appear in the ranking based on Sample 1. However, all of those industries rank in the bottom 10 in the results based on Sample 4, except for "Health Services," which is in 17th place (out of 35). Focusing on the ratio of sales acquired to absolute sales growth in the year of observation, *YASSG*, instead of cumulative shares of sales growth, the industry with the highest share in Table 20 is "Measuring, Photographic, Medical, & Optical Goods," ranking 2nd in *CASSG*. For Sample 4, the highest *YASSG*-industry only ranks 20th in *CASSG* ("Insurance Carriers"). That the two statistics do not always correlate is also evident in the increase of *YASSG* towards the bottoms of Table 19 and Table 20.

Employing the same analysis by firms and industry (instead of observations per industry) yields Table 21. The table ranks the industries by the sales-weighted mean of the final cumulative acquisition share of sales growth (WM *FCASSG*). Column 6 lists the corresponding (unweighted) mean of the final cumulative acquisition share of sales growth (M *FCASSG*, while column 7 shows the mean yearly acquisition share of sales growth (*YASSG*). The results are again based on Sample 2, while Table 22 depicts the ranking based on Sample 1. It seems that the weighted mean *FCASSG* is relatively robust to the change of the base sample: Three of the top-five industries in Sample 2 appear in this list of five for Sample 1 as well, though the other two ("Primary Metal" and "Wholesale Trade - Nondurable Goods") do not appear in Table 22. Again, we extend the analysis to Sample 4, where the two industries rank around the middle. On the other side, two of the five industries with the lowest weighted mean *FCASSG* in Table 21 appear in similar positions in Table 22, while the other three are not listed at all. Consulting Sample 4 shows that except for "Fabricated Metal Products" and "Health Services," the lowest weighted mean *FCASSG* industries of Table 21 also rank in the lowest quarter in Table 29, which shows the full ranking for Sample 4 and can be found in Appendix A.2. Surprisingly, "Fabricated Metal Products" and "Health Services" rank 9th and 15th (out of 35).

To summarize: The results on industry groups show that summary statistics vary immensely across industries. This implies that high mean values, such as mean *CASSG* in Table 17, are not necessarily an economy-wide phenomenon but are driven by fewer high-acquisition activity industries. Another result illustrated in Table 21 and Table 22, is the striking difference between the sales-weighted mean *FCASSG* and unweighted mean *FCASSG* for some industries. Table 17 shows that, on average, sales-weighted mean *FCASSG* is much lower than unweighted mean *FCASSG*, implying that it may often be smaller firms driving the high values in the statistics computed. The following paragraph analyzes this phenomenon in more detail. See Appendix A.2 for the full versions of the tables discussed in this paragraph.

Table 21: Summarizing Across All Firms by Industry - SAMPLE 2

Rank	SIC (2D)	Industry Description	Obs.	WM *FCASSG*	M *FCASSG*	M *YASSG*
1	87	Engineer., Accnt., R&D, and Mgmt Svcs	157	142.52	64.35	36.30
2	67	Holding and Other Investment Offices	134	90.60	89.47	10.31
3	33	Primary Metal Industries	91	78.53	115.44	100.75
4	28	Chemicals and Allied Products	349	74.04	401.02	76.22
5	51	Wholesale Trade - Nondurable Goods	75	65.27	580.52	110.30
...	...	...	...	...	...	
21	80	Health Services	147	28.43	39.16	21.94
22	73	Business Services	870	28.07	152.10	51.58
23	59	Miscellaneous Retail	89	27.63	73.91	25.71
24	20	Food and Kindred Products	132	24.42	35.08	52.62
25	34	Fabricated Metal Products	82	16.32	88.63	17.16

Table 22: Summarizing Across All Firms by Industry - SAMPLE 1

Rank	SIC (2D)	Industry Description	Obs.	WM *FCASSG*	M *FCASSG*	M *YASSG*
1	87	Engineer., Accnt., R&D, and Mgmt Svcs	50	259.38	79.24	18.37
2	67	Holding and Other Investment Offices	57	173.55	346.42	10.05
3	36	Electrical Equipment & Components	213	45.88	334.92	28.94
4	38	Photo., Medical, & Optic. Gds, & Clocks	147	31.32	179.60	112.52
5	28	Chemicals and Allied Products	163	29.45	42.76	19.47
...	...	...	...	...	...	
8	73	Business Services	318	21.94	98.10	29.59
9	48	Communications	118	20.84	30.39	10.43
10	13	Oil and Gas Extraction	193	20.31	106.25	21.95
11	10	Metal Mining	60	14.63	45.69	20.73
12	20	Food and Kindred Products	58	11.04	20.62	45.27

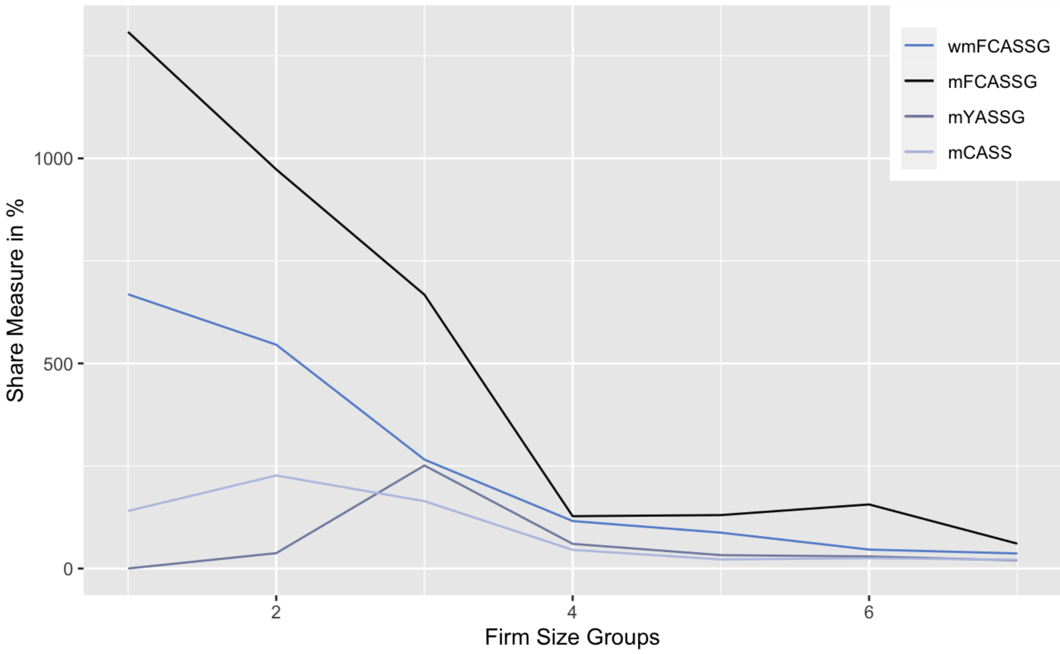
Results by Firm Size Table 23 shows that, indeed, the relationship between the weighted mean of the final cumulative acquisition share of growth and the size of the firm is negative, and this holds across all three samples analyzed. We use the average sales of the acquiror during the observations period as a measure for firm size and divide firms into 7 categories (based on logarithmic sales). *Sales Level* indicates the sales volume in million USD, corresponding to the 7 levels of *Size*.

Table 23: Summarizing Across All Firms by Size

Size	**Sales Level**	**Obs.**	**WM *FCASSG***	**M *FCASSG***	**M *YASSG***	**M *CASS***
SAMPLE 2						
1	0.10	6	668.58	1308.35	0.00	140.29
2	1.00	68	545.63	973.02	37.49	226.83
3	10.00	774	265.50	667.53	251.21	164.16
4	100.00	2341	115.70	127.57	60.10	45.43
5	1000.00	1887	87.45	130.23	32.62	22.11
6	10000.00	576	46.18	156.25	29.40	25.24
7	100000.00	65	36.70	60.65	19.75	21.18
SAMPLE 1						
1	0.10	3	1211.73	1308.35	0.00	350.72
2	1.00	11	94.27	92.01	21.33	461.46
3	10.00	169	498.03	884.08	282.63	364.88
4	100.00	748	65.52	113.71	51.05	48.47
5	1000.00	977	42.29	76.58	20.77	18.72
6	10000.00	421	38.53	159.21	11.72	9.11
7	100000.00	50	13.83	21.18	9.27	5.72
SAMPLE 4						
1	0.10	33	4421.18	9587.89	585.87	1104.54
2	1.00	255	887.40	1818.00	187.44	553.52
3	10.00	1783	255.79	1067.92	163.66	291.96
4	100.00	4103	117.66	218.85	101.77	64.87
5	1000.00	2595	105.37	195.21	56.54	32.46
6	10000.00	663	61.59	242.53	46.61	16.01
7	100000.00	70	23.68	38.89	19.93	9.00

The negative relationship holds for the other measures as well, with the exception of the mean yearly acquisition share of sales growth (M *YASSG*). Yearly acquisition shares of sales growth may be low for the smallest companies, as they might have very few years

Figure 6: Summary Statistics Dependant on Firm Size - SAMPLE 2



with acquisitions. However, as company size rises and reaches a level with higher M&A activity, the transactions executed seem to make up a large share of sales growth. This may imply that acquisition activity rises faster as firm size increases than the growth rates of sales generated within firms. The decrease of M *YASSG* as firms grow even larger could then be explained by a stagnating level in M&A activity while sales growth "catches up." For the cumulative measures *CASSG*, and *FCASSG*, the frequency of transactions per year is less influential, which may explain why this U-shaped relationship is not observed for these measures. Against this theory speak the low observation density for small firms, which may yield an incomplete picture. For Sample 4, which uses predicted values to increase the number of observations, the relationship is strictly negative. However, results for Sample 4 generally seem quite extreme, with strikingly high values for acquisition shares for small companies, of up to 9'588 percent. While even with predicted values, the number of observations is still low for the smallest firms, M *FCASSG* is still extremely high in the second group with more than 200 observations and a value of 1'818 percent. Overall, the results imply that larger companies depend less on growth through acquisition across the observation period (*FCASSG* measures cumulative growth from acquisitions compared to the total cumulative growth in the acquisition period) and that sales from acquisitions also make up less of their total revenues (*CASS*). For Sample 2, these results are summarized in Figure 6.

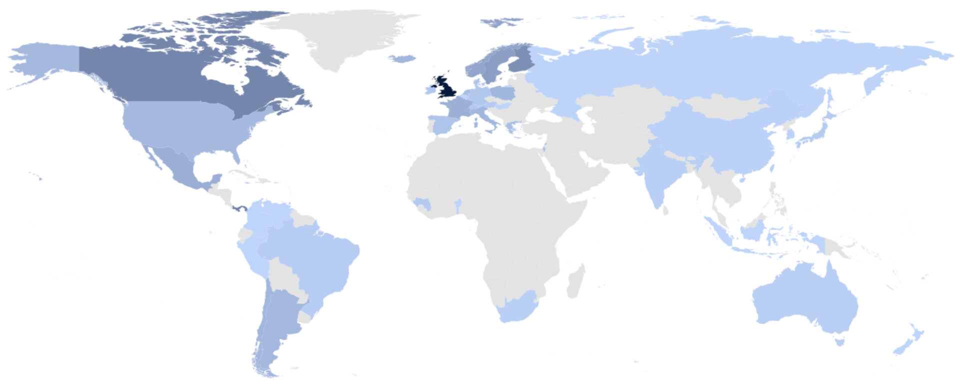
Results by Geographical Regions This paragraph analyses summary statistics by geographical location. As in the previous paragraph, results are firm based (we summarize across firms per region, instead of observations per region). Again we use Sample 2 as our primary data set. Table 24 show acquiror nations ranked by their weighted mean cumulative acquisition share of sales growth (WM *FCASSG*).

