ABSTRACT

Title of Document: WHEN DO TARGETS' PAST FINANCIAL RESULTS MATTER MOST TO ACQUIRERS? THE ROLE OF DISRUPTION OF TARGETS' EXISTING OPERATIONS

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This study examines how anticipated disruption in the target's existing operations affects the importance that acquirers place on the target's historical accounting information in the acquirer's merger pricing decisions. A target's past earnings and past earnings quality are informative about the performance of its stand-alone operations while its book value is informative about its adaptation value, which is the potential value from alternative uses of its resources. The information in past earnings and past earnings quality about a target's stand-alone operations is likely to be more important to acquirers that intend to keep the target's operations intact post-merger while the information in book value about its adaptation value is likely to be more important to acquirers that anticipate significant disruption of the target's operations.

I capture the level of disruption in two ways. First, I use the financial versus operating acquirer distinction used commonly in the finance literature. Prior research suggests that the merger goals of financial acquirers that buy operating companies require relatively less disruption of the target's operations than the merger goals of operating acquirers that buy operating companies. Second, to exploit cross-sectional variation in the degree of disruption among operating acquirers, I create an index comprised of the following four variables: (1) target management turnover, (2) target analyst turnover, (3) anticipated merger restructuring costs, and (4) the distance between acquirer and target headquarters.

For both measures, I find that acquirers assign greater discounts to targets' pre-merger earnings performance and pre-merger earnings quality in setting their bids as anticipated disruption of targets' operations increases, presumably because the information the target's past earnings conveys about its pre-merger operations is less important to acquirers that anticipate disrupting those operations. In addition, acquirers assign greater premiums on targets' pre-merger book values in setting their bids as anticipated disruption increases, presumably because the information the target's recent book value conveys about the adaptation value of its resources is more important to acquirers that plan to disrupt the target's operations.

To extend my main findings, I examine post-merger consequences related to disruption. First, I assess whether there are economic consequences when acquirers ignore disruption in their pricing decisions. I predict and find that the likelihood of post-merger goodwill impairment increases when acquirers do not vary the weight they placed on the target's accounting inputs (earnings, book value and earnings quality) based on anticipated disruption of the target's existing operations. Second, I examine how managers' ability to forecast merger performance varies by disruption. Goodman et al. (2014) argue that managers' general forecasting ability as reflected in their publicly released management forecasts translates into the ability to make the necessary forecasts for investments such as mergers and acquisitions. I argue and find that this relationship varies based on disruption and provide evidence that suggests that managers who make more accurate earnings forecasts are better able to assess external projects due to their ability to properly use past earnings to predict future earnings. Collectively, these findings provide important insights into the conditions under which particular types of accounting information are most useful in the merger context.

WHEN DO TARGETS' PAST FINANCIAL RESULTS MATTER MOST TO ACQUIRERS? THE ROLE OF DISRUPTION OF TARGETS' EXISTING OPERATIONS

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2014

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Acknowledgements

I am deeply grateful for my graduate school experience at the University of Maryland. These past five years have pushed me further as a researcher, a teacher and most of all, an individual. Joining the Robert H. Smith School of Business was one of the best opportunities I have been granted in my life, and as I move forward in my career as an academic, I bring with me the immense support that I received from the professors, staff and students.

I would particularly like to thank my advisor, Michael Kimbrough, for his extraordinary mentorship. I feel extremely grateful and fortunate in having the opportunity to work with someone whose intelligence is matched only by his kindness. It is impossible for me to imagine another advisor who would put in as much time, thought and effort into helping his students as Michael. Michael is my role model and it is my continuous goal to be able to think, write and express my thoughts like him.

I would like to thank my dissertation committee members: Shijun Cheng, Rebecca Hann, Laurent Fresard and David Sicilia for their time, interest and comments regarding my dissertation. I also thank Shijun, Rebecca and Laurent for their time over the years in advising me in matters ranging from paper topics to job opportunities. In addition, I thank Laurent for showing me pictures of his adorable son, Thomas.

In terms of emotional support and encouragement, I am most indebted to Seth Carnahan. For the past year, Seth has provided me with endless academic and personal support and has played an instrumental role in giving me the confidence I need to complete my dissertation and to pursue other research projects. Seth has become my best friend and my closest colleague and having him by my side makes me look forward to the road ahead. But even before Seth came into my life, I had Heather Pfleger and Gorana Smailagic to hold me up. I thank these girls for sticking with me through thick and thin and for treasuring our friendship as much as I do. There is nothing that can match a near 20-

year friendship when it comes to love and encouragement. And of course, above all, I thank my parents for their unconditional love and support. I thank my mother for bringing the laughter and lightness to any situation when I need it the most and for calling me every day to remind me to eat. I thank my father for instilling the work ethic and persistence I needed to complete this dissertation. This career path would never have been an option for me if it weren't for him. Furthermore, I thank him for taking such a great interest in my academic progress and for always providing me with honest and good advice.

The people with who I interacted every day is what made my time at R.H. Smith particularly special. I would like to express my heartfelt appreciation to our Ph.D. Program Coordinator, Justina Blanco. Justina's professional and personal support is what makes R.H. Smith as special as it is. I thank Justina for getting me through important milestones in the program and for making continual efforts to bring all the Ph.D. students together. Justina is the backbone of our student community and is responsible for the welcoming and homey spirit that our program fosters. I thank Lindsey Gallo for being my partner-in-crime from the very beginning and for providing me the laughs I needed to get through economics. I thank Chad Ham for his dance moves and for engaging in long discussions covering topics from econometrics to marriage proposals. I thank Congcong Li for being as sweet as can be and for bringing me delicious chocolate from China. I also thank the other accounting Ph.D. students: Wen-Feng Wang, Kyungran Lee, Sijing Wei, Yue Zheng, Yi Cao and and Heedong Kim for our time together. I also thank Danmo Lin for letting me be her roommate for a week during Snowmageddon 2010 and for always making me laugh. I thank Kyoung-Hun Bae (K-Honey) for helping me with my 2011 summer paper and for teaching me things about rock climbing and finance (which are both equally difficult). Last, but not least, I thank Onur Tosun for his board game house parties.

Finally, I would like to thank my co-authors, Hanna Lee and Emanuel Zur, for their emotional support and for giving me a chance to take part in exciting projects. In particular, I thank Hanna for checking up on me during the job market and for providing strong support and morale when I needed it most. I also thank Emanuel for his support and for being a great sounding board for research ideas.

It is this collection of people who made my five years at the University of Maryland the most enjoyable experience of my life. I thank you all for the part that you played in making that happen.

Table of Contents

List of Appendices

List of Tables

Chapter 1: Introduction

Mergers are common and economically significant strategic investments. In the year 2013 alone, there were approximately 12,000 announced mergers in North America with a total value of \$1.5 trillion dollars[1]. Analysis of the target's historical financial performance is an essential part of any acquirer's due diligence (Carney, 2009; Weston et al., 2004). Consistent with this notion, prior research examines the average importance of the target's earnings quality on the acquirer's bid price (Skaife and Wangerin, 2013; McNichols and Stubben, 2012; Raman et al., 2012). In this paper, I examine whether there is variation in the importance acquirers place on the target's historical accounting information in their merger pricing decisions. I focus on three accounting inputs: the target's recent earnings performance, the target's most recent book value of equity, and the target's recent earnings quality.

In light of the well-established importance of historical earnings in valuing firms on a stand-alone basis, their relevance in valuing targets in the merger context seems intuitive. However, it is not obvious that the target's historical earnings are equally relevant across all mergers because the factors that contribute to the importance of earnings in the traditional valuation context do not necessarily hold for all mergers. Specifically, the importance of earnings in the traditional valuation context derives from the ability of past earnings to predict future earnings via earnings persistence (Sloan, 1996; Ou and Penman, 1989; Bernard and Thomas, 1990; Fairfield and Yohn, 2001). The predictive ability of historical earnings may be undermined in the merger context if the underlying operations that drove the target's earnings generating process prior to the merger are disrupted as a result of the merger. Consistent with this possibility, Bruner (2004) argues that the target's historical accounting information is not useful in target valuation due to its backward looking properties.

[1] According to the Institute of Mergers, Acquisitions and Alliances, www.imaa-institute.org.

Because the merger context differs from the traditional valuation context, this study examines circumstances in which the target's historical earnings performance is more or less relevant in target valuation.

I extend this examination to include the target's book value and the target's past earnings quality because both are potentially useful inputs to acquirers' pricing decisions. Specifically, the target's book value reflects adaptation value, which is the value of the firm's resources independent of how they are used (Burgstahler and Dichev, 1997). Information about adaptation value is potentially useful to acquirers in assessing the value of alternative uses for the target's resources. The target's earnings quality can facilitate merger valuation by contributing to greater transparency about the target's operations.

The information in the target's past earnings and past earnings quality about its pre-existing operations is of limited usefulness in forecasting post-merger outcomes when the acquirer plans to substantially change the target's operations. Therefore, I predict that the acquirer discounts both the target's historical earnings and the target's earnings quality when setting merger premium to a greater degree as anticipated disruption of the target's existing operations increases. Because the target's book value reflects information about the adaptation value of its resources, book value may be more informative than earnings in determining merger value when the acquirer expects to disrupt the target's existing operations. I predict that the acquirer places greater weight on the target's book value in setting the merger premium as anticipated disruption of the target's existing operations increases.

My main empirical tests regress the premium paid by the acquirer on these accounting inputs. Because the denominator of the premium is the target's pre-merger stock price, the coefficients on the accounting inputs capture the average difference between acquirers' and the market's valuation of these inputs. An insignificant coefficient on an accounting input indicates no average difference between acquirers' and the market's valuation of the input. By contrast a positive (negative) coefficient on the accounting input indicates that acquirers assign a premium (discount) to the accounting input relative to the market's pre-merger valuation. To test my predictions, I examine whether there is cross-sectional variation in the premium or discount acquirers assign to these inputs based on the degree of disruption associated with the merger.

To capture the level of disruption, I first use the financial versus operating acquirer distinction used commonly in the finance literature (Bargeron et al., 2008; Gorbenko and Maleko, 2013; Dittmar et al., 2012; Martos-Vila et al., 2012). Financial acquirers include divisions of investment banks, private equity firms, and investor groups. Prior research identifies among the goals of financial acquirers that buy operating companies potential tax savings, access to internal markets, lower cost of capital, diversification of cash flow streams, and extraction of gains from well-managed but undervalued targets (Leland, 2007; Lewellen, 1970; Mueller, 1969; Hubbard and Palia, 1999). In general, the financial acquirer does not need to significantly alter the operations of its operating company target to achieve these benefits. By contrast, operating company acquirers seek to achieve gains through the synergistic combination of the acquirer's and target's resources. Realization of such synergies typically requires the acquirer to adapt or redeploy the target's resources. Specifically, acquirers can generate synergies by better managing underperforming assets of the target or by exploiting complementarities between the acquirer's and target's assets to create new products, services or delivery channels (Larsson and Finkelstein, 1999; Hoberg and Phillips, 2010; Rhodes-Kropf and Robinson, 2008). Therefore, I expect mergers with operating acquirers to entail more disruption of the target's existing operations than mergers with financial acquirers.

Although I expect mergers with operating acquirers to entail more disruption than mergers with financial acquirers on average, I also expect variation in the degree of disruption among operating acquirers. I, therefore, test whether the importance of the accounting inputs varies cross-sectionally among mergers completed by operating acquirers. To capture cross-sectional variation in disruption among operating acquirers, I create an index comprised of the following four variables: (1) target management turnover, (2) target analyst turnover, (3) anticipated merger restructuring costs, and (4) the distance between acquirer and target headquarters. Target management turnover, which is the turnover rate for the top executive of the target firm following the merger, captures the likelihood that the acquirer intends to intervene in the target's operations by installing a new top management team. Target analyst turnover is the post-merger turnover rate for target analysts and captures the extent to which they anticipate the target's earnings time series to remain relatively predictable. Analysts who anticipate significant changes in the earnings process are presumably more likely to drop coverage. Anticipated merger restructuring costs capture integration costs, which presumably correspond in degree to the disruption of the target's operations. Distance between acquirer and target headquarters locations captures acquirers' anticipation of actively managing targets' assets.

I validate the disruption index by examining the extent to which it identifies transactions in which targets' pre-merger earnings performance is less useful in predicting the performance of the merged entity. Specifically, I estimate the autoregressive parameter for the pre-merger earnings of a hypothetical firm comprised of both the acquirer and target. I find that this parameter is a worse predictor of the actual post-merger earnings of the merged firm as the disruption index increases, which indicates that the index captures changes in the earnings generating process associated with greater degrees of disruption.

My sample for tests that compare financial and operating acquirers consists of 120 merger transactions reported in the Securities Data Corporation (SDC) database completed by financial acquirers during 1980 to 2012 and 120 mergers by operating acquirers over the same period matched on target characteristics (operating-financial sample). I find that financial acquirers' valuation of accounting inputs aligns with the market's pre-merger valuation, consistent with the minimal disruption typically associated with mergers by financial firms. However, I find that operating acquirers' valuation of accounting inputs differs significantly from that of financial acquirers, consistent with the relatively greater disruption associated with mergers by operating firms. Specifically, I find that, unlike financial acquirers, operating acquirers discount the target's historical earnings and earnings quality. On the other hand, operating acquirers place greater weight on the target's book value than financial acquirers. This result indicates that, relative to financial acquirers, operating acquirers are more interested in the target's adaptation value as reflected in book value. Collectively, these results support my prediction that the relevance of the target's historical accounting information depends on the degree of anticipated disruption.

My sample for tests that examine cross-sectional variation in disruption among operating acquirers, also drawn from the SDC database, consists of 188 transactions completed between 1994 and 2010 in which both acquirer and target were public, operating companies (operating only sample). Consistent with my previous results, I find that operating acquirers' valuation of accounting inputs most closely aligns with the market's pre-merger valuation when disruption is minimal. However, as disruption increases, operating acquirers discount the target's historical earnings and earnings quality to a greater extent and assign greater weight to the target's book value. These findings further support the conclusion that the relevance of the target's historical accounting information depends on the anticipated degree of disruption.

I extend my main findings by examining the post-merger implications of disruption. First, I examine whether there are economic consequences when acquirers ignore disruption. To the extent disruption is an economically significant factor for acquirers to consider, failure to consider this factor may increase the risk of initial overpayment or may reflect insufficient attention to important details needed for successful integration (Zollo and Singh, 2004; Pablo et al., 1996; Jemison and Sitkin, 1986). In either case, the post-merger performance of the combined entity will fail to justify the initial purchase price, thereby giving rise to goodwill impairments. Therefore, I predict that the likelihood of post-merger goodwill impairment increases when acquirers do not vary the weight they placed on the target's accounting inputs (earnings, book value and earnings quality) based on anticipated disruption of the target's existing operations. I use residuals from a pricing model that incorporates anticipated disruption of the target's operations to capture deviations from predicted pricing behavior. I expect and find a positive relationship between these deviations and the likelihood of subsequent goodwill impairment using logit estimation. This finding suggests that the likelihood of post-merger goodwill impairment increases when acquirers do not vary the weight they place on the target's accounting inputs based on anticipated disruption of the target's existing operations. To better isolate the deviation that is specifically related to disruption, I regress goodwill impairment occurrence and the residual of a pricing model that *excludes* anticipated disruption. I predict and find that the residual from the full model that includes disruption provides a better fit for a model explaining subsequent goodwill impairments than the residual from the model that excludes disruption.

