



## Toward a complete definition of relatedness in merger and acquisition transactions

Yasser Alhenawi<sup>1</sup> · Martha L. Stilwell<sup>1</sup>

Published online: 20 August 2018  
© Springer Science+Business Media, LLC, part of Springer Nature 2018

### Abstract

The interrelation between different sources of relatedness in M&A transactions has been largely overlooked in extant literature. This paper offers theoretical and empirical investigation and introduces a few new measures of relatedness. We find that single-dimensional measures of relatedness are complements, not substitutes, of each other, and their impacts on the market's reaction are additive and interdependent. Specifically, each measure contains unique relatedness information and the market's perception of, and reaction to, the presence of relatedness in M&A deals is more sophisticated than the extant literature prescribes. The market seems to reward operational and marketing relatedness in small-vicinity mergers and out-of-state mergers. In contrast, related in-state mergers seem to be associated with a significantly negative market reaction. Similarly, technology affiliation induces an additional positive market reaction that is separate from simple industry matching, and the market seems to reward the acquisition of high-technology targets by high-technology acquirers and to penalize the acquisition of high-technology targets by non-high-technology acquirers. Furthermore, we find that horizontally and vertically related mergers are relatively more likely to be completed, while in-state and large-vicinity mergers are less likely to be completed. We also find that when the target is incorporated in a target-friendly state, the merger is less likely to be completed, though state-specific merger laws do not contribute significantly to mergers' valuation. Taken together, our results indicate that relatedness is a multidimensional metric composed of several interrelated components, and, thus, single-dimensional proxies are not sufficient to capture relatedness accurately and completely.

**Keywords** Mergers · Acquisitions · Related mergers · Unrelated mergers · Synergies · Diversification

**JEL Classification** G34

---

✉ Yasser Alhenawi  
ya22@evansville.edu  
Martha L. Stilwell  
ml86@evansville.edu

<sup>1</sup> Schroeder School of Business Administration, University of Evansville, 1800 Lincoln Ave., Evansville, IN 47722, USA

## 1 Introduction

In the extant mergers and acquisitions (M&As) literature, the term “relatedness” refers to several forms of similarity between the acquirer and the target. Understandably, relatedness has played a pivotal role in the development of our understanding of value creation in M&A transactions. Absent a unified definition and measurement tool of relatedness, however, authors employ different measures of relatedness (and often reach conflicting conclusions). The most straightforward method of measuring relatedness is the simple Standard Industry Classification (SIC) code matching procedure which results in a binary indicator of relatedness. Many authors raise concerns about the coarseness of this approach. To mention a few, Palepu (1985) develops a continuous SIC-based measure that captures the level of relatedness, and Alhenawi and Krishnaswami (2015) employ a continuous SIC-based variable that measures the change-in-focus resulting from mergers. Nevertheless, SIC-based measures, binary and continuous, inherently focus on similarities in taxation and regulatory environments for the acquirer and the target, and thus, they overlook several other important sources of synergy. Consequently, several alternatives have been proposed, such as measures of supply chain integration (Fan and Lang 2000), geographical proximity (Kang and Kim 2008), and operational and marketing similarities (Hoberg and Phillips 2010, 2016).

Our work responds to a gap in the existing literature of M&As. The literature has overlooked the possibility that relatedness may be multi-dimensional, i.e., existing measures of relatedness are complements, not substitutes, of each other. This may lead to erroneous conclusions because a single-dimensional measure of relatedness inherently captures only a single element of similarity between the merging firms. In other words, an M&A deal may carry several attributes of relatedness between the acquirer and the target, while current measures are designed to account for only one attribute. This is a serious omission because it implies that the impact of relatedness on M&A valuation is not “fully” analyzed. In fact, several authors have accused poor proxies for relatedness of distorting the relationship between merger premiums and relatedness [see Ahern and Harford (2014) and Barney (1988)]. In addition, certain proxies of relatedness might be more suitable than others in certain research designs. Finally, several additional attributes of relatedness are still unexplored. For instance, relatively little is known in current literature about the role of vicinity, technology, and applicable state-level laws in merger and acquisition transactions. How close should the merging firms be in order to be classified as geographically related? Do local regulations matter? Should a merger within the technology-intensive sector be considered as related as a merger between two firms in any non-technology-intensive industry? Anecdotal observation as well as simple economic reasoning indicate that these questions are important considerations in M&A transactions. The current literature does not provide clear answers to these questions.

Our research offers theoretical discussion as well as empirical investigation of these issues. Specifically, in this article we seek to answer two questions. First, is relatedness multi-dimensional? The notion *is* intuitive but has not been formally investigated or documented. Given the complex nature of merger and acquisition transactions, we hypothesize that none of the existing single-dimensional measures alone can capture relatedness accurately and completely. Second, are single-dimensional measures mutually exclusive?

To mention one example,<sup>1</sup> certain industries tend to cluster in certain geographical areas, which suggests that locational relatedness and operational relatedness are not mutually exclusive. We employ same-sample comparison to explore possible interactions between several existing and new measures of relatedness. Additionally, we explore several new inquiries on the market's perception and valuation of physical proximity, technological affiliation, and local regulations in M&A transactions.<sup>2</sup>

Using a sample of 14,398 completed mergers between publicly traded U.S. companies between 1998 and 2014, we show that relatedness in M&A deals cannot be fully captured by a single-dimensional relatedness metric. Further, we find that the market's reaction to the merger announcement is influenced *simultaneously* by several relatedness sources including familiarity with regulations, operational and marketing similarities, vicinity, state of incorporation, technological affiliation, and supply chain integration. The findings are robust to several alterations of the specifications of the tests and indicate that none of the single-dimensional measures is sufficient to capture the *full* relatedness information contained in an M&A transaction. We also examine the relationship between relatedness, in its multi-dimensional format, and the likelihood of completing the merger deal. We find that relatedness components exhibit additive and interdependent impacts on the probability of a merger occurring in the first place.

To better understand the complex mechanism of value creation in mergers, we investigate the roles of location and show that the market's perception of location is rather meticulous. We report evidence that investors praise out-of-state related mergers and small-vicinity related mergers. Conceivably, they see the former as an opportunity to penetrate new markets and the latter as a victory over a nearby rival. In contrast, the market does not seem to be impressed by unrelated in-state mergers. In addition, related in-state mergers are severely penalized. This is further supported but another finding indicating that in-state and large-vicinity mergers are less likely to be completed. The latter findings refine and develop a similar finding by Kang and Kim (2008) who find that in-state mergers create more value than out-of-state merger. Our findings imply that the market has a meticulous taste for relatedness, state of incorporation, and distance between merging firms.

Another indication of market sophistication pertains to how the market reacts when the merging firms belong to the high-technology sectors. Our results indicate that a merger that involves a high-technology target creates additional value only when the acquirer is also a high-technology firm. In contrast, the acquisition of a high-technology target by a non-high-technology acquirer has a negative impact on the market's reaction to the deal announcement. Furthermore, a merger between a high-technology acquirer and a non-high-technology target is not valued differently from a merger between two non-high-technology firms. This finding extends the work of Canace and Mann (2014) who report evidence that the market overreacts to technology-motivated M&A announcements because it overweights the impact of R&D intensity on the firms' future performance. This finding also relates to the recently increasing stream of literature on managerial learning from the market about firm-specific information. For instance, Ouyang and Szewczyk (2018) suggest

---

<sup>1</sup> More detailed discussion is presented inside the paper.

<sup>2</sup> Alhenawi and Krishnaswami (2015) use simple SIC classification and the continuous measure developed by Palepu (1985). In a robustness check, they applied Hoberg and Phillips's (2010, 2016) classification in a study that focuses on value creation and performance of related and unrelated mergers. Their work does not focus on comparing relatedness measures and does not incorporate the full list of measures considered in this study.

that managers learn from financial markets in identifying strategic merger investment opportunities.

Our work contributes to literature in several ways. First, while the role of relatedness in M&A valuation is undebatable, the literature does not seem to have reached a consensus on how to measure it. This is evidenced by the fact that several competing proxies currently exist, and authors continue to propose additional ones. Second, it is intuitive to propose that the relatedness between firms in M&A transactions is multi-dimensional. However, we are not aware of any previous work that formally investigates and empirically documents this proposition. Multi-dimensionality, however, raises another concern. How do these dimensions interact with each other? Our paper addresses the concerns of several authors about potential interrelation between relatedness factors (see Bhattacharyya and Nain 2011; Flanagan 1996; Kedia et al. 2011). Third, our work indicates that the market's perception of, and reaction to, the presence of relatedness in M&A deals is very meticulous. At least, it is more sophisticated than the extant literature prescribes. This paper shows that single-dimensional measures do a poor job in capturing the true relatedness between firms. Alternatively, it proposes that a few relatedness dimensions are more important than others and their importance depends on the other aspects of the merger, such as industry. Finally, certain relatedness elements, like vicinity and technology, interact in a complex manner. These interactions, of course, relate very well to plausible economic explanation and practical considerations. More importantly, the findings of this paper indicate the future research in this domain must take relatedness proxies very seriously. The use of simple SIC codes is not only weak but could lead to erroneous conclusions because the market does not see, and value, relatedness in a simple manner.

The paper is organized as follows. The next section reviews the theoretical ground of existing measures of relatedness. Section three motivates the hypotheses. Section four describes the sample and variables' construction. Section five explains the methodology and empirical results. Section six discusses and interprets the results, and section seven concludes the paper.

## 2 Literature review

Mergers and acquisitions are major business decisions that have been taken by modern corporations since at least the eighteenth century (DeYoung et al. 2009). In a typical M&A transaction, two business entities align their operations and management in order to survive in a fierce, competitive environment (Sharma 2016). There are two competing theoretical explanations of mergers and acquisitions: synergy and diversification.<sup>3</sup>

The first theory advocates synergy and subsequent efficiency (Anderson et al. 2012). It postulates that an M&A requires one business to make its operations and management style compatible with another business. The more similar the two businesses are, the more efficient the transaction becomes. This is because the merger would eliminate duplication and allow management to focus on core activities in a single larger entity. This synergy between merging firms often translates into added value for shareholders.

The second major theory of M&A suggests that diversification is the main motive behind M&A strategies (Berger and Ofek 1995; Adhikari et al. 2018; Nejadmalayeri et al.

<sup>3</sup> There are in fact several theories that explain the motivations behind M&A (e.g., agency and tax).

2017). Under this theory, value is created as a result of creating more stable entities. This is because diversification reduces relative variability of cash flows. Unlike synergy, diversification benefits are more profound in mergers between dissimilar firms.

When using either theory as a framework, an accurate measurement of similarity, or the lack of it, is a necessary metric for managers, investors, and academicians. Accordingly, several proxies have been proposed without reaching a consensus on which one is the best. In the following sections, we list major proxies of relatedness, their theoretical and practical applications, and their limitations.

## 2.1 Classical SIC code matching approach

The vast majority of research in mergers and acquisitions literature uses predefined industry coding systems such as the Standard Industry Classification (SIC) to distinguish between related and unrelated deals. For instance, a deal is considered related if the acquirer and the target are in the same two-digit SIC code (Adhikari et al. 2018; Nejadmalayeri et al. 2017; Berger and Ofek 1995; Comment and Jarrell 1995) or four-digit SIC code (Agrawal et al. 1992; Eckbo 1992; Anderson et al. 2011; Sharma 2016).

SIC codes are four-digit numerical codes established by the U.S. Government's Office of Management and Budget to classify enterprises into industries based on their primary economic activities. SIC codes date back about 80 years and had been updated numerous times until 1987.<sup>4</sup> SIC codes are the standard used by the SEC when sorting company filings and they appear in a company's disseminated EDGAR filings. They are also used in the SEC Division of Corporation Finance as a basis for assigning review responsibility for the company's filings. The IRS uses SIC codes in taxation. Auditing firms use SIC codes when comparing ratios of companies in similar industries. They are also used in determining eligibility for government contracts. Federal and state agencies use SIC codes in reporting statistical data and for legislative issues (e.g., the Department of Revenue uses the codes to inform taxpayers within a certain industry of law changes that may affect them).<sup>5</sup>

Despite its simplicity and intuitive appeal, the SIC code approach has been criticized by several authors, and several alternatives have been developed. The next section explores a few prominent criticisms and a few proposed alternatives.

## 2.2 Criticisms of classical SIC code matching approach and alternative approaches

For multi-division entities, the primary SIC code is the one that generates the highest revenue for that enterprise in the past year. This creates a conflict between four-digit and three- and two-digit classification. Clarke (1989) provides a good example. If a firm has 40% of its revenues in SIC 3211, and 30% in both SICs 2842 and 2845, the firm will be assigned SIC code 3211, which implies a three-digit SIC of 321 and a two-digit SIC of 32. However, 60% of the firm's revenues are in the 284 three-digit SIC and the 28 two-digit SIC.

<sup>4</sup> The North American Industry Classification System (NAICS) is a newer standard. The most recent NAICS was developed in 2007 under the auspices of the U.S. Office of Management and Budget (OMB) to replace SIC [1987]. The main objective is to allow for comparability in business statistics among the NAFTA countries (U.S., Canada and Mexico). In the U.S., government agencies (e.g. the SEC and the IRS) do not use NAICS. Since this research is concerned with U.S. M&As, we do not consider NAICS in our analyses.

<sup>5</sup> For more details see [www.siccode.com](http://www.siccode.com) and [www.secinfo.com](http://www.secinfo.com).

A similar argument is made by Nejadmalayeri et al. (2017) who show that the relative size of divisions has a critical impact on how diversification affects credit spreads and excess values. Further, non-parity among divisions correlates with greater costs that increase with the number of divisions.

King (1966) and Meyers (1973) use principal component analysis on market returns of 2-digit industries. They find that about 10% of the variance in rate of return could be explained by the industry codes. Using a similar methodology, Fertuck (1975) tests SIC codes' power of predicting returns across pseudo industries formed on return correlations. He finds that three-digit SIC groupings are moderately powerful (explain about 11% of variation in returns) while two- and one-digit SIC grouping are extremely weak (explain about 3% of variations in returns). Clarke (1989) tests the SIC system power in creating groups of firms with similar characteristics. He finds that the SIC system cannot identify homogeneous economic markets and, in contrast to Fertuck (1975), he reports that coarser (one-digit) grouping is more effective than finer (three- and four-digit) grouping.

Kahle and Walkling (1996) find that SIC classifications for the same firm differ between the CRSP and Compustat databases by 21% at the one-digit level, 36% at the two-digit level, 50% at the three-digit level, and 79% at the four-digit level. They state that these discrepancies suggest that research results and significance levels could differ because of the database chosen, irrespective of the underlying economics of the problem being analyzed. This is consistent with an earlier concern raised by Guenther and Rosman (1994). Further, Kahle and Walkling (1996) find that CRSP and Compustat disagree substantially on classification of mergers. 65% of the horizontal mergers identified by Compustat would have been reversed by CRSP, and 35% of the CRSP horizontal mergers would have been reversed by Compustat. This finding is disturbing because it implies that when a researcher uses SIC codes in Compustat (CRSP) to identify related deals, there is a 65% (35%) chance that the identification will be reversed if the study is replicated with SIC codes in CRSP (Compustat). These probabilities of misclassification are too high by almost any standard.

Palepu (1985) argues that a simple SIC matching procedure is too coarse because it does not recognize *the degree of relatedness*. Accordingly, he employs an entropy measure of firm focus,<sup>6</sup> and Alhenawi and Krishnaswami (2015) define relatedness as the difference between the pre-merger and post-merger values of the entropy measure.<sup>7</sup> These approaches resolve the coarseness concerns and partially respond to the misspecification concern raised by Clarke (1989). Nevertheless, they do not resolve other inherent problems of SIC codes.

Fan and Lang (2000) argue that SIC-based measures are unsatisfactory in several aspects. First, SIC codes do not reveal relatedness type (vertical vs. horizontal). Second, they are discrete, not continuous. Third, they are subject to classification error. As an alternative, Fan and Lang (2000) suggest a measure of relatedness that employs commodity flow data in U.S. Input–Output tables (provided by the Bureau of Economic Analysis). They construct two variables that capture vertical relatedness (one firm's output can be used as the other's input) and complementarity (the two firms purchase from a homogenous set of sellers and/or sell to a homogenous set of buyers) between industries. Several

<sup>6</sup> The measure was originally developed by Jacquemin and Berry (1979).

<sup>7</sup> Caves et al. (1980) and Wernerfelt and Montgomery (1988) use SIC codes to construct a concentric index measure of relatedness. Their measure is very similar to Palepu's (1985) continuous measure, but the latter is more sophisticated.

authors have employed this approach [see for example, Matsusaka (1996) and Fan and Goyal (2006)].

Kang and Kim (2008) examine the importance of geographic proximity. They argue that in-state acquirers may realize several advantages over out-of-state acquirers because the former have better access to relevant information on local markets, targets' performance, earnings forecasts, and state regulations. In addition, they argue that an in-state acquirer enjoys lower monitoring and transportation costs than an out-of-state acquirer after completion of the merger. Using state identifiers (a binary indicator of in-state mergers) and a topological distance measure, they find that in-state and local mergers experience both higher abnormal announcement returns and better post-acquisition operating performance than those of out-of-state and remote mergers. They also show that block acquirers exhibit a strong preference for in-state and local targets.

Hoberg and Phillips (2010, 2016) introduce a text-based analysis where relatedness is measured in the marketplace. Specifically, they define relatedness as high ex-ante similarity in product description between the acquirer and the target, as well as high ex-ante differentiation in product description between the target and the acquirer's rivals. They scanned about 50,000 10 K product descriptions from the SEC Edgar website to construct spatial representation of relatedness called Fixed Industry Classification (FIC). Just like SIC, the FIC measure is binary and can thus be employed in the same way SIC is employed. However, while SIC emphasizes similarities in taxation and regulation, FIC emphasizes operational and marketing similarities. Specifically, the FIC measure captures asset similarities, which allows for operational integration, and the ability to introduce differentiated products, which creates market power.

