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Human Capital Relatedness and Mergers and Acquisitions

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Abstract

We construct a measure of the pairwise relatedness of firms' human capital to examine whether human capital relatedness is a key factor in mergers and acquisitions. We find that mergers are more likely and merger returns and postmerger performance are higher when firms have related human capital. These relations are stronger or only present in acquisitions where the merging firms do not operate in the same industries or product markets. Reductions in employment and wages following mergers with high human capital relatedness suggest that the merged firm has greater ability to layoff low quality and/or duplicate employees and reduce labor costs. We further show in a falsification test that human capital relatedness has no effect on acquiring firm returns in asset sales when little or no labor is transferred, which helps validate our measure of human capital relatedness.

JEL classification: G34, J24, J41, L22, M51
Keywords: human capital relatedness, mergers and acquisitions, asset sales

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1. Introduction

The property rights theory of the firm developed by Grossman and Hart (1986) and Hart and Moore (1990) posits that complementary assets should be combined under common ownership when contracts are incomplete to reduce holdup problems.[1] Rhodes-Kropf and Robinson (2008) extend this view of the firm to a theory of mergers and show that it implies assortative matching (i.e., like buys like). Subsequent work by Hoberg and Phillips (2010) examines how real asset complementarities can be achieved when mergers between firms with related products spawns new products. However, the literature has paid less attention to the role of human capital relatedness in mergers. This paper attempts to fill this important gap in the literature by asking whether human capital relatedness encourages mergers and creates synergies.

A fundamental difference between real assets and human capital is that real assets can be purchased, while human capital is rented. It can therefore be difficult to realize human capital synergies in mergers because it is difficult to retain and redeploy the merging firms' workforces or layoff duplicate and/or less productive workers. However, we argue that human capital relatedness (i.e., overlapping employees with similar job skills) increases the acquiring firm's bargaining power over the merged firms' workforces, giving it greater ability to extract rents from employees in the form of lower wages and/or the option to retain only the most productive components of the overlapping workforces. Furthermore, the firm also has the option to keep the combined workforces intact to capitalize on economies of scale or to "winner-pick" the best ideas and new products or services.

The human capital relatedness between firms is likely to be related to the degree of industry and/or product overlap. This raises the question of whether human capital relatedness is

[1] See Hart (1995, 1998) for syntheses of the implications of incomplete contracting and the property rights theory of the firm. Teece (1982, 1986) also argues that market imperfections can motivate a theory of a diversified multiproduct firm that benefits from combining complementary assets.

more or less valuable when merging firms operate in similar product markets. Theoretical work by Fulghieri and Sevilir (2011) suggests a possible answer to this question. They argue that although mergers between firms operating in similar product markets can increase market power, this benefit is offset by a negative effect on employee incentives to innovate. This is because the merger decreases competition for human capital, allowing the postmerger firm to extract greater rents from employees. The net effect is that the merger can be rejected or create lower value because it is harmful for innovation and new product development. If the Fulghieri and Sevilir (2011) theory is broadly valid, we might expect that human capital relatedness discourages mergers between firms with operations in overlapping industries and similar product markets.

To examine the effect of human capital relatedness on mergers, we start by developing a measure of the relatedness of human capital between pairs of firms. Using data from the Occupational Employment Statistics (OES) of the Bureau of Labor Statistics (BLS), we first construct firms' human capital profiles based on the industries in which a firm's segments operate and the associated industry-based OES occupation profiles. Industries are defined in the OES data by three-digit Standard Industrial Classification (SIC) codes and four-digit North American Industry Classification System (NAICS) codes, and the occupation profiles are vectors containing fractions of a given industry's workers in over 800 different occupations. We use the OES industry occupation profiles and the primary industries in which a firm's segments operate, and we compute the firm's human capital profile as the segment sales-weighted average of its segments' OES industry occupation profiles. Our measure of human capital relatedness (denoted *HCR*) between pairs of firms is a measure of association between the firms' human capital profile vectors. This measure of association is computed as the scalar product of the firms' human capital profile vectors divided by the product of their lengths. It has the convenient properties that it is increasing in the similarity of firms' human capital profiles and is bounded between zero (no association) and one (perfect association).

In probit regressions using a large sample of merging and matched nonmerging firm pairs during the period 1997 to 2012, we find that the likelihood of merger is strongly increasing in *HCR*. When incorporating product market relatedness in the model, we find two features of this relation are especially noteworthy. First, although product market relatedness as measured by Hoberg and Phillips (2010, 2016) also influences the likelihood of merger, it does not subsume the effect of human capital relatedness. The separate effects of human capital relatedness and product market relatedness on merger likelihood are statistically and economically strong. Second, consistent with the theory in Fulghieri and Sevilir (2011), the positive effect of human capital relatedness on the likelihood of merger is attenuated when merging firms operate in similar product markets. Indeed, human capital relatedness decreases the likelihood of merger between firms with operations in the same industries (e.g., horizontal mergers).

