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Neoclassical Evidence on Merger Waves

An Empirical Analysis of the Drivers of M&A Waves, the Influence of Private Equity, and Evolution of Takeover Premiums

Fredrik Jørgensen and Herman Lynnebakken

Supervisor: Karin S. Thorburn

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Abstract

This thesis investigates the drivers of industry and aggregate merger waves from 2000 to 2019, with point of departure in revisiting previous research by Harford (2005). The formation of merger waves could be in response to fundamental economic, regulatory, or technological shocks, for which mergers facilitate change to the corporate environment, or due to managerial attempts to time the takeover market. The thesis adds value to existing research by applying Harford's (2005) methods to a more recent time period, controlling for new private equity variables, and by investigating the size of takeover premiums over the course of the wave.

We find that economic, regulatory, and technological shocks drive industry merger waves, but only when accompanied by the necessary capital liquidity to accommodate the transaction costs, consistent with previous research (Harford, 2005). Aggregate merger waves form when industry waves cluster in time. However, as many industries have become more agile, are already deregulated, and innovating at an increasingly faster pace making technological shocks more continuous, underlying economic shocks seem to have become less surprising and increasingly accounted for by anticipatory variables. Moreover, we find that capital raised by private equity funds significantly builds up prior to the waves, and that these funds participate in the waves on a scale that is significant in the aggregate, but not of sufficient magnitude to be driving them. Takeover premiums decrease over the course of the wave, as bidders fiercely compete for targets that best enable them to respond to the underlying shock in the initial phase of the wave, consistent with the neoclassical explanation of merger waves.

Preface

This thesis marks the beginning of the end of our master's degree in financial economics at the Norwegian School of Economics (NHH). We particularly want to thank Professor Karin Thorburn for excellent supervision and indispensable tutorship throughout the program. Our interest in mergers and acquisitions was first kindled when we took her legendary elective class on Mergers and Acquisitions (FIE443). Her academic rigor, genuine passion and sincere care for her students has inspired us to further pursue this fascinating field ever since.

We also wish to thank Eric de Bodt at the Californian Institute of Technology (Caltech) for patiently opening our eyes to the complexity of advanced econometrics and providing invaluable feedback to our models. Any errors are our own. Finally, we are thankful to Thompson SDC, Compustat and Preqin for supplying the data.

We dedicate this thesis to our families and friends for their continuous support throughout our time at NHH; without it this thesis would not have been possible.

Our work stands on the shoulders of the giants that has gone before us. We hope our thesis can add value to the research community and be useful to whomsoever might follow in our footsteps.

Bergen, December 19, 2020,

Fredrik Jørgensen

Sign:____________________

Herman Lynnebakken

Sign:____________________

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1. Introduction

The existence of merger waves, that is, the clustering of merger activity over time with its transaction peaks and troughs has long been observed in the corporate takeover market (Berk & DeMarzo, 2017, pp. 995-996), both within industries (Mitchell & Mulherin, 1996) and on an aggregate economic level (Harford, 2005). However, the primary *drivers* of merger waves have long been subject to debate. In fact, Brealey and Myers (1991, p. 923) coined the occurrence of merger waves one of the ten biggest unexplained puzzles of financial economics (Mitchell & Mulherin, 1996, p. 221). In the aftermath of the call for research, the last couple of decades has seen the emergence of two competing explanations: the neoclassical and behavioral hypothesis, as characterized by Harford (2005). The neoclassical hypothesis suggests waves are driven by industry restructuring as a response to fundamental economic, regulatory, or technological shocks (Mitchell and Mulherin, 1996) and facilitated by sufficiently low transaction costs (Eisfeldt and Rampini, 2006; Harford, 2005). The behavioral hypothesis claims that waves result from managerial attempts to exploit relatively overvalued equity to time the takeover market (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004).

Harford (2005) is the first to compare both neoclassical and behavioral variables. He finds that merger waves form in response to fundamental economic, regulatory, and technological shocks for which mergers facilitate change to the environment and propagate when transaction costs are sufficiently low to accommodate the necessary transactions. However, Harford (2005) and most of the available literature focuses on the 1980s and -90s. A lot has changed since then. Increased data availability, changing economic conditions, and increasing competition from financial buyers in the merger market driven by the increasing capital inflow to private equity, all warrant a second look at Harford's (2005) findings.

This thesis investigates the economic drivers of merger waves from 2000 to 2019, with point of departure in Harford (2005). We add value to existing research by applying Harford's (2005) methods on new data and innovate by controlling for private equity variables. Albeit recent years have seen increasing research on investment behavior in private equity funds (Axelson et. al, 2009; Kaplan and Strömberg, 2009; Buchner et. al., 2020) and their role in driving buyout waves (Harford et. al., 2016), little attention has been granted the role of committed capital to private equity in merger waves. Additionally, we investigate the evolution of takeover premiums over the course of the wave, which beknown to us, is largely unchartered territory in the context of merger waves.

The thesis follows the following structure: section 2 provides an extensive literature review on merger waves (2.1), the behavioral (2.2) and neoclassical hypothesis (2.3) as competing explanations for wave formations, recent developments in the field of research since Harford (2005) (2.4), and finally the influence of private equity and leveraged buyouts (2.5). Based on this review, section 3 derives research hypotheses and testable predictions that form the basis for the data sampled and variables constructed, as discussed in section 4. Section 5 provides an exhaustive discussion of methods used, findings and their robustness. Finally, section 6 concludes. Supplementary exhibits are found in the Appendix.

2. Literature Review

2.1 Historical Merger Waves

A brief review of historical merger waves is warranted before researching the underlying drivers of the phenomena. Modern post-war economic history has seen predominantly four major merger waves (Berk & DeMarzo, 2017, p. 996). The peaks in takeover activity in the 1960s, 1980s, 1990s and 2000s, have each been (ad-hoc) labeled according to their own inherent characteristics, perhaps because the drivers of the waves have been mystified (Mitchell & Mulherin, 1996, p. 194). The "conglomerate" wave of the 1960s is known for excessive conglomeration, because acquirers typically acquired firms in unrelated industries. Whether these acquisitions were motivated by business diversification, access to internal capital markets or merely a symptom of managerial hubris and "empire-building", the idea that managerial expertise was easily transferable across business lines later drew skepticism, and many of the takeovers at the time are thought to have been value decreasing, albeit they on average were not detrimental to shareholder wealth (Betton, Eckbo, & Thorburn, 2008, p. 4).

As a result, the "refocusing wave" of the 1980s saw increased specialization and downsizing of operations, many in response to excessive conglomeration, excess capacity in the aftermath of the 1970s recession, or technological advancements (Betton et al., 2008, p. 5). Because the 1980s also saw a lot of hostile takeovers, the wave is also known as the hostile or "bust-up" wave, in which many corporate raiders acquired poorly performing conglomerates and spun off its business divisions as individual assets, spawning various takeover defense mechanisms. The "strategic wave" of the 1990s, on the other hand, was a "friendly" wave known for global within-industry transactions, largely motivated by the necessary scale to compete globally (Berk & DeMarzo, 2017, p. 996).

Finally, the most recent wave started picking up in 2004, and saw heavy consolidation in many industries. The wave also saw private equity groups playing an increasingly influential role in the takeover market, taking ever-larger firms private, but this was brought to an abrupt end by the credit crunch associated with the financial crisis of 2008 (Berk & DeMarzo, 2017, p. 996). According to Berk and DeMarzo (2017, p. 996), takeover activity started picking up again in 2014-15 (at least in terms of dollar value), with an all-time high of $5 trillion worth of global M&A deals in 2015. Such merger waves can be explained by the behavioral or neoclassical hypotheses.

2.2 Behavioral Hypothesis

The behavioral hypothesis presumes that merger waves are driven by managerial attempts to time the takeover market, building on the observed correlation between stock market valuations and aggregate merger activity, as found by Golbe and White (1988), amongst others. Golbe and White (1988) claim to be among the first to conduct a time series analysis of merger activity. Working with the fragmented time series data available at the time, they use Tobin's Q (i.e., the ratio of market value to the replacement cost of a listed firm) to posit a "bargain hypothesis". They argue that the lower the Q ratio, the relatively cheaper (and therefore more of a bargain) the target is, making it more likely that an acquirer will step forward and buy the target. Therefore, they expect Q to be negatively related to aggregate merger activity, which in turn, implies a negative correlation between merger activity and market valuations (i.e., securities prices). To their surprise, they find the opposite, namely that merger activity is positively correlated with securities prices, but fail to provide an economic explanation for why that is. They neither consider stocks as acquisition currency in stock swaps, the access to which, according to more recent research by Brau and Fawcett (2006, p. 425) is the single most important motivator for CFOs to go public.

Shleifer and Vishny (2003) argue the observed correlation between merger activity and market valuations are likely because bull markets lead groups of bidders with relatively overvalued stock to use their stock to buy real assets from relatively undervalued targets. The argument presumes target managers with short-term time horizons are prone to accept overvalued equity. According to Shleifer and Vishny (2003), the neoclassical hypothesis is incomplete because it does not explain aggregate merger waves, but rather industry-specific responses to a shock.

Contemporaneously, Rhodes-Kropf and Viswanathan (2004) argue that market valuations and merger activity correlate because of opportunistic managerial behavior and uncertainty about sources of misvaluation. According to Rhodes-Kropf and Viswanathan (2004), rational targets with imperfect information are more likely to accept bids from overvalued bidders, as the targets are most likely to overestimate synergies in these periods. Consequently, overvaluation affects both deal probability and the means of exchange. When aggregate market valuations are high, stock swaps increase throughout the wave, implying that the proportion of cash deals are relatively high when market valuations are low. Contrary to Shleifer and Vishny (2003), Rhodes-Kropf and Viswanathan (2004) argue that it is the imperfect information rather than short time horizons that lead target managers to accept temporarily overvalued equity.

Rhodes–Kropf, Robinson, and Viswanathan (2005) similarly find that aggregate merger waves occur when market-to-book ratios (M/B) are relatively high compared to fundamental value, approximated by residual income models and industry multiples. They also find that "cash targets are undervalued relative to stock targets" while "cash acquirers are less overvalued than stock acquirers" (Rhodes–Kropf et al., 2005, p. 601). Albeit they recognize that the discrepancy between M/B ratios and fundamental value can be attributed to behavioral mispricing, or that merger activity spikes when growth opportunities are high and discount rates low (as claimed by the neoclassical view), they argue that mispricing is the most likely explanation. This is based on the notion that "even in industries that appear to have experienced an economic shock, most acquirers come from the highest misvaluation quantile" (Rhodes–Kropf et al., 2005, p. 601). They conclude that "economic shocks could well be the fundamental drivers of merger activity, but misvaluation affects how these shocks are propagated through the economy" (Rhodes–Kropf et al., 2005, p. 601).

Other notable contributors to behavioral merger theories include Ang and Cheng (2006) who, building on the findings of the abovementioned authors, find that overvalued acquirers are more likely to pay with stock and that acquirers in successful mergers are more overvalued than in withdrawn mergers. They also find that on average, the overvaluation of the stock acquirer exceeds the premium-adjusted overvaluation of the target. Dong, Hirshleifer, Richardson, and Teoh (2006) make similar findings. This is consistent with Rhodes-Kropf and Viswanathan (2004) findings that rational target managers are more likely to accept overvalued equity because they struggle to differentiate between market-specific and firm-specific sources of misvaluation.

2.3 Neoclassical Hypothesis

The neoclassical hypothesis presumes that the underlying drivers of rational merger waves is "an economic disturbance that leads to industry reorganization" (Harford, 2005, p. 532). This section reviews the most prominent neoclassical contributions leading up to Harford (2005) and concludes with a review of Harford's (2005) own hallmark paper.

The neoclassical argument can be traced back to Coase (1937), presumably one of the earliest to suggest that scale-increasing technological change could lead to mergers. Gort (1969, p. 627) posits that technological change could lead to economic disturbances generating increased discrepancies in firm valuations resulting in increased merger activity.

Mitchell and Mulherin (1996) document industry-level patterns in takeover and restructuring activity in the 1980s. They find significant differences in rate and clustering of activities, and attribute the patterns to economic, technological, or regulatory shocks. They argue that corporate restructurings such as mergers and leveraged buyouts are often the least-cost response to the industry restructuring brought about by industry shocks. Mulherin and Boone (2000) compare acquisitions and divestures in the 1990s and find clear clustering of both. Like Mitchell and Mulherin (1996) they also attribute the clustering to shocks, noting that acquisition activity in the period was significantly higher for industries undergoing deregulation. Based on the notion that firms can respond to shocks by either expansion (merger) or reduction (divesture) of investment activities, they document that both create almost symmetrical shareholder wealth and is directly related to deal size. This is consistent with the synergistic restructuring narrative of the neoclassical hypothesis and inconsistent with behavioral models emphasizing "managerial hubris" (Mitchell & Mulherin, 1996, p. 135). Andrade, Mitchell, and Stafford (2001) make similar findings, showing that deregulation was an important shock of the 1990s, with nearly half of the mergers since the 1980s being driven predominantly by deregulation.

Andrade and Stafford (2004) extend on these arguments comparing mergers with internal investment decisions. They find that mergers cluster in time and industry, whereas internal investment decisions do not. They add to existing literature by differentiating between expansionary and contractionary waves. Whereas the 1970s – and 80s saw industry consolidation (i.e. contraction) through mergers driven by excess capacity (following the 1970s recession (Betton et al., 2008, p. 6)), while peak capacity utilization triggered industry expansion through non-merger investments, this was reversed in the 1990s. Throughout the '90s, it was the profitable, high-growth, near-capacity industries that experienced the most intense merger activity (Andrade & Stafford, 2004).

Contemporaneously, Jovanovic and Rousseau (2001; 2002) find that merger waves facilitate reallocation of assets following a technological shock, in which the assets are reallocated to those best suited to operate the new technology, and that the wave settles when the reallocation is complete (Jovanovic & Rousseau, 2001, p. 2), emphasized by the finding that waves will be shorter when the pace of technological change is more dramatic (Jovanovic & Rousseau, 2001, p. 2). Building on valuation discrepancies and dispersion in Tobin's Q they find that high-Q firms acquire low-Q firms in waves, concluding that the merger waves of the 1900s, the 1920s, 1980s, and 1990s were probably reallocation waves, with the conglomerate wave of the 1960s being caused by "something else" (Jovanovic & Rousseau, 2002, pp. 1, 12).

Eisfeldt and Rampini (2006)[1] broadly interpret the cost of reallocating capital as "liquidity" and document that capital reallocation is procyclical. Shleifer and Vishny (1992) make similar arguments in a study of the link between asset liquidity and debt capacity. They argue that asset liquidity is an important component of capital liquidity because asset sales propose an alternative way to raise cash for firms nearing financial distress. According to Shleifer and Vishny (1992), mergers happen in booms because increases in cash flows simultaneously increase fundamental values and relax financing constraints, bridging the gap between prices and fundamental values. For instance, in recessions, many asset buyers are credit constrained and therefore unable to pay fundamental values.

This is particularly true when considering that most assets that change hands end up in the same industry (Bhagat, Shleifer, Vishny, Jarrel, & Summers, 1990), such that the seller and buyer of the asset are likely to experience similar financial distress. This prompts the seller to await better times in hopes of increased asset liquidity. Similarly, when cash flows are high (and financing constraints relaxed), buyers can afford to pay prices close to fundamental values, making sellers more prone to readily part with their assets. As a result, merger activity clusters in time and waves occur (Shleifer & Vishny, 1992, pp. 1361-1364). The argumentation is emphasized by noting that the horizontal mergers typical for the 1980s were a result of relaxed antitrust enforcement in the U.S (Bhagat et al., 1990). Moreover, asset liquidity enables firms to take on more debt. In the 1980s, many loans were granted with the expectation that asset selloffs were necessary to meet the payments. Many of the LBO's of the decade would therefore not have been possible without increased asset liquidity for divisions through carveouts and partial-firm acquisitions, causing increased debt capacity – an ingredient inherent to LBO's. This suggests that asset liquidity seem to create debt capacity, and not the other way around (Shleifer & Vishny, 1992, p. 1363).

Schlingemann, Stulz, and Walkling (2002) similarly find that industry-specific asset liquidity is an important determinator of asset divestures, by showing that firms with segments in relatively more liquid industries are more likely to conduct divestures. Additionally, among divesting firms, segment liquidity helps explain what assets are retained and divested (Schlingemann et al., 2002), consistent with Shleifer and Vishny (1992). The idea that

[1] Harford (2005) cites the working paper from 2003 that was circulating a few years before it was published in 2006.

transactions depend on relaxed capital constraints to occur is supported by Harford (1999) who finds that firms with large cash reserves are more acquisitive.

Harford (2005) modifies the neoclassical hypothesis by introducing an overall capital liquidity component (the rate spread). He argues that waves occur in response to industry-specific shocks that necessitates large-scale reallocation of assets, as suggested by Gort (1969). However, there must also be sufficient capital liquidity to accommodate the reallocation. He extends this argument to market valuation variables traditionally claimed by the behavioral camp by arguing that "because higher market valuations relax financing constraints, market valuations are an important part of capital liquidity" (Harford, 2005, p. 533). By investigating merger activity between 1981 and 2000 with a transaction value of at least $50 million, he identifies 35 industry merger waves (Harford, 2005, p. 536). Harford (2005) initially compares behavioral and neoclassical variables of industry characteristics in pre-wave years with the rest of the sample, using a rank sum test to investigate if the variables behave as predicted by their corresponding hypotheses. He finds that both changes to firm fundamentals and valuation variables precede industry merger waves. To further investigate the drivers of the waves, he embarks on a series of Logit and OLS regressions in which the variables compete against each other in various specifications. By sequentially adding valuation and capital liquidity variables to his specifications and comparing them, he finds that capital liquidity subsumes the explanatory power of the valuation variables.

Harford (2005, p. 530) therefore argues that the procyclical correlation between high market valuations and merger activity has been misattributed to behavioral misvaluation factors, since it only proxies for the capital liquidity effect in his models. This leads him to formally reject the behavioral hypothesis. Instead, he intuitively observes that "merger waves require both an economic motivation for transactions and relatively low transaction costs to generate a large volume of transactions" (Harford, 2005, p. 530). Moreover, the liquidity factor causes merger activity to cluster in time even if shocks do not, leading to aggregate merger waves (Harford, 2005, p. 559). Therefore, it is the availability of capital liquidity that determines whether a wave propagates following a shock (Harford, 2005).

Noting that divestures and other partial-firm acquisitions contradicts the behavioral hypothesis since single assets must be acquired with cash, Harford (2005) moves on to investigate if acquirers in partial-firm acquisitions are cash or stock bidders. He finds that stock bidders in mergers are also cash bidders in partial-firm acquisitions, that such transactions are increasingly common during merger waves, and therefore also more likely when the rate spread is low. Finally, Harford (2005, p. 558) also investigates operating performance, expecting target firms acquired by temporarily misvalued bidders to exhibit particularly poor long-run returns, but finds no support for this in further tests. All these findings are consistent with the neoclassical hypothesis, but at odds with the behavioral.

Since Harford's (2005) latter tests only serves to confirm the outcome of his initial findings, we will for the remainder of this thesis only consider Harford's first regression models (Harford, 2005, pp. 530-549). Instead of applying all his tests, we focus our attention on adding value to his initial findings by testing them on recent data (from 2000 to 2019), controlling for new private equity variables, and investigating takeover premiums in conjunction with these findings. To accommodate these adaptations, additional reviews of relevant literature since Harford (2005) and the influence of private equity on merger waves are warranted.

2.4 Research Developments in Merger Waves Since Harford (2005)

To ensure the relevance of our thesis, this section provides a brief overview of recent research developments in the field of merger waves since Harford (2005). Recent publications in the field indicate that since Harford (2005), there seems to have been a shift away from explaining the drivers of merger waves and towards wave and deal characteristics, ranging from efficiency gains, bidder tactics (e.g., Betton, Eckbo, Thompson, and Thorburn (2014), Gorbenko and Malenko (2017)), announcement returns (Cai, Song, & Walkling, 2011; Song & Walkling, 2000), inherent differences between financial and strategic buyers (Gorbenko & Malenko, 2014; Martos-Vila, Rhodes-Kropf, & Harford, 2019), LBO characteristics and the influence of private equity, to cash effects on corporate governance and financial policies (Gao, Harford, & Li, 2013; Harford, Mansi, & Maxwell, 2008), to mention a few. Most of these areas are beyond the scope of this paper. However, for the sake of completeness we provide a brief thematical review of the most notable publications that followed in the aftermath of Harford (2005) relevant to this thesis.

2.4.1 Bidding Activity, Payment Method and Announcement Returns

Betton et al. (2008, p. 8) find that the observable evidence is supportive of the neoclassical view, noting that "despite the market boom in the second half of the 1990s, the relative proportions of all-cash, all-stock, and mixed cash-stock offers in more than 15 000 merger bids did not change from the first half of the decade". Moreover, "during the 1996-2000 period with peak market valuations, the sum of all-cash and mixed cash-stock equals the number of all-stock merger bids" (Betton et al., 2008, p. 8). Both are inconsistent with the behavioral hypothesis.

Eckbo, Makaew, and Thorburn (2018) introduce a neoclassical alternative to the bidder opportunism implied by the behavioral hypothesis, labeled "rational payment design", in which any bidder opportunism is not driven by misvaluation (discrepancies in M/B-ratios) but fundamental information asymmetry. Under the rational payment design hypothesis, bidders choose to pay with stock not because of opportunism, but because bidders are concerned with adverse selection on the target side of the deal (Eckbo et al., 2018, p. 444). As a result, "the more correctly the target values the bidder shares, the lower is the predicted fraction of stock in the deal payment under bidder opportunism and the higher is this fraction under rational payment design" (Eckbo et al., 2018, p. 463). They find that public bidders systematically pay with more stock the more the target knows about the bidder, consistent with the rational payment design hypothesis. Interestingly, they also find that within-industry competition from financial acquirers exerts pressure for public (strategic) bidders to also pay in cash (Eckbo et al., 2018).

Recent developments have also granted announcement returns and peer dynamics in the takeover market increased attention. Song and Walkling (2000) find that industry peers of initial acquisition targets earn abnormal announcement returns "because of the increased probability that they will become targets themselves", and that this holds regardless of the form or outcome of the acquisition (Song and Walkling, 2000, p. 143). The returns increase with the magnitude of the surprise (Song & Walkling, 2000). Cai et al. (2011) further document market anticipation of merger bids and find that less anticipated bids earn higher announcement returns. They find that bidding, on average, is a wealth-creating activity, regardless of whether the target is public or private and the means of exchange. Interestingly, they also find that bidders earn significantly higher returns in non-wave, pre-wave, and in-wave periods, but conversely negative returns in the post-wave period (Cai et al., 2011).

Servaes and Tamayo (2014) study the reactions of industry peers when a company is victim to a hostile takeover. They find that industry peers of the takeover target respond with more conservative (or truthful) accounting practices, and defensive investment and capital budgeting policies, including reduced capital spending, free cash flow and cash holdings, and increased leverage and dividend payouts. They document positive peer announcement returns and that these are increasing in capital spending and free cash flow, indicating clear evidence of industry spillover effects and resource complementarities between firms (Servaes & Tamayo, 2014).

2.4.2 Wave Participation by Strategic and Financial Bidders

Maksimovic, Phillips, and Yang (2013) compare the participation of private and public firms in merger waves. They find that public firms are more active in merger waves than private, even after controlling for size and productivity. Public firms are more sensitive to credit spreads and market valuations, but they claim this goes beyond Harford's (2005) findings on capital liquidity, by arguing that more productive firms with higher growth prospects self-select into going public, and later become more active in the acquisition market. This is consistent with Brau and Fawcett (2006) and emphasized by the finding that public firms realize higher productivity gains in the acquired assets than do private firms, not just because of better access to capital markets but also because of inherent differences in firm quality. They also show that high-productivity firms are more likely to buy assets and that low-productivity firms are more likely to sell assets, consistent with the reallocation narrative of neoclassical explanations. Moreover, on-the-wave acquisitions are associated with higher productivity gains, especially for public firms, largely driven by capital liquidity (credit spreads and market valuations) and the (expected) realization of synergies. This makes sense if mergers are the least-cost response to fundamental shocks, as claimed by the neoclassical hypothesis.

Gorbenko and Malenko (2014) investigate maximum willingness to pay (as evident by auction bids) for strategic and financial bidders. They find that most targets are valued higher by strategic bidders, but financial bidders value mature, poorly performing companies higher, suggesting "different targets appeal to different types of bidders, rather than that strategic bidders always value targets more because of synergies" (Gorbenko and Malenko, 2014, p. 2513). This is supported by the findings that strategic valuations are more dispersed, and that financial valuations are more sensitive to aggregate economic conditions (Gorbenko and Malenko, 2014). Gorbenko and Malenko (2017) find that cash is positively related to synergies. Neither Song and Walkling (2000) nor Cai, et al. (2011) investigate offer premiums over the course of the wave, but Gorbenko and Malenko (2014) welcome more research on the link between valuations and the different premiums known to be paid by strategic and financial bidders.

Martos-Vila et al. (2019) argue that just as overvalued equity could lead to increased merger activity for strategic buyers, overvalued debt could lead to increased takeover activity for financial buyers. They find that financial acquirers gain a competitive advantage over strategic acquirers when debt markets are overvalued, and attribute this to the coinsurance effect[2] and moral hazard. According to Martos-Vila et. al (2019), the coinsurance effect works at the disadvantage of the strategic buyers, because as strategic buyers combine firms, individual valuation errors will eventually (on average) offset each other, making overvaluation of targets synonymous with underestimating the coinsurance effect, de-facto enabling strategic acquirers to pay lower prices than their financial counterparts (Martos-Vila et al., 2019, p. 2638). Moreover, financial buyers in private equity (PE) are commonly associated with corporate governance structures providing better oversight and lower monitoring costs, making financial buyers better equipped to cope with managerial moral hazard, which in turn, make lenders prone to favor financial borrowers over strategic, effectively providing financial buyers with relatively better access to cheap debt, and in turn, higher willingness-to-pay (c.f. Gorbenko and Malenko, 2014). This suggests private equity has a bigger influence on merger activity than previously anticipated, which brings us to the next chapter: the influence of committed capital to private equity (PE).

2.5 Buyout Waves and the Influence of Private Capital

Gompers and Lerner (2000) find that the inflow of capital to venture funds increase the valuation of these fund's investments. They note that indifferences in the success rates of these investments suggest that it is the increased demand pressure for investments that drive prices in

[2] The idea that unless two projects (or firms) have perfectly correlated cash flows (correlation coefficient of unity), the merger will lead to increased bond prices because if one company faces financial distress costs, the excess cash flow of the other company can be used to pay the first company's outstanding debt obligations, working as a "coinsurance" that effectively lowers the probability of bankruptcy and therefore expected bankruptcy costs to the creditors of the merged firm, resulting in lower interest rates. Because the coinsurance is de-facto provided by the shareholders, the rise in bond prices is accompanied by a drop in share prices (Higgins & Schall, 1975; Lewellen, 1971).

high-inflow periods, implying that investment standards are lowered in “hot” periods, only to be raised in “cold” periods when capital dries up. Holmström and Kaplan (2001) present similar findings for the leveraged buyouts (LBO) of the 1980s.

Axelson, Strömberg, and Weisbach (2009) study the financial structure of private equity funds and document that private equity funds are typically structured as “finite-lived limited partnerships that raise equity capital from limited partners (LPs) before investments are made (or even discovered) and then supplement this equity financing with third-party outside financing” (typically leverage) on a deal-by-deal basis whenever possible (Axelson, et al., 2009, p. 1574). When faced with the option to raise funds ex ante (raising an entire fund to finance future projects), or ex post (i.e., as projects are discovered on a deal-by-deal basis), general partners (GPs) choose the financial structure that maximize fund value, which is usually a combination of the two (Axelson, et al., 2009). They model that overinvestment in good economic states and underinvestment in bad states amplify natural industry cycles, such that PE investments exhibit particularly large cyclicality. When lenders lend more aggressively, more marginal investments are made. This implies that an “overhang” of uninvested (committed) capital affects GPs willingness to take on marginal projects. Therefore, in their model, PE returns are negatively related to deal activity, such that fund raising and investments are procyclical, and returns countercyclical. Kaplan and Strömberg (2009) present similar findings.

Martos-Vila et al. (2019) argue that just as overvalued equity could lead to increased merger activity for strategic buyers, overvalued debt could lead to increased takeover activity for financial buyers. They find that financial acquirers gain a competitive advantage over strategic acquirers when debt markets are overvalued, and attribute this to the coinsurance effect[3] and moral hazard. According to Martos-Vila et. al (2019), the coinsurance effect works at the disadvantage of the strategic buyers, because as strategic buyers combine firms, individual valuation errors will eventually (on average) offset each other, making overvaluation of targets synonymous with underestimating the coinsurance effect, de-facto enabling strategic acquirers to pay lower prices than their financial counterparts (Martos-Vila et al., 2019, p. 2638).

[3] The idea that unless two projects (or firms) have perfectly correlated cash flows (correlation coefficient of unity), the merger will lead to increased bond prices because if one company faces financial distress costs, the excess cash flow of the other company can be used to pay the first company’s outstanding debt obligations, working as a “coinsurance” that effectively lowers the probability of bankruptcy and therefore expected bankruptcy costs to the creditors of the merged firm, resulting in lower interest rates. Because the coinsurance is de-facto provided by the shareholders, the rise in bond prices is accompanied by a drop in share prices (Higgins & Schall, 1975; Lewellen, 1971).

Moreover, financial buyers in private equity (PE) are commonly associated with corporate governance structures providing better oversight and lower monitoring costs, making financial buyers better equipped to cope with managerial moral hazard, which in turn, make lenders prone to favor financial borrowers over strategic, effectively providing financial buyers with relatively better access to cheap debt, and in turn, higher willingness-to-pay (c.f. Gorbenko and Malenko, 2014). This suggests private equity has a bigger influence on merger activity than previously anticipated, which brings us to the next chapter: the influence of committed capital to private equity (PE).

2.6 Buyout Waves and the Influence of Private Capital

Gompers and Lerner (2000) find that the inflow of capital to venture funds increase the valuation of these fund's investments. They note that indifferences in the success rates of these investments suggest that it is the increased demand pressure for investments that drive prices in high-inflow periods, implying that investment standards are lowered in "hot" periods, only to be raised in "cold" periods when capital dries up. Holmström and Kaplan (2001) present similar findings for the leveraged buyouts (LBO) of the 1980s.

Axelson et al. (2009) study the financial structure of private equity funds and document that private equity funds are typically structured as "finite-lived limited partnerships that raise equity capital from limited partners (LPs) before investments are made (or even discovered) and then supplement this equity financing with third-party outside financing" (typically leverage) on a deal-by-deal basis whenever possible (Axelson, et al., 2009, p. 1574). When faced with the option to raise funds ex ante (raising an entire fund to finance future projects), or ex post (i.e., as projects are discovered on a deal-by-deal basis), general partners (GPs) choose the financial structure that maximize fund value, which is usually a combination of the two (Axelson, et al., 2009). They model that overinvestment in good economic states and underinvestment in bad states amplify natural industry cycles, such that PE investments exhibit particularly large cyclicality. When lenders lend more aggressively, more marginal investments are made. This implies that an "overhang" of uninvested (committed) capital affects GPs willingness to take on marginal projects. Therefore, in their model, PE returns are negatively related to deal activity, such that fund raising and investments are procyclical, and returns countercyclical. Kaplan and Strömberg (2009) present similar findings.

