CLASSIFYING THE INDUSTRIAL ORGANIZATION OF CORPORATE MERGERS AND TESTING THEORIES: THE HUMAN EYE VERSUS MACHINE READABLE METHODS

by

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(Under the Direction of Harold Mulherin)

ABSTRACT

I examine wealth effects of merger announcements using a sample of 223 (U.S.) domestic mergers during a 3 year period (2011 through 2013) after the "Great Recession." Specifically, I partition the mergers in my sample into their horizontal, vertical, and conglomerate industrial organization types using a document-based, Human Eye method of classification and then calculate the equity-wealth effects for each merger type. I also perform similar event study analysis for the rivals of my sample of merging firms. Overall, my results provide evidence that recent corporate diversification activity via mergers has not been value-destroying and that the "synergy" and "collusion" hypotheses cannot fully explain merger returns for my sample. A comparison of results achieved under two different methods of classifying merger industrial organization also reveals evidence suggesting that significant differences exist between document-based methods of industrial organization classification and the popular SIC/IO method that is based on fixed industry codes.

INDEX WORDS: Mergers, Acquisitions, Industrial organization classification methods, Corporate diversification, Synergy hypothesis, Collusion hypothesis, SIC codes, Input-output tables, Event study

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DEDICATION

For my heroes- Dad, Mom, and Kristen.

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CHAPTER 1

INTRODUCTION AND MOTIVATION

The global financial crisis of 2007 to 2009 was an impetus for change across a wide range of social, economic, and financial platforms. Not only did the magnitude of the collapse famously cause market participants and pundits to question the very constructs upon which our financial system was formed, but it also generated an environment in which corporations themselves began to re-evaluate the way that they did business. From an academic perspective, this widespread transformation in corporate financial policy, behavior, and profits represents an opportunity to re-assess some of the most widely debated issues in financial economics with a new bevy of exogenous shocks, economic conditions, and refined methodologies at our disposal. As with all enthusiastic pursuits however, before financial economists are to exploit the uniqueness of our current time period, we should take inventory of our current set of tools. With that in mind, this paper attempts to capitalize on the idiosyncrasies of our time period by offering new evidence on age-old theoretical debates in corporate finance, while also providing a benchmark comparison of current methodologies.

Ever since the seminal study of Fama, Fisher, Jensen, & Roll (1969), event study analysis has become a staple of financial economic research- particularly as related to corporate mergers and acquisitions (hereafter referred to simply as "mergers").[1] While much of the actual methodology underlying event study analysis has remained fairly consistent since this early work, researchers have been very successful and creative in terms of how they have been able to

[1] A quick search of "Event Study of Mergers and Acquisitions" in Google Scholar yields some 100,000 plus results. For a review of event study analysis in economics and finance research see MacKinlay (1997).

formulate new ways to apply the event study framework in positing answers to various theoretical debates within the literature. One very popular way in which researchers have leveraged the capabilities of event study analysis in merger research has been to *first* classify the industrial organization of mergers and *then* employ event study analysis in order to compare the equity-wealth effects between different merger types.[2] Eckbo (1983) and Stillman (1983), for instance, cleverly use a classification of the industrial organization of mergers as well as an analysis of merging firms' rivals to posit answers to a long-standing debate over the sources of gains in mergers- namely whether or not they are due to an increased probability of collusion. Similarly, recent studies such as Becher et al. (2012) and Chevalier (2004) classify the industrial organization of mergers in testing (again) theories related to the sources of merger gains and theories related to the value of corporate diversification. It is in fact the case that many of the theories on corporate mergers necessitate the classification of mergers into industrial organizational types for adequate testing, and thus, it becomes imperative that the methods by which researchers make these classifications are as copasetic as possible.

Recently, some researchers have begun to question, and have attempted to improve upon, the traditional methods for classifying the industrial organization of mergers. Historically, these methods have been based on fixed industry codes such as NAICS, SIC, or others, whereby mergers are classified as horizontal if the target and bidder have identical industry codes and as "non-horizontal" or "diversifying" otherwise. As pointed out by researchers such as Kahle & Walkling (1996), Fan & Goyal (2006), Hoberg & Phillips (2010), Frésard, Hoberg, & Phillips (2014), and others, there are several issues that can arise when using this approach. First, while mergers can quickly be classified as horizontal and non-horizontal, making a reliable vertical

[2] Industrial organization classifications define the relation between merging firms into "types" such as vertical, horizontal, and conglomerate.

merger classification is not possible. Fan and Goyal (2006) illustrate this through an example based on the oil and gas industry: "A merger between a petroleum-refining (SIC 29) and a petroleum exploration (SIC 13) company would be classified as a diversifying merger because the refining and exploration businesses are in different two-digit SIC industries. But the two industries have obvious vertical linkages." This particular merger clearly should be classified more finely as vertical, but with standard industry-based methods this is not possible. Other issues have also been brought up about the overall accuracy of strictly industry-based methods of merger classification. Kahle & Walkling (1996) disconcertingly report that, due to differences in the databases' categorization procedures, information sources, and update frequencies, nearly 40% (80%) of the two- (four-) digit SIC codes of companies classified by CRSP differ from those reported by Compustat.[3] Additionally, Hoberg & Phillips (2010) and Frésard, Hoberg, & Phillips (2014) raise concerns about the overall granularity of industry-based methods and the fact that such granularity does a poor job of dealing with heterogeneity within industries.

The methodological shortcomings of standard industry-based methods for classifying the industrial organization of mergers have led researchers to both increase their cleverness and to seek further innovation so that they can continue to better test theories. For those choosing to implement a method based strictly on fixed industry codes, the key has become to use the method within the scope it was intended and to construct a testing environment that is most conducive to eliminating common pitfalls.[4] For researchers looking to make finer classifications

[3] For explicit examples of the differences found to be contributing to these reporting discrepancies, consider the following: Compustat does not provide historical SIC codes, but CRSP does. Further, Compustat SIC codes are said to be based on an evaluation of product-line breakdowns reported in firm 10-K's, whereas CRSP SIC codes supposedly rely on a channel of SIC code reporting beginning with the SEC Directory and ending with Interactive Data Corporation. Lastly, and again relevant to the issue of accuracy in general, consider that Kahle & Walkling (1996) also report evidence suggesting that each database may do a poor job of even following its own set of categorization rules.

[4] Becher et al. (2012), for instance, recognize the issues relating to both the granularity of industry codes and the accuracy of SIC code reporting. As such, they limit their study to a single industry (utilities) to increase the focus of

or to avoid the standard industry-based methods altogether, several options have begun to materialize. Maybe most notably, Fan & Lang (2000), Fan & Goyal (2006), Acemoglu et al. (2009), Kedia et al. (2011), and others have advocated using the input-output (IO) tables published by the Bureau of Economic Analysis (BEA), in combination with SIC codes, to define the vertical relatedness between target and bidder firms. By doing so, these researchers have been able to expand the feasible set of merger classifications to now include the vertical industrial organization type, and they have provided evidence that seems to substantiate concerns that an over-counting of diversifying/unrelated mergers is taking place under strict industry-based methods. In general, it is almost certain that this new "SIC/IO approach" has increased the flexibility of research in this area, as evidenced by its fairly widespread adoption.[5]

Still, other researchers such as Hoberg & Phillips (2010) and Frésard, Hoberg, & Phillips (2014) are not satisfied with the existing classification schemes and are seeking to push the envelope even further. They point out that while the SIC/IO method offers significant improvements over standard industry-based methods, its continued reliance on fixed industry codes means that it does little to eradicate many of the inherent flaws of its predecessor, including issues relating to granularity and accuracy. As such, Hoberg & Phillips (2010) and Frésard, Hoberg, & Phillips (2014) have devised a firm-specific method for classifying the industrial organization of mergers that uses "web-crawling" and textual analysis software to scan product descriptions of firm 10-K filings as well as commodity descriptions from the BEA's input-output tables in order to define the horizontal and vertical relatedness of merging firm

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their classifications, and they supplement SIC information with industry information from Value Line Investment Surveys to mitigate reporting errors. Similarly, but under different constructs, Eckbo (1983) essentially bypasses the granularity issue altogether by using firm-level product descriptions to make his own firm-specific SIC classifications. In both studies, classifications were limited to the horizontal and non-horizontal level.

[5] As already stated, there was, for instance, no reliable heuristic for classifying mergers as vertical on a large scale prior to the arrival of this SIC/IO method.

pairs. Although different in that it is machine-based and thus incapable of evaluating context, this approach is somewhat analogous to actually hand-reading merger documents and therefore represents another significant and positive step in solidifying our methods of merger classification.[6] With that being said, this method then also begs an important question: Why have we not compared the SIC/IO method to the most fundamental method of classifying the industrial organization of mergers? That is, why have we not compared it to a method based on the Human Eye?[7]

In this paper, I implement tests of two different sets of competing theories on corporate mergers, both of which rely on an accurate classification of industrial organization. More specifically, I employ an event study analysis and a comparison of the equity-wealth effects of vertical, horizontal, and conglomerate mergers during the 2011 through 2013 timeframe in order to provide updated evidence on the value of corporate diversification and the sources of gains in mergers.[8] In order to make my vertical, horizontal, and conglomerate classifications, I rely on a Human Eye method of classification in which I read merger documents for context and then determine the appropriate industrial organizational classification between merging firm pairs. Importantly, I also conduct secondary analysis using the SIC/IO method of classification so that direct comparisons between methods can be made.

Comparing merger classification schemes within the context of explicitly testing corporate finance theories, as opposed to juxtaposing the schemes in isolation, is advantageous

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[6] For a full description of the methods for classifying the industrial organization of mergers, including the pros and cons of each, see *Panel A* and *Panel B* of *table 1*.

[7] I should pause here to note that Fan & Goyal (2006) do in fact compare classifications made under their SIC/IO method to those made under a method based on analysis by the FTC, but that these FTC classifications were made only in terms of large manufacturing and mining companies and they were made at a different level of classification. Also, these FTC classifications were based on a 1980 publication and therefore do not represent a viable means of classifying mergers moving forward. As such, and as Fan & Goyal (2006) themselves allude to (footnote #9, p. 888), researchers should not consider this sample of FTC classifications to represent a comprehensive set of classifications based off of the Human Eye.

[8] A detailed account of these two debates is provided in chapter 2 of this paper.

for several reasons. First, this approach allows a practical look at the real effects that method selection can have on empirical results. Second, implementing a new Human Eye method of merger classification in my primary analysis adds to the literature on corporate diversification and sources of gain in mergers by approaching the theories with a slightly new set of tools. In total, the structure and scope of my analysis enables me to address the following questions: How have the characteristics and value-effects of mergers changed in the post-crisis period? What is the value of corporate diversification in the post-crisis period? What are the explicit pathways for value-creation displayed by mergers occurring after the crisis? How does the SIC/IO method of classifying the industrial organization of mergers differ from a Human Eye method, and what are the implications of these differences?

To preview my results, I find that combined firm abnormal returns for conglomerate mergers are nonnegative in the most recent period under a Human Eye method of merger classification, and significantly positive under the SIC/IO method. These results are not at all consistent with value-decreasing theories of corporate diversification. Further, I find that the mergers in my sample (overall and for the horizontal sub-sample) create wealth for the combined, bidder, and target firm, which is consistent with both the synergy and collusion hypotheses of merger value creation. In order to distinguish between these two hypotheses I follow the lead of Eckbo (1983) and Stillman (1983) and evaluate abnormal returns to the rivals of my merging firms. Rival firm abnormal returns are significantly positive, a result that is inconsistent with the synergy hypothesis. Abnormal stock returns to rival firms in horizontal mergers, however, are not greater than in the other two merger types which would seem to indicate that the collusion hypothesis also cannot fully explain merger returns for my sample. Lastly, I find rather stark differences between a Human Eye method of classifying the industrial organization of mergers and the popular SIC/IO method of classification, as well as intra-method differences within the SIC/IO method depending on whether vertical mergers are defined at a 1%, 5%, or 10% vertical relatedness cutoff. These differences have an effect on statistical inference in some cases, and indicate that additional research on classifying the industrial organization of corporate mergers is warranted.

My results contribute to the literature on several dimensions. First, they provide updated evidence on the value of corporate diversification. Kuppuswamy and Villalonga (2010) find that the value of corporate diversification increased *during* the crisis, but note that it remains an open question as to whether or not it this would continue *after* the crisis. This paper helps to answer that question. My results also add to the literature on the sources of gains in mergers by providing a multi-industry test of the synergy and collusion hypotheses that is based on a new Human Eye method of classifying the industrial organization of mergers. In their own single-industry analysis on the sources of gains in mergers, Becher et al. (2012) note that multi-industry studies have typically found convincing first-order evidence against the collusion hypothesis. My results thus represent somewhat of a departure from these previous multi-industry findings, and may reflect a change in methodology depending on the extent to which these studies relied upon industrial organization classifications. Lastly then, my results have important implications for how researchers classify the industrial organization of mergers. Particularly, they suggest that ongoing research in this area, including evaluating and expanding upon the methods of Hoberg & Phillips (2010) and Frésard, Hoberg, & Phillips (2014), is critical if we are to reach a reliable methodological equilibrium. My results also have additional implications relating to public policy- particularly in terms of antitrust. Though the relevant market in an antitrust case is said to be based on a given product in a given region (Baker, 2007), a merger classified as horizontal might undoubtedly garner more attention from antitrust authorities, and thus, my analysis indicates that the choice of classification method made by researchers assessing these cases could turn out to be a critical factor and even a point of contention.[9]

The remainder of the paper is structured as follows. Chapter 2 discusses the competing theories being tested and their empirical predictions. Chapter 3 reviews literature related to the value of corporate diversification and the sources of gain in mergers. Chapter 4 describes the data and sampling procedure. Chapter 5 details the primary and secondary methods used to classify my sample of mergers into industrial organization type. Chapter 6 presents summary statistics on sample distribution and sample characteristics. Chapter 7 explains the method of analysis. Chapter 8 outlines both the primary and secondary results. Chapter 9 concludes.

[9] As an illustration that horizontally classified mergers could indeed face more scrutiny from antitrust authorities, consider the fact that the DOJ and FTC have periodically issued guidelines for antitrust evaluation entitled: "*Horizontal* Merger Guidelines." Also, Whinston (2007) in his *Handbook of Industrial Organization*, points out that antitrust laws dealing with collusion are majorly concerned with two things: "price fixing (cartels) and *horizontal mergers*."

CHAPTER 2

THEORIES AND TESTABLE PREDICTIONS

There are two main theoretical issues that this paper aims to address. First, there is the long-standing debate over the value of corporate diversification. The ideas behind this debate are quite simple: some argue that corporate diversification destroys value, while others argue the opposite.[10] Those who argue in the value-destroying direction point to the fact that, in general, shareholders should be able to more effectively diversify on their own and that companies should stay focused on their core competencies. Those who argue that corporate diversification is value-enhancing point to the more beneficial effects of corporate diversification- things like decreased reliance on specific industries/customers and lower overall business risk. By breaking my merger sample into vertical, horizontal, and conglomerate classifications I am able to generate unique, testable hypotheses that directly address this corporate diversification debate.[11] Further, examination of a post-crisis time period allows me to extend the analysis of Kuppuswamy & Villalonga (2010), who find that the value-effects of corporate diversification became significantly more positive *during* the crisis, by evaluating the value of corporate diversification *after* the crisis.

A second part of this paper is aimed at determining the channels of value creation that were most active during my post-crisis sample period by testing competing theories on the fundamental causes of mergers. More specifically, it is aimed at differentiating between some of

[10] See *table 2* for a summary of the theory on both sides of this debate, including a discussion directly related to conglomerate mergers in *Panel C*. See also, Martin & Sayrak (2003) for a detailed review of the corporate diversification debate.