I also examine how managers' ability to forecast merger performance varies by disruption. Goodman et al. (2014) argue that managers' general forecasting ability as reflected in their publicly released management forecasts translates into the general ability to make the necessary forecasts for investments such as mergers and acquisitions. Consistent with this notion they find that acquirers with greater forecast accuracy experience superior post-merger performance and lower likelihood of goodwill impairment. I examine whether this finding varies by disruption. If their finding is driven by managers' ability to properly use past earnings to predict future earnings then the negative relation they document between acquirers' forecast accuracy and subsequent goodwill impairments will be less pronounced as disruption increases. By contrast, if their finding is driven by managers' ability to forecast outcomes that are independent of past earnings then the negative relation between acquirers' forecast accuracy and subsequent goodwill impairments will be more pronounced as disruption increases. I regress goodwill impairment occurrence on the acquiring manager's three-year forecast accuracy average and examine whether there are any cross-sectional differences based on the degree of disruption associated with the merger. I find that the negative association between the acquirer's historical management forecast accuracy and likelihood of post-merger goodwill impairment becomes less pronounced as disruption increases. This finding suggests that managers' ability to use past earnings to predict future earnings contributes to better post-merger outcomes, particularly in mergers with low disruption.

This study makes several contributions. First, it adds to an emerging literature on the role of accounting information in target valuation. Prior research finds that target earnings quality plays an important role in merger pricing and outcomes (Skaife and Wangerin, 2013; Raman et al., 2012; McNichols and Stubben, 2012; Martin and Shalev, 2009; Marquardt and Zur, 2014). Whereas this stream of research documents the importance of targets' historical earnings information in the merger setting, *on average*, I demonstrate that its importance varies with the degree of disruption associated with a merger. This insight should be relevant to acquirers that must determine the appropriate degree of reliance on historical target accounting information in formulating their bids and to analysts and investors who must determine the appropriate response to merger announcements.

Second, this paper provides insights on whether managers appropriately use accounting information in pricing transactions. Despite the prevalence of mergers, there is mixed evidence on whether they create or destroy value (Louis, 2004; Andrade et al., 2001; Berger and Ofek, 1995; Lang and Stulz, 1994; Healy et al., 1992, 1997), calling into question whether acquirers make decisions that maximize firm value when pursuing such deals. I find that acquirers' valuation of accounting inputs aligns with the market's pre-merger valuation in cases where anticipated disruption is minimal. However, as anticipated disruption increases, acquirers' valuation of accounting inputs departs from the market's pre-merger valuation in economically sensible ways. This evidence that acquirers adjust their use of targets' historical accounting information based on the anticipated degree of disruption of targets' operations is consistent with managers' appropriate use of accounting information in their pricing decisions.

Finally, this paper provides evidence on the different information provided by the target's historical earnings and book values in the merger setting. Specifically, the predictive information content of the target's historical earnings for future earnings of the merged firm is less relevant to acquirers when they anticipate significant disruption to the target's operations as a result of the merger. By contrast, the information contained in the target's book value about adaptation value is more relevant to acquirers in transactions where they anticipate significant disruption as a result of adapting or redeploying the target's resources.

The remainder of this study proceeds as follows. Chapter 2 discusses the relevant literature and develops the hypotheses. Chapter 3 describes variable measurement and research design. Chapter 4 discusses the sample. Chapter 5 discusses the empirical results. Finally, Chapter 6 concludes.

Chapter 2: Related Literature and Hypothesis Development

2.1 The potential payoffs to mergers

Mergers and acquisitions represent a common form of corporate strategic investment that can generate payoffs to the acquirer in a variety of ways. At the most basic level, an acquirer can realize gains simply by buying a well-managed but undervalued target without disrupting the target's existing operations— a strategy Warren Buffett famously advocates (Greenwald et al., 2001). In this case, the target's already established earnings generating process drives the anticipated merger payoffs.

An acquirer can also achieve gains through the synergistic combination of the acquirer's and target's resources. The realization of synergies typically requires the acquirer to disrupt the target's existing operations and to adapt or redeploy the target's resources. For example, the q-theory argues that mergers can generate synergies by unlocking the value in underperforming assets by placing them under better management (Manne, 1965; Jovanovic and Rousseau, 2002). This process traditionally involves more efficient acquirers purchasing less efficient targets so that the acquirers' relative expertise can be transferred to the target's assets (Martin and McConnell, 1991).[2] On the other hand, Rhodes-Kropf and Robinson (2008) argue that another way for mergers to create synergies is by bringing complementary assets under common control, thereby reducing the hold-up problems and underinvestment related to incomplete contracting (Grossman and Hart, 1986; Hart and Moore, 1990; Hart, 1995). In either case, the expected merger payoffs from synergies are driven by anticipated new uses of the target's resources rather than by the target's already established earnings generating process.

Regardless of the anticipated source of payoff, an acquirer must pay no more than the present value of the future payoffs the merger is expected to generate to ensure that the merger

[2] However, an acquirer can also achieve gains when it merges with a more productive target (Maksimovic and Phillips, 2001).

enhances value. That is, an acquirer must estimate the merger's future payoffs to guard against overpayment. Accounting has a natural conceptual role to play in facilitating the forecasts of merger payoffs given that the key objective of general purpose financial reporting as set forth by the Financial Accounting Standards Board in Statement of Financial Accounting Concepts (SFAC) No. 8 is to provide information that is useful to investors in assessing "the amount, timing, and uncertainty of (the prospects for) future net cash inflows of an entity" (SFAC No. 8, paragraph OB3). Therefore, I examine the potential usefulness of accounting inputs for forecasting merger payoffs. I also explore the possibility that the usefulness of accounting inputs for this purpose varies based on the degree of disruption of target operations that the merger entails.

2.2 The information content of various accounting inputs for merger valuation

2.2.1 Accounting and valuation

As discussed in section 2.1, the key objective of financial reports is to provide information that facilitates the formulation of forecasts for investment purposes. Accounting researchers have devoted considerable attention to examining the role of accounting information for valuation. Ohlson (1995) derives a model of equity value based only on book value and earnings, which are the two primary summary measures from the accounting system. A large body of empirical research documents strong associations between these accounting measures and stock prices, indicating that these measures are highly value relevant (e.g. Barth et al., 1998, Collins et al., 1997, Collins et al., 1999, Core et al., 2003, Francis and Schipper, 1999, Penman and Sougiannis, 1998). More recently, researchers have posited and provided evidence that earnings quality, which captures the extent to which reported earnings reflect the firm's underlying economics (Barth et al., 2001), is also useful for valuation by lowering investors' estimation risk (e.g. Francis et al.; 2008; Francis et al., 2004; Francis et al., 2005; Barth et al., 2013). Prior research focuses on the role of accounting in valuing firms on a stand-alone basis. Implicit in this focus is the going concern assumption wherein an entity is expected to continue without disruption (Accounting Standards Codification 205-40). Because this assumption is violated to varying degrees in the merger context, I examine how the disruption associated with mergers affects the usefulness of earnings, book value, and earnings quality for valuation in the merger context.

2.2.2 Earnings

The dividend discount model is the conceptual benchmark for all equity valuation (Gordon and Shapiro, 1956). In response to the practical challenge of forecasting an infinite stream of future dividends, researchers have derived various models for valuing an individual firm's equity that are consistent with the dividend discount model but that are stated only in terms of current and forecasted accounting inputs (Penman, 1998; Penman and Sougiannis, 1998; Frankel and Lee, 1998; Francis et al., 2000; Courteau et al., 2001). A key insight underlying accounting-based valuation is that an analyst can derive equity value estimates that are consistent with the dividend discount model by forecasting a firm's dividend paying ability rather than by explicitly forecasting the stream of future dividends (Ohlson, 1995). Because future earnings coincides with a firm's dividend paying ability (Beaver, 1989), forecasting future earnings is a key valuation task. Prior research demonstrates that earnings exhibit strong first-order autocorrelation (Beaver, 1970; Ball and Watts, 1972). This time-series dependence in earnings provides a basis for past earnings to be useful in predicting future earnings (Albrecht et al., 1977; Watts and Leftwich, 1977; Lev, 1983). Implicit in the use of current earnings to predict future earnings in traditional valuation is the assumption of intertemporal stability in the firm's earnings generating process and the assumption that the firm is anticipated to operate without disruption (the going concern assumption).

In the merger context, the persistent property of historical earnings is most valuable in quantifying merger payoffs that depend on the target's established operations and earnings generating process (i.e., mergers with little anticipated disruption). By contrast, this property is less useful in quantifying benefits that do not depend on the target's established operations and earnings generating process (i.e., mergers with more significant anticipated disruption). In particular, if the acquirer anticipates altering how the target's resources are managed or deployed, then the historical time series becomes less relevant in predicting future outcomes. Consistent with this idea, Subramanyam and Wild (1996) find an inverse relationship between earnings informativeness and the firm's probability of termination, suggesting that the firm's going-concern status has a fundamental role in determining the usefulness of earnings and hence, earnings persistence. Choi and Jeter (1992) find a significant decrease in market responsiveness to earnings announcements after the issuance of qualified audit reports that call into question the entity's ability to continue as a going concern. Similarly, Hayn (1995) argues that because shareholders have a liquidation option, losses are not expected to perpetuate. Consistent with the hypothesis, she finds that reported losses are less persistent than reported profits. Overall, prior research has established that the persistent properties of earnings may not hold in situations where the firm's future operations face disruption (e.g. mergers).

2.2.3 Book value

In cases where earnings are of limited usefulness, accounting offers another potentially useful signal in the form of book value. Book value measures the net realizable value of a firm's assets and is a close reflection of liquidation value (Barth et al., 1998). As a firm's existing earnings generation process approaches jeopardy (e.g. when a firm's financial health decreases), its book value becomes relatively more relevant, as compared to earnings, to equity investors because liquidation values affect equity values (Barth et al. 1998; Collins et al., 1999). In addition to reflecting liquidation value, Burgstahler and Dichev (1997) argue that book value reflects adaptation value, which is the value of the firm's resources independent of how well the firm uses those resources. Adaptation value exists when a firm can either sell its resources to an external entity (e.g. asset sale or merger) and/or if its resources can be used internally in a different way (e.g. restructuring). In the merger context, Hand and Lynch (1999) state that adaptation value "arises from the option the bidder has to put the target's assets to alternative new uses" (Hand and Lynch, 1999, p. 6). Therefore, book value may be a greater source of information in quantifying merger payoffs that are driven by anticipated new uses of the target's resources (i.e. mergers with more significant anticipated disruption) rather than by the target's already established earnings generating process.

2.2.4 Earnings quality

The target's earnings quality is potentially useful to acquirers by enhancing the informativeness of the target's pre-merger earnings about its existing operations. The target's past earnings quality is likely to be most relevant to acquirers when they desire precise information about the target's existing operations because they expect such operations to continue. By contrast, the target's past earnings quality is likely to be less relevant to acquirers that do not anticipate relying heavily on the target's existing operations to generate payoffs.

Prior research finds a negative relation between premium and earnings quality (Skaife and Wangerin, 2013; Raman et al., 2012; McNichols and Stubben, 2012). McNichols and Stubben (2012) argue that acquiring firms of high accounting quality target firms are able to bid more effectively and pay less than acquiring firms of low accounting quality target firms, since higher quality accounting information reduces uncertainty about the value of the target. Another prevailing explanation for the negative relationship between premium and earnings quality is that acquirers of targets with low earnings quality have identified, and are willing to pay for, sources of value of the target that are not well reflected in either the target's pre-merger earnings performance or its stock price. Because such hidden sources are value are likely to be more present in mergers that entail greater disruption, I examine whether the previously documented negative relation between premium and earnings quality is more pronounced for mergers that entail greater disruption.

2.3 Acquirers' use of accounting inputs in merger valuation

The preceding discussion demonstrates that accounting inputs differ in their importance in quantifying merger payoffs based on disruption. Accordingly, the weight acquirers place on these inputs when formulating their bids should vary in similar fashion if they seek to maximize the net present value (NPV) of their merger investments. However, it is not obvious that acquirers actually do consider disruption when determining the weight they place on accounting inputs given evidence that acquirers undertake mergers for reasons other than profit maximization. Specifically, Roll (1986) finds evidence that some managers suffer from hubris, leading them to enter into transactions where there are little to no synergistic gains. Jensen and Meckling (1976) raise the possibility of empire building as a motivation for mergers, wherein managers buy other companies to expand their power instead of maximizing the value of the firm. Finally, Shleifer and Vishny (1989) argue that managers may pursue mergers to "entrench" themselves so that it becomes too costly to replace them.

2.4 Acquirers' use of accounting information and post-merger outcomes

The previous discussion indicates that there is uncertainty about whether acquirers will consider disruption when deciding the weights they place on accounting inputs in formulating their bids. A natural question that arises is whether there are economic consequences when acquirers ignore disruption. To the extent disruption is an economically significant factor for acquirers to consider, failure to consider this factor may increase the risk of merger underperformance via two routes. First, failure to consider a relevant factor in merger pricing increases the risk of initial overpayment. Second, failure to consider a relevant factor may reflect insufficient attention to important details needed for successful integration (Zollo and Singh, 2004; Pablo et al., 1996; Jemison and Sitkin, 1986). In either case, the post-merger performance of the combined entity will fail to justify the initial purchase price, thereby giving rise to goodwill impairments.

Accounting Standards Codification (ASC) 805, effective June 30, 2001, requires acquiring firms to recognize the targets' assets and liabilities at their acquisition-date fair values and to allocate the excess of the price paid over the fair value of the target's identifiable net assets acquired to goodwill. Under ASC 350, firms must test for goodwill impairment at least annually or if events or changes in circumstances indicate that the carrying amount of the goodwill obtained in an acquisition may not be recoverable. Thus goodwill impairments may arise if implementation of the acquirer's strategy goes awry and/or if the acquirer overpaid for the target (Ramanna and Watts, 2012; Li et al., 2011).

Prior research finds that goodwill impairments occur relatively frequently with 30-40% of firms with existing goodwill balances and high book to market ratios reporting goodwill impairments within a 3-year time period (Ramanna and Watts, 2012). Recent anecdotal examples of goodwill impairments include Hewlett-Packard's $8.8 billion write-off of its 2011 acquisition of Autonomy Corporation and Caterpillar's $580 million goodwill write-off of its 2012 Siwei acquisition in China. A major source of goodwill impairments for acquiring firms comes from target overpayment. For example, Hayn and Hughes (2005) and Li et al. (2011) argue that significant premiums, presence of multiple bidders, and stock financing, bid characteristics that explain target overpayment, are predictors of future goodwill impairments. Gu and Lev (2011) also find that acquirers with overpriced shares at the time of the merger announcement often pay more for their targets and are more likely to take goodwill write-offs following the merger.

Another major source of goodwill impairments for acquiring firms comes from insufficient attention to important details needed for successful integration (Zollo and Singh, 2004; Pablo et al., 1996; Jemison and Sitkin, 1986). These details range from cultural compatibility to organizational fit

(Larsson and Finkelstein, 1999). For example, analysts claim that eBay and Skype were not able to merge successfully in 2005 because their technological systems were incompatible (Reardon, 2007). Consistent with analyst speculations, eBay issued a statement in 2011 claiming that it "wanted to unload Skype after failing to integrate the company into its core operations" (eBay, 2011).

In this study, I also examine whether merger underperformance as reflected in goodwill write-offs is more likely for transactions where acquirers ignore disruption.

2.5 Goodwill impairments and management forecast accuracy

As previously discussed, purchase price determination requires forecasting merger payoffs. Goodman et al. (2014) argue that managers' general forecasting ability as reflected in their publicly released management forecasts translates into the ability to make the necessary forecasts for investments such as mergers and acquisitions. Consistent with this notion they find that acquirers with greater forecast accuracy experience superior post-merger performance and lower likelihood of goodwill impairment. I examine the possibility that this average finding varies by disruption. Specifically, managers' forecast accuracy can be attributed either to their ability to effectively use past earnings to predict future outcomes or to their ability to predict future outcomes independent of past earnings.[3] It is an open question from Goodman et al. (2014) which source of management forecast accuracy drives their overall finding. If Goodman et al. (2014)'s finding is driven by managers' ability to properly use past earnings to predict future earnings then the negative relation they document between acquirers' forecast accuracy and subsequent goodwill impairments will be less pronounced as disruption increases (based on arguments in section 2.2 that the target's past earnings is less important for merger pricing as disruption increases). By contrast, if their finding is

[3] Although most prior studies consider overall management forecast accuracy, Xu (2009) and Gong, Li, and Wang (2011) specifically examine managers' ability to use past earnings to generate accurate forecasts.

driven by managers' ability to forecast outcomes that are independent of past earnings then the negative relation between acquirers' forecast accuracy and subsequent goodwill impairments will be more pronounced as disruption increases (based on arguments in section 2.2 that acquirers in mergers with greater disruption are more likely to seek sources of value that are unrelated to the target's past earnings). Given these contrasting possibilities, I examine whether the negative relation between acquirers' forecast accuracy and subsequent goodwill impairments varies by disruption.