2.7 Buyout Waves and the Influence of Private Capital

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Axelson, Jenkinson, Strömberg, and Weisbach (2013) match and compare the financial structure of leveraged buyouts with public firms. To their surprise, they find no cross-sectional relationship whatsoever. Instead, whereas firm leverage for public companies is driven by firm characteristics, leverage in buyouts is almost entirely driven by the price and availability of debt. "When credit is abundant and cheap, buyouts become more levered" (Axelson et al., 2013, p. 2264). They document a negative relationship between buyout leverage and fund returns, consistent with Axelson's, et al. (2009) model. Higher leverage is associated with higher prices and lower returns, suggesting GPs overpay when debt capacity is high (Axelson et al., 2013).

Much like Song and Walkling (2000) and Cai, et al. (2011), but in an LBO context, Harford, Stanfield, and Zhang (2016) study the implication of an LBO for the target firm's industry peers. They find that LBOs lead merger waves and are a significant determinant of follow-on LBOs and within-industry strategic merger activity. Interestingly, they find that the predictive power of the LBO is stronger in periods of low capital liquidity, and not driven by economic or deregulatory shocks as traditionally associated with merger waves (Harford, 2005). The LBOs affect the target industry, as industry peers of the target adopt changes to investment policies such as increased R&D spending, enter into strategic alliances and increase defensive takeover provisions such as reductions in board independence and share repurchases, as a response to the changes it their competitive environment, consistent with Servaes and Tamayo (2014). Harford, et al. (2016) conclude LBOs causes and to some extent signals private information about optimal changes to an industry, rather than LBO sponsors self-selecting into already changing industries. On the other hand, Haddad, Loualiche, and Plosser (2017) find buyout waves form in response to declines in the aggregate risk premium and subsequently lower discount rates. They find the equity risk premium determines buyout booms more so than credit conditions, arguing that a lower equity risk premium increases the NPV of performance gains and reduces the cost of holding illiquid investments (such as private equity).

Buchner, Mohamed, and Schwienbacher (2020) document "herd behavior" (i.e., the correlation of investment choices) amongst international buyout funds, leading to similar investment strategies and outcomes. They differentiate between "contemporaneous" and "following" herding, and find that large funds typically herd simultaneously, whereas smaller and less experienced funds herd as followers (i.e., with a lag) of the top players, defined as the top quartile in terms of committed capital. They find that herding is more common during market contractions and when committed capital dries up. This is consistent with the idea that fund managers shy away from unique (or risky) strategies in tough times because it could potentially hamper their ambitions to raise new funds at a later stage. This implies that capital raised by PE funds can cluster in both industries and time, and if the capital inflow is sufficiently large, therefore drive merger waves.

3. Hypotheses

Hypothesis 1: *Merger waves are primarily driven by neoclassical variables capturing economic, regulatory, and technological shocks, and sufficient capital liquidity*

Accepting the null hypothesis implies that the neoclassical hypothesis remains the most reasonable explanation for M&A activity clustering in waves, also in recent times. If accepted, industry waves form in response to underlying shocks and propagate when capital liquidity is sufficiently high to accommodate the transactions. Aggregate merger waves form as industry waves cluster in time. On the contrary, rejecting the null hypothesis would imply that we find support for the alternative behavioral hypothesis, suggesting merger waves result from managerial attempts to time the takeover market in recent decades. The hypothesis is interesting because there are fundamental differences in the underlying economic conditions between our sample period (2000 – 2019), and Harford's (1981 – 1999) (Harford, 2005, p. 536). This affects both the neoclassical and behavioral variables.

The neoclassical hypothesis might be less relevant today as manufacturing has lost its dominant position to services in the U. S. economy, making many industries more responsive to economic shocks. Moreover, increased pace of technological innovations, and advancements in research and development (R&D) with the emergence of open innovation models (Chesbrough, 2003), could make technological shocks less disruptive today compared to previous decades. Finally, as most industries are already deregulated, the influence of deregulation might have decreased since Harford (2005).

Contrary, the behavioral hypothesis might be more relevant given that we have seen the longest running bull-market in history during our sample period. Moreover, if the takeover process has become more responsive with the digitization of financial markets, it could be easier to take advantage of short-lived valuation spikes to conduct acquisitions. Therefore, retesting Harford's (2005) findings on more recent time periods is interesting.

Hypothesis 2: *The amount of capital raised by private equity funds is associated with aggregate merger waves*

Given that private equity (PE) funds are structured as limited partnerships with a finite time horizon they are more restricted in terms of investment timing. Contrary to strategic buyers, who can wait for the perfect timing of their acquisition activity, GPs are forced to conduct transactions following successful fundraising to generate profit before the fund is dissolved. Hence, PE transaction volume is largely governed by the amount of raised capital rather than external market conditions. High levels of fundraising should therefore precede high levels of M&A activity. A similar implication is found by Harford et al. (2016) who find that LBOs become an increasingly important determinant of merger activity in periods of low capital liquidity, irrespective of economic and deregulatory shocks.

Moreover, we know that increased capital inflows to PE yield higher investment valuations (Gompers and Lerner, 2000; Holmstrom and Kaplan, 2001), fund managers herd towards similar investments (Buchner et al., 2020), and LBOs lead merger waves (Harford et al., 2016). Committed capital to PE could therefore spark, accelerate, or even drive entire within-industry and perhaps even aggregate merger waves if the capital influx is sufficient. This proposition is emphasized by increased competition for viable targets, leading GPs to ramp up the pace of acquisitions to compensate for reduced project quality when capital constraints loosen and put on the breaks when credit markets tighten (Axelson et. al, 2009; 2013). This could cause PE investments to exhibit particularly large cyclicality. These combined effects might work in tandem causing over-valued, herded, and hyped-up private equity to drive entire merger waves if the magnitude of committed capital is sufficiently large.

We therefore hypothesize that committed capital has an increasingly significant explanatory power in the formation of merger waves. To our knowledge, this is an explanation largely left unaccounted for in the previous literature on merger waves. Our null hypothesis is that PE funds increase their fundraising prior to aggregate merger waves, while the alternative hypothesis is that PE fundraising is independent of such waves.

Hypothesis 3: *The average size of takeover premiums changes over the course of the wave*

Takeover premiums are surprisingly unresearched in the context of merger waves. Chidambaran, John, Shangguan, and Vasudevan (2010) find that premiums are higher and that the returns to the acquiring company shareholders are lower during merger waves, but they do not investigate the evolution of premiums *over the course* of the wave. However, we know that the magnitude of premiums paid by strategic and financial bidders differ on average (Gorbenko and Malenko, 2014) and that the relative dominance of financial and strategic acquirers fluctuates over the wave depending on credit and equity markets (Martos-Vila et. al, 2019; Haddad et. al, 2017). Coupled with the observation that LBOs lead merger waves (Harford, et. al, 2016), we propose that takeover premiums change over the wave.

On the one hand, public bidders earn higher announcement returns in the pre-wave period (Cai, et al., 2011), suggesting the risk of overpayment is higher during and after the peak of a wave. This implies increasing takeover premiums towards the peak of the wave, all else equal. However, as the wave propagates and acquisition anticipation effects are increasingly priced in (c.f. Song and Walkling, 2000; Servaes and Tamayo, 2014), holding synergies and the bidder's maximum willingness-to-pay fixed, this implies lower markup above the baseline market valuation, and in turn, decreasing premiums over the course of the wave.

On the other hand, the fact that premiums are increasing in cash payments (Gorbenko and Malenko, 2017) could also suggest they are increasing in financial bids, since strategic acquirers have the option to pay in stocks. Moreover, financial bidders typically value their own targets higher than their strategic counterparts (Gorbenko and Malenko, 2014; Martos-Vila, et al., 2019), making them more likely to win the auctions in which they participate. However, this effect can be hard to dissect because strategic bidders tend to pay in cash to level the playing field with financial bidders (Eckbo et al., 2018). Therefore, the evolution of takeover premiums might follow from the timing of maximum PE influence over the wave (c.f. Hypothesis 2), which in turn is subject to aggregate economic conditions (Axelson et. al. 2009; 2013, c.f. Hypothesis 1).

Finally, assuming the neoclassical hypothesis holds, bidders should compete fiercely for the targets that best enable them to respond to a shock. If the targets that has the highest achievable synergies due to their shock-responsive capabilities are acquired first, premiums might decrease over the wave, as decreasingly attractive targets enjoy fewer bids, driving competition down.

Alternatively, this effect could be counteracted by sustained competition for a decreasing number of available targets resulting in increasing average winning bids reflected in higher premiums towards the end of the wave.

Since it is an empirical issue what effect dominates the other, our null hypothesis is that takeover premiums on average change over the wave, that be an increase or a decrease. The alternative hypothesis is that premiums remain unchanged over the course of the wave.

3.1 Predictions

Table 1: Prediction Table

This is a cause-and-effect table related to the hypotheses. The table is based on Harford (2005, p. 536), but it is modified to accommodate our supplementary hypotheses, variables, and tests. The table contains central elements and predictions of observable changes to these elements under different hypotheses, as well as the findings of Harford (2005), were applicable.

	Neoclassical	Behavioral	PE Influence	Harford´s (2005) Findings
Cause of industry wave	Economic and/or deregulatory shocks accompanied by relaxed capital liquidity constraints	Temporary overvaluations and increased dispersion of said valuations	No prediction	Economic and deregulatory shocks, accompanied by eased credit constraints, drive industry waves
Cause of aggregate wave	Within-industry merger waves cluster in time due to relaxed capital liquidty constraints	Temporary simultaneous overvaluations and increased dispersion of said valuations *across industries*	Increases in commited (aggregate) capital *precede* merger waves	Industry waves cluster in time because of capital liquidty
Pre-wave M/B-ratio	High if increased valuations are linked to relaxed capital liquidity constraints and/or economic shocks	High	No prediction	High
Dispersion in pre-wave M/B-ratio	No prediction	High	No prediction	Normal
C&I Rate Spread	Low preceding waves	No prediction	Low preceding waves	Low
Payment method during waves	No change	Significantly increased proportions of stock transactions from public acquirers during waves	Increase in cash payment if P/E is a driving force	
Correlation between PE capital and overall M&A activity	No prediction	No prediction	Significant positive and negative relationship to capital called and dry powder, respectively, if P/E participate in aggregate waves	
Premium payments	Increase or decrease	No prediction	Increase, decrease or remain unchanged	

Valuations

Table 1 summarizes expected outcomes under the different hypotheses. The neoclassical hypothesis predicts that economic, deregulatory, and technological shock variables and capital liquidity should drive out the explanatory power of both the magnitude and dispersion of M/B ratios in explaining industry merger waves. The M/B ratio captures the market value of a company relative to book value. Contrary, if the behavioral hypothesis holds, we should observe both increased magnitude and dispersion of pre-wave M/B ratios across industries, resulting from a misvaluation effect independent of capital liquidity and economic shocks. Therefore, a high dispersion in M/B ratio could imply that overvalued acquirers can purchase undervalued targets, thereby taking advantage of temporary misvaluations.

Private Equity Capital

In the aggregate, increasing total committed capital to private equity should precede aggregate merger waves. Note that dry powder, i.e., the committed capital not yet called for investment, is a function of the difference between capital raised and capital called over time. Thus, the amount of dry powder will be high in periods of high capital inflow to PE, but also in periods of low investment. It is therefore not a good predictor of activity due to reversed causality issues. However, if PE contributes to driving aggregate waves, increases in raised capital should precede periods of increased activity. Similarly, if PE participates in the overall aggregate waves, capital called should increase while dry powder depletes during aggregate merger waves.

Payment Method

Under the behavioral hypothesis, most bids by public acquirers in periods characterized by relatively high M/B ratios, should involve a stock offer. Therefore, the proportion of stock relative to cash offers should increase during merger waves. Since financial buyers such as PE funds can only pay in cash, the behavioral hypothesis also presumes limited influence of private capital on aggregate merger waves. The neoclassical hypothesis, on the other hand, predicts that there should be no correlation between payment method and merger waves. Finally, if PE is a driving force in aggregate waves, cash offers should increase during waves.

Capital Liquidity

For economical, technological, or deregulatory shocks to propagate merger waves, as postulated by the neoclassical hypothesis, the constraints on capital liquidity needs to be low when the shock occurs (Harford, 2005). We should therefore observe a low rate spread prior to merger waves. Given that PE funds are dependent on leveraging their acquisitions to achieve satisfactory returns (Axelson, et al., 2009), they too should only increase activity during periods characterized by low capital constraints. According to the behavioral hypothesis, transactions are financed by overvalued equity, and we should therefore observe merger waves independent of rate spreads.

Takeover Premiums

We predict that premiums either increase or decrease if the neoclassical hypothesis holds true, depending on whether bidding competition is strongest during the beginning or towards the end of the wave. Moreover, the size of premiums could be influenced by the timing of PE participation in waves. If PE lead waves (Harford et. al, 2016), and financial acquirer participation is associated with higher premiums (Gorbenko and Malenko, 2014; Martos-Vila et al., 2019), premiums should decrease over the wave. However, if herding by financial acquirers (Buchner, et al., 2020) results in increased financial buyer participation over the wave, premiums could increase over the wave. Alternatively, if strategic acquirers level the playing field by offering cash (Eckbo et al., 2018), premiums might remain unaffected by PE participation over the wave.

4. Data and Merger Wave Identification

4.1 Data Sources and Sample Criteria

4.1.1 SDC Platinum

Our transaction data is gathered from the Thomson Financial Securities Data Company's (SDC) Platinum database. We define our selection criteria as all US target transactions between January 1st, 2000 and December 31st, 2019. Moreover, to ensure comparability of results to those of Harford (2005), we exclude transactions with a deal value below \$50 million. The result is a total of 36 084 transactions, of which 23 332 are made by public acquirers and the remaining 12 627 by private acquirers. Relevant variables include announcement date, standard industry classification (SIC) code, transaction value and offer premiums, i.e., offer price relative to the stock price 4 weeks prior to announcement.

4.1.2 Compustat

Our data on company fundamentals are gathered from the Compustat North America Database by S&P Global Market Intelligence. Through this database we collect accounting data on all publicly traded companies in the US. Relevant variables include SIC codes, total asset value, book value of shareholders equity, revenue, net income, R&D spending, Capital Expenditures (Capex), number of employees, market value and stock price (end of calendar year).

4.1.3 Preqin

We obtain data on the private equity (PE) sector from contact with Preqin, an independent analytics company that specializes in alternative asset classes. Preqin has collected data within this sector since year 2000 and are especially renowned for their tracking of dry powder, i.e., committed capital that are yet to be invested by PE funds. Relevant variables include aggregate annual capital raised, capital called for investments and dry powder.

4.1.4 Federal Reserve

We use data on capital liquidity based on the Survey of Terms of Business Lending conducted by the Board of Governors of the Federal Reserve System. The survey investigates gross loan extensions at 348 domestically chartered commercial banks and 50 U.S. branches and agencies of foreign banks on a quarterly basis. In relation to the survey, they calculate and publish the weighted average commercial and industrial (C&I) loan rate (Board of Governors of the Federal Reserve System, 2020b). Furthermore, we use the Federal Funds rate (Board of Governors of the Federal Reserve System, 2020a).

4.2 Explanation of Variables

4.2.1 Dependent Variables

The dependent variables used in regressions, i.e., the occurrence of industry and aggregate merger waves, and the average size of takeover premiums, will be thoroughly described and defined leading into models where they are relevant throughout the thesis.

4.2.2 Independent Variables

Company – Specific Fundamentals

Table 2: Annual Company Fundamentals

Annual Company Fundamentals gathered from Compustat. 126 548 annual observations of publicly listed companies between 1999 and 2019 is gathered. The table shows descriptive statistics for annual raw data, constructed variables, and absolute changes in constructed variables. The data presented is not winsorized or adjusted in any way.

Raw data	Units	Min	Max	Mean	Median	First Quartile	Third Quartile	NAs	Missing (%)
Assets	$ Millions	0	3 771 200	12 194	567	117	2 636	11 521	9 %
Book Value	$ Millions	-86 154	424 791	2 112	188	44	840	11 520	9 %
Revenue	$ Millions	-15 009	511 729	3 461	264	50	1 371	11 687	9 %
Net Income	$ Millions	-99 289	98 806	218	8	-7	76	11 687	9 %
R&D Spending	$ Millions	-1	35 931	136	8	1	40	67 378	53 %
Capital Expenditures	$ Millions	-994	50 234	257	9	1	68	16 433	13 %
Employees	Thousands	0	2 545	10	1	0	5	14 874	12 %
Market Value	$ Millions	0	1 073 391	3 866	342	73	1 577	23 508	19 %
Stock Price	$	0	141 600	31	14	6	28	136	0 %
Common Shares Outstanding	Millions	0	29 058	122	27	10	69	546	0 %
Constructed Variables									**Calculation Explanation**
Net Income Margin	%	-2931900 %	154257 %	-506 %	4 %	-5 %	12 %		$\frac{Net\ Income}{Revenue}$
Asset Turnover	%	-188 %	222929 %	92 %	65 %	21 %	122 %		$\frac{Revenue}{Assets_{t-1}}$
R&D (Scaled by Assets)	%	-1 %	3207 %	11 %	4 %	0 %	13 %		$\frac{R\&D\ Spending}{Assets_{t-1}}$
Capital Expenditures (Scaled by Assets)	%	-12 %	62 %	5 %	3 %	1 %	6 %		$\frac{Capex\ Spending}{Assets_{t-1}}$
Employee Growth	%	-100 %	5666 %	41 %	2 %	-5 %	12 %		$\frac{Employees_t}{Employees_{t-1}} - 1$
Return On Assets	%	-12000 %	28005 %	-2 %	2 %	-4 %	7 %		$\frac{Net\ Income}{Assets_{t-1}}$
Revenue Growth	%	-23700 %	1273900 %	75 %	7 %	-4 %	21 %		$\frac{Revenue_t}{Revenue_{t-1}} - 1$
3-Year Return	%	-100 %	925118 %	116 %	19 %	-29 %	87 %		$\frac{Market\ Value}{Market\ Value_{t-3}} - 1$
1-Year Return	%	-100 %	249900 %	50 %	5 %	-24 %	38 %		$\frac{Market\ Value}{Market\ Value_{t-1}} - 1$
Market-to-Book (M/B)	1	0	113 538	8	2	1	3		$\frac{Market\ Value}{Book\ Value}$
Market Value (Alternative)	$ Millions	0	1 304 756	3 988	301	71	1 411		$Stock\ Price * Common\ Shares\ Outstanding$
Annual Absolute Changes									
Net Income Margin	Percentage Points	0	2 701 352	554	4.1	1.3	14.7		$Net\ Income\ Margin_t - Net\ Income\ Margin_{t-1}$
Asset Turnover	Percentage Points	0	222 643	23.5	7.2	1.3	20.5		$Asset\ Turnover_t - Asset\ Turnover_{t-1}$
R&D (Scaled by Assets)	Percentage Points	0	3 188	5	0	0	2		$R\&D_t - R\&D_{t-1}$
Capital Expenditures (Scaled by Assets)	Percentage Points	0	6 471	3.1	0.8	0.2	2.4		$Capex_t - Capex_{t-1}$
Employee Growth	Percentage Points	0	566 490	74	11	4	25		$Employee\ Growth_t - Employee\ Growth_{t-1}$
Return On Assets	Percentage Points	0	26 515	12.9	2.9	0.8	9.2		$ROA_t - ROA_{t-1}$
Revenue Growth	Percentage Points	0	1 274 000	149.1	13.2	5.1	20.5		$Revenue\ Growth_t - Revenue\ Growth_{t-1}$
Market-to-Book (M/B)	1	0	113 532	9.12	0.49	0.19	1.3		$M/B_t - M/B_{t-1}$

As evident from Table 2[4], the existence of extreme outliers in many of the independent variables concerning company fundamentals are pulling heavily on the means. Thus, we prefer using medians whenever fundamentals are included in statistical models, i.e., in the rank-sum test

[4] One specific issue we ran into was that the total market value was only registered in Compustat from 1998. Thus, the 3-year return, based on market value, is missing for year 1999 and 2000. We calculate the 3-year return based on stock price and common shares outstanding for these specific years (c.f. Market Value (Alternative), Table 2).

(Table 6), merger wave regressions (Table 7 and 7,1) and premiums regressions (Table 9 and 10).

Deregulatory Events

Shocks to an industry environment can also result from regulatory changes (Harford, 2005, p. 542). Inspired by Mitchell & Mulherin (1996) and Harford (2005), we control for the effect of deregulatory events in our merger wave regressions (Table 7 and 7.1). Since regulations can have ambiguous directional impact depending on the nature of the legislation, we only control for deregulatory events which by nature always improve operating conditions within the affected industries.

We have based the Deregulatory Events Index (Table 3) on industry-specific studies related to legislative deregulations. Sherman (2009) and Orhangazi (2014) summarizes major recent financial deregulations in the US. Loveland, Mulherin, Okoeguale, and Athletic (2018, p. 41) study the effect of deregulations on additional industries up until 2017, such as utilities and natural resources. Moreover, we have added deregulatory events based on recent congressional and presidential orders and other policy changes deemed relevant (Federal Energy Regulatory Commisson, 1999; The White House, 2017; US Congress 115th, 2018; World Trade Organization, 2004). The result is 9 major deregulatory events, as evident by Table 3. This is significantly fewer than those found by Harford (2005), but deregulation was a particularly important driver of the waves in his sample, the 1980s and -90s, with the majority of highly regulated industries undergoing deregulation at the time (Andrade et al., 2001).

One could argue a similar index would be warranted for technological shocks (c.f. Jovanovic & Rousseau, 2001; 2002) to fully account for the three drivers of the neoclassical hypothesis (i.e., economic, deregulatory, and technological shocks). However, technological innovations are more continuous by nature and therefore harder to quantify. However, Harford (2005) makes no such distinction. Instead, we assume that successful technological innovations are only successful to the extent they impact fundamental economic factors and therefore accounted for in the economic variables already included (Table 2).

Table 3: Deregulatory Events and Industries Affected

Industry specific deregulatory events, in the form of changes in U.S. legislations, is tabulated together with the year they went into effect and the FF49 industries that should be affected by the change in legislation.

Year	Deregulatory Event	Industry Affected	Source
1999	Gramm–Leach–Bliley Act (GLBA) (also known as the Financial Services Modernization Act)	Banking	(Sherman, 2009)
2000	FERC Order 2000	Utilities	(Federal Energy Regulatory Commission, 1999)
2000	Employee Retirement Income Security Act	Insurence	(Orhangazi, 2014)
2000	The Commodity Futures Modernization Act	Banking, Trading	(Sherman, 2009)
2004	Consolidated Supervised Entities (CSE) program	Banking	(Sherman, 2009)
2005	Agreement on Textiles and Clothing (ATC) dissmantled	Apparel	(WTO, 2004)
2005	Energy Policy Act of 2005	Utilities, Petroleum and Natural Gas, Trading	(Loveland et. al, 2018)
2018	Crapo Bill	Banking	(US Congress, 2018)
2019	EPA roll back	Petroleum and Natural Gas	(The White House, 2017)

C&I Rate Spread

As a measure of ease of financing in the economy we use the spread between the C&I loan rate and the federal funds rate, similar to Harford (2005). The rate spread isolates the variations in risk compensation demanded by lenders. Thus, it widens when lending requirements are strict, and narrows when financing is easily accessible. Unfortunately, publishing of the weighted average C&I rate was discontinued by the FED in 2017. We will therefore make assumptions regarding the last two years of our sample period. In 2018, the federal funds rate increased by 0.83 percentage points, which naturally carries over to the loan rate obtained by businesses. However, according to the quarterly survey of business lending, most lenders in the US reported eased credit terms over the year. This was largely a result of increased competition for borrowers, but also other considerations:

> "*In addition, significant fractions of banks mentioned a more favorable or less uncertain economic outlook, increased tolerance for risk, and increased liquidity in the secondary market for these loans as important reasons for easing" (Board of Governors of the Federal Reserve System, 2018, p. 2).*

For the surveys put forth in 2019, lenders report that credit terms remained unchanged over the year. The practical implication of these assumptions for our dataset is that the rate spread is reduced to 1.20 percent in 2018 as the increasing federal funds rate is not fully absorbed in the C&I rate due to ease of credit terms, while the spread is assumed to remain constant in 2019 (i.e., the entire increase in the federal funds rate was carried forward to business loans this year). Table 4 depicts the rate spread for every year in the sampling period.

Table 4: Capital Liquidity Variables

Weighted-average effective loan rate for all commercial and industrial (C&I) loans, the federal funds rate and the rate spread between the two is tabulated.

Year	Weighted Average C&I Loan Rate (%)	Federal Funds Rate (%)	Rate Spread (%)
1999	6.66	4.97	1.69
2000	7.91	6.23	1.68
2001	5.72	3.88	1.84
2002	3.62	1.67	1.96
2003	3.15	1.12	2.03
2004	3.39	1.35	2.04
2005	5.06	3.21	1.85
2006	6.66	4.96	1.70
2007	6.81	5.02	1.79
2008	3.85	1.92	1.93
2009	2.40	0.16	2.24
2010	2.75	0.17	2.58
2011	2.56	0.10	2.46
2012	2.31	0.14	2.17
2013	2.21	0.11	2.11
2014	2.25	0.09	2.16
2015	2.16	0.13	2.03
2016	2.29	0.40	1.90
2017	2.53	1.00	1.53
2018	**3.03**	1.83	1.20
2019	**3.36**	2.16	1.20
Average	3.85	1.94	1.26

Private Equity Variables

The Private Equity (PE) variables used in preliminary data exploration (Figure 4, 5 and 6) and in regression models (Table 7 and 7.1) are not modified. They can be found in the Appendix under exhibit A.1.

4.3 Identification of Merger Waves

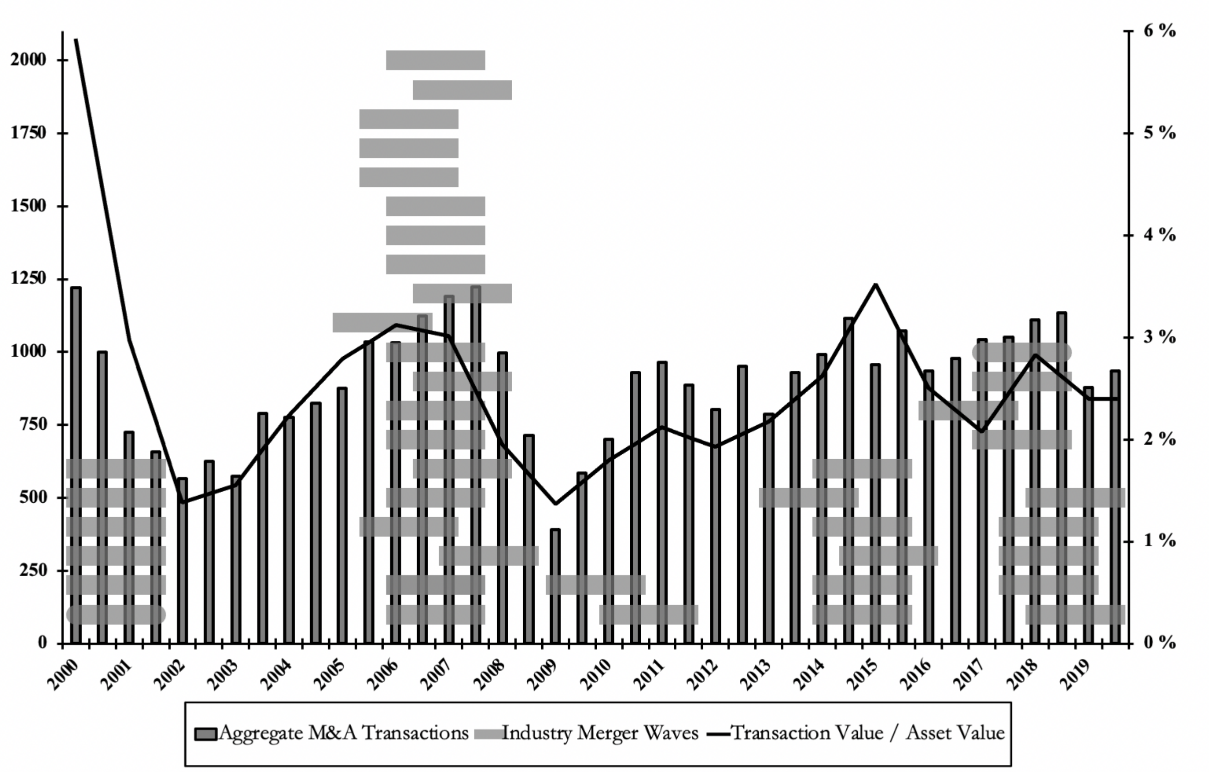


Fig. 1. Aggregate merger activity, total annual transaction value to asset value and industry merger waves. The line represents the total annual transaction value in our SDC sample divided by total book value of assets from our Compustat sample (right axis). The vertical bars represent the total number of transactions with a minimum transaction value of $50 million (left axis). The horizontal bars represent the occurrence of industry merger waves.

To identify industry-specific merger waves, we assign each acquirer and target to their appropriate industries based on the FF49[5] industry classification, as outlined by Fama and French (1997), based on the industries' SIC code. Consistent with previous research (Mitchell & Mulherin, 1996; Harford, 2005), we set the length of industry waves to 24 months.

The aggregate transaction activity in Figure 1 is characterized by several waves with substantial activity droughts following the burst of the dotcom bubble in 2000/2001 and during the 2008/2009 financial crisis. The identification process of industry merger waves follows the same procedure as Harford (2005) which ensures comparability of results. First, we investigate whether the acquirer and target are operating within the same industry. If they are, the transaction will only be counted once towards merger activity in that industry. If not, the industry of both the target and acquirer are assigned merger activity in the given month. Thus,

[5] A complete list of the industries in this framework, and their corresponding SIC codes, can be found in the Appendix under A.15.

we avoid double counting activity within the same industry. Note that the distinction is done on an industry level, and not simply by comparing SIC codes which would be too granular. The result is a total of 51 789 merger events in either target or acquirer industries that are not identical.

We subset the activity on an industry level and calculate the number of transactions for every 24-month period over the sample (i.e., there are 240 months in our sample, and therefore 216 24-month intervals). Subsequently, we uniformly distribute (i.e., a distribution with equal probability (1/240) for a merger event taking place each month) the number of merger events corresponding to the total activity for that specific industry over the 20-year period. This gives an empirical distribution with random allocation of activity over the entire period. Next, we calculate the maximum occurrence of events within a 24-month period for this empirical distribution. The maximum occurrence is saved, and the process is repeated a thousand times. The result is a simulated distribution of a thousand 24-month activity maximums in a world where transactions occur arbitrarily. Lastly, we compare the observed real-world 24-month merger event concentrations to the 95th percentile of the simulated empirical distribution. If the actual concentration exceeds the 95th percentile of empirical maximum occurrences, the period is coded as a wave for that industry. The rationale is that by exceeding this empirical threshold, the observed concentration is too large to have occurred randomly, and therefore constitutes a wave spurred by some underlying drivers.

For example, within the transportation industry, there were 1064 merger events between January 1st, 2000 and December 31st, 2019. 14 percent (amounting to 150 transactions) of these took place within a 24-month period starting February 1st, 2006. This proportion exceeds the 95th percentile of the simulated empirical distribution at 13 percent with a maximum threshold of 138 events for any given 24-month period. Thus, this period within the transportation industry is characterized by abnormal M&A activity and is regarded as an industry wave. Furthermore, two more waves were discovered for this industry, depicted in Figure 2.