[11] See *Panel A* of *table 3* for a full account of my testable hypotheses as related to this debate.

the leading neoclassical theories on the sources of merger gains: namely the synergy and the collusion hypotheses.[12] The title of each respective theory is fairly self-explanatory. The first argues that merger gains emanate from some sort of synergistic/efficiency-based effect by which the merged firm essentially operates "better" or "cheaper" than either of the two participating firms could have on their own. The second views any perceived value creation for the transacting firms in a merger to be caused by increased market power and collusion that has resulted in monopolistic pricing and/or overall anticompetitive behavior. In general, each of these hypotheses strings from the value-enhancing side of a wider theoretical debate on the principal drivers of value in mergers.[13] Again, the contributions of my analysis to this theoretical framework are partially rooted in my ability to uniquely evaluate merger effects across industrial organization type within a multi-industry setting.

Ultimately, the testable predictions that I am able to generate in my analysis are simple and direct. As related to corporate diversification, I am able to formulate hypotheses both in terms of its absolute and its relative value. On an absolute level, I hypothesize that positive combined firm abnormal returns in conglomerate ("diversifying") mergers will provide evidence that corporate diversification has been value-enhancing during my post-crisis sample period, whereas negative combined firm abnormal returns in conglomerate mergers will suggest that corporate diversification has been value-destroying. On more of a relative basis, I posit that high combined firm abnormal returns in conglomerate mergers, as compared to the other two industrial organization types, will offer support for value-enhancing theories of corporate diversification, whereas relatively low returns in conglomerate mergers will signal more of a value-destroying diversification effect (again, "enhancing" and "destroying" stated this time in

[12] Many, such as Trautwein (1990), have concluded that these are the two theories in this area garnering the most empirical support. For an outline of the testable predictions generated by these two theories, see *Panel B* of *table 3*.
[13] See, for instance, Fee & Thomas (2004).

the relative, sub-optimal investment sense). Next, in terms of testing the synergy and the collusion hypotheses on the sources of gains in corporate mergers, both theories in fact predict that combined firm abnormal returns for mergers in my sample should be positive. Therefore, in order to distinguish between the two theories, I adopt the approach established by Eckbo (1983) and Stillman (1983) and evaluate the stock price responses for the *rivals* of *horizontally* merging firms upon the announcement of the merger deal.[14] Based on logical theory such as that outlined by Demsetz (1973), the synergy hypothesis for merger value creation should predict a negative stock market response for the rivals of merging firms, as market participants rationally adjust rival firms' valuations downward to account for the fact that they now face an increased quality of competition. In contrast, the collusion hypothesis should predict a positive stock market response for the rivals of *horizontally* merging firms, as market participants rationally respond to an increase in industry concentration (and thus, according to the collusion hypothesis, an increased ability for the remaining firms to collude and raise prices) by bidding up the prices of the remaining firms.[15] For a full account of my testable hypotheses as described above, please see *table 3*.

[14] Where rival firms are defined, in a manner similar to that described in Song & Walkling (2000), as those firms in the target firm's primary SIC industry upon the announcement of each merger deal

[15] Similarly then, if rival returns are indeed positive, it becomes important to further check that rival returns are highest in horizontally related mergers, as this is where the collusive effects of increased industry concentration should be the greatest (see, for instance, Song & Walkling, 2000 or Becher et al., 2012).

CHAPTER 3

LITERATURE REVIEW

As discussed in detail in the introduction of this paper, a significant source of motivation for researchers studying corporate mergers can be found simply in evaluating the methods by which we classify their industrial organization in testing theories.[16] With that being said, in order to provide adequate background on the specific tests being implemented in this paper, and in order to fully appreciate the overall complexity of merger research, it is also necessary to discuss the existing evidence on the value of corporate diversification and on the sources of gains in mergers.

When reviewing the literature on both of these topics, two main observations begin to emerge. First, it becomes clear that the proliferation of merger-based research across a wide range of disciplines (for instance, finance, economics, strategy, management, psychology, and accounting) has significantly deepened our understanding of both the behavior and the consequences of mergers.[17] Second however, it becomes clear that there is still much more to be learned in both of these areas. Becher et al. (2012) sum up much of what we know by commenting on the "stylized facts" established thus far: "On average, targets gain, bidders lose or break even and merged firms returns are positive." Others, such as Jensen and Ruback (1983), point to the unfinished nature of merger research by commenting that many questions remain about the fundamental drivers of value in mergers. These authors, quite famously, allude

[16] Again, see *table 1* for a breakdown of these current methods, including a list of relevant literature.
[17] For a review of the merger literature see classic reviews by Jensen & Ruback (1983) or Jarrell et al. (1988). For more recent reviews see, for instance, Andrade et al. (2001), Martynova & Renneboog (2008), or Haleblian et al. (2009).

to the fickle nature of merger research in general and conclude that studies which look at abnormal returns to merger participants in isolation (i.e. not across industrial organization type, characteristics, etc.) will at times not be able to distinguish between competing theories. The rest of this chapter outlines the existing empirical evidence on both of the major theoretical debates being considered in this paper and briefly discusses my proposed contribution.[18]

3.1 Existing Evidence on the Value of Corporate Diversification

Many of the questions related to the value of corporate diversification, despite the popularity of the topic, appear to still be relatively unresolved. Early research on corporate diversification seemed to reach a (general) consensus on its value-destroying effects. Wernerfelt & Montgomery (1988), Lang & Stulz (1996), and Berger & Ofek (1995), for example, evaluate diversification's effect on Tobin's Q (or similar performance measures) and find a negative relationship. Similarly, Gillan et al. (2000), conduct an in-depth study of the highly publicized corporate restructuring taking place at Sears, Roebuck & Co. during the 1980's and early 1990's and find that "homemade diversification at the investor level would have outperformed Sears' corporate diversification program." As Martin & Sayrak (2003) point out, corporate diversification eventually received such a "bad rap" that popular MBA textbooks such as Ross et al. (1999, p.775) and Brealey and Myers (2000, p.946) espoused, "diversification, by itself, cannot produce increases in value" and "diversification is easier and cheaper for the stockholder than the corporation."

More recently, studies such as those by Graham et al. (2002), Chevalier (2004), and others have highlighted the inherent difficulty of research in this area and have provided a basis for rethinking our view on the value effects of corporate diversification. Graham et al. (2002), for instance, find that the so-called "diversification discount" does not persist once we control for

[18] For a preview of some of the literature that is relevant to the analysis in this paper see *table 4*.

the fact that targets are in fact already being purchased at a discount. Similarly, some of the latest studies, such as those by Villalonga (2004) and Borghesi (2007), point out other methodological issues that could be clouding results and provide evidence of a need for new and innovative ways to solve this corporate diversification debate.

Such innovation could come in the form of an old finance friend- the event study. In general, standard event study analysis in the corporate diversification realm seems to have been used to a lesser degree than with research in other areas of finance. Notable exceptions include event studies such as those outlined in *table 4* by Morck et al. (1990), Kaplan & Wesibach (1992), and Chevalier (2004). While these studies provide conflicting results in terms of the value of corporate diversification, they are examples of ways in which we can measure diversification's effect without relying on potentially misleading accounting information. Further, extension of event study analysis to include classification of merger industrial organization type should lead to more easily translatable results than with these previous studies.[19]

3.2 Existing Evidence on the Synergy & Collusion Hypotheses

Staying consistent with finance fundamentals, rankings of what is known about the sources of merger gains is strictly relative to what is known about merger outcomes. In other words, our understanding of the causes and sources of gains in mergers, while incomplete, is still considerably developed. In particular, and most relevant to the analysis in this paper, there is much empirical work that uses event study methodology to attempt to parse out support for different theories in this area.[20] Singal (1996), for instance, evaluates the stock market response to 14 airline mergers during a period of low regulation from 1985 to 1988 and finds enough

[19] For instance, by fully partitioning my sample into vertical, horizontal, and conglomerate mergers I am able to posit answers to the *relative* value of corporate diversification.
[20] *Table 4* maps out a sample of such studies.

evidence in support of the collusion hypothesis to conclude that "a selective tightening of the antitrust policy governing airline mergers may have enhanced consumer welfare." More recently, Becher et al. (2012), use both stock and product market data to analyze a comprehensive sample of 384 utility mergers from 1980 to 2004. Their results provide compelling evidence that is "consistent with the synergy hypotheses and inconsistent with collusion." Similarly, but this time in a multi-industry test of a broader set of theories, Mulherin & Boone (2000) couple acquisitions and divestitures during the period from 1989 to 1999 and again employ an event study analysis to produce results consistent with a range of value-enhancing merger theories similar to those emanating from Coase (1937). Additional analyses of the kind outlined above are detailed in *table 4,* and include studies by Eckbo (1983), Bradley et al. (1988), Slovin et al. (1991), Fee & Thomas (2004), and Fan & Goyal (2006).[21]

3.3 Summary of Proposed Empirical Contribution

A common strain in the above analyses, both in terms of research on the value of corporate diversification and on the sources of merger gains, is that they do not focus on a period following the 2007 to 2009 financial crisis, and they do not explicitly segment their study into vertical, horizontal, and conglomerate classifications. In this paper, I address a post-crisis time period, and I implement an event study approach that analyzes mergers independently across industrial organization type while using multiple methods of industrial organization classification. In doing so, I am in fact able to make contributions that expand beyond the purview of issues relating to merger classification and that directly relate to two major ongoing theoretical debates within the corporate finance literature. Specifically, I am able to provide an

[21] The reader may note the relatively small sample sizes recorded for the Slovin et al. (1991) and Singal (1996) studies in *table 4* (both of which provide support for the collusion hypothesis). This is no accident, as both of these studies focus on a single industry (airline). As Becher et al. (2012) point out, this single industry approach is implemented in these cases so as to more precisely define firm rivals by avoiding SIC-based methods of rival classification.

updated multi-industry test of the synergy and the collusion hypotheses, and I am able to extend the work of Kuppuswamy and Villalonga (2010) by analyzing whether or not corporate diversification has continued its ascent into favor during the years following the 2007 to 2009 financial crisis.

CHAPTER 4

DATA AND SAMPLING

4.1 Description of Sampling Procedure

I investigate domestic (U.S.) mergers and acquisitions from 1/01/2011-1/01/2014 using data reported by Securities Data Corp (SDC).[22] I include only those deals that were ultimately completed and require both the bidder and target firms to be publically listed (so as to try to ensure retrieval of stock price data from CRSP). Following methodology similar to that of Becher et al. (2012), I restrict my results to include only those deals in which the bidder acquired 50% or more of the target firm. This approach is helpful in my case for several reasons. First, it allows me to construct a more manageable dataset, which in turn enables me to implement a Human Eye method of industrial organization classification that is based on the highest level of merger-by-merger scrutiny. Second, and along the same lines, it ensures that the events that I am analyzing represent material strategic decisions for the participating firms (i.e. a target accepting acquisition of 1% of its company probably is not representative of the type of focused decision making that I am looking to evaluate in this analysis). Lastly, consistent with Fan & Goyal (2006), I exclude financial service firms from my analysis. This, again, is done for several reasons. It further manages the size of my dataset, and also allows me to focus on the causes of mergers in the context of more "typical" industries where some of the motives for the deals may be less opaque.[23] My initial sample consists of 223 domestic mergers. Following a merging of

[22] "U.S. merger" classified via SDC standards (i.e. if the target is a U.S. firm).

[23] Ultimately it would be interesting for future researchers to have three separate samples: financial services excluded, financial services included, and financial services only. This should allow some additional analysis that

SDC data with data available from the Center for Research in Security Prices (CRSP), the final sample size used in my event study analysis includes 180, 178, and 152 mergers for evaluating target, bidder, and combined firm returns respectively.[24]

4.2 A Note on Detail

As already alluded to, the manageable size of my overall dataset is consistent with the sample sizes of many previous merger-related studies, and it allows me to seek explicit detail in my classification of merger industrial organization.[25] The value of detail has been demonstrated in the finance literature through studies such as those of Boone & Mulherin (2007 & 2011). These researchers use a detailed analysis of merger documents, similar to the one being implemented in this paper, to provide new and corrected evidence on the takeover process and the parties that participate in it. Such success in terms of applying detailed methods of analysis to heavily researched areas of corporate finance and producing novel findings has undoubtedly served as significant motivation for this current paper. Nevertheless, it is important to pause here and acknowledge the "give-and-take" relationship that exists between seeking detail and generating results that are generalizable to the highest degree. Netter et al. (2011, p.2353) sum this relationship up perfectly and give a good account of how the results within any paper should ultimately be handled: "Detailed data on the firms involved in a transaction can enable a researcher to identify important relations in M&As. However, one must be careful in extending the implications of the work to firms that are not in the samples." As such, though I have judiciously attempted to construct a sample in this study that is both as detailed and as

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will likely prove to be valuable. In particular, including financial services will most certainly increase the number of conglomerate mergers that are in the sample.

[24] For a tabulated account of all the steps in my sampling procedure see *table 5*. Also, for discussion specifically related to the CRSP matching portion of my sampling procedure see footnote 41 on the same page.

[25] In terms of sample size, Bradley et al. (1998) evaluate 236 mergers, Slovin et al. (1991) look at 42, Kaplan & Weisbach (1992) view 282, Singal (1996) considers 14, Chevalier (2004) analyzes 215, Boone & Mulherin (2007) investigate 400, and Becher et al. (2012) study 384.

representative as possible, it is always wise to recognize the possibility that results in empirical studies may not perfectly generalize.

CHAPTER 5

MERGER CLASSIFICATION STRATEGY

5.1 Primary Human Eye Classification Method

Table 1 provides a list and description of the various methods by which mergers can be classified into their vertical, horizontal, and conglomerate industrial organization types.[26] Ultimately, in this study, I implement a Human Eye method of industrial organization classification for my primary analysis that is simple, direct, and detailed. This method is based on reading merger documents for every merger deal within my sample and then classifying each of the deals appropriately based off all the relevant and available information.[27] For nearly every merger in my sample, I am indeed able to make a definitive industrial organization classification on my own by following this method. In the few cases where a definitive classification still eludes me after reading all of the relevant merger documents, I consult an expert from the industry related to the merger in question, and together, we reach a definitive classification.[28] Illustrations of my Human Eye method "in action" will be presented in *section 5.3* of this chapter.

[26] See also the discussion in the introduction of this paper on the literature related to industrial organization classification.

[27] This includes reading information from 10-K & 8-K filings, news articles, Prem14a filings, industry & product descriptions, etc. In some ways, this method of analysis is likely similar to the process used by many market participants, including regulatory and industry analysts.

[28] This measure was necessary in a very few number of cases where I felt that the complexity of the industry underlying the merger warranted a second opinion. For instance, I consulted a computer software expert in classifying the merger between Oracle and Acme Packet on March 28, 2013, because I felt that, even after reading extensive information about the merger, I still did not adequately understand the underlying technology that shaped the deal itself. Similarly, I consulted an expert on the pharmaceutical industry in order to solidify my classifications in some of the more opaquely constructed pharmaceutical mergers. In general, expert classifications ultimately turned out to be in line with my initial intuition, but nevertheless, conferring with an expert when classifications were in question can be viewed as a significant step taken to ensure that the Human Eye method of classification implemented in this paper was as accurate as possible.

5.2 Secondary SIC/IO Classification Method

As stated in the introduction, I also conduct secondary analysis in this paper using the popular SIC/IO method of industrial organization classification so that the results obtained under this method can be directly compared to those obtained under the primary Human Eye method of classifying industrial organization. In implementing the SIC/IO method, I follow the methodology of Fan & Goyal (2006) and first calculate a "vertical relatedness coefficient" (VRC) to define the degree of vertical relatedness between each pair of merging firms in my sample. The VRC for each merger pair is calculated based off of figures reported in the 2007 Direct Requirements Table of the newly integrated Annual Industry Accounts for the U.S. Economy.[29] This table is published by the Bureau of Economic Analysis (BEA) and reports commodity flow information between 388 individual BEA industries. Specifically, the Direct Requirements Table reports for each pair of industries, *i* and *j*, the dollar value of industry *i'*s output that is required to produce one dollar's worth of industry *j'*s output as well as the dollar value of industry *j'*s output that is required to produce one dollar's worth of industry *i'*s output. For the purposes of this paper, I will mimic the terminology of Fan & Goyal (2006) and call these entries in the Direct Requirements Table the "input requirement coefficients" and denote them as V_{ij} and V_{ji} respectively.