### 3 Hypotheses development

The previous section cited relatedness proxies that have been used in literature. To summarize, SIC code matching is a classical procedure found in many academic and practical applications. Despite its simplicity and intuitive appeal, the SIC code matching approach has been criticized by several authors. Coarseness and high probabilities of misclassification are two major criticisms. In response, authors have developed several alternatives. The SIC-based continuous measure developed by Palepu (1985) solves the coarseness problem but focuses only on the similarity in legislative and regulatory environment. The same applies to Alhenawi and Krishnaswami's (2015) SIC-based focus differential measure. Fan and Lang (2000) define relatedness in terms of vertical and horizontal integrations in supply chains of the acquirer and the target. The geographical distance and same-state measures developed by Kang and Kim (2008) capture familiarity with local markets and laws, access to relevant information, and lower monitoring costs. The FIC clusters developed by Hoberg and Phillips (2010, 2016) define relatedness in terms of marketing and operational integration between the merging firms.

The literature summarized above indicates that scholars have used the term "relatedness" to describe a wide range of similarities and potential integrations between merging firms. This variation in defining and measuring relatedness begs the question: is relatedness multi-dimensional? Each measure of relatedness discussed above has its own merits and limitations. However, given the complex nature of M&A transactions, it is hard to believe that any of these measures alone can capture relatedness accurately and completely. For instance, a merger between multi-segment entities can be vertically- and

horizontally-related at the same time. Furthermore, a horizontally- or vertically-related merger may create *additional* value through added market power, operational integration, or familiarity with local markets and laws.

### 3.1 An illustrative example

Consider Firm A which is made of two segments: A1 and A2 where A1 produces rubber and A2 produces tennis balls. Firm B produces basketballs, and therefore, it belongs to the same industry—sports products—as A2. If Firms A and B merge to form a new entity, AB, the merger would be correctly labelled as vertical *and* horizontal as per Fan and Lang (2000) definitions. It is vertical because of the connection between A1 and B and horizontal because of the connection between A2 and B.

At the same time, the product description of Firm A may emphasize A1's product, rubber, and the transaction, therefore, will be classified as weakly related by the text-based measure of Hoberg and Phillips (2010, 2016). However, if the product description of Firm A emphasizes A2's product, tennis balls, the transaction will be classified as strongly related by the text-based measure. In both scenarios, vertical relatedness goes under the radar of the text-based measures that rely on product descriptions only. Additionally, if Firms A and B were located in the same state, the work of Kang and Kim (2008) predicts that additional value may be created through lower monitoring costs and familiarity with local markets and regulations.<sup>8</sup>

In summary, the merger between A and B may be correctly described as vertical, horizontal, operationally related, and locationally related. Thus, none of the single-dimensional measures is capable of capturing relatedness in this merger accurately and completely. Accordingly, this paper tests the following core hypothesis:

#### H1 Relatedness is multi-dimensional.

Two testable implications of this hypothesis are explored. First, relatedness measures are complements, not substitutes. Second, each relatedness measure carries its own relatedness, and thus, valuation information.

In addition to the relatedness measures discussed in literature, this paper explores a few new measures of relatedness introduced below.

#### 3.1.1 SDC-based variables

We use the Securities Data Company (SDC) database to construct three dichotomous variables that compare the contents of the “Industry Sector”, “Short Business Description”, and “High Tech Industry” fields for the acquirer and the target. We anticipate that the “Industry Sector” field contains similar information as the two-digit SIC codes. The other two fields, “Short Business Description” and “High Tech Industry” supply a finer comparison. We anticipate that mergers between companies that share similar business descriptions

---

<sup>8</sup> See also Meng and Sutton (2017) for an international extension of this notion. They show that acquirers of private targets fare worse in cross-border takeovers, while acquirers of public targets experience significantly higher gains in acquisitions of foreign targets. The positive benefit for acquirers of public targets is more pronounced if the target is from a country with a less competitive takeover market.

or belong to high-technology sectors create more value because the acquirer is more familiar with the peculiarities of the target's business environment. Accordingly, we use SDC to construct three dichotomous measures:  $Rel_{d,Industry}$ ,  $Rel_{d,Business}$ , and  $Rel_{d,HighTech}$  and test the following hypotheses:

**H2a** Mergers between firms with similar business descriptions create more value than mergers between firms with different business descriptions.

**H2b** High-technology mergers create more value than non-high-technology mergers.

### 3.1.2 Same-state mergers

We also use SDC to construct a dichotomous measure,  $Rel_{d,State}$ , where

$$Rel_{d,State} = \begin{cases} 1 & \text{in-state merger} \\ 0 & \text{out-of-state merger} \end{cases}$$

When the merging firms are headquartered in the same state, there is an additional advantage of familiarity with state-specific laws and lower monitoring costs (see Kang and Kim 2008). Therefore, we test the following hypothesis:

**H2c** In-state mergers create more value than out-of-state mergers.

### 3.1.3 Local regulations

Further, certain states have adopted anti-takeover laws that discourage unfriendly takeover attempts and, therefore, make firms in these states less attractive as potential targets. Ohio, Pennsylvania, and Delaware are regarded historically as "target-friendly" states (CFA Institute 2015). Accordingly, we define

$$Rel_{d,TargetFriendly} = \begin{cases} 1 & \text{The target is incorporated in a target-friendly state} \\ 0 & \text{otherwise} \end{cases}$$

and we test the following hypothesis:

**H2d** A merger adds less value when the target is incorporated in a target-friendly state.

### 3.1.4 Vicinity

We use Compustat to obtain the addresses of acquirers and targets in our sample; then, we define vicinity as

$$Rel_{d,ZIP} = |ZIP_A - ZIP_T|$$

where  $ZIP_A$  and  $ZIP_T$  are the zip codes of the acquirer and the target, respectively.

ZIP Codes are a system of postal codes used by the United States Postal Service (USPS) since 1963. A Zip Code is a group of five numbers that represents a specific geographical area. The first digit designates a broad area (usually a certain group of adjacent U.S. states). The two following digits are the code of a central post office facility in that region (or sometimes a large city) and the last two digits designate smaller zones within that region.

The result is a five-digit number that increases systematically as we move from the Northeast to the far West. Accordingly, the absolute zip code difference has a minimum value of zero indicating that the two merging firms are located in the same zip code area. A greater  $Rel_{d,ZIP}$  indicates a larger ZIP-distance between the merging firms.

Kang and Kim (2008) shows that geographically close mergers create more value because of lower monitoring costs and increased acquirers' familiarity with local markets and regulations. In M&A context, the difference in zip codes is more informative than the physical distance variable developed by Kang and Kim (2008) because the dispersion of zip codes signifies population density and often local regulations. For instance, the physical distance between two firms, A and B, located in different states on the east coast of the U.S. may be equal to the physical distance between two firms, C and D, located in a single state, or even a single zip code, in the Midwest or in the Mountain regions. Obviously, although the physical distance between A and B is equal to the physical distance between C and D, the legislative and market similarities between C and D are greater than between A and B. Therefore, zip code differentials can capture the similarity in legal environment and familiarity with local markets more accurately than geographic distance does. Accordingly, we test the following hypothesis:

**H2e** Small-vicinity mergers create more value than large-vicinity mergers.

## 4 Sample and variables construction

### 4.1 Data and sample

We use the SDC database to obtain a list of U.S. M&A deals completed between 1998<sup>9</sup> and 2014. Following extant literature, we require that the value of the deal is greater than \$20 million and the sample excludes acquirers or targets listed in the financial services industry (SIC 6000–6999) or regulated utilities industry (SIC 4900–4999). These restrictions result in a final sample of 14,389 mergers. The following sections explain the variables' construction.

### 4.2 SIC-based and other dichotomous measures of relatedness

Following the literature, simple SIC-based measures are constructed. For each transaction  $d$ , we compute four dichotomous variables,  $Rel_{d,SIC4}$ ,  $Rel_{d,SIC3}$ ,  $Rel_{d,SIC2}$ , and  $Rel_{d,SIC1}$ , based on 4-digit SIC, 3-digit SIC, 2-digit SIC, and 1-digit SIC matching procedures, respectively.

We also construct a set of dichotomous variables based on FIC classification developed by Hoberg and Phillips (2010, 2016). They calculate firm-by-firm pairwise similarity scores by parsing the product descriptions from the firms' product description included in the 10Ks. Next, they use the product similarity scores to develop clusters of FIC-500, FIC-400, FIC-300, FIC-200, FIC-100, and FIC-50 related industries. The classification is updated annually and is obtainable from Hoberg–Phillips Industry

<sup>9</sup> We chose 1998 because of a major change in business segment reporting post 1997. See Rajan et al. (2000) for more details.

Classification Library.<sup>10</sup> Using this database, we compute six dichotomous variables,  $Rel_{d,FIC500}$ ,  $Rel_{d,FIC400}$ ,  $Rel_{d,FIC300}$ ,  $Rel_{d,FIC200}$ ,  $Rel_{d,FIC100}$ , and  $Rel_{d,FIC50}$ . In the SIC- and FIC-based measures, each variable equals 1 if the merging firms belong to the same digit group or cluster and 0 otherwise.

### 4.3 Change in focus

Following Alhenawi and Krishnaswami (2015), two variables are constructed to capture the change in focus that results from a merger. In a certain year, the  $N$  segments ( $i = 1, 2, \dots, N$ ) of each multi-segment firm  $d$  are classified into  $M$  related industry groups ( $j = 1, 2, \dots, M$ ) based on their 2-digit SIC code. Let  $K_j$  be the number of segments within industry group  $j$  and let  $DR_j$  be the relatedness of the  $j$ th industry group computed as

$$DR_j = \sum_{i=1}^{K_j} P_i \ln(P_i)$$

where  $P_i$  is the share of the  $i$ th segment assets in the assets of the industry group  $j$ .  $DR_j$  captures the concentration within each related industry group. Second, the assets-based entropy measure of relatedness of the multi-segment firm, in a certain year  $t$ , is defined as

$$AEMR_{d,t} = \sum_{j=1}^M DR_j P_j$$

where  $P_j$  is the share of the  $j$ th industry group assets in the assets of the firm  $d$ .  $AEMR_{d,t}$  captures the differentiation or diversification across the different industry groups of the firm in year  $t$ .

Then, the relatedness of a merger by firm  $d$  is defined as

$$Rel_{d,Asset} = AEMR_{d,t=0} - AEMR_{d,t=1}$$

where  $AEMR_{d,t=0}$  is computed at the end of the year prior to the merger completion and  $AEMR_{d,t=1}$  is computed at the end of the year of the merger completion. A positive (negative)  $Rel_{d,Asset}$  indicates an increase (decrease) in focus and thus, a related (unrelated) merger. The magnitude of the difference captures the level of relatedness (or unrelatedness). In an analogous manner, a sales-based entropy measure of relatedness  $SEMR_d$  is also computed and the following variable is calculated:

$$Rel_{d,Sales} = SEMR_{d,t=0} - SEMR_{d,t=1}$$

### 4.4 Supply chain integration

We follow Fan and Lang (2000) who use U.S. Input–Output Tables to define vertical relatedness and complementarity between industries. Then, they assign the vertical relatedness coefficient and the complementarity coefficient of each pair of industries to corresponding pairs of merging firms.

<sup>10</sup> See <http://hobergphillips.usc.edu>.

We use the 2007 purchaser prices after redefinition table.<sup>11</sup> We use the “Use Table” which, according to the Bureau of Economic Analysis, is the most frequently used table because of its applications to the estimates of GDP.<sup>12</sup> The Input–Output accounts show how industries interact; specifically, they show how industries provide input to, and use output from, each other to produce Gross Domestic Product (GDP). In other words, they show the flows of the goods and services amongst industries.

For each pair of industries, the table reports  $a_{ij}$  which is the dollar value of industry  $i$ 's output used by industry  $j$ . Let us use  $Q_i$  and  $Q_j$  to denote the dollar value of total output for industries  $i$  and  $j$ , respectively. Then, we calculate

$$v_{ij} = \frac{a_{ij}}{Q_i}, \quad v_{ji} = \frac{a_{ji}}{Q_j}, \quad V_{ij} = \frac{v_{ij} + v_{ji}}{2}$$

where  $V_{ij}$  represents the vertical relatedness between the two industries  $i$  and  $j$ .<sup>13</sup>

Next, we compute  $b_{ik}$  which represent the percentage of industry  $i$ 's output supplied to each intermediate industry  $k$ . We also compute  $b_{jk}$  in an analogous manner. Then, the correlation between  $b_{ik}$  and  $b_{jk}$  across all  $k$ s (except for  $i$  and  $j$ ) represents the overlap between the markets to which industries  $i$  and  $j$  sell.

Variables  $v_{ik}$  and  $v_{jk}$  are computed in a similar manner as the percentage of industries  $i$  and  $j$ 's inputs procured from each intermediate industry  $k$ . Thus the correlation between  $v_{ik}$  and  $v_{jk}$  across all  $k$ s (except for  $i$  and  $j$ ) represents the overlap in the sectors from which industries  $i$  and  $j$  buy.

Next, the complementarity coefficient between two industries  $i$  and  $j$  is defined as

$$C_{ij} = \frac{Corr(b_{ik}, b_{jk}) + Corr(v_{ik}, v_{jk})}{2}$$

We assign a vertical relatedness coefficient  $V_{ij}$  and a complementarity coefficient  $C_{ij}$  to each pair of merging firms in our sample. To do that, we apply a text-based matching procedure similar to that employed by Hoberg and Phillips (2010, 2016).<sup>14</sup> Specifically, we match the “Industry Sector” and “Short Business Description” fields from SDC with the U.S. Input–Output Tables as follows. First, we use “Industry Sector” to form word vectors for each target in the SDC sample. In a similar manner, we use “Commodity/industry” description to form word vectors for each industry in the U.S. Input–Output Tables. Vectors are then used to compute a measure of similarity for each firm–industry pair. Each score is a real number in the interval [0, 1] that describes how similar the words are in the two vectors.

Each target is assigned 389 scores that represent how similar its “Industry Sector” in SDC is to “Commodity/Industry” description of the 389 industries in the U.S. Input–Output Tables. For each target, if the top score is greater than 0.80, the firm is assigned to the corresponding industry. A total of 10,405 targets are assigned to industries this way. For the remaining targets, we repeat the procedure with vectors created with the “Short

<sup>11</sup> Fan and Lang (2000) use Tables 1982, 1987, 1992. The tables are updated every 5 years. At the time this paper was written, the most recent table was 2007, which was released November 13, 2014.

<sup>12</sup> This is the table used by Fan and Lang (2000).

<sup>13</sup> Fan and Goyal (2006) also employs this procedure (but they take the maximum, not the average, of  $v_{ij}$  and  $v_{ji}$ ).

<sup>14</sup> They compute similarity in product description of the acquirer and the merger. Their text-based measures are also used in this paper (see above).

Business Description” field from SDC. Again, if the top score is greater than 0.80, the firm is assigned to the corresponding industry. An additional 3045 targets are assigned to industries this way. The remaining 939 targets are not assigned to any industry (these are firms whose top similarity score is less than 80% with “Industry Sector” and less than 80% with “Short Business Description”).

We repeat the procedure with acquirers. Using the first screening procedure (i.e., using “Industry Sector” field in SDC), 9774 are assigned to industries; 3421 are assigned to industries using the second screening procedure (i.e., using “Short Business Description” field in SDC), and 1194 are not assigned to any industry. The algorithm we use controls for possible mismatch caused by negating expressions (e.g. except, excluding ... etc.), uninformative words (e.g., the, industry, firm, company ... etc.), and word repetition (e.g., in a statement like “computers and computer parts” the word computer is counted only once).<sup>15</sup>

Once the two databases have been linked, the vertical relatedness and complementarity of an industry pair in the U.S. Input–Output Tables are assigned to the corresponding acquirer–target pair (i.e., a merger transaction) in SDC. Accordingly, we obtain two variables  $Rel_{d,Ver}$  and  $Rel_{d,Com}$  which represent vertical relatedness and complementarity of a deal  $d$ , respectively.<sup>16</sup>

## 5 Empirical analyses

### 5.1 Descriptive statistics and initial observations

Table 1 displays summary statistics for the sample. Panel A presents the number of transactions by merger announcement year as well as the descriptive statistics of transaction value. Panel B displays the summary statistics for the binary measures of relatedness, and Panel C reports the descriptive statistics for the continuous measures of relatedness.

Panel A shows that the sample is reasonably balanced over time. Panel B shows that FIC measures are more conservative than SIC measures because the latter produce more related classifications than the former. As expected, a coarser specification, for both FIC and SIC variables, identifies more related transactions than a finer specification. Furthermore, the range of the SIC means (44.86–76.20%) is much wider than the range of the FIC means (27.03–30.43%). This initial finding suggests that the two measures are not good substitutes of each other and, perhaps, they carry different valuation information. Another interesting observation from Panel B is the substantial fraction of mergers between firms in the same state (28.92%) and the non-trivial fraction of mergers where the target is incorporated in a “target friendly” state (8.18%). Panel B also shows that 64.62% of the acquirer–target pairs share the same content of the “Industry Sector” field and 12.01% of the acquirer–target pairs share the same content of the “Short Business Description” field. Finally, 43.37% of mergers in the sample are between companies in the high-technology sectors. Given the economic advantages realized by these mergers (see previous sections), these percentages signify the importance of incorporating this information into M&A analyses.

<sup>15</sup> The overall findings of the paper are robust when we employ 75 and 70% cutoffs instead of 80%.

<sup>16</sup> Fan and Lang (2000) use SIC code to match the two databases. We use a more complex text-matching procedure. This approach ensures a more accurate classification and avoids the repeated use of SIC codes in this study.