2.6 Hypothesis Development

As discussed in section 2.1, mergers can generate payoffs to the acquirer in a variety of ways that entail varying degrees of disruption to the target's existing operations. As discussed in section 2.2., earnings, book value, and earnings quality are potentially useful inputs in predicting these payoffs. However, the usefulness of each of these accounting inputs varies based on the disruption of the target's operations. Specifically, earnings and earnings quality are less useful for predicting merger payoffs as disruption increases while book value is more useful for predicting merger payoffs as disruption increases. As discussed in section 2.3, acquirers will vary the weight they place on these accounting inputs accordingly if they seek to maximize the NPV of their merger investments. However, evidence that acquirers undertake mergers for reasons other than profit maximization raises the possibility that they might not adjust their use of accounting information accordingly.

Based on these arguments, I propose the following hypotheses, stated in alternative form, to test whether managers appropriately adjust their use of accounting information for merger valuation.

H1. *Merger premium is less associated with the target's historical earnings as disruption of the target's existing operations increases.*

H2. *Merger premium is more associated with the target's book value as disruption of the target's existing operations increases.*

H3. *Merger premium is more negatively associated with the target's historical earnings quality as disruption of the target's existing operations increases.*

As discussed in section 2.4, acquirers' failure to adequately consider disruption when using accounting information may increase the risk of initial overpayment or the risk of poor execution, both of which lead to merger underperformance. In either event, the underperformance will be reflected in subsequent goodwill impairments. Therefore, I test the following hypothesis, stated in the alternative form.

H4: *The likelihood of post-merger goodwill impairment increases when acquirers do not vary the weight they placed on the target's accounting inputs based on anticipated disruption of the target's existing operations.*

As discussed in section 2.5, Goodman et al. (2014) find a negative association between acquirers' prior management forecast accuracy and subsequent goodwill impairments. This finding implies that managers who make more accurate earnings forecasts are better able to assess external projects, including merger opportunities. It is possible that this finding varies based on disruption. Specifically, managers' forecast accuracy can derive from their ability to effectively use past earnings to predict future outcomes or from their ability to predict future outcomes independent of past earnings. Since mergers with greater disruption are less dependent on the target's prior earnings generating process, the negative association between management forecast accuracy and subsequent goodwill impairments will be less pronounced as disruption increases if this association is driven primarily by managers' ability to use past earnings to predict future earnings. On the other hand, the negative association will be more pronounced as disruption increases if this association is driven by managers' ability to predict future earnings independent of past earnings. Given these contrasting possibilities, I propose the following non-directional hypothesis.

H5: *The association between the acquirer's historical management forecast accuracy and the likelihood of post-merger goodwill impairment differs based on disruption.*

Chapter 3: Variable Measurement and Research Design

3.1 Measuring disruption

I measure disruption in two ways. First, I use the financial versus operating company distinction commonly used in the finance literature to identify transactions where acquirers are more likely to disrupt their targets' operations. Second, I construct a disruption index based on observable merger characteristics. I discuss each approach in detail below.

3.1.1 Measuring disruption based on the financial versus operating acquirer distinction

The financial versus operating distinction is commonly used in the finance literature (Dittmar et al., 2012; Bargeron et al., 2008; Gorbenko and Maleko, 2013). Financial acquirers, such as divisions of investment banks, private equity firms, and investor groups, generally seek to exploit finance-related benefits such as potential tax savings, access to internal markets, lower cost of capital, diversification of cash flow streams and/or the realization of gains from buying well-managed but undervalued targets (Leland, 2007; Lewellen, 1971). About 4% of US acquirers of public, US target firms are financial firms[4]. Prior research finds that acquirers pursuing finance-related benefits are more likely to keep targets as autonomous divisions and less likely to integrate them or fire their top management teams (Nahavandi and Malekzadeh, 1988; Pablo, 1994; Mueller, 1969; Hubbard and Palia, 1999). Financial acquirers, because they generally must either hire specialists or rely on the incumbent management to manage target assets (Fidrmuc et al., 2012), "rely primarily on improving the stand-alone value of the target firm" (Dittmar et al., 2012, p. 901).

On the other hand, operating acquirers generally pursue synergies created through the combination of the acquirer's and target's assets (Larsonn and Finkelstein, 1999; Megginson and Smart, 2008; Chatterjee, 1986). Realization of operating synergies typically requires the acquirer to

[4] Percentage calculated based on a sample that consists of public targets with values of less than $1 billion and more than $10 million recorded in the SDC Platinum data base from 1980 to 2012.

adapt and/or redeploy the target's resources by better managing underperforming assets of the target or by exploiting complementarities between the acquirer's and target's assets to create new products, services or delivery channels (Larsonn and Finkelstein, 1999; Hoberg and Phillips, 2010; Rhodes-Kropf and Robinson, 2008). Therefore, operating acquirers typically integrate the target's assets into their existing operations (Fidrmuc et al., 2012). Hence, mergers with operating acquirers generally entail more disruption of the target's underlying operations than mergers with financial acquirers.

3.1.2 Measuring disruption using a self-constructed disruption index

Although I expect mergers with operating acquirers to entail more disruption than mergers with financial acquirers on average, I also expect variation in the degree of disruption among operating acquirers. To examine the cross-sectional variation in disruption for mergers completed by operating acquirers, I create an index comprised of four variables. These variables are target management turnover of the combined firm (MTO), target analyst turnover (TATO), anticipated merger restructuring costs (RESTRUCT) and the distance between acquirer and target headquarters (LOCAL).

Target management turnover, which is the turnover rate for the top executive of the target firm following the merger, captures the likelihood that the acquirer intends to intervene in the target's operations by installing a new top management team. Prior research provides evidence that target management turnover surrounding merger events is high (Martin and McConnell, 1991) and is mostly due to overlapping skill sets (Krishnan et al., 1997). Therefore, low target management turnover suggests that the target's management has a special skill that does not overlap with that of the acquirer and therefore, the acquirer does not intend to significantly disrupt the target's underlying operations.

Target analyst turnover is the turnover rate for the target's analysts following the merger. Tehranian et al. (2013) find that target analysts who cover a target firm before the merger decide to cover the merged firm if they believe the outcome to be favorable and if they can accurately forecast its earnings. Analysts are likely to drop coverage if they anticipate the target earnings process to change significantly consequent to a merger. Target analyst turnover captures the extent to which analysts anticipate the target's earnings time series to remain relatively predictable after the merger.

Anticipated merger restructuring costs capture integration costs. Management usually estimates target integration cost as the cost of restructuring charges (Houston et al., 2001). This charge is usually an estimate of severance payments, asset write-downs, lease buyouts and costs to shut down duplicative facilities. Lower anticipated restructuring costs imply less disruption to the target's earnings generation process since the acquirer intends to retain more of the target's pre-merger operations.

Distance between acquirer and target headquarters location, which captures the likelihood that an acquirer anticipates actively managing target assets, may influence acquirers' purchasing decisions (Chakrabarti and Mitchell, 2013; Coval and Moskowitz, 2001). Because acquirers that anticipate integrating their operations to a greater degree prefer targets that are more proximate (Chakrabarti and Mitchell, 2013), targets with headquarters further removed (more than 50 kilometers) from acquirers are more likely to operate much as they did before the merger.

I collect target executive management information during the two-year period after the merger to see if the target management is still affiliated with the acquirer. Consistent with prior research, I consult annual reports, 10-Ks, proxy statements, and news reports for information regarding target management turnover (McNeil et al., 2004). Following Houston et al. (2001), I search acquirer 10-Ks filed the same year as mergers for information regarding restructuring costs. If managers do not estimate these charges, I treat the merger expense reported in the annual report published at the end of the merger year as an ex ante estimate of merger expense (Houston et al., 2001). In the absence of both estimate and expense, I assume restructuring costs to be zero and immaterial.[5] I collect target analyst turnover information from I/B/E/S, and obtain headquarter locations of targets and acquirers from the SDC database, convert them to longitude and latitude coordinates, and use the Haversine formula to find the distance between them.[6]

For each merger transaction, I assign a zero or one ranking to each criterion, sum the four criteria, and divide by four to calculate the disruption variable, DR_INDEX. For the management turnover variable, I assign a one (zero) to merger transactions in which, over the course of the two-year post-merger period, the CEO leaves (remains with) the merged company. For the target analyst turnover variable, I assign a one (zero) to merger transactions in which 100% (less than 100%) of target analysts decide not to cover the merged firm.[7] For restructuring cost, I assign a one (zero) to observations that fall below (above) the sample median, indicating relatively less (more) disruption. For the distance variable, I assign a one (zero) if the distance between acquirer and target headquarters is less than or equal to (greater than) 50 kilometers. DR_INDEX takes values from zero (least disruptive) to one (most disruptive). A DR_INDEX equal to zero indicates a merger transaction with minimal disruption in which the target firm is left to operate as an autonomous division of the acquirer, operated by the same management team that controlled it before the merger. A DR_INDEX equal to one indicates a merger with the highest level of disruption, such as bust-up takeovers, which are characterized by significant post-merger divestitures of target assets (Mitchell and Lehn, 1990; Berger and Ofek, 1996).

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[5] According to SFAS 146 (and EITF Issue 94-3 prior to passage of SFAS 146), costs associated with restructuring activity should be disclosed in notes to the financial statements.

[6] I calculate the arc length, d_{ab}, between acquirer and target as $d_{ab} = C\{\ \arccos[\sin(lat_a)\sin(lat_b) + \cos(lat_a)\cos(lat_b)\cos(|long_a - long_b|)\}$ where lat and long refer to the latitude and longitude of locations a and b. C is a constant that converts the result to kilometers.

[7] Tehranian et al. (2013) find that 75% of target analysts do not retain coverage of merged firms.

A potential limitation of DR_INDEX is that MTO and TATO are ex post measures of disruption and therefore the coefficient estimate of DR_INDEX may suffer from look-ahead bias. The underlying assumption that I make is that these ex post measures reflect ex ante levels of anticipated disruption and that at the time of the merger announcement, the acquiring manager knows the extent of anticipated disruption of the target. Since acquiring managers must estimate merger synergies in the determination of target valuation (Bruner 2004; Carney, 2009; Weston et al., 2004) and therefore must determine the target's role in the merged firm before the effective date of the merger, I believe that the underlying assumption is valid. I relax this assumption with the first measure of disruption, the financial versus operating acquirer distinction, which is an ex ante measure. The main conclusions of this study are consistent using both measures.

As described in Appendix B, I assess the construct validity of the disruption index by examining whether it identifies transactions in which targets' pre-merger earnings performance is less useful in predicting the post-merger performance of the combined firm.

3.2 Regression model for tests of H1 and H2

I examine how managers use accounting information in setting merger premia by estimating the following regression (firm and time subscripts are not shown except when needed for clarity):

$$\begin{aligned} PREMIUM = {} & \alpha_0 + \alpha_1 DISRUPT + \alpha_{2a} DISRUPT \times ROA\_T + \alpha_{2b} DISRUPT \times BV\_T \\ & + \alpha_{3a} ROA\_T + \alpha_{3b} BV\_T + \alpha_4 MULTIBID + \alpha_5 CASH + \alpha_6 LIQUIDITY \\ & + \alpha_7 LEVERAGE + \alpha_8 MTB + \alpha_9 PUBLICACQ + \delta_{YEAR} + \lambda_{INDUSTRY} + \varepsilon \qquad (1) \end{aligned}$$

where:

PREMIUM is the ratio of deal value to target market value four weeks prior to merger announcement date;

DISRUPT = OP_ACQ or DR_INDEX;

OP_ACQ is an indicator variable equal to one (zero) if the acquirer is an operating (financial) firm;

DR_INDEX is an index variable—comprised of the four subvariables: target management turnover, target analyst turnover, anticipated restructuring cost, and distance between acquirer and target headquarters—for which a value of 0 (1) is indicative of the least (most) disruption;

ROA_T is a target's industry-adjusted return on assets measured one year before the merger announcement year;

BV_T is target net assets divided by target market value measured four weeks prior to merger announcement date;

MULTIBID is an indicator variable equal to one if the number of acquirers bidding on a target is greater than one, and zero otherwise;

CASH is an indicator variable equal to one if the deal was financed 100% with cash, and zero otherwise;

LIQUIDITY is a target's current assets minus current liabilities divided by book value of equity measured one year before the merger announcement;

LEVERAGE is a target's long-term debt divided by book value of equity measured one year before the merger announcement;

MTB is a target's market value divided by book value of equity measured one year before the merger announcement;

PUBLICACQ is an indicator variable equal to one if the acquirer is a public firm, and zero otherwise.

Because the denominator of the premium is the target's pre-merger stock price, the coefficients on the accounting inputs capture the average difference between acquirers' and the market's valuation of these inputs. An insignificant coefficient on an accounting input indicates no average difference between acquirers' valuation of the input and the market's pre-merger valuation of the input. By contrast a positive (negative) coefficient on the accounting input indicates that acquirers assign a premium (discount) to the accounting input relative to the market's pre-merger valuation. Accordingly, the coefficient on ROA_T captures the extent to which the acquirer values the target's recent earnings (scaled by assets) at a premium or discount relative to the market's pre-merger valuation when disruption is minimal (i.e., when DISRUPT equals zero) while the coefficient on the interaction of ROA_T and DISRUPT captures the incremental premium or discount acquirers assign to the target's recent earnings as disruption increases. H1 predicts that the target's recent earnings are less important to acquirers as anticipated disruption increases (i.e., $\alpha_{2a} < 0$). The coefficient on BV_T captures the extent to which the acquirer values the target's book value at a premium or discount relative to the market's pre-merger valuation when disruption is minimal (i.e., when DISRUPT equals zero) while the coefficient on the interaction of BV_T and DISRUPT captures the incremental premium or discount acquirers assign to the target's book value as disruption increases. H2 predicts that the target's book value becomes more important to acquirers as anticipated disruption increases (i.e., $\alpha_{2b} > 0$).

I include MULTIBID to control for the positive effect of the number of competing acquirers on bid premium (Walkling and Edmister, 1985). I include CASH to control for valuation effects. On one hand, prior studies find that cash payments are positively associated with target bid premium because cash payments are often only used when the acquirer is more confident in the success of the merger and would like to retain the future positive returns to the existing shareholders (Abhyankar et al., 2005; Travlos, 1987). On the other hand, Louis (2004) finds no statistical difference between premiums paid by stock-for-stock acquirers and cash acquirers. Jensen (1986)'s free cash flow theory suggests that large free cash flows occur in poorly run firms and that acquirers have more to gain by acquiring highly liquid targets. On the other hand, Schwert (2000) does not find any evidence consistent with this prediction. Therefore, I include the control variable, LIQUIDITY, but do not predict a direction. Following Skaife and Wangerin (2013), I also include control variables, such as LEVERAGE and MTB, meant to capture target firm operating and financial risk that may increase or decrease premia. Finally, I include PUBLICACQ based on prior research that finds public acquirers to generally pay more than private acquirers for targets (Bargeron et al., 2008), and year and four-digit SIC code industry fixed effects to control for systematic differences in merger premia over time and across industries.