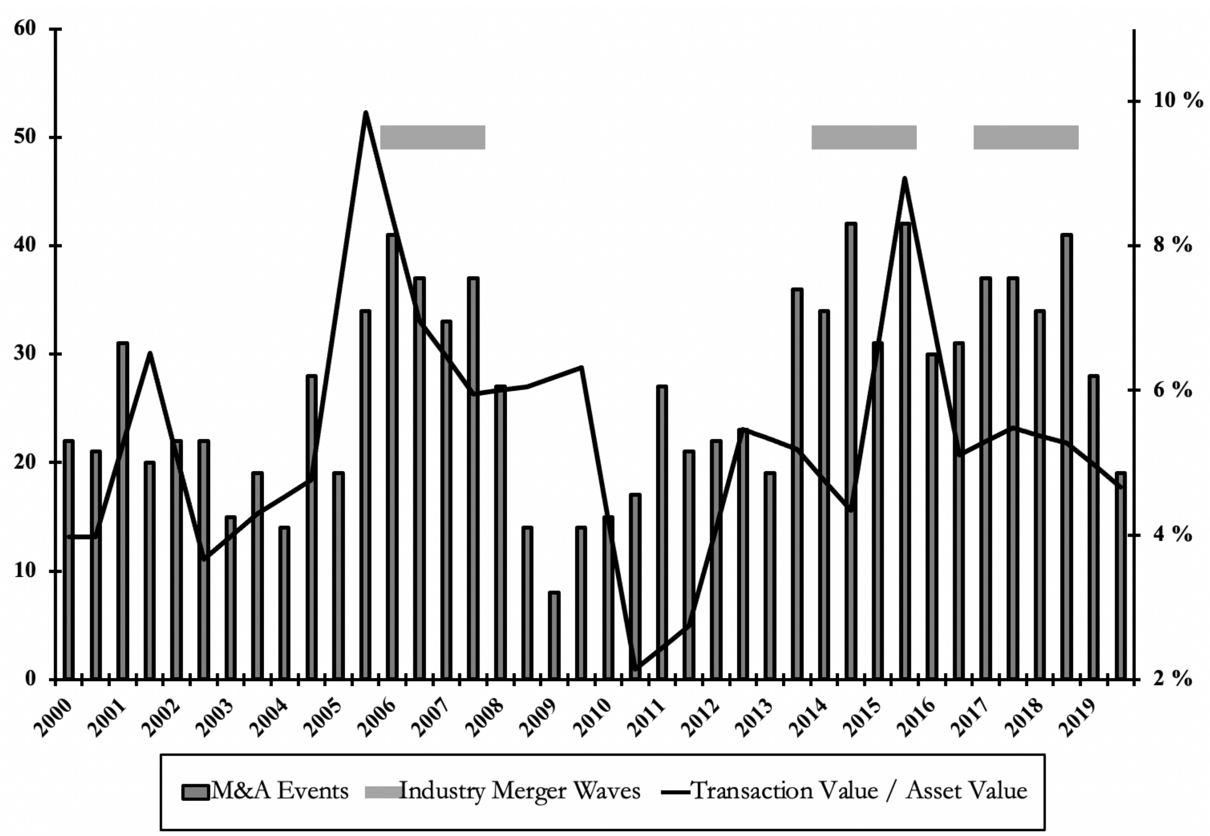


Fig. 2. Annual M&A transactions, annual transaction value to asset value and merger waves within the transportation industry. The line represents the total transaction value divided by total book value of assets (right axis). The vertical bars represent the total number of transactions with a minimum transaction value of $50 million within the Transportation industry (left axis). The horizontal bars represent the periods coded as merger waves within this industry.

When repeating the process for every other industry, the result is a total of 44 industry merger waves within 36 separate industries. This implies that 8 of the industries has more than one distinct wave, as is the case for the Transportation industry (Figure 2). Within these 36 industries, the average number of M&A events over a 24-month wave period is 224. For a non-wave 24-month period within the same industries the average number of M&A events is 129. Thus, there are, on average, 74 percent more mergers occurring during a wave compared to non-wave periods.

Additionally, as a benchmark inspired by Moeller, Schlingemann, and Stulz (2004), we compute the total annual transaction value within an industry and compare that to the total asset value of all public firms within the same industry. This should increase the robustness of our industry merger wave findings. Transaction values are gathered from the SDC database while the asset values of US public firms are collected through Standard & Poor's Compustat. We merge the data using SIC codes corresponding to the FF49 classification of industries as previously. Thus, by revisiting our previous example from the transportation industry we can conclude that an average of 6.2 percent of total industry asset value is reallocated during an industry wave year. For the average non-wave year, the ratio sits at 4.2 percent.

Table 5: Industry Merger Waves

Industry Merger Waves and the corresponding start date for each wave. Furthermore, the total number of M&A events (if the acquirer and target reside in different industries, a transaction will be counted as an M&A event in both industries. If, however, they operate in the same industry the transaction only counts as one M&A event to avoid double counting). Thus, the total number of M&A events (51 872) are higher than the total number of M&A Transactions (36 084). This approach is based on the procedure outlined by Harford (2005). Annual industry transaction value is the sum of all deal values (where deal values were disclosed) as recorded by the SDC, while annual industry asset value is the sum of all asset values recorded in Compustat for the relevant industry. The ratio between the two therefore serves as a proxy for asset exchange rate. The transaction value to asset value ratio for merger wave years is the average ratio over the years included in the wave, while the ratio for the average year is averaged over every year included in the sample.

Industry	Start of 24-Month Wave	Total Number of M&A Events Within Industry	Number of M&A Events During Wave	M&A Events During Wave as Proportion of Total	Annual Industry Transaction Value / Annual Industry Asset Value (Average Year)	Annual Industry Transaction Value / Annual Industry Asset Value (Average Wave Year)	Asset Exchange Rate Above Average During Wave
Apparel	Sep, 2006	278	49	18 %	9 %	16 %	67 %
Automobiles and Trucks	Feb, 2006	443	68	15 %	1 %	1 %	-35 %
Banking	Aug, 2005	2625	343	13 %	0,5 %	0,5 %	-4 %
	Nov, 2016		350	13 %	0,5 %	0,4 %	-15 %
Business Services	Jul, 2006	3250	416	13 %	16 %	27 %	68 %
	Jun, 2017		465	14 %	16 %	16 %	-1 %
Business Supplies	Jan, 2000	315	52	17 %	5 %	9 %	96 %
Candy and Soda	Noov, 2013	174	31	18 %	12 %	15 %	28 %
Chemicals	Now, 2013	810	116	14 %	9 %	19 %	121 %
Communication	Jan, 2000	1569	360	23 %	4 %	6 %	51 %
	Oct, 2004		218	14 %	4 %	6 %	45 %
Computer Software	Jan, 2000	3725	579	16 %	13 %	21 %	62 %
	Dec, 2017		585	16 %	13 %	12 %	-3 %
Computers	Jan, 2000	650	125	19 %	12 %	24 %	96 %
Construction	Sep, 2017	477	70	15 %	6 %	6 %	-1 %
Construction Materials	Jan, 2006	690	103	15 %	9 %	17 %	90 %
Electronic Equipment	Jan, 2000	1670	335	20 %	9 %	19 %	120 %
	Jan, 2006		230	14 %	9 %	8 %	-4 %
Food Products	Nov, 2013	571	84	15 %	10 %	15 %	46 %
Healthcare	Sep, 2005	1010	153	15 %	20 %	36 %	80 %
	Aug, 2014		141	14 %	20 %	22 %	8 %
Insurance	Jul, 2006	1295	218	17 %	1 %	1 %	2 %
Machinery	Jan, 2006	897	129	14 %	6 %	10 %	53 %
Medical Equipment	Apr, 2010	929	123	13 %	14 %	13 %	-1 %
Non-Metallic and Industrial Metal Mining	Aug, 2006	160	31	19 %	1 %	5 %	262 %
Personal Services	Jul, 2017	480	71	15 %	7 %	4 %	-36 %
Petroleum and Natural Gas	Dec, 2005	2426	305	13 %	4 %	6 %	51 %
	Oct, 2012		348	14 %	4 %	3 %	-23 %
Pharmaceutical Products	Dec, 2017	1588	245	15 %	12 %	12 %	-1 %
Precious Metals	Dec, 2008	81	22	27 %	4 %	3 %	-23 %
Printing and Publishing	Feb, 2000	451	74	16 %	15 %	24 %	62 %
	Feb, 2006	451	84	19 %	15 %	35 %	138 %
Real Estate	Feb, 2016	3229	617	19 %	34 %	36 %	6 %
Recreation	Feb, 2006	264	44	17 %	18 %	32 %	79 %
Restaurants, Hotels and Motels	Aug, 2005	1454	234	16 %	21 %	34 %	59 %
Retail	Jul, 2005	1495	189	13 %	7 %	10 %	50 %
Shipping Containers	Mar, 2016	140	27	19 %	5 %	7 %	33 %
Steel Works Etc	Jul, 2006	465	91	20 %	4 %	6 %	63 %
Trading	Jan, 2006	11228	1461	13 %	2 %	2 %	56 %
	Nov, 2016		1695	15 %	2 %	1 %	-4 %
Transportation	Feb, 2006	1064	150	14 %	5 %	6 %	20 %
	Nov, 2013		157	15 %	5 %	7 %	23 %
	Feb, 2017		152	14 %	5 %	5 %	0 %
Wholesale	Dec, 2005	1121	156	14 %	6 %	9 %	40 %
Total / *Average*		47475	11496	*16 %*	*9 %*	*13 %*	*41 %*

In the industries experiencing a merger wave (Table 5), we find that companies exchange an average of 9 percent of asset value during an average year. However, for the average industry-wave year, this number increases to 13 percent. Hence, transaction value as a proportion of total asset value is 41 percent higher for the average wave-year compared to the average year. While this difference is not huge, these findings indicate that the selected periods likely represent periods of abnormally high merger activity. Like Harford (2005) we conduct a qualitative analysis of industry trends at the time the waves occurred, providing insights into possible motivations for the consolidation. The analysis can be found in the Appendix, under exhibit A.2.

5. Results

5.1 Investigation and Exploration of Data

5.1.1 Capital Liquidity

The macro component proxying for capital liquidity used by Harford (2005), namely the rate spread, is based on previous arguments made by Shleifer and Vishny (1992) and Eisfeldt & Rampini (2006). Findings by Lown, Morgan, and Rohatgi (2000) suggest that this is a good proxy for the overall availability of liquidity in the economy. During a credit crunch, as loan standards tighten, the spread tends to increase, which is a natural consequence of lenders contracting credit due to increased default risk considerations (Lown et al., 2000). Just like Harford (2005), we do not claim that there exists a direct causal relationship between the rate spread and M&A activity since there are alternative ways of financing a company transaction. However, as Harford (2005) puts it:

> *"Instead, I assert that, based on the Lown et al. paper, the rate spread may be used as a proxy for overall liquidity or ease of financing (in whatever form) in the economy" (Harford, 2005, p. 543).*

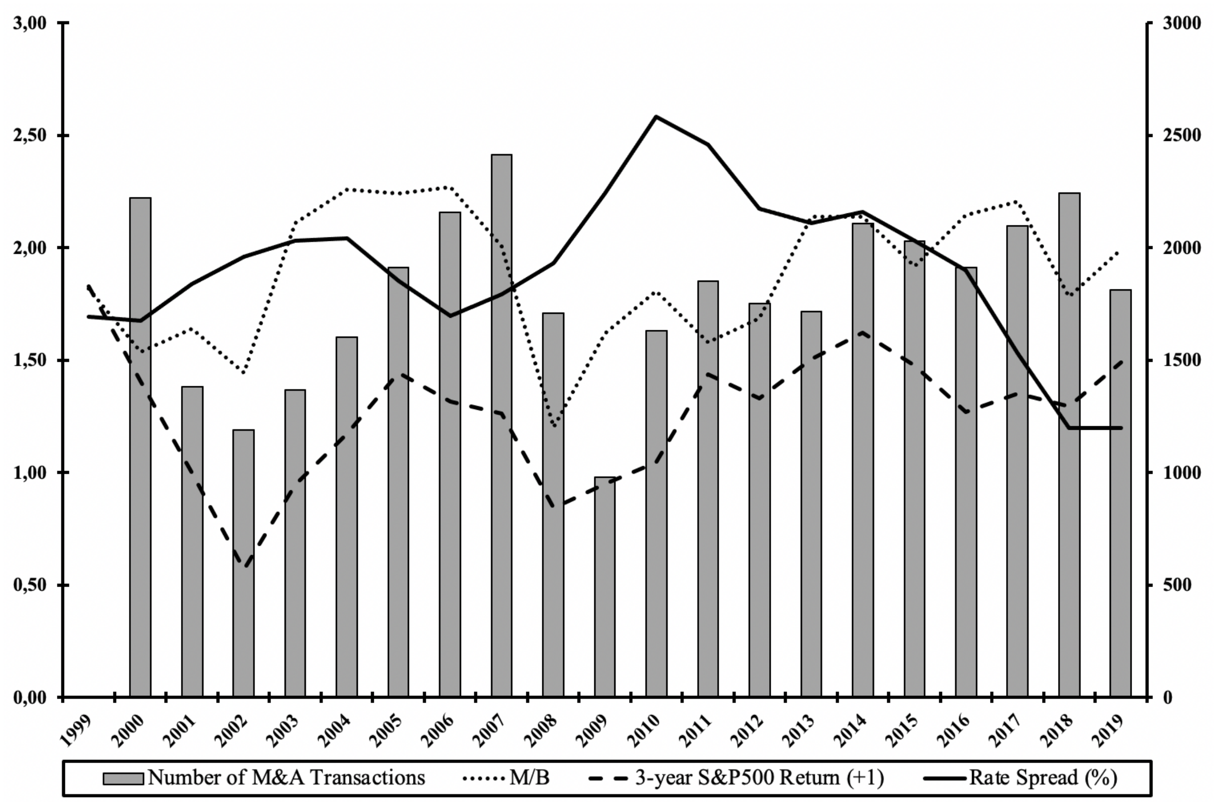


Fig. 3. Time series relationship between aggregate M&A activity, the spread between the annual weighted average C&I loan rate and the Federal Funds rate, annual M/B ratio and 3-year market returns. M&A activity is illustrated by the number of transactions annually (right). The rate spread is measured in percentage points (left axis). M/B-ratio is the annual median of all firms registered in our Compustat sample. S&P500 is the 3-year compounded return of the S&P500 index plus one (left). Thus, a value of 1.5 on the left axis represents a spread of 1,5 percent, an M/B-ratio of 1,5 and a 3-year return on the S&P500 index of 50 percent.

In Figure 3, the rate spread is plotted against the aggregate merger activity within our sample. There is an inversed relationship between them. Periods with a relatively low rate spread coincides with periods of relatively high transaction activity, and vice versa. These findings are consistent with Harford (2005) and indicate that M&A activity cluster in periods characterized by easy access to capital liquidity.

Capital Liquidity and M&A Activity During the Financial Crisis

The driving force of capital liquidity is demonstrated by the financial crisis. Although the financial crisis did not make its full entrance in financial markets before late 2008, credit constraints already started to increase in 2007. As the Fed increased rates due to widespread fear of inflation between 2004 and 2007, many sub-prime loans eventually defaulted (Bernanke, 2007). As a result, major U. S. financial institutions had to write down their mortgage portfolio values drastically in 2007. One prominent incident was the suspension of withdrawals from two major hedge funds at Bear Stearns (Quental, 2007). Naturally, the collapse resulted in considerably tightened credit requirements across all financial institutions. The inevitable credit crunch was a reality and M&A activity fell by 30 percent in the aggregate by 2008. However, stock transactions could still move through as the contraction in market valuations remained modest in the first half of 2008. By early 2009, however, the credit crunch and financial market crash resulted in a drop in M&A activity of 43 percent that year. Events like the financial crisis illustrate that the relationship between M&A and capital liquidity remains highly relevant.

Market Collapses and Broken Correlations

However, the interaction between the rate spread and the valuation variable, the M/B ratio, show some conflicting findings to those of Harford (2005). First, the correlation between the rate spread and the M/B ratio (the complete correlation table is available in A.3) is non-significant (-0.28). Moreover, we do not find the same significant correlation as Harford (2005) for lagged changes in rate spread preceding current changes in overall M/B ratio (we find a correlation of -0.03 compared to Harford's (2005) -0.38). This indicates that the inverse relationship between the rate spread and market valuations is less obvious in our sample period. The implication of this finding is that other factors than the rate spread, to a larger extent than in previous decades, determine market valuations.

Historically, as credit constraints increase, economic activity and outlooks decrease, resulting in reductions in market values. However, the performance of "main street" (small businesses and investors) have been increasingly separated from "Wall Street" (major banks and financial institutions) over the last decades (Samuelson, 1991). To fully understand why such separation have occurred, we need to understand some underlying mechanics of the financial system.

An increase in the rate spread should result in depleting economic growth and potentially higher risk premiums (Lown et al., 2000). Both of which should result in decreasing M/B ratios. However, since our sample contains two of the most severe market crashes in recent history, the previously significant negative correlation between the two variables have been distorted. By year 2000, many financial institutions had become so large and heavily intervened in the financial system that the Federal Reserve could not risk letting them default. They had become too big to fail. Thus, following the market crash, a monetary policy that enable financial markets to recover was implemented in the market for repurchasing agreements (repo-market). The repo-market is essential for the health of the modern US financial system. Every day, between $2 and $4 trillion is exchanged through repo-agreements were treasury bills or other highly liquid securities are exchanged for cash over a short period of time until they are repurchased along with interest (Kolchin, Podziemska, & Mostafa, 2020). Thus, those in need of cash can obtain liquidity, while those holding cash reserves are able to earn interest rather than stockpiling.

After a market collapse, the purchasing part in such agreements dramatically increase their demanded interest, and a cash crunch occurs. The federal reserve has, through legislations like the Emergency Economic Stabilization Act of 2008, intervened in this cornerstone market and bought up financial securities following a market crash (US Congress 110th, 2008). This intervention floods the major financial institutions with cash, which allows them to stay afloat and eventually are reinvested in the market. The result is the impressive recovery of financial markets following the market crashes in 2000 and 2009. On "main street" however, businesses do not recover as quickly, and it took the US civil unemployment rate 10 years to recover to the pre-crisis levels of 2007 (US Bureau of Labor Statistics, 2020). Therefore, we observe that the C&I rate spread increased from 2002 to 2004 and 2008 to 2010 while market valuations and returns did the same, and not the opposite. This paradoxical relationship between the rate spread and valuations is somewhat unique to our period compared to that of Harford (2005).

Implications for Statistical Models

Harford (2005) argues that the significant correlations between the capital liquidity proxy, rate spread, and valuations could cause issues with multicollinearity in multivariate tests. However, we do not observe the same significant correlations. Therefore, the influence of valuation-linked variables might not be captured by the liquidity proxy, as found by Harford (2005). The variables could therefore yield significant explanatory power simultaneously. If the valuation-linked variables in fact are significant when included in the same model as the rate spread, they should provide individual explanatory power in the models (Table 7, 7.1).

5.1.2 The Influence of Private Equity

Increasing Capital Inflow

The capital inflow to private equity has been steadily increasing since the turn of the millennium (A.1). During 2000 and 2001, $157 bn and $94 bn, respectively, were raised by private equity funds in the US. That increased to $303 bn and $397 bn by 2018 and 2019, respectively. Even though the amount of capital raised by funds are cyclical with boom-and-bust cycles, there has been an increasing trend in investor appetite for alternative asset classes. Similarly, the dry powder, i.e., committed capital yet to be invested by private equity funds, has been steadily increasing from $192 bn in 2000 to $785 bn in 2019. This constitutes almost a quadrupling of the available capital to private equity funds over the period.

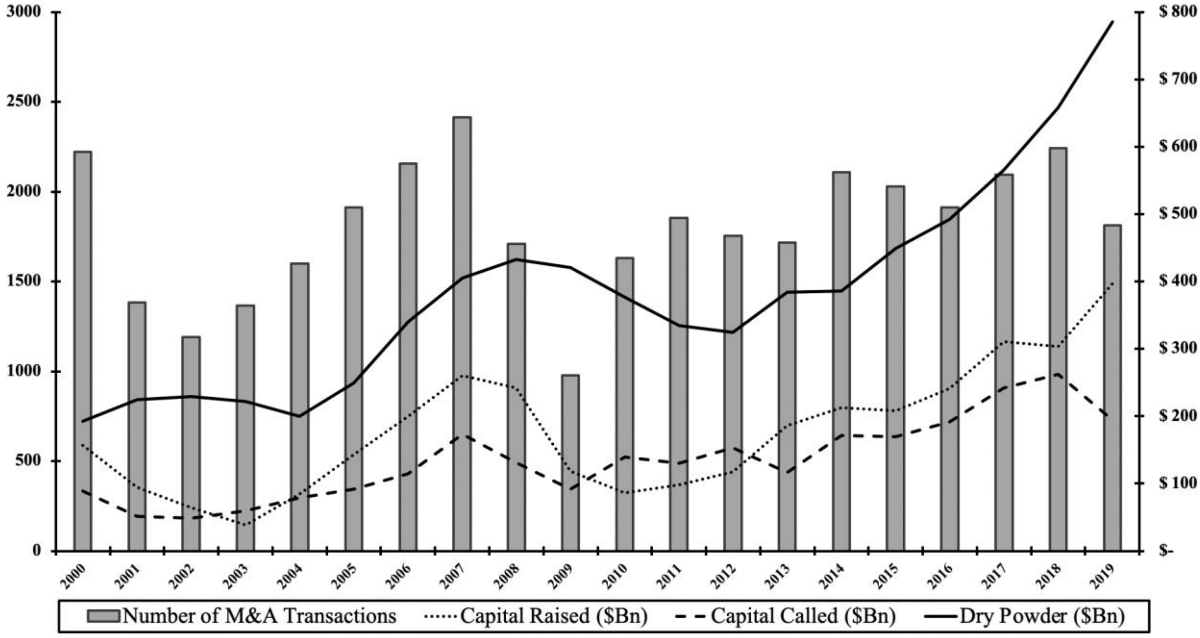


Fig. 4. Time series relationship between total M&A transactions (left), annual PE capital raised, capital called and build-up of dry powder in USD billions (right).

In Figure 4, PE funds raise more money in periods of high M&A activity, and vice versa. Furthermore, dry powder is the result of the spread between capital raised and capital called for investment over time. When PE funds, on aggregate, raise more than they invest there is accumulation of dry powder. Such periods coincide with strong market returns and valuations (Figure 3). Contrary, when market conditions are unfavorable the funds are investing more than they raise, leading to a decreasing dry powder base. Capital called, i.e., capital invested by funds, follow the overall market trends in M&A, thus indicating that private equity participates in the aggregate M&A cycle.

The Purchasing Power of Private Equity

In Figure 5, we investigate the real purchasing power of private equity funds. By scaling capital raised and dry powder by the total market value of public companies listed in the US, inspired by Kaplan and Strömberg (2009), we report their actual purchasing power.

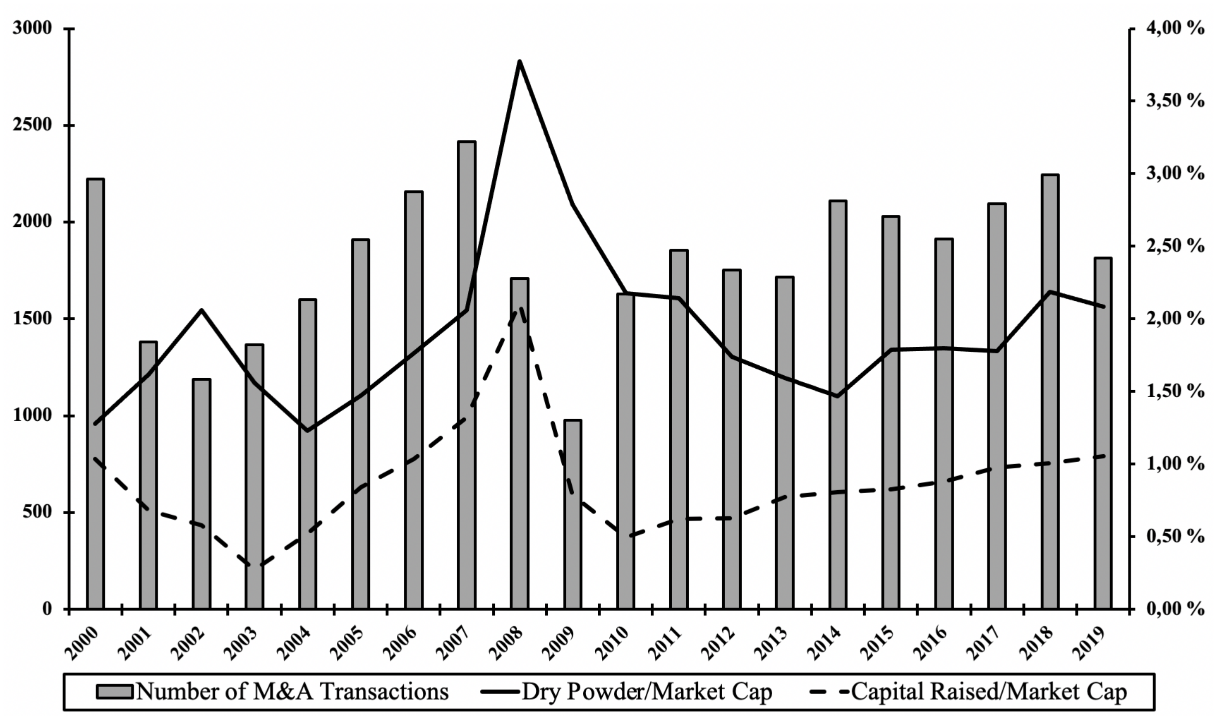


Fig. 5. Time series relationship between aggregate M&A activity (left), PE dry powder scaled by total US market value (right axis) and annual capital raised by PE funds scaled by total US market value (right axis). The variables can be found in A.1.

As evident by Figure 5, dry powder scaled by total market value and overall M&A activity has somewhat of an inverse relationship. The real purchasing power of private equity funds peaks in 2008 due to the market collapse under the global financial crisis. Subsequently, it fell rapidly due to a large reduction in fund raising paired with a strong recovery of market valuations. However, the value of private equity capital raised relative to overall market value has been steadily increasing ever since. Although this period is regarded as the longest running bull market in history, the real purchasing power of raised capital doubled between 2010 and 2019. As such, private equity is becoming an increasingly influential player in M&A.

Increasing Fund Competition

The number of active private equity funds has increased over the period (see A.1, and A.4 for a more detailed discussion regarding the evolution of the median PE fund over the period). However, the actual magnitude of their impact remains to be explored.

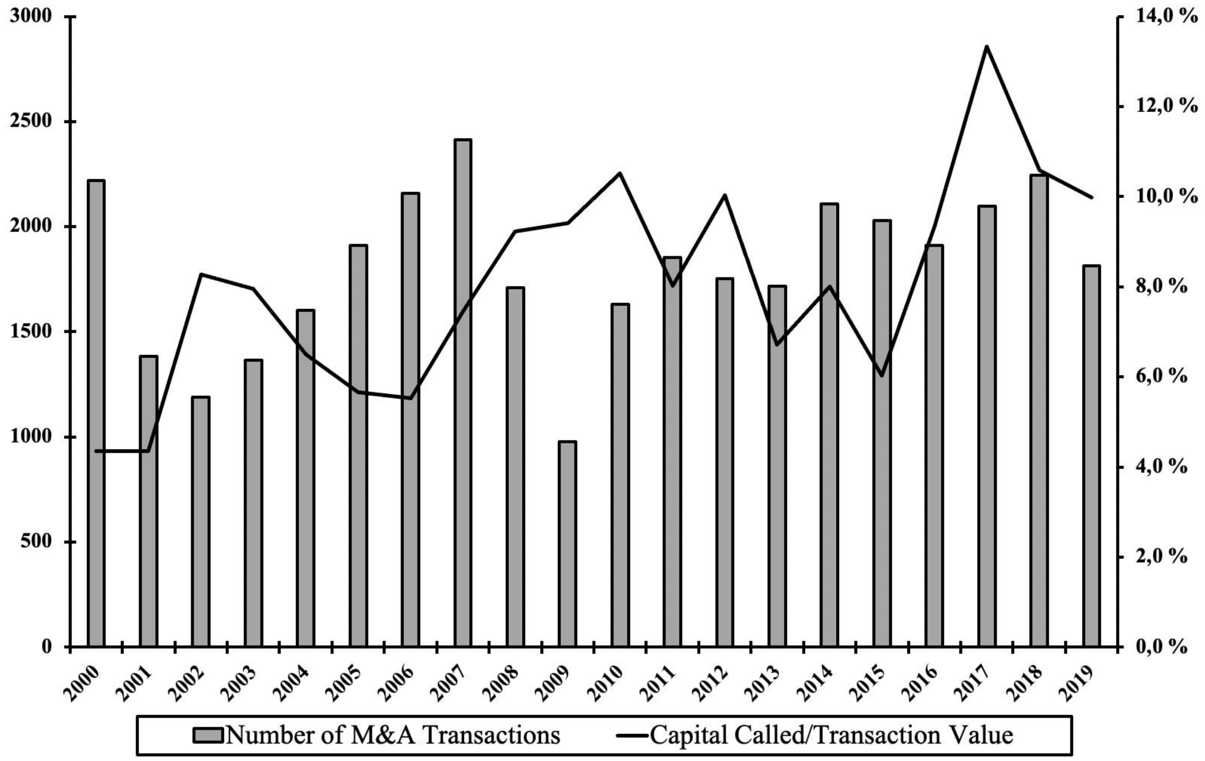


Fig. 7. Time series relationship between aggregate M&A activity (left) and aggregate capital called for investment by private equity funds scaled by total annual M&A transaction value (right).

In Figure 7, the share of total M&A transaction value made up of capital calls from private equity funds are plotted against the aggregate deal volume. There is an inverse relationship between the two series. The private equity proportion of deal value increases during low points in overall activity. This is likely a result of their limited lifetime. General partners (GPs) are forced to invest promptly after raising capital, irrespective of market conditions. After periods of strong capital inflow to private equity, such as in 2008, the GPs must invest, thereby increasing their share of total transaction value. However, strategic buyers seem to dominate aggregate M&A waves, accounting for a larger share of the total transaction value, consistent with Maksimovic et al. (2013). Albeit cyclical, there seems to be an increasing trend in private equity contributions to total transaction value. Capital called made up 6.3 percent of total transaction value on average during the first 5 years of the sample, and 9.9 percent during the last 5 years of the sample.

5.2 Univariate Evidence

In this section we test the relevance of the explanatory variables from Harford (2005) in our sample period. The variables of interest linked to the neoclassical hypothesis are supposed to capture economic shocks to an industry. They are based on previous contributions by Healy, Palepu, and Ruback (1992) and Mitchell & Mulherin (1996) before being formalized by Harford (2005). The variables include net income to sales, asset turnover (scaled by beginning-of-period assets), R&D spending (scaled by beginning-of-period-assets), capital expenditures (scaled by beginning-of-period-assets), employee growth, return on assets and revenue growth. The scaling of variables ensures comparability across individual firms. As Harford (2005) points out, the M/B ratio could be considered both neoclassical and behavioral, as shocks to the economic conditions of a company should impact the market value. The strictly behavioral variables are the three-year and one-year stock returns as well as their intra-industry dispersion, calculated as the standard deviation of the returns.

Since we are interested in discovering economic shocks, which we define as changes in fundamental conditions that has a significant effect on outcomes and/or economic performance, the annual change in the neoclassical variables is what we focus on. Given that there are fundamental differences between firms, and that relevant changes can be both positive and negative, we calculate the firm-specific absolute change in each variable (Table 2). As the behavioral variables are not capturing shocks, but rather relative valuation levels, they are not expressed as absolute changes. Subsequently, each firm is assigned to its appropriate industry based on the FF49 framework (Fama & French, 1997). After careful inspection, we winsorize all the firm-specific variables at the 95th percentile to avoid over-influence of outliers on our estimates (only mean and standard deviations as medians remains unaffected). Subsequently, the intra-industry annual median absolute change in the abovementioned neoclassical and behavioral variables are calculated. As a result, we obtain 21 (1999-2019)[6] annual medians across 49 FF-industries for each explanatory variable[7].