Consistent with the overall proposition of this paper, the figures in Panel A and Panel B indicate, collectively, that the classification of an M&A deal as related or unrelated is highly contingent on the way the researcher defines relatedness. For instance, using the same database, SDC, two thirds of the deals are classified as related at the industry level while less than an eighth of the deals are classified as related at the business description level. Similarly, approximately half of the deals are classified as SIC-related, while less than a third are classified as FIC-related.

Panel C reports the descriptive statistics of the remaining continuous measures of relatedness. Expectedly, the means of both complementarity ( $Rel_{d,Com}$ ) and vertical relatedness ( $Rel_{d,Ver}$ ) are positive with the former being larger in magnitude. Similar findings are reported by Fan and Lang (2000). Also unsurprisingly, the means of assets-based and sales-based change-in-focus variables,  $Rel_{d,Asset}$  and  $Rel_{d,Sales}$ , are negative with a maximum of zero. Alhenawi and Krishnaswami (2015) report a similar finding. The average mean of the vicinity measure ( $Rel_{d,ZIP}$ ) is 27,168 with an expected minimum of zero (when the acquirer and the target share the same zip code) and a maximum of 98,009. Overall, Panel C demonstrates that the continuous measures of relatedness employed in this paper are appropriately constructed.

## 5.2 Comparison of relatedness measures

### 5.2.1 Correlation analysis

Table 2 reports the simple correlation coefficients between the continuous measures of relatedness.

The correlation coefficients in Table 2 indicate that complementarity ( $Rel_{d,Com}$ ) and vertical relatedness ( $Rel_{d,Ver}$ ) are positively but not perfectly correlated (0.3931). In contrast, the asset-based entropy measure of relatedness ( $Rel_{d,Asset}$ ) and its sales-based counterpart ( $Rel_{d,Sales}$ ) are highly positively correlated (0.7253).  $Rel_{d,Asset}$  and  $Rel_{d,Sales}$  are almost uncorrelated with  $Rel_{d,Com}$  ( $-0.0251$  and  $0.0930$ , respectively) and  $Rel_{d,Ver}$  ( $-0.0399$  and  $0.0265$ , respectively). Not surprisingly,  $Rel_{d,ZIP}$  is almost uncorrelated with the four other variables ( $-0.0049$ ,  $-0.0270$ ,  $-0.0139$ , and  $0.0255$ ). Taken together, the correlation coefficients in Table 2 imply that each measure carries unique relatedness, and perhaps valuation, information that is not captured by other variables. This is consistent with the core hypothesis in this paper (H1).

### 5.2.2 Binary relatedness measures

Table 3 displays the results of a double-sorting procedure that aims at investigating the correlation between the binary relatedness variables. It compares the classification power of the SDC-based measures ( $Rel_{d,Industry}$ ,  $Rel_{d,Business}$ , and  $Rel_{d,HighTech}$ ) to the classification power of two sets of SIC-based and FIC-based indicators of relatedness.

Panel A in Table 3 shows that out of 9298 transactions identified as related by  $Rel_{d,Industry}$ , 9032, 8896, 7696, and 6455 transactions are concurrently identified as related by  $Rel_{d,SIC1}$ ,  $Rel_{d,SIC2}$ ,  $Rel_{d,SIC3}$ , and  $Rel_{d,SIC4}$ , respectively. The corresponding identical classification percentages are 97.14, 95.68, 82.77, and 69.42%, respectively. In contrast, Panel B shows that out of 9298 transactions identified as related by  $Rel_{d,Industry}$ , 985, 951, 951, 915, 930, and 912 are concurrently identified as related by

**Table 1** Summary statistics

Year	Obs.	Mean	SD	Min	Max	Median	
<i>Panel A: Value of transaction (\$mil)</i>							
1998	1415	508.16	3495.98	20.00	78,945.79	75.75	
1999	1379	610.51	3640.58	20.00	89,167.72	84.00	
2000	1309	581.23	2304.83	20.00	42,872.30	97.80	
2001	797	493.15	2956.69	20.00	72,041.15	75.00	
2002	713	324.48	2359.89	20.00	59,515.02	72.00	
2003	733	294.56	1082.62	20.00	15,432.27	78.50	
2004	836	458.89	2389.40	20.00	41,005.41	80.00	
2005	944	545.63	2655.49	20.00	54,906.81	85.00	
2006	996	542.17	3030.66	20.00	72,671.00	92.00	
2007	961	454.88	1236.41	20.00	17,298.66	96.00	
2008	640	436.63	1832.81	20.00	28,100.00	80.00	
2009	446	818.66	4405.49	20.00	67,285.70	94.75	
2010	636	458.04	1393.10	20.00	22,276.24	115.00	
2011	695	525.68	1907.98	20.00	29,370.07	122.80	
2012	705	400.68	789.94	20.00	7183.42	121.80	
2013	622	556.89	1560.67	20.00	16,700.00	149.25	
2014	562	479.28	1574.37	20.00	25,110.37	131.41	
All years	14,389	502.98	2560.47	20.00	89,167.72	91.00	
Variable	Obs.	Mean	SD	Min	Max	Median	# of Related mergers
<i>Panel B: Binary relatedness measures</i>							
Rel_SIC4	14,389	0.4486	0.4974	0.00	1.00	0.00	6455
Rel_SIC3	14,389	0.5658	0.4957	0.00	1.00	1.00	8141
Rel_SIC2	14,389	0.6688	0.4707	0.00	1.00	1.00	9623
Rel_SIC1	14,389	0.7620	0.4258	0.00	1.00	1.00	10,965
Rel_FIC500	3618	0.2703	0.4400	0.00	1.00	0.00	978
Rel_FIC400	3618	0.2742	0.4462	0.00	1.00	0.00	992
Rel_FIC300	3618	0.2734	0.4457	0.00	1.00	0.00	989
Rel_FIC200	3618	0.2852	0.4516	0.00	1.00	0.00	1032
Rel_FIC100	3618	0.2869	0.4524	0.00	1.00	0.00	1038
Rel_FIC050	3618	0.3043	0.4602	0.00	1.00	0.00	1101
Rel_State	14,389	0.2892	0.4534	0.00	1.00	0.00	4161
Rel_Target Friendly	14,389	0.0818	0.2741	0.00	1.00	0.00	1177
Rel_Industry	14,389	0.6462	0.4782	0.00	1.00	1.00	9298
Rel_Business	14,389	0.1201	0.3251	0.00	1.00	0.00	1728
Rel_HighTech	14,389	0.4337	0.4956	0.00	1.00	0.00	6241
Variable	Obs.	Mean	SD	Min	Max	Median	
<i>Panel C: Continuous relatedness measures</i>							
Rel_Com (Complementarity)	4361	0.2068	0.1654	- 0.0113	0.8289	0.1796	
Rel_Ver (Vertical relatedness)	3939	0.0108	0.0302	0.0000	0.3068	0.0030	
Rel_Assets (Asset-based change in focus)	10,978	- 0.1170	0.1696	- 0.8785	0.0000	0.0000	

**Table 1** (continued)

Variable	Obs.	Mean	SD	Min	Max	Median
Rel_Sales (Asset-based change in focus)	10,978	- 0.2648	0.2263	- 1.2048	0.0000	- 0.2837
Rel_ZIP (Vicinity)	2579	27,168	29,919	0	98,009	15,384

Panel A reports the summary statistics for the sample, which includes 14,389 completed U.S. mergers between 1998 and 2014 identified from the Securities Data Company’s database of Mergers & Acquisitions (SDC). This paper constructs several binary and continuous measures of relatedness in M&A transactions. Panel B is devoted to the binary measures. Rel\_SICX is a binary that classifies a merger as related if the acquirer and target have the same primary X-digit SIC code and as unrelated otherwise. Rel\_FICXXX is a binary that classifies a merger as related if the acquirer and target have the same FIC-XXX industry code based on Hoberg and Phillips 2010 firm-by-firm pairwise similarity scorings. Rel\_State classifies a merger as related if the two merging firms are located in the same state, and Rel\_TargetFriendly classifies a merger as related if the target is located in a state designated as target-friendly. Rel\_Industry and Rel\_Business classify a merger as related if the merging firms belong to the same industry and have similar business descriptions, respectively. These two variables are constructed based on the contents of the corresponding fields in the SDC database. Rel\_HighTech classifies a merger as related if the acquirer and the target belong to the high-technology sector. This variable is constructed based on the content of the “High Technology Industry” field in the SDC database. Panel C reports the summary statistics for five continuous relatedness variables used in this paper. Rel\_Com and Rel\_Ver capture supply chain integration between the acquirer and target as in Fan and Lang 2000. Rel\_Assets and Rel\_Sales capture the change-in-focus in the combined firm as in Alhenawi and Krishnaswami (2015). Rel\_ZIP is a new vicinity measure proposed by these authors. It is computed as the absolute difference in ZIP codes of the addresses of the two firms.

**Table 2** Correlation between the continuous measures of relatedness

	Rel_Com	Rel_Ver	Rel_Assets	Rel_Sales	Rel_ZIP
Rel_Com	1.0000 <i>4361</i>				
Rel_Ver	0.3931 <i>3764</i>	1.0000 <i>3939</i>			
Rel_Assets	- 0.0251 <i>3470</i>	- 0.0399 <i>3120</i>	1.0000 <i>10,978</i>		
Rel_Sales	0.0930 <i>3470</i>	0.0265 <i>3120</i>	0.7253 <i>10,978</i>	1.0000 <i>10,978</i>	
Rel_ZIP	- 0.0049 <i>676</i>	- 0.0270 <i>580</i>	- 0.0139 <i>2579</i>	0.0255 <i>2579</i>	1.0000 <i>2579</i>

This table presents the coefficients of correlations between the five continuous measures of relatedness employed in this paper. See Table 1 for detailed explanation for each measure. The italicized number under each correlation coefficient reports the number of observations. All figures are significant at the 1% level

$Rel_{d,FIC50}$ ,  $Rel_{d,FIC100}$ ,  $Rel_{d,FIC200}$ ,  $Rel_{d,FIC300}$ ,  $Rel_{d,FIC400}$ , and  $Rel_{d,FIC500}$ , respectively. Thus, the percentages of identical classifications by the SIC-based measures and  $Rel_{d,Industry}$  (69.42–97.14%) are considerably greater than the percentages of identical classifications by the FIC-based measures and  $Rel_{d,Industry}$  (9.81–10.59%).

The opposite is true with  $Rel_{d,Business}$ . The percentages of identical classifications by the SIC-based measures and  $Rel_{d,Business}$  are between 9.26 and 9.95% (Panel A) and are systematically smaller than the percentages of identical classifications by the FIC-based measures and  $Rel_{d,Business}$  which ranges from 42.01 to 42.30% (Panel B). This is expected because SIC codes reflect an industry-based classification while FIC clusters are constructed

**Table 3** The interrelation between binary measures of relatedness

	All	Rel_SIC1	Rel_SIC2	Rel_SIC3	Rel_SIC4		
<i>Panel A: SIC</i>							
Rel_Industry	9298	9032	8896	7696	6455		
		97.14%	95.68%	82.77%	69.42%		
Rel_Business	1728	172	169	165	160		
		9.95%	9.78%	9.55%	9.26%		
Re_HighTech	6241	4786	4401	3879	2727		
		76.69%	70.52%	62.15%	43.69%		
	All	Rel_FIC050	Rel_FIC100	Rel_FIC200	Rel_FIC300	Rel_FIC400	Rel_FIC500
<i>Panel B: FIC</i>							
Rel_Industry	9298	985	951	951	915	930	912
		10.59%	10.23%	10.23%	9.84%	10.00%	9.81%
Rel_Business	1728	731	728	732	727	729	726
		42.30%	42.13%	42.36%	42.07%	42.19%	42.01%
Re_HighTech	6241	589	538	534	508	509	498
		9.44%	8.62%	8.56%	8.14%	8.16%	7.98%

This table compares the classification power of the SIC-based and the FIC-based measures of relatedness across other binary measures of relatedness employed in this paper. Specifically, Panel A reports the number of SIC-related mergers that are also classified as related by the SDC-based measures (Rel\_Industry, Rel\_Business, Rel\_Industry&Business, and Rel\_Technology). Panel B reports the number of FIC-related mergers that are also classified as related by the SDC-based measures (Rel\_Industry, Rel\_Business, Rel\_Industry&Business, and Rel\_Technology). The percentage under each number represents the fraction of identical classifications

based on a product description matching procedure which is likely to be closer to business description than to broad industry classification. Nevertheless, the percentage of identical prediction by the FIC-based measures and  $Rel_{d,Business}$  is rather modest (42.01–42.30%), which suggests that they are not substitutes of each other and each carries different relatedness information. We conclude that the content of the “Industry Sector” field in SDC is similar to the content of the SIC codes. and, to a lesser extent, the content of the “Business Description” field in SDC is similar to the content of the FIC codes.

The overlap with  $Rel_{d,HighTech}$  is modest for the SIC-based measures (43.69–76.69%) and weak for the FIC-based measures (7.98–9.44%). This indicates that  $Rel_{d,HighTech}$  carries additional relatedness information that is not captured by the SIC and FIC binaries and is potentially an important factor in M&A analyses.

### 5.2.3 SIC, FIC, and continuous relatedness measures

Table 4 displays the summary statistics for the continuous measures of relatedness segregated by the SIC and FIC binaries. The table is organized into five panels, A, B, C, D, and E, corresponding to five continuous measures,  $Rel_{d,Com}$ ,  $Rel_{d,Ver}$ ,  $Rel_{d,Asset}$ ,  $Rel_{d,Sales}$ , and  $Rel_{d,ZIP}$ , respectively. The table also reports the differences between the means and the t-statistics of the differences.

Panel A illustrates how the complementarity variable  $Rel_{d,Com}$  behaves when the sample is divided into related and unrelated mergers by the SIC codes (left), then by the FIC

**Table 4** Complementarity, vertical relatedness, and change in focus

	Obs.	Mean	SD	Median	SIC <sub>t</sub> -SIC <sub>0</sub>	<i>t</i>	Obs.	Mean	SD	Median	FIC <sub>t</sub> -FIC <sub>0</sub>	<i>t</i>
<i>Panel A: Complementarity (Rel_Com)</i>												
SIC1=1	1796	0.2479	0.11497	0.2059			FIC50=1	97	0.1610	0.1321	0.1454	
SIC1=0	2565	0.1780	0.11698	0.1207	0.0699	14.34	FIC50=0	907	0.2050	0.1682	0.1691	-3.03
SIC2=1	955	0.2789	0.11460	0.2059			FIC100=1	75	0.1886	0.1573	0.1720	
SIC2=0	3406	0.1865	0.11649	0.1457	0.0924	16.78	FIC100=0	929	0.2017	0.1662	0.1686	-0.69
SIC3=1	594	0.2607	0.11312	0.2059			FIC200=1	74	0.1915	0.1631	0.1720	
SIC3=0	3767	0.1983	0.11687	0.1588	0.0624	10.32	FIC200=0	930	0.2015	0.1658	0.1686	-0.51
SIC4=1	96	0.4041	0.11809	0.4304			FIC300=1	65	0.1869	0.1652	0.1588	
SIC4=0	4265	0.2023	0.11720	0.1720	0.2018	10.83	FIC300=0	939	0.2017	0.1656	0.1686	-0.70
All	4361	0.2068	0.11654	0.1796			FIC400=1	56	0.1838	0.1676	0.1656	
							FIC400=0	948	0.2017	0.1654	0.1686	-0.78
							FIC500=1	60	0.1913	0.1820	0.1656	
							FIC500=0	944	0.2014	0.1645	0.1686	-0.42
							All	1004	0.2007	0.1655	0.1686	
<i>Panel B: Vertical relatedness (Rel_Ver)</i>												
SIC1=1	1568	0.0172	0.0431	0.0036			FIC50=1	89	0.0106	0.0381	0.0005	
SIC1=0	2371	0.0065	0.0154	0.0011	0.0107	9.46	FIC50=0	778	0.0112	0.0348	0.0023	-0.15
SIC2=1	928	0.0209	0.0519	0.0036			FIC100=1	67	0.0146	0.0429	0.0009	
SIC2=0	3011	0.0077	0.0179	0.0016	0.0133	7.64	FIC100=0	800	0.0109	0.0345	0.0023	0.69
SIC3=1	586	0.0225	0.0590	0.0036			FIC200=1	68	0.0132	0.0408	0.0005	
SIC3=0	3353	0.0087	0.0209	0.0021	0.0138	5.61	FIC200=0	799	0.0110	0.0347	0.0023	0.43
SIC4=1	91	0.0661	0.0894	0.0171			FIC300=1	58	0.0170	0.0461	0.0005	
SIC4=0	3848	0.0095	0.0259	0.0029	0.0566	6.04	FIC300=0	809	0.0107	0.0343	0.0023	1.02
All	3939	0.0108	0.0302	0.0030			FIC400=1	51	0.0148	0.0457	0.0005	
							FIC400=0	816	0.0109	0.0344	0.0023	0.59
							FIC500=1	54	0.0194	0.0585	0.0005	
							FIC500=0	813	0.0106	0.0330	0.0023	1.09
							All	867	0.0111	0.0352	0.0023	