Table 24: Summarizing Across All Firms by Acquiror Nation - SAMPLE 2

Rank	Nation	Obs.	WM *FCASSG*	M *FCASSG*	M *YASSG*	M *CASS*
1	UK	123	325.25	1619.54	132.06	83.02
2	Canada	540	125.28	216.88	72.62	60.96
3	Sweden	18	85.39	40.15	68.17	13.21
4	Norway	7	76.23	20.02	1.43	3.30
5	Bermuda	13	68.51	63.99	13.77	14.85
...	...	...	...	...	...	...
27	South Africa	9	7.62	35.91	39.16	30.77
28	China	22	4.45	18.76	7.87	16.88
29	South Korea	7	4.27	12.16	46.12	8.80
30	Russia	7	2.01	3.83	0.99	1.65
31	Belgium	7	0.68	30.06	7.67	4.45

The United Kingdom is the country where acquirors have the highest weighted mean *FCASSG*, with a value of 325.25 percent. Interestingly, in Table 24, all summary statistics yield the same ranking in most positions. Note that countries with less than 5 observations have been filtered from the table (although this is still a very low value, a higher bound would exclude too many countries from the table). As is visible in the observations column, the number of observations varies strongly. Figure 7 colors all acquiror nations (not filtered by observation count) by their weighted mean *FCASSG*. As visible in the United Kingdom's coloring, darker tones correspond to higher values. Countries without any data are colored gray; hence Figure 7 also yields some insights into the geographical dimension of global M&A activity for U.S. listed acquirors (the United States ranks 10th in this sample, with a value of 42.22 percent). Compared to analyses by other groups, such as firm size in Section 4.2, summary values are considerably lower for the bottom groups. In this sample, it seems that acquisition has almost no share in sales growth in countries such as Russia and Belgium. However, the small observation numbers call for caution. In the case of Belgium, we see radical deviations between samples: In Sample 4, Belgium ranks fourth out of 35, and in Sample 5, it ranks 13th out of 35. While this nicely exemplifies the issue of low observation numbers, it is an extreme example in our case: Comparing, for example, Russia, China, and South Korea across the other samples, they consistently rank in the lowest 20 percent of the distribution. Full tables are available in Appendix A.2.

Figure 7: Weighted Mean *FCASSG* by Country - Dark Colors Imply High Values



As we have put only minor restrictions on the minimum group size for consideration, some countries' results depend on very few observations, which raises suspicion that the results might not be robust to a change in the underlying sample. Instead of manually comparing rankings and values, another approach to list comparison is the Kendall tau distance (Kumar and Vassilvitskii, 2010). It assigns a value of distance to a pair of ranking lists based on the necessary number of element swaps in a bubble sort algorithm. Lower values correspond to a higher degree of similarity; hence, two identical rankings would be assigned the value 0. We apply this algorithm to compare the results obtained from samples two (Table 24), one, and four. As Sample 1 is the smallest, we compare results only for acquiror nations, which appear in this sample, which is a total of 39 countries. We assign each country a rank in each sample based on weighted mean *FCASSG*. In a final step, the distance algorithm is applied to those rankings.[12] As suspected, the rankings show significant differences: Sample 2 and Sample 1 results have a distance of 45, while the distance from Sample 2 to Sample 4 is 62. Considerably closer are the rankings of Sample 1 and Sample 4, with a distance of 27. A lower distance may be expected, as both Samples are exclusively based on Compustat values. For comparison, if we rank the entries in Section 4.2 by weighted mean *FCASSG*, the distance between Sample 2 and Sample 4 is 0, and the distance between Sample 2 to Sample 1 is exactly 1 (of course these rankings are much shorter).

Table 25: Summarizing Across All Firms by Acquiror State - SAMPLE 2

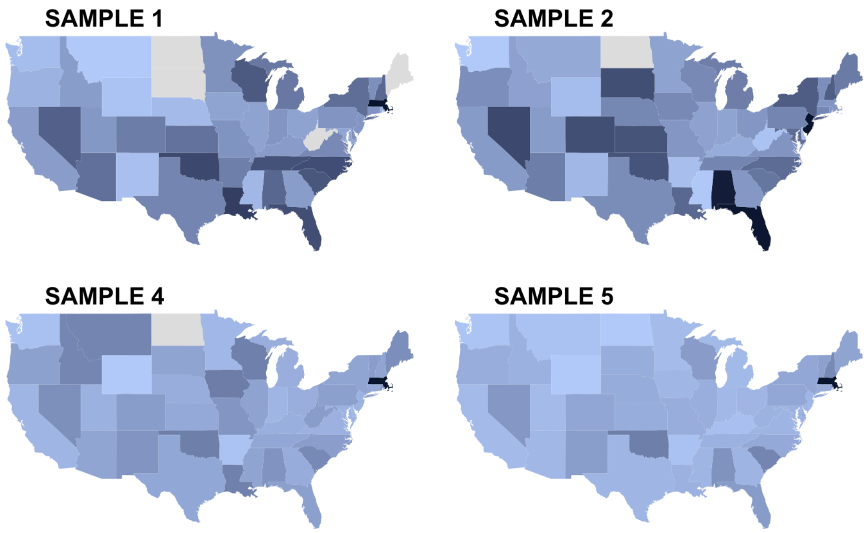
Rank	**Nation**	**Obs.**	**WM *FCASSG***	**M *FCASSG***	**M *YASSG***	**M *CASS***
1	New Jersey	208	121.76	228.28	650.62	77.96
2	Florida	227	118.35	302.43	65.54	55.38
3	Alabama	28	111.19	139.70	14.26	19.46
4	Nevada	37	76.27	116.18	34.28	147.48
5	Colorado	129	72.21	154.22	27.33	34.12
...	...	...	...	...	...	...
41	Delaware	24	11.97	60.85	21.07	15.93
42	District Of Columbia	13	10.40	30.19	19.40	12.69
43	West Virginia	6	10.05	20.83	41.49	8.33
44	Mississippi	9	7.67	54.86	567.87	28.62
45	Washington	71	7.21	83.62	21.86	14.63

The United States is by far the most frequent acquiror nation, with a total of 4'609 observed firms in Sample 2. It is possible to break down the geographical location of acquiror firms further by employing the identifier *AcquirorState*, which assigns U.S. acquirors their home state. Table 25 shows the results. The values for the summary statistics are generally lower and have lower variance compared to the international counterpart in Table 24. Again, we select only locations with at least five observations, although the average number of observations is larger in this case. Nevertheless, we analyze robustness through a comparison to Sample 1, Sample 4, and Sample 5. The results are summarized in Figure 8. Note that Figure 8 does not exclude states with a low observation count. In all samples, except number 2, Massachusetts has the highest mean *FCASSG*. Due to a large number of observations for Massachusetts in all samples, this inconsistency is surprising. Generally, however, although values for the summary statistics vary across the samples (which affects

[12]The computation is executed in R, using the package “rankdist“ by Qian (2019).

the tone contrast between states), Figure 8 shows that the distribution is overall similar: Although the shading differs, with exceptions, the four plots seem to have a common color pattern. Looking, for example, at the southern states, the variation from lighter to darker tones between neighboring states and the assignment of "darkest to lightest" is very similar in all four samples. The full tables of all results presented in this section are attached to Appendix A.2.

Figure 8: Weighted Mean *FCASSG* by State and Sample - Dark Colors Imply High Values



4.3 Limitations

As has been mentioned at various points throughout this text, several complications may affect the general validity of the results presented above. As is the case for most empirical studies, one potential source of bias lies in the data selection. The primary data sources for this analysis are Compustat and SDC Platinum. Few restrictions have been imposed during the sample selection in SDC: The data set should encompass all completed M&A transactions worldwide. The only deliberate exclusion of SDC data stems from exclusively selecting deals with a known transaction value. It is unclear whether deals with an undisclosed value may hold systematic differences from the deals in our sample. In addition to limitations arising from selection decisions, the general question concerning completeness of the data source cannot be omitted either: What percentage of deals SDC actually covers or whether this coverage is of equal density throughout the world cannot be answered conclusively. On the other side, the selection bias stemming from working with Compustat data is known: Selecting only U.S listed firms clearly yields a particular subset of the company universe. Aside from the apparent geographical specification, other characteristics of this subset have been studied: De Loecker, Eeckhout, and Unger (2020), who use a similar set of Compustat firms, note that publicly traded firms do not represent the universe of companies, as they are, on average, bigger, older, and more capital- and skill-intensive. Further, the number of multinational firms is above average among listed companies.

Next to the potential biases arising from data selection from external providers, we inadvertently engage in a selection of specific transactions in the process of creating our final data structure. An especially critical step in the process is the data matching between SDC and Compustat. We managed to attribute SDC data to about half of the firms in our Compustat samples. While we employed various matching methods and reviewed unmatched firms carefully, it cannot be conclusively ruled out that we could not create links between a significant number of identical entities. Assuming that most of the Compustat firms that we were unable to match simply do not exist in SDC and that the M&A database is relatively complete, another source of bias lies in the matched companies themselves: Of all the firms in Compustat, we may only measure the significance of acquisitions to a companies sales growth for companies, which have actually engaged in M&A transactions. Companies that are never involved in corporate transactions, which would yield zero percent values for all of our summary statistics, are not included in the analysis. While this aspect does not invalidate the summary values obtained, it is important to note that the results are specific to certain firm characteristics prevalent in our sample and that, if our matching approach functions reasonably well, even a large share of listed firms does not systematically engage in mergers or acquisitions.

A more specific limitation, but one that has had a significant impact on the methodology of the analysis, is the unknown number of inflated sales values assigned to targets in SDC transactions. These circumstances led to a trade-off between sample size and data quality and resulted in the creation of five distinct final samples, some including predicted values. It is difficult to say which sample is optimal. We often used Sample 2 as a primary sample, which includes both Compustat and SDC values, and then controlled with other samples (mainly Sample 1 and 4). As was argued earlier, this is because Sample 2 counts around twice as many distinct firms compared to Sample 1 yet does not employ any predicted values. On average, the predicted values should be reasonably accurate, as the test samples have shown. However, whether they are also suited for a more detailed analysis of subgroups with few observations remains unclear. Sales predictions based on Compustat are, on average higher than values predicted from SDC and, in the median, also exceed actual known SDC values.[13] This overestimation may arise from the special sub-sample which targets with known Compustat-sales value constitute: These companies used to be publicly traded as well, and hence the characteristics mentioned by De Loecker, Eeckhout, and Unger (2020) potentially apply to them as well. Transaction value is one of the main drivers behind this estimation - the relationship between sales and transaction value could be different in the acquisition of an (at the point of transaction) listed target.

Overall, the previous subsections have shown that the selection of the sales value's source does influence final results to some extent, as the main summary statistics show some variation in their absolute values depending on the underlying sample. However, differences in the sample size partially explain this variation. Further, the relative distributions of the different statistics within each specific sample are stable (e.g., median $YASSG$ is the lowest value in every sample). To allow for a thorough comparison between samples and subgroups, we considered rankings in the evaluation, which mitigates the problem of varying absolute values. With this approach, we were able to show that most results are relatively robust to a change in the underlying sample, despite the potential limitations to the data outlined in this paragraph.

[13] Predicted values based on Compustat exceed those estimated from SDC by USD 34.93 million on average. For the median firm, the predicted sales value based on Compustat exceeds the known sales value from SDC by USD 6.65 million. These figures concern the matched sample.