We find that combined acquirer and target firm announcement returns (i.e., merger synergy) are strongly increasing in human capital relatedness. A one standard deviation increase in human capital relatedness increases merger synergy by approximately 42% of the combined mean return. We also find a positive relation between human capital relatedness and post-merger operating performance. However, consistent with the result that human capital relatedness is a more important predictor of unrelated acquisitions, we find that product market relatedness significantly attenuates the effect of human capital relatedness on merger gains.

We next examine changes in employment and wages around mergers to investigate possible channels through which human capital relatedness influences the decision to merge and the gains from merger. We find that human capital relatedness predicts decreases in postmerger employment and total salaries relative to premerger levels. These decreases, however, are significant only in unrelated acquisitions. The results are consistent with our argument that human capital relatedness increases the bargaining power of the postmerger firm, allowing it to layoff redundant and/or low quality duplicate workers and extract wage concessions from those that stay. The evidence of no significant change in employment for related mergers is consistent with Fulghieri and Sevilir (2011) who predict that in mergers between firms operating in similar product markets (e.g., horizontal mergers), the postmerger firm will almost always optimally retain both firms' workforces.

Lastly, we use asset sales in a falsification test of our measure of human capital relatedness. Asset sales differ from mergers in that labor may not transfer with the asset sold to the acquiring firm. Nevertheless, human capital relatedness can be computed for the asset and the acquiring firm. If our measure validly reflects an important human capital factor in acquisitions, then acquiring firm returns in asset sales should not be related to human capital relatedness when there is no transfer of employees from the parent to the acquiring firm. To implement this test, we construct a sample of asset sales during the period 1997 to 2013 and compute the change in employment of the parent firm around the asset sale. We then examine the influence of human capital relatedness on acquiring firm announcement returns in subsamples where human capital is likely not transferred (i.e., little or no change in parent firm employment) and when it is transferred. We find little evidence that human capital relatedness influences acquiring firm returns when human capital is not transferred. In contrast, acquiring firm returns are reliably positively related to human capital relatedness when employees accompany the asset. Overall, our measure of human capital relatedness appears to reliably capture value creation in mergers associated with human capital.

Our paper makes two primary contributions to the literature. First, we develop a measure of human capital relatedness between pairs of firms that allows for an examination of the role of human capital in mergers. Second, we show how human capital relatedness contributes to our understanding of both the likelihood and benefits of mergers. Our analysis contributes to the literature that examines the role of asset complementarity and product market relatedness in mergers (e.g., Rhodes-Kropf and Robinson, 2008; Hoberg and Phillips, 2010) by establishing that human capital relatedness is an additional important factor in mergers. As such, human capital relatedness can be viewed as a key determinant of the boundaries of the firm.

Our paper also contributes to a growing literature on the role of labor and human capital in finance. Reviving an important topic, several recent papers examine the role of human capital in asset pricing.[2] Eisfeldt and Papanikolaou (2013) and Donangelo (2014) find that organizational capital (i.e., the production factor embodied in key personnel) and labor mobility, respectively, are priced risks and significantly increase equity returns. The importance of human capital relative to other asset classes is supported by Palacios (2015) who estimates that the weight of human capital in aggregate wealth is over 90%. In the mergers and acquisitions literature, Gao and Ma (2016) and Ouimet and Zarutskie (2016) find evidence that firms pursue mergers and acquisitions to acquire employees.[3] Along similar lines, Tate and Yang (2016) find that inter-industry worker mobility motivates diversifying acquisitions.[4] They show that labor productivity increases and the likelihood of divestiture decreases when firms undertake diversifying acquisitions in industries with high human capital transferability. Still other papers

[2] See Mayers (1972, 1973) and Fama and Schwert (1977) for the seminal papers on human capital and capital asset pricing.
[3] However, John, Knyazeva, and Knyazeva (2015) find that employee-shareholder conflicts decrease gains from mergers and acquisitions. See also Kole and Lehn (2000) for an analysis of how the complexities of workforce integration can destroy value in mergers.
[4] Tate and Yang (2015) find that workers in diversified firms develop skills that transfer across multiple lines of business, allowing diversified firms to benefit from a real option to redeploy labor in response to changing opportunities.

examine the role of human capital in corporate financing decisions (see, e.g., Berk, Stanton, and Zechner, 2010; Chemmanur, Cheng, and Zhang, 2013; Agrawal and Matsa, 2013).

Our paper is also related to the literature in strategy that draws on the resource-based view of the firm developed by Wernerfelt (1984). This view argues that a key factor motivating merger and acquisition activity is the exchange of firm-specific resources that are otherwise difficult to access because of high inter-firm transaction costs. The literature examines how the relatedness of worker skills and products (Farjoun, 1994, 1998), inter-industry labor mobility (Neffke and Henning, 2013), and marketing resources (Capron and Hulland, 1999) influence acquisition decisions. Lastly, our analysis of the influence of human capital relatedness on postmerger employment and wages is related to a literature in economics and strategy that studies the employment effects of mergers.[5]

The remainder of the paper is organized as follows. Section 2 develops testable hypotheses for the impact of human capital relatedness on mergers. Section 3 describes the data and discusses the construction of our human capital relatedness measure. Section 4 presents empirical tests of the impact of human capital relatedness on the likelihood of merger and merger returns. Section 5 presents empirical tests of the impact of human capital relatedness on postmerger operating performance, employment, wages, and labor efficiency. Section 6 uses asset sales in a falsification test of our human capital relatedness measure. Section 7 concludes.