To calculate the VRC for each merger pair in my sample, I first must ensure that the industry information for my target and bidder firms is expressed in terms of BEA industries. To do this, I complete a step-by-step process of converting from SIC codes, to NAICS codes, to BEA codes using concordance tables provided by the United States Census Bureau and the

[29] The Direct Requirements Table from 2007 is used because this is the most recent year in which data is provided at the detailed 388 firm level. Other studies implementing the SIC/IO method, including all of those previously mentioned in this paper, experience a similar lag between detailed IO data and their sample periods. As outlined in *table 1*, this is in fact one of the inherent costs of using the SIC/IO method.

BEA.[30] Next, I finally calculate the VRC for each merger pair in my sample by taking the maximum of their two corresponding industry input requirement coefficients (or in notational form: VRC = max{V_{ij}, V_{ji}}).[31] Once the VRC's are calculated, I then follow the procedure used by Fan & Goyal (2006) and classify each merger in my sample as vertical if the target and bidder firms have a VRC greater than my required vertical relatedness cutoff, horizontal if they belong to the same BEA industry and do not have a VRC that exceeds my required cutoff, and conglomerate if they belong to different BEA industries and do not have a VRC that exceeds my required cutoff. In the interest of thoroughness and in order to eventually make additional comparisons, I consider three different vertical relatedness cutoffs when making my industrial organization classifications (at the 1%, 5%, and 10% levels).

For a demonstration of how the SIC/IO method works, consider the merger between Time Warner Cable (TWC) (BEA industry code: 517110) and NaviSite Inc. (NAVI) (BEA industry code: 54151A) in February of 2011. *Table 6* provides a simplified version of the information for this merger as it would appear in the BEA's Direct Requirement table. If we label TWC's industry as industry *i* and NAVI's industry as industry *j*, then we observe that the two relevant input requirement coefficients (V_{ij} & V_{ji}) are .012003 and .0015119 respectively.[32] Consistent with the discussion above, the VRC for these two merging firms is then equal to the larger of the two input requirement coefficients- or .012003. In order to classify this merger into

[30] This conversion process is very similar to the one used in Fan & Goyal (2006) as well as the other SIC/IO-based studies mentioned in this paper.

[31] This is the form of VRC calculation famously implemented by Fan & Goyal (2006). Other researchers have favored calculating the VRC as the equally weighted average of the two input requirement coefficients. In general, given the use of multiple vertical relatedness cutoffs in most SIC/IO studies, it is doubtful that the method of calculating the VRC ultimately has a large impact on overall empirical results, but it may be nonetheless interesting for future researchers to consider that the most logical way of calculating the VRC might be to simply *sum* the two input requirement coefficients. This calculation strategy would seem to better account for the fact that when companies decide to make vertical acquisitions, they are likely often inspired to do so by vertical integration opportunities in *both* directions.

[32] In words, this means that 1.2 cents worth of the output from TWC's industry is required to produce a dollar's amount of output for NAVI's industry. Likewise then, less than one –tenth of one cent of the output from NAVI's industry is required to produce a dollar's amount of output for TWC's industry.

its industrial organization type at the 1%, 5%, and 10% vertical relatedness cutoff levels, we then simply compare the VRC to each stated cutoff level. Because the two firms in this merger are from different BEA industries, we are left to choose between a vertical or conglomerate classification- if the VRC is greater than the specified cutoff we classify the merger as vertical, if it is below, we classify the merger as conglomerate. The SIC/IO method of industrial organization classification thus classifies this merger as vertical, conglomerate, or conglomerate depending on whether a 1%, 5%, or 10% vertical relatedness cutoff is implemented.[33]

5.3 Demonstrations of Classification Methods "In Action"

My primary method of Human Eye classification, as well as some of the differences it displays with the other methods of industrial organization classification like the SIC/IO method, may best be demonstrated with a few examples.[34] Let's first consider my method in classifying the merger between General Dynamics Corp. (GD) and Force Protection Inc. (FRPT) in late 2011. GD has a primary SIC (BEA) code of 3812 (334511) while FRPT has a primary SIC (BEA) code of 3711 (336992). Right away, observe that under an industry-based method relying strictly on SIC codes, this merger is immediately classified as non-horizontal or diversifying. Also, note that these two companies have a vertical relatedness coefficient of zero, and that this merger is therefore even more finely classified as conglomerate under the SIC/IO method of classification.[35] Turning to a Human Eye method of classification however, the transaction is examined in more detail to make a definitive classification. Reading through press releases related to the merger indicates that GD and FRPT are strict rivals, and that they both compete

[33] This is one of the many instances I discovered in my sample where industrial organization classifications based on the SIC/IO method are dependent upon the vertical relatedness cutoff being used. As expressed in *table 1*, this is potentially a significant downside of the SIC/IO method of classification.

[34] An outline of such examples can also be referred to in *table 7*.

[35] Given the fact that the two firms do also turn out to have varying BEA codes (given in parentheses) after the SIC conversion process

heavily in the “tracked and wheeled military vehicle” market, which is the market that the deal appears to be centered around. Such detail clearly signals to me that the merger is horizontal, and so it is classified as such.

Next, let’s consider a more peculiar example- the deal between Express Scripts Inc. (ESRX) and Medco Health Solutions Inc. (MHS) in the summer of 2011. ESRX has a primary SIC (BEA) code of 5122 (4A0000) while MHS has a primary SIC (BEA) code of 8099 (621900). In almost any application of an exclusively industry-based method, this merger is swiftly classified as diversifying. Likewise, with divergent target/bidder BEA codes and a VRC of 0.001167, the SIC/IO method classifies this merger as conglomerate at any realistic vertical relatedness cutoff level. Turning to a Human Eye method of classification however, merger documents are again consulted and another definitive merger classification is reached. Reading through relevant merger documents reveals that these two companies are “two of the largest pharmacy benefit managers in the U.S.” and that the merger has significant antitrust concerns.[36] Such detail immediately leads to a horizontal classification for the merger under a Human Eye method.

Lastly, let’s consider one final example in which the Human Eye method produces a vertical industrial organization classification. This time, the deal is between Kindred Healthcare Inc. (KND) and RehabCare Group Inc. (RHB) in February of 2011. KND has a primary SIC (BEA) code of 8051 (623A00), RHB has a primary SIC (BEA) code of 8062 (622000), and the VRC for this deal is zero. In this merger, a strictly industry-based method of industrial organization classification yields different results depending on whether two-digit or four-digit SIC codes are being used to make classifications. If two-digit SIC codes are being utilized, then the two firms are identified as having identical industry codes, and the deal is classified as

[36] The ultimate FTC approval for this merger was in fact not unanimous.

horizontal. Contrastingly, if four-digit SIC codes are being used, then the industry codes are recognized as different, and the merger is classified as non-horizontal or diversifying. The SIC/IO method, due to a zero VRC and differing target/bidder BEA codes, immediately classifies this merger as conglomerate.[37] As for a Human Eye method of classification, analysis of merger documents exposes the fact that Kindred Healthcare is an acute-care hospital that has a history of providing a pipeline of patients to outpatient facilities such as the centers run by RehabCare Group. As one healthcare industry expert remarked to me upon reading the details of the merger, "This is as clear a vertical relationship as it gets." Thus, in this case, a Human Eye method of classifying the industrial organization of mergers yields a rather decisive vertical classification.

5.4 Summary of Merger Classification Strategy

In this paper, I implement two methods of classifying the industrial organization of corporate mergers. A Human Eye method is used as my primary method, and the SIC/IO method (at 1%, 5%, & 10% cutoff levels) is used as my secondary method for ultimate comparison. My Human Eye method of classification relies on reading relevant merger documents for context and making the appropriate classification. The SIC/IO method on the other hand, is based on the work of Fan & Lang (2000), Fan & Goyal (2006), Acemoglu et al. (2009), Kedia et al. (2011), and others, and uses input-output data from the Bureau of Economic Analysis (BEA) in order to make industrial organization classifications. The next chapter will discuss in more detail the distributional and statistical characteristics of the classifications attained under each of these methods.

[37] Note that the two firms, despite having identical *two-digit* SIC codes, do turn out to have different BEA codes.

CHAPTER 6

SUMMARY STATISTICS

6.1 Sample Distribution

Table 8 presents a breakdown of the sample of 223 mergers by year. *Panel A* displays the distribution for the entire sample, while *Panel B* through *Panel E* lay forth the yearly distributional breakdown for vertical, horizontal, and conglomerate type mergers as classified under a Human Eye method and SIC/IO method of industrial organization classification. In general terms, there appears to be an uptick of mergers in 2012 compared to 2011 and 2013. More careful comparison of the summary results exhibited in *Panel B* through *Panel E,* however, quickly reveals significant differences between my primary and secondary methods of merger classification. For instance, horizontal mergers make up 64% of the total mergers in the sample according to a primary Human Eye method of classification whereas they compose 14%, 34%, and 39% of the sample according to the secondary SIC/IO method at its 1%, 5% and 10% vertical relatedness cutoff levels.[38] Similar differences can be observed when comparing vertical and conglomerate classifications across the two methods (15% vs. 42%, 15%, or 7%, and 21% vs. 43%, 52%, or 53%), or when comparing intra-year reported figures between the two.

6.2 Cross Tabulations between Human Eye and SIC/IO Classifications

Moving to *table 9*, cross tabulations between my Human Eye method and the SIC/IO method illustrate a less than stellar degree of overlap in their industrial organization classifications. Of the 223 mergers in my 2011 through 2013 sample, a Human Eye method classifies 143 as horizontal, 34 as vertical, and 46 as conglomerate. Of the 143 classified as

[38] This is represents a potential discrepancy of 50%!

horizontal by a Human Eye method, the SIC/IO method classifies 28 (20%), 68 (48%), or 81 (57%) as horizontal, 81(57%), 31 (22%), or 16 (11%) as vertical, and 34 (24%), 44 (31%), or 46 (32%) as conglomerate- depending on whether a 1%, 5%, or 10% vertical relatedness cutoff is being implemented. These figures illustrate a potentially pervasive misclassification between horizontal and vertical/conglomerate mergers, but also show that a huge improvement in the overlap of horizontal classifications between these two methods is achieved by moving from a 1% cutoff level to a 5% cutoff level in the SIC/IO method. Next, moving to another major classification disparity observed in my sample, the 34 mergers classified as vertically oriented by a Human Eye method are largely classified as conglomerate by the SIC/IO method- with 20 (59%), 25 (74%), and 27 (79%) earning a conglomerate designation at the 1%, 5%, and 10% vertical relatedness cutoff levels respectively. Again however, a fairly significant improvement in the overlap between the two classification methods appears to take place upon moving up the vertical relatedness cutoff ladder from 1% to 5%. Finally, in terms of the 46 mergers classified as conglomerate under a Human Eye method, nearly all of them are likewise classified as conglomerate under the SIC/IO method, regardless of what cutoff level is being implemented.[39]

6.3 Sample Statistics

Table 10 reports attributes of the 223 mergers within my 2011 through 2013 sample. *Panel A* displays summary statistics for the entire sample, while *Panel B* through *Panel E* exhibit summary statistics for vertical, horizontal, and conglomerate merger types as identified by a Human Eye method and SIC/IO method of industrial organization classification. Beginning with *Panel A*, the mean transaction value for the entire sample of mergers is $2.16 billion and 222 of

[39] Unfortunately, this fact is of only minor consolation given the previously discussed discrepancies discovered between the other two classification types. For examples of some of the inconsistencies described in this section refer to *table 7*.

the total 223 the deals are classified as "friendly" via SDC standards.[40] The average number of segments added for mergers in the total sample is .62, indicating that, on average, bidders during this 2011 through 2013 period acquired less than one COMPUSTAT business segment by merging with targets. This relatively low "segments added" figure is consistent with the aforementioned distributional results displayed in *table 8* in which over 60% of the mergers are classified as horizontal using a Human Eye method. Also notable from *Panel A*, is that 62% of the mergers are pure cash deals which is a bit of an increase compared to studies from previous periods such as Moeller et al. (2005) or Andrade et al. (2001), which document a proportion closer to around 30-40%.

Moving to *Panel B* of *table 10* offers opportunity for an assessment of how each type of merger, as classified under my primary Human Eye method, differs in makeup. Horizontal mergers have the highest average transaction value over the sample at just over $2.3 billion, while conglomerate mergers follow closely with an average value of $2.2 billion, and vertical mergers lag behind at $1.3 billion.[41] Results for the average number of segments added per merger type are consistent with expectations. Horizontal mergers average .4 segments around the transaction, while vertical mergers average slightly more at .76 segments added and conglomerate mergers average the most at 1.23 segments added.[42] Additional items of interest displayed in *Panel B* include a slightly higher proportion of "cash only" deals observed for vertical and conglomerate mergers as compared to horizontal mergers. In fact, a regression of "cash only" consideration structure on merger industrial organization type yields results,

[40] This "friendly setting" is consistent with prior literature that documents a drastic decrease in the occurrence of hostile takeovers (e.g. Holmstrom and Kaplan (2001)).
[41] *Panel B* of t*able 16* displays results from a regression of (log) transaction value on merger type- both before and after controlling for other explanatory factors. In both cases, no significant relationship between merger type and (log) transaction value is found.
[42] The interested reader may note the positive average "segments added" figure for horizontal mergers and wonder why it is not zero. This is due to the general complexity in the makeup of the modern corporation- often, even a firm's closest related rival may differ in terms of what secondary industry segments they operate within.

displayed in *Panel A* of *table 16*, that suggest that horizontal merger type does indeed have a significantly negative linear relationship with "cash only" consideration structure after controlling for other possible determinants of merger consideration structure.[43]

It is also interesting to observe differences in the summary statistics received from using a Human Eye method of industrial organization classification and those obtained under the SIC/IO method. Secondary industrial organization classifications based on the SIC/IO method produce results (*Panels C-E* of *table 10*) in which horizontal, vertical, and conglomerate mergers display a different type of "segments added" relationship than they did under a Human Eye method. In particular, though conglomerate mergers continue to average the highest number of segments added under this secondary classification method, horizontal mergers actually register a higher average number of added segments than do vertical mergers.[44] Additional items of note gathered from a comparison of *Panel B* with *Panels C* through *E* of *table 10*, include figures which report a general increase in the average transaction value for vertical mergers when classified under the SIC/IO method, and summary statistics across industrial organization type that fluctuate within the SIC/IO method based on what vertical relatedness cutoff is used.

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[43] Two separate regressions are run- one with no controls and one controlling for transaction value as well as year and industry effects. In both instances, the coefficient on horizontal deal type is significant at a 5% level.

[44] It is thus notable that results derived from using a document-based method of industrial organization classification, such as a Human Eye method, appear to be more consistent with expectations than those generated by the SIC/IO method, in that they yield more discernable cuts between merger type in terms of "segments added" (at least in terms of my sample).