**Table 4** (continued)

	Obs.	Mean	SD	Median	SIC <sub>t</sub> -SIC <sub>0</sub>	<i>t</i>	Obs.	Mean	SD	Median	FIC <sub>t</sub> -FIC <sub>0</sub>	<i>t</i>
<i>Panel C: Asset-based change in focus (Rel_Asset)</i>												
SIC1=1	8290	-0.1167	0.1707	0.0000			FIC50=1	1101	-0.1227	0.1738	0.0000	
SIC1=0	2688	-0.1179	0.1661	0.0000	0.0012	0.32	FIC50=0	2517	-0.1146	0.1668	0.0000	-1.32
SIC2=1	7218	-0.1143	0.1707	0.0000			FIC100=1	1038	-0.1260	0.1748	0.0000	-1.98
SIC2=0	3760	-0.1223	0.1673	0.0000	0.0080	2.37	FIC100=0	2580	-0.1135	0.1665	0.0000	-1.98
SIC3=1	6078	-0.1113	0.1689	0.0000			FIC200=1	1032	-0.1267	0.1749	0.0000	-2.13
SIC3=0	4900	-0.1241	0.1701	0.0000	0.0128	3.93	FIC200=0	2586	-0.1132	0.1664	0.0000	-2.13
SIC4=1	4688	-0.1093	0.1669	0.0000			FIC300=1	989	-0.1254	0.1745	0.0000	-1.79
SIC4=0	6290	-0.1228	0.1713	0.0000	0.0135	4.15	FIC300=0	2629	-0.1139	0.1668	0.0000	-1.79
All	10,978	-0.1170	0.1696	0.0000			FIC400=1	992	-0.1259	0.1738	0.0000	-1.90
							FIC400=0	2626	-0.1137	0.1670	0.0000	-1.90
							FIC500=1	978	-0.1257	0.1740	0.0000	-1.83
							FIC500=0	2640	-0.1139	0.1670	0.0000	-1.83
							All	3618	-0.1171	0.1690	0.0000	
<i>Panel D: Sales-based change in focus (Rel_Sales)</i>												
SIC1=1	8290	-0.2637	0.2283	-0.2829			FIC50=1	1101	-0.3121	0.2310	-0.3010	-7.62
SIC1=0	2688	-0.2682	0.2199	-0.2896	0.0045	0.91	FIC50=0	2517	-0.2489	0.2256	-0.2623	-7.62
SIC2=1	7218	-0.2617	0.2298	-0.2835			FIC100=1	1038	-0.3069	0.2296	-0.3010	-6.46
SIC2=0	3760	-0.2709	0.2192	-0.2850	0.0092	2.05	FIC100=0	2580	-0.2525	0.2271	-0.2675	-6.46
SIC3=1	6078	-0.2616	0.2319	-0.2855			FIC200=1	1032	-0.3087	0.2302	-0.3010	-6.73
SIC3=0	4900	-0.2688	0.2190	-0.2830	0.0072	1.65	FIC200=0	2586	-0.2519	0.2267	-0.2648	-6.73
SIC4=1	4688	-0.2562	0.2328	-0.2785			FIC300=1	989	-0.3035	0.2294	-0.3010	-5.70
SIC4=0	6290	-0.2712	0.2211	-0.2883	0.0150	3.41	FIC300=0	2629	-0.2548	0.2276	-0.2718	-5.70
All	10,978	-0.2648	0.2263	-0.2837			FIC400=1	992	-0.3054	0.2311	-0.3010	-6.00
							FIC400=0	2626	-0.2540	0.2268	-0.2710	-6.00
							FIC500=1	978	-0.3038	0.2311	-0.3010	-5.68
							FIC500=0	2640	-0.2549	0.2270	-0.2733	-5.68
							All	3618	-0.2681	0.2291	-0.2895	

**Table 4** (continued)

	Obs.	Mean	SD	Median	SIC <sub>1</sub> -SIC <sub>0</sub>	t	Obs.	Mean	SD	Median	FIC <sub>1</sub> -FIC <sub>0</sub>	t
<i>Panel E: Vicinity (Rel_ZIP)</i>												
SIC1=1	2069	24,609	29,331	10,914			FIC50=1	1071	14,255	25,783	0	
SIC1=0	510	37,550	30,064	30,297	-12,941	-8.75	FIC50=0	1508	36,340	29,269	29,558	-22,085
SIC2=1	1883	23,446	28,974	9032			FIC100=1	1020	13,634	25,271	0	
SIC2=0	696	37,239	30,133	29,954	-13,793	-10.43	FIC100=0	1559	36,023	29,413	28,256	-22,389
SIC3=1	1669	22,070	28,922	5613			FIC200=1	1011	12,929	24,605	0	
SIC3=0	910	36,518	29,471	29,344	-14,448	-11.98	FIC200=0	1568	36,349	29,450	29,193	-23,420
SIC4=1	1401	19,611	28,229	1859			FIC300=1	976	12,366	24,244	0	
SIC4=0	1178	36,156	29,394	29,423	-16,545	-14.50	FIC300=0	1603	36,181	29,462	28,256	-23,814
All	2579	27,168	29,919	15,384			FIC400=1	977	12,082	23,999	0	
							FIC400=0	1602	36,369	29,440	29,305	-24,287
							FIC500=1	967	11,451	23,314	0	
							FIC500=0	1612	36,597	29,484	29,791	-25,145
							All	2579	27,168	29,919	15,384	-23.96

This table compares the classification power of SIC and FIC measures of relatedness across five continuous measures of relatedness. Specifically, we split the sample into SIC-related subsample and SIC-unrelated subsample and observe the statistical summaries of the supply chain integration variables (Rel\_Com and Rel\_Ver), the change-in-focus variables (Rel\_Asset and Rel\_Sales), and the vicinity variable (Rel\_ZIP). Then, we repeat the procedure with FIC. For each of the continuous variables, we report the mean, standard deviation, and median for the related and unrelated subsamples. We also report the differences in the means between the two subsamples and the t-statistics of the differences

clusters (right). In all four specifications of the SIC-based indicator,  $\overline{Rel_{d,Com}}|_{Rel_{d,SIC}=1}$  is greater than  $\overline{Rel_{d,Com}}|_{Rel_{d,SIC}=0}$ , and the differences are statistically and economically significant. Starting with the 1-digit SIC indicator, the average of complementarity in the related subsample is 0.2479, while the average of complementarity in the unrelated subsample is 0.1780. The difference (0.0699) is statistically significant at the 1% level and is 33.8% greater than the average of complementarity in the original sample (0.2068). As we move to finer SIC indicators (down), the differences between the two averages continue to be statistically and economically significant. At the 4-digit SIC level, the average of complementarity for the related subsample (0.4041), is almost double the average of complementarity for the unrelated subsample (0.2023). This indicates that the binary indicator  $Rel_{d,SIC}$  identifies related mergers with higher complementarity. The same patterns can be observed in Panel B which shows how the vertical relatedness variable  $Rel_{d,Ver}$  behaves across SIC-related and SIC-unrelated mergers. The findings also extend to  $Rel_{d,Asset}$  in Panel C and  $Rel_{d,Sales}$  in Panel D but with a lesser economical and statistical significance. Overall, the findings explained above are consistent with Fan and Lang's (2000) finding that the means of the complementarity and vertical relatedness measures are significantly larger when two industries have similar SIC codes. These findings are also consistent with the Alhenawi and Krishnaswami (2015) finding that SIC-relatedness increases focus.

The findings with the FIC binary indicators,  $Rel_{d,FIC}$ , are vastly different. In Panels A and B, the differences between the means are statistically insignificant. This implies that an acquirer-target pair that belongs to the same FIC cluster is not more complementary (Panel A) or more vertically related (see Panel B) than an acquirer-target pair with different FIC codes. With  $Rel_{d,Assets}$  (Panel C) and  $Rel_{d,Sales}$  (Panel D), the differences between the means are statistically significant (though weaker for  $Rel_{d,Assets}$ ) but are negative, which suggests that a merger between an acquirer and a target that belong to the same FIC cluster is more likely to reduce, not improve, focus. Taken together, our findings conflict with Hoberg and Phillips's (2010, 2016) conclusion that merger pairs within the same FIC cluster are more similar than SIC- or NAICS-based classification would suggest. More importantly, our findings suggest that the relatedness information captured by  $Rel_{d,FIC}$  is not captured by  $Rel_{d,Asset}$ ,  $Rel_{d,Sales}$ ,  $Rel_{d,Ver}$ , and  $Rel_{d,Com}$  which supports the overarching hypothesis of this paper (H1).

Panel E of Table 4 is devoted to the vicinity variable,  $Rel_{d,ZIP}$ , which is introduced by this research. Conceptually, we anticipate that this variable exhibits no meaningful correlation with either the industry-based SIC variables nor the product description-based FIC variables. This is not what the figures in the table indicate.  $\overline{Rel_{d,ZIP}}|_{Rel_{d,SIC}=1}$  is systematically smaller than  $\overline{Rel_{d,ZIP}}|_{Rel_{d,SIC}=0}$  which means that the average  $Rel_{d,ZIP}$  of SIC-related mergers is smaller than the average  $Rel_{d,ZIP}$  of SIC-unrelated mergers. Specifically, the ZIP differentials between the acquirer and the target in SIC-related mergers is smaller by 12,941–16,545 than the ZIP differentials in SIC-unrelated mergers. Similarly, the ZIP differentials in FIC-related mergers is smaller by 22,085–25,145 than the ZIP differentials in FIC-unrelated mergers. The differences are statistically significant, indicating that related pairs of acquirer-target tend to cluster more than unrelated pairs. There are a few possible interpretations of this observation. First, in related mergers, managers prefer neighboring targets. Second, industries tend to cluster in certain vicinities. Either way, the finding implies that vicinity is potentially an important factor in M&A transactions.

### 5.3 Relatedness and the wealth effect of mergers

The deductions of this research so far are consistent with the overarching hypothesis (H1), which postulates that each measure of relatedness contains unique information that is not captured by other measures, and thus, relatedness is multi-dimensional. This conclusion remains incomplete unless it is buttressed by an analysis that focuses on the valuation content of various relatedness measures. Accordingly, this section tests whether, and to what extent, different relatedness measures contain unique valuation information.

Theory and anecdote suggest that relatedness may cause systematic changes in wealth for shareholders of the merging firms (Chuang 2017; Agrawal et al. 1992; Berger and Ofek 1995; Maksimovic et al. 2011; Alhenawi and Krishnaswami 2015). Nevertheless, we often see authors reach conflicting conclusions. To mention one example, Fan and Lang (2000) find that vertical relatedness is associated with poor performance in multi-segment firms, while complementarity (share of input and/or output) increases value in multi-segment firms. In contrast, Fan and Goyal (2006) show that vertical mergers generate significantly positive wealth effect comparable to that in horizontal mergers. This ambiguity calls for a side-by-side investigation of the wealth effect of the different measures of relatedness.

We examine the impact of various relatedness measures on the abnormal returns around the announcement period [as in Branch and Yang (2006); Bouwman et al. (2009); and Ishii and Xuan (2014)]. We calculate cumulative abnormal returns (CARs) over the three-day event window  $[-1, +1]$ , the five-day event window  $[-2, +2]$ , and the seven-day event window  $[-3, +3]$  for the acquirer, the target, and the combined firm. In the interest of space, we report and discuss the CAR  $[-3, +3]$  results only.<sup>17</sup>

#### 5.3.1 Distribution of CARs across binary indicators of relatedness

In this subsection, we conduct univariate analyses. We split the sample into related and unrelated subsamples based on the binary measures of relatedness: SIC, FIC,  $Rel_{d,State}$ ,  $Rel_{d,TargetFriendly}$ ,  $Rel_{d,Industry}$ ,  $Rel_{d,Business}$ , and  $Rel_{d,HighTech}$ . Then, we observe the behavior of CARs  $[-3, +3]$  for the acquirer, the target, and the combined firm. The results are reported in Table 5.

The first row in Panel A shows the seven-day CAR  $[-3, +3]$  around the announcement date for the full sample. It is negative for the acquirer ( $-5.23\%$ ), positive for the target ( $19.69\%$ ), and positive for the combined entity ( $2.10\%$ ). The first row in Panel B and the first row in Panel C reveal similar findings. The acquirer's stock reacts negatively ( $-3.14\%$ ) to the deal announcement for the full sample while the target's stock reacts positively ( $21.13\%$ ) for the full sample. The combined value of the acquirer and the target rises by  $2.39\%$  for the full sample. As prior research suggests, the negative reaction for the acquirer's stock and the positive reaction for the target's stock might result from overpaying the target. Overall, our findings are consistent with prior research [see for example Andrade et al. (2001), Ishii and Xuan (2014), and Chuang (2017)].

Panel A of Table 5 shows the breakout of the seven-day CARs  $[-3, +3]$  for the acquirer, the target, and the combined firm based on the FIC binaries. For the acquirers, the negative reaction of the acquirer's stock is less severe in FIC-related transactions. The difference ranges from  $4.87\text{--}5.37\%$  which is almost three times as large in magnitude as that

<sup>17</sup> The CAR  $[-1, +1]$  and CAR  $[-2, +2]$  results are not tabulated in the paper. They are generally comparable with the CAR  $[-3, +3]$  results and are available upon request from the authors.

**Table 5** CARs and Binary Measures of Relatedness

	Acquirer CAR [-3, +3]			Target CAR [-3, +3]			Combined CAR [-3, +3]								
	Obs.	Mean (%)	SD (%)	Diff (%)	$t$	Obs.	Mean (%)	SD (%)	Diff (%)	$t$	Obs.	Mean (%)	SD (%)	Diff (%)	$t$
	<i>Panel A: FIC relatedness</i>														
All FIC (full sample)	2956	-5.23	22.28			2852	19.69	24.58			2218	2.10	16.60		
FIC50=1	1008	-1.69	12.37			1021	12.08	24.31			907	1.27	8.70		
FIC50=0	1948	-7.06	25.77	5.37	7.65	1831	23.93	23.70	-11.85	-12.60	1311	2.67	20.33	-1.40	-2.22
FIC100=1	959	-1.64	10.53			968	11.03	23.92			864	1.17	8.64		
FIC100=0	1997	-6.95	25.93	5.31	7.89	1884	24.14	23.72	-13.11	-13.90	1354	2.69	20.08	-1.52	-2.46
FIC200=1	951	-1.82	10.70			963	10.69	23.66			859	0.96	8.47		
FIC200=0	2005	-6.85	25.87	5.03	7.47	1889	24.28	23.76	-13.59	-14.48	1359	2.82	20.08	-1.86	-3.01
FIC300=1	916	-1.74	10.70			926	9.70	21.21			827	1.01	8.60		
FIC300=0	2040	-6.80	25.69	5.06	7.55	1926	24.49	24.65	-14.79	-16.52	1391	2.75	19.86	-1.74	-2.84
FIC400=1	919	-1.86	10.48			929	9.97	22.42			829	0.93	8.34		
FIC400=0	2037	-6.75	25.75	4.89	7.33	1923	24.38	24.21	-14.41	-15.67	1389	2.80	19.94	-1.87	-3.07
FIC500=1	905	-1.85	9.31			916	9.38	20.64			817	0.92	7.84		
FIC500=0	2051	-6.72	25.88	4.87	7.49	1936	24.57	24.79	-15.19	-17.17	1401	2.79	19.99	-1.87	-3.11
<i>Panel B: SIC relatedness</i>															
All SIC (full sample)	10,563	-3.14	17.44			7498	21.31	27.04			4628	2.39	14.95		
SIC1=1	8044	-3.02	16.50			5769	20.67	26.51			3560	2.61	14.70		
SIC1=0	2519	-3.52	20.14	0.50	1.12	1729	23.43	28.67	-2.76	-3.57	1068	1.65	15.71	0.97	1.39
SIC2=1	7003	-2.95	16.52			5103	20.35	26.35			3127	2.57	14.98		
SIC2=0	3560	-3.52	19.11	0.58	1.53	2395	23.34	28.37	-2.99	-4.34	1501	2.02	14.87	0.55	1.16
SIC3=1	5915	-3.06	16.76			4355	20.07	26.76			2670	2.45	14.79		
SIC3=0	4648	-3.25	18.26	0.19	0.56	3143	23.01	27.34	-2.94	-4.63	1958	2.31	15.16	0.14	0.30
SIC4=1	4613	-3.07	16.40			3510	18.70	25.14			2115	2.26	14.10		
SIC4=0	5950	-3.19	18.20	0.12	0.37	3988	23.60	28.42	-4.90	-7.93	2513	2.50	15.62	-0.24	-0.55

Table 5 (continued)

	Acquirer CAR [-3, +3]			Target CAR [-3, +3]			Combined CAR [-3, +3]								
	Obs.	Mean (%)	SD (%)	Diff (%)	t	Obs.	Mean (%)	SD (%)	Diff (%)	t	Obs.	Mean (%)	SD (%)	Diff (%)	t
<i>Panel C: Other relatedness binary variables</i>															
Full Sample	10,563	- 3.14	17.44			7498	21.31	27.04			4628	2.39	14.95		
Rel_Industry = 1	6737	- 3.06	16.43			4920	20.28	26.43			3000	2.55	14.81		
Rel_Industry = 0	3826	- 3.28	19.08	0.22	0.60	2578	23.25	28.08	- 2.97	- 4.44	1628	2.09	15.20	0.47	1.00
Rel_Business = 1	1220	- 3.04	14.70			1152	10.79	20.24			769	0.42	10.28		
Rel_Business = 0	9343	- 3.15	17.76	0.12	0.26	6346	23.21	27.68	- 12.42	- 18.00	3859	2.78	15.68	- 2.37	- 5.28
Re_HighTech = 1	4944	- 2.29	17.64			3472	21.89	27.85			2432	2.52	12.79		
Re_HighTech = 0	5619	- 3.89	17.22	1.61	4.72	4026	20.80	26.32	1.09	1.74	2196	2.25	14.30	0.28	0.63
Rel_State = 1	3095	- 3.89	20.33			2391	17.23	25.52			1556	1.27	15.60		
Rel_State = 0	7468	- 2.83	16.08	- 1.05	- 2.57	5107	23.21	27.52	- 5.98	- 9.22	3072	2.96	14.57	- 1.69	- 3.55
Rel_Target Friendly = 1	855	- 2.96	18.73			588	20.92	25.76			350	2.85	12.45		
Rel_Target Friendly = 0	9708	- 3.16	17.32	0.20	0.30	6910	21.34	27.15	- 0.42	- 0.38	4278	2.35	15.13	0.50	0.71

This table presents the results of several univariate analyses that focus on cumulative abnormal returns (CARs) around the announcement date for the acquirer's stock, the target's stock, and the combined firms (computed as the market value-weighted average of the CARs for the acquirer's stock and the CARs for the target's stock). Abnormal return is computed as the difference between the observed daily return and a hypothetical predicted return computed using the market model approach. The market model used is the three-factor model of Fama and French with the market index being the CRSP value-weighted portfolio. The parameters of the model are estimated using data from outside the event window. Following Ishii and Xuan (2014), we use a 180-day estimation period ending 20 days before the event date, and we require a minimum estimation length of 30 days. Then, cumulative abnormal return (CAR) is calculated by accumulating daily abnormal returns within three event windows spanning [-1, +1], [-2, +2], and [-3, +3] trading days around the deal announcement date. The CAR for the combined firm is computed as market value-weighted average of the CAR for the acquirer and the CAR for the target. We present the summary statistics of the CARs for the full sample followed by a breakout based on FIC binaries (Panel A), SIC binaries (Panel B), and other relatedness binaries (Panel C). In the interest of space, we report the CAR [-3 + 3] results only

for acquirers in FIC-related mergers. For the targets, the positive reaction of the target's stock is smaller in FIC-related transactions. The difference ranges from 11.85 to 15.19% and the CAR of the target's stock in FIC-unrelated transactions is at least twice as large as that for targets in FIC-related mergers. For the combined entity, FIC-related mergers create less value than FIC-unrelated mergers. The difference ranges from 1.40 to 1.87%. All differences are statistically significant at the 1% level. This suggests that the similarity in product description between the acquirer and the target—the underlying concept of FIC binaries—is associated with a smaller loss of value to the acquirer's shareholders, a smaller gain to the target's shareholders, and a smaller gain in value to the combined pool of shareholders of the acquirer and the target.