Furthermore, for each of our 44 observed industry-specific merger waves we create a dummy variable equal to one in the year preceding the wave. Subsequently, we test for significant differences in the changes to fundamental conditions in the year before industries experience an M&A wave, and the non-wave years for the same industries. This is done through a one-sample Wilcoxon's Signed Rank Sum Test. This test is chosen as we are comparing non-

[6] As some waves start in year 2000, we register observations from 1999 to facilitate lagging.

[7] On a practical note, observations on the absolute change in R&D for certain industries in certain years is missing. This is because no firms in these industries record R&D-spending for those years in our Compustat sample. This is either a result of some industries not focusing on R&D, or a result of accounting procedures, since R&D is expensed under U.S. GAAP (Bogle, 2020). Regardless, NAs are presumed to be 0 in these cases to obtain a balanced panel.

parametric (i.e., non-normally distributed variables) within the same sample. The results are summarized in Table 6.

Table 6: One-Sample Wilcoxon Signed Rank-Sum Test

The state of neoclassical and behavioral variables in pre-wave years are summarized in this table. The neoclassical variables are net income margin, asset turnover, R&D, capital expenditures, employee growth, ROA, and revenue growth. The M/B variable is claimed by both hypotheses while the strictly behavioral variables are 3-year and 1-year returns and dispersion of said returns. The mean presented in the table is the mean of industry specific medians in industries that are experiencing a merger wave the following year. For each of the 36 industries experiencing waves, all the industry-year medians between 1999 and 2019 are ranked into quartiles. Then the mean rank over the 44 pre-wave years is presented for each variable. Subsequently, a Wilcoxon signed rank sum test is conducted to compare the mean rank in pre-wave years to a middle rank of 2.5 $\left(\frac{1+2+3+4}{4}\right)$. The H_0-hypothesis is that these ranks are not significantly different from the middle rank of 2.5, while the alternative hypothesis is that the explanatory variables in fact are systematically higher in industries about to experience merger waves. The numbers presented in brackets are the p-values resulting from the test. Significant p-values (at the α = 10 percent level) are highlighted in **bold**.

Variables Related to the Neclassical Hypothesis (Median absolute change in ...)	Mean	Rank	Variables Related to the Behavioral Hypothesis (Median)	Mean	Rank
Net Income/Revenue	0.071	2.45	3-Year Return	0.577	3.22
H_0: Rank = 2.5		[0.593]	H_0: Rank = 2.5		**[<0.001]**
Asset Turnover	0.098	2.43	σ (3-Year Return)	1.124	3.04
H_0: Rank = 2.5		[0.656]	H_0: Rank = 2.5		**[0.001]**
R&D	0.006	2.45	1-Year Return	0.151	2.84
H_0: Rank = 2.5		[0.579]	H_0: Rank = 2.5		**[0.008]**
Capital Expenditures	0.015	2.72	σ (1-Year Return)	0.513	2.75
H_0: Rank = 2.5		**[0.097]**	H_0: Rank = 2.5		**[0.047]**
			Variables Related to Both Hypothesis (Median)		
Employee Growth	0.115	2.50	Market to Book (M/B)	2.479	2.93
H_0: Rank = 2.5		[0.516]	H_0: Rank = 2.5		**[0.003]**
ROA	0.037	2.38	Industry σ (M/B)	2.700	2.79
H_0: Rank = 2.5		[0.742]	H_0: Rank = 2.5		**[0.035]**
Revenue Growth	0.150	2.59	Change in M/B	0.583	2.40
H_0: Rank = 2.5		[0.296]	H_0: Rank = 2.5		[0.716]

Inspecting the results from Table 6 reveals several interesting findings. First, the means of the industry-specific medians are strikingly similar to those of Harford (2005). For instance, Harford (2005) reports means of 0.096 and 0.004 for asset turnover and R&D in pre-wave years. We find 0.098 and 0.006, respectively. This implies that the changes to company fundamentals preceding industry waves are largely the same today. As such, the stability of Harford's (2005, p. 541) results are impressive.

However, the mean rank for the industry medians suggest that our data is fundamentally different to that of Harford (2005). Whereas Harford (2005, p. 541) finds that virtually all the medians for the neoclassical variables are abnormally high (i.e., at least in the third quartile) in pre-wave years, we can only make the same inference for Capital Expenditures at a 10 percent significance level. This makes sense given that Capital Expenditures capture investments in new assets, primarily PP&E, to accommodate new growth opportunities. Growth opportunities, paired with high capital liquidity, are associated with increases in available positive NPV projects which in turn should spur increased M&A activity. In contrast, for the behavioral variables, Harford (2005) finds that neither the returns nor their dispersion is significantly higher in pre-wave years, whereas we find that *both* the returns and their dispersion are significantly higher in years preceding a wave, even at a 5 percent level. Our findings are more coherent for the M/B variables, which are claimed by both hypotheses. We find that both M/B ratio and its industry dispersion are significantly higher in pre-wave years. Albeit slightly lower, both ranking and significance are again similar to Harford's (2005, p. 541) findings, apart from the change in the M/B ratio, which is not significantly different in our sample.

In sum, these preliminary findings indicate that the behavioral variables have become increasingly influential, relative to Harford's (2005) sample. The M/B variables are largely similar in terms of ranking, but with substantially higher means, implying the effects are more concentrated than before. This discrepancy could be driven by new economic trends since Harford (2005). For instance, increasingly immaterial assets less accounted for "on the books" could explain why many industries enjoy systematically higher M/B ratios today. Alternatively, the difference could be because our sample is heavily influenced by two major market crashes: the dot-com bubble burst and the financial crises. To test this presumption, we exclude the years 2000-2001 and 2008-2009, and repeat the rank-sum test. The results are summarized in Table 6.1.

Table 6.1: One-Sample Wilcoxon Signed Rank-Sum Test (Excluding Market Crashes)

The test and variables are identical to that of Table 6. However, the years 2000-2001 and 2008-2009 are excluded from the sample. These years were characterized by market crashes, i.e., the burst of the dotcom bubble (2000-2001) and the financial crisis (2008-2009) and could therefore impact the test largely. By excluding such "extreme" years it is easier to identify deviations from normal conditions in our variables. Significant p-values (at the α = 10% level) are highlighted in **bold**.

Variables Related to the Neclassical Hypothesis (Median absolute change in ...)	Mean	Rank	Variables Related to the Behavioral Hypothesis (Median)	Mean	Rank
Net Income/Revenue	0.071	2.48	3-Year Return	0.594	3.07
H_0: Rank = 2.5		[0.519]	H_0: Rank = 2.5		**[0.001]**
Asset Turnover	0.098	2.55	σ (3-Year Return)	1.137	3.06
H_0: Rank = 2.5		[0.372]	H_0: Rank = 2.5		**[<0.001]**
R&D	0.006	2.46	1-Year Return	0.149	2.69
H_0: Rank = 2.5		[0.569]	H_0: Rank = 2.5		**[0.092]**
Capital Expenditures	0.015	2.86	σ (1-Year Return)	0.509	2.83
H_0: Rank = 2.5		**[0.027]**	H_0: Rank = 2.5		**[0.019]**
			Variables Related to Both Hypothesis (Median)		
Employee Growth	0.115	2.60	Market to Book (M/B)	2.482	2.76
H_0: Rank = 2.5		[0.277]	H_0: Rank = 2.5		**[0.051]**
ROA	0.037	2.46	Industry σ (M/B)	2.692	2.74
H_0: Rank = 2.5		[0.576]	H_0: Rank = 2.5		**[0.076]**
Revenue Growth	0.151	2.74	Change in M/B	0.583	2.39
H_0: Rank = 2.5		**[0.078]**	H_0: Rank = 2.5		[0.734]

As evident by Table 6.1, the means of our modified sample are only marginally affected when excluding market crash years. This is because no industries, apart from Medical Equipment, experienced a merger wave immediately following the excluded periods. Thus, the pre-wave sample is largely unchanged. The ranks, however, change slightly because some of the extreme cases in non-pre-wave years are removed. Absolute changes in Capital Expenditures becomes increasingly significant. The same goes for median absolute changes to Revenue Growth which is now significant at the 10 percent level. This indicates changing operating conditions in an industry. Note that the changes are not strictly positive, since we are dealing with absolute changes and worsening operating conditions could result in divestures. Therefore, both positive and negative revenue growth could spur consolidation.

5.3 Regression Models

5.3.1 Methodology

Methodology for Industry Specific Models

The forthcoming models attempts to uncover drivers of merger waves on both an industry level and in the aggregate. For the models predicting industry merger waves (Table 7, Column 1-4) the dependent variable, the occurrence of industry specific merger waves, is binary, i.e., 1 in the years an industry is experiencing the start of a merger wave and 0 otherwise. Since we want to follow the approach of Harford (2005), at least initially, we use a binominal logistic regression model (Logit). This ensures comparability of results, even though, the disadvantages of such a model, compared to that of a linear probability model (LPM), is that it is non-linear in parameters. The non-linearity makes interpretation less intuitive as the effect of marginal changes to explanatory variables are dependent on the base value of those variables. Because the original coefficients reported under this specification does not provide any interpretation (they are reported as log-odds), we report marginal effects at the mean on the probability of observing a merger wave following a one unit increase in the independent variable.

The behavioral and neoclassical explanatory variables are the same as analyzed in Table 6. The model specifications of Harford (2005) involve a transformation of the seven neoclassical variables. A First Principal Component (PC1) analysis is conducted, resulting in a feature extraction by creating a new independent variable, the first principal component (PC1) (Kassambara, 2017).

The PC1 is the combination of loadings in the seven neoclassical variables that can explain the largest possible proportion of the variance in said variables by itself. The first principal component captures 46 percent of the variance in the original seven neoclassical variables (A.5). This component is also interacted with a dummy representing tight capital years (characterized by annual industry median M/B ratio below the industry timeseries median and rate spread above the time series median). The rational for including this interaction term is that neoclassical shocks are less likely to propagate a wave in periods where capital liquidity is low (Harford, 2005).

Methodology for Aggregate Models

The models predicting merger waves in the aggregate (Table 7, Column 5-7) are OLS models identical to those of Harford (2005). The dependent variable scales the aggregate merger activity from 1-3, where the numbers indicate activity in the bottom, middle or top third over the period (top third years can be viewed as aggregate merger wave years and are 1999-2000, 2006-2007, 2014 and 2017-2018). The independent variables are weighted averages, based on firm count in each FF49 industry, of the same variables used to predict industry specific merger waves. The tight capital dummy is modified and now equals 1 if the weighted average annual M/B ratio across *all* industries are below its timeseries median while the rate spread is above its time series median, simultaneously. Deregulatory events are considered industry-specific and therefore excluded from the aggregate models, based on the notion that industry-specific deregulations are unable to affect the entire economy. Even though Harford (2005) includes deregulatory events on the right-hand side in his aggregate regressions, he does not elaborate on the process of extrapolating this variable from industry-specific into the aggregate. Thus, we have no way of accurately reproducing his procedure, and therefore leave the variable out of the aggregate models.

5.3.2 Findings and Discussion of Initial Models

Table 7: Models Predicting Merger Waves Within Industries and In the Aggregate

These regressions are based on those of Harford (2005) and are replicated for comparability of results (except for the removal of the interaction term, tight capital, in Column 4 due to issues with multicollinearity, and deregulatory events in the aggregate). Column 1 to 4 are logit models predicting the occurrence of industry specific merger waves. The panel data contains 49 industries with annual observations from 1999 to 2019. The dependent variable is a dummy indicating the first year of an industry specific merger wave. The explanatory variables linked to valuations, i.e., M/B, 3-year return and σ(3-year return), are the annual median company specific observations within each industry. The C&I rate spread is the difference between the annual weighted average C&I loan rate and the federal funds rate. The deregulatory events variable is a dummy indicating major industry specific deregulations (see Table 3). The neoclassical explanatory variables, i.e., annual absolute changes in net income margin, asset turnover, R&D spending (scaled by assets), capital expenditures (scaled by assets), employee growth, ROA, and revenue growth, is represented by their first principal component (Econ Shock Index). This component is also interacted with a dummy representing tight capital years (M/B ratio below the industry timeseries median and rate spread above the time series median). All the variables are measured at time t-1, except tight capital. Marginal effects at the mean are reported instead of log-odds.

Column 5-7 are predicting merger waves in the aggregate. The tight capital dummy is modified and now equals 1 if the weighted average annual M/B across industries are below its timeseries median while the rate spread is above its time series median, simultaneously. The remaining explanatory variables are weighted averages (based on firm count in each FF49 industry) of the industry specific variables. The deregulatory index is not included as this is an industry-specific variable that should not influence the economy as a whole. The dependent variable scales the aggregate number of M&A transaction from 1-3 where the numbers represent years in the bottom, middle and top third over the period (the top years can be regarded as wave years, and are 1999-2000, 2006-2007, 2014 and 2017-2018). Heteroscedasticity-robust standard errors are used for all models. Standard deviations are reported in parentheses.

	Merger Waves						
	Industry				Aggregate		
	Logit				*OLS*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept					1.077	3.385^{**}	3.508
					(2.290)	(1.399)	(2.773)
$(M/B)_{t-1}$	0.016^{***}	0.005		0.006	1.361^{**}		0.909
	(0.005)	(0.006)		(0.006)	(0.546)		(0.589)
$3-\text{year Return}_{t-1}$		0.049^{***}		0.045^{***}	1.471		3.636^{**}
		(0.014)		(0.014)	(1.083)		(1.564)
$\sigma(3-\text{year Return})_{t-1}$		0.019		0.018	-2.276		-5.263^{**}
		(0.014)		(0.015)	(1.697)		(2.373)
C&I Rate Spread_{t-1}			0.036^{***}	0.009		-0.591	0.465
			(0.011)	(0.010)		(0.712)	(0.613)
Deregulatory Event_{t-1}			0.198^{*}	0.186^{*}			
			(0.117)	(0.110)			
Econ Shock Index_{t-1}			0.003	0.001		-0.498	0.841
			(0.003)	(0.003)		(0.569)	(0.604)
Econ Shock Index_{t-1} * (Tight Capital)			0.0005			-0.093	-0.467
			(0.003)			(0.514)	(0.429)
Pseudo-R2	0.0173	0.0746	0.0647	0.0926			
Adjusted R^2					0.521	0.068	0.490

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Initial Findings for Industry Waves

Table 7 presents the results. In Column 1, the model is estimated using only the M/B ratio, which has some explanatory power, However, it is subsumed by 3-year-return when including the behavioral variables (Column 2), whereas the dispersion of the return is insignificant[8]. This suggests that it is the compounding of market value that drives industry merger waves, instead of relative misvaluation measures as captured by a behavioral understanding of M/B and the dispersion in 3-year-returns. This is consistent with the neoclassical narrative, in which the M/B and 3-year return reflects increased valuations because of increased availability of positive NPV projects, including M&A, and therefore an increase in the present value of growth opportunities (PVGO). Albeit the M/B and 3-year return are somewhat correlated since they largely measure the same increase in valuations, we observe acceptable VIF-scores in the 1.1-1.5 interval (c.f. A.6).

When including the strictly neoclassical variables in the specification (Column 3), the rate spread and deregulatory event index emerge as significantly positive drivers of industry waves. Since an increase in the rate spread implies a tightening of capital constraints, this is contrary to our own predictions and inconsistent with previous findings by Harford (2005) and Shleifer and Vishny (1992). On the other hand, the influence of deregulatory events in Column 3 and 4 (at the 10 percent level) is strikingly similar in magnitude to Harford (2005) and consistent with previous findings for the 1980s and -90s by Mitchell & Mulherin (1996) and Andrade et al. (2001).

Contrary to Harford (2005), the remaining neoclassical variables as captured by the economic shock index has no explanatory power, that be with or without the interaction of tight capital (Column 3-4). This is presumably because Harford's (2005) First Principal Component Analysis captures more of the variation in the underlying variables than our analysis, reflecting fundamental differences in the underlying data for the period. Alternatively, the economic shock variables included in the index might have lost some of their shock-measuring capabilities since the 1980s and -90s, as technological advances and increased outsourcing has possibly made many industries more agile. For instance, a general shift in the economy from manufacturing to services and increased digitization coupled with an increasingly educated

[8] Harford (2005, p. 545) does not control for dispersion in M/B due to multicollinearity issues. To consistently replicate Harford (2005), we do not include the dispersion of M/B to any of the specifications in Table 7. Instead, we substitute the return variables for the M/B variables in Table 7.1.

workforce can have made many industries more shock-responsive, since assets and employees can more easily be repurposed. This could effectively allow companies to better adapt the way they do business following a shock. This would be consistent with the preliminary findings of the ranked sum test (Table 6), which revealed that albeit the change in the neoclassical variables preceding a wave was largely the same as in Harford (2005), most of the rang-sums in pre-wave years were no longer significantly different to the rest of the sample, indicating that economic shocks to industry fundamentals have become less abnormal since Harford (2005).

Notably, in Column 4, the significance of the rate spread disappears when controlling for the behavioral variables and removing the interaction term with tight capital (Column 4). Separate specifications not reported in the table confirms that it is the exclusion of tight capital and not the inclusion of the behavioral variables that depletes the rate spread, suggesting that the interaction term disturbs or amplifies the effect of the rate spread, as it is partially a function of the rate spread itself. Note that when including both behavioral and neoclassical variables into the specification (Column 4), we do not observe the same subsumption of the behavioral variables by the neoclassical ones as Harford (2005), as both the 3-year return and the deregulatory index are simultaneously significant, while the rate spread is not. However, the rate spread and market returns are also somewhat correlated since the procyclical nature of the stock market implies that market valuations are higher when default risks are low.

Initial Findings for Aggregate Waves

In the aggregate (Column 5-7), the probability of merger waves increases in the M/B ratio, which consistent with Harford (2005), is the only of the behavioral variables with any explanatory power before the neoclassical variables are controlled for (Column 5). The notable increase in the magnitude of the coefficients in the aggregate is largely due to the scaling of the dependent variable, since it no longer measures wave probability, but M&A activity on a scale from 1 to 3.

Unlike Harford (2005), none of the strictly neoclassical variables have any predictive power (Column 6). When including all variables into the specification (Column 7), 3-year return and its dispersion emerge as positively and negatively related to aggregate merger waves. We thereby observe the same reversal of the behavioral variables as in the industry models (Column 1-2 and 4), namely that 3-year return outperforms M/B when included in the specification. The significant positive relationship implies the probability of aggregate merger waves increase when preceded by 3-years of strong market performance. Interestingly, and contrary to the behavioral hypothesis, aggregate merger waves are significantly decreasing in the dispersion of 3-year return, implying aggregate merger waves are primarily driven by high market valuations and not managerial attempts to exploit temporary misvaluations. Albeit we must interpret the specification with caution due to multicollinearity issues, this gives reason to reject the behavioral hypothesis, which predicts a positive relationship.

Alternatively, the negative relationship can be interpreted as a general sign of caution when markets are volatile during bust periods, such as the dot com bubble or the financial crisis. The rate spread remains insignificant in the aggregate. Therefore, unlike Harford (2005), we cannot at this stage conclude that the behavioral variables only proxy for capital liquidity, neither at an industry level (Column 1-4), nor in the aggregate (Column 5-7). However, our findings so far suggest a neoclassical understanding of market returns, inconsistent with systematic misvaluations as presumed by the behavioral hypothesis.

5.3.3 Robustness

General Considerations

The following discussion deals with threats to the validity of the above findings, and measures taken to ensure robustness. The variables are based on all available public firms in the Compustat database and should be reliable in terms of estimation accuracy. They are, however, biased given that these observations are of public companies only, while the merger waves identified through SDC data contain both private and public companies (see Table 5). Thus, our findings will be valid for public firms only.

Moreover, to avoid issues with reversed causality as frequent mergers in an industry could affect the valuations of companies through anticipation (Song & Walkling, 2000) and industry spillover effects (Cai et al., 2011; Servaes & Tamayo, 2014), and based on the assumption that merger decisions are sticky, we measure the explanatory variables at time t-1. Therefore, since some of the waves in our sample started in year 2000, explanatory variables are recorded from 1999. Due to issues with multicollinearity between the one and three-year returns investigated in Table 6, only the three-year returns, dispersion of said return and the market to book ratio is continued of the behavioral variables, which imitates Harford’s (2005) approach. Finally, we implement robust standard errors for all models (HC1). These are consistent, even in the presence of homoscedasticity, and are therefore always preferred.

Considerations Regarding Industry Specific Models

In the models predicting industry merger waves (Table 7, Column 1-4) multicollinearity does not seem to constitute a threat to the power of the models based on their VIF scores (A.6, Column 2-4). That being said, the interaction term, tight capital, is clearly causing issues, resulting in wrongfully significant positive marginal effects of C&I rate spread (Table 7, Column 3). This is likely a result of the variable being a function of other variables included in the specification. Therefore, we exclude the interaction term from the full model (Table 7, Column 4) even though Harford (2005) does not. Moreover, the high number of observations in our sample is a testimony to its power. We have 44 occurrences of the least frequent outcome, which is industry merger wave years, compared to nearly 1000 observations of the most frequent outcome, namely industry non-merger wave years. Due to the sample size, we can assume asymptotic normality for the industry models through the Central Limit Theorem, which suggests the estimators follow an asymptotic standard normal distribution (Wooldrigde, 2002, p. 767).

Considerations Regarding Aggregate Models

A substantial threat to the power of the *aggregate* models (Table 7, Column 5-7), on the other hand, is the small number of observations. The sample only contains 21 observations of each variable, one for each year in our sample. Consequently, the central limit theorem no longer holds (Wooldridge, 2002). Moreover, we are no longer working with panel data, but with time series observations. This could result in autocorrelated residuals. We therefore test for autocorrelation through a Durbin-Watson test (Durbin & Watson, 1950). The test does not detect autocorrelated residuals (see A.7), and we therefore do not implement autocorrelation-robust standard errors. However, multicollinearity is a threat. This is confirmed by high VIF-scores for the full model (A.6, Column 7), which makes it impossible to control for all observable variables and ensure robust findings, simultaneously. We later address this issue through a modified model in Table 7.1.

5.3.4 Methodology Modifications

General Methodology Modifications

In the next section, we modify Harford's (2005) method to mitigate the robustness issues discussed above and provide additional value by introducing new variables in similar regressions. The first modification is to drop the lagging of the C&I rate spread. Since the variable captures fluctuations in the risk premiums demanded by lenders over time, it is most impactful at the time when the transaction moves through rather than the year prior. Reversed causality should not constitute an issue as it is unaffected by M&A activity. Furthermore, the economic shock index (the first principal component of the seven neoclassical variables) previously constructed to replicate Harford (2005) can be regarded as a “black box”. Under Harford’s (2005) specification we are unable to distinguish between the actual drivers in the index. We therefore unpack the index by introducing the variables individually. However, two of the seven neoclassical variables are excluded in the following models. First, Net Income Margin is dropped because it is primarily an industry characteristic. Because some industries naturally operate under tight margins irrespective of shocks, we find Revenue Growth more capable of capturing changing operating conditions in response to a shock. Second, since Asset Turnover and ROA captures two sides of the same coin, only ROA is carried forward in the following specifications.

Methodology Modifications for Industry Specific Models

Although we report marginal effects, the coefficients of the Logit model used by Harford (2005) makes for complicated interpretation, and the marginal value added by the model does not compensate for the added complexity. We therefore change to a Linear Probability Model (LPM) in our modified models (Table 7.1, Column 1-6). Additionally, there could be *“*unobserved time-invariant heterogeneities across the entities*”* (Hanck, Arnold, Gerber, & Schmelzer, 2019, p. 222), such as leverage ratios, competition, or investor perceptions of industries (e.g., related to environmental, social and governance (ESG) concerns). To control for this, we implement industry fixed effects in the full model specification (Table 7.1, Column 6). However, due to a combination of introducing the LPM and the “unboxing” of the first principal component, the fit of the models as measured by their adjusted R-squared are depleted compared to the results in Table 7. This is particularly true for the full model (Column 6) since the industry fixed effects introduced implies multiple intercepts. However, the ability to uncover linear relationships as drivers of merger waves should be unaffected.

Methodology Modifications for Aggregate Models

We introduce a series of new variables related to the activity level of private equity firms (A.1). Aggregate capital raised by private equity funds is introduced as a potential driver of aggregate M&A activity, at time $t-1$ (Table 7.1, Column 10, 12). Moreover, we investigate the relationship between the level of dry powder held by PE funds and the capital called annually by the same funds during waves (i.e., at time t) to investigate if activity is associated with aggregate M&A wave trends (Table 7.1, Column 11), in accordance with Hypothesis 2.

5.3.5 Findings and Discussion of Modified Models

Table 7.1: *Modified* Models Predicting Merger Waves Within Industries and In the Aggregate

These regressions are based on those of Harford (2005); however, they are modified to provide additional value. Column 1 to 6 are LPM models predicting the occurrence of industry specific merger waves. The panel contains 49 industries with annual observations from 1999 to 2019. The dependent variable is a dummy indicating the first year in industry specific merger waves. The explanatory valuation linked variables, i.e., M/B and σ(M/B), are the annual median company specific observation within each industry. C&I rate spread is the annual difference between the weighted average C&I loan rate and the federal funds rate, i.e., equal for all industries. The Deregulatory Events variable is a dummy for major industry-specific deregulations (see Table 3). The neoclassical variables included is the annual industry median absolute change in said variables. Column 6 is fitted with industry fixed effects, and clustered standard errors, to control for OVB.

Column 7-13 predicts merger waves in the aggregate. The explanatory variables are weighted averages (based on firm count in each industry) of the industry specific variables. The deregulatory index is not included as this is an industry specific variable that should not influence the economy as a whole. The dependent variable scales the aggregate number of M&A transaction from 1-3 where the numbers represent years in the bottom, middle and top third over the period (the top third years can be regarded as wave years, and are 1999-2000, 2006-2007, 2014 and 2017-2018). Capital raised is the aggregate capital raised by private equity funds annually the year prior, while Capital Called is the current capital called for investment by the same funds. Dry powder is the level of accumulated committed capital that has yet to be called for investment. All private equity (PE) variables are nominal amounts in $bn. Robust standard errors are used for all models. Standard deviations are reported in parentheses.

	Merger Waves												
	Industry *LPM*					*Industry Fixed Effects*	Aggregate *OLS*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Intercept	0.003	0.041**	-0.003	0.106***	0.050		-2.326	8.468***	-0.721	1.286***	1.099***	0.777	4.795**
	(0.019)	(0.016)	(0.032)	(0.030)	(0.044)		(1.456)	(1.161)	(1.345)	(0.359)	(0.357)	(3.857)	(1.906)
$(M/B)_{t-1}$	0.022**		0.023**		0.023**	0.056***	1.561***		1.567***			-0.048	0.830**
	(0.009)		(0.010)		(0.010)	(0.016)	(0.545)		(0.403)			(0.755)	(0.403)
$\sigma(M/B)_{t-1}$	-0.003		-0.003		-0.003	-0.007	0.406					2.821	
	(0.007)		(0.008)		(0.008)	(0.010)	(0.878)					(2.222)	
C&I Rate Spread				-0.037**	-0.030**	-0.027*		-2.239***	-0.306			-1.691**	-1.451***
				(0.015)	(0.015)	(0.016)		(0.679)	(0.357)			(0.836)	(0.470)
$\text{Deregulatory Event}_{t-1}$				0.200	0.208	0.191*							
				(0.129)	(0.128)	(0.102)							
$\text{Capital Expenditures}_{t-1}$		1.474	1.466*	1.507*	1.507*	2.258*		54.870				-42.888	
		(0.899)	(0.886)	(0.896)	(0.887)	(1.233)		(114.835)				(100.656)	
$\text{Revenue Growth}_{t-1}$		-0.024	0.002	-0.004	0.015	0.088		5.226				-4.859	
		(0.072)	(0.073)	(0.075)	(0.076)	(0.098)		(6.634)				(11.018)	
$\text{Employee Growth}_{t-1}$		0.011	0.061	-0.016	0.033	-0.009		4.769				17.556	
		(0.126)	(0.131)	(0.122)	(0.127)	(0.157)		(13.654)				(16.292)	
$\text{R\&D}_{t-1}$		1.970**	1.371	1.793**	1.222	3.120		-156.746				-392.952*	-222.290***
		(0.889)	(0.921)	(0.874)	(0.919)	(2.466)		(130.685)				(206.442)	(49.663)
$\text{Return on Assets}_{t-1}$		-0.618**	-0.674**	-0.520*	-0.565**	-0.461		-69.438**				4.499	
		(0.279)	(0.275)	(0.278)	(0.276)	(0.310)		(33.878)				(67.038)	
$\text{PE Capital Raised}_{t-1}$										0.004*		-0.002	
										(0.002)		(0.005)	
PE Dry Powder											-0.003**		
											(0.001)		
PE Capital Called											0.016***		
											(0.003)		
Adjusted R^2	0.005	0.003	0.007	0.017	0.021	-0.015	0.468	0.513	0.475	0.085	0.443	0.528	0.646
Note:											*p<0.1; **p<0.05; ***p<0.01		

Drivers of Industry Merger Waves

The results are depicted in Table 7.1. As before, M/B is significant alone (c.f. Table 7). To further test the behavioral hypothesis, we substitute the return variables for the dispersion in M/B[9], which has no explanatory power. This confirms our neoclassical understanding of the M/B ratio, since a behavioral understanding presumes that relatively overvalued bidders acquire relatively undervalued targets, which should have been reflected in a significant and positive relationship (Column 1).

When unpacking the neoclassical variables previously merged in the Econ Shock Index (c.f. Table 7) in Column 2, we find that R&D and ROA emerge as significant variables. The probability of industry merger waves increases in changes in R&D spending but decreases in changes in ROA. In this specification, one unit increase in median absolute change of R&D spending (scaled to assets) is associated with a 197 percent increase in the probability that the respective industry-year is the first year of an industry merger wave[10]. Since the unit increase is in median *absolute* change, the economic change can be either an increase or decrease in R&D spending, but as for the rest of the neoclassical variables we cannot tell which one. The economic interpretation is therefore that R&D spending tends to change significantly in years preceding industry merger waves, that be positively (increase) or negatively (decrease) for expansionary or contractionary waves, respectively (Andrade & Stafford, 2004). Both makes economic sense in light of the neoclassical hypothesis.

First, because R&D spending proxies for long-term organic growth opportunities, and R&D-heavy firms presumably tend to be acquired in expansionary waves. Since managers face the choice between innovating internally through R&D spending or externally through acquiring innovative firms, and R&D entails huge costs whereas the potential gain is highly uncertain, acquiring smaller firms whose research capabilities have just proven successful could be a winning strategy for bigger high-growth firms. With the emergence of open innovation models (Chesbrough, 2003), many knowledge-intensive industries have increasingly seen such outsourcing of innovation (Ozcan, 2016). Additionally, if these mergers are in response to underlying economic shocks as claimed by the neoclassical hypothesis, responding bidders will

[9] The dispersion in 3-year-return and M/B are too highly correlated to enter the specification at the same time.

[10] Note that the magnitude of the coefficient is a consequence of the linear probability model (LPM), which unlike the logit can predict probabilities smaller than 0 and greater than 1. Also note that since R&D is scaled to assets, a one-unit increase is completely unrealistic, since that implies that the median absolute change in R&D spending is an increase or decrease of 100 percent of asset value – across the entire industry.

exhibit a preference for acquiring innovative firms that best allow them to respond to the shock, as captured by relatively higher baseline R&D spending. Since we measure median absolute change in R&D, but the spending is scaled to assets, such acquisitions of smaller and more innovative (i.e., less assets and higher R&D-spending) firms will spur greater changes in the medians, and therefore make both economic and econometric sense. As such, the significance of the R&D variable could proxy for underlying firm characteristics such as growth, which would also explain why it is subsumed by market-to-book, which is robust to industry fixed effects (Column 5-6). Significant increases in R&D spending preceding waves could also be symptomatic of changing investment policies as a takeover defense amongst target industry peers (Harford, et al., 2016; Servaes and Tamayo, 2014).