CHAPTER 7

ANALYSIS

7.1 Summary of Methodology

Each of the merger theories being evaluated in this paper generates testable hypotheses in terms of the stock market's response to the news of a particular type of merger announcement. As such, in order to differentiate between these theories, I conduct a basic event study analysis on the mergers in my sample to calculate abnormal returns to shareholders of the target, bidder, and combined firms upon announcement of each merger deal. I also extend this event study analysis to include an evaluation of rival firms so as to try to distinguish between the synergy and collusion hypotheses on the sources of gains in mergers. In order to make additional meaningful comparisons, I then partition my analysis even further by calculating the abnormal returns across vertical, horizontal, and conglomerate merger classifications- using the Human Eye method for primary analysis and the SIC/IO method at its 1%, 5%, and 10% vertical relatedness cutoff levels for secondary analysis. Primary and secondary analysis is presented in *table 11* and *table 12* respectively and is based off of a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. Analysis of industry rivals is presented in *table 13* and *table 14* and is based off of a similar (-1,+1) window.[45] Robustness checks for the primary and secondary analysis, as well for the analysis of industry rivals, are provided in *table 15* and involve evaluating abnormal returns based off of alternative (-2,+2) and (-5,+5) windows, where, again, day 0 is the merger announcement date as reported by SDC.

[45] Rival firms are defined, in a manner similar to that described in Song & Walkling (2000), as those firms classified by CRSP as belonging to the same SIC industry as the target firm on the date of merger announcement.

7.2 Calculating CARs

In the interest of thoroughness and completeness, cumulative abnormal returns (CARs) are calculated using three different measures: “Raw Returns,” “Net of Market” returns, and “Market Model” returns. “Raw Returns” are simply calculated as the cumulative returns over the event window (i.e. with expected returns equal to zero). “Net of Market” abnormal returns are calculated by subtracting expected returns on the CRSP value-weighted index over the event window from the “Raw Returns” experienced by the merging firm in question. “Market Model” abnormal returns are calculated by subtracting each individual security’s expected return based on the so-called “empirical CAPM” from the “Raw Returns” experienced over the event period, where the expected returns from the “empirical CAPM” are estimated with a (-255,-22) estimation period. In general, and as is usually the case in event studies with short windows, the inferences made from the results in this analysis do not change based on the return measure being utilized.[46]

[46] The reader will note that *table 15* reports only the “Market Model” returns. This is done in the interest of space, and as noted, the results are qualitatively similar using either of the other two return measures.

CHAPTER 8

RESULTS

Primary results from the event study analysis are presented in *table 11*. *Panel A* displays the announcement returns for the entire sample, partitioned to display CARs for the combined, bidder, and target firms respectively, while *Panel B* lays forth similar tables for vertical, horizontal, and conglomerate mergers as classified under a Human Eye method of industrial organization classification. Secondary event study results, based on classifications made under the SIC/IO method, are likewise presented in *table 12* with *Panels A, B, and C* corresponding to the 1%, 5%, and 10% vertical relatedness cutoff levels respectively. Results from primary and secondary analysis of rival firms are similarly presented in *table 13* and *table 14*, and robustness results for all of the analyses are offered in *table 15*.[47]

8.1 Merger Wealth Effects in Recent Time Periods

Evaluation of *Panel A* in *table 11* is directly relevant in gaining insight on the equity-wealth effects of mergers in the most recent 2011 through 2013 post-crisis period. Tabulated results reveal a combined firm average abnormal return of 6.1%, a bidder average abnormal return of 1.4%, and a target average abnormal return of 29.5% over this 2011 through 2013 time period. It is particularly interesting to note that bidder returns during this sample period are significantly positive, which is contrary to the findings of numerous studies conducted on previous time periods documenting significantly negative bidder returns in mergers. Moeller et al. (2005), for instance, document negative returns of $.12, or $240 billion in aggregate losses,

[47] Note that no explicit section in the results is ultimately devoted to discussing robustness analysis, but that inference from primary and secondary event study analysis is indeed quite similar under either of the two alternative (-2,+2) , (-5,+5) windows.

for bidder shareholders around merger announcement in their analysis of mergers from 1998 to 2001. Likewise, Andrade et al. (2001) document average CARs for bidders from 1973 to 1998 to be -.7% over a (-1,+1) event study window. In this recent sample of mergers, the average abnormal return to bidders is not only significantly positive, but the median is positive as well, and greater than half of the bidders in the sample actually earn positive abnormal returns around the announcement of the merger. Along similar lines, it is also notable then that the average abnormal return to the combined firms in my sample, at around 6%, is also higher than that documented in previous studies. Prior studies, such as (again) Andrade et al. (2001), do document positive combined firm returns, but at a level closer to around 1-2%. In total, basic event study analysis conducted on my 2011 through 2013 sample of mergers provides evidence that the wealth effects of corporate mergers may have undergone significant changes in the most recent, post-crisis time period.

8.2 The Value of Corporate Diversification

When determining the value of any action or item, it is always important to make two separate, but equally fundamental, judgments. First, the action or item should be evaluated based on its absolute return, that is, it should pass the most basic test of worth: does it create value? Once the action or item has been tested in terms of this necessary condition for worth however, it should ideally then be subjected to a second, more sufficient, valuation test: does it create more value than other available actions or items? It is only after passing the second of these tests that an action or item can be declared value-enhancing on a relative basis.

The results in *Panel B* of *table 11* provide figures upon which to conduct both of the aforementioned "tests" in determining the value of corporate diversification during the most recent post-crisis period. Combined firm returns reported in *Panel B* indicate that conglomerate (diversifying) mergers do not generate positive announcement returns that are statistically different from zero at a 10% level of significance. On the other hand, even though, at 4%, the average abnormal returns are not significantly positive in a statistical sense, they do nothing to indicate that corporate diversification is value-destroying on any sort of absolute level. As such, and as consistent with financial theory, analysis moves to valuing corporate diversification on a relative basis by evaluating how conglomerate mergers fare compared to the other two industrial organization types.[48]

Panel B of *table 11* also lists the combined firm returns for horizontal and vertical mergers in my sample. For both types of merger, combined firm average abnormal returns are significantly positive at 6.6%. Also, over 75% of the deals in either industrial organization classification actually produce combined returns greater than zero. Though the returns across all three merger types do not display a precise "walking down" relationship (i.e. horizontal returns > vertical returns > conglomerate returns), the fact that abnormal returns for combined firms in conglomerate mergers are incrementally less than those for combined firms in vertical and horizontal mergers does, at first glance, appear to satisfy the most critical condition for relative value-destruction. In total however, the difference of 2.8% in CARs between diversifying and non-diversifying mergers turns out not to be statistically significant at a 10% level, and so there in fact does not appear to be any strong evidence pointing to corporate diversification being value-destroying for firms in my sample (even in a relative sense).[49]

[48] I.e. analysis moves to addressing the second part of *Panel A* in *table 3*.
[49] Regression results presented in *Panel C* of *table 16* also suggest that there is no difference between vertical/horizontal mergers and conglomerate mergers in terms of their differential effect on combined firm CARs (either before or after controlling for other factors driving returns).

8.3 Synergy vs. Collusion Hypothesis

Table 13, in addition to *Panel A* of *table 11*, displays information relevant to the debate over the sources of gains in mergers. First, as reported in *Panel A* of *table 11*, primary event study analysis of the merging firms within my sample reveals that the average combined firm experiences a statistically positive 6.1% uptick in shareholder value upon the announcement of the merger. These results are consistent with a range of value-enhancing merger theories- including the synergy and collusion hypotheses.[50] Next then, in order to try and distinguish between these two hypotheses, results in *table 13* from an event study analysis of rival firms are consulted. Average abnormal returns for the entire set of rival firms in my sample are significantly positive at 1.6%. Further, average abnormal returns to the rivals of horizontally merging firms are significantly positive as well at 1.2%. This result is inconsistent with the predictions of the synergy hypothesis, and consistent with those of the collusion hypothesis. Returns to rivals in horizontal deals however, are not statistically higher than returns to the rivals in non-horizontal deals (they are, in fact, qualitatively smaller). This result would seem to indicate that the collusion hypothesis also cannot fully characterize the wealth effects of mergers in my sample and that another channel of value-creation may have been active in my post-crisis sample period.[51]

8.4 Comparison of Primary and Secondary Results

Secondary event study results based on the SIC/IO method of industrial organization classification are contained in t*able 12* and *table 14* and are meant to provide a comparison of

[50] I.e. the first order condition for both theories, as described in part 1 of *Panel A* in *table 3*, is satisfied.

[51] For instance, one theory on the sources of merger gains which has garnered recent support is the "anticipation hypothesis" (see, for instance, Song & Walkling, 2000 or Becher et al., 2012). While the collusion hypothesis would predict that rival returns are highest in horizontally related mergers due to the fact that is where the collusive effects of increased industry concentration should be felt the most, the anticipation hypothesis makes no such prediction.

methodologies in the context of explicit empirical testing. Overall inferences drawn from this secondary analysis in terms of the value of corporate diversification and the sources of gains in mergers are relatively similar to those obtained in the primary analysis, but some significant differences do exist. In regards to the value of corporate diversification, results displayed in *table 12* indicate that combined firm returns in conglomerate mergers, as defined by the SIC/IO method at any of its cutoff levels, are significantly positive at around 4.2%. This is in slight contrast to the primary event study results where combined firm returns in conglomerate mergers were qualitatively, though not statistically, greater than zero. Additionally, whereas no significant difference was found between conglomerate and non-conglomerate combined firm returns in the primary analysis, a difference in means test conducted to compare these two groups as defined under the SIC/IO method does identify returns to the combined firm in conglomerate mergers as significantly lower.[52] In total, results from secondary analysis provide stronger evidence than those from primary analysis that corporate diversification is value-enhancing on an absolute level, while also providing slightly different evidence in terms of corporate diversification's value on a relative basis.[53]

Next, moving to inferences regarding the sources of gains in mergers, *table 14* reports results from a secondary event study analysis of rival firms that again reject the synergy hypothesis but have slightly different implications in terms of the collusion hypothesis. This time, under an SIC/IO method of industrial organization classification, returns to the rival firms in horizontal mergers (at around 2%) are indeed qualitatively greater than those to rival firms in non-horizontal deals. These secondary results thus provide evidence that is potentially more

[52] Though, interestingly, this test does not hold at a 5% level significance for every vertical relatedness cutoff level.
[53] Note that still no direct conclusion of relative value-destruction can be reached under this secondary analysis because the combined firm returns in conglomerate merges do not display the exact "walking-down" relationship with corporate diversification that is predicted in *Panel B* of *table 3*.

consistent with the collusion hypothesis than results reached under primary analysis. Ultimately, when taken together, the reported figures in *table 12* and *table 14* provide evidence that in some cases of analysis, a significant difference does indeed exist between using a document-based method such as a Human Eye method of industrial organization classification and a method based on fixed industry codes such as the SIC/IO method.

CHAPTER 9

SUMMARY AND CONCLUSIONS

For most companies, engaging in a corporate merger is the single largest event in their economic lives. As such, it comes as no surprise that economic events centered on corporate restructuring garner an almost unparalleled amount of public, academic, industry, and indeed, regulatory attention. In terms of merger research, having such a broad set of interested parties, coupled with the inherently complex nature of mergers themselves, has meant not just that researchers have had a bevy of empirical questions to address, but also that they have been forced to seek constant evolution and innovation in their methodological approaches in order to continue to provide best answers.

In this paper, I add to the methodological and empirical literature on corporate mergers by conducting an event study analysis of 223 (U.S.) domestic mergers taking place during the most recent 2011 through 2013 post-crisis period. I use a primary Human Eye method and secondary SIC/IO method of industrial organization classification in order to categorize my sample into horizontal, vertical, and conglomerate mergers, and I then compare the equity-wealth effects between merger types and the empirical results across classification methods. I find that combined firm abnormal returns for conglomerate mergers are nonnegative in the most recent period under a Human Eye method of merger classification, and significantly positive under the SIC/IO method. These results are not at all consistent with value-decreasing theories of corporate diversification. Further, I find that the mergers in my sample (overall and for the horizontal sub-sample) create wealth for the combined, bidder, and target firm, which is consistent with both the synergy and collusion hypotheses of merger value creation. In order to distinguish between these two hypotheses, I employ the popular approach of Eckbo (1983) and Stillman (1983) and evaluate abnormal returns to the rivals of my merging firms. Rival firm abnormal returns are significantly positive, a result that is inconsistent with the synergy hypothesis. Abnormal stock returns to rival firms in horizontal mergers, however, are not greater than in the other two merger types indicating that the collusion hypothesis also does not fully describe the channels of merger value creation that were active in my post-crisis sample period. Lastly, I find rather stark differences between a document-based, Human Eye method of classifying the industrial organization of mergers and the popular SIC/IO method of classification, as well as intra-method differences within the SIC/IO method depending on whether vertical mergers are defined at a 1%, 5%, or 10% vertical relatedness cutoff. These differences have an effect on statistical inference in some cases, and indicate that additional research on classifying the industrial organization of corporate mergers is warranted.

My results are significant across several dimensions. First, they provide updated evidence on the value of corporate diversification. Kuppuswamy and Villalonga (2010) find that the value of corporate diversification increased *during* the crisis, but note that it remains an open question as to whether or not it this would continue *after* the crisis. This paper helps to answer that question and indicates that corporate diversification, as measured through conglomerate mergers, has maintained its more favorable status. My results also add to the literature on the sources of gains in mergers by providing a multi-industry test of the synergy and collusion hypotheses that is based on a new Human Eye method of classifying the industrial organization of mergers. In their own single-industry analysis on the sources of gains in mergers, Becher et al. (2012) note that multi-industry studies have typically found convincing first-order evidence against the collusion hypothesis. My results thus represent somewhat of a departure from these previous multi-industry findings, and may reflect a change in methodology depending on the extent to which these studies relied upon industrial organization classifications. From a strictly methodological standpoint then, my results have important implications for how researchers classify the industrial organization of mergers. Particularly, they suggest that ongoing research in this area, including evaluating and expanding upon the algorithmic, document-based methods of Hoberg & Phillips (2010) and Frésard, Hoberg, & Phillips (2014), is critical if we are to reach a reliable methodological equilibrium. Lastly, my results have several implications relating to public policy and antitrust. Though the relevant market in an antitrust case is said to be based on a given product in a given region (Baker, 2007), a merger classified as horizontal might undoubtedly garner more attention from antitrust authorities, and thus, my analysis indicates that the choice of classification method made by researchers evaluating these cases could turn out to be a critical factor and even a point of contention.[54]

[54] As an illustration that horizontally classified mergers could indeed face more scrutiny from antitrust authorities, consider again facts previously discussed in the introduction of this paper: The DOJ and FTC have periodically issued guidelines for antitrust evaluation entitled: "*Horizontal* Merger Guidelines." Also, Whinston (2007) in his *Handbook of Industrial Organization*, points out that antitrust laws dealing with collusion are majorly concerned with two things: "price fixing (cartels) and *horizontal mergers*."

TABLES

Table 1- Overview of the Methods Used to Classify the Industrial Organization of Corporate Mergers

Panel A: Industry-level Classification Methods

Panel A provides a discussion of industry-level methods of classifying the industrial organization of corporate mergers. Column 2 offers a summary of each method, columns 3 & 4 list the pros and cons of implementing any one particular method, and column 5 contains selected literature related to each method.