Panel B of Table 5 shows the breakout of the seven-day CARs  $[-3, +3]$  for the acquirer, the target, and the combined firm based on SIC relatedness. A shocking result is that SIC relatedness is not associated with a significant value change for the acquirer or for the combined entity. The differences in means of CAR between SIC-related and SIC-unrelated mergers are statistically indistinguishable from zero for the acquirer and the combined entity. The middle block in panel B does show that the target's stock reacts less positively to the deal announcement when the merger is SIC-related. The differences, however, are smaller in magnitude (2.67–4.90%) than those observed in Panel A (11.85–15.19%). This indicates that the SIC binaries are less powerful in capturing relatedness than the FIC binaries.

Panel C of Table 5 exhibits the breakout of seven-day CARs  $[-3, +3]$  for the acquirer, the target, and the combined entity based on the rest of the binary indicators of relatedness used in this research. Consistent with Panel B above, the broad industry relatedness indicator ( $Rel_{d,Industry}$ ) is not associated with a significant difference in value change between related and unrelated mergers for the acquirer and the combined entity. For the target,  $Rel_{d,Industry} = 1$  implies a smaller value gain in related mergers. This is identical to the findings of Panel B and the earlier findings in Table 3, which indicates that SIC relatedness and  $Rel_{d,Industry}$  may contain similar information. In contrast, the same business description indicator ( $Rel_{d,Business}$ ) produces results consistent with FIC relatedness (with the exception that there is no difference in the change of value between related and unrelated mergers for the acquirer). FIC binaries and  $Rel_{d,Business}$ , therefore, may carry similar information.

$Rel_{d,HighTech} = 1$  when the target and the acquirer are high-technology firms. Mergers within the high-technology industries seem to be profitable to all shareholders. In high-technology mergers, the acquirer's stock's negative reaction is smaller in magnitude by 1.61%, the target's stock's positive reaction is greater by 1.09%, and the combined entity's value gain is greater by 0.28%. These findings are consistent with the predictions of hypothesis H2b. In subsequent sections, we conduct further analyses on the impact of technology sector affiliation on M&A valuation.

The same-state indicator  $Rel_{d,State}$  produces interesting results. When the acquirer and the target are located in the same state, the deal diminishes wealth for all shareholders. The acquirer's stock's negative reaction is greater in magnitude by 1.05%. The target's stock's positive reaction is smaller by 5.98%. The combined entity's CAR is lower by 1.69%. This finding highlights the importance of considering state of incorporation in merger and acquisition analyses and implies that out-of-state mergers create more value than in-state mergers. This notion opposes the prediction of hypothesis H2c. Perhaps, the market perceives inter-state mergers as a strategy to penetrate new markets. This possibility is explored in subsequent sections.

The last two rows of Panel C of Table 5 show that local merger and acquisition laws in the target's state are irrelevant. This does not support hypothesis H2d.

Overall, the findings of Table 5 can be summarized as follows. First, FIC and SIC may not be used interchangeably and, more importantly, FIC binaries are more powerful in capturing relatedness than SIC binaries. Generally speaking, product description similarity implied by the FIC clusters and  $Rel_{d,Business}$  is more powerful in capturing relatedness than the broad industry matching procedure implied by the SIC codes and  $Rel_{d,Industry}$ . Second, it is important to consider state of incorporation and high-technology factors in M&A analyses. Out-of-state mergers create more value than in-state mergers, and mergers between high-technology firms create relatively more value than mergers outside the technology sector.

### 5.3.2 Regression analysis

It is well-documented in literature that value creation in M&A transactions takes place through a complex mechanism affected by numerous firm-specific and deal-specific factors [see for example Andrade et al. (2001) and Ishii and Xuan (2014)]. Thus, this section employs multivariate ordinary least squares (OLS) regressions, which allows us to explicitly control for other factors, e.g., deal-specific characteristics that simultaneously affect the stock market's reaction to the merger announcement.

We organize this section around the following model:

$$CAR_d = a_0 + a'_1 R_d + a'_2 X_d + \varepsilon_i$$

where  $d$  indexes transactions.  $CAR_d$  is cumulative abnormal returns of transaction  $d$ .  $R_d$  includes the key relatedness variables:  $Rel_{d,SIC}$ ,  $Rel_{d,FIC}$ ,  $Rel_{d,Com}$ ,  $Rel_{d,Ver}$ ,  $Rel_{d,Asset}$ , and  $Rel_{d,Sales}$ . Therefore, vector  $a'_1$  captures the joint effect of relatedness on wealth. The null hypothesis is that  $a'_1$  is not significantly different from zero, which implies that relatedness, as specified in this paper, is irrelevant. More importantly, the relative strengths of the elements of vector  $a'_1$  reveals the simultaneous contribution of various relatedness measures to wealth.  $X_d$  controls for the potential effects of other factors and includes size (*SIZE*), relative value (*VALUE*), access to capital (*ACT*), and method of payment (*CASH*).<sup>18</sup> In addition,  $X_d$  includes the acquirer's pre-merger return on assets (*ROA*), return on equity (*ROE*), profitability (*PROF*), and debt ratio (*DEBT*) computed at the end of the year prior to the year of the event.

In Table 6, the dependent variable is the seven-day CAR  $[-3, +3]$  for the acquirer, target, and the combined firm. In models 1, 5, and 9, we include the relatedness variables only, and in the rest of the models, we add standard controls and alter the models' specifications.

<sup>18</sup> *SIZE* is defined as the log of the acquirer's market value. Moeller et al. (2004) finds that M&A announcement returns are lower for acquisitions by larger firms. *VALUE* is defined as the deal's value relative to the acquirer's market value. Prior research has shown negative market reaction to M&A announcement when the ratio of target equity to the acquirer's equity is smaller (Asquith et al. 1983) and when the deal's value relative to acquirer's market value is smaller (Ishii and Xuan 2014). *ATC* captures access to capital markets and takes the value one if the firm pays a dividend and 0 otherwise. Following Fazzari et al. (1988) and Servaes (1996), a firm that pays a dividend is not likely to be capital-constrained. Lewellen (1971) pointed out that a diversification strategy could be motivated by the desire of enhancing access to capital markets. Therefore, the measures of M&A performance might be upward biased because it reflects improvement in borrowing capacity. *CASH* equals one in case of a pure cash deal, zero otherwise. Prior research has shown positive market reaction to M&A announcement when the acquirer uses cash as a method of payment (Moeller et al. 2004).

**Table 6** Relatedness and cumulative abnormal returns for the acquirer, the target, and the combined entity

Regression #	Acquirer CAR [-3, +3]			Target CAR [-3, +3]			Combined CAR [-3, +3]					
	1	2	3	4	5	6	7	8	9	10	11	12
# of Obs.	1489	1364	1364	1364	1468	1350	1350	1350	1394	1323	1323	1323
R <sup>2</sup>	0.14	0.17	0.17	0.17	0.13	0.18	0.18	0.18	0.13	0.27	0.26	0.28
Complementarity	0.72	0.72	0.75	0.89*	0.73	0.51	0.46	0.46	0.78	0.74	0.78	0.83
Vertical relatedness	0.94***	0.64**	0.66**	0.18	3.41*	4.38**	4.41**	4.58**	0.06	0.26**	0.23**	0.73**
Change-in-focus (Sales)	0.25*	0.15*	0.23*	0.08*	-0.94*	-1.31**	-1.62**	-1.35**	-1.10***	-0.03*	-0.03*	-0.09*
Vicinity	-0.32*	-0.32*	-0.36**	-0.31*	-0.27*	-0.01*	-0.10*	-0.02*	-0.76**	-0.39**	-0.34**	-0.40**
SIC2	2.39	0.67	0.67		-3.78	-5.68	-5.53		-1.83	-0.63	-0.53	
FIC300	1.46*	2.08*	2.09*		-3.78*	-5.26**			-0.48*	-2.09**		-1.98*
Same state?	-0.66*	-0.15*	-0.10*	-0.16*	-1.06	-0.13	-0.04	-0.10	-1.51**	-0.88*	-0.88*	-0.88*
Target-Friendly?	4.87	4.68	4.72	4.74	-2.58	-2.97	-3.05	-3.45	4.00	4.79	4.75	4.91
High tech merger?	2.38***	2.03***	2.25***	1.80**	3.10**	2.87**	2.26*	2.07*	0.25*	1.29**	1.59**	0.90**
Same industry? (SDC)				-3.82								-4.76
Same business? (SDC)			8.85***			-32.20***					-0.87*	
Cash?		1.68	1.59	1.92		12.31**	12.49**	11.68**		3.31**	3.21**	3.37***
Acquirer ROE		-1.01*	-1.09*	-1.04*		2.70	2.62	2.84		0.22	0.27	0.20
Acquirer debt ratio		1.06	1.44	0.93		-6.70	-7.64	-6.40		-0.04	0.27	-0.10*
Access to capital?		0.00	0.11	-0.01		-2.80	-3.04	-2.00		0.36	0.41	0.55

**Table 6** (continued)

Regression #	Acquirer CAR [-3, +3]			Target CAR [-3, +3]			Combined CAR [-3, +3]					
	1	2	3	4	5	6	7	8	9	10	11	12
Size (logged)		0.34	0.21	0.40		-1.75	-1.43	-1.79		-0.41	-0.52	-0.31***
Value		7.82**	6.88**	7.97**		-18.38**	-16.11**	-18.72**		12.90***	12.21***	13.16*

This table reports the results of OLS regressions for the acquirer's, target's, and combined entity's cumulative abnormal returns (CAR) around the announcement date. We calculate CARs over the three-day event window [-1, +1], the five-day event window [-2, +2], and the seven-day event window [-3, +3]. In the interest of space, we report the CAR [-3 +3] results only. The results with CAR [-1, +1] and CAR [-2, +2] are generally consistent and available upon request from the authors. CAR calculations and assumptions are explained in a previous table. The independent variables are complementarity, vertical relatedness, change-in-focus, vicinity, SIC, FIC, same-state indicator, target in target-friendly state indicator, same-industry indicator from SDC, same business description indicator from SDC, and merger within the high-technology industries indicator. Following extant literature, we use SIC2 and FIC300 [see for example Ishii and Xuan (2014) and Alhenawi and Krishnaswami (2015)], but we conduct robustness checks (not tabulated) with all specifications of SIC and FIC binaries. Control variables include a dummy variable indicating whether the transaction is financed with cash, pre-merger return on equity for the acquirer, pre-merger debt ratio for the acquirer, pre-merger access to capital market for the acquirer, size of the acquirer (logged), and the relative size of the acquisition. Based on previous findings of high correlation between SIC and  $Rel_{i,Industry}$  and between FIC and  $Rel_{i,Business}$ , we alternate these variables. The independent variables for complementarity, vertical relatedness, change-in-focus, and vicinity are scaled differently. Therefore, for a better interpretation of results, these variables enter the model as number of standard deviations from the mean. Accordingly, the coefficients on these variables are interpreted as the change in the dependent variable that results from a one standard deviation increase in the corresponding independent variable. All coefficients are reported as percentage points. Standard errors (not tabulated) are heteroskedastic-consistent. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), or 10% (\*) level

In models 1, 5, and 9, the coefficients on vertical relatedness, change-in-focus, vicinity, FIC relatedness same state, and high-technology are statistically significant at the 10% level or better. With the addition of the controls in the rest of the models, most relatedness coefficients remain statistically and economically significant for the acquirer, the target, and the combined firm (with a few exceptions discussed below). This finding indicates that each of the relatedness variables included in the model, except for complementarity and SIC relatedness, contributes unique valuation information that is not captured by other variables. This is consistent with hypothesis H1.

Further, the findings in Table 6 indicate that relatedness variables have varying impacts on shareholders' wealth for the acquirer and the target and consequently, the combined firm. A one standard deviation increase in vertical relatedness between the acquirer and the target (0.0302<sup>19</sup>) increases the seven-day CAR for the acquirer by 18–94 basis points; for the target by 3.41–4.58 percentage points; and for the combined firm by 6–73 basis points. In contrast, a one standard deviation increase in the sales-based change-in-focus (0.2263) increases the seven-day CAR for the acquirer by 8–25 basis points but decreases the seven-day CAR for the target by 94–162 basis points and for the combined firm by 3–110 basis points.<sup>20</sup> In other words, vertical relatedness and change-in-focus exhibit a similar positive impact on the acquirer's stock but have different impacts on the value of the target and the combined firm.

Consistent with hypothesis H2e, the vicinity coefficient is negative and significant at the 10% level or better in all regressions. This indicates that small-vicinity mergers are associated with greater CARs relative to large-vicinity mergers. Specifically, a one standard deviation *decrease* in ZIP code differential (29,919) increases the seven-day CAR for the acquirer by 31–36 basis points. For the target and the combined firm, the corresponding increase in CARs ranges from one to 27 basis points for the target and from 34 to 76 basis points for the combined firm. Furthermore, vicinity is priced separately from other relatedness variables, including same-state indicator.

In-state mergers carry their own negative impact on CAR for the acquirer and the combined firm (but not the target). This is inconsistent with hypothesis H2c. In-state mergers are associated with an average decrease in seven-day CAR for the acquirer by 10–66 basis points and for the combined firm by 88–151 basis points.

The findings with vicinity and same-state variables present a paradox because they indicate that out-of-state mergers create more value than in-state mergers, while large-vicinity mergers are less constructive than small-vicinity mergers. According to Kang and Kim (2008), in-state mergers are associated with greater CARs because the acquirer in these mergers is more familiar with local markets and laws. This paradox is investigated further in a subsequent section.

All the regressions in Table 6 confirm an earlier finding in this paper signifying that SIC codes do not carry any additional valuation information. In non-tabulated results, when the SIC binary enters the model alone, it demonstrates a positive impact on CAR for the combined firm and a negative impact on CAR for the target. What makes SIC-relatedness effect disappear in the full model? From a strictly statistical perspective, this indicates that the variation pattern of the SIC binary is captured by the rest of the relatedness variables. This is not the case with the FIC binary. Consistent with an earlier finding in Table 5, FIC-relatedness

<sup>19</sup> Table 1 shows the standard deviations of all variables.

<sup>20</sup> In a non-tabulated finding, a one standard deviation increase in complementarity (0.1654), when it enters the model alone, increases the seven-day CAR for the acquirer, the target, and the combined firm by 11, 24, and 11 basis points, respectively. In the full model, however, complementarity does not seem to contain its own pricing information. This is consistent with an earlier finding in this paper indicating that the coefficient of correlation between complementarity ( $Rel_{d,Com}$ ) and vertical relatedness ( $Rel_{d,Ver}$ ) is high (0.3931).