Second, because R&D spending is a long-term capital investment and therefore likely amongst the first activities to undergo budget cuts in bust periods, in which managers likely prefer to prioritize cash flows to operating activities to keep the business afloat in the short term. Therefore, R&D heavy business units could potentially be acquired in contractionary industry waves as non-core assets are divested to ensure sufficient capital liquidity towards the end of the busines cycle or for firms nearing financial distress, consistent with Shleifer and Vishny (1992).

Changes in ROA is negatively related to industry waves, a finding that is robust to other controls (Column 2-4 and 8). This is likely because ROA reflects the cash-generating ability and thereby attractiveness of current assets. When ROA increases, the need for acquiring new ones decrease, while a decrease in ROA results in increased need of acquiring new ones to avoid stranded assets. Moreover, as the number of underperforming incumbents in an industry becomes sufficiently large, this is likely to spur restructuring such as scale-increasing consolidation or simply divestures of non-core assets. Alternatively, ROA simply captures the flipside of the R&D dynamics in the sense that high R&D spending yields lower profitability and ROA, since R&D expenses are expensed and not capitalized under U.S GAAP (Bogle, 2020). However, ROA is not robust to industry fixed effects, suggesting the variable only proxies for underlying industry characteristics associated with high merger activity, such as high growth or low profitability (Column 6). This is consistent with the notion that such industries have seen increasing merger activity over the period.

On an industry level, when controlling for the behavioral variables (Column 3), R&D spending is subsumed by the M/B ratio, which is significantly positively related to industry merger waves. This is likely because M/B captures the anticipated long-term effects of R&D investments not yet accounted for "on the books". This emphasized by the fact the R&D becomes significant again when removing M/B from the controls (Column 4). Capital Expenditures (CAPEX) also has some explanatory power, robust to M/B (Column 4). The CAPEX variable captures the investment in and maintenance of *new and current* assets such as PP&E, which is also associated with future growth opportunities, and therefore in turn make for attractive acquisition targets, in the event of positive changes to the medians. Similar to R&D, in the event of negative changes to the medians, CAPEX is also usually subject to short-term cuts in bad times, but likely not to the same extent since CAPEX spending is necessary to maintain the cash generation ability of current assets and business operations. This could explain why CAPEX is more robust to other controls than R&D. For M/B on the other hand, the median is simply the median and a unit increase in M/B is therefore associated with an actual increased probability of industry merger waves.

Controlling for all variables (Column 5) yields a significant and negative rate spread, consistent with Harford (2005). Interestingly, and contrary to our initial findings (Table 7), this relationship only holds when removing the lag imposed on the rate spread by Harford (2005) (Table 7.1). This suggests merger activity reacts faster to changes in capital constraints, or that the stickiness of economic decision-making has decreased with increased digitalization in the economy, which is perhaps amplified by the digitization of financial markets. However, unlike Harford (2005), the rate spread does not subsume the M/B variable which remains significant in all our specifications with the exemption of Column 12. The deregulation index becomes significantly positive when controlling for industry fixed effects (Column 6) and is again strikingly similar in magnitude as for previous models (c.f. Table 7), and consistent with the neoclassical narrative (Mitchell and Mulherin, 1996; Andrade, et al., 2001), and our presumption that deregulations only affect targeted industries. The market-to-book, the rate spread, and CAPEX are robust to the controls of the industry fixed effects. This is consistent with the neoclassical explanation for merger waves.

Drivers of Aggregate Merger Waves

In the aggregate (Column 7-13), M/B and the rate spread both has significant predictive power in separate specifications (Column 7-8), but not together (Column 9). At first, we observe the opposite subsumption to Harford (2005) in that the M/B outperforms the rate spread, and not the other way around. However, the variables are somewhat correlated since a low rate spread is associated with high market valuations over the business cycle. This is reversed when the remaining original controls are added in Column 12, in which the rate spread subsumes the M/B and R&D spending remains the only significant control, now with a notably negative coefficient in the aggregate. This is likely because of the lagging of the variable. If changes in R&D correlates with the occurrence of merger waves, then lagging the variable can push the variable out of the peak of the wave period (where merger activity is lower), since the dependent variable is now the level of the aggregate merger activity on a scale from 1 to 3. As such, by nature of the aggregate wave, observing a year of high changes in R&D at t-1 (the year preceding the wave) yields lower probability that the next year is classified as a wave (i.e., a 3 on the scale), effectively causing aggregate merger activity to decrease in changes to R&D. Since we (consistent with Harford, 2005), only apply this scaling in the aggregate, in which waves are characterized by year and not 24-month periods as at the industry level, this could explain why we only observe this reversal from positive to negative R&D coefficients in the aggregate. Consistent with this presumption, the variable loses its significance in the aggregate when it enters the specification without the lag (not reported in Table 7.1). This suggests changes in R&D spending is not as sticky in its shock-responsiveness as initially assumed by Harford (2005).

Consistent with Harford (2005), we observe that the M/B largely proxies for overall capital liquidity as captured by the rate spread, congruent with the neoclassical explanation of aggregate merger waves (Column 9, 12). However, we do not observe the same effect at the industry level. This is presumably because the rate spread is an economy-wide variable (i.e., the same across all industries), which makes the correlation with M/B by nature of the business cycle larger in the aggregate than at the industry level, therefore allowing for greater variation in M/B in the industry specifications.

The added PE variables are all significant at a 10 percent level or less (Column 10-11). As predicted, capital raised the year preceding the start of the wave and capital called are positively related to aggregate merger waves, whereas the underutilized residual of dry powder is negative. Since both dry powder and capital called is a function of capital raised, these variables can be both drivers and the byproduct of merger activity, such that the dependent and independent variables mutually affect each other in the specification. We therefore lag capital raised to mitigate reversed causality issues. The significant positive relationship between capital raised in pre-wave years and merger activity (Column 10) suggests that PE firms predominantly raise funds ex ante, and that fundraising activity ramps up before the start of the wave as market conditions improve and buyers prepare to invest, consistent with previous research (Axelson et al., 2009; Kaplan & Strömberg, 2009). Column 11 intuitively suggests that dry powder builds up in periods of low merger activity in the economy. Capital raised is not robust to the remaining controls (Column 12) such as the rate spread, suggesting that PE funds actively *partake* in merger waves on a scale that is significant in the aggregate rather than *driving* them. This is consistent with previous research, which finds that merger waves are dominated by strategic acquirers (Martos-Vila et al., 2019), and that PE activity is subject to leverage constraints (Axelson et al., 2009; Kaplan & Strömberg, 2009). In sum, the findings support the null hypothesis that private capital is associated with merger waves (c.f. Hypothesis 2).

5.3.6 Robustness

Considerations Regarding Industry Specific Models

This section examines threats and measures taken to ensure robustness of the above findings. There are several drawbacks of using a LPM, which we will address briefly. First, the predicted probabilities of an industry merger wave might exceed one when using the LPM as opposed to a Logit model. However, as Wooldrigde (2002, p. 236) puts it, "predicted probabilities outside the unit interval are a little troubling when we want to make predictions, but this is rarely central to an analysis".

The aim of this model is not to be predictive, i.e., to make accurate predictions of when an industry merger wave will occur, but rather to explain the underlying drivers of such waves. Although the fit of the model will decrease under an LPM model, it will allow us to investigate linear relationships between the variables all the same. Second, the LPM assumes constant partial marginal effects irrespective of the base value of independent variables. Even though it makes interpretation of coefficients more straight forward, it might be viewed as inaccurate. That being said, Angrist and Pischke (2009) compare average marginal effects of a nonlinear model to the constant marginal effects of the linear model and find that they are similar in magnitude. When comparing our findings between the Logit (Table 7, Column 1-4) and LPM specification (Table 7.1, Column 1-6) we find the same. Thus, this should not constitute a large threat to the explanatory power of our models. Finally, heteroskedasticity issues are delt with using robust standard errors.

Considerations Regarding Aggregate Models

When estimating the aggregate models, we are dealing with a much smaller sample than on an industry level. The result of this is that multicollinearity is a much larger problem that could lead to high variance in estimates which, in turn, reduces the ability to detect statistical significance. We therefore have to deal with what is referred to as "bias-variance trade-off" (Hanck et al., 2019, p. 131). On the one hand we want to control for all observable variables to avoid omitted variable bias (OVB), while at the same time ensure robust findings. In addition to the full model specification (Table 7.1, Column 12), we therefore include a specification that maximizes the explanatory power through adjusted R^2 (Table 7.1, Column 13) based on an automatic both-way stepwise variable selector in R (Venables & Ripley, 2002). Maximizing adjusted R^2 is not the goal in itself. However, this specification will not be subject to the multicollinearity issues of the full model (see A.8), albeit subject to omitted variable bias. By estimating both we can compare findings between the two. Issues with autocorrelation (A.9) is discovered when Capital Raised is included alone (Table 7.1, Column 10). Therefore, we implement heteroskedasticity and autocorrelation robust standard errors (HAC) for this specification.

5.4 Payment Method on the Wave

Altogether, strictly cash offers have a dominant position in our sample (A.10). Its dominance was established after the market crash of 2000 while the proportion of stock offers went the opposite direction. The slight increase in stock offers, and corresponding decrease in cash offers, during the financial crisis is likely a result of the credit crunch, making stock offers the only viable option for some acquirers. Mixed offers constituting a combination of cash and equity account for approximately 10 percent, and remains stable throughout the period, consistent with the neoclassical hypothesis.

For the industries experiencing M&A waves (Table 5) we calculate the compositions of payment methods on and off these waves (A.11). We find that cash offers constitute 84 percent outside the wave periods, and 79 percent during the waves, on aggregate. The reduction is largely absorbed by stock offers, which are 4 percentage points higher during industry merger waves. These observations are consistent with Eckbo et al. (2018) and could be the result of a number of factors.

First, acquirers in merger waves are mainly public strategic buyers (Maksimovic et al., 2013), competing to answer a technological, economic or deregulatory shock, as predicted by the neoclassical hypothesis (Harford, 2005). Thus, the external pressure from financial and private acquirers offering cash is reduced, resulting in a higher probability of targets accepting stock offers (Eckbo et al., 2018). Second, albeit previous empirical findings suggest otherwise, it could also be a result of opportunistic acquirers taking advantage of high market valuations, in accordance with the behavioral hypothesis (Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003), which we have shown often coincides with industry merger wave periods. There are however, as emphasized by Eckbo et al. (2018), a large number of considerations that precedes the choice of payment method. Pinpointing the exact causal relationships and distinguishing the effect of each potential factor is, as a result, difficult. Therefore, we cannot conclude any definitive support for the behavioral hypothesis based on these findings.

Finally, the fact that cash considerations decrease during industry waves indicates a modest influence of private equity. Given that cash is the only viable option for PE, the proportion of cash considerations should increase during waves if they are a driving force, which is not the case. This reaffirms our previous conclusion that PE participates, but not on a sufficient scale to drive aggregate M&A waves.

5.5 Inference for Hypothesis 1 and 2

The initial data exploration, Rank-Sum tests (Table 6 and 6.1), regressions models (Table 7 and 7.1) and the investigation of payment methods during waves create the foundation for formally assessing whether to accept or reject Hypothesis 1 and 2.

First, we have tested the following null hypothesis (Hypothesis 1):

H_0: *Merger waves are primarily driven by neoclassical variables capturing economic, regulatory, and technological shocks, and sufficient capital liquidity*

H_1: *Merger waves are primarily driven by managerial attempts to exploit temporary misvaluations to time the takeover market*

Based on our findings, we accept the neoclassical null hypothesis and reject the behavioral alternative. The neoclassical hypothesis remains the superior explanation for M&A activity clustering in waves on an industry and aggregate level.

Second, we have tested the following null hypothesis (Hypothesis 2):

H_0: *The amount of capital raised by private equity funds* is *associated with aggregate merger waves*

H_1: *The amount of capital raised by private equity funds* is not *associated with aggregate merger waves*

Based on our findings, we accept the null hypothesis. Private equity capital is associated with aggregate merger waves. However, the capital influx is not of sufficient scale to be driving them.

5.6 Takeover Premiums

5.6.1 Descriptive Statistics

When calculating premiums in our sample, we look at the extent to which the offer exceeds the market price 4 weeks prior to announcement. This is because private information and rumors tend to leak out to the market in the run-up period before announcement. Consequently, the anticipation of an imminent deal results in increasing market values and reduced announcement returns. One issue is the scarcity of takeover premium observations. Of the 36 084 transactions in our sample, only 7 294 observations on premiums were registered by the SDC. Due to the outliers in our sample, we winsorize the data at the 95th percentile.

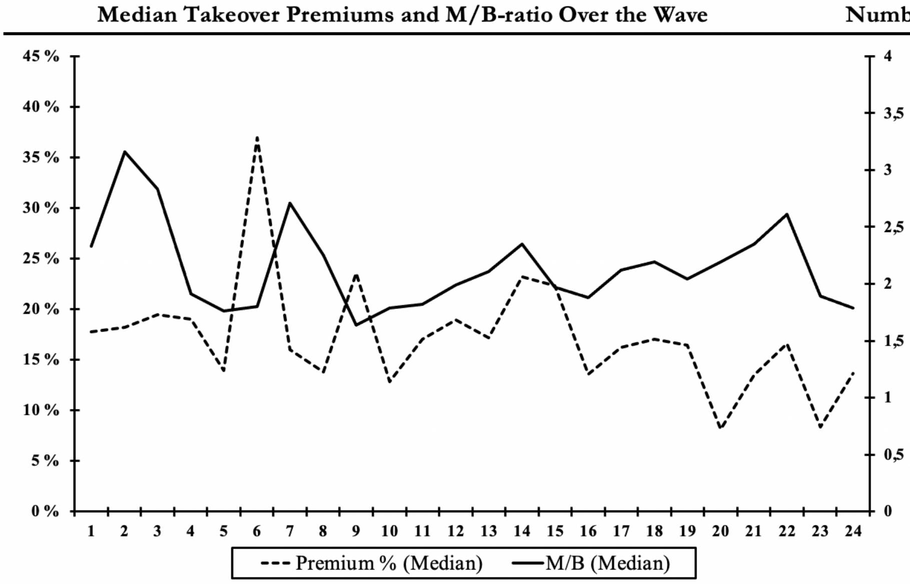
Table 8: Takeover Premiums

Descriptive statistics, proportions by premium size and top FF49 industries by average premium paid.

Descriptive Statistics			**Top Industries by Average Premiums**	**Observations**	**Mean**	**Median**
Observations	36 084		Beer and Liquor	18	54 %	51 %
Missing (%)	28 790	(79.8%)	Precious Metals	35	47 %	41 %
Mean (SD)	27.2%	(30.9%)	Pharmaceutical Products	369	44 %	41 %
Median [Min, Max]	21.1%	[-14.7%, 104%]	Computers	122	40 %	35 %
First Quartile	3.8%		Recreation	41	38 %	31 %
Third Quartile	42.5%		Computer Software	671	37 %	32 %
Proportions by premium size	**Number**	**Proportion**	Medical Equipment	230	36 %	30 %
< 0%	1 357	19 %	Measuring and Control Equipment	99	33 %	31 %
1 - 25%	2 680	37 %	Consumer Goods	73	31 %	22 %
25 - 50%	1 829	25 %	Textiles	11	31 %	27 %
50 - 75%	736	10 %	Coal	8	31 %	28 %
75 - 100%	300	4 %	Rubber and Plastic Products	30	31 %	22 %
> 100%	392	5 %	Healthcare	136	31 %	25 %
Total	7294	100 %	Electronic Equipment	362	31 %	27 %

5.6.2 Takeover Premiums Over the Wave

We want to investigate how the occurrence of industry merger waves affects the takeover premiums over the course of the wave (Hypothesis 3). First, we allocate the target in each transaction to its appropriate FF49 industry. Subsequently, we subset the industries that experience a 24-month industry M&A wave (Table 5) and calculate the cross-sectional median premium paid during each of the waves 24 months. Additionally, for the targets in the same transactions we calculate the median M/B ratio based on market value 4 weeks prior to deal announcement.



Number of Monthly Observations

Month	M/B	Premium
1	40	45
2	64	67
3	50	54
4	48	50
5	64	71
6	46	49
7	57	60
8	64	72
9	39	48
10	65	68
11	43	46
12	45	49
13	61	66
14	56	61
15	46	51
16	56	61
17	75	81
18	60	67
19	47	51
20	42	48
21	42	44
22	40	44
23	52	57
24	47	60
Total	1249	1370

Fig. 11. Monthly median takeover premiums (left axis) and monthly median M/B-ratio (right axis) for targets during 24-month merger waves.

It seems that takeover premiums decrease over the course of the wave. The reason we observe this trend could be twofold. First, merger waves are dominated by strategic acquirers responding to an industry-specific shock (Maksimovic, et al., 2013; Harford, 2005). Thus, the targets that have shock-responsive capabilities have the highest achievable synergies and valuations. Because the most attractive targets are acquired during the initial phase of the wave, takeover premiums are highest during the first months. As the wave progresses, fewer attractive targets with relatively lower potential synergies remain available for acquisition, resulting in diminishing premiums over time. Second, as investors recognize the existence of a merger wave they price in the anticipation of future mergers for potential targets (Song and Walkling, 2000). The result is increased valuations prior to announcement, and ultimately lower bid premiums and announcement returns. This explanation seems plausible, yet not obvious, based on the trend in median M/B ratio towards the end of the wave (Figure 11). There is a negative correlation between the two variables which could illustrate that the size of offer premiums is governed by market valuations. This warrants further tests.

5.6.3 Difference-in-Difference Methodology

Methodological Hurdles

There might be external market conditions governing the size of takeover premiums, such as access to capital liquidity over time. Generalizing the size of premiums in all merger wave periods, across the entire timeframe of the sample might therefore yield biased results. To mitigate this bias, we implement a difference-in-difference analysis between industries experiencing merger waves, as treatment group, and similar industries not experiencing a wave, as control group, over the same 24-month wave period. Thus, we can control for fluctuations over time and isolate the treatment effect of an industry wave occurring.

The first challenge to such an approach is that by definition, industries experiencing a wave have more transactions taking place than industries not experiencing a wave. Thus, the number of observations will be relatively lower for the control group resulting in potential estimation biases. Furthermore, there could be issues with general equilibrium behavior between the groups, i.e., untreated industries adapting to the waves taking place in treated industries. Investors in an industry that are currently not experiencing a wave, could observe a wave taking place in connected industries, and subsequently anticipate that the wave will transfer to related industries. The anticipation will result in spillover effects on premiums to non-wave industries as market valuations increase in anticipation of increased bidding (Ahern & Harford, 2014; Song & Walkling, 2000). Similarly, if herding by financial acquirers as found by Buchner et al. (2020) result in increased investor interest in wave industries at the expense of non-wave industries, there could be feedback effects. That is, premium dynamics that would not have been observed if competition remained unaffected by merger waves in non-wave industries.

Unfortunately, completely removing such threats to validity are impossible. There are, however, ways to ensure that the treatment and control groups are as similar in observable drivers of takeover premiums as possible. This is to ensure comparability between the two groups. Therefore, we start by investigating the observable fundamentals of an industry that could significantly influence the size of premiums.

Identifying the Right Matching Criteria

Through use of a panel regression, we uncover fundamentals that significantly influence the size of the average annual industry premiums. The reason we use average rather than median premiums lies in the small number of observations for some industry-years. In such cases, average estimates will be less skewed. The explanatory variables tested are annual industry medians of the following fundamentals: R&D spending (scaled by assets), Assets ($M), Net Income Margin (%), Revenue Growth (%), Capital Expenditures (scaled by assets), Return on Assets (%) and M/B ratio.

As we are working with panel data, i.e., record observations of a series of cross-sectional entities (49 industries) over time (2000-2019), we estimate four model specifications with increasing degrees of fixed effects (Wooldrigde, 2012). By implementing dummy variables for years (Table 9, Column 2) we exclude omitted variable bias caused by unobserved variables that vary over time, but are constant across industries (Hanck et al., 2019). For example, economic boom and bust cycles, access to capital liquidity or risk tolerance. Similarly, unobservable factors could vary across industries, while staying constant over time, thus affecting premiums differently across industries (Hanck et al., 2019). For example, high intra-industry competition for targets or a certain type of acquirer (strategic vs. financial) dominating the industry (Martos-Vila et al., 2019). Therefore, we implement industry specific intercepts to mitigate this potential bias (Table 9, Column 3). Finally, we estimate a specification with both time and industry fixed effects (Table 9, Column 4). Sophisticated software packages ease the estimation and reporting of results (Croissant & Millo, 2008; Hlavac, 2018; Millo, 2017).

5.6.4 Findings of Matching Criteria

Table 9 Industry Characteristics Potentially Determining the Size of Premiums

This regression is part of the matching procedure and seeks to uncover relevant industry characteristics to base the matching on. The dependent variable is the average annual premiums within each of the FF49 industries measured in percentage points. The independent variables are the annual industry medians of relevant accounting metrics across all firms within each industry. Potentially relevant accounting metrics tested are annual industry median R&D spending (scaled by assets), Assets ($M), Net Income Margin (%), Revenue Growth (%), Capital Expenditures (scaled by assets), Return on Assets (%) and Market-to-book Ratio. Column 1 is a naive OLS without any fixed effects. Column 2 has time fixed effects through inclusion of year dummies. Column 3 has industry fixed effects through industry-specific intercepts. Lastly, Column 4 has both industry and time fixed effects. All fixed effects coefficients are omitted from the table below. Column 1 is fitted with robust standard errors, while Column 2, 3 and 4 are fitted with clustered standard errors. VIF-scores can be found in the appendix (A.12).

	Dependent variable:			
	Average Annual Industry Premium (%)			
	Naive OLS	Fixed Effects Models		
	(1)	(2)	(3)	(4)
Intercept	22.379***	32.647***		
	(1.886)	(3.271)		
R&D Spending (Scaled by Assets)	90.231***	88.136***	210.595**	203.754**
	(21.605)	(20.530)	(103.416)	(100.265)
Revenue Growth	-4.296	4.562	-1.366	5.771
	(9.377)	(9.589)	(13.520)	(12.398)
Capital Expenditures (Scaled by Assets)	47.317**	40.849**	28.901	45.753
	(20.485)	(18.706)	(61.098)	(55.192)
Assets	-0.0003	-0.0005**	0.001**	0.0004
	(0.0003)	(0.0002)	(0.0004)	(0.0003)
Net Income Margin	8.349	4.167	7.670	0.669
	(5.434)	(5.009)	(5.373)	(4.674)
ROA	-29.194	-6.252	-12.223	25.425
	(22.283)	(22.119)	(34.368)	(31.965)
M/B	0.201	1.335	-1.503	0.506
	(1.016)	(1.038)	(1.055)	(1.054)
Time Fixed Effects?		YES		YES
Industry Fixed Effects?			YES	YES
Robust Standard Errors?	YES			
Clustered Standard Errors?		YES	YES	YES
Observations	774	774	774	774
R^2	0.058	0.171	0.014	0.016
Adjusted R^2	0.050	0.142	-0.060	-0.087
Note:		*p<0.1; **p<0.05; ***p<0.01		

The matching criteria are tabulated in Table 9. The only variable that retains significance after controlling for time and industry fixed effects is the annual industry median R&D spending (scaled by assets). Thus, in years where target industries spend a large proportion of their asset values on R&D, they enjoy higher average premiums upon acquisition. This is consistent with the neoclassical hypothesis as companies that are making efforts to modernize their capabilities are more capable of responding to disruptive shocks, and therefore make for valuable targets.

The value could both be reflected in large achievable synergies as well as in winning bids being higher than normal due to competition for shock-responding capabilities.

Robustness

In this paragraph we briefly address two main concerns related to the robustness of the above findings. First, there are cases where no premiums are observed for certain industries in certain years. This results from low transaction volume combined with a high degree of missing observations in the SDC data. The reason for premiums not being recorded is unknown to us, however, we must assume that whether the value is missing is independent from the observation itself. As a result, we are dealing with an unbalanced panel where average annual takeover premiums are recorded for 774 industry-years out of the total 980. Second, the low number of premium observations could lead to skewed average premium estimates. However, winsorizing should mitigate extreme cases to some extent. As always, assumptions regarding heteroskedasticity and autocorrelation are dealt with through robust and/or clustered standard errors.

5.6.5 Difference-in-Difference Analysis

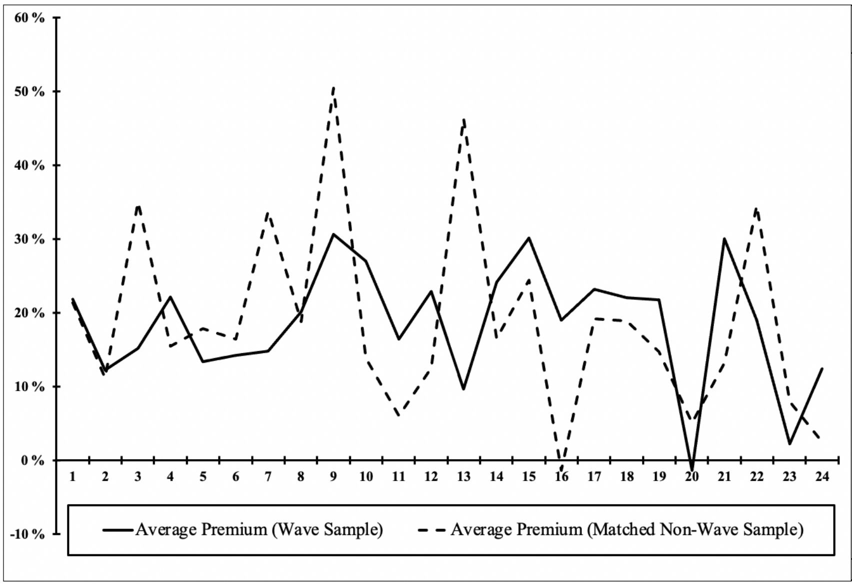
Propensity Score Matching

We use propensity score matching to create an appropriate control group based on the matching criteria uncovered in Table 9. The procedure ensures that we select industries that are as similar as possible in covariates, namely R&D spending (scaled by assets), to the industries experiencing waves. Thus, we aim to isolate the treatment effect to the largest extent possible. Our analysis will revolve around 24-month M&A waves taking place in 2006 and 2007. This period is selected because it has the largest concentration of industry waves in our sample (see Table 5), and therefore the highest probability of sufficient observations to ensure unbiased estimates. Before selecting control industries, we exclude those that are partially experiencing a merger wave in this period (a wave that ends in 2006 or starts in 2007) to ensure this group is independent of the treatment.

The matching procedure starts with a logit model used to estimate the probability of an industry experiencing a merger wave based on R&D spending. Subsequently, for each industry experiencing a wave, a control industry not experiencing a wave is selected such that the global average absolute difference in probability of experiencing a wave is minimized for all the matched pairs (Ho, Imai, King, & Stuart, 2011). This procedure is referred to as optimal matching, and as opposed to a greedy nearest neighbor approach where the closest match is selected for one pair at a time, it chooses pairs that minimizes the difference in propensity score across all pairs. Optimal matching has been found by Gu and Rosenbaum (1993) to outperform greedy alternatives, especially when the number of available controls is limited, which is a highly relevant concern in our case. Of the 27 available control industries, a matched control group containing 13 industries is selected (see A.13 for comparison of propensity score between the two groups). Lastly, the average premium paid during each of the 24 months of merger waves starting in 2006 and the matched control group over the same wave period is calculated. The results are presented in Figure 12.

Takeover Premiums

Average Monthly Premiums on the Wave vs. Matched Control Group (2006 - 2007)



Number of Monthly Observations

Month	Treatment Group	Control Group (Matched)
1	10	4
2	19	5
3	13	4
4	10	4
5	22	3
6	10	5
7	15	5
8	21	8
9	12	2
10	20	5
11	22	3
12	15	5
13	17	7
14	26	5
15	17	8
16	20	3
17	30	1
18	22	8
19	17	10
20	15	7
21	13	3
22	11	5
23	21	6
24	26	7
Total	424	123

Fig. 12. Average monthly takeover premiums for industries experiencing a 24-month M&A wave, and a matched control group, between 2006 and 2007 (left). Moreover, the number of monthly observations for each group is tabulated (right).

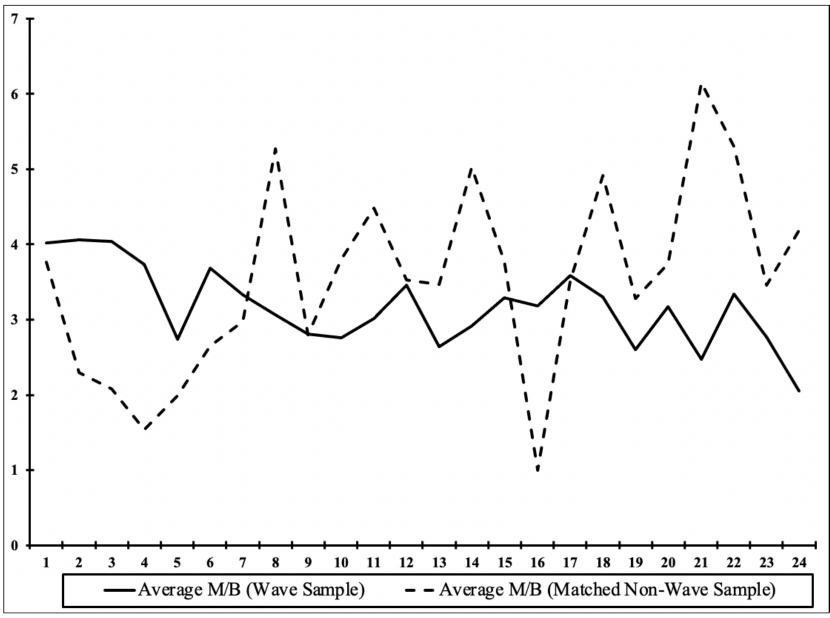
The development in average premiums for the industries experiencing a wave between 2006 and 2007 reflect similar tendencies to the aggregate estimate presented in Figure 11. There is a slight negative trend towards the end of the wave. The average monthly premium is 14.3 percent during the first year, and 12.6 percent during the second year.

However, we observe the same trend for the control group. Therefore, the reduction could be a result of other factors than the merger wave itself. As often the case when trying to implement a perfectly controlled experiment on an imperfect reality, there are some issues with the robustness of our matched control group findings. Since the number of observations are limited in this group (Figure 12), we might have inaccurate estimates. As a result, we cannot be completely sure that the monthly estimate reflects the actual average premiums in these industries during the period.

Valuations

If the anticipation effect of investors, as found by Song and Walkling (2000), results in decreasing premiums over the wave we should observe an opposite trend in valuations. Thus, as the wave progresses the M/B ratio of targets should increase. In Figure 13, we test this by calculating the average monthly M/B ratio (based on market value 4-weeks prior to announcement) of targets in the transactions happening within the same treatment and control group used in Figure 12.

Average M/B-ratio on the Wave vs. Matched Control Group (2006 - 2007)



Number of Observations in Each Group

Month	Treatment Group	Control Group (Matched)
1	15	4
2	28	8
3	18	4
4	18	5
5	29	4
6	24	5
7	23	8
8	27	7
9	20	8
10	30	8
11	36	4
12	26	7
13	22	8
14	44	15
15	21	6
16	35	1
17	46	13
18	29	11
19	26	11
20	43	12
21	23	4
22	23	9
23	50	18
24	36	12
Total	**692**	**192**

Fig. 13. Average monthly M/B ratio (based on market value 4-weeks prior to announcement) for industries experiencing a 24-month wave, and a matched control sample, between 2006 and 2007 (left). Moreover, the number of monthly observations for each group is tabulated (right).