Method of Classifying the Industrial Organization of Corporate Mergers	Summary of Method	Pros	Cons	Selected Studies Using the Method
SIC, NAICS, Value Line, & Other Industry-Based Methods	• SIC, NAICS, Value Line, and other industry codes are used to classify mergers as horizontal and non-horizontal (or "non-diversifying" and "diversifying"). Merging companies with identical industry codes are classified as horizontal.	• Easy to use/implement • Applicable to large datasets	• No way to reliably classify mergers as vertical & conglomerate • SIC industry classifications in particular have historically been rather erroneous and inconsistent	• Eckbo (1985, 1992) • Song & Walkling (2000) • Shahrur (2005) • Becher et al. (2012)
SIC/IO Method	• An extension of the SIC or "industry-based" method. Firms with identical industry codes are again initially classified as horizontal, but commodity flow data from the Bureau of Economic Analysis's (BEA) input-output tables is then used to define the vertical relatedness between merging firms. Vertical, horizontal, and conglomerate classifications are subsequently made.	• Slightly higher startup costs compared to the SIC or "industry-based" method, but still relatively easy to implement • Applicable to large datasets • Provides a programmable heuristic for classifying mergers as vertical & conglomerate	• Classifications vary widely based upon chosen vertical relatedness cutoff • Time-lag in input-output data makes exact year-to-year matching difficult. Researchers may have to accept using input-output data from years "most recent" to their sample. • Classifications still rely on fixed industry codes and thus do not account for idiosyncrasies between firms within an industry. Significant concerns about misclassification therefore still remain.	• Fan & Lang (2000) • Fan & Goyal (2006) • Acemoglu (2009) • Kedia et al. (2011)

Table 1 (cont.)- Overview of the Methods Used to Classify the Industrial Organization of Corporate Mergers

Panel B: Content-based/Firm-specific Classification Methods

Panel B provides a discussion of content-based/firm-specific methods of classifying the industrial organization of corporate mergers. Column 2 offers a summary of each method, columns 3 & 4 list the pros and cons of implementing any one particular method, and column 5 contains selected literature related to each method.

Method of Classifying the Industrial Organization of Corporate Mergers	Summary of Method	Pros	Cons	Selected Studies Using the Method
Hoberg & Phillips (2010, 2014) Text-Based Analysis	• A text-based method of classifying industrial organization. "Web-crawling" and textual analysis software is used to scan firm 10-K filings as well as BEA input-output commodity tables in order to define the horizontal and vertical relatedness of merging firms. Broadly speaking, overlap in unique words used in firms' 10-K product descriptions signals a horizontal relationship, whereas overlap between vocabulary in one firm's 10-K and another's commodity input/output description signals a vertical relationship.	• Applicable to large datasets • Enables vertical, horizontal, and conglomerate classifications to be made on a firm-specific level, rather than on an industry-wide basis, thus potentially avoiding many common pitfalls of analysis based on fixed industry codes • Integrates evaluation of firm production processes AND specific firm products into the classification process • Further integration of the method, such as fusing horizontal and vertical relatedness measures, will undoubtedly ease implementation.	• "Startup costs" are relatively high compared to the previous two industry-based methods. The method is new, and the advanced web-crawling techniques utilized may be a barrier to entry for many researchers. • Analysis of merging firms is restricted solely to information listed in the product and business description portions of firm 10-K filings, ignoring other valuable information contained in press releases, news stories, etc. •Unable to incorporate "context" in its analysis	• Hoberg & Phillips (2009) • Fresard, Hoberg, & Phillips (2014)
Human Eye Method	• Reading of relevant merger documents such as 10-K and 8-K filings, news articles, Prem14a filings, and related industry/product information, as well as possible consultation of industry experts is utilized to classify the industrial organization of corporate mergers.	• Enables detailed classification of mergers into vertical, horizontal, conglomerate, etc. • Classification decisions are made on a merger-by-merger, firm-by-firm, and document-by-document level and are based on context. • Complex deals that may create issues with other classifications can be identified and evaluated in depth to reach the appropriate merger classification. There is no reliance on a programmed heuristic- decisions are made at the highest level of human analytic capability. • Provides a basis of comparison for other, more scalable, methods of classification	• Less translatable to extremely large datasets • Does not provide a "tangible" heuristic that can be universalized	• Ellis (2014)

Table 2- Theory: “The Good, the Bad, and the Why” of Corporate Diversification

Panel A: The “Good” of Corporate Diversification

This table provides an overview of some of the theory on corporate diversification. *Panel A* provides a summary of the potential benefits of corporate diversification as well as a list of selected literature that is related to each major theoretical bullet point.

Potential Benefits	Related Literature
• By combining businesses with less than perfectly correlated cash flows, firms may reduce company-wide cash flow variance (the “co-insurance” effect). o This may increase the debt capacity of the firm, which could lead to increased firm value (depending on the real effects of increased debt capacity). o This also may generally insulate diversified firms from adverse market shocks due to decreased reliance on specific customer, product, labor, and financial markets.	• Lewellen (1971)
• Diversified firms may be able to better fund their own internal capital markets than compared to their focused counterparts. o To the extent that the cost of internally raised capital is less than the cost of raising external funds, this could create value for the firm. o Internal financing may allow managers to utilize their expertise and make independent investment decisions without resorting to the potentially costly process of seeking approval from outside investors who may be comparatively less informed.	• Alchain (1969) • Weston (1970) • Williamson (1975) • Myers & Majluf (1984) • Stein (1997, 2003)
• Economies of scope- the average total cost of production decreases as a result of increasing the number of different goods produced. To the extent that diversified firms are able to capitalize on economies of scope, this could create value.	• Teece (1980)

Table 2 (cont.)- Theory: "The Good, the Bad, and the Why" of Corporate Diversification

Panel B: The "Bad" of Corporate Diversification

This is a continuation of *table 2* that provides an overview of some of the theory on corporate diversification. *Panel B* provides a summary of the potential costs of corporate diversification as well as list of selected literature that is related to each major theoretical bullet point.

Potential Costs	Related Literature
• The increased organizational complexity of diversified firms may increase the potential for organizational inefficiencies and/or lack of corporate focus. o "Cross-subsidization" between segments of a diversified firm may create a situation where laggard segments soak up funding, thus diverting capital away from segments with higher promise. To the extent that this "cross-subsidization" occurs, and to the extent that it is unidirectional in that it diverts funding from healthy to troubled business segments, it could destroy value for diversifying firms. o Diversified firms may (generally) be pulled away from focusing on their core competencies. This, again, could create a scenario where businesses most fundamental to a diversified firm's success do not elicit adequate "attention."	• Jensen (1986) • Berger & Ofek (1995) • Rajan et al. (2000)
• Diversification may increase agency costs within the firm. o Access to internal capital markets may create issues relating to "excess free cash flow." Managers in diversified firms may be able to generate internal funds at a high rate and, with little need to subject themselves to the scrutiny of raising external financing, may overinvest or make otherwise "bad" investments. o Corporate diversification could reduce the efficacy of incentive compensation, as the link between divisional performance and the value of equity compensation packages could become less tangible. To the extent that this diminishing relationship exists, this could lead to an overall loss of firm value. o As organizational complexity increases, diversified firms may encounter issues arising from "managerial entrenchment." That is, "bad managers" may become more difficult to replace in diversified firms because their job may become so complex that finding a suitably informed replacement manager may become difficult. Further, once entrenched, bad managers may continue to increase their perceived marginal value over a replacement by making additional "manager-specific" investments, regardless of the investments' quality. To the extent that this entrenchment takes place, and to the extent that is "snowballs" as described previously, it could generate an overall loss of value for diversifying firms.	• Berle & Means (1932) • Jensen & Meckling (1976) • Klein, Crawford, & Alchian (1978) • Jensen (1986) • Shleifer & Vishny (1989)

<u>Table 2</u> (cont.)- Theory: "The Good, the Bad, and the Why" of Corporate Diversification

Panel C: The "Why" of Diversifying Mergers

This is a continuation of *table 2* that provides an overview of some of the theory on corporate diversification. *Panel C* is slightly different than the previous two panels in that it provides a summary of the potential *motives* for corporate diversification, specifically as *related to undertaking conglomerate mergers.* Literature related to each major theoretical bullet point is again listed in column 2.

Potential motives for undertaking conglomerate mergers	Related Literature
• Agency theory o Managers may diversify to increase their compensation & overall prestige, entrench themselves, diversify their own portfolio risk, or for other self-reinforcing & firm-divergent reasons.	• Berle & Means (1932) • Jensen & Meckling (1976) • Klein, Crawford, & Alchian (1978) • Jensen (1986) • Shleifer & Vishny (1989)
• The resource based view o Firms may have transferable skills and resources that they believe can be applied in other business segments. Whether to stave off declining profits, or in hopes of spurring further growth, firms may seek to enter other lines of business to put skills and resources to use.	• Penrose (1959) • Montgomery (1994) • Matsusaka (2001)
• Market power o The firm may seek to diversify into other business segments in order to increase market power in one or all segments. For instance, a firm may think that it can drive out competition in one business segment by using profits from another to support a temporary intra-industry deflation in prices. Likewise, it may be entering the upstream or downstream markets of its suppliers so as to engage in reciprocal buying, or it may be motivated to try and halt price wars in its main line of business by inducing mutual forbearance.	• Edwards (1955) • Gribbin (1976) • Montgomery (1994)
• Macroeconomic/industry shocks o Diversifying mergers and acquisitions, much like mergers and acquisitions as a whole, are undertaken as responses to macroeconomic shocks within, and across, industries. Under this view, corporate diversification is often undertaken as a response to technological change, globalization, shifts in the political environment, or other broad-based changes in macro-fundamentals.	• Jensen (1993) • Mitchell & Mulherin (1996)

Table 3- Testable Hypotheses and Predictions

This table compares and contrasts predictions made by two separate sets of competing theories. *Panel A* outlines results predicted under the value-destroying versus the value-enhancing side of the corporate diversification debate, with predictions presented in terms of both absolute and relative value. *Panel B* outlines results predicted by the synergy versus the collusion hypotheses of merger value creation, with predictions made in terms of the stock price response for firms participating in the merger and for the rivals of the participating firms.

Panel A: The Value of Corporate Diversification

i. Testing for the *absolute value* of corporate diversification

	Value-Destroying	Value-Enhancing
Combined Firm Returns in Conglomerate Mergers	**Negative**	**Positive**

ii. Testing for the *relative value* of corporate diversification

Merger Type	Relatively Value-Destroying	Relatively Value-Enhancing
Horizontal	Highest	Lowest
Vertical	Middle	Middle
Conglomerate	**Lowest**	**Highest**

** "Lowest", "Middle", and "Highest" is in terms of (combined firm) CARs in relation to the other merger types.*

Panel B: Pathways for Merger Value Creation- Synergy vs. Collusion

i. First order conditions for the synergy & collusion hypotheses

	Synergy	Collusion
Combined Firm Returns	**Positive**	**Positive**

ii. Distinguishing predictions made by the synergy & collusion hypotheses

	Synergy	Collusion
Rival Firm Returns in Horizontal Deals	**Negative**	**Positive**

Table 4- Related Literature

This table presents a summary of some of the literature relevant to this analysis. *Panel A* reports selected merger *event studies* that provide results on whether corporate diversification is value-enhancing or value-destroying. *Panel B* reports selected studies that offer evidence on the causes of and sources of gain from merger activity. *Panel C* presents a snapshot of *event studies* that have made merger industrial organization type classifications, with the last column identifying what method they used to make the distinction. For a richer discussion of these and other related literatures see the conversation on "Previous Literature" in this paper's text.

Panel A. Selected event studies offering evidence on the value of corporate diversification

Study	Time period	Number of mergers	Corporate diversification verdict
Morck et al. (1990)	1975-1987	326	Destroying
Kaplan & Weisbach (1992)	1971-1982	282	Enhancing
Chevalier (2004)	1980-1995	215	Enhancing

Panel B. Selected studies offering evidence on the synergy v.s. collusion debate, but with no classification of merger type

Study	Time period	Number of mergers	Supports synergy or collusion
Bradley et al. (1988)	1963-1984	236	Synergy
Slovin et al. (1991)	1965-1988	42	Collusion
Singal (1996)	1985-1988	14	Collusion
Mulherin & Boone (2000)	1989-1999	400	Synergy
Fee & Thomas (2004)	1980-1997	554	Synergy/Efficiency

Panel C. Selected event studies that distinguish between vertical, horizontal, or conglomerate mergers

Study	Time period	Number of mergers	Theory Supported	Merger Type Classification	Method
Eckbo (1983)	1963-1978	259	Synergy/Efficiency	V,H	SIC Codes
Fan & Goyal (2006)	1962-1996	2162	N/A*	V,H,C	IO Tables
Becher et al. (2012)	1980-2004	384	Synergy	H, "Non-H"	SIC Codes/Value Line
Kedia et al. (2011)	1979-2002	1692	N/A*	V,H,C	IO Tables

* This was not the intended nature of the study.

Table 5- Sample Selection

This is a summary of the sample selection technique used to acquire and compile a list of U.S. mergers during the period from 1/01/2011 to 1/01/2014.[55] The data was collected from Securities Data Corp. (SDC), with requirements that the bidder owned more than 50% of the acquired firm after the merger, that the deal was eventually completed, that both the target and bidder were publically traded, and that neither participating company was a financial services firm. Careful analysis of the data before and after implementing the "target & bidder publically traded" restriction reveals that the drop from step 3 to step 4 is indeed consistent with proper sampling technique. Further, such a drop does not appear atypical when imposing public restrictions on the target.[56] The initial sample size consists of 223 domestic mergers. After merging the initial sample with data available from the Center for Research in Security Prices (CSRP), I am left with a "final" sample of 180 domestic mergers from 2011 through 2013.[57]

Imposed Restrictions:	Sample Size
Initial Sample Restrictions	
1) Domestic Mergers, 1/01/2011-1/01/2014	29275
2) Percent of Target Shares Acquired > 50%	20344
3) Deal Status: Completed	20333
4) Target Publically Traded	706
4) Bidder Publically Traded	350
5) Non-financial services	223
Initial Sample	223
Additional Data Restrictions	
6) Price and related data available from CRSP	180
Final Sample	180

[55] "U.S. merger" classified via SDC standards (i.e. if the target is a U.S. firm).
[56] Netter et al. (2011), for instance, encounter a significant decrease in sample size when imposing a "public restriction" on targets in their 1992-2009 study.
[57] "Final" in the sense that this 180 figure corresponds to a matching of target firms; I also conduct analysis on returns to bidders and combined firms, and thus receive slightly different "final" sample sizes after matching for each of these individual groupings of firms (178 and 152 mergers respectively). In general, a dropping of observations in step 6 (CRSP matching) appears to be due to the bidder not being a U.S. firm or either the bidder or target not in fact being publically listed. For example, LDK Solar's acquisition of Solar Power, Inc. for $33 Million on 01/06/01 is dropped in the target and combined firm return calculations because SPI is not listed on the NYSE, NYSE-AMEX, NASDAQ, or arca exchange that are covered by CSRP (rather, it was traded on the OTC Bulletin Board).

Table 6- Example of SIC/IO Method of Classifying Industrial Organization

This table is meant to provide a demonstration of how the SIC/IO method works. It is a simplied version of the Bureau of Economic Analysis's (BEA) Direct Requirements Table and is based on the merger between Time Warner Cable (TWC) (BEA industry code: 517110) and NaviSite Inc. (NAVI) (BEA industry code: 54151A) on February 1, 2011. Consider TWC's industry as industry *i* and NAVI's industry as industry *j*. The two relevant input requirement coefficients (V*ij* & V*ji*) are then .012003 and .0015119 respectively. The vertical relatedness coefficient (VRC) for these two merging firms is equal to the larger of the two input requirement coefficients- or .012003. In order to classify this merger into its industrial organization type at the 1%, 5%, and 10% vertical relatedness cutoff levels, simply compare the VRC to each stated cutoff level. In this case, because these two firms are from different BEA industries, the choice is made solely between a vertical or conglomerate classification; if the VRC is greater than the specified cutoff the merger is classified as vertical, if it is below the cutoff level the merger is classified as conglomerate. The SIC/IO method of industrial organization classification thus classifies this merger as vertical, conglomerate, or conglomerate depending on whether a 1%, 5%, or 10% vertical relatedness cutoff is applied.

Snippet of BEA's Direct Requirements Table

		Industry (*i*)	
		517110	54151A
Industry (*j*)	517110	0.113416	0.012003
	54151A	0.001512	0.01273

Table 7- Comparative Examples of Industrial Organization Classification Methods

This table provides a description of six of the mergers from within my sample, along with their accompanying industrial organization classifications. Results from strictly industry-based classification methods are stated in terms of non-horizontal ("Non-H") and horizontal ("H") classifications. Results from the SIC/IO and Human Eye method are stated in terms of vertical, horizontal, and conglomerate ("V", "H", & "C") classifications. For the SIC/IO method, classification results are reported at the 1%, 5%, & 10% vertical relatedness cutoff levels.