**Table 7** Robustness Checks

Regression#	Acquirer CAR [-63, + 3]			Target CAR [-63, + 3]			Combined CAR [-63, + 3]					
	1	2	3	4	5	6	7	8	9	10	11	12
# of Obs.	1484	1363	1363	1363	1476	1347	1347	1347	1383	1317	1317	1317
R <sup>2</sup>	0.13	0.18	0.18	0.18	0.12	0.21	0.21	0.19	0.13	0.22	0.22	0.22
Complementarity	-3.38***	-3.01**	-2.97**	-2.97**	0.52*	2.95**	2.99**	1.88*	-1.26**	-1.22*	-1.13*	-1.38**
Vertical relatedness	1.55**	1.26	1.19	0.75	3.85**	4.30	4.22	4.45	1.54**	1.81	1.72	1.49
Change-in-focus (Sales)	-0.20*	-2.76**	-2.87*	-2.70**	-1.15	-1.37	-1.50	-1.35	-0.81*	-2.60**	-2.70**	-2.55**
Vicinity	-1.99**	-1.75**	-1.74**	-1.79**	-1.40*	-2.48**	-2.47**	-2.42**	-3.37***	-1.92**	-1.88**	-1.91**
SIC2	1.24	2.53	2.97		-11.40	-14.57	-14.05		-3.30	-0.98	-0.52	
FIC300	7.39***	4.46**		4.77**	-6.00**	-4.76*		-3.51*	-5.31***	-4.93**		-4.94**
Same state?	-1.46*	-1.46*	-1.59*	-1.45*	-3.07*	-6.56**	-6.87**	-6.68**	-0.80*	-1.13*	-1.32*	-1.15*
Target-Friendly?	-0.54*	-0.73**	-0.73**	-0.75**	-3.01	-2.67	-3.20	-4.19	-1.51	-3.73	-4.27	-3.88
High tech merger?	3.65**	6.08***	5.56***	5.46**	3.42**	6.03**	6.72**	4.21**	5.55***	4.76**	3.98**	4.61**
Same industry? (SDC)			2.01***	6.08				-9.57				-2.39
Same business? (SDC)												
Cash?	4.20	4.06	4.06	4.27	31.41***	31.21***	31.21***	29.69***	9.85	9.65	9.65	9.66
Acquirer ROE	3.76*	3.64*	3.64*	3.74*	-0.65	-0.54	-0.54	-0.25	2.70	2.83	2.83	2.75
Acquirer debt ratio	7.50	8.00	8.00	7.43	-6.13	-5.73	-5.07	-5.07	7.36	7.90	7.90	7.49
Access to capital?	-0.08	0.06	0.06	-0.50	-1.55	-1.57	-1.57	0.35	-0.84	-0.75	-0.75	-0.75
Size (logged)	-3.30	-3.48*	-3.48*	-3.42	-1.17	-1.33	-1.33	-1.34	-2.89	-3.11	-3.11	-2.96
Value	1.91	0.99	0.99	1.64	-24.57*	-25.12*	-25.12*	-25.76*	15.37*	14.56*	14.56*	15.20*

**Table 7** Robustness Checks

Regression#	Acquirer CAR [-63, +3]		Target CAR [-63, +3]		Combined CAR [-63, +3]							
	2	3	4	5	6	7	8	9	10	11	12	
Year fixed effects?	Yes	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
M&A wage effects?	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No

This table reports the results of OLS regressions for the acquirer's, the target's, and the combined entity's cumulative abnormal returns (CAR) around the announcement date. Unlike Table 6 above, the dependent variable is CARs computed over extended event windows [-63, +1], [-63, +2], and [-63, +3] in order to minimize the effect of possible leakage of information as suggested by Mulherin and Simsir (2015). We use a model estimation period spanning a window of (-720, -90) trading days preceding the announcement date. The exclusion of 90-day pre-event window minimizes the effect of possible leakage of information (Scholes and Williams 1977). We report the CAR [-63 + 3] results only. The results with CAR [-63, +1] and CAR [-63, +2] are generally comparable to the results obtained with CAR [-63, +3] and are available upon request from the authors. The independent variables and the control variables in this table are specified and scaled as described in Table 6. However, the regressions in this table include additional controls for year fixed effects as well as a merger wave indicator computed as the ratio of the number of mergers in the announcement year to the number of mergers in the sample. All coefficients are reported as percentage points. The independent variables for complementarity, vertical relatedness, change-in-focus, and vicinity enter the model as number of standard deviations from the mean (see Table 6). Standard errors (not tabulated) are heteroskedastic-consistent. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), or 10% (\*) level

increases CAR for the shareholders of the acquirer by 1.46–2.09 percentage points. FIC-relatedness reduces the seven-day CAR for the target by 3.78–5.78 percentage points and for the combined entity by 48–209 basis points. All coefficients are statistically significant at the 10% level or better. This is further evidence of the superiority of FIC clusters over SIC codes.

Also consistent with an earlier finding in Table 5, the impact of the SDC same-industry variable is similar to the impact of the SIC binary (see models 4, 8, and 12), and the impact of the SDC same-business-description variable is similar to the impact of the FIC binary (see models 3, 7, and 11).<sup>21</sup>

The figures in Table 6 do not support hypothesis H2d. The coefficients on the target-friendly state variable are statistically indistinguishable from zero in all models.

The signs and the magnitudes of the coefficients on the high-technology variable are supportive of hypothesis H2b. A merger between two firms that belong to the high-technology sector generates an impressive additional seven-day CAR of 1.80–2.38 percentage points for the acquirer. For the target, the corresponding value gain is 2.07–3.10 percentage points. For the combined firm, the value gain is 25–159 basis points. All coefficients are statistically significant at the 10% level or better. In a subsequent section, we perform additional analyses on the impact of high-technology sector affiliation.

Overall, the results in Table 6 agree with the univariate results presented earlier and indicate that, consistent with the core hypothesis of this research (H1), relatedness is a multi-dimensional metric with several additive and interrelated components. Each component carries its own relatedness, and therefore, valuation information. Generally speaking, the studied relatedness proxies seem to be complements, not substitutes, of each other. The results with CAR [−2, + 2] and CAR [−1, + 1] are generally consistent with the CAR [−3, + 3] results and are available upon request from the authors.

### 5.3.3 Robustness checks

Mulherin and Simsir (2015) present legitimate concerns with the use of the “Date of Announcement” field in SDC when the merger is publicized prior to the merger announcement date. They suggest three methods to correct the bias. As a robustness check, we employ the first method they suggest, which is incorporating Schwert’s (2000) run up period of 63 days around the announcement date. We compute CARs over three windows spanning [−63, + 1], [−63, + 2], and [−63, + 3] trading days around the deal announcement date.

Further, one might take issue with the results presented so far on the grounds that the OLS technique captures cross-sectional variations but not time variations in the strengths of the included measures. Therefore, we include year dummies and an M&A wave index that explicitly controls for possible time variation effect. The M&A wave index in year  $y$  is computed as:

$$MWI_y = \frac{\text{Number of Mergers in Year } y}{\text{Number of Mergers in the Sample}}$$

then each merger is assigned an  $MWI_y$  that corresponds to the year of announcement.

Table 7 shows the results of running alternative specifications of the OLS regressions presented in Table 6. The dependent variable is the CAR [−63, + 3] for the target, the

<sup>21</sup> See Table 5 and subsequent discussions on the overlap between SIC-relatedness and  $Rel_{d,Industry}$  and between FIC-relatedness and  $Rel_{d,Business}$ .

acquirer, and the combined firm. The results with CAR  $[-63, +2]$  and CAR  $[-63, +1]$  are generally consistent with the results for CAR  $[-63, +3]$  and are available upon request from the authors.

Except for the anticipated differences in coefficients' magnitudes, the results reported in Table 7 with CAR  $[-63, +3]$  are generally comparable to the results obtained with CAR  $[-3, +3]$  in Table 6 with a few exceptions. First, the complementarity between the acquirer and the target has a significant impact on all shareholders. A one standard deviation increase in complementarity (0.1654)<sup>22</sup> decreases the CAR  $[-63, +3]$  for the acquirer by 2.97–3.38 percentage points and for the combined firm by 1.13–1.38 percentage points. The same increase in complementarity increases the CAR  $[-63, +3]$  for the target by 52–299 basis points. All coefficients are statistically significant at the 10% level or better. In contrast, vertical relatedness coefficients are insignificantly different from zero (except for regressions 1, 5, and 9). In a non-tabulated finding, the same result is obtained when vertical relatedness enters the model alone.<sup>23</sup>

Second, the change-in-focus coefficient is statistically significant with a negative sign for the acquirer and for the combined entity (but not for the target). A one standard deviation increase in the sales-based change-in-focus (0.2263) decreases the CAR  $[-63, +3]$  for the acquirer by 20–287 basis points and for the combined firm by 81–270 basis points. This is inconsistent with Table 6 where the change-in-focus variable demonstrated a statistically significant positive impact on CAR  $[-3, +3]$  for the acquirer and a statistically significant negative impact on CAR  $[-3, +3]$  for the target and the combined firm.

Third, same-state binary has a negative impact on CAR  $[-63, +3]$  which is consistent with the findings in Table 6 with one exception: same-state binary did not have an impact on target's stock CAR  $[-3, +3]$ . Fourth, the acquisition of a target in a target-friendly state significantly reduces CAR  $[-63, +3]$  for the acquirer's stock by 54–75 basis points. In contrast, the acquisition of a target in a target-friendly state did not exhibit any impact on CAR  $[-3, +3]$  for all shareholders in Table 6.

The last two rows in Table 7 indicate a considerable year effect for the target and the combined firm and a considerable M&A wave effect for the acquirer. We find a positive effect of years 2000 and 2008 on the target's and combined firm's CAR. The magnitude of the effect, however, is economically small (2–12 basis points). We also find a significant M&A wave effect on CAR  $[-63, +3]$  for the acquirer in years 1998, 1999, and 2000 (18–25 basis points). In an additional robustness check (not tabulated), we excluded transactions completed in years 1998, 1999, 2000, and 2008 from the sample and obtained comparable results.

The results of the OLS regression analyses are generally robust to other alterations of the models' specifications. For instance, we substituted ROE with ROA then PROF and obtained similar results. The results are also robust to substituting  $Rel_{d,Sales}$  with  $Rel_{d,Assets}$ , but the latter seems to have a much weaker effect than the former.

Overall, the robustness checks indicate that the overall validity of the central argument of this research is intact. In fact, the minor differences between Tables 6 and 7 provide only variations on the same theme. Consistent with hypothesis H1, the relatedness between the

<sup>22</sup> Table 1 shows the standard deviations of all variables.

<sup>23</sup> While it may be interesting to explore what makes certain relatedness components appear in the CAR  $[-63, +3]$  models and not in the CAR  $[-3, +3]$  models, this inquiry is outside the scope of this paper. Perhaps, certain relatedness components (e.g., complementarity) are more observable in the pre-merger market than others (e.g., vertical relatedness). This might be a fertile field for future research.

acquirer and the target is multi-dimensional, and the impacts of several relatedness proxies are additive. Therefore, the use of a single-dimensional relatedness designation, in any analysis, may lead to erroneous conclusions. Further, Table 7 confirms a few of our earlier findings that: 1) SDC supplies reliable content for constructing relatedness variables that can substitute more complex ones such as FIC (hypothesis H2a); 2) the high-technology sector affiliation creates additional value in merger transactions (hypothesis H2b); and 3) the new vicinity variable introduced by this research carries its own valuation information (hypothesis H2e). Though Table 7 shows evidence that local merger laws impact value, the impact is weak and limited to the acquirer's stock and does not extend to Table 6. Therefore, this paper does not present strong support for hypothesis H2d.

## 5.4 Further empirical analyses

This section sheds more light on two somewhat paradoxical deductions of earlier sections. First, we find that small-vicinity mergers are associated with greater CARs relative to large-vicinity mergers, while in-state mergers are associated with smaller CARs relative to out-of-state mergers. This is an intriguing conclusion because small-vicinity mergers are presumably more likely to be in-state mergers and large-vicinity mergers are presumably more likely to be out-of-state mergers. Second, the results of the univariate analyses presented in Table 5 and the OLS regression analyses presented in Tables 6 and 7 indicate that mergers within the high-technology industries induce an *additional* positive market reaction (i.e. a reaction beyond the same-industry effect). In this section we focus on these two issues. We perform additional empirical analysis and link the findings to plausible economic explanations.

### 5.4.1 Location: vicinity vs. state

Why do earlier findings present an apparent contradiction between vicinity and state variables? One possibility is that the market preference for small-vicinity mergers and out-of-state mergers is driven by strategic and operational considerations. Small-vicinity mergers may imply acquisition of a nearby rival. If this was the case, we anticipate to find that the positive effect of small-vicinity mergers on CAR, relative to large-vicinity mergers, is intensified for related mergers relative to unrelated mergers. This is because an unrelated nearby target would not be considered a rival. Formally, we test the following hypothesis:

**H3a** The positive impact of small-vicinity mergers on CAR is stronger in related mergers.

Analogously, we argue that the market discounts in-state mergers more than out-of-state mergers because the latter allow for penetrating remote markets. Thus, we anticipate to find that the positive (or precisely the less negative) effect of out-of-state mergers on CAR, relative to in-state mergers, is stronger in related mergers because acquiring an out-of-state unrelated target does not necessarily open a new market for the parent. Accordingly, we test this hypothesis:

**H3b** Related out-of-state mergers are associated with a greater positive (or smaller negative) impact on CAR.

Empirically, we test hypothesis H3a by interacting the vicinity variable ( $Rel_{d,ZIP}$ ) with the FIC relatedness variable ( $Rel_{d,FIC300}$ ). We test hypothesis H3b by interacting the same-state variable ( $Rel_{d,State}$ ) with the FIC relatedness variable ( $Rel_{d,FIC300}$ ). The results are reported in Table 8 where the dependent variable is CAR  $[-3, +3]$  for the acquirer, the target, and the combined firm. All explanatory variables in Table 8 are defined in the same way as in Table 6 but with the addition of two interaction terms:  $Rel_{d,ZIP} \times Rel_{d,FIC300}$  and  $Rel_{d,State} \times Rel_{d,FIC300}$ .<sup>24</sup> A significantly negative coefficient on  $Rel_{d,ZIP} \times Rel_{d,FIC300}$  implies that relatedness yields a larger CAR for smaller-vicinity mergers, which supports H3a. Similarly, a significantly negative coefficient on  $Rel_{d,State} \times Rel_{d,FIC300}$  implies that there is a negative interaction effect between relatedness and in-state status which means that, consistent with H3b, relatedness yields a greater CAR for out-of-state mergers.

Models 1, 3, and 5 in Table 8 include an interaction between vicinity and relatedness  $Rel_{d,ZIP} \times Rel_{d,FIC300}$ . When interpreted carefully, the coefficients on  $Rel_{d,FIC300}$ ,  $Rel_{d,ZIP}$ , and  $Rel_{d,ZIP} \times Rel_{d,FIC300}$  reveal the difference in vicinity slopes based on FIC-relatedness. The idea is that FIC-relatedness might have a different effect on CAR for mergers with different vicinity. The null hypothesis is that the change in CAR that is induced by vicinity is the same for related and unrelated mergers.

The striking finding in Table 8 is that the coefficients on  $Rel_{d,FIC300}$  have become significantly positive. This might appear as a contradiction to the findings in Tables 6 and 7, but it is not. Unlike Tables 6 and 7 above, the coefficients on  $Rel_{d,FIC300}$  in regressions 1, 3, and 5 in Table 8 do not capture the direct effect of FIC-relatedness on CAR. Instead, they measure the effect of FIC-relatedness on CAR when the merging firms are strictly located in the same zip code (i.e., when  $Rel_{d,ZIP} = 0$ ). The positive signs indicate that FIC-related mergers between firms located in the same zip code area increase wealth for all shareholders. This is indirectly consistent with hypothesis H3a. Further, the coefficients on the interaction terms  $Rel_{d,ZIP} \times Rel_{d,FIC300}$  measure the effect of a one standard deviation increase in vicinity on CAR for FIC-related mergers. All the interaction coefficients are statistically and economically significant with a negative sign. A one standard deviation decrease in  $Rel_{d,ZIP}$  (i.e., smaller vicinity) for FIC-related mergers increases seven-day CAR  $[-3, +3]$  by 1.10 percentage points for the acquirer, by 19.64 percentage points for the target, and by 2.44 percentage points for the combined firm. This finding directly supports hypothesis H3a. The coefficients on  $Rel_{d,ZIP}$  capture the effect of a one standard deviation increase in  $Rel_{d,ZIP}$  (i.e., larger vicinity) on CAR for FIC-unrelated mergers, and they are all statistically insignificant from zero. This indicates that vicinity does not affect value in unrelated mergers.

In regressions 2, 4, and 6, the interaction term  $Rel_{d,State} \times Rel_{d,FIC300}$  allows the in-state discount (or the out-of-state premium) to depend on FIC-relatedness. By construction, the base group is out-of-state FIC-unrelated mergers, and the coefficients on  $Rel_{d,State}$ ,  $Rel_{d,FIC300}$ , and  $Rel_{d,State} \times Rel_{d,FIC300}$  are sufficient to reveal CAR differentials across all possible combinations of  $[Rel_{d,State}, Rel_{d,FIC300}]$  relative to the base group  $[Rel_{d,State} = 0, Rel_{d,FIC300} = 0]$ . The null hypothesis is that the CAR differentials are the same for all four combinations.

Once again, a striking finding presents itself in the form of a positive coefficient on  $Rel_{d,FIC300}$  which might appear to conflict with Tables 6 and 7 above, but that is not true.

<sup>24</sup> We also tested the interactions with SIC variables but obtained insignificant results. This is consistent with an earlier result indicating that SIC-relatedness is dominated by FIC-relatedness and does not impact value.

We have added the interaction term  $Rel_{d,State} \times Rel_{d,FIC300}$  to the model and, therefore, the coefficient on  $Rel_{d,FIC300}$  is now interpreted differently. Specifically, this coefficient now measures the impact on CAR for FIC-related out-of-state mergers over the base group of out-of-state FIC-unrelated mergers. The positive and statistically significant coefficients on  $Rel_{d,FIC300}$  indicate that out-of-state FIC-related mergers realize a higher CAR. The increase is 1.05 percentage points for the acquirer, 8.91 percentage points for the target, and 2.62 percentage points for the combined firm. This is consistent with hypothesis H3b.

The  $Rel_{d,State}$  coefficient captures the estimated CAR differential for in-state FIC-unrelated mergers relative to FIC-unrelated out-of-state mergers. It is statistically insignificant from zero which means that in-state FIC-unrelated mergers are not valued differently from the reference group of out-of-state FIC-unrelated mergers. The estimated CAR differential for in-state FIC-related mergers (the  $Rel_{d,State} \times Rel_{d,FIC300}$  coefficient) is significantly negative for the acquirer ( $-6.01\%$ ), the target ( $-15.80\%$ ), and the combined entity ( $-4.75\%$ ), which indicates that in-state FIC-related mergers are severely penalized. This further ascertains that FIC-related out-of-state mergers dominate all other combinations of relatedness and state. This is supportive of hypothesis H3b.

Overall, the results in Table 8 strongly suggest that the market has a meticulous taste for operational and marketing relatedness (measured by FIC), state of incorporation, and distance between the acquirer and the target in M&A transactions. The market appears to praise out-of-state mergers and small-vicinity mergers when the acquirer and the target are similar in operations and marketing. We are not aware of any previous research that analyzed relatedness and location at this deep level. However, we admit that a much more thorough analysis is required before one can formulate a solid theory. At this juncture, it suffices to say that *perhaps* small-vicinity related mergers signify victory against a nearby rival and out-of-state related mergers signify access to new markets. This is a good starting point for future researchers interested in this domain.