The findings are, contrary to our expectation, that the average monthly M/B ratio of the targets getting acquired in the wave industries decreases over the wave. Naturally, market valuations are a rather complex story, and there could be many reasons for this trend apart from the isolated effect of merger waves. However, based on this finding we find it hard to believe that the decrease in premiums (Figure 12) stems solely from an anticipation effect, and needs to be explained by something else. Contrary, the matched control group has an increasing trend over the period (Figure 13), which could explain the opposite development in offer premiums for this group illustrated in Figure 12.

Summarizing Findings

The finding suggests that it is the competition for targets that dictates premiums over the course of the merger waves between 2006 and 2007 rather than anticipation effects, all else equal. These findings are consistent with our "best first" hypothesis and reaffirms our belief in its relevancy. The most attractive targets are acquired during the initial phase of the wave due to their superior ability to answer neoclassical shocks. As a result, they have higher achievable synergies and potential value for acquirers, and therefore also higher premiums. Towards the end of the wave, less attractive targets with lower PVGO are available for acquisition, illustrated by a decreasing trend in M/B ratio, which leads to lower premiums.

5.6.6 Methodology Modifications

The previous difference-in-difference approach based on propensity score matching has inherent weaknesses. The robustness of these findings depends on subjective choices when selecting the relevant matching criteria. Therefore, whether the matched control sample is truly comparable to the treatment group is subject to bias. An alternative difference-in-difference approach is to formulate a fixed effects regression that isolates the effect of a merger wave on takeover premiums within industries, as formulated in Equation 1.

$$y_{i,t} = \alpha_i + \beta_t + \gamma_1 D_{1,i,t} + \gamma_2 D_{2,i,t} + controls_{i,t} + \epsilon_{i,t}, \qquad \text{(Equation 1)}$$

where:

$$y_{i,t} = Annual\ Average\ Industry\ Premium\ for\ Industry\ i\ at\ Time\ t,$$
$$\alpha_i = Industry\ Specific\ Intercept\ for\ Industry\ i,$$
$$\beta_t = Time\ Specific\ Intercept\ at\ Time\ t,$$

$$\gamma_1 D_{1,i,t} = Treatment\ Effect\ During\ the\ First\ Year\ of\ an\ M\&A\ Wave$$
$$for\ Industry\ i\ at\ Time\ t,$$

$$\gamma_2 D_{2,i,t} = Treatment\ Effect\ During\ the\ Second\ Year\ of\ an\ M\&A\ Wave$$
$$for\ Industry\ i\ at\ Time\ t,$$

$$controls_{i,t} = Observable\ Control\ Variables\ for\ Industry\ i\ at\ Time\ t,$$
$$\epsilon_{i,t} = Error\ Term\ for\ Industry\ i\ at\ Time\ t.$$

If the treatment effect during the first and second year of a merger wave are significant when controlling for observable and omitted variables, we can pinpoint the effect of waves on premiums. Additionally, based on differences in coefficient magnitude, we can identify differences in direction and magnitude of treatment effect during the beginning and towards the end of the wave. The results are depicted in Table 10, with Column 4 corresponding to Equation 1.

5.6.7 Findings

Table 10: Difference-in-Difference Panel Regression

The dependent variable is the average annual premiums (presented in percentage points) within industry *i* (FF49 industries) measured at time *t* (2000 – 2019). The control variables are the annual industry median R&D spending (scaled by assets), Assets ($M), Net Income Margin (%), Revenue Growth (%), Capital Expenditures (scaled by assets), Return on Assets (%) and Market-to-book Ratio. Column 1 is a naive OLS model without any fixed effects. Column 2, 3 and 4 are based on *Equation 1* with an increasing degree of controls implemented. *1st Wave Year* and *2nd Wave Year* is the isolated treatment effect during the beginning and end of an M&A wave, respectively. Column 1 is fitted with robust standard errors, while Column 2, 3 and 4 are fitted with clustered standard errors. VIF-scores based on column 1 (they are insensible with time and industry fixed effects) can be found in the appendix (A.14).

	Dependent variable:			
	Average Annual Industry Premium (%)			
	Naive OLS	Fixed Effects Models		
	(1)	(2)	(3)	(4)
Intercept	22.491***			
	(1.883)			
R&D Spending (Scaled by Assets)	88.514***		161.498**	203.238**
	(21.650)		(63.730)	(100.948)
M/B	0.311		1.334	0.563
	(1.021)		(1.083)	(1.047)
Assets	-0.0003			0.0004
	(0.0003)			(0.0003)
Net Income Margin	8.649*			1.009
	(5.242)			(4.769)
Revenue Growth	-3.191			5.982
	(9.443)			(12.542)
ROA	-31.541			24.280
	(22.211)			(32.905)
Capital Expenditures (Scaled by Assets)	49.726**			49.711
	(20.392)			(54.646)
1st. Wave Year	-2.558	-0.172	-0.931	-1.324
	(2.185)	(2.583)	(2.599)	(2.710)
2nd. Wave Year	-4.647**	-1.256	-1.302	-1.184
	(2.060)	(2.002)	(1.946)	(2.128)
Time Fixed Effects?		YES	YES	YES
Industry Fixed Effects?		YES	YES	YES
Clustered Standard Errors?		YES	YES	YES
Robust Standard Errors?	YES			
Observations	774	774	774	774
R^2	0.062	0.0002	0.011	0.016
Adjusted R^2	0.051	-0.096	-0.088	-0.089
Note:		*p<0.1; **p<0.05; ***p<0.01		

When fitting a naïve specification with observable controls, but without any fixed effects controlling for OVB, there is a significant negative coefficient during the second year implying that industries experiencing a wave exhibit lower premiums towards the end of the wave (Column 1). As we introduce industry and time fixed effects, and an increasing number of observable control variables, throughout Column 2 to 4, the negative direction and magnitude of the coefficient (mostly) remain largest for the second year. This indicates that premiums in fact are lower during the second year of a wave, and hence, decreasing. However, when implementing all observable control variables, and controlling for time and industry fixed effects, we cannot statistically prove this with sufficient significance (Column 4). Even though the lack of robustness forces us to conclude with caution, decreasing premiums over the course of the wave seems likely.

5.7 Inference for Hypothesis 3

The development in monthly median takeover premiums during waves (Figure 11), compared to the average monthly offer premiums in wave industries to a matched control sample (Figure 12), and the difference-in-difference panel regression (Table 10) gives basis for formally assessing whether to accept or reject Hypothesis 3.

We have tested the following null hypothesis (Hypothesis 3):

H_0: *The average size of takeover premiums changes over the course of the wave*

H_1: *The average size of takeover premiums remains unaffected by industry merger waves*

In sum, based on the findings in this section, we accept the null hypothesis. The average size of takeover premiums changes over the course of the wave, and more specifically decrease. The decrease is likely a result of the most attractive targets being acquired during the initial phase due to their shock-responsive capabilities to neoclassical shocks.

6. Conclusion

In this thesis we investigate the empirical drivers of merger waves from 2000-2019. We do this with point of departure in Harford's (2005) iconic paper, who largely settled the academic dispute between neoclassical and behavioral scholars. Most academic research on merger waves, including Harford (2005), is based on data from the 1980s and 90s. A lot has changed since then. Increased data availability, changing economic conditions and increased competition from financial buyers such as private equity funds all warrant a second look at Harford's (2005) findings. We therefore add value to existing research by testing Harford's (2005) methods on new data from 2000 to 2019 and by controlling for new private equity variables. Additionally, we add value by investigating the evolution of takeover premiums over the course of the wave, which beknown to us, is largely unchartered territory in the context of merger waves. We provide an extensive review of existing literature for both the neoclassical and behavioral hypothesis, research developments since Harford (2005) and the influence of private equity on merger waves. Based on this review, we formulate 3 hypotheses. First, we hypothesize that economic, regulatory, and technological shocks enabled by sufficient capital liquidity still drive industry merger waves, and that aggregate waves form as industry waves cluster in time, consistent with the neoclassical hypothesis (Harford, 2005). Second, that the amount of capital inflow to PE funds is associated with aggregate merger waves, and third, that the size of takeover premiums changes over the course of the wave.

When replicating Harford (2005) (Table 7) to test the first hypothesis, we initially find that industry merger waves are no longer driven by the first principal component of economic shock variables and the relaxation of capital constraints, but by deregulation and market returns. Aggregate waves are driven by market returns, but decrease in the dispersion of these returns, inconsistent with the behavioral hypothesis but consistent with a neoclassical understanding of market performance and efficient markets. This suggests that albeit some economic variables have lost their explanatory power, both industry and aggregate merger waves form in response to fundamental shocks to the economy, as claimed by the neoclassical hypothesis. However, the role of sufficient capital liquidity to facilitate the necessary reallocation of assets *in response* to the shock has become less prominent than before (c.f. Harford, 2005).

When modifying Harford's (2005) approach by unpacking the economic variables to better understand the underlying drivers (Table 7.1), we find that the relaxation of capital constraints and deregulation drive industry merger waves, consistent with previous research (Mitchell and

Mulherin, 1996; Andrade et. al., 2001; Harford, 2005). The significance of capital liquidity only holds when removing the lag imposed by Harford (2005) on the C&I rate spread, suggesting merger activity has become more responsive to capital constraints, or that the stickiness of economic decision-making has decreased with increased digitalization. Unlike Harford (2005), we do not find that the market-to-book ratio proxy for capital liquidity, but overall evidence suggests that the ratio captures valuations rather than misvaluations, also consistent with the neoclassical narrative. In the aggregate, merger waves are driven by increased capital liquidity, consistent with Harford (2005), who finds that shocks must be accompanied by relaxed capital constraints to propagate, causing aggregate waves to form as industry waves cluster in time, even if the shocks do not.

In conclusion, we find that economic, deregulatory, and technological shocks as well as capital liquidity drive merger waves, rather than managerial attempts to exploit temporary misvaluations to time the takeover market (Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004). However, as many industries have become more agile, are already deregulated, and innovating at an increasingly faster pace (making technological shocks more continuous), shocks seem to have become less surprising, and increasingly accounted for by more anticipatory variables (e.g., market-to-book). Albeit the market-to-book variable is claimed by both hypotheses, overall evidence rules in favor of the neoclassical. Although it would be disingenuous to claim that no mergers can be motivated by managerial opportunism, we find it unlikely that temporary misvaluations persist on a sufficient scale to over time enable such fundamental dynamics as merger waves, as temporary misvaluations in efficient markets must be just that – temporary. For Hypothesis 1, we therefore accept the null hypothesis and conclude that merger waves form in response to neoclassical shocks and propagate when capital liquidity is sufficient. Consequently, we reject the alternative behavioral hypothesis, consistent with previous research (Harford, 2005).

Regarding the second hypothesis, we find that the magnitude of capital raised by PE funds are associated with aggregate merger waves. Consistent with previous research, we find that PE firms predominantly raise funds ex ante and that fundraising activity increase in pre-wave years before capital is called for investments as buyers gain momentum in the wave (Axelson et al., 2009; Kaplan & Strömberg, 2009). As expected, dry powder increases in periods of low merger activity. Capital raised is not robust to controls, suggesting that despite the dramatic increase of capital inflow to PE seen over the years, merger waves are still dominated by strategic acquirers in the aggregate, consistent with previous research (Maksimovic et al., 2013; Martos-Vila et al., 2019). Therefore, we can only conclude that PE funds participate in merger waves on a scale that is significant in the aggregate, rather than driving them. However, our findings are sufficient to accept the null hypothesis that capital raised by PE funds is associated with aggregate merger waves.

Finally, our findings suggest that takeover premiums decrease over the course of the wave (c.f. Hypothesis 3). Using panel regressions to uncover matching criteria and propensity score matching to create an appropriate control group, we compare the evolution of premium payments over the wave with a non-wave control group. We find that premiums slightly decrease over the course of the wave, with the average premium being 14.3 percent in the first year and 12.6 percent in the second. Decreasing market-to-book ratio in the treatment group (and increasing in the control group) suggests this is because of decreasing competition for less attractive targets, and not due to increasing anticipation effects (Servaes & Tamayo, 2014; Song & Walkling, 2000) over the course of the wave. This is consistent with the neoclassical presumption that bidders compete fiercely for shock-responsive assets in the merger market. Moreover, difference-in-difference regressions suggest takeover premiums decrease over the course of the wave, and that the decrease is of almost twice the size towards the end of the wave. However, the model is not robust to time and industry fixed effects when controlling for all observable control variables. In sum, however, our findings are sufficient to accept the null hypothesis that takeover premiums change over the wave.

Further research is necessary to strengthen the validity of our findings. Albeit we are confident in the methods employed, increasing the number of premium observations to obtain a balanced panel could add additional robustness to our difference-in-difference analysis. We also welcome further research on the influence of committed capital to private equity funds on *industry* merger waves. Albeit *aggregate* waves are dominated by the sheer magnitude of strategic buyers (Maksimovic, et. al., 2013; Martos-Vila, et. al., 2019), this does not exclude that private equity can drive within-industry waves in appropriate industries (Harford et al., 2016), but testing this presumption necessitates more granular data. We therefore leave this open for further research.

7. References

Ahern, K., & Harford, J. (2014). The Importance of Industry Links in Merger Waves. *Journal of Finance, 69*(2), 527-576.

Andrade, G., Mitchell, M., & Stafford, E. (2001). New Evidence and Perspectives on Mergers. *The Journal of Economic Perspectives, 15*(2), 103-120.

Andrade, G., & Stafford, E. (2004). Investigating the economic role of mergers. *Journal of Corporate Finance, 10*(1), 1-36. doi:10.1016/s0929-1199(02)00023-8

Ang, J. S., & Cheng, Y. (2006). DIRECT EVIDENCE ON THE MARKET-DRIVEN ACQUISITION THEORY. *Journal of Financial Research, 29*(2), 199-216. doi:https://doi.org/10.1111/j.1475-6803.2006.00174.x

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Axelson, U., Jenkinson, T., Strömberg, P., & Weisbach, M. S. (2013). Borrow Cheap, Buy High? The Determinants of Leverage and Pricing in Buyouts. *The Journal of Finance, 68*(6), 2223-2267. doi:10.1111/jofi.12082

Axelson, U., Strömberg, P., & Weisbach, M. S. (2009). Why are buyouts levered? The financial structure of private equity funds. *The Journal of Finance, 64*(4), 1549-1582.

Berk, J., & DeMarzo, P. (2017). *Corporate Finance* (4th Edition ed.). Essex, England: Pearson Education.

Bernanke, B. S. (2007). *Semiannual Monetary Policy Report to the Congress*. Federal Reserve Retrieved from https://www.federalreserve.gov/newsevents/testimony/bernanke20070214a.htm.

Betton, S., Eckbo, B. E., Thompson, R., & Thorburn, K. S. (2014). Merger Negotiations with Stock Market Feedback. *The Journal of Finance, 69*(4), 1705-1745. doi:https://doi.org/10.1111/jofi.12151

Betton, S., Eckbo, B. E., & Thorburn, K. S. (2008). Corporate Takeovers. *HANDBOOK OF CORPORATE FINANCE: EMPIRICAL CORPORATE FINANCE (B. E., Eckbo, ed., Elsevier/North-Holland Handbook of Finance Series), 2, Chapter 15* (Tuck School of Business Working Paper No. 2008-47), 291-430. doi:https://ssrn.com/abstract=1131033

Bhagat, S., Shleifer, A., Vishny, R. W., Jarrel, G., & Summers, L. (1990). Hostile Takeovers in the 1980s: The Return to Corporate Specialization. *Brookings Papers on Economic Activity. Microeconomics, 1990*, 1-84. doi:10.2307/2534780

Board of Governors of the Federal Reserve System. (2018). *The July 2018 Senior Loan Officer Opinion Survey on Bank Lending Practices*. Washington, D. C. Retrieved from https://www.federalreserve.gov/data/documents/sloos-201807-fullreport.pdf.

Board of Governors of the Federal Reserve System. (2020a). *Effective Federal Funds Rate [FEDFUNDS]*. Retrieved from: https://fred.stlouisfed.org/series/FEDFUNDS

Board of Governors of the Federal Reserve System. (2020b). *Weighted-Average Effective Loan Rate for All Commercial and Industry Loans, All Commercial Banks (DISCONTINUED) [EEANQ]*. Retrieved from: https://fred.stlouisfed.org/series/EEANQ

Bogle, K. (2020). IFRS vs. US GAAP: R&D costs. Retrieved from https://advisory.kpmg.us/articles/2017/ifrs-vs-us-gaap-rd-costs.html

Brau, J. C., & Fawcett, S. E. (2006). Initial Public Offerings: An Analysis of Theory and Practice. *The Journal of Finance, 61*(1), 399-436. doi:https://doi.org/10.1111/j.1540-6261.2006.00840.x

Brealey, R. A., & Myers, S. C. (1991). *Principles of Corporate Finance* (4th Edition ed.). New York, NY: McGrawHill.

Buchner, A., Mohamed, A., & Schwienbacher, A. (2020). Herd behaviour in buyout investments. *Journal of Corporate Finance, 60*. doi:10.1016/j.jcorpfin.2019.101503

Cai, J., Song, M. H., & Walkling, R. A. (2011). Anticipation, Acquisitions, and Bidder Returns: Industry Shocks and the Transfer of Information across Rivals. *Review of Financial Studies, 24*(7), 2242-2285. doi:10.1093/rfs/hhr035

Chesbrough, H. W. (2003). *Open innovation: The new imperative for creating and profiting from technology*: Harvard Business Press.

Chidambaran, N. K., John, K., Shangguan, Z., & Vasudevan, G. (2010). Hot and cold merger markets. *Review of Quantitative Finance and Accounting, 34*(3), 327-349. doi:https://10.1007/s11156-009-0133-z

Coase, R. H. (1937). The Nature of the Firm. *Economica, 4*(16), 386-405. doi:10.2307/2626876

Croissant, Y., & Millo, G. (2008). Panel Data Econometrics in R: The plm Package. *2008, 27*(2), 43. doi:10.18637/jss.v027.i02

Dong, M., Hirshleifer, D., Richardson, S., & Teoh, S. H. (2006). Does Investor Misvaluation Drive the Takeover Market? *The Journal of Finance, 61*(2), 725-762. doi:https://doi.org/10.1111/j.1540-6261.2006.00853.x

Durbin, J., & Watson, G. S. (1950). Testing for Serial Correlation in Least Squares Regression: I. *Biometrika, 37*(3/4), 409-428. doi:10.2307/2332391

Eckbo, B. E., Makaew, T., & Thorburn, K. S. (2018). Are stock-financed takeovers opportunistic? *Journal of Financial Economics, 128*(3), 443-465. doi:10.1016/j.jfineco.2018.03.006

Eisfeldt, A. L., & Rampini, A. A. (2006). Capital reallocation and liquidity. *Journal of Monetary Economics, 53*(3), 369-399. doi:https://doi.org/10.1016/j.jmoneco.2005.04.006

Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics, 43*(2), 153-193. doi:https://doi.org/10.1016/S0304-405X(96)00896-3

Federal Energy Regulatory Commisson, U. S. o. A. (1999). *Docket No. RM99-2-000; Order No. 2000*. Retrieved from https://www.ferc.gov/sites/default/files/2020-06/RM99-2-00K_1.pdf

Fox, J., & Monette, G. (1992). Generalized Collinearity Diagnostics. *Journal of the American Statistical Association, 87*(417), 178-183. doi:10.1080/01621459.1992.10475190

French, K. R. (2020). Detail for 49 Industry Portfolios. Retrieved from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html

Gao, H., Harford, J., & Li, K. (2013). Determinants of corporate cash policy: Insights from private firms. *Journal of Financial Economics*, *109*(3), 623-639. doi:https://doi.org/10.1016/j.jfineco.2013.04.008

Golbe, D. L., & White, L. J. (1988). A time-series analysis of mergers and acquisitions in the US economy. In *Corporate takeovers: Causes and consequences* (pp. 265-310): University of Chicago press.

Gompers, P., & Lerner, J. (2000). Money chasing deals? The impact of fund inflows on private equity valuations. *Journal of Financial Economics, 55*(2), 281-325. doi:https://doi.org/10.1016/S0304-405X(99)00052-5

Gorbenko, A., & Malenko, A. (2014). Strategic and Financial Bidders in Takeover Auctions. *The Journal of Finance, 69*(6), 2513-2555. doi:10.1111/jofi.12194

Gorbenko, A., & Malenko, A. (2017). The Timing and Method of Payment in Mergers when Acquirers Are Financially Constrained. *The Review of Financial Studies, 31*(10), 3937-3978. doi:10.1093/rfs/hhx126

Gort, M. (1969). An Economic Disturbance Theory of Mergers. *The Quarterly Journal of Economics, 83*(4), 624-642. doi:10.2307/1885453

Gu, X. S., & Rosenbaum, P. R. (1993). Comparison of Multivariate Matching Methods: Structures, Distances, and Algorithms. *Journal of Computational and Graphical Statistics, 2*(4), 405-420. doi:10.2307/1390693

Haddad, V., Loualiche, E., & Plosser, M. (2017). Buyout Activity: The Impact of Aggregate Discount Rates. *The Journal of Finance, 72*(1), 371-414. doi:10.1111/jofi.12464

Hanck, C., Arnold, M., Gerber, A., & Schmelzer, M. (2019). *Introduction to Econometrics with R*. Essen, Germany: University of Duisburg-Essen.

Harford, J. (1999). Corporate Cash Reserves and Acquisitions. *The Journal of Finance, 54*(6), 1969-1997. doi:https://doi.org/10.1111/0022-1082.00179

Harford, J. (2005). What drives merger waves? *Journal of Financial Economics, 77*(3), 529-560. doi:https://10.1016/j.jfineco.2004.05.004

Harford, J., Mansi, S. A., & Maxwell, W. F. (2008). Corporate governance and firm cash holdings in the US. *Journal of Financial Economics, 87*(3), 535-555. doi:https://doi.org/10.1016/j.jfineco.2007.04.002

Harford, J., Stanfield, J. R., & Zhang, F. (2016). *How Does an LBO Impact the Target's Industry?*

Healy, P. M., Palepu, K. G., & Ruback, R. S. (1992). Does corporate performance improve after mergers? *Journal of Financial Economics, 31*(2), 135-175. doi:https://doi.org/10.1016/0304-405X(92)90002-F

Higgins, R. C., & Schall, L. D. (1975). Corporate Bankruptcy and Conglomerate Merger. *The Journal of Finance, 30*(1), 93-113. doi:10.2307/2978433

Hlavac, M. (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables. *R package version 5.2.2*.

Ho, D., Imai, K., King, G., & Stuart, E. A. (2011). MatchIt: Nonparametric Preprocessing for Parametric Causal Inference. *2011, 42*(8), 28. doi:10.18637/jss.v042.i08

Holmström, B., & Kaplan, S. N. (2001). Corporate Governance and Merger Activity in the United States: Making Sense of the 1980s and 1990s. *Journal of Economic Perspectives, 15*(2), 121-144. doi:10.1257/jep.15.2.121

Jovanovic, B., & Rousseau, P. (2001). *Mergers and Technological Change: 1885-1998*. Retrieved from https://EconPapers.repec.org/RePEc:van:wpaper:0116

Jovanovic, B., & Rousseau, P. L. (2002). The Q-Theory of Mergers. *American Economic Review, 92*(2), 198-204. doi:10.1257/000282802320189249

Kaplan, S. N., & Strömberg, P. (2009). Leveraged buyouts and private equity. *Journal of Economic Perspectives, 23*(1), 121-146.

Kassambara, A. (2017). *Practical Guide to Principal Component Methods in R* (Edition 1 ed.): sthda.com.

Kolchin, K., Podziemska, J., & Mostafa, A. (2020). *SIFMA Research: US Repo Market Fact Sheet*. Retrieved from https://www.sifma.org/wp-content/uploads/2020/04/2020-Repo-Factsheet_final2.pdf

Lewellen, W. G. (1971). A Pure Financial Rationale for the Conglomerate Merger. *The Journal of Finance, 26*(2), 521-537. doi:10.2307/2326063

Loveland, R., Mulherin, J. H., Okoeguale, K., & Athletic, G. (2018). Deregulation, Listing and Delisting.

Lown, C. S., Morgan, D. P., & Rohatgi, S. (2000). Listening to loan officers: The impact of commercial credit standards on lending and output. *Economic Policy Review, 6*(2).

Maksimovic, V., Phillips, G., & Yang, L. I. U. (2013). Private and Public Merger Waves. *The Journal of Finance, 68*(5), 2177-2217. doi:10.1111/jofi.12055

Martos-Vila, M., Rhodes-Kropf, M., & Harford, J. (2019). Financial versus Strategic Buyers. *Journal of Financial and Quantitative Analysis, 54*(6), 2635-2661. doi:10.1017/s0022109019000139

Millo, G. (2017). Robust Standard Error Estimators for Panel Models: A Unifying Approach. *2017, 82*(3), 27. doi:10.18637/jss.v082.i03

Mitchell, M. L., & Mulherin, J. H. (1996). The impact of industry shocks on takeover and restructuring activity. *Journal of Financial Economics, 41*(2), 193-229. doi:https://doi.org/10.1016/0304-405X(95)00860-H

Moeller, S. B., Schlingemann, F. P., & Stulz, R. M. (2004). Firm size and the gains from acquisitions. *Journal of Financial Economics, 73*(2), 201-228. doi:https://doi.org/10.1016/j.jfineco.2003.07.002

Mulherin, J. H., & Boone, A. L. (2000). Comparing acquisitions and divestitures. *Journal of Corporate Finance, 6*(2), 117-139. doi:https://doi.org/10.1016/S0929-1199(00)00010-9

Orhangazi, O. (2014). *Financial deregulation and the 2007-08 US financial crisis*. Retrieved from https://EconPapers.repec.org/RePEc:fes:wpaper:wpaper49

Ozcan, Y. (2016). Innovation and acquisition: two-sided matching in M&A markets. *Unpublished working paper, Northwestern University*.

Preqin. (2018). *Private Capital Performance Data Guide*.

Quental, G. G. (2007). *Letter for High-Grade SCS Enhanced Lev LP investors*. Retrieved from http://fcic-static.law.stanford.edu/cdn_media/fcic-docs/2007-06-07%20Bear%20Stearns%20Gregory%20Quental%20letter.pdf

Rhodes-Kropf, M., & Viswanathan, S. (2004). Market Valuation and Merger Waves. *The Journal of Finance, 59*(6), 2685-2718. doi:https://doi.org/10.1111/j.1540-6261.2004.00713.x

Rhodes–Kropf, M., Robinson, D. T., & Viswanathan, S. (2005). Valuation waves and merger activity: The empirical evidence. *Journal of Financial Economics, 77*(3), 561-603. doi:https://doi.org/10.1016/j.jfineco.2004.06.015

Samuelson, P. A. (1991). Wall street and main street. *Japan and the World Economy, 3*(1), 93-101. doi:https://doi.org/10.1016/0922-1425(91)90019-9

Schlingemann, F. P., Stulz, R. M., & Walkling, R. A. (2002). Divestitures and the liquidity of the market for corporate assets. *Journal of Financial Economics, 64*(1), 117-144. doi:https://doi.org/10.1016/S0304-405X(02)00073-9

Servaes, H., & Tamayo, A. (2014). How do industry peers respond to control threats? *Management Science, 60*(2), 380-399.

Sherman, M. (2009). A short history of financial deregulation in the United States.

Shleifer, A., & Vishny, R. W. (1992). Liquidation Values and Debt Capacity: A Market Equilibrium Approach. *The Journal of Finance, 47*(4), 1343-1366. doi:10.2307/2328943

Shleifer, A., & Vishny, R. W. (2003). Stock market driven acquisitions. *Journal of Financial Economics, 70*(3), 295-311. doi:10.1016/s0304-405x(03)00211-3

Song, M. H., & Walkling, R. A. (2000). Abnormal returns to rivals of acquisition targets: A test of the `acquisition probability hypothesis'. *Journal of Financial Economics, 55*(2), 143-171. doi:https://doi.org/10.1016/S0304-405X(99)00048-3

The White House. (2017). *Presidential Executive Order on Promoting Energy Independence and Economic Growth*. Washington D.C. Retrieved from https://www.whitehouse.gov/presidential-actions/presidential-executive-order-promoting-energy-independence-economic-growth/?utm_source=link.

US Bureau of Labor Statistics. (2020). Civilian unemployment rate. *Graphics for Economic News Releases.* Retrieved from https://www.bls.gov/charts/employment-situation/civilian-unemployment-rate.htm

US Congress 110th. (2008). *Emergency Economic Stabilization Act of 2008*. (122 STAT. 3765). Washington, D. C.: Authenticated U.S Government Information Retrieved from https://www.congress.gov/110/plaws/publ343/PLAW-110publ343.pdf.

US Congress 115th. (2018). *Economic Growth, Regulatory Relief, and Consumer Protection Act*. Retrieved from https://www.congress.gov/115/plaws/publ174/PLAW-115publ174.pdf.

Venables, W. N., & Ripley, B. D. (2002). *Modern Applied Statistics with S* (4th ed.): Springer.

Wooldrigde, J. M. (2002). *Introductory Econometrics: A Modern Approach* (2nd ed.): South-Western College Publication.

Wooldrigde, J. M. (2012). *Introductory Econometrics: A Modern Approach*. In. Retrieved from https://economics.ut.ac.ir/documents/3030266/14100645/Jeffrey_M._Wooldridge_Introductory_Econometrics_A_Modern_Approach__2012.pdf

World Trade Organization. (2004). *Agreement on Textiles and Clothing (ATC)*. Retrieved from https://www.wto.org/english/docs_e/legal_e/16-tex.pdf

8. Appendix

A.1: Private Equity Variables

Annual capital raised, capital called for investment and accumulated dry powder by private equity funds in USD billions. Additionally, number of active funds in the U.S. and the average size of these are presented. Moreover, dry powder and capital raised scaled by total market capitalization of all U.S. based public companies listed on the New York Stock Exchange, Nasdaq Stock Market and OTCQX U.S. Market is presented. Lastly, annual capital called scaled by total transaction value within our sample is tabulated.

Year	Number of Funds	Average Size of Funds ($M)	Capital Raised ($Bn)	Capital Called ($Bn)	Dry Powder ($Bn)	Dry Powder/ Total Market Capitalization	Capital Raised/ Total Market Capitalization	Capital Called / Total Transaction Value
2000	426	420	157	89	193	1.3 %	1.0 %	4.4 %
2001	312	363	94	51	224	1.6 %	0.7 %	4.4 %
2002	239	340	65	48	229	2.1 %	0.6 %	8.3 %
2003	187	250	39	59	222	1.6 %	0.3 %	8.0 %
2004	296	321	85	79	200	1.2 %	0.5 %	6.5 %
2005	374	421	143	92	249	1.5 %	0.8 %	5.7 %
2006	380	587	200	114	340	1.8 %	1.0 %	5.5 %
2007	438	670	260	174	405	2.1 %	1.3 %	7.5 %
2008	442	613	242	131	433	3.8 %	2.1 %	9.2 %
2009	287	486	119	91	421	2.8 %	0.8 %	9.4 %
2010	302	338	86	139	376	2.2 %	0.5 %	10.5 %
2011	334	349	98	130	335	2.1 %	0.6 %	8.0 %
2012	402	341	118	153	325	1.7 %	0.6 %	10.0 %
2013	485	461	186	116	384	1.6 %	0.8 %	6.7 %
2014	625	426	213	171	386	1.5 %	0.8 %	8.0 %
2015	605	442	208	170	449	1.8 %	0.8 %	6.0 %
2016	762	401	241	192	492	1.8 %	0.9 %	9.3 %
2017	790	503	310	242	565	1.8 %	1.0 %	13.3 %
2018	911	427	303	262	658	2.2 %	1.0 %	10.6 %
2019	809	568	397	194	785	2.1 %	1.1 %	10.0 %
Total / *Average*	***470***	***436***	**3562**	**2697**	***384***	***1.9 %***	***0.9 %***	***8.1 %***

A2: Qualitative Analysis of Industry Trends as Potential Merger Wave Motivations

Various news articles, consultancy reports and company statements are researched and used to further understand the industry conditions that lead to consolidation within the previously discovered merger waves.