3.3 Regression model for test of H3

I examine the relative importance of target earnings quality in setting merger premia by estimating the following regression (firm and time subscripts are not shown except when needed for clarity):

$$\begin{aligned} PREMIUM = {} & \alpha_0 + \alpha_1 DISRUPT + \alpha_{2a} DISRUPT \times ROA\_T + \alpha_{2b} DISRUPT \times BV\_T \\ & + \alpha_{2c} DISRUPT \times EQ\_T + \alpha_{3a} ROA\_T + \alpha_{3b} BV\_T + \alpha_{3c} EQ\_T + \\ & + \alpha_4 MULTIBID + \alpha_5 CASH + \alpha_6 LIQUIDITY + \alpha_7 LEVERAGE + \alpha_8 MTB \\ & + \alpha_9 PUBLICACQ + \delta_{YEAR} + \lambda_{INDUSTRY} + \varepsilon \end{aligned} \tag{2}$$

where:

EQ_T = EQ1 or EQ2;

EQ1 is the target's earnings quality measured per the Kothari et al. (2005) performance-adjusted discretionary total accruals method;

EQ2 is the target's earnings quality measured per the Dechow and Dichev (2002) accruals quality method;

and all other variables are as defined previously.

The coefficient on EQ_T captures the extent to which an acquirer values a target's recent earnings quality at a premium or discount relative to the market's pre-merger valuation when disruption is minimal (i.e., when DISRUPT equals zero). The coefficient on the interaction of EQ_T and DISRUPT captures the incremental premium or discount acquirers assign to the target's recent earnings quality as disruption increases. H3 predicts that the target's recent earnings quality is less important to acquirers as anticipated disruption increases (i.e., $\alpha_{2c} < 0$).

I use two alternative measures of earnings quality. The first is the magnitude of a target's performance-adjusted discretionary total accruals measured at the end of the fiscal year immediately preceding the merger announcement (Kothari et al., 2005). I estimate targets' expected accruals by running the following regression by two-digit SIC industry, *j*, to obtain industry-specific estimates (α_{1jt}, $\alpha_{2jt,}$ α_{3jt}) of the coefficients:

$$TA_{i,t} = \alpha_0 + \alpha_1(1/A_{i,t-1}) + \alpha_2\Delta REV_{i,t} + \alpha_3 PPE_{i,t} + \varepsilon_{i,t} \tag{3}$$

where:

$TA_{i,t}$ is total accruals defined as the change in non-cash current assets minus the change in current liabilities excluding the portion of long-term debt, minus depreciation and amortization for firm *i* in year *t*, with TA scaled by $A_{i,t}$;

$A_{i,t}$ is the average of year *t* and year *t -1* assets for firm *i*;

$\Delta REV_{i,t}$ is the change in net revenues for firm *i* in year *t*, scaled by $A_{i,t}$;

$PPE_{i,t}$ is gross property, plant, and equipment for firm *i* in year *t*, scaled by $A_{i,t}$.

These annual cross-sectional estimations yield firm- and year-specific residuals that represent a firm's discretionary accrual for a particular year. Like Skaife and Wangerin (2013), I form ten portfolios for each two-digit SIC industry group based on the decile rankings of the prior year return on assets (ROA). Performance-adjusted discretionary accruals are defined as the negative of the absolute value of unadjusted discretionary accruals calculated at the end of the fiscal year immediately preceding the merger announcement, year *t*-1, minus the matched median discretionary accrual for each ROA-decile portfolio.

The second measure of earnings quality, based on the Dechow and Dichev (2002) model, measures accruals quality as the standard deviation of residuals from the following model:

$$ACC_{i,t} = \alpha_0 + \alpha_1 CFO_{i,t-1} + \alpha_2 CFO_{i,t} + \alpha_3 CFO_{i,t+1} + \alpha_4 \Delta REV_{i,t} + \alpha_5 PPE_{i,t} + \varepsilon_t \tag{4}$$

where:

$ACC_{i,t}$ is firm *i*'s accruals in year *t* measured as the change in non-cash current assets minus the change in current liabilities plus the portion of long-term debt, minus depreciation and amortization;

$CFO_{i,t}$ is firm *i*'s cash flow from operations in year *t*;

and all other variables are as defined previously.

I extend the Dechow-Dichev model by including the control variables ΔREV_t and PPE_t, per

McNichols (2002). All variables are standardized by average total assets and winsorized at the 1st and 99th percentiles for each year.

To obtain a firm-specific, cross-sectional measure of accruals quality, I estimate equation (4) for each year at the industry (two-digit SIC code) level, where the annual cross-sectional estimations yield firm- and year-specific residuals. This procedure is consistent with Raman et al. (2012) and McNichols and Stubben (2012).[8] Consistent with Aboody et al.'s (2005) third measure, I compute earnings quality (EQ2) for target *i* in year *t* as the absolute value of a firm's residual at the end of the fiscal year immediately preceding the merger announcement. I focus on the absolute value of residuals instead of the standard deviation of residuals over time because targets tend to be younger firms with only a few years of publicly available financial information.

3.4 Regression model for test of H4

H4 predicts that there is a greater risk of goodwill impairments due either to overpayment or poor execution when acquirers do not vary the weight they place on targets' accounting inputs based on disruption as predicted in H1 - H3. Because equation (2) models predicted pricing behavior, residuals from equation (2), which I label RESIDUAL, represent deviations from predicted pricing behavior. I estimate the following regression to determine whether these deviations are associated with a heightened risk of goodwill impairments (firm and time subscripts are not shown except when needed for clarity):

$$\begin{aligned}\Pr(GW\_IMPAIR = 1) = \text{logit}\,(&\alpha_0 + \alpha_1 RESIDUAL + \alpha_2 \Delta SALES + \alpha_3 \Delta OCF + \alpha_4 LEVERAGE \\ &+ \alpha_5 SIZE + \alpha_6 NUMSEG + \alpha_7 BTM\_IND + \alpha_8 BHRET + \alpha_9 RANK \\ &+ \alpha_{10} BONUS + \alpha_{11} BATH + \alpha_{12} TENURE + \alpha_{13} GW\% + \delta_{YEAR} + \varepsilon \qquad (5)\end{aligned}$$

where:

GW_IMPAIR is an indicator variable equal to one if the acquiring firm reported a goodwill impairment within three years of the merger, zero otherwise;

[8] I further require at least 20 firms in year *t* to estimate the industry-level regressions.

ΔSALES is the change of sales from year *t-1* to year *t* divided by total assets in year *t-1*;

ΔOCF is the change in cash flows from operations from year *t-1* to year *t* divided by total assets in year *t-1*;

LEVERAGE is the long-term debt divided by book value of equity measured at year *t*;

SIZE is the natural log of the market value in year *t*;

NUMSEG is the natural log of 1 + the number of reporting segments at year *t*;

BTM_IND is an indicator variable equal to one if the firm has a ratio of market value divided by book value of equity greater than one, zero otherwise;

BHRET is the buy-and-hold return for fiscal year *t*;

RANK is the insample rank of cash plus all investments and advance minus debt and preferred equity divided by total assets minus liabilities in year *t*;

BONUS is an indicator variable equal to one if the CEO receives a cash bonus in year *t*;

BATH is an indicator variable equal to one if the change in the pre-goodwill impairment net income from year *t-1* to *t* falls below the median of all negative values, zero otherwise;

TENURE is the tenure in years of the CEO in year *t*;

GW% is the balance of goodwill in year *t-1* divided by total assets in year *t-2*;

I predict that as RESIDUAL increases (i.e. as acquirers' pricing decisions conform less with that predicted in H1 and H2), the likelihood of future goodwill impairments increases ($\alpha_1 > 0$).

Leading indicators of goodwill impairment mirror the leading indicators of a company's ability to survive. These indicators include recurring operating losses, negative working capital and cash flows from operating activities and financial ratios that capture financial health (Hayn and Hughes, 2005). Consistent with prior research, I include variables that capture these dimensions such as ΔSALES and ΔOCF. As per Wangerin (2012), I include LEV to capture the closeness to debt violation. Prior research shows that as initial flexibility of allocating goodwill increases, the later likelihood of a goodwill impairment decreases (Ramanna and Watts, 2012). A greater number of reporting units is associated with greater flexibility, because managers have more allocation options, so I include NUMSEG. BTM_IND and BHRET proxy for the economic necessity of a write-off. Prior research predicts that higher BTM ratios indicate higher likelihood of goodwill write-offs, since growth opportunities are relatively low (Wangerin, 2012; Beatty and Weber, 2006). Similarly, higher levels of BHRET reflects the market's favorable assessment of the firm's value and growth opportunities and is negatively related to the likelihood of goodwill impairments. Firms with net assets that are more unverifiable are more likely to take a goodwill write-off (Ramanna and Watts, 2012), so I include RANK. Ramanna and Watts (2012) and Beatty and Weber (2006) argue that reputational and compensation concerns limit manager's interests in taking goodwill write-offs, so I include TENURE and BONUS. I also control for "big bath" reporting incentives and include BATH. Finally, I include GW% to reflect the increased likelihood of goodwill impairment.

A limitation in my use of equation (5) to test H4 is that the deviations from predicted behavior represented by the residuals from equation (2) are not necessarily attributable to disruption. To better isolate the deviation that is specifically related to disruption, I estimate the following variant of equation (2) that excludes DISRUPT and its interactions with the accounting inputs.

$$\begin{aligned} \text{PREMIUM} = {} & \alpha_0 + \alpha_1 \text{ROA\_T} + \alpha_2 \text{BV\_T} + \alpha_3 \text{EQ\_T} + \alpha_4 \text{MULTIBID} + \alpha_5 \text{CASH} \\ & + \alpha_6 \text{LIQUIDITY} + \alpha_7 \text{LEVERAGE} + \alpha_8 \text{MTB} + \alpha_9 \text{PUBLICACQ} \\ & + \delta_{\text{YEAR}} + \lambda_{\text{INDUSTRY}} + \varepsilon \end{aligned} \qquad (2')$$

All variables are as defined previously.

I substitute the residual from equation (2') in equation 4, RESIDUAL'. I compare the model fit of equation (4) when estimated using the residual from equation (2) versus the residual from equation (2'). Since the only difference between equations (2) and (2') is whether DISRUPT and the related interactions are included, this comparison allows me to isolate the portion of the deviation that is due to improper weight on disruption. I compare model fit using the Bayesian information criterion (BIC) and Akaike information criterion (AIC). Given any two estimated models, the model with the lower BIC and AIC is the better fitting one (Schwarz, 1978; Akaike, 1974)[9]. A finding that the residual from the full model that includes disruption (equation (2)) provides a better fit for equation (4) than the residual from the model that excludes disruption (equation (2′)) suggests that improper attention to disruption contributes to any relation I document between RESIDUAL and the likelihood of subsequent goodwill impairments.

3.5 Regression model for test of H5

Goodman et al. (2014) document a negative relation between the acquirer's management forecast accuracy and the likelihood of subsequent goodwill impairment. To examine how disruption affects this relation, I estimate the following logit regression (firm and time subscripts are not shown except when needed for clarity):

$$\begin{aligned} Pr(GW\_IMPAIR = 1) = logit\,(&\alpha_0 + \alpha_1 DR\_LO + \alpha_2 FORACC\_HI + \alpha_3 DR\_LO \times FORACC\_HI \\ &+ \alpha_4 \Delta SALES + \alpha_5 \Delta OCF + \alpha_6 LEV + \alpha_7 SIZE + \alpha_8 NUMSEG + \alpha_9 BTM\_IND \\ &+ \alpha_{10} BHRET + \alpha_{11} RANK + \alpha_{12} BONUS + \alpha_{13} BATH + \alpha_{14} TENURE + \alpha_{15} GW\% \\ &+ \delta_{YEAR} + \varepsilon\,) \end{aligned} \tag{6}$$

where:

DR_LO is an indicator variable equal to one if DR_INDEX is equal to 0 or .25, zero if DR_INDEX is equal to .5, .75 or 1.

FORACC_HI is an indicator variable equal to one if the management forecast accuracy is above the sample median, zero otherwise.

All variables are ad defined previously.

Consistent with Goodman et al. (2014), I calculate forecast accuracy as the average accuracy for all annual forecasts issued in the three-year period before the merger announcement. Accuracy is measured as the absolute value of the difference between the manager’s EPS forecast and actual

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[9] The AIC and BIC are used extensively in the literature for both nested and non-nested model selection (Cremers, 2002; Pesaran and Timmermann, 1995; Bossaerts and Hillion, 1999). Both criteria are measures of the quality of a statistical model of a given dataset *relative* to other statistical models of the same dataset. Like the adjusted-R^2, both criteria include a penalty term for the number of parameters in the model. Furthermore, both criteria are based on the likelihood function of a statistical model and penalize for unexplained variation in the dependent variable. Hence, a lower AIC (BIC) implies either fewer explanatory variables, better fit, or both. However, neither criteria provides any information about the absolute quality of the model (i.e., if all models are poor fit to the data, neither AIC or BIC will provide any indication of this).

EPS scaled by the beginning of year stock price. I then multiply the average three-year forecast accuracy by negative one so that an increase in forecast accuracy corresponds to an increase in accuracy.

A finding of $\alpha_2 < 0$ is consistent with evidence in Goodman et al. (2014). As discussed in section 2.5, this negative relation may vary based on disruption but how the relation varies depends on which source of management forecast accuracy drives Goodman et al.'s (2014) finding. The coefficient on the interaction of DR_LO and FORACC_HI captures how the negative relation varies based on disruption. H5 predicts a non-zero effect of disruption on this relation (i.e. $\alpha_3 \neq 0$).

Chapter 4: Sample

4.1 Sample overview

I use two samples that correspond to the different data requirements associated with the two approaches to measuring disruption. The sample I use when measuring disruption using the financial versus operating acquirer distinction (hereafter, the financial-operating sample) consists of transactions involving financial acquirers and a matched set of transactions involving operating acquirers. The sample I use when measuring disruption using the disruption index (hereafter, the operating only sample) consists entirely of transactions involving operating acquirers.

4.1.1 Sample selection procedures for the financial-operating sample

I first search the SDC online database for completed mergers announced between January 1, 1980 and December 31, 2010 that involve financial acquirers and meet the following criteria: (1) the target is publicly traded in the United States; (2) the acquirer is a financial firm (SIC codes between 6000 and 6999) but not a creditor group; (3) the target is not a financial firm; (4) the acquirer purchases 100% of the target's shares; and (5) relevant financial accounting information for the target is not missing. Although I include both public and private acquirers in the sample, due to the need for publicly available accounting information, I focus exclusively on publicly traded target firms. Because traditional profitability measures are not comparable between financial firms and firms in other industries, I exclude financial target firms, which thereby limits the possibility that my sample includes financial acquirers seeking operating synergies.[10] These procedures, summarized in Panel A of Table 1, yield 120 transactions involving 113 unique acquirers.

[Insert Table 1]

[10] Because financial acquirers may pursue operational synergies by merging with other financial-related targets, to increase the likelihood that a merger with a financial acquirer will entail relatively minimal disruption of target operations, I consider only mergers between operating targets and financial acquirers.

I next identify a matched sample of transactions involving operating company acquirers.[11] Identifying targets as economically similar as possible to the targets in the financial company sample helps to ensure that any differences between the samples in the use of accounting information for merger valuation can be attributed to the type of acquirer. I use the following criteria to identify matches: (1) target four-digit SIC code industry membership, (2) announced year of merger, (3) net target asset size measured the year before the merger, and (4) target return on assets measured the year before the merger. After identifying target firms based on four-digit SIC code industry membership, I identify potential target matches by further limiting the control sample to merger announcement dates that fall within two years of the merger announcement date of the treatment (financial acquirer) group. I next eliminate target matches for which net target assets are more than 200% and less than 50% of the treatment target's net assets.[12] For the set of potential targets that meet these criteria, I choose the target closest in terms of the treatment target's return on assets.

4.1.2 Sample selection procedures for the operating only sample

I select from the SDC online database mergers and acquisitions announced between January 1, 1994[13] and December 31, 2010 that meet the following criteria: (1) the acquirer and target are publicly traded in the United States; (2) the target is not a financial firm (SIC codes between 6000 and 6999); (3) relevant financial accounting information is available for both target and acquirer; (4) the acquirer has no pre-existing toehold in the target; and (5) the value of the target is at least 50% but no greater than 100% of the value of the acquirer. Due to the need for publicly available

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[11] I use a matched-sample design technique because prior research has found the targets of private equity firms are inherently different than targets of public operating firms (Bargeron et al., 2008). Kernal density estimation graphs show the probability density function of size and ROA of operating targets of financial and non-financial acquirers to be significantly different. According to Rubin (1979), a matching procedure is preferred to a regression framework when there is an imbalance of the covariates. Other papers that employ the same technique include Song and Walkling (1993) and Bris et al. (2008).