## 5.4.2 Technology

Does the technology sector have peculiar trends in M&As? In other words, is it possible that the market has a special taste for M&A deals that occur within, or cross the boundaries of, the technology sector? In this section, we delve more deeply into the role of technology affiliation in M&A valuation. The simple binary technology variable  $Rel_{d,HighTech}$  equals 1 if the acquirer *and* the target are high-technology firms. Therefore, the reference group is “acquirer *or* target are not-high-technology firms.” In order to better understand the effect of technology affiliation, we replace  $Rel_{d,HighTech}$  with three variables that represent the effects of high-technology affiliation on CAR relative to a reference group of strictly non-high-technology mergers (see the legend of Table 9 for more details). In Table 9, the dependent variable is the seven-day CAR [ $-3, +3$ ] for the acquirer, target, and the combined firm. In models 1, 3, and 5, we include the relatedness variables only, and in the rest of the models, we add standard controls (see previous sections).

In a previous section, we presented evidence that technology affiliation has a positive impact on CAR for the acquirer, the target, and the combined firm (see Tables 6, 7). The results in Table 9 indicate that this finding extends only to the strictly high-technology mergers, i.e., a merger where both the acquirer and the target belong to the high-technology sector. In strictly high-technology mergers, the merger yields an additional 1.10–1.89 percentage points in CAR for the acquirer, 8.61–12.65 percentage points in CAR for the

**Table 8** Regression models with interaction terms for state and vicinity

	Acquirer CAR [-3, +3]		Target CAR [-3, +3]		Combined CAR [-3, +3]	
	1	2	3	4	5	6
# of Obs.	1364	1478	1350	1350	1323	1387
R <sup>2</sup>	0.17	0.18	0.21	0.17	0.27	0.24
Complementarity	0.78	1.42	-0.11	-0.13	0.70	1.27
Vertical relatedness	0.61**	0.33	3.94*	3.95*	0.21**	0.55**
Change-in-focus (Sales)	-0.13*	-2.22***	-1.21**	-1.02**	-0.04*	-0.85**
FIC300	2.26***	1.05*	4.32*	8.91**	2.07**	2.62**
Vicinity	0.22		-1.85		-0.66	
Vicinity × FIC300	-1.10**		-19.64***		-2.44***	
Same state?		-2.30		1.88		-2.35
Same state × FIC300		-6.01**		-15.80**		-4.75**
Target-Friendly?	4.78	4.84	-1.80	-2.77	4.87	4.79
High tech merger?	1.99***	1.81**	1.18*	1.64*	1.18**	1.00*
Cash?	1.76	8.29***	10.94**	6.82**	3.16**	12.33***
Acquirer ROE	-1.10*	-1.68	2.81	3.18	0.19	-1.06
Acquirer debt ratio	1.05	3.25	-6.24	-4.21	-0.08	2.71
Access to capital?	-0.08	2.93	-2.90	-2.00	0.35	1.42
Size (logged)	0.37	3.53**	-1.46	-1.80	-0.38	2.37*
Value	7.97**	8.24	-17.38**	-15.58**	13.09***	17.91***

This table reports the results of OLS regressions for the acquirer's, the target's, and the combined entity's cumulative abnormal returns (CAR) around the announcement date. CAR calculations and assumptions are explained in a previous table. We report the CAR [-3, +3] results only. The results with CAR [-1, +1] and CAR [-2, +2] are generally consistent and are available upon request from the authors. All dependent variables and control variables are specified as in Table 6 with the addition of two interaction terms.  $Rel_{d,State} \times Rel_{d,FIC300}$  interacts two binary variables and, therefore, it allows the in-state premium to depend on relatedness. By construction, the base group is out-of-state unrelated mergers and the coefficients on  $Rel_{d,State}$ ,  $Rel_{d,FIC300}$ , and  $Rel_{d,State} \times Rel_{d,FIC300}$  are sufficient to reveal CAR differentials across all four relatedness-state combinations. In contrast,  $Rel_{d,ZIP} \times Rel_{d,FIC300}$  interacts a binary variable with a continuous variable and allows for a difference in slopes. Therefore, we must interpret the coefficients in the model with extreme care. The interaction coefficient captures the incremental effect of vicinity on CAR for related mergers.  $Rel_{d,ZIP}$  captures the vicinity effect in unrelated mergers (i.e., when  $Rel_{d,FIC300} = 0$ ) and  $Rel_{d,FIC300}$  captures the relatedness effect when  $Rel_{d,ZIP} = 0$ . In summary, the coefficients on  $Rel_{d,State}$ ,  $Rel_{d,FIC300}$ , and  $Rel_{d,ZIP}$  in this table are interpreted differently from Tables 6 and 7. Following extant literature, we show the results for FIC300 only (see Table 6). The results with the remaining FIC variables (not tabulated) are generally comparable to the results presented in this table and are available upon request from the authors. All coefficients are reported as percentage points. Standard errors (not tabulated) are heteroskedastic-consistent. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), or 10% (\*) level

target, and 2.01–3.79 percentage points in CAR for the combined entity. The estimated CAR differential for an acquisition of a high-technology target by a non-high-technology acquirer is significantly negative for the acquirer (-2.89 to -4.30%), the target (-4.50 to 7.44%), and the combined entity (-0.08 to -0.41%), which indicates that the market tends to penalize these mergers. On the other hand, the estimated CAR differential for an acquisition of a non-high-technology target by a high-technology acquirer is insignificantly different from zero in all regressions. This indicates that such acquisition does not generate a

CAR different from that generated by a strictly non-high-technology merger (i.e., a merger where both the acquirer and the target are not high-technology firms).

In another test (non-tabulated), we interact the technology binary with the FIC-relatedness binary to create an interaction term  $Rel_{d,HighTech} \times Rel_{d,FIC300}$ , which allows the technology premium to depend on FIC-relatedness. By construction, the base group is non-high-technology FIC-unrelated mergers, and the coefficients on  $Rel_{d,HighTech}$ ,  $Rel_{d,FIC300}$ , and  $Rel_{d,HighTech} \times Rel_{d,FIC300}$  reveal CAR differentials across all possible relatedness-technology combinations relative to the base group. The null hypothesis is that there is no interaction between technology relatedness and FIC-relatedness, and thus, CAR differential is the same for all four combinations. This procedure disentangles the effect of relatedness and technology affiliation on CAR. We find that technology affiliation and FIC-relatedness do not interact.

Taken together, our analyses of technology affiliation indicate the following. The market reaction to the deal announcement seems to be sophisticated. Acquisitions within the high-technology sector are generously rewarded, and this reward does not stem from conventional relatedness premium. The market seems to be able to draw boundaries around the high-technology sector. Acquisitions that cross the boundaries inbound are not well received by the market. Specifically, the acquisition of a high-technology target by a non-high-technology acquirer is penalized (while the opposite is not). More research on this domain is encouraged.

### 5.4.3 Relatedness and the probability of deal completion

Prior research has shown that relatedness does not only impact shareholders' wealth but also could have an impact on the probability of the acquisition being completed in the first place (see Ishii and Xuan 2014; Alhenawi and Krishnaswami 2015). The results presented in the previous sections support this intuition. For instance, one expects that acquirers are less likely to pull out of vertically related deals because they are likely to induce, holding everything else constant, a desirable market reaction.

In this section, we compare the relatedness between the acquirers and the targets in our sample to the relatedness between the acquirers and the targets in a randomly selected control sample of announced but not completed transactions. The construction of the control sample is explained in the legend of Table 10. First, we conduct a simple bivariate comparison. Second, we run a binary logistic regression to examine the impact of relatedness on the likelihood of completion.

Table 10 reports the means of the binary and continuous measures of relatedness in our sample (Column 2) to the means of the corresponding measures in the control sample (Column 3) and the difference between the two (Column 4). Column 5 reports the coefficients obtained from the logistic regression.

The results of the univariate analysis in Columns 2, 3, and 4 indicate that SIC-relatedness and FIC-relatedness in the non-completed deals is significantly higher than they are in the completed deals. The SIC-relatedness means for the completed mergers (44.86–76.20%) are consistently lower than the SIC-relatedness means for the non-completed mergers (52.57–79.31%). Similarly, the FIC-relatedness means for the completed mergers (27.03–30.43%) are consistently lower than the FIC-relatedness means for the non-completed mergers (33.85–39.69%). Similar findings are obtained with SDC industry and business description variables. These patterns indicate that announced acquisitions are more likely to be completed in SIC-unrelated and FIC-unrelated mergers relative to

**Table 9** Technology affiliation and cumulative abnormal returns in mergers and acquisitions transactions

	Acquirer CAR [-3, + 3]		Target CAR [-3, + 3]		Combined CAR [-3, + 3]	
	1	2	3	4	5	6
# of Obs.	1489	1364	1486	1350	1394	1323
R <sup>2</sup>	0.14	0.18	0.13	0.18	0.14	0.27
Complementarity	0.86	0.85	0.64	0.41	0.89	0.79
Vertical relatedness	1.01***	0.76**	3.48*	4.49**	0.01*	0.23**
Change-in-focus (Sales)	- 0.20*	- 0.12*	- 0.86*	- 1.31**	- 1.07***	- 0.03*
Vicinity	- 0.29*	- 0.38**	- 0.24*	- 0.02*	- 0.73**	- 0.37**
SIC2	2.31	0.54	- 4.01	- 5.58	- 2.02	- 0.70
FIC300	1.68**	1.77**	- 3.48*	- 5.01*	- 0.35*	- 1.97**
Same state?	- 0.47*	- 0.04*	- 0.93*	- 0.05*	- 1.73**	- 0.97**
Target-Friendly?	5.25	5.01	- 2.81	- 3.45	4.24	4.94
Strictly High-Tech Merger?	1.89*	1.10*	8.63**	12.65**	3.79**	2.01*
Target only is High Tech?	- 2.89**	- 4.30*	- 4.50**	- 7.44**	- 0.08*	- 0.41*
Acquirer only is High Tech?	- 2.34	- 0.58	- 2.56	- 4.99	- 4.64	- 1.39
Cash?		1.52		12.38**		3.29**
Acquirer ROE		- 1.13*		2.77		0.13
Acquirer debt ratio		0.74		- 6.13		- 0.06
Access to capital?		- 0.08		- 3.02		0.25
Size (logged)		0.48		- 1.85		- 0.35
Value		8.16**		- 19.65**		12.78***

This table reports the results of OLS regressions for the acquirer's, the target's, and the combined entity's cumulative abnormal returns (CAR) around the announcement date. CAR calculations and assumptions are explained in previous tables. We report the CAR [-3, + 3] results only. The results with CAR [-1, + 1] and CAR [-2, + 2] are generally consistent and are available upon request from the authors. All dependent variables and control variables are specified as in Table 6. In order to better understand the effect of technology affiliation, we replace  $Rel_{d,HighTech}$  with three variables specified as:

$$\begin{aligned}
 Rel_{d,HighTech\_Both} &= \begin{cases} 1 & \text{when the acquirer and the target are high tech} \\ 0 & \text{otherwise} \end{cases} \\
 Rel_{d,HighTech\_Tgt} &= \begin{cases} 1 & \text{when the target is high tech but the acquirer is not} \\ 0 & \text{otherwise} \end{cases} \\
 Rel_{d,HighTech\_Aqr} &= \begin{cases} 1 & \text{when the acquirer is high tech but the target is not} \\ 0 & \text{otherwise} \end{cases}
 \end{aligned}$$

The three variables enter the models as binaries; thus, the reference group is “the acquirer and the target are not high-technology firms.” The coefficients on these variables represent the effects of high-technology affiliation on CAR relative to a reference group of strictly non-high-technology mergers. Following extant literature, we show the results for FIC300 only (see Table 6). The results with the remaining FIC variables (not tabulated) are generally comparable to the results presented in this table and are available upon request from the authors. All coefficients are reported as percentage points. Standard errors (not tabulated) are heteroskedastic-consistent. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), or 10% (\*) level

**Table 10** Probability of deal completion

Variable	1 Obs.	2 Mean completed mergers	3 Mean non-completed mergers	4 Difference (2)–(3)	5 Coefficient in probability model
Rel_SIC4	14,389	0.4486	0.5257	– 0.0771*	–
Rel_SIC3	14,389	0.5658	0.6242	– 0.0584**	–
Rel_SIC2	14,389	0.6688	0.7107	– 0.0419**	–
Rel_SIC1	14,389	0.7620	0.7931	– 0.0311***	0
Rel_FIC500	3618	0.2703	0.3585	– 0.0882***	–
Rel_FIC400	3618	0.2742	0.3690	– 0.0948***	–
Rel_FIC300	3618	0.2734	0.3704	– 0.0970***	–
Rel_FIC200	3618	0.2852	0.3751	– 0.0899***	–
Rel_FIC100	3618	0.2869	0.3856	– 0.0987***	0
Rel_FIC050	3618	0.3043	0.3969	– 0.0926***	0
Rel_State	14,389	0.2892	0.3851	– 0.0959***	–
Rel_Target Friendly	14,389	0.0818	0.1997	– 0.1179***	–
Rel_Industry	14,389	0.6462	0.6941	– 0.0479***	–
Rel_Business	14,389	0.1201	0.2330	– 0.1129***	–
Re_HighTech	14,389	0.4337	0.3884	0.0453***	+
Rel_Com	4361	0.2068	0.1861	0.0207***	+
Rel_Ver	3939	0.0108	0.0097	0.0011***	+
Rel_Assets	10,978	– 0.1170	–	–	–
Rel_Sales	10,978	– 0.2648	–	–	–
Rel_ZIP	2579	27,168	45,376	– 18,208***	–
Cash?	14,389	0.1847	0.1635	0.0212***	+
Acquirer ROE	10,839	0.0455	0.0657	– 0.0202	0
Acquirer debt ratio	10,844	0.6371	1.0302	– 0.3931***	–
Access to capital?	10,978	0.4203	0.3717	0.0486	0
Size (logged)	9854	3.1389	3.0761	0.0628**	+
Value	8693	0.1514	0.3951	– 0.2437***	–

This table examines whether an acquisition is more or less likely to be completed when the merging firms are related. Columns 2, 3, and 4 report the results of simple univariate comparison of relatedness in the original sample and relatedness in a randomly constructed control sample drawn from SDC. We match each completed transaction in our sample with a transaction that has been announced, but not completed, in the same year and has the closest combination of acquirer's size, then transaction relative size. This approach is adapted from Alhenawi and Krishnaswami (2015). As a result, the control sample includes 14,389 mergers announced but eventually not completed in 1998–2014. The first column reports the number of observations. The second column reports the relatedness between the acquirers and the targets in the original sample. The third column reports the relatedness between the acquirers and the targets in the control sample. Column four reports the difference between column 2 and column 3. Change-in-focus variables cannot be computed for non-completed mergers. Column 5 reports the results of running a binary logistic regression where the dependent variable is a dichotomous that equals 1 for completed mergers and 0 for non-completed mergers. The regressors are explanatory variables theorized to influence the probability of observing a completed merger and include relatedness variables, as well as standard controls used in this study. The independent variables for complementarity, vertical relatedness, change-in-focus, and vicinity enter the regression model as number of standard deviations (see Table 6). Because of the nonlinear nature of binary logistic regression, the magnitude of the coefficients does not have a well-defined unit of measurement, and thus, does not have a meaningful interpretation. The signs, however, indicate the direction of the effect of the independent variables on the likelihood of observing a completed merger. Therefore, only the signs of the coefficients are presented below. Standard errors (not tabulated) are heteroskedastic-consistent. Asterisks denote statistical significance at the 1% (\*\*\*), 5% (\*\*), or 10% (\*) level

SIC-related and FIC-related mergers, respectively. For FIC-related mergers, this is consistent with the finding that these mergers are associated with a negative market reaction.<sup>25</sup>

In the completed mergers subsample, 28.92% of deals are in-state mergers and 8.18% of the targets are incorporated in a target-friendly state. In the non-completed mergers subsample, 38.51% of the transactions are in-state and 19.97% of the targets are located in target-friendly states. Similarly, the average ZIP code differential in the completed mergers subsample is about 27,168 while in the non-completed subsample the average is 45,376. Together, these findings indicate that state of incorporation and vicinity, as well as state-level merger laws, play a significant role in merger completion decision. Specifically in-state and large-vicinity mergers are less likely to be completed. This is consistent with an earlier finding in this paper indicating that in-state and larger vicinity mergers decrease shareholders' wealth (see Tables 6, 7). While state-specific merger laws do not induce any specific market reaction, they seem to influence the decision to complete the deal (i.e., acquisitions of targets in target-friendly states are less likely to be completed).

The presence of complementarity and vertical relatedness in a merger increases the likelihood that the deal will be completed. In the completed sample, complementarity and vertical relatedness between the acquirers and the targets are about 10% higher. This is also consistent with the findings of Tables 6 and 7 where complementarity and vertical relatedness appear to increase wealth for the combined pool of shareholders.<sup>26</sup>

The univariate results are further supported by the results of the multivariate logistic regression analysis reported in Column 5 with a few exceptions (e.g., SIC1-, FIC050-, and FIC100-relatedness do not seem to impact the likelihood of the completion of the deal). Further, the results are consistent with the notion that relatedness between the acquirer and the target influences the probability of completing an acquisition in a multi-dimensional manner (hypothesis H1). Each individual relatedness measure carries its own impact on the likelihood that the announced deal will be completed. The impacts are additive, which implies that these factors are complements, not substitutes of each other. This is additional support for hypothesis H1.

## 6 Summary and discussion of results

This paper is motivated by a literature review that reveals that relatedness classification is highly contingent on the way a researcher defines relatedness. Although researchers cite many reasons for how relatedness creates value in M&A transactions, they have not reached a compelling consensus on what exactly relatedness is or how to measure it. As a result, the extant M&A literature presents extensively differing definitions and measures of relatedness.