5 Conclusions

This study analyses companies which engage in merger or acquisition activities and examines their sales across an average observation period of 18 years. During this time, the mean firm makes 1.2 acquisitions, on which it spends USD 1.429 billion. In return, it attains USD 922 million in sales from the target. Using 5 different samples, we compute the share of such sales from incorporated targets, in the acquirors sales growth, and in their absolute sales. In our primary sample, we observe 5'717 firms and find that, on average, by the end of the observation period, such sales accumulate to 227 percent of total cumulative sales growth and 99 percent of the absolute sales in that period. Values above 100 percent imply that acquiring companies do not manage to permanently add the target's level of sales to their own total sales and that, therefore, the acquirors sales after the acquisition remain below the sum of the two companies' sales before the transaction. However, these high mean shares are driven by few companies: The median cumulative acquisition share of sales growth is much lower and lies at 14 percent. In the last period observed, the median company's accumulated sales from acquisition make up 9 percent of its total absolute sales in this period. Also far below 100 percent is the yearly acquisition share of sales growth which lies at 73 percent. As the average company only engages in one acquisition in the recorded period, the value for this statistic is 0 percent in most years, and consequently, the median is only 7 percent. Further, firm size considerably impacts the statistics outlined above: If we compute a sales-weighted mean for the cumulative acquisition share of sales growth in the last period, an average value of 53 percent results. Splitting companies into different size groups based on their average sales illustrates this more clearly: In the primary sample, the weighted mean of the cumulative acquisition share of sales growth in the final period is 669 percent for the smallest companies with approximately USD 100'000 in sales, while it lies at 37 percent for the most prominent companies with sales around USD 100 billion. Accordingly, for large companies, with 21 percent, these accumulated sales from acquisition also make up a small share of total absolute sales.

We additionally analyze specific subgroups of the samples. The summary statistics between these subgroups vary greatly. In our primary sample, the "Engineering, Accounting, Research, and Management Services" industry has the highest weighted mean cumulative acquisition share of sales growth in the final period, at 143 percent. It is followed by "Holding and Other Investment Offices" with 91 percent. On the other end, the two industries with the lowest shares are "Fabricated Metal Products" and "Food and Kindred Products," with values of 16 and 24 percent. Summary statistics also vary across geographical locations: Again, focusing on the weighted mean of the cumulative acquisition share of sales growth in the final period, the United Kingdom is the country with the highest value, at 325 percent, followed by Canada and Sweden (125 and 85 percent). The country with the lowest share is Belgium, where this value is below 1 percent (0.68 percent). Ranks 29 and 30 in this set of 31 countries go to South Korea and Russia with values of 4.3 and 2 percent. Note that the numbers for these three countries are based on only 7 companies each. Despite our efforts to create a large sample by using various matching methods in linking M&A deals to Compustat companies, some subgroups remain small.

Aside from sample size issues for specific subgroups, some other limitations apply to this analysis. For one, we found discrepancies between different sources of target-sales data and errors in some of the values stemming from SDC. Results differ depending on the sales-data source, though in most cases, they are relatively robust to a change in the base sample (where samples constitute different combinations of data sources). Further, we are working with a specific subset of firms, which does not represent the universe of all companies; namely, our acquiror sample contains only U.S listed firms based on Compustat. Applying a similar approach to a more general and international set of firms may yield more insight into the generalizability of the results presented in this study. To more conclusively evaluate whether the high mean acquisition shares of sales growth are connected to impaired performance of acquiring companies overall, future studies could be extended by including and analyzing a more comprehensive set of company financials.

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Appendices

A Supplementary Tables

A.1 Full Tables - Section 3

Table 26: Full Table: Final Data Structure with Computed Results for “Advanced Micro Devices Inc“

conml	Year	Sales	SalG	CuSalG	TarAcq	RevAcq	TarSo	RevSo	NetRev	CuRevAcq	IntRev	RevSrCu	RevSrYr	GSrAcq	SVsrc
AMD Inc	1972	11.20		0.00		0.00		0.00	0.00	0.00	11.20	0.00			
AMD Inc	1973	26.43	15.23	15.23		0.00		0.00	0.00	0.00	26.43	0.00	0.00	0.00	
AMD Inc	1974	25.82	-0.61	14.62		0.00		0.00	0.00	0.00	25.82	0.00	-0.00	0.00	
AMD Inc	1975	34.39	8.57	23.19		0.00		0.00	0.00	0.00	34.39	0.00	0.00	0.00	
AMD Inc	1976	62.12	27.73	50.92		0.00		0.00	0.00	0.00	62.12	0.00	0.00	0.00	
AMD Inc	1977	92.33	30.22	81.13		0.00		0.00	0.00	0.00	92.33	0.00	0.00	0.00	
AMD Inc	1978	148.28	55.95	137.08		0.00		0.00	0.00	0.00	148.28	0.00	0.00	0.00	
AMD Inc	1979	225.59	77.32	214.39		0.00		0.00	0.00	0.00	225.59	0.00	0.00	0.00	
AMD Inc	1980	309.39	83.80	298.19		0.00		0.00	0.00	0.00	309.39	0.00	0.00	0.00	
AMD Inc	1981	281.58	-27.81	270.38		0.00		0.00	0.00	0.00	281.58	0.00	-0.00	0.00	
AMD Inc	1982	358.35	76.77	347.15		0.00		0.00	0.00	0.00	358.35	0.00	0.00	0.00	
AMD Inc	1983	583.35	225.00	572.15		0.00		0.00	0.00	0.00	583.35	0.00	0.00	0.00	
AMD Inc	1984	931.08	347.73	919.88		0.00		0.00	0.00	0.00	931.08	0.00	0.00	0.00	
AMD Inc	1985	576.12	-354.95	564.92		0.00		0.00	0.00	0.00	576.12	0.00	-0.00	0.00	
AMD Inc	1986	631.98	55.86	620.78		0.00		0.00	0.00	0.00	631.98	0.00	0.00	0.00	
AMD Inc	1987	997.08	365.10	985.88	MM Inc	204.88		0.00	204.88	204.88	792.20	0.20	0.56	0.21	C
AMD Inc	1988	1125.86	128.77	1114.66		0.00		0.00	0.00	204.88	920.98	0.18	0.00	0.18	
AMD Inc	1989	1104.61	-21.25	1093.41		0.00		0.00	0.00	204.88	899.73	0.18	-0.00	0.19	
AMD Inc	1990	1059.24	-45.36	1048.04		0.00		0.00	0.00	204.88	854.36	0.19	-0.00	0.20	
AMD Inc	1991	1226.65	167.41	1215.45		0.00		0.00	0.00	204.88	1021.77	0.17	0.00	0.17	
AMD Inc	1992	1514.49	287.84	1503.29		0.00		0.00	0.00	204.88	1309.61	0.14	0.00	0.14	
AMD Inc	1993	1648.28	133.79	1637.08		0.00		0.00	0.00	204.88	1443.40	0.12	0.00	0.12	
AMD Inc	1994	2134.66	486.38	2123.46		0.00		0.00	0.00	204.88	1929.78	0.10	0.00	0.10	
AMD Inc	1995	2429.72	295.07	2418.53		0.00		0.00	0.00	204.88	2224.84	0.08	0.00	0.09	
AMD Inc	1996	1953.02	-476.71	1941.82	NG Inc	20.79		0.00	20.79	225.67	1727.35	0.12		0.12	C
AMD Inc	1997	2356.38	403.36	2345.18		0.00		0.00	0.00	225.67	2130.70	0.10	0.00	0.10	
AMD Inc	1998	2542.14	185.77	2530.94		0.00		0.00	0.00	225.67	2316.47	0.09	0.00	0.09	
AMD Inc	1999	2857.60	315.46	2846.40		0.00		0.00	0.00	225.67	2631.93	0.08	0.00	0.08	
AMD Inc	2000	4644.19	1786.58	4632.99		0.00		0.00	0.00	225.67	4418.51	0.05	0.00	0.05	
AMD Inc	2001	3891.75	-752.43	3880.55		0.00		0.00	0.00	225.67	3666.08	0.06	-0.00	0.06	
AMD Inc	2002	2697.03	-1194.72	2685.83		0.00		0.00	0.00	225.67	2471.36	0.08	-0.00	0.08	
AMD Inc	2003	3519.17	822.14	3507.97		0.00		0.00	0.00	225.67	3293.49	0.06	0.00	0.06	
AMD Inc	2004	5001.44	1482.27	4990.24		0.00		0.00	0.00	225.67	4775.76	0.04	0.00	0.04	
AMD Inc	2005	5847.58	846.14	5836.38		0.00		0.00	0.00	225.67	5621.90	0.04	0.00	0.04	
AMD Inc	2006	5649.00	-198.58	5637.80	ATI Inc	2222.51		0.00	2222.51	2448.18	3200.82	0.43		0.43	C
AMD Inc	2007	6013.00	364.00	6001.80		0.00		0.00	0.00	2448.18	3564.82	0.41	0.00	0.41	
AMD Inc	2008	5808.00	-205.00	5796.80		0.00		0.00	0.00	2448.18	3359.82	0.42	-0.00	0.42	
AMD Inc	2009	5403.00	-405.00	5391.80		0.00		0.00	0.00	2448.18	2954.82	0.45	-0.00	0.45	
AMD Inc	2010	6494.00	1091.00	6482.80		0.00		0.00	0.00	2448.18	4045.82	0.38	0.00	0.38	
AMD Inc	2011	6568.00	74.00	6556.80		0.00		0.00	0.00	2448.18	4119.82	0.37	0.00	0.37	
AMD Inc	2012	5422.00	-1146.00	5410.80		0.00		0.00	0.00	2448.18	2973.82	0.45	-0.00	0.45	
AMD Inc	2013	5299.00	-123.00	5287.80		0.00		0.00	0.00	2448.18	2850.82	0.46	-0.00	0.46	
AMD Inc	2014	5506.00	207.00	5494.80		0.00		0.00	0.00	2448.18	3057.82	0.45	0.00	0.45	
AMD Inc	2015	3991.00	-1515.00	3979.80		0.00		0.00	0.00	2448.18	1542.82	0.61	-0.00	0.61	
AMD Inc	2016	4272.00	281.00	4260.80		0.00		0.00	0.00	2448.18	1823.82	0.57	0.00	0.57	

Note: “Advanced Micro Devices Inc“ is abbreviated to “AMD Inc“, “Monolithic Memories Inc“ to “MM Inc“, “NexGen Inc“ to “NG Inc“, and “ATI Technologies Inc“ to “ATI Inc“.