[12] Hadlock et al. (1999) use a similar matching criterion. For their sample, the restriction regarding target asset size ranged from no more than 200% and no less than 50% of the assets of the actual target.

[13] Public SEC filings are available beginning in 1994; restructuring cost information used to measure disruption is gleaned from annual reports.

accounting information, I focus exclusively on publicly traded firms. I impose a minimum deal ratio requirement to ensure that the target is material to the combined firm, and eliminate transactions in which acquirers have a pre-merger equity stake in the target to avoid confounding effects in my analyses. Consistent with Raman et al. (2012), I exclude transactions in which the bid premium is less than the target's pre-merger market value because interpretation is problematic. These procedures yield 322 merger transactions. As explained above, I use four variables, including target analyst and target management turnover, to measure disruption in target operations. I eliminated 134 targets with either no pre-merger analyst following or no available information on management turnover. The final sample consists of 188 merger transactions. See Panel B of Table 1 for sample selection procedures.

4.2 Descriptive statistics for the operating-financial sample

Panel A of Table 2 reports descriptive statistics for the entire operating-financial sample as well as separate statistics for the financial acquirer and operating acquirer target subsamples. Since I match each operating target of a financial acquirer to another operating target of an operating acquirer along four dimensions (see Section 4.1.1), it is not surprising that there are almost no significant differences between the two samples. A few differences are, however, noteworthy. First, I find the targets of financial acquirers to be significantly less liquid than the targets of operating acquirers, and mergers with financial acquirers to be more frequently financed with cash. These findings are consistent with prior findings that targets of financial acquirers are financially constrained and need access to financial resources in order to grow (Weston et al., 2004). I further find that financial acquirers are significantly more likely than operating acquirers to be private companies. More than 75% of financial acquirers are private equity firms (not tabulated).

[Insert Table 2 here]

Panel B of Table 2 provides some description of the industries represented by two-digit SIC codes. Before the merger, approximately 42% of targets operated in services, 23% in manufacturing, and 11% in transportation industries. Similar proportions are observed among operating acquirers, 36% of which operated in services, 30% in manufacturing, and 12% in transportation industries.

Panel A of Table 3 reports correlations, which, for the most part, reflect the findings in Table 2. I do find, however, a negative correlation between operating acquirer status and targets' historical ROA. Although I match each operating target of a financial acquirer to an operating target of an operating acquirer based on historical ROA (the fourth criterion in the matching process; see Section 4.1.1), targets of operating acquirers tend to be less profitable before the merger, and a close match on this dimension is difficult to find. The relationship is, however, consistent with my expectation that operating acquirers find targets' historical earnings performance less relevant in determining bid price.

[Insert Table 3 here]

4.3 Descriptive statistics for the operating only sample

Panel C of Table 2 reports descriptive statistics for the operating only sample. Consistent with prior research, target analyst and target management turnover rates are high after mergers (Martin and McConnell, 1991; Tehranian et al., 2013). In my sample, approximately 60% of target CEOs leave within two years of a merger and approximately 50% of target firms experience 100% analyst turnover. The financial characteristics of targets in my sample are also consistent with prior literature. The average market-to-book (MTB) ratio of 2.82, for example, is consistent with target firm ratios reported by Rhodes-Kropf et al. (2005) and Skaife and Wangerin (2013), and leverage and liquidity rates are consistent with those reported by Skaife and Wangerin (2013) and Raman et al. (2012), respectively.

Panel B of Table 3 documents correlations. PREMIUM is significantly negatively correlated with CASH, LIQUIDITY, LEVERAGE, and MTB and positively related to BV_T, TATO, and MTO. With the exception of CASH, these negative correlations are consistent with prior literature. The negative correlation with CASH may be due to my sample including only public acquirers, whereas previous samples include both private and public acquirers.

4.4 Descriptive statistics for post-merger acquirers

Panel D of Table 2 reports post-merger descriptive statistics for a subsample of the operating acquirers reported in Panel C of Table 2. Operating acquirers reported in Panel C are reported in Panel D if the required financial accounting information to examine goodwill impairment is available on COMPUSTAT within any of the three years after the effective date of the merger. Out of the 287 unique operating acquirers reported in Panel C of Table 2, 141 of them are included in Panel D (not tabulated). In my sample, approximately 29 % of acquirers take at least one goodwill impairment within the three years of the merger (not tabulated).

Panel C of Table 3 documents correlations for these operating acquirers. GW_IMPAIR is significantly positively correlated with GW%, BHRET and BTM_IND and negatively related to BONUS and FORACC_HI. These correlations are consistent with prior literature. Correlations relating to deal characteristics mostly reflect the correlations documented in Panels A and B.

Chapter 5: Empirical Findings

5.1 Hypotheses 1 and 2

Panel A of Table 4 reports the results of estimating equation (1) on the sample consisting of transactions involving both financial and operating acquirers. I include several specifications to show the stability of the coefficients of interest, but for brevity discuss the results from estimating the full model (Specification 4). The insignificant coefficients on ROA_T and BV_T indicate that there is no average difference between acquirers' valuation of these inputs and the market's pre-merger valuation of these inputs when disruption is minimal. The coefficient on the interaction term, OP_ACQ × ROA_T, is significantly negative across all specifications (coefficient = -0.07, p-value < 0.10), which is consistent with H1. This finding indicates that, relative to financial acquirers, operating acquirers discount the information in the target's past earnings, presumably because the information the target's past earnings conveys about its pre-merger operations is less important to acquirers that anticipate disrupting those operations.

[Insert Table 4]

The coefficient on the interaction term, OP_ACQ × BV_T, is significantly positive across all specifications (coefficient = 0.38, p-value < 0.01), which is consistent with H2. This finding indicates that operating acquirers place significantly more weight on the target's book value than do financial acquirers, presumably because the information the target's recent book value conveys about the adaptation value of its resources is more important to acquirers that plan to disrupt the target's operations.

Given that Bhojraj et al. (2003) find GIC classifications to be significantly better than SIC codes at explaining cross-sectional variation in key financial ratios, I replicate the preceding analysis by matching, based on GIC codes, operating targets of financial acquirers to operating targets of operating acquirers. Panel B of Table 4 reports the results of this analysis, which corroborate those reported in Panel A of Table 4. The increase in the number of observations is attributable to the greater number of matching pairs that result from the broader GIC classification scheme.

Table 5 reports the results of estimating equation (1) on the sample consisting only of transactions involving operating acquirers. Because premium determination may differ between same-industry versus cross-industry deals (Raman et al., 2012; Skaife and Wangerin, 2013), I also include an indicator variable, IND, set equal to one if the acquirer and target operate in the same two-digit SIC code before the merger and zero otherwise. For brevity, I discuss the results from estimating the full model (Specification 3). The coefficient on the interaction term, DR_INDEX × ROA_T, is significantly negative across all specifications (coefficient = -0.17, p-value = 0.02), which provides further evidence in support of H1. This finding indicates that operating acquirers discount the information in the target's past earnings as disruption increases, presumably because the information the target's past earnings conveys about its pre-merger operations is less important to acquirers that anticipate disrupting those operations. The coefficient on the interaction term, DR_INDEX × BV_T, is significantly positive across all specifications (coefficient = 1.03, p-value = 0.01), which provides further support for H2.

[Insert Table 5]

With respect to the control variables, the signs and significance of most of the coefficients are consistent with prior literature. However, the negative sign on MULTIBID is not consistent with prior literature but this is mainly due to the lack of variation of multibids in the sample. More than 90% of the merger deals in the sample involve only one bidder.

Taken collectively, the results support my prediction that the relevance of the target's historical accounting information depends on the degree of anticipated disruption. The results also highlight the circumstances under which the target's historical earnings and book values are relatively more important in the merger setting.

5.2 Hypothesis 3

Table 6 reports the results of estimating equation (2) on the sample consisting of transactions involving both financial and operating acquirers. The decrease in the number of observations is due to the additional data requirements for computing the earnings quality measures. The coefficient on the interaction term, OP_ACQ × EQ_T, is significantly negative for the earnings quality measure based on Kothari et al. (2005), (coefficient = -1.88, p-value = 0.02), which is consistent with H3 and suggests that operating acquirers discount the contribution of high earnings quality to precise information about the target's existing operations because operating acquirers do not intend for such operations to continue. I obtain similar albeit weaker inferences when I measure earnings quality using the Dechow and Dichev (2002) methodology (coefficient = -1.72, p-value = 0.10).

This result is consistent with the negative relation between merger premium and earnings quality documented in prior studies (Skaife and Wangerin, 2013; Raman et al., 2012; McNichols and Stubben, 2012). As discussed previously, Skaife and Wangerin (2013) interpret the negative relation as an indication that acquirers of targets with low earnings quality have identified, and are willing to pay for, sources of value of the target that are not well reflected in either the target's pre-merger earnings performance or its stock price. My finding that this negative relation becomes more pronounced as disruption increases suggests that the previous finding is attributable primarily to acquirers anticipating significant disruption.

[Insert Table 6]

Table 7 reports the results of estimating equation (2) on the sample that consists only of operating acquirers. Again, the decrease in the number of observations is due to the additional data requirements for computing the earnings quality measures. The coefficient on the interaction term, DR_INDEX × EQ_T, is significantly negative for the earnings quality measure based on Kothari et al. (2005), (coefficient = -6.55, p-value = 0.03), providing further support for H3. I obtain similar inferences when I measure earnings quality using the Dechow and Dichev (2002) methodology (coefficient = -5.94, p-value = 0.07).

[Insert Table 7]

Collectively, these results support the prediction that earnings quality varies in importance based on acquirer intent. Specifically, acquirers that intend to disrupt target operations appear to discount the information earnings quality conveys about a target's pre-merger operations.

5.3 Hypothesis 4

Table 8 reports the result of estimating equation (5) on the sample that consists only of operating acquirers. I do not analyze the data on the sample consisting of transactions involving both financial and operating acquirers because I need publicly available information for the acquirer to examine post-merger goodwill impairment occurrence. The decrease in the number of observations from H1 – H3 is due to the additional data requirements for computing the control variables related to goodwill impairment. In the first specification, the coefficient on RESIDUAL is significantly positive (coefficient = 3.91, p-value = 0.05), which is consistent with H4 and suggests that as acquirers' pricing decisions conform less with predicted pricing behavior as modeled in equation (2), the likelihood of future goodwill impairments increases.

To examine whether the deviation from predicted pricing behavior represented by RESIDUAL is specifically related to disruption, I report a second specification that includes the residual from equation (2'), RESIDUAL'. First, I find that the coefficient on RESIDUAL' is not significantly positive (coefficient = .68, p-value 0.38), which suggests that the residual from the model that excludes disruption does not significantly explain subsequent goodwill impairments. Second, I find that the BIC and AIC for the full model that includes disruption is lower, and hence a better fit for the data, than the residual from the model that excludes disruption. This finding suggests that improper attention to disruption contributes to the significant positive relation that I document in the first specification between RESIDUAL and the likelihood of subsequent goodwill impairments. Collectively, these results support the prediction that the likelihood of post-merger goodwill impairment increases when acquirers do not vary the weight they placed on the target's accounting inputs based on anticipated disruption of the target's existing operations.

[Insert Table 8]

5.4 Hypothesis 5

Table 9 reports the result of estimating equation (6) on the sample that consists only of operating acquirers. Again, I do not analyze the data on the sample consisting of transactions involving both financial and operating acquirers because I need publicly available information for the acquirer to examine the relationship between post-merger goodwill impairment occurrence and management forecasts. In the first specification, I report results consistent with Goodman et al. (2014) and find that the coefficient on FORACC_HI is significantly negative (coefficient = -1.07, p-value = 0.09). In the second specification, I find that the coefficient on the interaction term, DR_LO × FORACC_HI, is significantly negative, (coefficient = -4.78, p-value = 0.01), which is consistent with H5 and suggests that disruption affects the relation between the acquirer's management forecast accuracy and the likelihood of subsequent goodwill impairment. Furthermore, I find that if disruption is high (DR_LO = 0), then the significantly negative relation between FORACC_HI and subsequent goodwill impairment is less pronounced (coefficient = -.22, p-value = 0.82). These findings suggest that the negative relation between management forecast accuracy and subsequent goodwill impairments, as documented by Goodman et al. (2014), is driven by managers' ability to properly use past earnings to predict future earnings.

[Insert Table 9]

5.5 Supplemental analysis

As discussed above, the results I report are robust to the use of alternative measures of earnings quality, and to matching operating targets of financial acquirers to operating targets of operating acquirers based on GIC rather than SIC codes. As an additional robustness test, I measure earnings performance as a target's change in ROA measured the fiscal year immediately preceding the merger announcement. Table 10 reports the results of this additional analysis. When disruption is measured based on the financial versus operating acquirer distinction (i.e., when DISRUPT = OP_ACQ), the coefficient on DISRUPT × ΔROA_T is negative and marginally significant (coefficient = -0.07, p-value = 0.10). This finding corroborates the results reported in Table 4. The slightly weaker results are likely due to the smaller number of observations resulting from the need for an additional year of data to calculate the change in ROA. When disruption is measured based on the disruption index (i.e., when DISRUPT = DR_INDEX), the coefficient on DISRUPT × ΔROA_T is negative and strongly significant (coefficient = -0.63, p-value < 0.01), consistent with the inferences in Table 5.

[Insert Table 10]

Chapter 6: Summary and Conclusions

In this study, I examine the effect of disruption of target operations on the relevance of the target's historical accounting information in merger pricing. Historical earnings information is traditionally used to value firms on a stand-alone basis due to the ability of past earnings to predict future earnings via earnings persistence (Sloan, 1996; Ou and Penman, 1989; Bernard and Thomas, 1990; Fairfield and Yohn, 2001). However, in the merger context where the acquirer must value the target based on its anticipated use of the target, the predictive ability of historical earnings may be undermined if the acquirer intends to disrupt the target's underlying operations, and hence, earnings generating process. On the other hand, if the merger's source of the value comes from disruption of the target's underlying operations, acquirers may find the target's book value useful to the extent that it reflects adaptation value, or the value of the firm's resources independent of how well the firm utilizes those resources. Therefore, I expect the relevance of the target's historical accounting information for merger pricing to vary with the anticipated degree of disruption.

I use the financial versus operating acquirer distinction to measure anticipated disruption in target operations based on prior research that finds that financial firms generally pursue mergers to exploit financial-related benefits that do not significantly alter targets' operations, whereas operating firms are more likely to seek merger gains that require adapting and/or redeploying target resources. I find that operating, relative to financial, acquirers discount target historical earnings and earnings quality in setting merger premia. On the other hand, I find that operating acquirers place greater weight than financial acquirers on target book value, which indicates that target adaptation value as reflected in book value is of greater interest to operating than to financial acquirers.

I examine cross-sectional variation in the relevance of target historical accounting information in mergers involving operating acquirers by creating an index that captures the anticipated degree of disruption. Consistent with my previous results, I find that operating acquirers discount target historical earnings and earnings quality to a greater degree, and place greater weight on target book value, as the level of disruption increases. These findings lend further support to the conclusion that the relevance of target historical accounting information depends on the anticipated degree of disruption.

To extend my main findings, I examine post-merger consequences related to disruption. First, I assess whether there are economic consequences when acquirers ignore disruption in their pricing decisions. I predict and find that the likelihood of post-merger goodwill impairment increases when acquirers do not vary the weight they placed on the target's accounting inputs (earnings, book value and earnings quality) based on anticipated disruption of the target's existing operations. Second, I examine how manager's ability to forecast merger performance varies by disruption. Goodman et al. (2014) argue that managers' general forecasting ability as reflected in their publicly released management forecasts translates into the ability to make the necessary forecasts for investments such as mergers and acquisitions. I argue and find that this relationship varies based on disruption and provide evidence that suggests that managers who make more accurate earnings forecasts are better able to assess external projects due to their ability to properly use past earnings to predict future earnings. Collectively, these findings provide important insights into the conditions under which particular types of accounting information are most useful in the merger context.