Date Announced	Target Name	Target Primary SIC (BEA) Code	Bidder Name	Bidder Primary SIC (BEA) Code	VRC	Merger Details	Classification Method: Strictly Industry-Based	Classification Method: SIC/IO @ 1%,5%,10% Cutoffs	Classification Method: Human Eye
11/07/11	Force Protection Inc.	3711 (336992)	General Dynamics Corp.	3812 (334511)	0	Companies are strict rivals and compete heavily in "tracked & wheeled military vehicle" market.	Non-H	C, C, C	H
07/21/11	Medco Health Solutions Inc.	8099 (621900)	Express Scripts Inc.	5122 (4A0000)	0.001167	"Two of the largest pharmacy benefit managers in the U.S." Deal posed significant antitrust concerns.	Non-H	C, C, C	H
02/08/11	RehabCare Group Inc.	8062 (622000)	Kindred Healthcare Inc.	8051 (623A00)	0	Kindred's in-patient healthcare business provides a pipeline of patients to RehabCare's outpatient clinics.	H or Non-H	C, C, C	V
08/27/12	Dollar Thrifty Automotive Group	7514 (532100)	Hertz Global Holdings Inc.	7514 (532100)	0.0106	Two major players in the rental care space. Deal withstood an 8-month compliance review from the FTC before being conditionally approved.	H	V, H, H	H
04/05/13	Intelligent Living Inc	7372 (511200)	Feel Golf Co Inc	3949 (339920)	0.0001782	A golf club manufacturer acquires a health software company.	Non-H	C, C, C	C
02/01/11	NaviSite Inc.	7376 (5415A)	Time Warner Cable Inc.	4841 (517110)	0.012003	Time Warner makes a move into the cloud computing business. The NaviSite deal "represents significant new growth opportunities."	Non-H	V, C, C	C

Table 8- Sample Distribution

Panel A provides a breakdown of the number of mergers occurring per year in my 2011-2013 sample. *Panel B* through *Panel E* further partition the sample into its vertical, horizontal, and conglomerate classifications and provide figures on the yearly frequency of each classification as well as the share of the total that each classification accounts for per year. *Panel B* corresponds to distributional results achieved under the primary Human Eye method of classifying merger industrial organization. *Panel C* through *Panel E* correspond to classifications obtained under the secondary SIC/IO method when using a 1%, 5%, and 10% vertical relatedness cutoff respectively.

Panel A: Overall Distribution by Year

Year	Frequency
2011	69
2012	91
2013	63
Total	223

Panel B: Human Eye Classification Distribution by Year

Year	Overall	Vertical	%	Horizontal	%	Conglomerate	%
2011	69	14	20%	41	59%	14	20%
2012	91	15	16%	54	59%	22	24%
2013	63	5	8%	48	76%	10	16%
Total	223	34	15%	143	64%	46	21%

Panel C: SIC/IO Classification @ 1% Cutoff Distribution by Year

Year	Overall	Vertical	%	Horizontal	%	Conglomerate	%
2011	69	27	39%	12	17%	30	43%
2012	91	37	41%	10	11%	44	48%
2013	63	30	48%	10	16%	23	37%
Total	223	94	42%	32	14%	97	43%

Table 8 (cont.)- Sample Distribution

Panel D and *Panel E* of *table 8* are here displayed. *Panel A* provides a breakdown of the number of mergers occurring per year in my 2011-2013 sample. *Panel B* through *Panel E* further partition the sample into its vertical, horizontal, and conglomerate classifications and provide figures on the yearly frequency of each classification as well as the share of the total that each classification accounts for per year. *Panel B* corresponds to distributional results achieved under the primary Human Eye method of classifying merger industrial organization. *Panel C* through *Panel E* correspond to classifications obtained under the secondary SIC/IO method when using a 1%, 5%, and 10% vertical relatedness cutoff respectively.

Panel D: SIC/IO Classification @ 5% Cutoff Distribution by Year

Year	Overall	Vertical	%	Horizontal	%	Conglomerate	%
2011	69	9	13%	22	32%	38	55%
2012	91	14	15%	26	29%	51	56%
2013	63	10	16%	27	43%	26	41%
Total	223	33	15%	75	34%	115	52%

Panel E: SIC/IO Classification @ 10% Cutoff Distribution by Year

Year	Overall	Vertical	%	Horizontal	%	Conglomerate	%
2011	69	4	6%	25	36%	40	58%
2012	91	6	7%	32	35%	53	58%
2013	63	6	10%	31	49%	26	41%
Total	223	16	7%	88	39%	119	53%

Table 9- Cross Tabulations between Human Eye Method and SIC/IO Method

This table provides a breakdown of the number of mergers classified as vertical, horizontal, and conglomerate under the Human Eye method and the SIC/IO method as well as cross tabulations of the overlap between classification method for my 2011-2013 sample. *Panel A, Panel B, and Panel C* depict cross tabulations between the Human Eye method and the SIC/IO method, in which vertical classifications made by the SIC/IO method are defined at the 1%, 5%, and 10% level of vertical relatedness cutoff respectively. *Italicized numbers* are percentages of column totals. ***Bolded & italicized numbers*** are percentages of row totals.

Panel A: Human Eye vs. SIC/IO Method @ 1% cutoff

	SIC/IO Method @ 1% cutoff		
	Vertical	Horizontal	Conglomerate
Human Eye	94	32	97
Vertical	10	4	20
34	*11%*	*13%*	*21%*
	29%	***12%***	***59%***
Horizontal	81	28	34
143	*86%*	*88%*	*35%*
	57%	***20%***	***24%***
Conglomerate	3	0	43
46	*3%*	*0%*	*44%*
	7%	***0%***	***93%***

Panel B: Human Eye vs. SIC/IO Method @ 5% cutoff

	SIC/IO Method @ 5% cutoff		
	Vertical	Horizontal	Conglomerate
Human Eye	33	75	115
Vertical	2	7	25
34	*6%*	*9%*	*22%*
	6%	***21%***	***74%***
Horizontal	31	68	44
143	*94%*	*91%*	*38%*
	22%	***48%***	***31%***
Conglomerate	0	0	46
46	*0%*	*0%*	*40%*
	0%	***0%***	***100%***

Table 9 (cont.)- Cross Tabulations between Human Eye Method and SIC/IO Method

This is a continuation of *table 9* which provides a breakdown of the number of mergers classified as vertical, horizontal, and conglomerate under the Human Eye method and the SIC/IO method as well as cross tabulations of the overlap between classification method for my 2011-2013 sample. *Panel A, Panel B, and Panel C* depict cross tabulations between the Human Eye method and the SIC/IO method, in which vertical classifications made by the SIC/IO method are defined at the 1%, 5%, and 10% level of vertical relatedness cutoff respectively. *Italicized numbers* are percentages of column totals. ***Bolded & italicized numbers*** are percentages of row totals.

Panel C: Human Eye vs. SIC/IO Method @ 10% cutoff

	SIC/IO Method @ 10% cutoff		
	Vertical	Horizontal	Conglomerate
Human Eye	16	88	119
Vertical	0	7	27
34	*0%*	*8%*	*23%*
	0%	***21%***	***79%***
Horizontal	16	81	46
143	*100%*	*92%*	*39%*
	11%	***57%***	***32%***
Conglomerate	0	0	46
46	*0%*	*0%*	*39%*
	0%	***0%***	***100%***

Table 10- Summary Statistics

Panel A: Summary Statistics for Initial Sample

Panel A provides summary statistics on the 223 domestic mergers in my initial 2011-2013 sample. "Transaction value" is measured in millions of dollars and corresponds to the merger deal value as reported by SDC. "Segments added" is in terms of reported COMPUSTAT industry segments and is calculated by subtracting reported segments in the year before the merger transaction, from reported segments in the year after the transaction. A lower bound of zero is imposed on the "segments added" variable in order to eliminate noise and prevent clear non-merger related segment fluctuation from biasing the results downward. The "vertical relatedness coefficient" is an industry-based measure used in the SIC/IO method of classification and is calculated as described in *section 5.2*. "Friendly" refers to the attitude of the merger, and "consideration structure" refers to the type of payment used in the merger deal, both as reported by SDC.

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	2164.80	607.83	29370.07	0.54	223	
Segments Added	0.62	0.00	12.00	0.00	146	
Vertical Rel. Coefficient	0.024	0.005	0.169	0.000	223	
"Friendly"					222	99.6%
Consideration Structure:						
cash					138	61.9%
stock					26	11.7%
other					13	5.8%
hybrid					43	19.3%
unknown					3	1.3%

Table 10 (cont.)- Summary Statistics

Panel B: Summary Statistics for V, H, & C via Primary Human Eye Method

Panel B provides summary statistics on the 223 domestic mergers in my initial 2011-2013 sample, partitioned via vertical, horizontal, and conglomerate as classified using a Human Eye method of industrial organization classification. "Transaction value" is measured in millions of dollars and corresponds to the merger deal value as reported by SDC. "Segments added" is in terms of reported COMPUSTAT industry segments and is calculated as described in previous sections (see *Panel A*). The "vertical relatedness coefficient" is an industry-based measure used in the SIC/IO method of classification and is calculated as described in *section 5.2*.

Horizontal

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	2348.92	760.22	29370.07	7.02	143	
Segments Added	0.41	0.00	6.00	0.00	95	
Vertical Rel. Coefficient	0.033	0.017	0.169	0.000	143	
Consideration Structure:						
cash					82	57.3%
stock					19	13.3%
other					10	7.0%
hybrid					30	21.0%
unknown					2	1.4%

Vertical

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	1332.81	328.56	16182.72	0.77	34	
Segments Added	0.76	0.00	6.00	0.00	25	
Vertical Rel. Coefficient	0.012	0.002	0.073	0.000	34	
Consideration Structure:						
cash					24	70.6%
stock					4	11.8%
other					1	2.9%
hybrid					5	14.7%
unknown					0	0.0%

Conglomerate

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	2207.39	605.88	20097.79	0.54	46	
Segments Added	1.23	0.00	12.00	0.00	26	
Vertical Rel. Coefficient	0.003	0.001	0.043	0.000	46	
Consideration Structure:						
cash					32	69.6%
stock					3	6.5%
other					2	4.3%
hybrid					8	17.4%
unknown					1	2.2%

Table 10 (cont.)- Summary Statistics

Panel C: Summary Statistics for V, H, & C via SIC/IO Method @ 1% Cutoff

Panel C provides summary statistics on the 223 domestic mergers in my initial 2011-2013 sample, partitioned via vertical, horizontal, and conglomerate as classified using the SIC/IO method at a 1% vertical relatedness cutoff. "Transaction value" is measured in millions of dollars and corresponds to the merger deal value as reported by SDC. "Segments added" is in terms of reported COMPUSTAT industry segments and is calculated as described in previous sections (see *Panel A*). The "vertical relatedness coefficient" is an industry-based measure used in the SIC/IO method of classification and is calculated as described in *section 5.2*.

Horizontal

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	3385.09	1529.51	24002.09	7.56	32	
Segments Added	0.56	0.00	5.00	0.00	16	
Vertical Rel. Coefficient	0.003	0.002	0.009	0.000	32	
Consideration Structure:						
cash					14	43.8%
stock					4	12.5%
other					3	9.4%
hybrid					11	34.4%
unknown					0	0.0%

Vertical

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	1693.85	540.20	16381.39	7.56	94	
Segments Added	0.47	0.00	6.00	0.00	66	
Vertical Rel. Coefficient	0.054	0.042	0.169	0.010	94	
Consideration Structure:						
cash					57	60.6%
stock					13	13.8%
other					6	6.4%
hybrid					18	19.1%
unknown					0	0.0%

Conglomerate

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	2218.62	387.96	29370.07	0.54	97	
Segments Added	0.78	0.00	12.00	0.00	64	
Vertical Rel. Coefficient	0.002	0.001	0.010	0.000	97	
Consideration Structure:						
cash					67	69.1%
stock					9	9.3%
other					4	4.1%
hybrid					14	14.4%
unknown					3	3.1%

Table 10 (cont.)- Summary Statistics

Panel D: Summary Statistics for V, H, & C via SIC/IO Method @ 5% Cutoff

Panel D provides summary statistics on the 223 domestic mergers in my initial 2011-2013 sample, partitioned via vertical, horizontal, and conglomerate as classified using the SIC/IO method at a 5% vertical relatedness cutoff. "Transaction value" is measured in millions of dollars and corresponds to the merger deal value as reported by SDC. "Segments added" is in terms of reported COMPUSTAT industry segments and is calculated as described in previous sections (see *Panel A*). The "vertical relatedness coefficient" is an industry-based measure used in the SIC/IO method of classification and is calculated as described in *section 5.2*.

Horizontal

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	2440.71	886.86	24002.09	7.56	75	
Segments Added	0.53	0.00	5.00	0.00	43	
Vertical Rel. Coefficient	0.015	0.017	0.042	0.000	75.00	
Consideration Structure:						
cash					42	56.0%
stock					10	13.3%
other					7	9.3%
hybrid					16	21.3%
unknown					0	0.0%

Vertical

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	2041.36	543.27	16381.39	7.56	33	
Segments Added	0.26	0.00	3.00	0.00	23	
Vertical Rel. Coefficient	0.107	0.098	0.169	0.050	33	
Consideration Structure:						
cash					17	51.5%
stock					4	12.1%
other					2	6.1%
hybrid					10	30.3%
unknown					0	0.0%

Conglomerate

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	2020.28	369.68	29370.07	0.54	115	
Segments Added	0.76	0.00	12.00	0.00	80	
Vertical Rel. Coefficient	0.005	0.001	0.047	0.000	115	
Consideration Structure:						
cash					79	68.7%
stock					12	10.4%
other					4	3.5%
hybrid					17	14.8%
unknown					3	2.6%

Table 10 (cont.)- Summary Statistics

Panel E: Summary Statistics for V, H, & C via SIC/IO Method @ 10% Cutoff

Panel E provides summary statistics on the 223 domestic mergers in my initial 2011-2013 sample, partitioned via vertical, horizontal, and conglomerate as classified using the SIC/IO method at a 10% vertical relatedness cutoff. "Transaction value" is measured in millions of dollars and corresponds to the merger deal value as reported by SDC. "Segments added" is in terms of reported COMPUSTAT industry segments and is calculated as described in previous sections (see *Panel A*). The "vertical relatedness coefficient" is an industry-based measure used in the SIC/IO method of classification and is calculated as described in *section 5.2*.