A.2 Full Tables - Section 4

Table 27: Full Table: Summarizing Across All Observations by Industry - SAMPLE 2

Rank	SIC (2D)	Industry Description	Obs.	Mean *CASSG*	Mean *YASSG*
1	30	Rubber and Miscellaneous Plastic Products	56	270.64	184.26
2	73	Business Services	870	215.41	38.51
3	10	Metal Mining	112	205.54	16.46
4	50	Wholesale Trade - Durable Goods	144	161.42	34.40
5	67	Holding and Other Investment Offices	134	133.54	10.92
6	39	Miscellaneous Manufacturing Industries	61	122.04	16.00
7	48	Communications	248	102.97	18.92
8	38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	359	84.20	42.87
9	28	Chemicals and Allied Products	349	77.47	46.57
10	36	Electronic & Other Electrical Equipment & Components	469	72.55	135.41
11	13	Oil and Gas Extraction	387	72.03	31.26
12	23	Apparel, Finished Products from Fabrics & Similar Materials	53	63.82	18.65
13	49	Electric, Gas and Sanitary Services	84	55.16	106.36
14	51	Wholesale Trade - Nondurable Goods	75	53.05	63.00
15	33	Primary Metal Industries	91	52.61	42.49
16	87	Engineering, Accounting, Research, and Management Services	157	51.40	37.00
17	37	Transportation Equipment	130	50.30	66.61
18	58	Eating and Drinking Places	76	47.39	26.15
19	35	Industrial and Commercial Machinery and Computer Equipment	359	41.10	17.69
20	27	Printing, Publishing and Allied Industries	77	39.77	13.56
21	34	Fabricated Metal Products	82	29.45	14.07
22	26	Paper and Allied Products	78	28.95	15.45
23	59	Miscellaneous Retail	89	27.77	22.48
24	80	Health Services	147	24.48	22.18
25	20	Food and Kindred Products	132	19.89	49.11

Table 28: Full Table: Summarizing Across All Observations by Industry - SAMPLE 1

Rank	SIC (2D)	Industry Description	Obs.	Mean *CASSG*	Mean *YASSG*
1	10	Metal Mining	60	186.36	13.58
2	38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	147	76.86	64.32
3	36	Electronic & Other Electrical Equipment & Components	213	63.92	18.56
4	37	Transportation Equipment	52	62.02	41.22
5	73	Business Services	318	48.30	22.81
6	13	Oil and Gas Extraction	193	39.79	26.61
7	67	Holding and Other Investment Offices	57	33.43	9.76
8	35	Industrial and Commercial Machinery and Computer Equipment	159	26.66	9.84
9	48	Communications	118	20.73	8.60
10	28	Chemicals and Allied Products	163	19.97	16.50
11	87	Engineering, Accounting, Research, and Management Services	50	16.20	15.11
12	20	Food and Kindred Products	58	8.94	57.92

Table 29: Full Table: Summarizing Across All Observations by Industry - SAMPLE 4

Rank	SIC (2D)	Industry Description	Obs.	Mean *CASSG*	Mean *YASSG*
1	51	Wholesale Trade - Nondurable Goods	124	659.42	47.04
2	30	Rubber and Miscellaneous Plastic Products	88	398.88	178.97
3	67	Holding and Other Investment Offices	284	296.72	83.85
4	13	Oil and Gas Extraction	751	296.21	95.60
5	49	Electric, Gas and Sanitary Services	159	177.62	109.21
6	50	Wholesale Trade - Durable Goods	226	169.87	87.24
7	24	Lumber and Wood Products, Except Furniture	53	166.89	60.13
8	65	Real Estate	75	161.73	44.44
9	70	Hotels, Rooming Houses, Camps, and Other Lodging Places	67	150.63	64.46
10	35	Industrial and Commercial Machinery and Computer Equipment	549	150.39	42.44
11	58	Eating and Drinking Places	118	146.66	54.45
12	38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	558	142.28	199.10
13	28	Chemicals and Allied Products	559	136.93	67.74
14	39	Miscellaneous Manufacturing Industries	90	135.48	50.95
15	73	Business Services	1470	134.55	54.13
16	87	Engineering, Accounting, Research, and Management Services	237	125.11	35.76
17	80	Health Services	237	122.97	55.11
18	10	Metal Mining	274	120.18	21.82
19	48	Communications	446	116.21	53.93
20	63	Insurance Carriers	75	109.88	551.78
21	36	Electronic & Other Electrical Equipment & Components	737	102.92	80.48
22	27	Printing, Publishing and Allied Industries	104	95.02	39.24
23	78	Motion Pictures	73	89.23	34.58
24	37	Transportation Equipment	185	86.56	43.18
25	23	Apparel, Finished Products from Fabrics & Similar Materials	78	77.96	39.26
26	44	Water Transportation	51	75.99	42.01
27	34	Fabricated Metal Products	121	74.59	46.04
28	59	Miscellaneous Retail	141	73.68	52.62
29	32	Stone, Clay, Glass, and Concrete Products	72	69.53	36.50
30	79	Amusement and Recreation Services	65	67.09	92.95
31	26	Paper and Allied Products	111	63.47	66.38
32	33	Primary Metal Industries	146	63.40	48.50
33	45	Transportation by Air	54	49.90	40.50
34	20	Food and Kindred Products	207	39.10	79.77
35	54	Food Stores	53	37.97	19.34

Table 30: Full Table: Summarizing Across All Firms by Industry - SAMPLE 2

Rank	SIC (2D)	Industry Description	Obs.	WM *FCASSG*	M *FCASSG*	M *YASSG*
1	87	Engineering, Accounting, Research, and Management Services	157	142.52	64.35	36.30
2	67	Holding and Other Investment Offices	134	90.60	89.47	10.31
3	33	Primary Metal Industries	91	78.53	115.44	100.75
4	28	Chemicals and Allied Products	349	74.04	401.02	76.22
5	51	Wholesale Trade - Nondurable Goods	75	65.27	580.52	110.30
6	36	Electronic & Other Electrical Equipment & Components	469	62.73	314.26	121.52
7	26	Paper and Allied Products	78	56.80	64.72	18.36
8	27	Printing, Publishing and Allied Industries	77	49.20	88.42	16.37
9	49	Electric, Gas and Sanitary Services	84	48.67	43.77	112.61
10	13	Oil and Gas Extraction	387	47.66	163.54	26.44
11	58	Eating and Drinking Places	76	47.58	114.78	43.20
12	39	Miscellaneous Manufacturing Industries	61	45.63	76.64	17.51
13	48	Communications	248	44.16	68.76	21.68
14	38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	359	43.89	238.53	60.16
15	23	Apparel, Finished Products from Fabrics & Similar Materials	53	43.25	127.48	24.29
16	50	Wholesale Trade - Durable Goods	144	33.71	551.25	48.98
17	10	Metal Mining	112	33.58	53.89	20.52
18	37	Transportation Equipment	130	31.98	171.69	56.66
19	30	Rubber and Miscellaneous Plastic Products	56	30.68	1502.13	616.37
20	35	Industrial and Commercial Machinery and Computer Equipment	359	30.02	98.78	23.88
21	80	Health Services	147	28.43	39.16	21.94
22	73	Business Services	870	28.07	152.10	51.58
23	59	Miscellaneous Retail	89	27.63	73.91	25.71
24	20	Food and Kindred Products	132	24.42	35.08	52.62
25	34	Fabricated Metal Products	82	16.32	88.63	17.16

Table 31: Full Table: Summarizing Across All Firms by Industry - SAMPLE 1

Rank	SIC (2D)	Industry Description	Obs.	WM *FCASSG*	M *FCASSG*	M *YASSG*
1	87	Engineering, Accounting, Research, and Management Services	50	259.38	79.24	18.37
2	67	Holding and Other Investment Offices	57	173.55	346.42	10.05
3	36	Electronic & Other Electrical Equipment & Components	213	45.88	334.92	28.94
4	38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	147	31.32	179.60	112.52
5	28	Chemicals and Allied Products	163	29.45	42.76	19.47
6	37	Transportation Equipment	52	26.61	294.61	54.74
7	35	Industrial and Commercial Machinery and Computer Equipment	159	21.94	55.28	11.20
8	73	Business Services	318	21.94	98.10	29.59
9	48	Communications	118	20.84	30.39	10.43
10	13	Oil and Gas Extraction	193	20.31	106.25	21.95
11	10	Metal Mining	60	14.63	45.69	20.73
12	20	Food and Kindred Products	58	11.04	20.62	45.27

Table 32: Full Table: Summarizing Across All Firms by Industry - SAMPLE 4

Rank	SIC (2D)	Industry Description	Obs.	WM *FCASSG*	M *FCASSG*	M *YASSG*
1	24	Lumber and Wood Products, Except Furniture	53	1193.27	383.81	197.90
2	67	Holding and Other Investment Offices	284	851.18	1283.46	152.28
3	87	Engineering, Accounting, Research, and Management Services	237	117.60	382.95	49.42
4	32	Stone, Clay, Glass, and Concrete Products	72	116.64	185.68	44.85
5	26	Paper and Allied Products	111	114.08	170.05	55.86
6	30	Rubber and Miscellaneous Plastic Products	88	94.05	1153.20	479.66
7	36	Electronic & Other Electrical Equipment & Components	737	89.93	369.13	100.43
8	27	Printing, Publishing and Allied Industries	104	87.48	187.26	45.77
9	34	Fabricated Metal Products	121	81.96	282.19	61.18
10	23	Apparel, Finished Products from Fabrics & Similar Materials	78	72.87	138.20	61.00
11	70	Hotels, Rooming Houses, Camps, and Other Lodging Places	67	71.35	410.52	126.30
12	54	Food Stores	53	61.32	68.95	23.82
13	39	Miscellaneous Manufacturing Industries	90	60.22	139.77	86.04
14	58	Eating and Drinking Places	118	60.05	282.52	90.40
15	80	Health Services	237	59.02	215.03	57.88
16	50	Wholesale Trade - Durable Goods	226	58.13	354.85	86.42
17	49	Electric, Gas and Sanitary Services	159	57.97	546.50	167.05
18	33	Primary Metal Industries	146	56.21	137.22	63.07
19	44	Water Transportation	51	54.41	150.09	56.13
20	38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	558	54.20	362.84	226.90
21	28	Chemicals and Allied Products	559	50.27	126.25	65.44
22	78	Motion Pictures	73	48.24	100.56	44.92
23	20	Food and Kindred Products	207	48.22	125.06	77.54
24	79	Amusement and Recreation Services	65	45.21	105.78	97.37
25	13	Oil and Gas Extraction	751	44.76	355.81	113.45
26	65	Real Estate	75	42.99	163.43	50.66
27	73	Business Services	1470	40.90	220.35	67.78
28	48	Communications	446	34.43	97.06	60.02
29	35	Industrial and Commercial Machinery and Computer Equipment	549	31.25	365.30	60.64
30	59	Miscellaneous Retail	141	31.02	153.20	77.62
31	37	Transportation Equipment	185	25.14	258.16	48.75
32	10	Metal Mining	274	24.28	127.18	20.60
33	63	Insurance Carriers	75	23.45	291.80	1270.82
34	51	Wholesale Trade - Nondurable Goods	124	22.47	8525.41	71.13
35	45	Transportation by Air	54	16.14	155.38	47.45

Table 33: Full Table: Summarizing Across All Firms by Acquiror Nation - SAMPLE 2

Rank	**Nation**	**Obs.**	**WM *FCASSG***	**M *FCASSG***	**M *YASSG***	**M *CASS***
1	UK	123	325.25	1619.54	132.06	83.02
2	Canada	540	125.28	216.88	72.62	60.96
3	Sweden	18	85.39	40.15	68.17	13.21
4	Norway	7	76.23	20.02	1.43	3.30
5	Bermuda	13	68.51	63.99	13.77	14.85
6	Mexico	14	58.08	29.39	12.15	15.19
7	France	23	56.18	58.52	19.72	13.17
8	Chile	6	44.59	31.27	17.58	11.03
9	Argentina	9	43.73	38.68	4.55	5.34
10	USA	4611	42.22	177.89	76.31	55.69
11	Luxembourg	6	39.31	49.10	14.24	14.81
12	Israel	38	37.33	980.12	15.88	30.02
13	Netherlands	35	35.92	28.22	11.07	12.73
14	Greece	6	34.63	124.35	31.83	16.75
15	Denmark	5	28.53	55.95	8.03	22.25
16	Spain	5	24.97	45.28	29.94	15.26
17	Ireland	12	22.05	43.57	9.69	17.86
18	Germany	17	20.71	15.78	12.37	7.60
19	Switzerland	18	18.14	21.16	55.15	12.70
20	Japan	42	14.53	156.72	42.36	41.56
21	Hong Kong	17	12.24	36.42	2.73	11.99
22	Brazil	19	11.87	30.40	10.92	12.44
23	Singapore	5	11.10	7.35	2.98	7.94
24	Australia	24	10.66	29.66	15.11	6.83
25	India	12	8.45	13.35	3.78	6.27
26	Taiwan	7	7.69	9.92	3.65	14.72
27	South Africa	9	7.62	35.91	39.16	30.77
28	China	22	4.45	18.76	7.87	16.88
29	South Korea	7	4.27	12.16	46.12	8.80
30	Russia	7	2.01	3.83	0.99	1.65
31	Belgium	7	0.68	30.06	7.67	4.45