This study adds to an emerging literature on the role of accounting information in target valuation. I provide evidence that the importance of target historical accounting information varies with the degree of disruption, which should be relevant to acquirers that must determine the appropriate degree of reliance on historical target accounting information in formulating their bids, and to analysts and investors who must determine the appropriate response to merger announcements.

Appendix A

Variable Definitions

Variable		Definition
BATH	=	An indicator variable equal to one if the change in the pre-goodwill impairment net income from year t-1 to t falls below the median of all negative values, zero otherwise.
BHRET	=	The buy-and-hold return for fiscal year t.
BONUS	=	An indicator variable equal to one if the CEO receives a cash bonus in year t.
BTM_IND	=	An indicator variable equal to one if the firm has a ratio of market value divided by book value of equity greater than one, zero otherwise.
BV_T	=	The target's net assets divided by the target's market value measured four weeks before the merger announcement date.
CASH	=	An indicator variable equal to one if the deal was financed with 100% cash, zero otherwise.
DR_INDEX	=	An index variable comprised of four subvariables meant to capture the disruption to the target's underlying assets. These four variables are target management turnover, target analyst turnover, anticipated restructuring costs, and the distance between the acquirer's and target's headquarters. A value of 0 (1) is indicative of the least (most) disruptive.
DR_LO	=	An indicator variable equal to one if DR_INDEX is equal to 0 or .25, zero if DR_INDEX is equal to .5, .75 or 1.
EQ1	=	Earnings quality per the Kothari et al (2005) performance-adjusted discretionary total accruals method.
EQ2	=	Earnings quality measured per the Dechow and Dichev (2002) accruals quality method.
FORACC_HI	=	An indicator variable equal to one if the management forecast accuracy is above the sample median, zero otherwise.
FORECASTERR	=	The absolute value of the difference between the actual and forecasted ROA two years after the effective year of merger.
GW%	=	The balance of goodwill in year t-1 divided by total assets in year t-2.
GW_IMPAIR	=	An indicator variable equal to one if the acquiring firm reported a goodwill impairment within three years of the merger, zero otherwise.
IND	=	An indicator variable equal to one if the acquirer and target operate in the same two-digit industry before the merger, zero otherwise.
LEVERAGE	=	The target's long term debt divided by book value of equity measured one year before the merger announcement.
LIQUIDITY	=	The target's current assets minus current liabilities divided by book value of equity measured one year before the merger announcement.
LOCAL	=	An indicator variable equal to one if the distance between the acquirer's and target's headquarters is within 50 kilometers, zero otherwise. Distance is calculated using the Haversine formula.
MTB	=	The target's market value divided by book value of equity measured one year before the merger announcement.
MTO	=	An indicator variable equal to one if the target CEO left the merged firm within two years after the merger, zero otherwise.
MULTIBID	=	An indicator variable equal to one if the number of bidders bidding on the target is greater than one, zero otherwise.
NUMSEG	=	The natural log of 1 + the number of reporting segments at year t.

ΔOCF	=	The change in cash flows from operations from year t-1 to year t divided by total assets in year t-1.
PREMIUM	=	The value of the transaction divided by the market value of the target four weeks before the merger.
PUBLICACQ	=	An indicator variable equal to one if the acquirer is a public firm, zero otherwise.
RANK	=	The insample rank of cash plus all investments and advance minus debt and preferred equity divided by total assets minus liabilities in year t.
RELSIZE	=	The ratio of the value of the transaction over the market value to the acquirer four weeks before the merger announcement.
RESCO	=	An indicator variable equal to one if the acquirer's anticipated merger restructuring expenses fall above the sample median, zero otherwise.
ROA_T	=	The target's industry-adjusted return on assets one year before the announcement year of the merger.
ΔROA_T	=	The change in the target's industry-adjusted ROA one year before the merger announcement date.
ΔSALES	=	The change of sales from year t-1 to year t divided by total assets in year t-1.
SIZE	=	The natural log of the market value in year t.
TATO	=	An indicator variable equal to one if 100% of the analysts that were following the target before the merger decide not to follow the merged firm, zero otherwise.
TENURE	=	The log of the tenure in years of the CEO in year t.

Appendix B

Validation Test of Disruption Index

I evaluate whether DR_INDEX captures anticipated disruption by examining the association between DR_INDEX and the extent to which the target's pre-merger earnings generation process is maintained in the post-merger setting. Specifically, I test whether the stability of the autoregressive properties of the target's earnings decreases as DR_INDEX increases. To calculate the stability of the autoregressive property of the target's earnings, I first run a pooled regression on the following autoregressive model two years before the merger:

$$ROA_t = \alpha_0 + \alpha_1 ROA_{t-1} + \varepsilon_t \qquad (5)$$

where:

> ROA_t is combined operating income of acquirer and target in year *t* / (combined net operating assets of acquirer and target in year *t* + mark-up in target assets at merger date);
>
> Mark-Up in Target assets = deal value - the book value of subsidiary net assets (only if transaction was accounted for under the purchase method).

I simulate a hypothetical combined firm prior to the merger by combining the pre-merger earnings and net operating assets of the acquirer and target. I use these combined values to calculate pre-merger values of ROA. Equation (1) is a simple first-order autocorrelation model used extensively in the forecasting literature (Ball and Watts, 1972; Watts and Leftwich, 1977) that directly tests the autoregressive properties I wish to examine. I estimate equation (5) on the pooled sample using data from two years before the merger for each transaction. I then apply the resulting parameter estimate to the realized values of ROA of the merged firm for the year after merger completion to predict future ROA for the second year after the merger. Due to the confounding effects of the one-time merger costs incurred during the year of merger, and partial year inclusion of the target's earnings under the purchase method, I do not apply the parameter estimates to the ROA value of the year of the merger (Healy et al., 1992; Hoberg and Phillips, 2010). For transactions accounted for under the purchase method, I adjust the pre-merger accounting numbers to incorporate the fair market value restatements. I determine the markup in subsidiary assets in the manner of Collins and Kim (2012) and Rau and Vermaelen (1998) by taking the difference between the deal value and book value of subsidiary net assets.[1] I provide an example of how I compute the pre-merger ROA of the hypothetical entity in Appendix C.

The accuracy of estimates based on the pre-merger time-series parameters provides an indication of the degree to which a merger disrupts or alters the earnings process and, hence, the degree to which assumptions of inter-temporal stability are applicable in the merger setting. Estimates based on pre-merger time-series parameters should be relatively more (less) accurate for mergers with less (more) disruption. I expect the forecast error to be increasing with disruption, as captured by DR_INDEX.

Because univariate analysis of forecast errors does not take into account other merger-specific factors that may explain variation in forecast errors, I run the following OLS regression to mitigate these concerns:

$$FORCASTERR_{t+2} = \alpha_0 + \alpha_1 DR\_INDEX + \alpha_2 RELSIZE + \sum YEAR + \sum INDUSTRY + \varepsilon_{t+2} \qquad (6)$$

where:

FORECASTERR is the absolute value of the difference between the actual and forecasted ROA two years after the effective year of merger, *t*, with predicted values determined by applying the coefficients from the regression of equation (5);

DR_INDEX is a disruption variable that takes values from zero (least disruptive) to one (most disruptive);

[1] Under the purchase method of accounting (ASC 805), the purchase price must be allocated to the target's assets and liabilities at their FMV. Hence, under the purchase method, the acquirer adds the FMV of the target's company's assets to its balance sheet. Therefore, the difference between the purchase price and the target's book value of net assets at the time of the merger represents the total markup in the target's assets. Note that both goodwill and asset write-ups are included in this variable. See Appendix C for a detailed example.

RELSIZE is the ratio of the value of the transaction to the market value of the acquirer four weeks before the merger announcement.

I include RELSIZE to control for larger (smaller) mergers that may cause more (less) disruption to acquirer operations. I predict that disruption, as captured by DR_INDEX, has a significantly positive relationship with forecast error (i.e., $\alpha_1 > 0$).

I report the results in Table A1. I display the variables included in DR_INDEX separately to illustrate how each affects forecast accuracy two years after the merger. Consistent with my expectations, an increase in MTO, LOCAL, and RESCO is associated with a significantly positive increase in FORECASTERR. TATO, however, has no explanatory power with respect to post-merger forecast accuracy. In the fifth specification, I include all variables to see if each captures a different dimension of disruption that explains forecast accuracy. As can be seen in Table A1, when each variable is included in one regression, LOCAL and MTO load positively (coefficient of 3.13 and 1.461, p-value <.01 and p-value <.10, respectively). I include in the last specification in Table A1 the main disruption variable, DR_INDEX. As expected, DR_INDEX is significantly positively associated with an increase in FORECASTERR (coefficient of 6.048, p-value < .01). Across all specifications, the relative size of the target (RELSIZE) is an economically significant predictor of how well the autoregressive parameter for the pre-merger earnings of the hypothetical firm explains actual post-merger earnings. These results suggest that DR_INDEX is an effective proxy for anticipated disruption of target operations.

Appendix C

Computation of Pre-Merger ROA Values

In this appendix, I illustrate how I account for the mark-up in target assets following a merger in which the purchase method of accounting is used. Under the purchase method, the target firm is recorded on the acquirer's book at the purchase price, which is assumed to be the fair market value of the entire entity acquired (ASC 805). As a result, the target's fixed assets are stepped up to their fair market value. Furthermore, goodwill may be created if there is any difference between the purchase price and fair market value of the target's identifiable assets. Therefore, the pre-merger assets of a hypothetical entity comprised of both the acquirer and target will not automatically include the mark-up in the target's assets. I address this problem by adding the mark-up, defined as the difference between the deal value and the book value of subsidiary net assets, to the pre-merger assets of the hypothetical entity.

Consider the merger between Lukens Inc, a steel plate manufacturer, and Bethlehem Steel Corporation, a steel and shipbuilder producer. On May 29, 1998, Bethlehem Steel acquired a 100% interest in Lukens, Inc for $ 700.2 billion in cash. Luken's net assets at the time of the merger were $626.5 million. The mark-up of assets is equal to $700.2 – $626.5 = $73.7 million. For the fiscal year ended December 31, 1997, Bethlehem Steel (Lukens) had earnings of $239 ($13.4) million and net operating assets of $1456 ($486) million. The return on assets of the hypothetical entity comprised of Bethlehem Steel and Lukens for the fiscal year ended December 31, 1997 is equal to $239 + $13.4 (=$252.4) divided by $1456 + $486 + $73.7 (=2,015.7), which equals 12.5%.

Table A1

Construct Validity Test of DR_INDEX

FORECASTERR = α_0 + α_1DR + α_2RELSIZE + ∑YEAR + ∑ INDUSTRY

	DR = RESCO		**DR = LOCAL**		**DR = MTO**		**DR = TATO**		**DR = MTO + RESCO + LOCAL + TATO**		**DR = DR_INDEX**	
Dependent Variable: **FORECASTERR**	Coefficient Estimate	p-value	Coefficient Estimate	p-value	Coefficient Estimate	p-value	Coefficient Estimate	p-value	Coefficient Estimate	p-value	Coefficient Estimate	p-value
Explanatory Factors:												
RESCO	1.841	0.03							0.894	0.29		
LOCAL			3.458	< 0.01					3.132	< 0.01		
MTO					2.017	0.02			1.461	0.08		
TATO							-0.214	0.80	0.6	0.48		
DR_INDEX											6.05	< 0.01
Other Factors:												
RELSIZE	8.283	0.00	6.393	0.03	8.416	< 0.01	8.99	< 0.01	5.826	0.04	6.658	0.02
Year Dummies	Y		Y		Y		Y		Y		Y	
Industry Dummies	Y		Y		Y		Y		Y		Y	
R^2	0.543		0.571		0.546		0.525		0.59		0.574	
n	126		126		126		126		126		126	

The table displays cross-sectional regressions in which the dependent variable is FORECASTERR. See Appendix A for variable definitions.

Table 1
Sample Procedures

Panel A: Financial vs. Operating Acquirer Merger Sample Selection Procedures

	Number of Transactions
Total completed merger and acquisition transactions listed on the SDC database involving public, non-financial targets and public or private acquirers with non-missing financial accounting information announced between January 1, 1980 and December 31, 2012	2,419
Transactions in which acquirer is not a financial firm	*(2,064)*
Financial Acquirer Sample	**355**
Number of financial acquirer targets that could not be matched with operating acquirer targets	*(235)*
Final Financial Acquirer Sample	**120**
Final Matched Operating Acquirer Sample	**120**
Final Sample	**240**

Panel B: Public Operating Acquirer Merger Sample Selection Procedures

	Number of Transactions
Total completed merger and acquisition transactions listed on the SDC database involving public, non-financial targets and public, non-financial acquirers with non-missing financial accounting information announced between January 1, 1994 and December 31, 2010	1,631
Transactions in which target relative value is less than 50% and greater than 100%	*(1,301)*
Transactions in which bid premium is less than the target's pre-merger market value	(8)
Initial Disruptive Sample	**322**
Transactions in which target management turnover information could not be found and/or target analyst turnover could not be calculated	*(134)*
Final Disruptive Sample	**188**

Table 2
Descriptive Statistics

Panel A: Financial vs. Operating Acquirer Merger Sample

	Full Sample **N = 240**	Financial Acquirers (OP_ACQ = 0) **N = 120**	Operating Acquirers (OP_ACQ = 1) **N = 120**
Variable	**Mean**	**Mean**	**Mean**
PREMIUM	2.05	2.08	2.01
ROA_T	0.01	0.08	-0.06
BV_T	0.87	0.88	0.86
MULTIBID	0.06	0.08	0.03
LEVERAGE	0.46	0.62	0.30
LIQUIDITY	0.23	**0.19**	**0.26**
MTB	2.05	1.93	2.16
PUBLICACQ	0.52	**0.19**	**0.85**
CASH	0.57	**0.74**	**0.39**
EQ1	-0.08	-0.09	-0.06
EQ2	-0.08	**-0.06**	**-0.10**

Panel B: Financial and Operating Acquirer Industry Characteristics

Industry Title	**SIC Two-Digit Code**	**% of Financial Acquirer Sample**	**% of Operating Acquirer Sample**
Agriculture, Forestry, Fishing	01-09	0.00%	0.00%
Mining	10-14	4.69%	3.91%
Construction	15-17	1.56%	3.12%
Manufacturing	20-39	22.66%	30.47%
Transportation, Communications and Utilities	40-49	10.93%	11.72%
Wholesale Trade	50-51	0.78%	0.78%
Retail Trade	52-59	17.18%	14.06%
Services	70-89	42.19%	35.94%
Public Administration	91-99	0.00%	0.00%

Panel C: Public Operating Acquirer Merger Sample						
Variable	**N**	**Mean**	**Median**	**StdDev**	**10th Percent**	**90th Percent**
BV_T	188	0.79	0.58	1.35	0.10	1.72
CASH	188	0.07	0.00	0.26	0.00	0.00
EQ1	172	-0.07	-0.04	0.09	-0.15	-0.01
EQ2	172	-0.07	-0.05	0.09	-0.16	0.00
FORECASTERR	126	0.56	0.30	0.67	0.06	1.24
IND	188	0.74	1.00	0.44	0.00	1.00
LEVERAGE	188	0.27	0.19	2.60	0.00	1.67
LIQUIDITY	185	0.27	0.23	0.26	-0.02	0.64
MTB	184	2.82	2.20	3.89	0.64	6.70
MTO	188	0.61	1.00	0.49	0.00	1.00
DR_INDEX	188	0.47	0.50	0.24	0.25	0.75
RESCO	188	0.49	0.00	0.50	0.00	1.00
LOCAL	188	0.21	0.00	0.41	0.00	1.00
MULTIBID	188	0.06	0.00	0.22	0.00	0.00
PREMIUM	188	1.79	1.49	1.05	1.10	2.60
PUBLICACQ	188	0.73	0.47	1.04	0.05	1.54
RELSIZE	126	0.71	0.70	0.14	0.54	0.93
ROA_T	188	0.11	0.02	1.60	-0.70	0.57
TATO	188	0.49	0.00	0.50	0.00	1.00
ΔROA_T	187	0.19	0.01	0.92	-0.26	0.64