Horizontal

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	2188.69	860.87	24002.09	7.56	88	
Segments Added	0.47	0.00	5.00	0.00	55	
Vertical Rel. Coefficient	0.025	0.017	0.098	0.000	88	
Consideration Structure:						
cash					53	60.2%
stock					10	11.4%
other					8	9.1%
hybrid					17	19.3%
unknown					0	0.0%

Vertical

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	3022.15	796.08	16381.39	29.69	16	
Segments Added	0.00	0.00	0.00	0.00	8	
Vertical Rel. Coefficient	0.138	0.150	0.169	0.101	16	
Consideration Structure:						
cash					4	25.0%
stock					4	25.0%
other					1	6.3%
hybrid					7	43.8%
unknown					0	0.0%

Conglomerate

Variable	Mean	Median	Maximum	Minimum	N	% of total
Transaction Value ($mill)	2031.86	370.99	29370.07	0.54	119	
Segments Added	0.77	0.00	12.00	0.00	83	
Vertical Rel. Coefficient	0.007	0.001	0.073	0.000	119	
Consideration Structure:						
cash					81	68.1%
stock					12	10.1%
other					4	3.4%
hybrid					19	16.0%
unknown					3	2.5%

Table 11- Primary Event Study Analysis (-1,+1)

Panel A: Announcement Returns for Full Sample

Panel A reports the cumulative abnormal returns (CARs) around announcement date for the entire set of sample firms. The table is partitioned to display CARs for the total combined, bidder, and target firms respectively, where combined firm returns are calculated as a market-value-weighted-average of bidder and target firm returns. Differences in sample size across firm and return type are simply due to data restrictions arising from requiring returns to be listed on CRSP. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Combined

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	152	0.063	0.038	0.561	-0.158	0.757	7.490	<.0001
Net of Market	152	0.061	0.031	0.558	-0.161	0.743	7.350	<.0001
Market Model	151	0.060	0.031	0.551	-0.165	0.743	7.290	<.0001

Bidder

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	178	0.015	0.012	0.320	-0.328	61.8%	2.460	0.0148
Net of Market	178	0.014	0.009	0.309	-0.345	59.0%	2.250	0.0258
Market Model	175	0.012	0.007	0.297	-0.350	57.3%	2.020	0.0452

Target

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	180	0.297	0.269	1.440	-0.248	91.7%	16.300	<.0001
Net of Market	180	0.295	0.259	1.429	-0.277	90.0%	16.230	<.0001
Market Model	179	0.295	0.259	1.396	-0.369	90.0%	16.070	<.0001

Table 11 (cont.)- Primary Event Study Analysis (-1,+1)

Panel B: Announcement Returns for V, H, & C via Human Eye Method

Panel B reports CARs around merger announcement date for horizontal, vertical, and conglomerate type mergers as defined by a Human Eye method of industrial organization classification. The table is partitioned into three parts to display CARs for the total combined, bidder, and target firms respectively, where combined firm returns are calculated as a market-value-weighted-average of bidder and target firm returns. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Combined Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	103	0.067	0.053	0.318	-0.118	79.6%	8.140	<.0001
Net of Market	103	0.066	0.043	0.327	-0.094	77.7%	8.170	<.0001
Market Model	102	0.066	0.044	0.340	-0.092	77.7%	8.130	<.0001

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	20	0.071	0.032	0.512	-0.066	75.0%	2.340	0.0303
Net of Market	20	0.066	0.027	0.484	-0.046	75.0%	2.300	0.0329
Market Model	20	0.064	0.030	0.458	-0.055	70.0%	2.270	0.0351

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	29	0.042	0.023	0.561	-0.158	62.1%	1.640	0.1123
Net of Market	29	0.038	0.012	0.558	-0.161	62.1%	1.460	0.1562
Market Model	29	0.036	0.010	0.551	-0.165	65.5%	1.410	0.1703

Difference in means: Cong. v.s. Non-Cong.

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	149	-1.42	0.157
Satterthwaite	Unequal	34	-1.1	0.279

Table 11 (cont.)- Primary Event Study Analysis (-1,+1)

Panel B (cont.): Announcement Returns for V, H, & C via Human Eye Method

This is a continuation of *Panel B* which reports CARs around merger announcement date for horizontal, vertical, and conglomerate type mergers as defined by a Human Eye method of industrial organization classification. Below results are for Target and Bidder firms respectively, with Combined firm returns reported on the previous page.

Bidder Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	118	0.026	0.016	0.320	-0.189	64.4%	3.460	0.0008
Net of Market	118	0.025	0.011	0.309	-0.198	61.9%	3.460	0.0008
Market Model	117	0.024	0.013	0.297	-0.215	61.0%	3.290	0.0013

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	25	-0.008	0.004	0.284	-0.328	52.0%	-0.380	0.7073
Net of Market	25	-0.013	0.000	0.277	-0.345	48.0%	-0.640	0.5309
Market Model	23	-0.016	-0.002	0.277	-0.350	40.0%	-0.690	0.4964

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	35	-0.004	0.008	0.069	-0.205	60.0%	-0.440	0.6621
Net of Market	35	-0.006	0.009	0.066	-0.208	57.1%	-0.630	0.5341
Market Model	35	-0.008	0.003	0.067	-0.212	57.1%	-0.800	0.4312

Target Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	121	0.277	0.240	1.440	-0.248	88.4%	11.880	<.0001
Net of Market	121	0.276	0.242	1.429	-0.277	86.8%	11.850	<.0001
Market Model	120	0.277	0.239	1.396	-0.369	86.8%	11.720	<.0001

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	25	0.386	0.401	0.914	0.049	100.0%	8.520	<.0001
Net of Market	25	0.382	0.397	0.909	0.036	100.0%	8.760	<.0001
Market Model	25	0.382	0.401	0.907	0.032	100.0%	8.710	<.0001

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	34	0.304	0.283	0.790	-0.097	97.1%	8.780	<.0001
Net of Market	34	0.298	0.277	0.786	-0.081	94.1%	8.480	<.0001
Market Model	34	0.296	0.275	0.778	-0.089	94.1%	8.390	<.0001

Table 12- Secondary Event Study Analysis (-1,+1)

Panel A: Announcement Returns for V, H, & C via SIC/IO Method @ 1% Cutoff

Panel A reports CARs around merger announcement date for horizontal, vertical, and conglomerate type mergers as defined by the SIC/IO method at a 1% vertical relatedness cutoff. The table is partitioned into three parts to display CARs for the total combined, bidder, and target firms respectively, where combined firm returns are calculated as a market-value-weighted-average of bidder and target firm returns. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Combined Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	26	0.059	0.038	0.297	-0.030	76.9%	3.490	0.0018
Net of Market	26	0.060	0.027	0.327	-0.048	80.8%	3.500	0.0017
Market Model	26	0.059	0.025	0.340	-0.044	76.9%	3.350	0.0026

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	68	0.080	0.065	0.512	-0.118	82.4%	6.670	<.0001
Net of Market	68	0.077	0.059	0.484	-0.094	80.9%	6.600	<.0001
Market Model	68	0.075	0.054	0.458	-0.092	80.9%	6.610	<.0001

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	58	0.044	0.023	0.561	-0.158	67.2%	2.980	0.0042
Net of Market	58	0.042	0.015	0.558	-0.161	63.8%	2.840	0.0062
Market Model	57	0.042	0.018	0.551	-0.165	65.5%	2.830	0.0064

Difference in means: Cong. v.s. Non-Cong.

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	149	-1.69	0.093
Satterthwaite	Unequal	101	-1.61	0.109

Table 12 (cont.)- Secondary Event Study Analysis (-1,+1)

Panel A (cont.): Announcement Returns for V, H, & C via SIC/IO Method @ 1% Cutoff

This is a continuation of *Panel A* which reports CARs around merger announcement date for horizontal, vertical, and conglomerate type mergers as defined by the SIC/IO method at a 1% vertical relatedness cutoff . Below results are for Target and Bidder firms respectively, with Combined firm returns reported on the previous page.

Bidder Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	27	0.018	0.009	0.201	-0.174	63.0%	1.120	0.2745
Net of Market	27	0.019	0.009	0.231	-0.198	66.7%	1.120	0.2731
Market Model	27	0.019	0.004	0.237	-0.215	55.6%	1.070	0.2936

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	77	0.026	0.023	0.320	-0.328	66.2%	2.400	0.0188
Net of Market	77	0.023	0.014	0.309	-0.345	59.7%	2.180	0.0327
Market Model	76	0.021	0.014	0.297	-0.350	59.7%	1.980	0.0518

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	74	0.002	0.004	0.284	-0.205	56.8%	0.330	0.7418
Net of Market	74	0.001	0.004	0.277	-0.208	55.4%	0.220	0.8288
Market Model	72	0.001	0.004	0.277	-0.212	55.4%	0.100	0.9213

Target Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	29	0.171	0.152	0.623	-0.098	86.2%	5.450	<.0001
Net of Market	29	0.172	0.158	0.584	-0.095	86.2%	5.500	<.0001
Market Model	29	0.169	0.154	0.584	-0.107	82.8%	5.350	<.0001

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	80	0.311	0.290	1.440	-0.248	92.5%	10.750	<.0001
Net of Market	80	0.308	0.281	1.429	-0.277	92.5%	10.760	<.0001
Market Model	80	0.305	0.273	1.396	-0.369	92.5%	10.530	<.0001

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	71	0.333	0.289	0.914	-0.097	93.0%	11.660	<.0001
Net of Market	71	0.330	0.290	0.909	-0.081	88.7%	11.470	<.0001
Market Model	70	0.335	0.280	0.907	-0.089	90.1%	11.600	<.0001

Table 12 (cont.)- Secondary Event Study Analysis (-1,+1)

Panel B: Announcement Returns for V, H, & C via SIC/IO Method @ 5% Cutoff

Panel B reports CARs around merger announcement date for horizontal, vertical, and conglomerate type mergers as defined by the SIC/IO method at a 5% vertical relatedness cutoff. The table is partitioned into three parts to display CARs for the total combined, bidder, and target firms respectively, where combined firm returns are calculated as a market-value-weighted-average of bidder and target firm returns. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Combined Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	57	0.069	0.048	0.512	-0.066	78.9%	5.340	<.0001
Net of Market	57	0.069	0.039	0.484	-0.048	80.7%	5.510	<.0001
Market Model	57	0.067	0.028	0.458	-0.044	80.7%	5.450	<.0001

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	23	0.109	0.074	0.318	-0.014	91.3%	5.370	<.0001
Net of Market	23	0.105	0.067	0.321	-0.022	87.0%	5.030	<.0001
Market Model	23	0.102	0.060	0.322	-0.021	82.6%	4.910	<.0001

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	72	0.043	0.030	0.561	-0.158	68.1%	3.460	0.0009
Net of Market	72	0.040	0.017	0.558	-0.161	65.3%	3.270	0.0016
Market Model	71	0.041	0.020	0.551	-0.165	66.7%	3.280	0.0016

Difference in means: Cong. v.s. Non-Cong.

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	149	-2.24	0.026
Satterthwaite	Unequal	143	-2.23	0.027

Table 12 (cont.)- Secondary Event Study Analysis (-1,+1)

Panel B (cont.): Announcement Returns for V, H, & C via SIC/IO Method @ 5% Cutoff

This is a continuation of *Panel B* which reports CARs around merger announcement date for horizontal, vertical, and conglomerate type mergers as defined by the SIC/IO method at a 5% vertical relatedness cutoff . Below results are for Target and Bidder firms respectively, with Combined firm returns reported on the previous page.

Bidder Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	59	0.019	0.011	0.201	-0.174	59.3%	1.850	0.0696
Net of Market	59	0.019	0.003	0.231	-0.198	57.6%	1.820	0.0732
Market Model	58	0.018	0.007	0.237	-0.215	54.2%	1.690	0.0959

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	29	0.066	0.035	0.320	-0.064	86.2%	4.020	0.0004
Net of Market	29	0.062	0.037	0.309	-0.064	75.9%	3.690	0.001
Market Model	29	0.057	0.036	0.297	-0.069	72.4%	3.460	0.0017

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	90	-0.004	0.004	0.284	-0.328	55.6%	-0.550	0.5869
Net of Market	90	-0.005	0.004	0.277	-0.345	54.4%	-0.700	0.4861
Market Model	88	-0.006	0.003	0.277	-0.350	54.4%	-0.770	0.4444

Target Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	68	0.230	0.193	0.822	-0.248	88.2%	8.900	<.0001
Net of Market	68	0.230	0.204	0.814	-0.277	88.2%	9.010	<.0001
Market Model	68	0.227	0.213	0.830	-0.369	86.8%	8.690	<.0001

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	25	0.267	0.263	0.658	-0.029	92.0%	7.360	<.0001
Net of Market	25	0.263	0.242	0.631	-0.043	92.0%	7.370	<.0001
Market Model	25	0.260	0.227	0.633	-0.051	92.0%	7.210	<.0001

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	87	0.358	0.303	1.440	-0.097	94.3%	12.420	<.0001
Net of Market	87	0.355	0.300	1.429	-0.081	90.8%	12.240	<.0001
Market Model	86	0.359	0.306	1.396	-0.089	92.0%	12.370	<.0001

Table 12 (cont.)- Secondary Event Study Analysis (-1,+1)

Panel C: Announcement Returns for V, H, & C via SIC/IO Method @ 10% Cutoff

Panel C reports CARs around merger announcement date for horizontal, vertical, and conglomerate type mergers as defined by the SIC/IO method at a 10% vertical relatedness cutoff. The table is partitioned into three parts to display CARs for the total combined, bidder, and target firms respectively, where combined firm returns are calculated as a market-value-weighted-average of bidder and target firm returns. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Combined Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	64	0.068	0.051	0.512	-0.066	79.7%	5.800	<.0001
Net of Market	64	0.067	0.040	0.484	-0.048	79.7%	5.930	<.0001
Market Model	64	0.066	0.035	0.458	-0.044	79.7%	5.900	<.0001

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	13	0.142	0.121	0.318	-0.014	92.3%	4.520	0.0007
Net of Market	13	0.136	0.125	0.321	-0.022	92.3%	4.320	0.001
Market Model	13	0.130	0.118	0.322	-0.021	92.3%	4.110	0.0014

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	75	0.045	0.031	0.561	-0.158	69.3%	3.730	0.0004
Net of Market	75	0.042	0.017	0.558	-0.161	66.7%	3.520	0.0007
Market Model	74	0.042	0.020	0.551	-0.165	66.7%	3.520	0.0007

Difference in means: Cong. v.s. Non-Cong.

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	149	-2.11	0.036
Satterthwaite	Unequal	147	-2.11	0.037

<u>Table 12</u> (cont.)- Secondary Event Study Analysis (-1,+1)

Panel C (cont.): Announcement Returns for V, H, & C via SIC/IO Method @ 10% Cutoff

This is a continuation of *Panel C* which reports CARs around merger announcement date for horizontal, vertical, and conglomerate type mergers as defined by the SIC/IO method at a 10% vertical relatedness cutoff . Below results are for Target and Bidder firms respectively, with Combined firm returns reported on the previous page.

Bidder Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	71	0.027	0.016	0.320	-0.174	64.8%	2.730	0.0081
Net of Market	71	0.026	0.010	0.309	-0.198	60.6%	2.650	0.0101
Market Model	70	0.025	0.011	0.295	-0.215	57.7%	2.510	0.0146

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	13	0.075	0.061	0.296	-0.064	76.9%	2.680	0.0201
Net of Market	13	0.070	0.043	0.299	-0.064	69.2%	2.460	0.0299
Market Model	13	0.063	0.041	0.297	-0.069	69.2%	2.220	0.0467

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	94	-0.002	0.008	0.284	-0.328	57.4%	-0.300	0.7686
Net of Market	94	-0.003	0.004	0.277	-0.345	56.4%	-0.470	0.6395
Market Model	92	-0.004	0.004	0.277	-0.350	55.3%	-0.570	0.5728

Target Firm Returns

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	75	0.235	0.210	0.822	-0.248	89.3%	9.820	<.0001
Net of Market	75	0.235	0.216	0.814	-0.277	89.3%	9.960	<.0001
Market Model	75	0.231	0.215	0.830	-0.369	88.0%	9.600	<.0001

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	15	0.232	0.201	0.627	-0.029	86.7%	4.860	0.0003
Net of Market	15	0.226	0.177	0.631	-0.043	86.7%	4.720	0.0003
Market Model	15	0.223	0.192	0.633	-0.051	86.7%	4.600	0.0004

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	90	0.360	0.310	1.440	-0.097	94.4%	12.780	<.0001
Net of Market	90	0.357	0.315	1.429	-0.081	91.1%	12.620	<.0001
Market Model	89	0.360	0.325	1.396	-0.089	92.2%	12.760	<.0001

Table 13- Rival Firm Primary Event Study Analysis (-1,+1)

Panel A: Rival Announcement Returns for Full Sample

Panel A reports the cumulative abnormal returns (CARs) around announcement date for the entire set of rival firms. Rival firms are defined as those firms in the same SIC industry as the target firm upon the announcement of each merger deal. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Total

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	180	0.018	0.005	0.457	-0.121	0.555	3.090	0.0023
Net of Market	180	0.016	0.002	0.443	-0.108	0.520	2.940	0.0037
Market Model	180	0.015	0.003	0.444	-0.114	0.532	2.900	0.0042

Table 13 (cont.)- Rival Firm Primary Event Study Analysis (-1,+1)

Panel B: Rival Announcement Returns for V, H, & C via Human Eye Method

Panel B reports CARs around merger announcement date for rival firms in horizontal, vertical, and conglomerate type mergers as defined by a Human Eye method of industrial organization classification. Rival firms are defined as those firms in the same SIC industry as the target firm upon the announcement of each merger deal. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	121	0.014	0.007	0.457	-0.121	0.571	2.150	0.0337
Net of Market	121	0.012	-0.001	0.443	-0.108	0.487	2.080	0.0397
Market Model	121	0.012	-0.001	0.444	-0.114	0.496	2.000	0.0478

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	25	0.015	0.009	0.230	-0.120	52.2%	0.950	0.3519
Net of Market	25	0.010	0.003	0.214	-0.085	56.5%	0.720	0.4784
Market Model	25	0.010	0.002	0.209	-0.069	52.2%	0.700	0.492

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	34	0.037	0.002	0.457	-0.065	51.6%	2.050	0.0496
Net of Market	34	0.034	0.008	0.435	-0.071	61.3%	2.020	0.0529
Market Model	34	0.034	0.012	0.418	-0.072	67.7%	2.070	0.0472

Difference in means: Horiz. v.s. Non-Horz.