---

<sup>25</sup> It is startling that mergers are less likely to be completed in the presence of SIC relatedness, albeit an earlier finding indicating that SIC relatedness does not impact the market's reaction around the deal announcement date (see Tables 6, 7 above). Perhaps, the benefits of SIC relatedness are more visible to decision makers who are in charge of approving the deal than they are to the market. This might be a good starting premise for future research.

<sup>26</sup> Consistent with findings in the extant literature, completed mergers are relatively more likely to be paid in cash and made by larger, less leveraged acquirers. They are also more likely to have smaller relative value. ROE for the acquirer and access to capital do not affect the probability of completing the deal.

Our work addresses an intuition that has received relatively less attention: relatedness is a multi-dimensional metric composed of several additive and interdependent components. This paper offers a theoretical and empirical comparison of existing relatedness measures and introduces a few new ones. The analysis includes the conventional SIC code matching approaches, which capture similarities in taxation and regulatory environment. It also includes the supply chain integration measures developed by Fan and Lang (2000) and the FIC measures of Hoberg and Phillips (2010, 2016), which emphasize operational and marketing similarities. In addition, this paper introduces new dimensions of relatedness. First, it introduces a new vicinity measure. Kang and Kim (2008) have developed an entropy measure of geographical proximity, which reflects familiarity with local markets and laws, access to relevant information, and lower monitoring costs. Our ZIP code-based measure continues in the spirit of Kang and Kim's (2008) physical distance variable but is much easier to construct and is more compatible with the economic principles underlying M&A analysis. Second, parsing the content of certain fields in the SDC database, a resource that is often overlooked in literature, we introduce and test a set of new relatedness measures including "Industry Sector", "Short Business Description" and "High Tech Industry." Finally, this paper tests whether state-level merger laws contribute to merger performance.

## 6.1 SIC, FIC, and other measures of relatedness

The empirical results suggest that broad industry-level relatedness indicators are inferior to more specific business-level indicators. Specifically, the business description-based relatedness measures developed by Hoberg and Phillips (2010, 2016) seem to be significantly more powerful than the broad industry-matching procedure implied by the traditional SIC code matching approach. This conclusion is further supported by consistent findings obtained with the broad industry relatedness indicator ( $Rel_{d,Industry}$ ) and a business description relatedness indicator ( $Rel_{d,Business}$ ) obtained by parsing the content of corresponding fields in the SDC database.

We also contrast SIC and FIC binaries with the complementarity and vertical relatedness variables introduced by Fan and Lang (2000) and the change-in-focus variables employed by Alhenawi and Krishnaswami (2015). We find that when the merging firms have similar SIC codes, they are generally more complementary and vertically related and the deal increases the focus of the combined entity. This is not the case with FIC binaries. Merging firms that belong to the same FIC cluster are neither more complementary nor more vertically related, and the merger between them does not always increase focus. This implies that SIC codes carry information on complementarity and vertical relatedness, while FIC clusters carry unique relatedness information.

For the target, the stock reacts more positively to deal announcement when the merger is FIC-unrelated or SIC-unrelated. The differences, however, are smaller in magnitude with SIC binaries. For the acquirer and the combined firm, FIC relatedness is associated with a smaller loss of value for the acquirer's shareholders and a smaller gain for the combined firm. In contrast, SIC relatedness is not associated with any value change for the acquirer or the combined firm. We conclude that FIC measures are more accurate in capturing relatedness than SIC measures.

## 6.2 Vicinity and location

Vicinity is a continuous ZIP code-based measure introduced by these authors. It is much simpler to construct than the physical distance variable suggested by Kang and Kim (2008). More importantly, this paper shows that this vicinity variable has many desirable properties and is an important factor in M&A analysis. First, vicinity is uncorrelated with other *continuous* relatedness variables. Second, and more interestingly, vicinity carries its own valuation information. OLS regression analysis indicates that mergers between firms that belong to smaller vicinities are more constructive. Further, the market seems to price the location of the merging firms in a meticulous manner. Specifically, it values mergers within smaller vicinities as well as out-of-state mergers. We show additional evidence suggesting that this effect extends only to related mergers. We conclude that the market perceives small-vicinity related mergers as a victory against a local rival and the related out-of-state mergers as an opportunity to penetrate a new market. This notion is further supported by another result indicating that related in-state larger-vicinity mergers are not valued differently from unrelated mergers.

## 6.3 Technology affiliation

This paper shows that linking the acquirers to the targets based on the content of the “High Technology Sector” field in SDC creates a binary indicator that contains considerable relatedness information that is not captured by the conventional SIC binaries or by the more advanced FIC binaries. Second, the analyses indicate that this information is priced separately and high-technology mergers create additional value. The market also seems to be meticulous when it comes to mergers that involve high-technology firms. Specifically, the market praises acquisitions of high-technology targets by high-technology acquirers and discounts acquisitions of high-technology targets by non-high-technology acquirers. This conclusion is further supported by another finding indicating that acquisition of a non-high-technology target by a high-technology acquirer is not valued differently from a strictly non-high-technology acquisition.

## 6.4 State of incorporation, and local merger regulations

We test whether the state of incorporation and local merger laws contribute to shareholder wealth. First, we show that a substantial fraction of mergers in our sample are between firms in the same state (28.92%). Similarly, 8.18% of mergers involve a target incorporated in a “target-friendly” state. These percentages are non-trivial. More importantly, OLS regression analysis indicates that these measures contribute to market reaction to merger announcement and to the probability of completing the deal.

## 6.5 Complementarity, vertical relatedness, and change-in-focus

This paper offers a side-by-side comparison of several continuous relatedness measures including the complementarity and vertical relatedness variables of Fan and Lang (2000) and the change-in-focus variables of Alhenawi and Krishnaswami (2015). The

complementarity and vertical relatedness capture supplier-purchaser integration and marketing and procurement integration, respectively. The change-in-focus variables measure how acquiring the target increases or decreases the concentration of the acquirer. Initial correlation analysis and double-sorting procedures indicate that complementarity, vertical relatedness, and focus are not strongly correlated. OLS regression analysis indicates that these measures contain different valuation information and logistic probability models show that these measures contribute separately and additively to the likelihood of completion of the deal.

## 7 Conclusion

No aspect of merger and acquisition transactions is as widely recognized or as vigorously debated as the relatedness between the acquirer and the target. Nevertheless, relatedness neither has a universal definition nor a standard measurement instrument. The extant literature focuses on developing sophisticated single-dimensional measures but overlooks the possibility that relatedness is multi-dimensional. Further, it overlooks several additional sources of relatedness, and little is known about the interaction between various sources of relatedness. This paper offers theoretical and empirical comparison of existing measures of relatedness and introduces new ones, such as vicinity, local merger laws, and technological advancement.

Our findings are summarized as follows. First, relatedness is a multi-dimensional metric composed of several additive and interdependent components such as vertical and horizontal supply chain integration, familiarity with local market, focus, vicinity, technology, and operational and marketing similarities. Our findings cast doubt on the validity of the traditional single-dimensional approach to capturing relatedness because single-dimensional proxies are shown to be unable to capture relatedness accurately and completely. In fact, existing proxies of relatedness are complements, not substitutes, of each other and their impacts are additive and interdependent. Second, we show that the market's perception and valuation of relatedness is more sophisticated than the current literature prescribes. Specifically, location and technology affiliation play a significant role in mergers' valuation and exhibit a somewhat complex interaction with other relatedness variables. Finally, we present additional empirical evidence on the connection between relatedness and the probability that the deal will be completed (conditional on being announced). Consistent with the overarching hypothesis of this paper, the relatedness effect on the likelihood of completion once again presents itself in a multi-dimensional, additive, and interdependent fashion.

The empirical work presented in this paper should improve future academic research in the M&A field and should help academicians and practitioners to better understand and adapt to the increasingly complex nature of corporate-transforming strategies.<sup>27</sup> Our work paves the road for more research in this domain. Until the research community agrees upon

---

<sup>27</sup> Additionally, this research presents several innovations in methodology and implementation. First, we introduce a new zip code-based vicinity variable. We also show that the Securities Data Company (SDC) database supplies reliable content for constructing relatedness indicators. Second, we report evidence that broad industry-level relatedness indicators, e.g., SIC codes, are inferior to business-level indicators, such as the FIC clusters of Hoberg and Phillips (2010, 2016). Further, SIC relatedness does not impact shareholders' value despite the fact that it negatively impacts the merger completion decision. We conclude that merger decision makers seem to rely on SIC codes more heavily than investors do.

a comprehensive definition of relatedness, the value of empirical studies in this domain will remain high.

## References

- Adhikari HP, Nguyen TT, Sutton NK (2018) The power of control: the acquisition decisions of newly public dual-class firms. *Rev Quant Finan Acc* 51(1):113–138. <https://doi.org/10.1007/s11156-017-0665-6>
- Agrawal A, Jaffe JF, Mandelker GN (1992) The post-merger performance of acquiring firms: a re-examination of an anomaly. *J Financ* 47(4):1605–1621. <https://doi.org/10.2307/2328956>
- Ahern KR, Harford J (2014) The importance of industry links in merger waves. *J Financ* 69(2):527–576. <https://doi.org/10.1111/jofi.12122>
- Alhenawi Y, Krishnaswami S (2015) Long-term impact of merger synergies on performance and value. *Q Rev Econ Financ* 58:93–118. <https://doi.org/10.1016/j.qref.2015.01.006>
- Anderson RI, Stowe JD, Xing X (2011) Does corporate diversification reduce firm risk? Evidence from diversifying acquisitions. *Rev Pac Basin Financ Mark Policies* 14(3):485–504. <https://doi.org/10.1142/S0219091511002214>
- Anderson RI, Medla H, Rottke NB, Schiereck D (2012) Real estate merger motives: an analytical review of the literature. *J Real Estate Lit* 20(1):37–48
- Andrade G, Mitchell M, Stafford E (2001) New evidence and perspectives on mergers. *J Econ Perspect* 15(2):103–120
- Asquith P, Bruner RF, Mullins DW Jr (1983) The gains to bidding firms from merger. *J Financ Econ* 11(1–4):121–139. [https://doi.org/10.1016/0304-405X\(83\)90007-7](https://doi.org/10.1016/0304-405X(83)90007-7)
- Barney JB (1988) Returns to bidding firms in mergers and acquisitions: reconsidering the relatedness hypothesis. *Strateg Manag J* 9(S1):71–78. <https://doi.org/10.1002/smj.4250090708>
- Berger PG, Ofek E (1995) Diversification's effect on firm value. *J Financ Econ* 37(1):39–65. [https://doi.org/10.1016/0304-405X\(94\)00798-6](https://doi.org/10.1016/0304-405X(94)00798-6)
- Bhattacharyya S, Nain A (2011) Horizontal acquisitions and buying power: a product market analysis. *J Financ Econ* 99(1):97–115. <https://doi.org/10.1016/j.jfineco.2010.08.007>
- Bouwman CHS, Fuller K, Nain AS (2009) Market valuation and acquisition quality: empirical evidence. *Rev Financ Stud* 22(2):633–679. <https://doi.org/10.1093/rfs/hhm073>
- Branch B, Yang TW (2006) The risk arbitrage performance: failed acquisition attempts. *Q J Bus Econ* 45(1/2):53–68
- Canace TG, Mann SV (2014) The impact of technology-motivated M&A and joint ventures on the value of IT and non-IT firms: a new examination. *Rev Quant Finance Acc* 43(2):333–366. <https://doi.org/10.1007/s11156-013-0374-8>
- Caves RE, Porter ME, Spence AM, Scott JT (1980) *Competition in an open economy a model applied to Canada*. Harvard University Press, Cambridge
- CFA Institute (2015) *CFA Level II volume 3 corporate finance*. Wiley Global Finance, 2014-07-14. VitalBook file
- Chuang KS (2017) The role of investment banks on the impact of firm performance in mergers and acquisitions: evidence from the Asia-Pacific market. *Rev Quant Finan Acc* 48(3):677–699. <https://doi.org/10.1007/s11156-016-0564-2>
- Clarke RN (1989) SICs as delineators of economic markets. *J Bus* 62(1):17–31. <https://doi.org/10.1086/296449>
- Comment R, Jarrell GA (1995) Corporate focus and stock returns. *J Financ Econ* 37(1):67–78
- DeYoung R, Evanoff DD, Molyneux P (2009) Mergers and acquisitions of financial institutions: a review of the post-2000 literature. *J Financ Serv Res* 36(2–3):87–110. <https://doi.org/10.1007/s10693-009-0066-7>
- Eckbo BE (1992) Mergers and the value of antitrust deterrence. *J Financ* 47(3):1005–1029. <https://doi.org/10.1111/j.1540-6261.1992.tb04003.x>
- Fan JPH, Goyal VK (2006) On the patterns and wealth effects of vertical mergers. *J Bus* 79(2):877–902. <https://doi.org/10.1086/499141>
- Fan JPH, Lang LHP (2000) The measurement of relatedness: an application to corporate diversification. *J Bus* 73(4):629–660. <https://doi.org/10.1086/209657>
- Fazzari SM, Hubbard GR, Peterson BG (1988) Financing constraints and corporate investment. *Brook Pap Econ Act* 1:141–206. <https://doi.org/10.2307/2534426>
- Fertuck L (1975) A test of industry indices based on SIC codes. *J Financ Quant Anal* 10(5):837–848

- Flanagan DJ (1996) Announcements of purely related and purely unrelated mergers and shareholder returns: reconciling the relatedness paradox. *J Manag* 22(6):823–835. <https://doi.org/10.1177/014920639602200602>
- Guenther DA, Rosman JA (1994) Differences between compustat and crsp sic codes and related effects on research. *J Account Econ* 18(1):115–128
- Hoberg G, Phillips G (2010) Product market synergies and competition in mergers and acquisitions: a text-based analysis. *Rev Financ Stud* 23(10):3773–3811. <https://doi.org/10.1093/rfs/hhq053>
- Hoberg G, Phillips G (2016) Text-based network industries and endogenous product differentiation. *J Polit Econ* 124(5):1423–1465. <https://doi.org/10.1086/688176>
- Ishii J, Xuan Y (2014) Acquirer-target social ties and merger outcomes. *J Financ Econ* 112(3):344–363. <https://doi.org/10.1016/j.jfineco.2014.02.007>
- Jacquemin AP, Berry CH (1979) Entropy measure of diversification and corporate growth. *J Ind Econ* 27(4):359–369
- Kahle MK, Walkling RA (1996) The impact of industry classifications on financial research. *J Financ Quant Anal* 31(3):309–335
- Kang J, Kim J (2008) The geography of block acquisitions. *J Financ* 63(6):2817–2858. <https://doi.org/10.1111/j.1540-6261.2008.01414.x>
- Kedia S, Ravid SA, Pons V (2011) When do vertical mergers create value. *Financ Manag* 40(4):845–877. <https://doi.org/10.1111/j.1755-053X.2011.01164.x>
- King B (1966) Market and industry factors in stock price behavior. *J Bus* 39:139–190
- Lewellen WG (1971) A pure financial rationale for the conglomerate merger. *J Financ* 26(2):521–537. <https://doi.org/10.2307/2326063>
- Maksimovic V, Phillips G, Prabhala NR (2011) Post-merger restructuring and the boundaries of the firm. *J Financ Econ* 102(2):317–343. <https://doi.org/10.1016/j.jfineco.2011.05.013>
- Matusaka JG (1996) Did tough antitrust enforcement cause the diversification of American corporations. *J Financ Quant Anal* 31:283–294
- Meng Y, Sutton NK (2017) Is the grass on the other side greener? Testing the cross-border effect for U.S. acquirers. *Rev Quant Finan Acc* 48(4):917–937. <https://doi.org/10.1007/s11156-016-0573-1>
- Meyers SL (1973) A re-examination of market and industry factors in stock price behavior. *J Financ* 28(3):695–705. <https://doi.org/10.1111/j.1540-6261.1973.tb01390.x>
- Moeller SB, Schlingemann FB, Stulz RM (2004) Firm size and the gains from acquisitions. *J Financ Econ* 73(2):201–228. <https://doi.org/10.1016/j.jfineco.2003.07.002>
- Mulherin H, Simsir SA (2015) Measuring deal premiums in takeovers. *Financ Manag* 44(1):1–14. <https://doi.org/10.1111/fima.12053>
- Nejadmalayeri A, Iyer SR, Singh M (2017) Is there an optimally diversified conglomerate? Gleaning answers from capital markets. *Rev Quant Finan Acc* 49(1):117–158. <https://doi.org/10.1007/s11156-016-0585-x>
- Ouyang W, Szcwcyk SH (2018) Stock price informativeness on the sensitivity of strategic M&A investment to Q. *Rev Quant Finan Acc* 50(3):745–774. <https://doi.org/10.1007/s11156-017-0645-x>
- Palepu K (1985) Diversification strategy, profit performance and the entropy measure. *Strateg Manag J* 6(3):239–255. <https://doi.org/10.1002/smj.4250060305>
- Rajan R, Servaes H, Zingales L (2000) The cost of diversity: the diversification discount and inefficient investment. *J Financ* 55(1):35–80. <https://doi.org/10.1111/0022-1082.00200>
- Scholes M, Williams J (1977) Estimating betas from nonsynchronous data. *J Financ Econ* 5(3):309–327
- Schwert GW (2000) Hostility in takeovers: in the eyes of the beholder? *J Financ* 55(6):2599–2640. <https://doi.org/10.1111/0022-1082.00301>
- Servaes H (1996) The value of diversification during the conglomerate merger wave. *J Financ* 51(4):1201–1225. <https://doi.org/10.1111/j.1540-6261.1996.tb04067.x>
- Sharma M (2016) Cross border mergers and acquisitions and the exchange rate: a literature review. *J Int Econ* 7(2):23–34
- Wernerfelt B, Montgomery CA (1988) Tobin's q and the importance of focus in firm performance. *Am Econ Rev* 78(1):246–250