Panel D: Deal Characteristics and Post-Merger Sample						
Variable	**N**	**Mean**	**Median**	**StdDev**	**10th Percent**	**90th Percent**
BATH	170	0.71	1.00	0.45	0.00	1.00
BHRET	170	0.15	0.08	0.50	-0.42	0.97
BONUS	122	0.61	1.00	0.50	0.00	1.00
BTM_IND	170	0.14	0.00	0.35	0.00	1.00
CASH	170	0.09	0.00	0.29	0.00	0.00
DR_INDEX	170	0.40	0.25	0.25	0.00	0.75
DR_LO	170	0.52	1.00	0.51	0.00	1.00
FORACC_HI	170	0.50	1.00	0.50	0.00	1.00
GW%	170	0.33	0.21	0.48	0.00	0.78
GW_IMPAIR	170	0.22	0.00	0.41	0.00	1.00
LEVERAGE	170	0.21	0.19	0.17	0.00	0.45
LOCAL	170	0.21	0.00	0.41	0.00	1.00
MTO	170	0.68	1.00	0.47	0.00	1.00
NUMSEG	170	0.96	0.69	0.65	0.00	1.80
MULTIBID	170	0.07	0.00	0.26	0.00	1.00
PREMIUM	170	1.67	1.47	0.89	1.08	2.35
RANK	170	85.00	85.50	48.80	17.50	152.50
RESCO	170	0.00	0.00	0.47	0.00	1.00
RESIDUAL	119	0.00	0.00	0.26	-0.22	0.27
RESIDUAL'	119	0.00	0.00	0.56	-0.54	0.48
SIZE	170	7.55	7.40	1.88	5.31	10.25
TATO	170	0.37	0.00	0.48	0.00	1.00
TENURE	107	1.67	1.80	0.88	0.00	2.63
ΔOCF	166	-0.01	0.00	0.09	-0.10	0.09
ΔSALES	166	0.14	0.10	0.24	-0.06	0.40

See Appendix A for variable definitions. Panel A reports descriptive statistics for the operating targets of financial vs. operating acquirers. Coefficients in bold represent statistically significant differences at less than the 10 percent level between the two groups. Panel B reports acquirer and target industry characteristics for the financial and operating acquirer sample. Panel C reports descriptive statistics for the sample of operating targets used to examine cross-sectional variation of the relevance of accounting information for public, operating acquirers. Panel D reports post-merger descriptive statistics for a subsample of the operating acquirers in Panel C.

Table 3
Correlations

Panel A: Financial vs. Operating Acquirer Merger Sample											
	1	2	3	4	5	6	7	8	9	10	11
1 **OP_ACQ**		0.06	**-0.34**	0.12	**0.15**	-0.05	**0.11**	0.06	**-0.13**	-0.02	**-0.19**
2 **BV_T**	-0.01		0.05	**0.18**	0.12	**-0.03**	0.08	**-0.30**	**0.13**	**0.25**	0.00
3 **CASH**	**-0.36**	-0.01		-0.03	-0.10	0.03	**0.22**	-0.01	**0.13**	-0.07	0.05
4 **EQ1**	0.12	**0.18**	-0.03		**0.89**	**0.14**	-0.04	**0.13**	0.09	-0.07	0.00
5 **EQ2**	**0.15**	0.12	-0.10	**0.89**		0.08	-0.12	0.05	0.07	-0.08	-0.06
6 **LEVERAGE**	-0.10	**0.14**	-0.02	**0.14**	0.08		**-0.12**	**0.57**	0.17	-0.14	0.02
7 **LIQUIDITY**	**0.12**	-0.05	**0.21**	-0.04	-0.12	**-0.12**		0.05	0.03	**-0.12**	0.03
8 **MTB**	0.05	**-0.27**	-0.04	**0.13**	0.05	**0.52**	0.09		0.13	**-0.25**	0.05
9 **MULTIBID**	**-0.11**	**0.11**	**0.15**	0.09	0.07	0.09	0.07	0.06		-0.05	-0.07
10 **PREMIUM**	-0.02	**0.50**	-0.06	-0.07	-0.08	0.00	**-0.16**	**-0.21**	-0.01		-0.07
11 **ROA_T**	**-0.16**	-0.02	0.05	0.00	-0.06	0.01	0.04	0.06	-0.06	-0.06	

Panel B: Public Operating Acquirer Merger Sample

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 **BV_T**		0.01	0.07	**0.14**	0.10	**0.17**	0.10	**-0.32**	-0.02	-0.05	**-0.11**	**-0.10**	**0.20**	-0.05	**0.28**	-0.08	0.06	-0.08
2 **CASH**	0.03		0.14	0.05	0.05	0.01	0.14	-0.08	**-0.12**	0.02	**-0.18**	0.05	**-0.12**	-0.06	**-0.16**	-0.02	0.07	-0.03
3 **EQ1**	0.07	0.14		**0.92**	**0.14**	-0.01	-0.10	**-0.34**	-0.05	0.06	-0.06	-0.06	-0.04	0.04	-0.03	-0.10	-0.06	-0.04
4 **EQ2**	**0.14**	0.05	**0.92**		0.09	0.01	-0.10	**-0.33**	-0.10	0.00	-0.11	-0.09	-0.01	0.05	-0.03	**-0.12**	-0.01	-0.04
5 **IND**	0.11	0.09	**0.14**	0.09		0.08	-0.09	-0.13	0.08	0.16	0.11	-0.08	-0.04	0.14	-0.01	-0.15	-0.01	-0.03
6 **LEVERAGE**	**0.13**	0.00	-0.01	0.01	0.04		-0.02	**0.46**	0.00	-0.05	**0.17**	0.01	-0.14	**-0.15**	**-0.35**	0.00	0.01	0.00
7 **LIQUIDITY**	0.05	0.07	-0.10	-0.10	-0.02	-0.07		**0.06**	0.09	0.00	0.03	**0.25**	-0.07	-0.09	**-0.08**	0.08	**0.17**	-0.01
8 **MTB**	**-0.32**	-0.09	**-0.34**	**-0.33**	-0.09	**0.41**	**0.16**		0.07	**-0.12**	**0.22**	**0.17**	-0.10	-0.02	**-0.30**	**0.22**	-0.01	-0.02
9 **DR_INDEX**	-0.04	**-0.19**	-0.05	-0.10	0.02	0.00	0.11	0.04		**0.49**	**0.60**	**0.47**	**0.45**	-0.04	0.08	0.12	0.11	-0.01
10 **MTO**	0.02	-0.01	0.06	0.00	0.05	-0.04	-0.03	**-0.16**	**0.49**		0.01	0.08	-0.12	0.04	**0.07**	-0.13	**-0.17**	0.06
11 **RESCO**	**-0.13**	**-0.19**	-0.06	-0.11	0.07	**0.18**	0.05	**0.21**	**0.53**	-0.09		0.11	0.04	-0.06	-0.03	0.12	0.18	0.03
12 **LOCAL**	**-0.13**	-0.01	-0.06	-0.09	-0.07	-0.04	**0.24**	**0.14**	**0.49**	0.06	0.11		-0.10	-0.04	-0.10	0.18	0.12	0.05
13 **TATO**	**0.15**	**-0.15**	-0.04	-0.01	-0.03	-0.10	-0.02	-0.10	**0.48**	-0.02	0.00	-0.08		-0.01	**0.19**	0.10	0.10	-0.14
14 **MULTIBID**	-0.01	-0.07	0.04	0.05	0.10	**-0.15**	-0.10	-0.08	-0.03	0.10	-0.11	-0.02	-0.03		-0.06	-0.02	-0.03	0.10
15 **PREMIUM**	**0.40**	**-0.16**	-0.03	-0.03	0.01	**-0.23**	**-0.14**	**-0.29**	0.08	**0.15**	-0.09	-0.09	**0.18**	-0.02		-0.08	-0.01	-0.18
16 **ROA_T**	-0.06	-0.02	-0.10	**-0.12**	-0.12	-0.01	0.09	**0.21**	0.11	-0.11	0.11	**0.16**	0.08	-0.02	-0.07		**0.45**	-0.04
17 **ΔROA_T**	0.03	0.04	-0.06	-0.01	0.03	0.00	**0.23**	0.11	0.01	**-0.13**	0.08	0.07	0.00	-0.04	-0.04	**0.39**		-0.08
18 **RELSIZE**	-0.07	0.01	-0.04	-0.04	-0.01	0.05	-0.05	-0.07	0.02	0.06	0.04	0.01	-0.06	-0.01	-0.07	-0.04	-0.06	

Panel C: Deal Characteristics and Post-Merger Sample

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1 **BATH**		-0.18	0.18	-0.25	-0.05	-0.04	0.08	0.00	-0.06	-0.06	-0.05	-0.06	-0.05	-0.01	0.07	-0.14	-0.15	0.13	0.03	0.00	0.15	-0.12	0.04	0.00	-0.20
2 **BHRET**	**-0.13**		-0.21	0.13	-0.04	-0.24	0.14	-0.02	0.21	0.25	0.36	-0.15	-0.32	-0.29	-0.09	0.09	0.27	-0.09	0.06	0.12	-0.35	-0.06	0.09	-0.03	0.20
3 **BONUS**	**0.16**	**-0.16**		-0.33	0.10	0.09	-0.06	-0.07	-0.13	-0.21	-0.03	-0.09	-0.04	0.03	-0.19	-0.09	0.02	0.05	-0.12	-0.11	0.06	0.27	-0.06	0.15	0.02
4 **BTM_IND**	**-0.16**	**0.13**	**-0.26**		0.06	-0.09	-0.02	-0.15	0.16	0.23	0.01	-0.13	-0.07	0.01	0.12	0.07	0.02	-0.05	0.12	0.11	-0.24	0.03	-0.01	-0.15	-0.02
5 **CASH**	0.02	0.01	-0.02	-0.02		-0.12	0.13	0.08	0.12	-0.13	-0.02	0.09	-0.02	-0.10	-0.15	-0.20	0.06	-0.25	0.07	0.01	-0.03	-0.08	0.01	-0.04	-0.01
6 **DR_INDEX**	0.07	**-0.19**	0.16	-0.11	**-0.20**		-0.87	-0.12	-0.06	-0.01	-0.14	0.58	0.59	-0.05	0.08	0.04	-0.24	0.69	-0.01	-0.27	-0.04	0.56	-0.05	-0.05	-0.14
7 **DR_LO**	-0.04	**0.14**	-0.08	0.05	**0.18**	**-0.85**		0.26	0.08	0.00	0.12	-0.54	-0.45	0.06	-0.02	-0.03	0.17	-0.64	0.04	0.25	0.06	-0.48	0.00	-0.01	0.13
8 **FORACC_HI**	-0.11	-0.07	-0.03	**-0.14**	**0.12**	**-0.13**	**0.18**		0.05	-0.15	0.01	-0.01	0.19	0.25	0.20	-0.10	0.15	-0.27	-0.16	0.01	0.12	-0.16	-0.07	0.10	0.28
9 **GW%**	0.02	0.08	-0.11	0.06	0.08	-0.01	-0.02	0.07		0.16	0.00	-0.03	0.12	-0.03	0.12	-0.15	0.08	-0.17	0.09	0.05	-0.12	-0.03	0.16	-0.25	0.21
10 **GW_IMPAIR**	-0.03	**0.14**	**-0.20**	**0.23**	-0.07	-0.01	0.06	**-0.13**	**0.21**		0.05	-0.02	-0.16	0.01	0.07	-0.11	-0.03	0.16	0.21	0.18	-0.33	-0.02	-0.02	-0.13	-0.04
11 **LEVERAGE**	**-0.11**	**0.11**	-0.06	-0.05	0.05	**-0.16**	**0.18**	**0.16**	0.08	0.00		0.00	-0.01	-0.27	-0.21	0.18	0.78	-0.21	0.07	0.13	-0.07	-0.10	0.40	-0.09	0.03
12 **LOCAL**	0.00	-0.10	-0.03	-0.05	-0.01	**0.58**	**-0.49**	-0.08	0.01	-0.01	**-0.12**		0.24	-0.03	-0.04	-0.12	-0.05	0.18	0.00	-0.30	0.20	0.05	-0.03	-0.13	-0.18
13 **MTO**	-0.01	**-0.16**	0.05	-0.04	-0.02	**0.46**	**-0.34**	**0.11**	0.06	-0.02	**0.22**	0.09		0.04	0.20	0.06	-0.10	0.24	-0.07	-0.11	0.07	0.04	-0.08	0.03	0.08
14 **NUMSEG**	-0.05	**-0.18**	-0.01	0.04	-0.10	0.05	-0.09	**0.28**	0.06	0.08	-0.09	-0.06	0.08		0.10	-0.24	-0.05	0.11	-0.20	-0.12	0.33	-0.22	-0.13	-0.01	0.14
15 **MULTIBID**	-0.02	0.08	**-0.14**	0.08	-0.08	0.05	-0.01	**0.12**	0.05	0.02	-0.07	-0.01	**0.16**	0.06		-0.07	0.01	0.03	0.13	0.01	0.30	0.03	0.05	0.00	0.12
16 **PREMIUM**	**-0.15**	-0.06	0.03	0.07	**-0.16**	0.07	-0.08	-0.09	-0.11	-0.12	0.06	**-0.12**	0.06	-0.01	-0.08		0.00	0.03	0.45	0.49	-0.10	0.10	0.05	0.06	0.08
17 **RANK**	**-0.18**	0.06	-0.02	-0.04	0.10	**-0.24**	**0.19**	**0.25**	0.07	-0.05	**0.85**	**-0.17**	**0.22**	0.01	0.03	0.03		-0.28	-0.03	-0.10	0.16	-0.13	0.40	-0.12	0.18
18 **RESCO**	**0.10**	**-0.10**	0.07	**-0.12**	**-0.17**	**0.57**	**-0.51**	**-0.13**	-0.04	0.04	**-0.21**	**0.12**	**-0.18**	**0.10**	-0.05	-0.02	**-0.21**		0.08	-0.18	0.01	0.19	-0.08	-0.03	-0.12
19 **RESIDUAL**	-0.01	0.00	-0.09	**0.18**	0.06	-0.03	0.04	-0.09	0.08	**0.19**	0.04	0.04	-0.02	**-0.16**	0.07	**0.36**	-0.01	-0.04		0.62	0.01	-0.04	0.22	-0.04	-0.04
20 **RESIDUAL'**	**-0.09**	-0.04	**-0.18**	0.12	0.01	**-0.32**	**0.30**	0.02	**0.16**	0.12	0.10	**-0.19**	0.07	-0.03	-0.04	**0.53**	0.03	**-0.19**	**0.57**		-0.17	-0.08	0.09	0.00	0.01
21 **SIZE**	0.00	**-0.15**	0.07	**-0.28**	0.00	-0.06	0.09	**0.29**	-0.04	**-0.25**	**0.21**	0.01	**0.16**	**0.14**	**0.22**	**-0.14**	**0.29**	0.01	-0.03	**-0.21**		-0.34	0.00	0.02	0.09
22 **TATO**	0.11	0.06	**0.25**	-0.03	-0.12	**0.55**	**-0.51**	**-0.18**	-0.11	-0.06	**-0.22**	0.04	-0.04	-0.07	0.00	**0.20**	**-0.24**	0.09	-0.04	-0.10	**-0.34**		0.06	0.01	-0.10
23 **TENURE**	0.00	0.07	**-0.20**	-0.02	**0.19**	-0.16	0.12	0.07	0.11	-0.03	**0.28**	-0.07	-0.17	-0.07	0.02	0.00	**0.26**	-0.12	**0.23**	**0.17**	-0.05	-0.04		0.06	0.08
24 **ΔOCF**	-0.01	**0.11**	0.13	-0.05	-0.02	0.09	-0.13	-0.04	-0.08	0.02	-0.08	-0.01	0.06	0.00	0.04	0.05	-0.11	0.03	-0.10	-0.07	0.00	0.03	0.03		0.19
25 **ΔSALES**	**-0.16**	0.02	0.09	0.06	-0.02	-0.07	0.07	0.04	0.06	-0.01	0.03	**-0.18**	0.02	0.05	0.00	0.09	0.11	-0.01	0.00	0.13	-0.12	-0.06	0.15	0.12	

Spearman (Pearson) correlation coefficients are presented above (below) the diagonal. See Appendix A for variable definitions. The coefficients in bold are statistically significant at less than the 10 percent level.