Table 34: Full Table: Summarizing Across All Firms by Acquiror Nation - SAMPLE 1

Rank	**Nation**	**Obs.**	**WM *FCASSG***	**M *FCASSG***	**M *YASSG***	**M *CASS***
1	Canada	250	162.75	315.47	42.11	66.07
2	Bermuda	8	60.54	64.77	7.50	14.23
3	UK	39	52.01	126.83	14.65	13.73
4	USA	1923	25.66	142.18	51.12	55.91
5	Israel	16	24.58	45.94	18.47	19.08
6	France	15	21.46	27.67	7.53	12.47
7	Switzerland	8	20.51	32.68	8.17	4.34
8	Ireland	5	18.57	32.46	7.59	8.74
9	Netherlands	13	15.48	25.94	8.09	8.35
10	Mexico	10	14.59	18.60	3.15	9.11
11	Germany	9	13.60	19.77	5.14	5.42
12	Brazil	8	5.78	12.50	14.29	3.47
13	Sweden	9	5.35	11.93	8.51	3.45
14	Japan	10	5.14	6.31	0.32	0.96
15	China	9	1.53	9.54	9.33	4.54

Table 35: Full Table: Summarizing Across All Firms by Acquiror Nation - SAMPLE 4

Rank	Nation	Obs.	WM ***FCASSG***	M ***FCASSG***	M ***YASSG***	M ***CASS***
1	Chile	17	192.29	151.79	41.05	36.70
2	Canada	1203	181.04	287.84	69.42	82.51
3	Luxembourg	5	112.71	90.70	50.93	19.92
4	Belgium	10	81.74	46.58	47.55	10.59
5	France	36	79.94	2711.05	46.30	160.06
6	UK	161	72.09	292.19	69.65	61.36
7	Spain	7	71.40	57.16	88.96	20.70
8	USA	7333	64.31	443.01	108.79	122.18
9	Finland	7	62.94	88.23	8.18	7.72
10	Ireland	15	59.14	133.61	100.49	40.51
11	Israel	78	50.20	1324.06	33.93	57.06
12	Argentina	19	45.89	41.86	22.16	16.63
13	Bermuda	26	35.23	75.60	40.24	57.04
14	Australia	40	35.16	66.90	519.49	22.17
15	Sweden	26	33.56	30.59	16.08	8.69
16	Greece	13	31.97	110.94	60.29	44.31
17	Bahamas	5	30.40	80.34	52.06	45.83
18	South Africa	16	29.25	45.61	23.72	17.58
19	Italy	9	26.90	43.04	7.54	16.15
20	Denmark	7	26.28	144.98	110.93	48.49
21	Mexico	25	25.88	55.93	33.64	22.51
22	Netherlands	43	25.19	59.61	35.41	16.92
23	Brazil	32	24.09	50.53	17.07	16.83
24	Norway	10	23.00	30.69	12.08	22.85
25	Germany	24	19.77	42.41	20.51	15.85
26	Switzerland	17	18.37	38.82	104.87	11.78
27	Japan	50	15.92	84.82	12.01	39.82
28	Russia	9	15.19	37.94	12.76	15.56
29	India	17	11.61	36.90	140.84	25.11
30	South Korea	12	11.45	67.40	478.20	9.48
31	Taiwan	11	9.22	12.46	9.60	62.49
32	China	112	8.39	56.99	17.11	82.33
33	Hong Kong	33	5.61	32.52	10.78	615.98
34	Singapore	11	2.81	8.71	39.88	9.27
35	New Zealand	8	0.69	17.95	10.81	27.58

Table 36: Full Table: Summarizing Across All Firms by Acquiror Nation - SAMPLE 5

Rank	Nation	Obs.	WM *FCASSG*	M *FCASSG*	M *YASSG*	M *CASS*
1	Canada	1207	125.31	226.01	43.55	49.96
2	Chile	17	114.17	125.79	25.95	16.68
3	Luxembourg	5	91.83	69.64	40.54	11.20
4	France	36	70.80	1564.87	26.69	97.88
5	UK	162	54.65	196.35	48.69	45.61
6	Spain	7	48.77	33.80	26.49	13.73
7	Finland	7	46.04	76.37	7.21	6.19
8	Denmark	7	43.10	108.36	76.81	36.49
9	USA	7365	38.03	205.75	60.89	75.84
10	Bahamas	5	35.99	58.92	35.55	39.19
11	Ireland	15	35.52	76.53	62.96	25.43
12	Israel	78	33.83	914.54	27.73	47.88
13	Belgium	10	32.35	27.58	25.81	10.17
14	Sweden	25	32.19	26.15	17.61	7.94
15	Greece	13	28.12	114.47	62.91	33.17
16	Mexico	25	27.89	54.16	28.68	24.61
17	Argentina	19	26.99	21.51	10.88	8.85
18	Netherlands	43	24.89	57.92	31.48	19.03
19	Norway	10	23.95	30.71	7.35	15.38
20	Brazil	32	22.86	38.09	17.48	14.90
21	Germany	24	20.46	44.31	19.94	13.43
22	Bermuda	26	19.46	74.89	37.75	77.92
23	South Africa	16	19.45	37.26	20.75	15.55
24	Japan	50	18.70	241.77	19.71	89.57
25	Australia	40	18.34	27.57	206.29	9.93
26	Italy	9	17.02	32.42	6.17	10.81
27	Switzerland	17	10.04	29.71	38.68	10.30
28	India	17	8.51	27.40	137.79	18.83
29	South Korea	12	7.98	29.05	272.14	7.13
30	Taiwan	11	7.73	9.32	6.97	36.17
31	Russia	9	5.96	15.28	8.68	8.87
32	China	112	2.95	39.68	7.86	37.11
33	Hong Kong	33	2.52	13.64	5.57	38.23
34	Singapore	11	1.15	3.16	18.46	4.94
35	New Zealand	8	0.29	7.70	4.01	12.23

Table 37: Full Table: Summarizing Across All Firms by Acquiror US State - SAMPLE 2

Rank	Nation	Obs.	WM ***FCASSG***	M ***FCASSG***	M ***YASSG***	M ***CASS***
1	New Jersey	208	121.76	228.28	650.62	77.96
2	Florida	227	118.35	302.43	65.54	55.38
3	Alabama	28	111.19	139.70	14.26	19.46
4	Nevada	37	76.27	116.18	34.28	147.48
5	Colorado	129	72.21	154.22	27.33	34.12
6	Oklahoma	50	69.39	133.36	18.84	30.74
7	Kansas	24	69.27	59.66	26.54	18.85
8	New York	418	63.60	125.33	31.15	48.48
9	New Hampshire	19	63.18	42.85	26.16	25.01
10	Louisiana	26	57.10	66.93	19.31	26.23
11	North Carolina	63	54.68	69.39	20.04	20.89
12	Maryland	66	54.58	902.12	45.49	249.08
13	South Carolina	25	48.90	187.20	32.18	23.48
14	Arizona	60	44.11	167.33	228.92	134.77
15	Michigan	94	43.74	114.93	31.89	18.14
16	Pennsylvania	186	40.36	819.14	61.59	72.67
17	Tennessee	66	40.29	36.07	18.97	11.83
18	Nebraska	24	39.15	40.47	10.90	15.66
19	Connecticut	125	39.01	150.30	26.16	43.81
20	Iowa	17	38.29	32.25	19.19	16.07
21	Wisconsin	54	38.11	51.93	88.93	24.11
22	Texas	457	36.74	81.82	32.25	76.76
23	Vermont	6	35.53	29.83	36.05	14.36
24	Oregon	44	35.38	238.59	19.36	25.30
25	Virginia	119	31.98	52.74	18.64	24.19
26	Massachusetts	257	31.71	140.74	51.21	20.21
27	Rhode Island	14	31.47	38.75	18.14	18.28
28	Missouri	67	31.03	52.18	27.07	16.02
29	Ohio	148	30.79	96.33	45.86	22.99
30	Georgia	138	30.24	70.61	42.53	21.29
31	California	776	29.19	119.62	39.36	57.80
32	Utah	41	28.82	63.99	46.31	30.46
33	Idaho	13	26.16	139.68	21.08	34.46
34	Illinois	198	25.63	66.13	56.75	47.74
35	Minnesota	134	25.37	708.52	261.66	189.42
36	Indiana	53	24.92	53.08	54.32	18.69
37	Montana	5	21.97	13.42	3.84	10.93
38	Kentucky	29	21.06	138.98	45.82	71.32
39	New Mexico	9	15.15	24.22	11.07	17.59
40	Arkansas	13	11.99	143.88	24.16	407.94
41	Delaware	24	11.97	60.85	21.07	15.93
42	District Of Columbia	13	10.40	30.19	19.40	12.69
43	West Virginia	6	10.05	20.83	41.49	8.33
44	Mississippi	9	7.67	54.86	567.87	28.62
45	Washington	71	7.21	83.62	21.86	14.63

Table 38: Full Table: Summarizing Across All Firms by Acquiror US State - SAMPLE 1

Rank	Nation	Obs.	WM ***FCASSG***	M ***FCASSG***	M ***YASSG***	M ***CASS***
1	Massachusetts	92	94.25	201.79	14.80	19.13
2	Louisiana	11	63.20	72.75	29.15	36.28
3	Oklahoma	19	57.74	211.88	11.75	10.01
4	North Carolina	29	54.57	66.93	10.29	13.88
5	Florida	82	54.21	90.04	17.59	40.20
6	Tennessee	22	52.57	51.82	18.12	16.48
7	South Carolina	12	49.85	146.64	25.13	25.99
8	Wisconsin	24	48.28	77.24	176.65	12.36
9	Nevada	16	44.15	38.39	25.30	14.99
10	Alabama	13	42.01	55.22	9.08	18.99
11	New Hampshire	10	41.27	25.65	7.92	18.62
12	New York	187	38.44	74.13	26.08	45.03
13	Arizona	22	37.28	48.45	14.93	22.04
14	Kansas	7	36.32	26.19	6.67	8.37
15	Michigan	32	33.60	159.24	57.86	12.27
16	Colorado	54	31.54	47.42	15.20	16.89
17	Arkansas	6	30.49	38.02	14.81	767.20
18	Texas	197	28.07	83.29	42.35	128.99
19	Virginia	38	26.12	45.73	8.96	12.24
20	Minnesota	59	22.69	1519.83	561.29	403.58
21	Delaware	14	22.52	91.69	17.89	15.25
22	Missouri	33	21.73	38.90	12.63	7.33
23	Connecticut	64	21.39	187.10	15.02	16.92
24	Pennsylvania	89	21.01	49.24	12.76	15.17
25	Indiana	21	20.83	58.10	34.99	16.16
26	New Jersey	82	20.74	52.25	28.09	19.19
27	Utah	16	19.85	52.48	87.80	28.48
28	Kentucky	11	18.11	267.13	44.19	72.06
29	Idaho	8	17.95	214.66	41.94	55.43
30	Georgia	65	17.85	44.51	35.09	15.99
31	California	334	17.77	145.44	47.03	71.18
32	Ohio	60	15.56	75.96	20.07	13.43
33	Illinois	83	15.51	74.19	78.22	24.05
34	Iowa	9	15.12	15.73	4.84	11.45
35	Maryland	17	14.83	19.62	5.44	6.78
36	Rhode Island	6	9.76	9.85	3.27	5.46
37	Oregon	24	9.29	369.15	8.31	11.99
38	Nebraska	10	6.21	22.78	7.87	6.88
39	Washington	21	5.36	26.95	17.14	10.16

Table 39: Full Table: Summarizing Across All Firms by Acquiror US State - SAMPLE 4