Industry	Wave start	Industry Trends as Possible Explanations for Merger Wave
Apparel	Sep, 2006	Adaptation to technological improvements in logistics networks, paired with a booming economy and transition to overseas production in relation to the dismantling of the Multi Fibre Arrangement (MFA).
Automobiles and Trucks	Feb, 2006	Companies aim to increase geographical footprint and market shares, as well as enhance technological capabilities through consolidation.
Banking	Aug, 2005	Innovations in financial derivatives leads to massive earnings increases. Deregulation allows for mergers between banks who in turn aim at becoming "too big to fail".
	Nov, 2016	Emerging fintech companies are attractive targets while smaller regional banks consolidate to become national players. The major banks, however, are heavily regulated and thus remain largely inactive.
Business Services	Jul, 2006	Services are overtaking manufacturing with strong growth. A booming economy and the need for new competencies within technologies and globalisation trends propogates a wave.
	Jun, 2016	Consulting firms are building digital marketing competencies through acquisitions. Business process outsourcing (BPO), such as SAS and cloud computing is becoming attractive to both financial and strategic players.
Business Supplies	Jan, 2000	Consolidation in response to a technological shift away from traditional ofice supplies.
Candy and Soda	Noov, 2013	Weak organic growth opportunities force incumbents to acquire new targets in growing segments such as snacks and energy drinks.
Chemicals	Now, 2013	Chemical companies are focusing on portfolio realignment and divesting non-core operations.
Communication	Jan, 2000	Sky rocketing share prices and growth expectations during the dotcom bubble initiated an M&A frenzy within the sector.
	Oct, 2004	Adaptation to new internet technologies spurred investment into fibre technologies and improved signal networks. Decreasing sales from 2G services shifts the focus towards emerging mobile technologies.
Computer Software	Jan, 2000	Internet and dotcom bubble
	Dec, 2017	Software as a service (SaaS) providers are attractive targets for vertical integration by strategic players, and become increasingly attractive to financial buyers due to the stable cash flows of subscription based business models.
Computers	Jan, 2000	Internet and dotcom bubble
Construction	Sep, 2017	A desire to grow, diversify business areas, expand capabilities and handle the shortage of quailified labor.
Construction Materials	Jan, 2006	Increasing raw meterial prices, record breaking house building and stable infrastructure projects.
Electronic Equipment	Jan, 2000	One of the fastest growing industries prior to this wave. Smaller regional players aim at becoming international suppliers.
	Jan, 2006	Increasing international competition pressure domestic players to consolidate.
Food Products	Nov, 2013	Strategic players respond to a stalling growth through acquisitions of new product lines while financial acquirers finds the sector highly attractive due to stable cash flows.
Healthcare	Sep, 2005	Healthcare services as a proportion of GDP has increased steadily leading to high growth expectations in a highly fragmented environment ripe for consolidation.
	Aug, 2014	The Affordable Care Act went into effect, and lead to a shift towards value-based reimburshment rather than fee-for-service, which made the post-acute industry attractive to acquirers.
Insurance	Jul, 2006	Insurance-linked securities (ILS) follows a wave of new financial instruments. Size equals security as the risk tolerance of the markets increases.

A.2 (Continued)

Machinery	Jan, 2006	Strong activity in downstream industries lead to high profitability and growth. Furthermore, automation capabilities became more sought after.
Medical Equipment	Apr, 2010	Healthcare reforms and budgetary cut backs result in financial pressure on the industry which in turn divest underperforming non-core business units and acquire technology assets with strong growth prospects.
Non-Metallic and Industrial Metal Mining	Aug, 2006	Response to increasing global demand for resources and tough competition for assets from Russian and Chinese competitors.
Personal Services	Jul, 2017	New technologies allow for efficiency gains and growth opportunities.
Petroleum and Natural Gas	Dec, 2005	Primarily consolidation within the upstream petroleum servicing units and P&E units looking to increase scale as demand and prices surge.
	Oct, 2012	A period characterised by high oil prices from 2010 -2013 made upstream targets attractive, followed by a collapse in oil prices leading to a wave of divestures.
Pharmaceutical Products	Dec, 2017	Tax cuts free up funds and make divestures in non-core assets more attractive. Furthermore, innovative target companies are the primary source of growth.
Precious Metals	Dec, 2008	Acquisitions is the easiest way to access new reserves, and recent increases in prices made these more attractive.
Printing and Publishing	Feb, 2000	The growing use of internet, printing-on-demand technologies and e-books are disrupting the industry.
	Feb, 2006	Amidst the transition from print to digital media, smaller players are consolidating to achieve the necessary investments in new technologies, economies of scale and afford marketing services.
Real Estate	Feb, 2016	Investors view the recent discounts on real estate companies with retail exposure as an overreaction by the markets, and increasing warehousing needs in the logistics industry increase attractiveness from acquirers.
Recreation	Feb, 2006	An economic boom left Americans stronger suited to pursue leisure activities. Also spurred by a growing tourism sector and more focus on a healthy lifestyle.
Restaurants, Hotels and Motels	Aug, 2005	Booming economy and tourism
Retail	Jul, 2005	Easy access to financing, growth in demand from P/E looking for stable cash flows and increased consumer confidence makes retial attractive.
Shipping Containers	Mar, 2016	Companies aim to improve margins through standardization, increased shelf life, recyclability and material choices. All of which are easier to make profitable through increased scale.
Steel Works Etc	Jul, 2006	A period of strong earnings and soaring market values lead to consolidation in the battle for scale advantages and market shares. Three major companies controls 70% of the market, up from 20% five years ago.
Trading	Jan, 2006	Low interest rates and booming economy resulted in attractive targets everywhere. Total deal value of private equity increased from $160 billion in 2000 to $650 billion in 2006.
	Nov, 2016	Strong inflow of capital and demand from investors leads to increased activity.
Transportation	Feb, 2006	Skyrocketing opertional costs and increased expectations from downstream players on carriers to provide both short range domestic and long range international services lead to consolidation.
	Nov, 2013	Consolidation is used to increase technological capabilities and pool efforts on R&D. Moreover, reduced opertional costs from recent decreases in oil prices free up capital for inorganic growth.
	Feb, 2017	Large availability of funding paired with an intense competition depleting margins motivates consolidation.
Wholesale	Dec, 2005	Inorganic growth emerges as the only option to respond to powerful competitors (the Amazon effect), and industry disruption (growth of centralized purchasing) motivates consoldiation.

A.*3 Capital Liquidity and Behavioral Variables Correlation Matrix*

	Rate Spread	M/B	S&P500 Return	Change in Rate Spread	Change in M/B	Change in S&P500 Return	Lag (Change in Rate Spread)	Lag (Change in M/B)	Lag (Change in S&P500 Return)
Rate Spread	1								
M/B	-0.287	1							
S&P500 Return	-0.176	0.447	1						
Change in Rate Spread	0.432	-0.362	-0.551	1					
Change in M/B	0.068	0.537	0.055	0.153	1				
Change in S&P500 Return	0.175	0.551	0.390	-0.101	0.533	1			
Lag (Change in Rate Spread)	0.712	-0.412	-0.469	0.523	-0.035	0.106	1		
Lag (Change in M/B)	0.243	0.390	0.262	-0.183	-0.148	0.257	0.151	1	
Lag (Change in S&P500 Return)	-0.043	0.294	0.563	-0.431	-0.251	0.222	-0.109	0.521	1

A.4: The Characteristics of the Median Private Equity fund over the Period

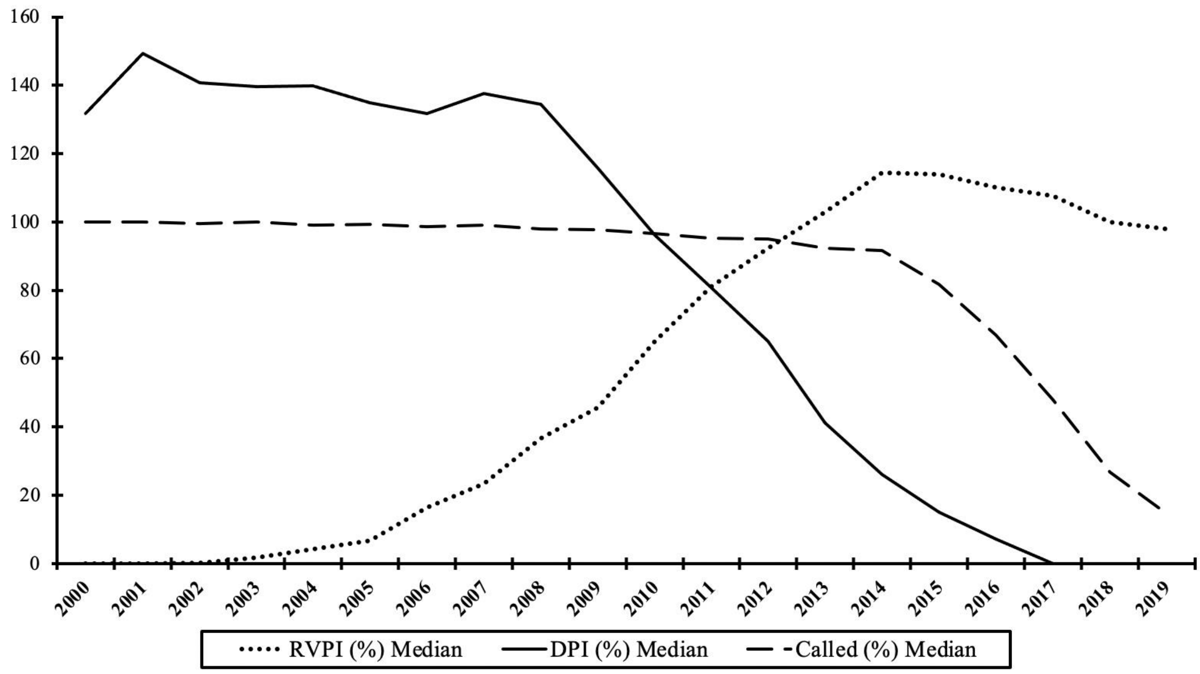


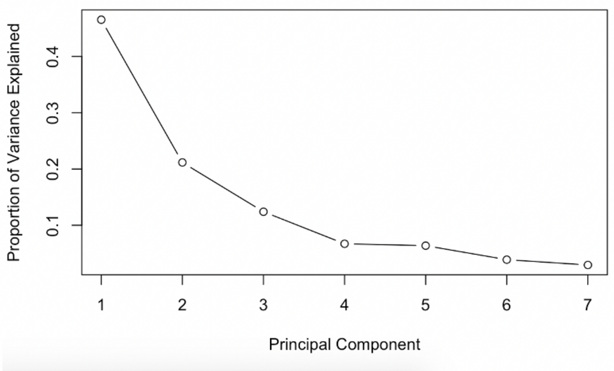
Fig. A.4. Time series relationship between Residual Value to Paid in Capital (RVPI), Distribution to Paid in Capital (DPI) and the Called-up ratio, all of which in percentage points. The RVPI is the fair market value of alle the assets owned by the fund divided by LP contributions net of carry/performance fees. DPI is the distributed capital to LPs net of carry/performance fees divided by LP contributions. The called ratio is the percentage of LP contributions that has been called for investment. All the above variables are defined and calculated by Preqin (2018).

Another noteworthy discovery is the recent increase in the number of active funds. This is particularly evident when we examine the characteristics of the median private equity fund over time as is illustrated in Figure A.4. It is hard to draw concrete conclusions regarding the state of the industry from this graph given that it only expresses the state of the median PE fund at each point in time. The conclusions we can draw, however, are the following: The median PE fund in year 2000 had already invested 100 percent of its committed capital. Furthermore, it distributed approximately 140 percent of that capital back to the LPs and had 0 percent of the capital called in active investments. Thus, the median private equity fund 20 years ago was at a late stage in its limited lifecycle. Fast-forward to 2019, the picture is quite different. The median PE fund is distributing 0 percent of committed capital back to LPs, it has only called 15 percent of its committed capital for investment and the estimated RVPI is close to 100 percent meaning no additional value creation, for limited partners at least, has occurred yet. This is not the same as saying PE funds on aggregate are less profitable or struggle with investing their committed capital. However, it does tell us that the current reality for the median fund is quite different today than it was 20 years ago. There is clearly an increase in the number of new funds, and they are likely battling it out for the same targets leading to increased competition, potential increases in transaction activity and perhaps increasing takeover premiums.

A.5: Principal Component Analysis Properties

Loadings in each Neoclassical Variable for each Principal Component	**PC1**	**PC2**	**PC3**	**PC4**	**PC5**	**PC6**	**PC7**
Annual Absolute Change in...							
Net Income Margin	0,42	-0,43	0,17	-0,03	0,01	-0,07	0,78
Asset Turnover (Scaled by Beginning of Period Assets)	0,21	0,50	-0,66	-0,38	-0,09	0,12	0,31
R&D Spending (Scaled by Beginning of Period Assets)	0,40	-0,45	-0,18	-0,09	-0,18	0,66	-0,37
Capital Expenditures (Scaled by Beginning of Period Assets)	0,23	0,46	0,69	-0,34	-0,30	0,24	-0,01
Employee Growth	0,39	0,33	-0,05	0,83	-0,23	0,03	0,02
ROA	0,48	-0,11	-0,07	-0,23	-0,27	-0,70	-0,37
Revenue Growth	0,43	0,18	0,09	-0,02	0,86	0,03	-0,17

Proportion of Variance Explained by each principal component



A.6: VIF-Scores for Logit and OSL Models in Table 7

Variables	Column 2	Column 3	Column 4	Column 5	Column 6	Column 7
M/B (t-1)	1,10		1,26	1,80		2,65
3-year return (t-1)	1,48		1,64	4,63		14,68
std. 3-year return (t-1)	1,39		1,62	3,31		9,07
C&I Rate Spread (t-1)		1,09	1,07		2,14	2,58
Deregulatory event (t-1)		1,04	1,07			6,83
Econ Shock Index (t-1)		1,07	1,25		2,52	2,53
Econ Shock Index (t-1)*TC		1,15			2,32	2,55

A.7 Autocorrelation Plots for OLS Models (Table 7)

These plots illustrate Durbin Watson Tests for autocorrelation of residuals in Table 7, Column 5, 6 and 7, respectively.

Table 3, Model 5

Durbin-Watson Test

Lag	Autocorrelation	DW-Statistic	P-Value
1	-0,07	1,92	0,55

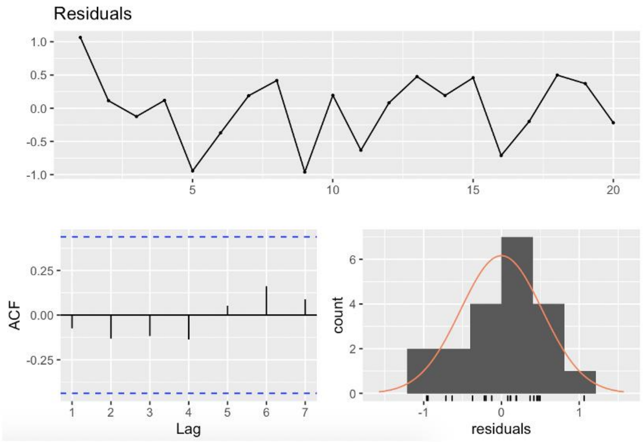


Table 3, Model 6

Durbin Watson Test

Lag	Autocorrelation	DW-Statistic	P-Value
1	0,04	1,72	0,30

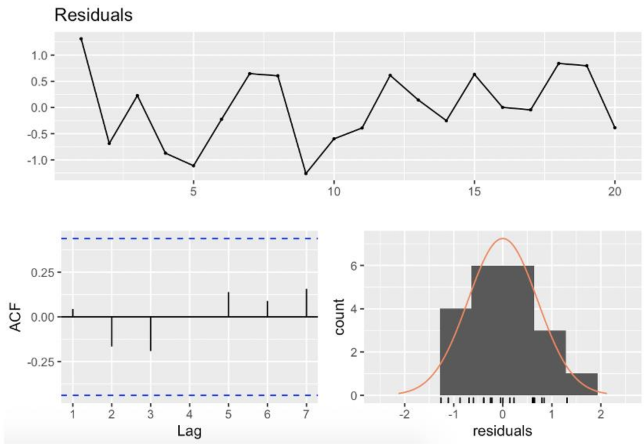
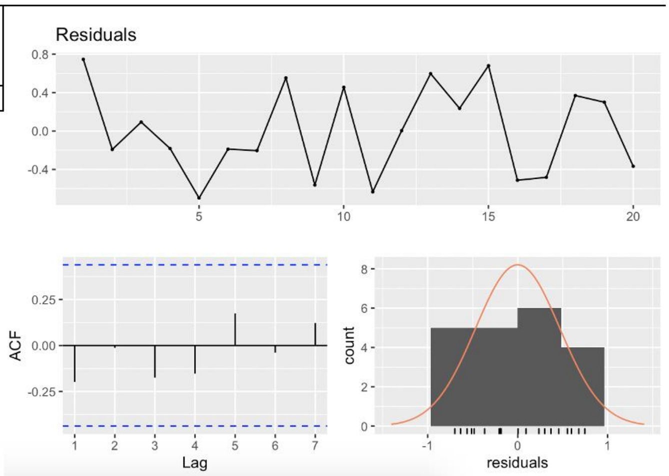


Table 3, Model 7			
Durbin Watson Test			
Lag	Autocorrelation	DW-Statistic	P-Value
1	-0,20	2,23	0,91



A.8: VIF-Scores for *Modified* LPM and OSL Models for industry and Aggregate merger waves (Table 7.1)

Variables	Column 1	Column 2	Column 3	Column 4	Column 5	Column 7	Column 8	Column 9	Column 11	Column 12	Column 13
M/B (t-1)	1,65		1,79		1,81	1,98		1,40		6,20	1,82
std. M/B (t-1)	1,65		1,68		1,68	1,98				12,04	
C&I Rate Spread				1,06	1,08		3,85	1,40		6,95	2,80
Deregulatory event (t-1)				1,02	1,02						
CapEx (t-1)		1,36	1,36	1,36	1,36		11,28			9,72	
Revenue Growth (t-1)		1,75	1,81	1,83	1,88		4,94			6,78	
Employee Growth (t-1)		1,59	1,62	1,59	1,62		18,26			19,31	
R&D (t-1)		1,88	2,03	1,89	2,03		6,85			14,82	2,04
ROA (t-1)		2,35	2,36	2,38	2,38		7,97			16,64	
P/E Capital Raised										6,19	
P/E Dry Powder									3,40		
P/E Capital Called									3,40		

A.9 Autocorrelation Plots for *Modified* Models (Table 7.1)

These plots illustrate Durbin Watson Tests for autocorrelation of residuals in Table 7.1, Column 7, 8, 9, 10, 11, 12 and 13, respectively.

Table 3.1, Model 7			
Durbin-Watson Test			
Lag	Autocorrelation	DW-Statistic	P-Value
1	-0,10	2,14	0,99

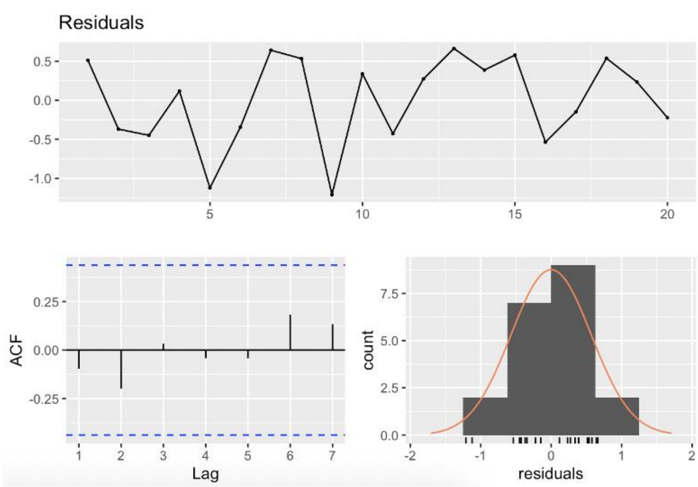


Table 3.1, Model 8			
Durbin Watson Test			
Lag	Autocorrelation	DW-Statistic	P-Value
1	-0,07	2,09	0,54

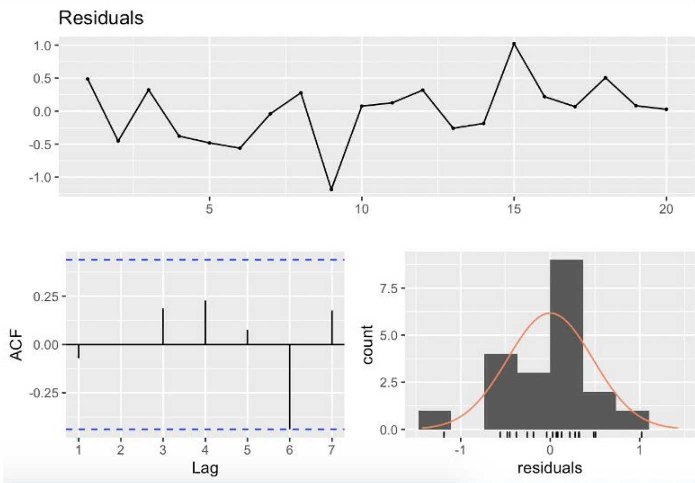


Table 3.1, Model 9			
Durbin Watson Test			
Lag	Autocorrelation	DW-Statistic	P-Value
1	-0,02	1,96	0,71

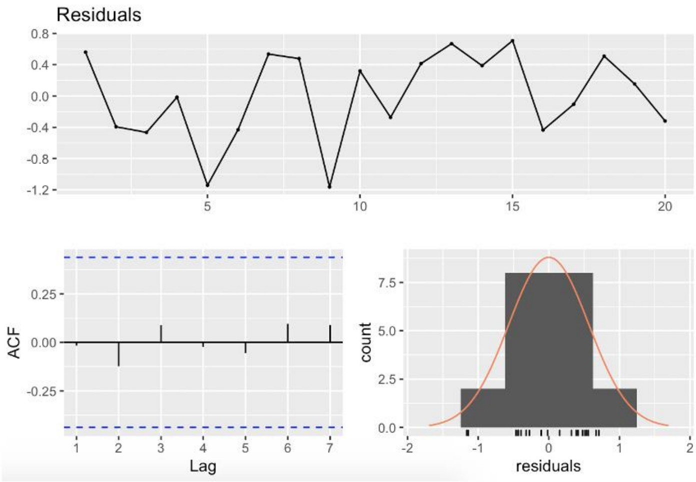


Table 3.1, Model 10			
Durbin Watson Test			
Lag	Autocorrelation	DW-Statistic	P-Value
1	0,40	1,11	0,02

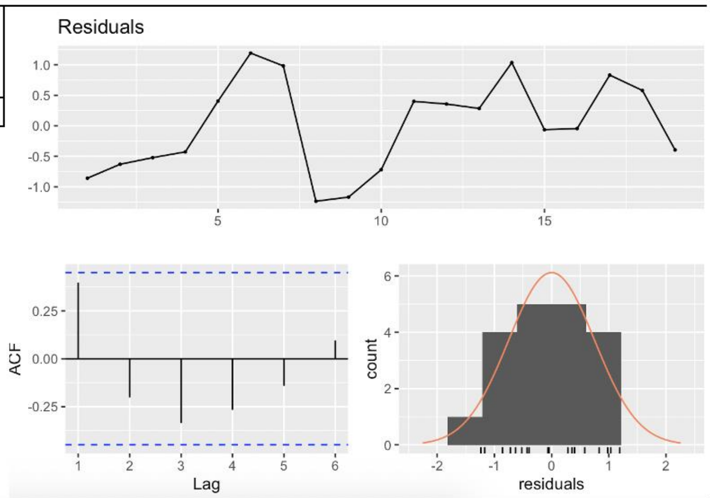


Table 3.1, Model 11			
Durbin Watson Test			
Lag	Autocorrelation	DW-Statistic	P-Value
1	0,12	1,52	0,14

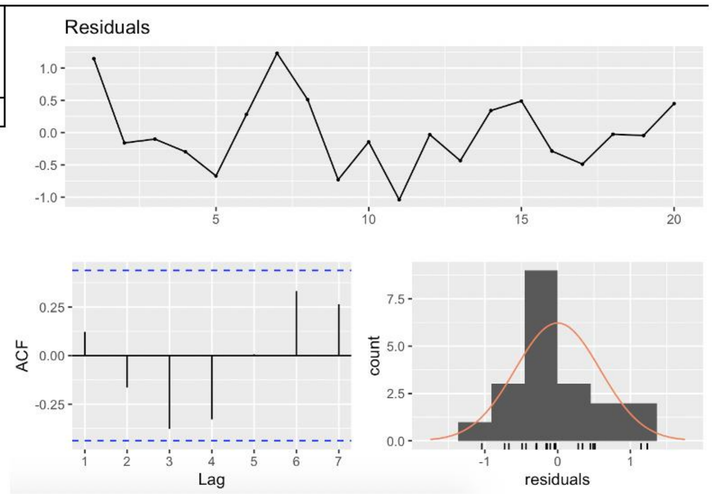


Table 3.1, Model 12			
Durbin Watson Test			
Lag	Autocorrelation	DW-Statistic	P-Value
1	-0,40	2,78	0,55

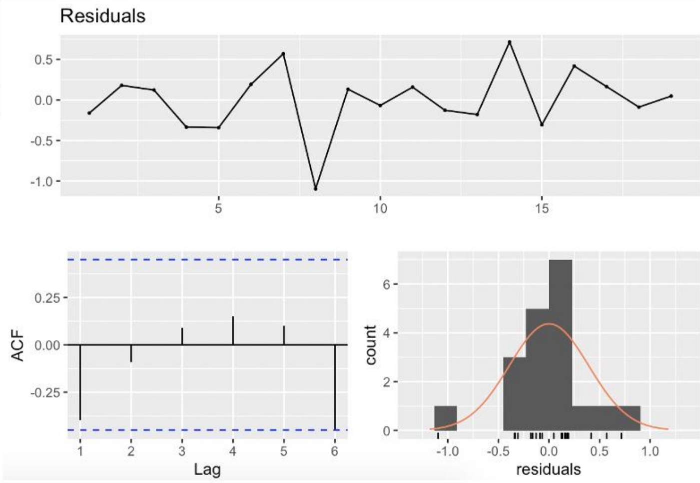
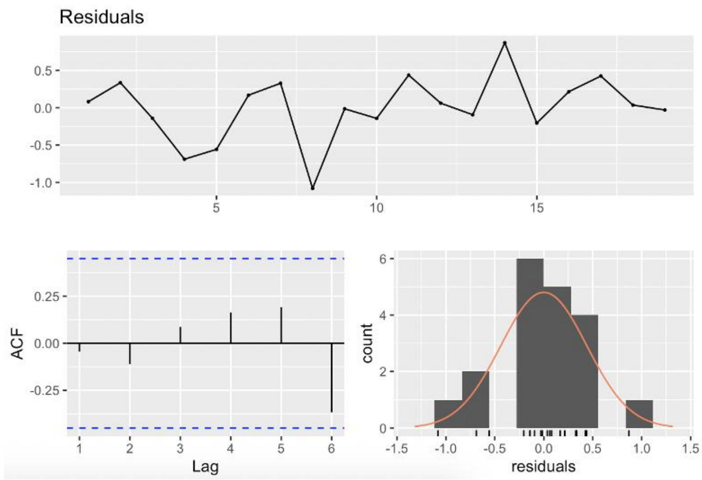
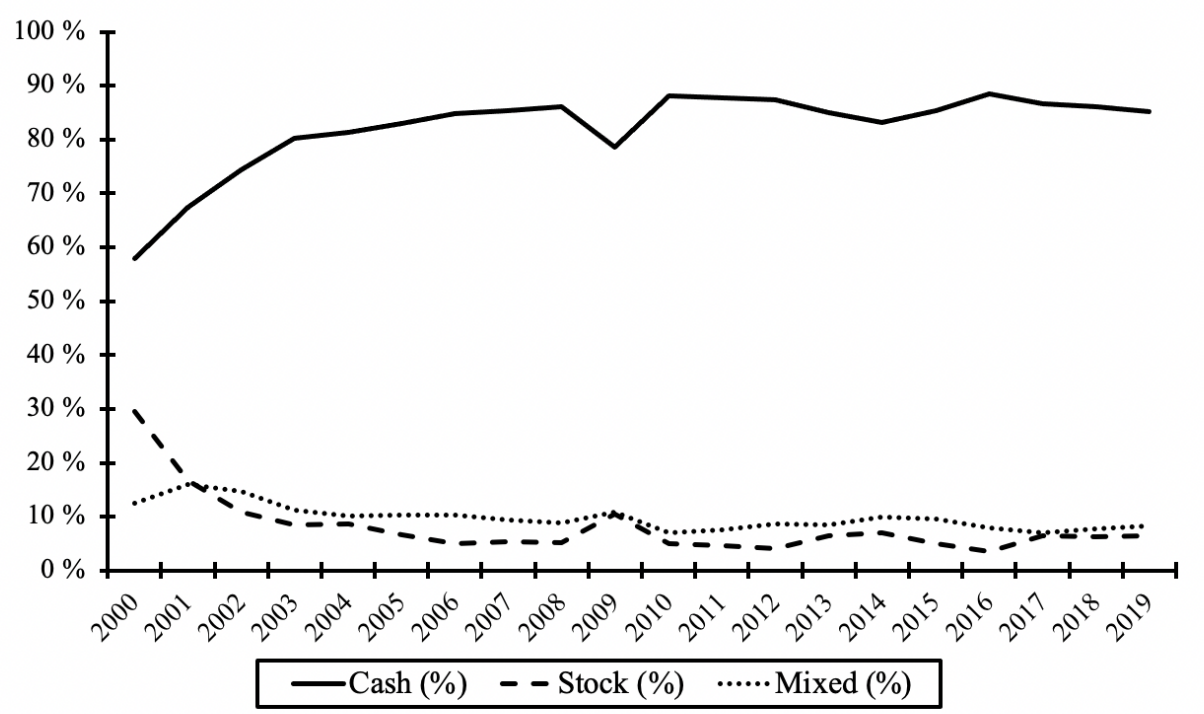


Table 3.1, Model 13			
Durbin Watson Test			
Lag	Autocorrelation	DW-Statistic	P-Value
1	-0,04	2,09	0,83

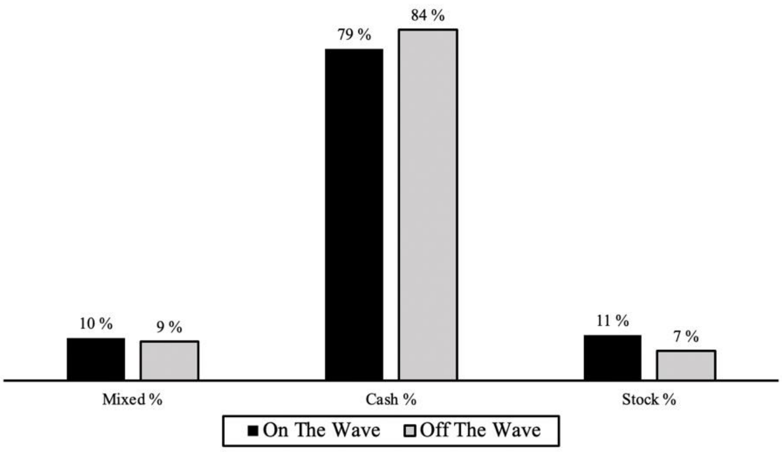


A.10: Payment Method by Proportion of Total in our Sample (between 2000 and 2019)



A.10: Time series development in the proportion of transactions constituted by strictly stock and cash offers or a mix of the two. The sample used are the same as the one used to uncover M&A waves. We start with the same sample as before, every M&A transaction with a deal value above $50 million between January 1st, 2000 and December 31st, 2019. Of the 36 084 transactions in total, 21 744 were strictly cash offers, another 2 053 were strictly stock offers while 2 488 used a mix of the two. According to SDC, the remaining 9 799 transactions had undisclosed, unknown or some other form of consideration offered, and are, therefore, excluded. There is obviously a bias arising from this exclusion if, for whatever reason, deals of a certain consideration type more often than others are undisclosed. However, we see no immediate solution to this problem, and will have to assume that the exclusions are somewhat evenly distributed between the three deal types.