Table 4

Operating Acquirers' Differential Use of Targets' ROA and Book Value in Setting Bid Premium

Panel A: Industry defined by 4-digit SIC code

$$\textbf{PREMIUM} = \alpha_0 + \alpha_1\text{OP\_ACQ} + \alpha_{2a}\text{OP\_ACQ} \times \text{ROA\_T} + \alpha_{2b}\text{OP\_ACQ} \times \text{BV\_T} + \alpha_{3a}\text{ROA\_T} + \alpha_{3b}\text{BV\_T} + \alpha_4\text{MULTIBID} + \alpha_5\text{CASH} + \alpha_6\text{LIQUIDITY} + \alpha_7\text{LEVERAGE} + \alpha_8\text{MTB} + \alpha_9\text{PUBLICACQ} + \varepsilon$$

	Specification 1		**Specification 2**		**Specification 3**		**Specification 4**	
Dependent Variable: **PREMIUM**	Coefficient Estimate	p-value	Coefficient Estimate	p-value	Coefficient Estimate	p-value	Coefficient Estimate	p-value
Explanatory Factors:								
OP_ACQ	0.11	0.06	0.13	0.10	-0.06	0.37	-0.05	0.61
OP_ACQ × ROA_T	-0.06	0.09	-0.07	0.07	-0.06	0.10	-0.07	0.07
OP_ACQ × BV_T					0.34	< 0.01	0.38	< 0.01
ROA_T	0.02	0.16	0.02	0.16	0.02	0.17	0.02	0.19
BV_T			0.03	0.29	0.00	0.93	0.00	0.93
Other Factors:								
MULTIBID			-0.01	0.97			-0.04	0.79
CASH			-0.16	0.02			-0.18	0.02
LIQUIDITY			0.12	0.29			0.12	0.68
LEVERAGE			0.04	0.11			0.00	0.98
MTB			-0.01	0.75			0.01	0.43
PUBLICACQ			-0.08	0.33			-0.13	0.14
Adj-R^2	0.02		0.04		0.32		0.34	
n	240		240		240		240	

Panel B: Industry defined by GIC code								
	Specification 1		**Specification 2**		**Specification 3**		**Specification 4**	
Dependent Variable: **PREMIUM**	Coefficient Estimate	p-value	Coefficient Estimate	p-value	Coefficient Estimate	p-value	Coefficient Estimate	p-value
Explanatory Factors:								
OP_ACQ	0.14	< 0.01	0.02	0.84	0.03	0.56	-0.12	0.17
OP_ACQ x ROA_T	-0.03	0.12	-0.03	0.08	-0.04	0.03	-0.03	0.09
OP_ACQ x BV_T					0.16	< 0.01	0.16	< 0.01
ROA_T	0.02	0.13	0.01	0.35	0.02	0.16	0.01	0.39
BV_T					-0.01	0.71	0.00	0.86
Other Factors:								
MULTIBID			0.08	0.51			0.06	0.62
CASH			-0.10	0.12			-0.07	0.27
LIQUIDITY			-0.11	0.27			-0.13	0.18
LEVERAGE			-0.01	0.10			-0.02	0.05
MTB			0.00	0.81			0.01	0.51
PUBLICACQ			0.07	0.43			0.13	0.14
Adj-R^2	0.04		0.03		0.07		0.09	
n	498		368		498		368	

The table displays cross-sectional regressions in which the dependent variable is the bid premium. In Panel A (B), SIC (GIC) codes are used as the industry classification scheme. See Appendix A for variable definitions.

Table 5

The Effect of Disruption on Acquirers' Use of Targets' ROA and Book Value in Setting Bid Premium

$$\textbf{PREMIUM} = \alpha_0 + \alpha_1\text{DR\_INDEX} + \alpha_{2a}\text{DR\_INDEX} \times \text{ROA\_T} + \alpha_{2b}\text{DR\_INDEX} \times \text{BV\_T} + \alpha_{3a}\text{ROA\_T} + \alpha_{3b}\text{BV\_T} + \alpha_4\text{MULTIBID} + \alpha_5\text{CASH} + \alpha_6\text{LIQUIDITY} + \alpha_7\text{LEVERAGE} + \alpha_8\text{MTB} + \alpha_9\text{IND} + \delta\text{YEAR} + \lambda\text{INDUSTRY} + \varepsilon$$

	Specification 1		**Specification 2**		**Specification 3**	
Dependent Variable: **PREMIUM**	Coefficient Estimate	p-value	Coefficient Estimate	p-value	Coefficient Estimate	p-value
Explanatory Factors:						
DR_INDEX	0.23	0.18	-0.13	0.58	0.02	0.66
DR_INDEX × ROA_T	-0.17	0.04			-0.17	0.02
DR_INDEX × BV_T			0.71	0.09	1.03	0.01
ROA_T	0.06	0.23			0.08	0.08
BV_T			0.02	0.94	-0.15	0.50
Other Factors:						
MULTIBID					-0.33	0.04
CASH					-0.04	0.79
LIQUIDITY					-0.39	0.05
LEVERAGE					-0.14	< 0.01
MTB					-0.02	0.02
IND					0.07	0.50
Year Dummies	Y		Y		Y	
Industry Dummies	Y		Y		Y	
Adj-R^2	0.42		0.46		0.59	
n	188		188		181	

The table displays cross-sectional regressions in which the dependent variable is the bid premium. All specifications include effective merger-year and 4-digit SIC code industry fixed-effects. See Appendix A for variable definitions.

Table 6
Operating Acquirers' Differential Use of Targets' Earnings Quality in Setting Bid Premium

$$\mathbf{PREMIUM = \alpha_0 + \alpha_1 OP\_ACQ + \alpha_{2a} OP\_ACQ \times ROA\_T + \alpha_{2b} OP\_ACQ \times BV\_T + \alpha_{2c} OP\_ACQ \times EQ\_T + \alpha_{3a} ROA\_T + \alpha_{3b} BV\_T + \alpha_{3c} EQ\_T + \alpha_4 MULTIBID + \alpha_5 CASH + \alpha_6 LIQUIDITY + \alpha_7 LEVERAGE + \alpha_8 MTB + \alpha_9 PUBLICACQ + \varepsilon}$$

	EQ_T = EQ1		**EQ_T = EQ2**	
Dependent Variable: **PREMIUM**	Coefficient Estimate	p-value	Coefficient Estimate	p-value
Explanatory Factors:				
OP_ACQ	-0.21	0.14	-0.18	0.22
OP_ACQ × ROA_T	-0.05	0.26	-0.05	0.23
OP_ACQ × BV_T	0.39	< 0.01	0.35	< 0.01
OP_ACQ × EQ_T	-1.88	0.02	-1.72	0.10
ROA_T	0.02	0.28	0.02	0.38
BV_T	0.06	0.41	0.07	0.36
EQ_T	0.06	0.89	-0.03	0.95
Other Factors:				
MULTIBID	0.00	0.99	0.02	0.93
CASH	-0.23	0.01	-0.25	< 0.01
LIQUIDITY	0.00	0.97	-0.07	0.66
LEVERAGE	-0.03	0.37	-0.03	0.37
MTB	0.02	0.31	0.01	0.55
PUBLICACQ	-0.10	0.40	-0.09	0.45
Adj-R^2	0.44		0.40	
n	172		172	

The table displays cross-sectional regressions in which the dependent variable is the bid premium. See Appendix A for variable definitions.

Table 7

The Effect of Disruption on Acquirers' Use of Targets' Earnings Quality in Setting Bid Premium

$$\textbf{PREMIUM} = \alpha_0 + \alpha_1 \textbf{DR\_INDEX} + \alpha_{2a}\textbf{DR\_INDEX} \times \textbf{ROA\_T} + \alpha_{2b}\textbf{DR\_INDEX} \times \textbf{BV\_T} + \alpha_{2c}\textbf{DR\_INDEX} \times \textbf{EQ\_T} + \alpha_{3a}\textbf{ROA\_T} + \alpha_{3b}\textbf{BV\_T} + \alpha_{3c}\textbf{EQ\_T} + \alpha_4\textbf{MULTIBID} + \alpha_5\textbf{CASH} + \alpha_6\textbf{LIQUIDITY} + \alpha_7\textbf{LEVERAGE} + \alpha_8\textbf{MTB} + \alpha_9\textbf{IND} + \delta\textbf{YEAR} + \lambda\textbf{INDUSTRY} + \varepsilon$$

	EQ_T = EQ1		**EQ_T = EQ2**	
Dependent Variable: **PREMIUM**	Coefficient Estimate	p-value	Coefficient Estimate	p-value
Explanatory Factors:				
DR_INDEX	-0.54	0.11	-0.57	0.13
DR_INDEX × ROA_T	-0.18	0.03	-0.17	0.04
DR_INDEX × BV_T	1.01	0.02	1.20	0.01
DR_INDEX × EQ_T	-6.55	0.03	-5.94	0.07
ROA_T	0.08	0.12	0.07	0.15
BV_T	-0.10	0.70	-0.21	0.38
EQ_T	2.68	0.07	1.84	0.28
Other Factors:				
MULTIBID	-0.31	0.06	-0.28	0.10
CASH	-0.14	0.42	-0.12	0.48
LIQUIDITY	-0.39	0.15	-0.40	0.13
LEVERAGE	-0.15	< 0.01	-0.15	< 0.01
MTB	-0.03	0.06	-0.03	0.01
IND	0.06	0.66	0.12	0.36
Year Dummies	Y		Y	
Industry Dummies	Y		Y	
Adj-R^2	0.34		0.36	
n	138		138	

The table displays cross-sectional regressions in which the dependent variable is the bid premium. See Appendix A for variable definitions.

Table 8

Acquirers' Use of Accounting Information and Goodwill Impairments

Pr(GW_IMPAIR = 1) = logit (α_0+ α_1 RESIDUAL + α_2 ΔSALES + α_3 ΔOCF + α_4 LEVERAGE + α_5 SIZE + α_6 NUMSEG + α_7 BTM_IND + α_8 BHRET + α_9 RANK + α_{10} BONUS + α_{11}BATH + α_{12}TENURE + α_{13} GW% + δYEAR + ε)

	RESIDUAL		**RESIDUAL'**	
Dependent Variable: GW_IMPAIR = 1	Coefficient Estimate	p-value	Coefficient Estimate	p-value
Explanatory Factors:				
RESIDUAL	3.91	0.05	0.68	0.38
Other Factors:				
ΔSALES	0.77	0.80	-1.60	0.07
ΔOCF	-2.02	0.25	-3.47	0.54
LEVERAGE	0.76	0.87	0.68	0.85
SIZE	-1.07	0.04	-0.67	0.06
NUMSEG	1.18	0.16	1.15	0.31
BTM_IND	0.61	0.53	0.27	0.74
BHRET	-2.55	0.03	-2.56	0.01
RANK	0.00	0.99	0.00	0.81
BONUS	-1.90	0.07	-2.28	0.03
BATH	0.05	0.96	0.13	0.85
TENURE	0.52	0.16	0.89	0.03
GW%	2.04	0.10	1.16	0.31
Year Dummies	Y		Y	
BIC	146.22		170.8	
AIC	97.83		117.84	
n	74		74	

The table displays cross-sectional regressions in which the dependent variable is the liklihood of a goodwill impairment. The results reported above are based on heteroskedasticity-robust standard errors (clustered at the acquiring firm level). See Appendix A for variable definitions.

Table 9

The Effect of Disruption on the Predictive Ability of Acquirers' Management

Pr(GW_IMPAIR = 1) = logit (α_0+ α_1 DR_LO + α_2 FORACC_HI + α_3 DR_LO × FORACC_HI + α_4 ΔSALES + α_5 ΔOCF + α_6 LEV + α_7 SIZE + α_8 NUMSEG + α_9 BTM_IND + α_{10} BHRET + α_{11} RANK + α_{12} BONUS + α_{13}BATH + α_{14}TENURE + α_{15} GW% + δYEAR + ε)

	DISRUPT = DR_INDEX		**DISRUPT = DR_INDEX**	
Dependent Variable: **GW_IMPAIR = 1**	Coefficient Estimate	p-value	Coefficient Estimate	p-value
Explanatory Factors:				
FORACC_HI	-1.07	0.09	-0.22	0.82
DISRUPT_LO			4.77	0.01
DISRUPT_LO × FORACC_HI			-4.78	0.02
Other Factors:				
ΔSALES	0.05	-0.05	-0.37	0.73
ΔOCF	-2.66	0.62	-5.28	0.39
LEV	2.43	0.50	2.78	0.54
SIZE	-0.58	0.03	-0.95	0.03
NUMSEG	1.51	0.01	-0.32	0.01
BTM_IND	0.12	0.89	-0.32	0.81
BHRET	0.03	0.92	0.05	0.89
RANK	0.00	0.69	-0.01	0.60
BONUS	-1.22	0.06	-0.12	0.89
BATH	0.89	0.19	-0.08	0.93
TENURE	-0.05	0.41	0.02	0.75
GW%	0.94	0.44	1.07	0.36
Year Dummies	Y		Y	
n	106		97	

The table displays cross-sectional regressions in which the dependent variable is the liklihood of a goodwill impairment. The results reported above are based on heteroskedasticity-robust standard errors (clustered at the acquiring firm level). See Appendix A for variable definitions.

Table 10

The Effect of Disruption on Acquirers' Use of the Change in Targets' ROA in Setting Bid Premium

$$\textbf{PREMIUM} = \alpha_0 + \alpha_1\textbf{DISRUPT} + \alpha_2\textbf{DISRUPT} \times \Delta\textbf{ROA\_T} + \alpha_{3a}\Delta\textbf{ROA\_T} + \alpha_{3b}\textbf{BV\_T} + \alpha_4\textbf{MULTIBID} + \alpha_5\textbf{CASH} + \alpha_6\textbf{LIQUIDITY} + \alpha_7\textbf{LEVERAGE} + \alpha_8\textbf{MTB} + \alpha_9\textbf{PUBLICACQ} + \alpha_{10}\textbf{IND} + \delta\textbf{YEAR} + \lambda\textbf{INDUSTRY} + \varepsilon$$

	DISRUPT = OP_ACQ		**DISRUPT = DR_INDEX**	
Dependent Variable: **PREMIUM**	Coefficient Estimate	p-value	Coefficient Estimate	p-value
Explanatory Factors:				
DISRUPT	0.14	0.14	0.39	0.07
DISRUPT × ΔROA_T	-0.07	0.10	-0.63	< 0.01
ΔROA_T	0.02	0.14	0.20	0.06
BV_T	0.02	0.57	0.20	0.09
Other Factors:				
MULTIBID	0.00	0.99	-0.41	0.08
CASH	-0.20	0.01	-0.01	0.96
LIQUIDITY	0.16	0.17	-0.58	0.04
LEVERAGE	0.04	0.10	-0.11	< 0.01
MTB	-0.01	0.67	-0.01	0.45
PUBLICACQ	-0.14	0.13		
IND			-0.16	0.36
Year Dummies	N		Y	
Industry Dummies	N		Y	
Adj-R^2	0.04		0.19	
n	234		181	

The table displays cross-sectional regressions in which the dependent variable is the bid premium. See Appendix A for variable definitions.

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