Rank	Nation	Obs.	WM ***FCASSG***	M ***FCASSG***	M ***YASSG***	M ***CASS***
1	Massachusetts	375	423.66	557.16	297.34	40.38
2	Iowa	33	137.62	439.47	138.84	137.77
3	Oklahoma	86	134.56	582.91	58.07	104.69
4	Wisconsin	82	132.11	145.46	102.87	42.76
5	Louisiana	43	130.80	528.42	134.18	162.74
6	Idaho	20	120.56	2223.97	188.71	184.99
7	South Carolina	33	115.66	102.21	78.35	31.42
8	Maine	8	104.64	92.16	53.99	85.81
9	Nevada	62	102.67	438.79	139.91	137.64
10	Alabama	37	93.85	122.96	41.14	28.40
11	New Mexico	13	91.94	74.82	46.42	63.28
12	Missouri	101	90.13	9741.00	155.90	71.84
13	Rhode Island	22	81.39	120.91	63.14	95.27
14	West Virginia	10	77.80	119.94	140.68	39.12
15	Colorado	240	77.79	282.21	70.46	139.37
16	North Carolina	98	76.54	115.68	49.84	40.17
17	Vermont	8	76.46	91.03	132.58	38.84
18	Pennsylvania	299	72.26	612.90	58.15	93.44
19	Florida	374	71.82	300.81	81.62	642.95
20	Oregon	65	70.08	359.58	76.18	72.91
21	Illinois	308	67.17	131.38	70.71	80.43
22	South Dakota	6	65.86	64.57	32.07	57.45
23	Mississippi	20	65.40	313.98	412.92	60.49
24	Arizona	102	63.73	182.20	65.87	78.95
25	New York	662	63.61	438.56	70.87	103.55
26	New Hampshire	32	63.08	72.57	42.40	36.10
27	Texas	767	59.80	238.41	100.80	153.97
28	Tennessee	96	59.05	101.64	66.05	49.24
29	Connecticut	186	56.65	222.68	42.87	46.07
30	Kansas	41	55.42	76.65	76.07	66.75
31	Georgia	193	50.02	235.27	139.96	62.98
32	Nebraska	30	48.48	58.02	52.06	45.07
33	Ohio	230	46.35	231.43	50.95	44.68
34	Michigan	122	45.94	289.60	54.26	50.84
35	Kentucky	39	45.02	259.59	99.15	65.35
36	Utah	82	41.08	173.43	204.14	116.68
37	Virginia	173	39.84	234.98	51.02	61.16
38	New Jersey	316	38.71	489.08	350.35	191.09
39	Maryland	122	38.30	187.95	87.19	47.34
40	Indiana	74	35.25	85.44	62.91	35.21
41	California	1297	35.02	193.10	83.34	87.66
42	Minnesota	206	29.46	781.08	207.45	146.25
43	Delaware	37	28.71	278.71	91.35	52.58
44	District Of Columbia	20	19.85	73.05	48.52	33.65
45	Washington	113	14.22	143.98	82.58	54.61
46	Arkansas	18	10.14	172.39	51.37	360.76
47	Wyoming	7	0.24	7.03	5.11	6.89

Table 40: Full Table: Summarizing Across All Firms by Acquiror US State - SAMPLE 5

Rank	Nation	Obs.	WM ***FCASSG***	M ***FCASSG***	M ***YASSG***	M ***CASS***
1	Massachusetts	375	309.70	415.77	221.19	32.87
2	Oklahoma	87	98.82	436.61	44.70	111.69
3	South Carolina	33	91.09	70.88	34.55	18.59
4	New Hampshire	32	85.24	60.21	28.64	28.51
5	Alabama	37	70.78	99.49	24.67	19.25
6	Nevada	61	62.95	378.23	64.62	169.85
7	Florida	374	59.29	243.29	59.47	335.31
8	Wisconsin	82	58.34	68.79	41.84	27.07
9	New Mexico	13	56.28	59.74	37.95	53.06
10	Vermont	8	51.74	68.20	81.29	28.82
11	Rhode Island	22	51.47	61.83	31.26	97.11
12	Maine	8	48.55	38.28	21.10	42.20
13	Colorado	241	44.36	122.24	39.09	66.98
14	New York	661	43.40	274.62	76.02	71.60
15	Pennsylvania	300	42.91	369.96	26.74	47.06
16	North Carolina	98	41.19	73.64	32.67	28.38
17	Nebraska	30	38.05	36.19	59.24	20.96
18	Connecticut	186	37.47	165.17	33.55	31.65
19	South Dakota	6	36.76	26.93	8.67	15.46
20	Kansas	41	36.53	54.81	43.46	49.17
21	Oregon	65	36.15	160.18	35.86	43.44
22	Missouri	101	35.98	1641.71	60.81	25.22
23	Delaware	37	34.65	236.36	41.53	42.75
24	Illinois	309	33.86	74.64	48.01	65.96
25	Idaho	20	30.67	699.40	46.22	99.24
26	Tennessee	97	30.40	49.73	34.35	25.87
27	Louisiana	43	29.71	84.28	28.88	28.99
28	Maryland	122	29.22	93.58	42.54	37.15
29	West Virginia	10	28.91	44.60	68.33	16.13
30	Virginia	174	27.85	158.38	38.19	49.61
31	Georgia	194	27.82	122.60	61.69	37.95
32	Texas	767	25.59	209.16	48.84	127.93
33	Mississippi	21	25.51	118.09	72.97	29.16
34	Ohio	231	25.06	116.54	30.18	28.37
35	Iowa	33	23.89	85.69	23.28	28.90
36	New Jersey	317	23.56	175.04	182.37	93.68
37	Arizona	103	23.11	88.19	28.31	37.04
38	Indiana	74	21.19	42.88	38.86	17.20
39	Michigan	122	20.38	122.03	31.33	29.46
40	California	1299	18.72	130.45	43.89	61.00
41	Utah	82	18.22	61.82	82.56	51.95
42	Minnesota	206	16.39	250.08	31.57	27.17
43	Kentucky	39	12.60	305.11	29.80	124.45
44	District Of Columbia	20	11.50	42.01	21.48	22.04
45	Montana	11	9.99	14.99	9.79	7.91
46	Arkansas	19	9.91	113.21	30.47	403.26
47	Washington	114	6.35	56.25	26.49	20.97
48	Wyoming	7	0.78	32.07	15.99	22.56

B Supplementary Plots

Figure 9: Histogram of the Last Year with an Observation for Delisted Companies

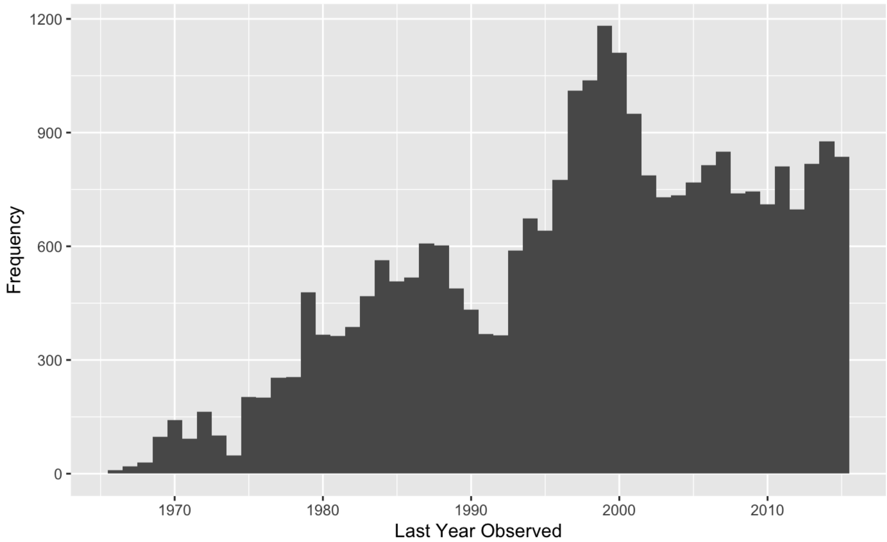
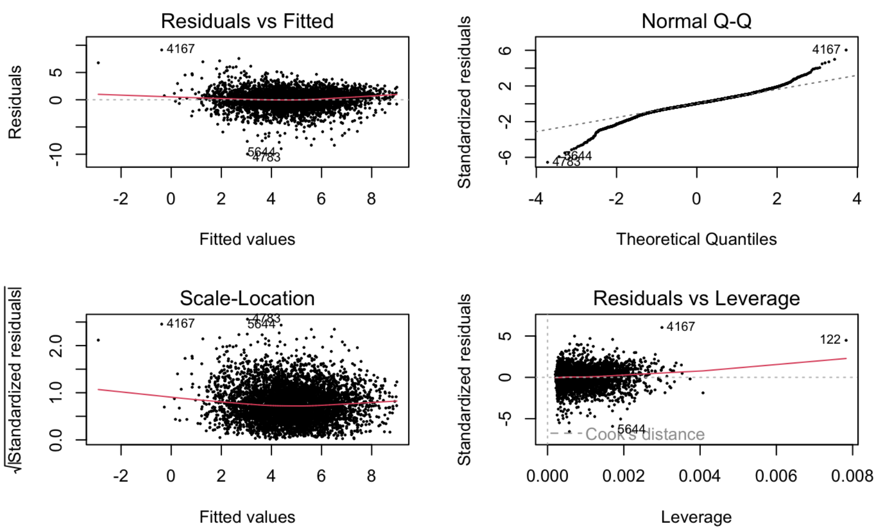


Figure 10: Diagnostic Plots of Model Used to Estimate Sales Values Based on Compustat Values



C Code

C.1 R-Code

This sections contains some of the R-codes used in this analysis. The code was run and created in R-Studio, using R-Markdown.