A.11: Payment Method on the Wave vs. Off the Wave



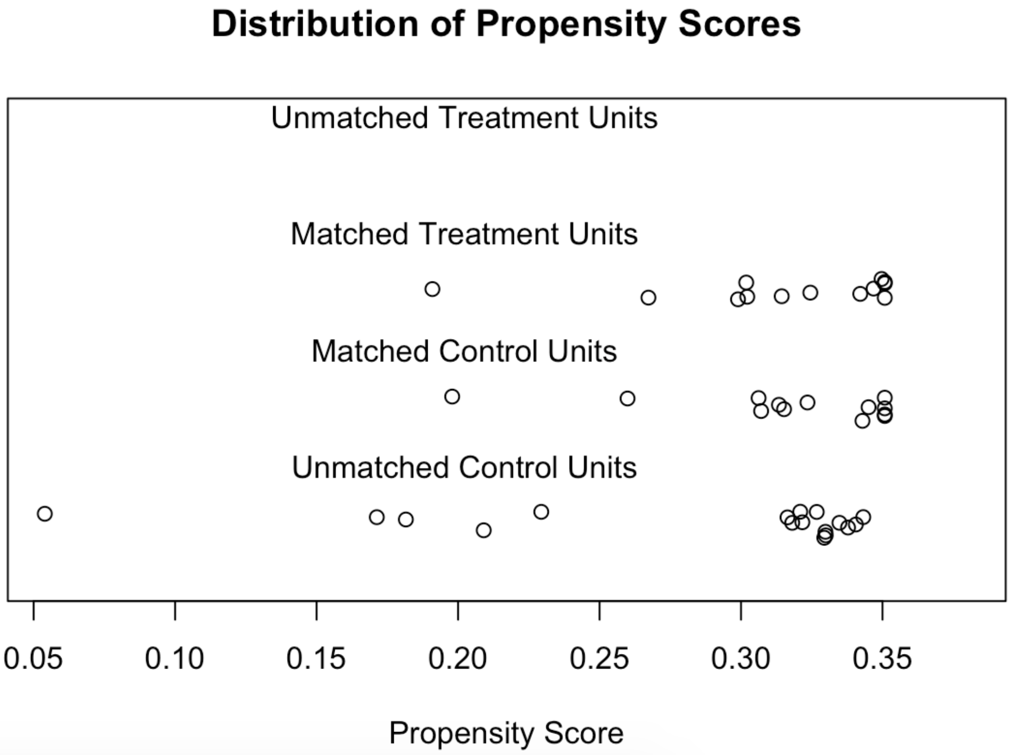
A.11: Payment method composition for transactions taking place during an industry merger wave and during non-wave periods. Black pillars illustrate the composition on the wave, while the grey pillars illustrate the composition off the wave.

A.12: VIF Scores for Models on Premium Payments (Table 4)

Variables	Column 1	Column 2 (GVIF^(1/(2*Df))
R&D (Scale	2,99	1,74
Revenue Gr	1,14	1,26
Capex (Scal	1,17	1,10
Assets	1,51	1,26
Net Income	4,22	2,07
ROA	4,78	2,23
M/B	1,64	1,36
Year		1,01

A.12: If a linear model contains categorical coefficients, i.e., years in Column 2, the generalized variance-inflation factors, GVIF (Fox & Monette, 1992), are calculated instead of VIF-scores. To compare across different degrees of freedom an adjustment, (GVIF^(1/(2*Df)), is used. The rule of thumb used by us is that this value squared should be lower than 10. For Column 3 and 4, the high number of categorical variables makes the calculation of VIF insensible, thus they are not reported.

A.13: Propensity Score Matching Between Treatment and Control Group



A.14: VIF-Scores for Difference-in-Difference Model on Premium Payments (Table 10)

Variables	Column 1
R&D (Scaled by Assets)	3,00
M/B	1,65
Assets	1,52
Net Income Margin	4,21
Revenue Growth	1,16
ROA	4,79
Capex (Scaled by Assets)	1,17
1st. Wave Year	1,03
2md. Wave year	1,02

A.15 Industry Classification

Source: Adopted from French (2020).

Fama French Industry Classification

1 Agriculture
- 0100-0199 Agricultural production - crops
- 0200-0299 Agricultural production - livestock
- 0700-0799 Agricultural services
- 0910-0919 Commercial fishing
- 2048-2048 Prepared feeds for animals

2 Food Products
- 2000-2009 Food and kindred products
- 2010-2019 Meat products
- 2020-2029 Dairy products
- 2030-2039 Canned & preserved fruits & vegetables
- 2040-2046 Flour and other grain mill products
- 2050-2059 Bakery products
- 2060-2063 Sugar and confectionery products
- 2070-2079 Fats and oils
- 2090-2092 Misc food preparations and kindred products
- 2095-2095 Roasted coffee
- 2098-2099 Misc food preparations

3 Candy & Soda
- 2064-2068 Candy and other confectionery
- 2086-2086 Bottled-canned soft drinks
- 2087-2087 Flavoring syrup
- 2096-2096 Potato chips
- 2097-2097 Manufactured ice

4 Beer & Liquor
- 2080-2080 Beverages
- 2082-2082 Malt beverages
- 2083-2083 Malt
- 2084-2084 Wine
- 2085-2085 Distilled and blended liquors

5 Tobacco Products
- 2100-2199 Tobacco products

6 Recreation
- 0920-0999 Fishing, hunting & trapping
- 3650-3651 Household audio visual equipment
- 3652-3652 Phonograph records
- 3732-3732 Boat building and repairing
- 3930-3931 Musical instruments
- 3940-3949 Toys

7 Entertainment
- 7800-7829 Services - motion picture production and distribution
- 7830-7833 Services - motion picture theaters
- 7840-7841 Services - video rental
- 7900-7900 Services - amusement and recreation
- 7910-7911 Services - dance studios
- 7920-7929 Services - bands, entertainers
- 7930-7933 Services - bowling centers
- 7940-7949 Services - professional sports
- 7980-7980 Amusement and recreation services (?)
- 7990-7999 Services - Misc entertainment

8 Printing and Publishing
- 2700-2709 Printing publishing and allied
- 2710-2719 Newspapers: publishing-printing

23 Automobiles and Trucks
- 2296-2296 Tire cord and fabric
- 2396-2396 Automotive trimmings, apparel findings & related products
- 3010-3011 Tires and inner tubes
- 3537-3537 Industrial trucks, tractors, trailers & stackers
- 3647-3647 Vehicular lighting equipment
- 3694-3694 Electrical equipment for internal combustion engines
- 3700-3700 Transportation equipment
- 3710-3710 Motor vehicles and motor vehicle equipment
- 3711-3711 Motor vehicles & passenger car bodies
- 3713-3713 Truck & bus bodies
- 3714-3714 Motor vehicle parts & accessories
- 3715-3715 Truck trailers
- 3716-3716 Motor homes
- 3792-3792 Travel trailers and campers
- 3790-3791 Misc transportation equipment
- 3799-3799 Misc transportation equipment

24 Aircraft
- 3720-3720 Aircraft & parts
- 3721-3721 Aircraft
- 3723-3724 Aircraft engines & engine parts
- 3725-3725 Aircraft parts
- 3728-3729 Misc aircraft parts & auxiliary equipment

25 Shipbuilding, Railroad Equipment
- 3730-3731 Ship building and repairing
- 3740-3743 Railroad Equipment

26 Defense
- 3760-3769 Guided missiles and space vehicles and parts
- 3795-3795 Tanks and tank components
- 3480-3489 Ordnance & accessories

27 Precious Metals
- 1040-1049 Gold & silver ores

28 Non-Metallic and Industrial Metal Mining
- 1000-1009 Metal mining
- 1010-1019 Iron ores
- 1020-1029 Copper ores
- 1030-1039 Lead and zinc ores
- 1050-1059 Bauxite and other aluminum ores
- 1060-1069 Ferroalloy ores
- 1070-1079 Mining
- 1080-1089 Metal mining services
- 1090-1099 Misc metal ores
- 1100-1119 Anthracite mining
- 1400-1499 Mining and quarrying nonmetallic minerals

29 Coal
- 1200-1299 Bituminous coal and lignite mining

30 Petroleum and Natural Gas
- 1300-1300 Oil and gas extraction
- 1310-1319 Crude petroleum & natural gas
- 1320-1329 Natural gas liquids
- 1330-1339 Petroleum and natural gas
- 1370-1379 Petroleum and natural gas
- 1380-1380 Oil and gas field services

41 Transportation
- 4000-4013 Railroads, line-haul operating
- 4040-4049 Railway express service
- 4100-4100 Local & suburban transit & interurban highway passenger transportation
- 4110-4119 Local & suburban passenger transportation
- 4120-4121 Taxicabs
- 4130-4131 Intercity & rural bus transportation
- 4140-4142 Bus charter service
- 4150-4151 School buses
- 4170-4173 Motor vehicle terminals & service facilities
- 4190-4199 Misc transit and passenger transportation
- 4200-4200 Trucking & warehousing
- 4210-4219 Trucking & courier services, except air
- 4230-4231 Terminal & joint terminal maintenance
- 4240-4249 Transportation
- 4400-4499 Water transport
- 4500-4599 Air transportation
- 4600-4699 Pipelines, except natural gas
- 4700-4700 Transportation services
- 4710-4712 Freight forwarding
- 4720-4729 Arrangement of passenger transportation
- 4730-4739 Arrangement of transportation of freight and cargo
- 4740-4749 Rental of railroad cars
- 4780-4780 Misc services incidental to transportation
- 4782-4782 Inspection and weighing services
- 4783-4783 Packing and crating
- 4784-4784 Misc fixed facilities for vehicles
- 4785-4785 Motor vehicle inspection
- 4789-4789 Misc transportation services

42 Wholesale
- 5000-5000 Wholesale - durable goods
- 5010-5015 Wholesale - automotive vehicles & automotive parts & supplies
- 5020-5023 Wholesale - furniture and home furnishings
- 5030-5039 Wholesale - lumber and construction materials
- 5040-5042 Wholesale - professional and commercial equipment and supplies
- 5043-5043 Wholesale - photographic equipment & supplies
- 5044-5044 Wholesale - office equipment
- 5045-5045 Wholesale - computers & peripheral equipment & software
- 5046-5046 Wholesale - commercial equipment
- 5047-5047 Wholesale - medical, dental & hospital equipment
- 5048-5048 Wholesale - ophthalmic goods
- 5049-5049 Wholesale - professional equipment and supplies
- 5050-5059 Wholesale - metals and minerals, except petroleum
- 5060-5060 Wholesale - electrical goods
- 5063-5063 Wholesale - electrical apparatus and equipment
- 5064-5064 Wholesale - electrical appliance, TV and radio sets
- 5065-5065 Wholesale - electronic parts & equipment
- 5070-5078 Wholesale - hardware, plumbing & heating equipment
- 5080-5080 Wholesale - machinery, equipment & supplies
- 5081-5081 Wholesale - machinery & equipment (?)
- 5082-5082 Wholesale - construction and mining machinery &equipment
- 5083-5083 Wholesale - farm and garden machinery & equipment
- 5084-5084 Wholesale - industrial machinery & equipment
- 5085-5085 Wholesale - industrial supplies
- 5086-5087 Wholesale - service establishment machinery & equipment
- 5088-5088 Wholesale - transportation equipment, except motor vehicles
- 5090-5090 Wholesale - Misc durable goods
- 5091-5092 Wholesale - sporting goods & toys
- 5093-5093 Wholesale - scrap and waste materials

Table A.15 continued

2720-2729 Periodicals: publishing-printing
2730-2739 Books: publishing-printing
2740-2749 Misc publishing
2770-2771 Greeting card
2780-2789 Bookbinding
2790-2799 Service industries for the print trade

9 Consumer Goods
2047-2047 Dog and cat food
2391-2392 Curtains, home furnishings
2510-2519 Household furniture
2590-2599 Misc furniture and fixtures
2840-2843 Soap & other detergents
2844-2844 Perfumes, cosmetics and other toilet preparations
3160-3161 Luggage
3170-3171 Handbags and purses
3172-3172 Personal leather goods, except handbags and purses
3190-3199 Leather goods
3229-3229 Pressed and blown glass
3260-3260 Pottery and related products
3262-3263 China and earthenware table articles
3269-3269 Pottery products
3230-3231 Glass products
3630-3639 Household appliances
3750-3751 Motorcycles, bicycles and parts
3800-3800 Misc instruments, photo goods & watches
3860-3861 Photographic equipment
3870-3873 Watches, clocks and parts
3910-3911 Jewelry, precious metals
3914-3914 Silverware
3915-3915 Jewelers' findings and materials
3960-3962 Costume jewelry and novelties
3991-3991 Brooms and brushes
3995-3995 Burial caskets

10 Apparel
2300-2390 Apparel and other finished products
3020-3021 Rubber and plastics footwear
3100-3111 Leather tanning and finishing
3130-3131 Boot & shoe cut stock & findings
3140-3149 Footwear, except rubber
3150-3151 Leather gloves and mittens
3963-3965 Fasteners, buttons, needles, pins

11 Healthcare
8000-8099 Services - health

12 Medical Equipment
3693-3693 X-ray, electromedical app
3840-3849 Surgical, medical, and dental instruments and supplies
3850-3851 Ophthalmic goods

13 Pharmaceutical Products
2830-2830 Drugs
2831-2831 Biological products
2833-2833 Medicinal chemicals
2834-2834 Pharmaceutical preparations
2835-2835 In vitro, in vivo diagnostic substances

1381-1381 Drilling oil & gas wells
1382-1382 Oil & gas field exploration services
1389-1389 Misc oil & gas field services
2900-2912 Petroleum refining
2990-2999 Misc products of petroleum & coal

31 Utilities
4900-4900 Electric, gas & sanitary services
4910-4911 Electric services
4920-4922 Natural gas transmission
4923-4923 Natural gas transmission & distribution
4924-4925 Natural gas distribution
4930-4931 Electric and other services combined
4932-4932 Gas and other services combined
4939-4939 Misc combination utilities
4940-4942 Water supply

32 Communication
4800-4800 Communications
4810-4813 Telephone communications
4820-4822 Telegraph and other message communication
4830-4839 Radio & TV broadcasters
4840-4841 Cable and other pay TV services
4880-4889 Communications
4890-4890 Communication services (Comsat)
4891-4891 Cable TV operators
4892-4892 Telephone interconnect
4899-4899 Misc communication services

33 Personal Services
7020-7021 Rooming and boarding houses
7030-7033 Camps and recreational vehicle parks
7200-7200 Services - personal
7210-7212 Services - laundry, cleaning & garment services
7214-7214 Services - diaper service
7215-7216 Services - coin-operated cleaners, dry cleaners
7217-7217 Services - carpet & upholstery cleaning
7219-7219 Services - Misc laundry & garment services
7220-7221 Services - photographic studios, portrait
7230-7231 Services - beauty shops
7240-7241 Services - barber shops
7250-7251 Services - shoe repair shops & shoeshine parlors
7260-7269 Services - funeral service & crematories
7270-7290 Services – Misc
7291-7291 Services - tax return
7292-7299 Services - Misc
7395-7395 Services - photofinishing labs (School pictures)
7500-7500 Services - auto repair, services & parking
7520-7529 Services - automobile parking
7530-7539 Services - automotive repair shops
7540-7549 Services - automotive services, except repair
7600-7600 Services - Misc repair services
7620-7620 Services - Electrical repair shops
7622-7622 Services - Radio and TV repair shops
7623-7623 Services - Refrigeration and air conditioning service & repair shops
7629-7629 Services - Electrical & electronic repair shops
7630-7631 Services - Watch, clock and jewelry repair
7640-7641 Services - Reupholster & furniture repair

5094-5094 Wholesale - jewelry, watches, precious stones & metals
5099-5099 Wholesale - durable goods
5100-5100 Wholesale - nondurable goods
5110-5113 Wholesale - paper and paper products
5120-5122 Wholesale - drugs & drug proprietaries
5130-5139 Wholesale - apparel, piece goods & notions
5140-5149 Wholesale - groceries & related products
5150-5159 Wholesale - farm product raw materials
5160-5169 Wholesale - chemicals & allied products
5170-5172 Wholesale - petroleum and petroleum products
5180-5182 Wholesale - beer, wine & distilled alcoholic beverages
5190-5199 Wholesale - Misc nondurable goods

43 Retail
5200-5200 Retail - retail-building materials, hardware, garden supply
5210-5219 Retail - lumber & other building materials
5220-5229 Retail
5230-5231 Retail - paint, glass & wallpaper stores
5250-5251 Retail - hardware stores
5260-5261 Retail - nurseries, lawn & garden supply stores
5270-5271 Retail - mobile home dealers
5300-5300 Retail - general merchandise stores
5310-5311 Retail - department stores
5320-5320 Retail - general merchandise stores (?)
5330-5331 Retail - variety stores
5334-5334 Retail - catalog showroom
5340-5349 Retail
5390-5399 Retail - Misc general merchandise stores
5400-5400 Retail - food stores
5410-5411 Retail - grocery stores
5412-5412 Retail - convenience stores
5420-5429 Retail - meat & fish markets
5430-5439 Retail - fruit and vegetable markets
5440-5449 Retail - candy, nut & confectionary stores
5450-5459 Retail - dairy products stores
5460-5469 Retail - bakeries
5490-5499 Retail - Misc food stores
5500-5500 Retail - automotive dealers and gas stations
5510-5529 Retail - automotive dealers
5530-5539 Retail - automotive and home supply stores
5540-5549 Retail - gasoline service stations
5550-5559 Retail - boat dealers
5560-5569 Retail - recreation vehicle dealers
5570-5579 Retail - motorcycle dealers
5590-5599 Retail - automotive dealers
5600-5699 Retail - apparel & accessory stores
5700-5700 Retail - home furniture and equipment stores
5710-5719 Retail - home furnishings stores
5720-5722 Retail - household appliance stores
5730-5733 Retail - radio, TV and consumer electronic stores
5734-5734 Retail - computer and computer software stores
5735-5735 Retail - record and tape stores
5736-5736 Retail - musical instrument stores
5750-5799 Retail
5900-5900 Retail - Misc
5910-5912 Retail - drug & proprietary stores
5920-5929 Retail - liquor stores
5930-5932 Retail - used merchandise stores

A.15 continued

2836-2836 Biological products, except diagnostic substances

14 Chemicals

2800-2809 Chemicals and allied products
2810-2819 Industrial inorganic chemicals
2820-2829 Plastic material & synthetic resin/rubber
2850-2859 Paints
2860-2869 Industrial organic chemicals
2870-2879 Agriculture chemicals
2890-2899 Misc chemical products

15 Rubber and Plastic Products

3031-3031 Reclaimed rubber
3041-3041 Rubber & plastic hose & belting
3050-3053 Gaskets, hoses, etc
3060-3069 Fabricated rubber products
3070-3079 Misc rubber products (?)
3080-3089 Misc plastic products
3090-3099 Misc rubber and plastic products (?)

16 Textiles

2200-2269 Textile mill products
2270-2279 Floor covering mills
2280-2284 Yarn and thread mills
2290-2295 Misc textile goods
2297-2297 Non-woven fabrics
2298-2298 Cordage and twine
2299-2299 Misc textile products
2393-2395 Textile bags, canvas products
2397-2399 Misc textile products

17 Construction Materials

0800-0899 Forestry
2400-2439 Lumber and wood products
2450-2459 Wood buildings & mobile homes
2490-2499 Misc wood products
2660-2661 Building paper and board mills
2950-2952 Paving & roofing materials
3200-3200 Stone, clay, glass, concrete, etc
3210-3211 Flat glass
3240-3241 Cement, hydraulic
3250-3259 Structural clay products
3261-3261 Vitreous china plumbing fixtures
3264-3264 Porcelain electrical supplies
3270-3275 Concrete, gypsum & plaster products
3280-3281 Cut stone and stone products
3290-3293 Abrasive and asbestos products
3295-3299 Misc nonmetallic mineral products
3420-3429 Cutlery, hand tools and general hardware
3430-3433 Heating equipment & plumbing fixtures
3440-3441 Fabricated structural metal products
3442-3442 Metal doors, frames
3446-3446 Architectural or ornamental metal work
3448-3448 Prefabricated metal buildings and components
3449-3449 Misc structural metal work
3450-3451 Screw machine products
3452-3452 Bolts, nuts, screws, rivets and washers
3490-3499 Misc fabricated metal products
3996-3996 Hard surface floor coverings

18 Construction

1500-1511 Build construction - general contractors
1520-1529 General building contractors - residential
1530-1539 Operative builders
1540-1549 General building contractors - non-residential
1600-1699 Heavy construction - not building contractors
1700-1799 Construction - special contractors

19 Steel Works Etc

3300-3300 Primary metal industries
3310-3317 Blast furnaces & steel works
3320-3325 Iron & steel foundries

7690-7699 Services - Misc repair shops & related services
8100-8199 Services - legal
8200-8299 Services - educational
8300-8399 Services - social services
8400-8499 Services - museums, art galleries, botanical and zoological gardens
8600-8699 Services - membership organizations
8800-8899 Services - private households
7510-7515 Services - truck & auto rental and leasing

34 Business Services

2750-2759 Commercial printing
3993-3993 Signs & advertising specialties
7218-7218 Services - industrial launderers
7300-7300 Services - business services
7310-7319 Services - advertising
7320-7329 Services - consumer credit reporting agencies, collection services
7330-7339 Services - mailing, reproduction, commercial art & photography
7340-7342 Services - services to dwellings & other buildings
7349-7349 Services - building cleaning & maintenance
7350-7351 Services - Misc equipment rental and leasing
7352-7352 Services - medical equipment rental and leasing
7353-7353 Services - heavy construction equipment rental and leasing
7359-7359 Services - equipment rental and leasing
7360-7369 Services - personnel supply services
7374-7374 Services - computer processing, data preparation and processing
7376-7376 Services - computer facilities management service
7377-7377 Services - computer rental and leasing
7378-7378 Services - computer maintenance and repair
7379-7379 Services - computer related services
7380-7380 Services - Misc business services
7381-7382 Services - security
7383-7383 Services - news syndicates
7384-7384 Services - photofinishing labs
7385-7385 Services - telephone interconnect systems
7389-7390 Services - Misc business services
7391-7391 Services - R&D labs
7392-7392 Services - management consulting & P.R.
7393-7393 Services - detective and protective (ADT)
7394-7394 Services - equipment rental & leasing
7396-7396 Services - trading stamp services
7397-7397 Services - commercial testing labs
7399-7399 Services - business services
7519-7519 Services - utility trailer & recreational vehicle rental
8700-8700 Services - engineering, accounting, research, management
8710-8713 Services - engineering, accounting, surveying
8720-8721 Services - accounting, auditing, bookkeeping
8730-8734 Services - research, development, testing labs
8740-8748 Services - management, public relations, consulting
8900-8910 Services - Misc
8911-8911 Services - Misc engineering & architect
8920-8999 Services - Misc
4220-4229 Public warehousing and storage

35 Computers

3570-3579 Computer & office equipment
3680-3680 Computers
3681-3681 Computers - mini
3682-3682 Computers - mainframe
3683-3683 Computers - terminals
3684-3684 Computers - disk & tape drives
3685-3685 Computers - optical scanners
3686-3686 Computers - graphics
3687-3687 Computers - office automation systems
3688-3688 Computers - peripherals
3689-3689 Computers - equipment
3695-3695 Magnetic and optical recording media

36 Computer Software

7370-7372 Services - computer programming and data processing
7375-7375 Services - information retrieval services
7373-7373 Computer integrated systems design

5940-5940 Retail - Misc
5941-5941 Retail - sporting goods stores & bike shops
5942-5942 Retail - book stores
5943-5943 Retail - stationery stores
5944-5944 Retail - jewelry stores
5945-5945 Retail - hobby, toy and game shops
5946-5946 Retail - camera and photographic supply stores
5947-5947 Retail - gift, novelty & souvenir shops
5948-5948 Retail - luggage & leather goods stores
5949-5949 Retail - sewing & needlework stores
5950-5959 Retail
5960-5969 Retail - non-store retailers (catalogs, etc)
5970-5979 Retail
5980-5989 Retail - fuel dealers & ice stores
5990-5990 Retail - Misc retail stores
5992-5992 Retail - florists
5993-5993 Retail - tobacco stores and stands
5994-5994 Retail - newsdealers and news stands
5995-5995 Retail - optical goods stores
5999-5999 Misc retail stores

44 Restaurants, Hotels, Motels

5800-5819 Retail - eating places
5820-5829 Restaurants, hotels, motels
5890-5899 Eating and drinking places
7000-7000 Hotels & other lodging places
7010-7019 Hotels & motels
7040-7049 Membership hotels and lodging houses
7213-7213 Services - linen supply

45 Banking

6000-6000 Depository institutions
6010-6019 Federal reserve banks
6020-6020 Commercial banks
6021-6021 National commercial banks
6022-6022 State commercial banks - Fed Res System
6023-6024 State commercial banks - not Fed Res System
6025-6025 National commercial banks - Fed Res System
6026-6026 National commercial banks - not Fed Res System
6027-6027 National commercial banks, not FDIC
6028-6029 Misc commercial banks
6030-6036 Savings institutions
6040-6059 Banks (?)
6060-6062 Credit unions
6080-6082 Foreign banks
6090-6099 Functions related to depository banking
6100-6100 Non-depository credit institutions
6110-6111 Federal credit agencies
6112-6113 FNMA
6120-6129 S&Ls
6130-6139 Agricultural credit institutions
6140-6149 Personal credit institutions (Beneficial)
6150-6159 Business credit institutions
6160-6169 Mortgage bankers and brokers
6170-6179 Finance lessors
6190-6199 Financial services

46 Insurance

6300-6300 Insurance
6310-6319 Life insurance
6320-6329 Accident and health insurance
6330-6331 Fire, marine & casualty insurance
6350-6351 Surety insurance
6360-6361 Title insurance
6370-6379 Pension, health & welfare funds
6390-6399 Misc insurance carriers
6400-6411 Insurance agents, brokers & service

47 Real Estate

6500-6500 Real estate
6510-6510 Real estate operators and lessors
6512-6512 Operators - non-resident buildings

A.15 continued

3330-3339 Primary smelting & refining of nonferrous metals

3340-3341 Secondary smelting & refining of nonferrous metals

3350-3357 Rolling, drawing & extruding of nonferrous metals
3360-3369 Nonferrous foundries and casting

3370-3379 Steel works etc
3390-3399 Misc primary metal products

20 Fabricated Products

3400-3400 Fabricated metal, except machinery and trans eq
3443-3443 Fabricated plate work

3444-3444 Sheet metal work

3460-3469 Metal forgings and stampings
3470-3479 Coating, engraving and allied services

21 Machinery
3510-3519 Engines & turbines
3520-3529 Farm and garden machinery and equipment
3530-3530 Construction, mining & material handling machinery & equipment

3531-3531 Construction machinery & equipment

3532-3532 Mining machinery & equipment, except oil field

3533-3533 Oil & gas field machinery & equipment
3534-3534 Elevators & moving stairways
3535-3535 Conveyors & conveying equipment
3536-3536 Cranes, hoists and monorail systems
3538-3538 Machinery
3540-3549 Metalworking machinery & equipment
3550-3559 Special industry machinery
3560-3569 General industrial machinery & equipment
3580-3580 Refrigeration & service industry machinery
3581-3581 Automatic vending machines

3582-3582 Commercial laundry and dry cleaning machines
3585-3585 Air conditioning, warm air heating and refrigeration equipment
3586-3586 Measuring and dispensing pumps
3589-3589 Service industry machinery
3590-3599 Misc industrial and commercial equipment and machinery

22 Electrical Equipment
3600-3600 Electronic & other electrical equipment

3610-3613 Electric transmission and distribution equipment
3620-3621 Electrical industrial apparatus
3623-3629 Electrical industrial apparatus
3640-3644 Electric lighting & wiring equipment
3645-3645 Residential electric lighting fixtures
3646-3646 Commercial, industrial and institutional electric lighting fixtures
3648-3649 Misc lighting equipment
3660-3660 Communications equipment
3690-3690 Misc electrical machinery and equipment
3691-3692 Storage batteries

3699-3699 Misc electrical machinery, equipment and supplies

37 Electronic Equipment

3622-3622 Industrial controls

3661-3661 Telephone and telegraph apparatus
3662-3662 Communications equipment
3663-3663 Radio & TV broadcasting & communications equipment
3664-3664 Search, navigation, guidance systems
3665-3665 Training equipment & simulators
3666-3666 Alarm & signaling products

3669-3669 Communication equipment
3670-3679 Electronic components & accessories
3810-3810 Search, detection, navigation, guidance, aeronautical & nautical systems, instruments & equipment
3812-3812 Search, detection, navigation, guidance, aeronautical & nautical systems & instruments

38 Measuring and Control Equipment
3811-3811 Engr laboratory and research equipment
3820-3820 Measuring and controlling equipment
3821-3821 Laboratory apparatus and furniture
3822-3822 Automatic controls for regulating residential & commercial environments & appliances
3823-3823 Industrial measurement instruments & related products

3824-3824 Totalizing fluid meters & counting devices
3825-3825 Instruments for measuring & testing of electricity & electrical instruments
3826-3826 Lab analytical instruments
3827-3827 Optical instruments and lenses
3829-3829 Misc measuring and controlling devices
3830-3839 Optical instruments and lenses

39 Business Supplies
2520-2549 Office furniture and fixtures
2600-2639 Paper and allied products
2670-2699 Paper and allied products

2760-2761 Manifold business forms

3950-3955 Pens, pencils & other artists' supplies

40 Shipping Containers

2440-2449 Wood containers
2640-2659 Paperboard containers, boxes, drums, tubs
3220-3221 Glass containers
3410-3412 Metal cans and shipping containers

6513-6513 Operators - apartment buildings

6514-6514 Operators - other than apartment

6515-6515 Operators - residential mobile home
6517-6519 Lessors of railroad & real property

6520-6529 Real estate
6530-6531 Real estate agents and managers
6532-6532 Real estate dealers
6540-6541 Title abstract offices

6550-6553 Land subdividers & developers
6590-6599 Real estate

6610-6611 Combined real estate, insurance, etc

48 Trading
6200-6299 Security and commodity brokers, dealers, exchanges & services
6700-6700 Holding & other investment offices
6710-6719 Holding offices
6720-6722 Management investment offices, open-end

6723-6723 Management investment offices, closed-end

6724-6724 Unit investment trusts

6725-6725 Face-amount certificate offices

6726-6726 Unit investment trusts, closed-end
6730-6733 Trusts
6740-6779 Investment offices
6790-6791 Misc investing
6792-6792 Oil royalty traders
6793-6793 Commodity traders
6794-6794 Patent owners & lessors
6795-6795 Mineral royalty traders
6798-6798 REIT
6799-6799 Investors, NEC

49 Almost Nothing
4950-4959 Sanitary services
4960-4961 Steam & air conditioning supplies

4970-4971 Irrigation systems
4990-4991 Cogeneration - SM power producer