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	178	-1.01	0.3128
Satterthwaite	Unequal	84	-0.93	0.3558

Table 14- Rival Firm Secondary Event Study Analysis (-1,+1)

Panel A: Rival Announcement Returns for V, H, & C via SIC/IO Method @ 1% Cutoff

Panel A reports CARs around merger announcement date for rival firms in horizontal, vertical, and conglomerate type mergers as defined by the SIC/IO method at a 1% vertical relatedness cutoff. Rival firms are defined as those firms in the same SIC industry as the target firm upon the announcement of each merger deal. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	29	0.025	0.026	0.226	-0.121	0.655	2.120	0.0432
Net of Market	29	0.025	0.019	0.168	-0.108	0.655	2.380	0.0245
Market Model	29	0.021	0.022	0.136	-0.114	0.655	2.210	0.0358

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	80	0.016	0.004	0.457	-0.120	55.1%	1.690	0.0953
Net of Market	80	0.011	-0.004	0.443	-0.083	46.2%	1.330	0.1877
Market Model	80	0.011	-0.005	0.444	-0.084	44.9%	1.320	0.1914

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	71	0.018	0.003	0.457	-0.095	51.5%	1.870	0.0659
Net of Market	71	0.018	0.002	0.435	-0.085	53.0%	1.950	0.056
Market Model	71	0.018	0.005	0.418	-0.072	57.6%	2.020	0.0472

Difference in means: Horiz. v.s. Non-Horz.

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	178	0.5	0.6144
Satterthwaite	Unequal	53	0.63	0.5324

Table 14 (cont.)- Rival Firm Secondary Event Study Analysis (-1,+1)

Panel B: Rival Announcement Returns for V, H, & C via SIC/IO Method @ 5% Cutoff

Panel B reports CARs around merger announcement date for rival firms in horizontal, vertical, and conglomerate type mergers as defined by the SIC/IO method at a 5% vertical relatedness cutoff. Rival firms are defined as those firms in the same SIC industry as the target firm upon the announcement of each merger deal. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	68	0.026	0.012	0.457	-0.121	0.597	2.370	0.0208
Net of Market	68	0.024	0.011	0.443	-0.108	0.567	2.440	0.0174
Market Model	68	0.023	0.010	0.444	-0.114	0.567	2.340	0.0224

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	25	0.008	0.003	0.118	-0.099	62.5%	0.800	0.4334
Net of Market	25	0.000	-0.005	0.108	-0.083	33.3%	-0.040	0.9714
Market Model	25	-0.001	-0.005	0.109	-0.084	33.3%	-0.100	0.9228

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	87	0.015	0.001	0.457	-0.095	50.0%	1.830	0.071
Net of Market	87	0.014	0.003	0.435	-0.085	53.7%	1.830	0.0705
Market Model	87	0.014	0.005	0.418	-0.072	56.1%	1.910	0.0602

Difference in means: Horiz. v.s. Non-Horz.

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	178	1.13	0.2615
Satterthwaite	Unequal	116	1.07	0.2889

Table 14 (cont.)- Rival Firm Secondary Event Study Analysis (-1,+1)

Panel C: Rival Announcement Returns for V, H, & C via SIC/IO Method @ 10% Cutoff

Panel C reports CARs around merger announcement date for rival firms in horizontal, vertical, and conglomerate type mergers as defined by the SIC/IO method at a 10% vertical relatedness cutoff. Rival firms are defined as those firms in the same SIC industry as the target firm upon the announcement of each merger deal. Three methods of calculating CARs are implemented, all of which are calculated using a (-1,+1) window where day 0 is the merger announcement date as reported by SDC. "Net of Market" returns are calculated by subtracting the CRSP value-weighted index from "Raw Returns," and "Market Model" excess returns are calculated using an estimation period of (-255,-22), where day 0 is again announcement date. "% Positive" refers to the proportion of total calculated CARs that are greater than zero, and p-values ("Pr>|t|") are in terms of testing whether CARs are statistically different from zero.

Horizontal

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	75	0.021	0.008	0.457	-0.121	0.581	2.120	0.0378
Net of Market	75	0.019	0.005	0.443	-0.108	0.514	2.070	0.0424
Market Model	75	0.018	0.003	0.444	-0.114	0.514	1.960	0.0533

Vertical

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	15	0.017	0.005	0.118	-0.044	64.3%	1.340	0.2031
Net of Market	15	0.010	-0.001	0.108	-0.059	42.9%	0.800	0.4378
Market Model	15	0.011	-0.001	0.109	-0.050	42.9%	0.850	0.409

Conglomerate

Return Measure	N	Mean	Median	Max	Min	% Positive	t-Value	Pr > |t|
Raw Returns	90	0.016	0.004	0.457	-0.095	51.8%	1.970	0.0519
Net of Market	90	0.014	0.003	0.435	-0.085	54.1%	1.940	0.0562
Market Model	90	0.014	0.005	0.418	-0.072	56.5%	1.970	0.0525

Difference in means: Horiz. v.s. Non-Horz.

Method	Variances	DF	t Value	Pr > |t|
Pooled	Equal	178	0.4	0.6877
Satterthwaite	Unequal	137	0.39	0.6968

Table 15- Event Study Analysis Alternate Windows (Robustness)

Panel A: Announcement Returns for Full Sample

Panel A reports alternative windows for CARs around merger announcement date for the entire set of sample firms. The panel is partitioned in terms of combined, bidder, and target firm returns. Abnormal returns are in terms of calculations based on using the market model with estimation period (-255, -22).

	Total Returns	
	Mean	*(P-Value)*
Combined Firm		
(-2,+2)	6.02%	<.0001
(-5,+5)	5.84%	<.0001
Target		
(-2,+2)	29.90%	<.0001
(-5,+5)	32.62%	<.0001
Bidder		
(-2,+2)	1.28%	0.0723
(-5,+5)	1.17%	0.1449

Table 15 (cont.)- Event Study Analysis Alternate Windows (Robustness)

Panel B: Announcement Returns for V, H, & C Classifications

Panel B reports alternative windows for CARs around merger announcement date for horizontal, vertical, and conglomerate type mergers as defined by both a Human Eye method of industrial organization classification as well as the SIC/IO method at each of its 1%, 5%, and 10% vertical relatedness cutoffs. The panel is partitioned in terms of combined, bidder, and target firm returns. Abnormal returns are in terms of calculations based on using the market model with estimation period (-255, -22).

	Horizontal Returns		Vertical Returns		Conglomerate Returns	
	Mean	*(P-Value)*	*Mean*	*(P-Value)*	*Mean*	*(P-Value)*
Human Eye						
Combined Firm						
(-2,+2)	6.84%	<.0001	5.60%	0.0721	3.42%	0.2027
(-5,+5)	6.57%	<.0001	6.34%	0.0662	2.93%	0.2105
Target						
(-2,+2)	28.03%	<.0001	38.99%	<.0001	29.79%	<.0001
(-5,+5)	31.59%	<.0001	39.47%	<.0001	31.25%	<.0001
Bidder						
(-2,+2)	2.68%	0.0012	-2.42%	0.4052	-0.97%	0.4014
(-5,+5)	2.67%	0.005	5.46%	0.0039	-0.79%	0.42
IO Method @ 1%						
Combined Firm						
(-2,+2)	6.15%	0.0027	7.50%	<.0001	4.18%	0.0074
(-5,+5)	6.29%	0.0057	6.77%	<.0001	4.53%	0.0037
Target						
(-2,+2)	18.26%	<.0001	30.88%	<.0001	33.60%	<.0001
(-5,+5)	25.68%	<.0001	32.63%	<.0001	35.49%	<.0001
Bidder						
(-2,+2)	2.37%	0.1936	1.67%	0.1988	0.45%	0.582
(-5,+5)	2.86%	0.1719	1.09%	0.4614	0.62%	0.4896
IO Method @ 5%						
Combined Firm						
(-2,+2)	7.21%	<.0001	10.51%	0.0002	3.60%	0.0067
(-5,+5)	6.76%	<.0001	10.50%	0.0003	3.60%	0.008
Target						
(-2,+2)	23.53%	<.0001	26.35%	<.0001	35.96%	<.0001
(-5,+5)	29.09%	<.0001	25.87%	<.0001	37.38%	<.0001
Bidder						
(-2,+2)	2.33%	0.053	5.46%	0.0039	-0.79%	0.42
(-5,+5)	1.90%	0.1356	6.05%	0.0064	-0.92%	0.4161
IO Method @ 10%						
Combined Firm						
(-2,+2)	7.09%	<.0001	13.47%	0.0035	3.78%	0.0036
(-5,+5)	6.74%	<.0001	13.05%	0.0053	3.81%	0.0042
Target						
(-2,+2)	23.83%	<.0001	23.01%	0.0005	36.17%	<.0001
(-5,+5)	28.97%	<.0001	21.94%	0.0006	37.50%	<.0001
Bidder						
(-2,+2)	2.84%	0.0085	6.23%	0.087	-0.61%	0.5205
(-5,+5)	2.77%	0.0169	6.27%	0.1442	-0.77%	0.4834

Table 15 (cont.)- Event Study Analysis Alternate Windows (Robustness)

Panel C reports alternative windows for CARs around merger announcement date for the entire set of rival firms. *Panel D* reports alternative windows for CARs around merger announcement date for the rival firms in horizontal, vertical, and conglomerate type mergers as defined by both a Human Eye method of industrial organization classification as well as the SIC/IO method at each of its 1%, 5%, and 10% vertical relatedness cutoffs. Abnormal returns are in terms of calculations based on using the market model with estimation period (-255, -22).

Panel C: Rival Announcement Returns for Full Sample

	Total Returns	
	Mean	*(P-Value)*
(-2,+2)	1.49%	0.0117
(-5,+5)	1.63%	0.061

Panel D: Rival Announcement Returns for V, H, & C Classifications

	Human Eye Returns		IO @ 1% Returns		IO @ 5% Returns		IO @ 10% Returns	
	Mean	*(P-Value)*	*Mean*	*(P-Value)*	*Mean*	*(P-Value)*	*Mean*	*(P-Value)*
Horizontal								
(-2,+2)	1.61%	0.0197	3.57%	0.0165	2.28%	0.0221	1.64%	0.0792
(-5,+5)	2.13%	0.0416	2.15%	0.2401	0.81%	0.5246	0.59%	0.6335
Vertical								
(-2,+2)	-0.49%	0.74	0.76%	0.3821	0.37%	0.8297	2.50%	0.346
(-5,+5)	-1.68%	0.41	0.60%	0.6429	1.68%	0.5261	3.22%	0.3949
Conglomerate								
(-2,+2)	2.49%	0.1356	1.43%	0.1383	1.17%	0.1518	1.19%	0.1315
(-5,+5)	2.15%	0.353	2.62%	0.0832	2.28%	0.0834	2.27%	0.0755

Table 16- Regression Analysis: Relation between Merger Type and Select Variables of Interest

Panel A: "Cash Only" Consideration Structure on Merger Type

Panel A reports the results of an OLS regression of the "cash only" consideration structure dummy variable on variables for merger type- once without controls and once while controlling for transaction value as well as industry and year effects. The conglomerate merger variable is the "omitted contrast." In other words, it is left out of the regression equation due to multicollinearity considerations, but its effect is (at least partly) represented in the constant term. Due to nonlinearity created by having the "cash" dummy variable on the LHS, the coefficients on the explanatory variables are difficult to interpret, but the OLS equation remains the best *linear* predictor of "cash" in theory, and comparison of the coefficients is in fact still meaningful in terms of testing theories.

VARIABLES	(1) cash
vdummy	-0.059
	(-0.45)
hdummy	-0.196**
	(-2.08)
Constant	0.759***
	(9.45)
Observations	152
R-squared	0.028

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(With Controls)

VARIABLES	(1) cash
vdummy	-0.112
	(-0.85)
hdummy	-0.278**
	(-2.57)
logtransvalue	0.010
	(0.31)
Constant	-0.226
	(-0.75)
Industry & Year Effects	Controlled
Observations	152
R-squared	0.351

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16 (cont.)- Regression Analysis: Relation between Merger Type and Select Variables of Interest

Panel B: (Log) Transaction Value on Merger Type

Panel B reports the results of an OLS regression of the of the log of transaction value on variables for merger type, once without controls and once while controlling for consideration structure as well as industry and year effects. The conglomerate merger variable is the "omitted contrast." In other words, it is left out of the regression equation due to multicollinearity considerations, but its effect is (at least partly) represented in the constant term (note: "other" was also omitted in the control regression for similar multicollinearity considerations).

VARIABLES	(1) logtransvalue
vdummy	-0.366
	(-0.78)
hdummy	0.162
	(0.47)
Constant	6.801***
	(21.57)
Observations	152
R-squared	0.014

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(With controls)

VARIABLES	(1) logtransvalue
vdummy	-0.584
	(-1.11)
hdummy	0.393
	(0.89)
cash	0.382
	(0.93)
stock	-0.663
	(-0.99)
hybrid	0.663
	(1.43)
Constant	8.259***
	(16.91)
Industry & Year Effects	Controlled
Observations	152
R-squared	0.409

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16 (cont.)- Regression Analysis: Relation between Merger Type and Select Variables of Interest

Panel C: Combined Firm Net of Market Returns on Merger Type

Panel C reports the results of an OLS regression of combined firm CARs (net of market) on merger type, once without controls and once while controlling for consideration structure, transaction value, and tender offers, as well as industry and year effects. The conglomerate merger variable is the "omitted contrast." In other words, it is left out of the regression equation due to multicollinearity considerations, but its effect is (at least partly) represented in the constant term (note: "other" was also omitted in the control regression for similar multicollinearity considerations).

VARIABLES	(1) ccarm
vdummy	0.029
	(0.74)
hdummy	0.028
	(1.05)
Constant	0.038
	(1.47)
Observations	152
R-squared	0.012

(With controls)

VARIABLES	(1) ccarm
vdummy	0.010
	(0.20)
hdummy	-0.003
	(-0.08)
cash	-0.048
	(-1.44)
stock	-0.006
	(-0.13)
hybrid	-0.014
	(-0.38)
logtransvalue	0.006
	(0.89)
tenderoffer	0.014
	(0.54)
Constant	-0.205***
	(-3.84)
Industry & Year Effects	Controlled
Observations	152
R-squared	0.312

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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