Matching SDC and Compustat This paragraph contains the codes used in the procedure described in Section 3.3. Code does not include reading of datasets and libraries. *SDC* is a dataset containing SDC merger data, while *SALESforMatching* contains Compustat financial data.

```
##SALESforMatching refers to the Compustat file
##################################################################
### MATCHING WITH PRIMARY CUSIP
SDC_CUSIP <- data.frame(SDC)
SDC_CUSIP$MATCHCUSIP <- SDC_CUSIP$AcquirorCUSIP
FIRMS_CUSIP <- data.frame(SALESforMatching)
FIRMS_CUSIP$cusip6D <- substr(FIRMS_CUSIP$cusip, start = 1, stop = 6
   )
FIRMS_CUSIP$MATCHCUSIP <- FIRMS_CUSIP$cusip6D
MERGED_CUSIP <- inner_join(FIRMS_CUSIP,SDC_CUSIP, by = "MATCHCUSIP",
    na_matches = "never")
MERGED_CUSIP <- select(MERGED_CUSIP, conml, AcquirorName, TargetName
   , DateEffective, everything())
MERGED_CUSIP <- arrange(MERGED_CUSIP, conml, DateEffective)
MERGED_CUSIP$COMP_SDC_ACQ <- str_replace_all(toupper(MERGED_CUSIP$
   AcquirorName),"[^[:alnum:]]", "")
MERGED_CUSIP$COMP_MAIN_ACQ <- str_replace_all(toupper(MERGED_CUSIP$
   conml),"[^[:alnum:]]", "")
MERGED_CUSIP$StringDistance <- 0
for (i in (1:length(MERGED_CUSIP$COMP_MAIN_ACQ))) {
MERGED_CUSIP$StringDistance[i] <- adist(MERGED_CUSIP$COMP_SDC_ACQ[i
   ], MERGED_CUSIP$COMP_MAIN_ACQ[i])
}
```

```
MERGED_CUSIP <- select(MERGED_CUSIP, conml, AcquirorName,
   StringDistance, TargetName, everything())
MERGED_CUSIP$METHOD <- "CUSIP"
n_distinct(MERGED_CUSIP$conml)

##################################################################
### MATCHING WITH UPDATED CUSIPS
SDC_NEW_CUSIP <- data.frame(SDC)
FIRMS_NEW_CUSIP <- data.frame(SALESforMatching)
FIRMS_NEW_CUSIP$cusip6D <- substr(FIRMS_NEW_CUSIP$cusip, start = 1,
   stop = 6)
FIRMS_NEW_CUSIP$MATCHCUSIP <- FIRMS_NEW_CUSIP$cusip6D
SDC_NEW_CUSIP$MATCHCUSIP <- SDC_NEW_CUSIP$Acq.New.CUSIP
MERGED_NEW_CUSIP <- inner_join(FIRMS_NEW_CUSIP,SDC_NEW_CUSIP, by = "
   MATCHCUSIP", na_matches = "never")
MERGED_NEW_CUSIP <- select(MERGED_NEW_CUSIP, conml, AcquirorName,
   TargetName, DateEffective, everything())
MERGED_NEW_CUSIP <- arrange(MERGED_NEW_CUSIP, conml, DateEffective)
MERGED_NEW_CUSIP$COMP_SDC_ACQ <- str_replace_all(toupper(MERGED_NEW_
   CUSIP$AcquirorName),"[^[:alnum:]]", "")
MERGED_NEW_CUSIP$COMP_MAIN_ACQ <- str_replace_all(toupper(MERGED_NEW
   _CUSIP$conml),"[^[:alnum:]]", "")
MERGED_NEW_CUSIP$StringDistance <- 0
for (i in (1:length(MERGED_NEW_CUSIP$COMP_MAIN_ACQ))) {
MERGED_NEW_CUSIP$StringDistance[i] <- adist(MERGED_NEW_CUSIP$COMP_
   SDC_ACQ[i], MERGED_NEW_CUSIP$COMP_MAIN_ACQ[i])
}
MERGED_NEW_CUSIP <- select(MERGED_NEW_CUSIP, conml, AcquirorName,
   StringDistance, TargetName, everything())
MERGED_NEW_CUSIP$METHOD <- "NewCUSIP"
n_distinct(MERGED_NEW_CUSIP$conml)

##################################################################
### MATCHING WITH IMMEDIATE PARENT CUSIP
SDC_IMMED_CUSIP <- data.frame(SDC)
```

```
FIRMS_IMMED_CUSIP <- data.frame(SALESforMatching)
FIRMS_IMMED_CUSIP$cusip6D <- substr(FIRMS_IMMED_CUSIP$cusip, start =
     1, stop = 6)
FIRMS_IMMED_CUSIP$MATCHCUSIP <- FIRMS_IMMED_CUSIP$cusip6D
SDC_IMMED_CUSIP$MATCHCUSIP <- SDC_IMMED_CUSIP$
   AcquirorImmediateParentCUSIP
MERGED_IMMED_CUSIP <- inner_join(FIRMS_IMMED_CUSIP,SDC_IMMED_CUSIP,
   by = "MATCHCUSIP", na_matches = "never")
MERGED_IMMED_CUSIP <- select(MERGED_IMMED_CUSIP, conml, AcquirorName
   , TargetName, DateEffective, everything())
MERGED_IMMED_CUSIP <- arrange(MERGED_IMMED_CUSIP, conml,
   DateEffective)
MERGED_IMMED_CUSIP$COMP_SDC_ACQ <- str_replace_all(toupper(MERGED_
   IMMED_CUSIP$AcquirorName),"[^[:alnum:]]", "")
MERGED_IMMED_CUSIP$COMP_MAIN_ACQ <- str_replace_all(toupper(MERGED_
   IMMED_CUSIP$conml),"[^[:alnum:]]", "")
MERGED_IMMED_CUSIP$StringDistance <- 0
for (i in (1:length(MERGED_IMMED_CUSIP$COMP_MAIN_ACQ))) {
MERGED_IMMED_CUSIP$StringDistance[i] <- adist(MERGED_IMMED_CUSIP$
   COMP_SDC_ACQ[i], MERGED_IMMED_CUSIP$COMP_MAIN_ACQ[i])
}
MERGED_IMMED_CUSIP <- select(MERGED_IMMED_CUSIP, conml, AcquirorName
   , StringDistance, TargetName, everything())
MERGED_IMMED_CUSIP$METHOD <- "ImmediateParentCUSIP"
n_distinct(MERGED_IMMED_CUSIP$conml)
###################################################################
### MATCHING WITH ULTIMATE PARENT CUSIP
SDC_ULTIMATE_CUSIP <- data.frame(SDC)
FIRMS_ULTIMATE_CUSIP <- data.frame(SALESforMatching)
FIRMS_ULTIMATE_CUSIP$cusip6D <- substr(FIRMS_ULTIMATE_CUSIP$cusip,
   start = 1, stop = 6)
FIRMS_ULTIMATE_CUSIP$MATCHCUSIP <- FIRMS_ULTIMATE_CUSIP$cusip6D
SDC_ULTIMATE_CUSIP$MATCHCUSIP <- SDC_ULTIMATE_CUSIP$
   AcquirorUltimateParentCUSIP
```

```
MERGED_ULTIMATE_CUSIP <- inner_join(FIRMS_ULTIMATE_CUSIP,SDC_
    ULTIMATE_CUSIP, by = "MATCHCUSIP", na_matches = "never")
MERGED_ULTIMATE_CUSIP <- select(MERGED_ULTIMATE_CUSIP, conml,
    AcquirorName, TargetName, DateEffective, everything())
MERGED_ULTIMATE_CUSIP <- arrange(MERGED_ULTIMATE_CUSIP, conml,
    DateEffective)
MERGED_ULTIMATE_CUSIP$COMP_SDC_ACQ <- str_replace_all(toupper(MERGED
    _ULTIMATE_CUSIP$AcquirorName),"[^[:alnum:]]", "")
MERGED_ULTIMATE_CUSIP$COMP_MAIN_ACQ <- str_replace_all(toupper(
    MERGED_ULTIMATE_CUSIP$conml),"[^[:alnum:]]", "")
MERGED_ULTIMATE_CUSIP$StringDistance <- 0
for (i in (1:length(MERGED_ULTIMATE_CUSIP$COMP_MAIN_ACQ))) {
MERGED_ULTIMATE_CUSIP$StringDistance[i] <- adist(MERGED_ULTIMATE_
    CUSIP$COMP_SDC_ACQ[i], MERGED_ULTIMATE_CUSIP$COMP_MAIN_ACQ[i])
}
MERGED_ULTIMATE_CUSIP <- select(MERGED_ULTIMATE_CUSIP, conml,
    AcquirorName, StringDistance, TargetName, everything())
MERGED_ULTIMATE_CUSIP$METHOD <- "UltimateParentCUSIP"
n_distinct(MERGED_ULTIMATE_CUSIP$conml)
##################################################################
### MATCHING WITH NAMES
SDC_for_NAME <- data.frame(SDC)
FIRMS_for_NAME <- data.frame(SALESforMatching)
SDC_for_NAME$AC_NAME <- SDC_for_NAME$AcquirorName
FIRMS_for_NAME$AC_NAME <- FIRMS_for_NAME$conml
SDC_for_NAME$AC_NAME <- toupper(SDC_for_NAME$AC_NAME)
FIRMS_for_NAME$AC_NAME <- toupper(FIRMS_for_NAME$AC_NAME)
SDC_for_NAME$AC_NAME <- str_replace_all(SDC_for_NAME$AC_NAME, "[^[:
    alnum:]]", "")
FIRMS_for_NAME$AC_NAME <- str_replace_all(FIRMS_for_NAME$AC_NAME, "
    [^[:alnum:]]", "")
MERGED_NAME <- inner_join(FIRMS_for_NAME,SDC_for_NAME, by = "AC_NAME
    ", na_matches = "never")
MERGED_NAME <- select(MERGED_NAME, conml, AcquirorName, TargetName,
    DateEffective, everything())
```

```
MERGED_NAME <- arrange(MERGED_NAME, conml, DateEffective)
MERGED_NAME$COMP_SDC_ACQ <- str_replace_all(toupper(MERGED_NAME$
   AcquirorName),"[^[:alnum:]]", "")
MERGED_NAME$COMP_MAIN_ACQ <- str_replace_all(toupper(MERGED_NAME$
   conml),"[^[:alnum:]]", "")
MERGED_NAME$StringDistance <- 0
for (i in (1:length(MERGED_NAME$COMP_MAIN_ACQ))) {
MERGED_NAME$StringDistance[i] <- adist(MERGED_NAME$COMP_SDC_ACQ[i],
   MERGED_NAME$COMP_MAIN_ACQ[i])
}
MERGED_NAME <- select(MERGED_NAME, conml, AcquirorName,
   StringDistance, TargetName, everything())
MERGED_NAME$METHOD <- "Name"
n_distinct(MERGED_NAME$conml)
##################################################################
### MATCHING WITH PRIMARY TICKER SYMBOL
SDC_for_TIC <- data.frame(SDC)
FIRMS_for_TIC <- data.frame(SALESforMatching)
SDC_for_TIC$TICMATCH <- SDC_for_TIC$AcquirorPrimaryTickerSymbol
FIRMS_for_TIC$TICMATCH <- FIRMS_for_TIC$tic
MERGED_TIC <- inner_join(FIRMS_for_TIC,SDC_for_TIC, by = "TICMATCH",
    na_matches = "never")
MERGED_TIC <- select(MERGED_TIC, conml, AcquirorName, TargetName,
   DateEffective, everything())
MERGED_TIC <- arrange(MERGED_TIC, conml, DateEffective)
MERGED_TIC$COMP_SDC_ACQ <- str_replace_all(toupper(MERGED_TIC$
   AcquirorName),"[^[:alnum:]]", "")
MERGED_TIC$COMP_MAIN_ACQ <- str_replace_all(toupper(MERGED_TIC$conml
   ),"[^[:alnum:]]", "")
MERGED_TIC$StringDistance <- 0
for (i in (1:length(MERGED_TIC$COMP_MAIN_ACQ))) {
MERGED_TIC$StringDistance[i] <- adist(MERGED_TIC$COMP_SDC_ACQ[i],
   MERGED_TIC$COMP_MAIN_ACQ[i])
}
```

```
MERGED_TIC <- select(MERGED_TIC, conml, AcquirorName, StringDistance
    , TargetName, everything())
MERGED_TIC$METHOD <- "Ticker"
n_distinct(MERGED_TIC$conml)
#################################################################
### MATCHING WITH ULTIMATE PARENT TICKER SYMBOL
SDC_for_PARENTTIC <- data.frame(SDC)
FIRMS_for_PAERNTTIC <- data.frame(SALESforMatching)
SDC_for_PARENTTIC$TICMATCH <- SDC_for_PARENTTIC$
    AcquirorUltimateParentPrimaryTickerSymbol
FIRMS_for_PAERNTTIC$TICMATCH <- FIRMS_for_PAERNTTIC$tic
MERGED_PARENTIC <- inner_join(FIRMS_for_PAERNTTIC, SDC_for_PARENTTIC
    , by = "TICMATCH", na_matches = "never")
MERGED_PARENTIC <- select(MERGED_PARENTIC, conml, AcquirorName,
    TargetName, DateEffective, everything())
MERGED_PARENTIC <- arrange(MERGED_PARENTIC, conml, DateEffective)
MERGED_PARENTIC$COMP_SDC_ACQ <- str_replace_all(toupper(MERGED_
    PARENTIC$AcquirorName),"[^[:alnum:]]", "")
MERGED_PARENTIC$COMP_MAIN_ACQ <- str_replace_all(toupper(MERGED_
    PARENTIC$conml),"[^[:alnum:]]", "")
MERGED_PARENTIC$StringDistance <- 0
for (i in (1:length(MERGED_PARENTIC$COMP_MAIN_ACQ))) {
MERGED_PARENTIC$StringDistance[i] <- adist(MERGED_PARENTIC$COMP_SDC_
    ACQ[i],MERGED_PARENTIC$COMP_MAIN_ACQ[i])
}
MERGED_PARENTIC <- select(MERGED_PARENTIC, conml, AcquirorName,
    StringDistance, TargetName, everything())
MERGED_PARENTIC$METHOD <- "ParentTicker"
n_distinct(MERGED_PARENTIC$conml)
#################################################################
### MATCHING WITH UPDATED TICKER SYMBOL
SDC_for_NEWTIC <- data.frame(SDC)
FIRMS_for_NEWTIC <- data.frame(SALESforMatching)
SDC_for_NEWTIC$TICMATCH <- SDC_for_NEWTIC$Acq.New.TICKER
FIRMS_for_NEWTIC$TICMATCH <- FIRMS_for_NEWTIC$tic
```

```
MERGED_NEWTIC <- inner_join(FIRMS_for_NEWTIC, SDC_for_NEWTIC, by = "
    TICMATCH", na_matches = "never")
MERGED_NEWTIC <- select(MERGED_NEWTIC, conml, AcquirorName,
    TargetName, DateEffective, everything())
MERGED_NEWTIC <- arrange(MERGED_NEWTIC, conml, DateEffective)
MERGED_NEWTIC$COMP_SDC_ACQ <- str_replace_all(toupper(MERGED_NEWTIC$
    AcquirorName),"[^[:alnum:]]", "")
MERGED_NEWTIC$COMP_MAIN_ACQ <- str_replace_all(toupper(MERGED_NEWTIC
    $conml),"[^[:alnum:]]", "")
MERGED_NEWTIC$StringDistance <- 0
for (i in (1:length(MERGED_NEWTIC$COMP_MAIN_ACQ))) {
MERGED_NEWTIC$StringDistance[i] <- adist(MERGED_NEWTIC$COMP_SDC_ACQ[
    i],MERGED_NEWTIC$COMP_MAIN_ACQ[i])
}
MERGED_NEWTIC <- select(MERGED_NEWTIC, conml, AcquirorName,
    StringDistance, TargetName, everything())
MERGED_NEWTIC$METHOD <- "NewTicker"
n_distinct(MERGED_NEWTIC$conml)
#################################################################
### MATCHING WITH WEBSCRAPED URLS
URLtoMATCH <- data.frame(URLMatchesSALES)
SDCURLMerge <- data.frame(SDC)
SDC_MERGE_URL <- left_join(URLtoMATCH, SDCURLMerge, by = "
    AcquirorName")
MERGED_URL <- left_join(SDC_MERGE_URL, SALESforMatching, by = "conml
    ")
MERGED_URL <- select(MERGED_URL, conml, AcquirorName, TargetName,
    DateEffective, everything())
MERGED_URL <- arrange(MERGED_URL, conml, DateEffective)
MERGED_URL$COMP_SDC_ACQ <- str_replace_all(toupper(MERGED_URL$
    AcquirorName),"[^[:alnum:]]", "")
MERGED_URL$COMP_MAIN_ACQ <- str_replace_all(toupper(MERGED_URL$conml
    ),"[^[:alnum:]]", "")
MERGED_URL$StringDistance <- 0
for (i in (1:length(MERGED_URL$COMP_MAIN_ACQ))) {
```

```
MERGED_URL$StringDistance[i] <- adist(MERGED_URL$COMP_SDC_ACQ[i],
    MERGED_URL$COMP_MAIN_ACQ[i])
}
MERGED_URL <- select(MERGED_URL, conml, AcquirorName, StringDistance
    , TargetName, everything())
MERGED_URL$METHOD <- "URLs"
n_distinct(MERGED_URL$conml)
```

Aggregating Matches This paragraph contains the codes used in the procedure described in Section 3.3. Data frames resulting from different matching methods are stacked, after ensuring that they have the same format. Later, only matches with an adequate URL-similarity are selected, unless they were matched with a unique identifier.

```
M_CUSIP <- select(MERGED_CUSIP, -c(cusip6D,MATCHCUSIP))
M_NEWCUSIP <- select(MERGED_NEW_CUSIP, -c(cusip6D,MATCHCUSIP))
M_ULTIMATE_CUSIP <- select(MERGED_ULTIMATE_CUSIP, -c(cusip6D,
    MATCHCUSIP))
M_IMMED_CUSIP <- select(MERGED_IMMED_CUSIP, -c(cusip6D,MATCHCUSIP))
M_NAME <- select(MERGED_NAME, -c(AC_NAME))
M_TIC <- select(MERGED_TIC, -c(TICMATCH))
M_PARENTIC <- select(MERGED_PARENTIC, -c(TICMATCH))
M_NEWTIC <- select(MERGED_NEWTIC, -c(TICMATCH))
M_URL <- select(MERGED_URL, -c(MATCHES))
M_URL <- M_URL[names(M_NEWTIC)]
for (i in (1:length(colnames(M_URL)))) {
ifelse(colnames(M_URL)[i]==colnames(M_NEWCUSIP)[i], FALSE,print(
    paste(colnames(M_URL)[i], "␣",i, "␣",colnames(M_NEWCUSIP)[i])))
}
SALES_FIRM_MATCHES <- rbind(M_CUSIP,M_NEWCUSIP,M_IMMED_CUSIP,M_
    ULTIMATE_CUSIP, M_NAME,M_TIC,M_PARENTIC,M_NEWTIC , M_URL)
SALES_FIRM_MATCHES <- select(SALES_FIRM_MATCHES, ROWINDEX.sdc, conml
    , AcquirorName, StringDistance, METHOD, TargetName, everything())
n_distinct(SALES_FIRM_MATCHES$conml)
SALES_FIRM_MATCHES_UNFILTERED <- data.frame(SALES_FIRM_MATCHES)
write.csv(SALES_FIRM_MATCHES, "SalesCUSIPMatches_UNFILTERED.csv")
```

```
write.csv(SALES_FIRM_MATCHES, "SalesCUSIPMatches_UNFILTERED_NABlank.
   csv", na = "")
SALES_FIRM_MATCHES <- filter(SALES_FIRM_MATCHES, !duplicated(
   ROWINDEX.sdc))
####################################################################
# ADD URLS
SALES_FIRM_MATCHES$URLMATCH <- NA
for (i in (1:length(SALES_FIRM_MATCHES$url))) {
splitURLx <- strsplit(as.character( SALES_FIRM_MATCHES$url[i] ), ","
   )[[1]]
spliturly <- strsplit( as.character( SALES_FIRM_MATCHES$AcquirorURL[
   i]), ",")[[1]]
intersection <- intersect(spliturlx,spliturly)
SALES_FIRM_MATCHES$URLMATCH[i] <- length(intersection)
}
####################################################################
SALES_FIRM_MATCHES <- select(SALES_FIRM_MATCHES, ROWINDEX.sdc, conml
   , AcquirorName, URLMATCH, METHOD, TargetName, everything())
write.csv(SALES_FIRM_MATCHES, "MatchesSCFirms.csv")
write.csv(SALES_FIRM_MATCHES, "MatchesSCFirms_NABlank.csv", na="")
n_distinct(SALES_FIRM_MATCHES$conml)
n_distinct(SALESforMatching$conml)
####################################################################
SCMatches <- data.frame(SALES_FIRM_MATCHES)
SCMatches <- filter(SCMatches, METHOD == "CUSIP" |
                      METHOD == "NewCUSIP" |
                      METHOD == "ImmediateParentCUSIP" |
                      METHOD == "UltimateParentCUSIP" |
                      METHOD == "Name" | URLMATCH > 2)
```

C.2 Python-Code

This sections contains the code for all computations which were executed using Python 3. The codes were run using a JupyterNotebook-extension in VS Code. Virtual environments were created with Anaconda.

URL-Scraping This paragraph contains the codes used in the procedure described in Section 3.3. This program runs company name search queries on Microsoft Bing and saves the results in a list, which is then assigned to said company.

```
from fake_useragent import UserAgent
import pandas as pd
from pandas import DataFrame
from selenium import webdriver
from selenium.common.exceptions import NoSuchElementException
from bs4 import BeautifulSoup as soup
import re
import time
from selenium.webdriver.chrome.options import Options
from selenium.webdriver.common.by import By
options = webdriver.ChromeOptions()
ua = UserAgent()
userAgent = ua.firefox
print(userAgent)

options.binary_location = "C:/..."
chrome_driver_binary = "C:/..."
options.add_experimental_option('excludeSwitches', ['enable-logging'
    ])
options.add_argument(f'user-agent={userAgent}')
driver = webdriver.Chrome(chrome_driver_binary, chrome_options=
    options)

df = pd.read_csv(r"MissingURLs.csv")
parents = df['conml'].tolist()
df["url"] = None
```

```
print(len(parents))

for index, comp in enumerate(parents):
#get list of urls for parent.
  if "&" in comp:
    comp = comp.replace("&","%26")
  url = "https://www.bing.com/search?q=" + comp
  print("FIRM ", index+1, " out of ", len(parents), " ",
        round((index+1)*100/len(parents),1), " %", " URL: ", url)

  driver.get(url)
  time.sleep(5)
  urls = driver.find_elements(By.CSS_SELECTOR, "h2 > a")
#append urls into list called links
  links = []
  for l in urls:
    links.append(l.get_attribute('href'))
  df["url"][index] = links
df.to_csv("MissingURLs_COMPLETE.csv", encoding = "utf-8")
```

Matrix Iterations (URL-Matching) This paragraph contains the codes used in the procedure described in Section 3.3. The code takes data frames which have a column with lists of URLs and some columns with company attributes such as name and gvkey as input. The variable “firms“ references the Compustat dataset.

```
import pandas as pd
import numpy as np
firms = pd.read_csv(r"COMPLETE_URLS_SALES.csv")
sdc = pd.read_csv(r"SDC_ACQUIROR_URLs.csv")
firms_names = firms['conml'].tolist()
sdc_names = sdc['AcquirorName'].tolist()
main_urls = firms['url'].tolist()
sdc_urls = sdc['url'].tolist()
#####################################################
firm_url_store = []
```

```
sdc_url_store = []
for index, url in enumerate(main_urls):
    url = str(url)
    url = url.split("'")
    for location, rawurl in enumerate(url):
        if len(rawurl) < 5:
            del url[location]
    firm_url_store.append(url)
for index, url in enumerate(sdc_urls):
    url = str(url)
    url = url.split("'")
    for location, rawurl in enumerate(url):
        if len(rawurl) < 5:
            del url[location]
    sdc_url_store.append(url)
#####################################################
url_matches = np.zeros((int(len(firm_url_store)),int(len(
   sdc_url_store))))
counter = 0
for frim_index, firm_url in enumerate(firm_url_store):
    for sdc_index, sdc_url in enumerate(sdc_url_store):
        intersection = set(sdc_url).intersection(firm_url)
        url_matches[frim_index,sdc_index] = len(intersection)
    counter = counter + 1
    if counter%50 == 0:
        print("At index: ", counter, " ", round(counter*100/len(
           firm_url_store),2), " %" )
#####################################################
named_matches = []
counter = 0
for firm_index, firm_name in enumerate(firms_names):
    for sdc_index, sdc_name in enumerate(sdc_names):
        matchcount = url_matches[firm_index,sdc_index]
        if matchcount > 0:
            match = [firm_name,sdc_name,matchcount]
```

```
            named_matches.append(match)
    counter = counter + 1
    if counter%50 == 0:
        print("At index: ", counter, " ", round(counter*100/len(
           firm_url_store),2), " %" )
#####################################################
matches_array = np.array(named_matches)
matches_df = pd.DataFrame(matches_array)
matches_df.to_csv("URLMatchesV1.csv", encoding = "utf-8")
```