2. Hypotheses

The property rights theory of the firm developed by Grossman and Hart (1986) and Hart and Moore (1990) and its extension to a theory of mergers by Rhodes-Kropf and Robinson

[5] Papers in this literature include Shleiffer and Summers (1988), Brown and Medoff (1988), Conyon et al. (2002), Krishnan, Hitt, and Park (2007), and Amess, Girma, and Wright (2014).

(2008), posits that complementary assets should be combined under common ownership in a world with incomplete contracting. The key implication of this theory is that when there are significant pair-wise complementarities between firms' assets, synergy gains can result from mergers. In principle, capitalizing on real asset complementarities is straightforward, since complementary assets can be purchased and combined under common ownership.[6] The same may not be true for human capital, since labor is rented and not owned. For instance, target employees, albeit desired by the acquiring firm, can be unhappy with their new position after the merger, which can lead to low productivity or even departure. Thus, mergers motivated by complementary human capital can have difficulty realizing gains because it may not be easy for an acquiring firm to retain and redeploy the target workforce, or fire low quality and/or duplicate employees to reduce labor costs and enhance productivity.[7]

To understand how complementary human capital can influence mergers and acquisitions, consider how human capital relatedness (i.e., overlapping job duties and skills among acquirer and target workforces) influences the bargaining power of the acquiring firm relative to the merged firm's employees. We argue that high human capital relatedness (*HCR*) enhances acquiring firm bargaining power, giving the acquirer greater ability to retain and redeploy desired employees at possibly lower wages and layoff/fire redundant, poor quality employees. Thus, if there is considerable overlap in the acquiring and target firm workforces (i.e., high *HCR*), the postmerger firm should enjoy greater ability to extract concessions from employees in the form of lower wages, or give the firm the option to retain only the most

[6] Hoberg and Phillips (2010) argue that mergers between firms with related products allow for valuable complementarity through the creation of new products. Sheen (2014) shows that mergers between product market competitors can achieve synergy by cost savings from consolidating production. Bena and Li (2014) show that technology overlap can create synergy in mergers and improve postmerger innovation activity.

[7] Horizontal mergers motivated by a desire to cut costs by firing target employees can run into problems from unions and policy makers (see, e.g., Brown and Medoff, 1988; Shleifer and Summers, 1988; Rosett, 1990; Ouimet and Zarutskie, 2016; Tian and Wang, 2016).

productive components of the duplicative workforce. Indeed, the postmerger firm can choose to keep both workforces intact and winner-pick in the sense of Stein (1997).[8] Thus, human capital relatedness should allow for greater human capital complementarities in mergers. In contrast, such benefits may not be possible if the acquirer and target have low human capital relatedness, since the lack of workforce overlap can increase the bargaining power of employees and enhance their ability to extract rents from the postmerger firm.

To illustrate these ideas, consider the following toy example of a coffee shop acquiring a bakery. Initially, assume the coffee shop has three employees—barista (owner), marketer, and accountant, and the bakery also has three employees—baker (owner), marketer, and accountant. We assume the coffee shop sells only coffee and the bakery sells only pastries. A merger between the two businesses is motivated by complementary human capital. For example, the barista and baker can collaborate to create a new menu, and the marketers can join forces to create an innovative marketing plan to promote the new menu.

The high *HCR* (0.67) of the two businesses—reflecting the marketers and accountants—enhances the acquirer's (barista) bargaining power with the merged firm's employees. Since the two accountants do not have business-specific job skills, the acquirer can layoff one and keep the other at equal or lower wage. The latter will depend on the going wage in the market for accountants and the ease with which the acquirer can hire an equally skilled accountant from outside the merged firm. The acquirer (barista) can also use the overlap of marketing skills to her advantage. On the one hand, as with the accounting overlap, she could choose the higher quality marketer and let go the poorly performing (or overpaid) one. On the other hand, she can choose

[8] Stein (1997) argues that internal capital markets can add value when corporate headquarters winner-pick by allocating funds to projects with better relative prospects. Fulghieri and Sevilir (2011) argue that mergers between firms with overlapping workforces give postmerger management the option to retain both workforces and increase the chances of developing innovations or winner-picking the best innovation. We discuss the implications of the Fulghieri and Sevilir (2011) theoretical analysis for our empirical predictions below.

to capitalize on the complementarities provided by having two marketers. By keeping both, she receives an insurance benefit in the sense that it increases the likelihood of developing a winning marketing strategy or allows her to winner-pick the most innovative marketing strategy. The merged firm may also be able to extract greater rents from both marketers, since they do a common job that reduces the competition for their services.

Now, let's assume the coffee shop (acquirer) has two employees—barista (owner) and accountant, and the bakery has two employees—baker (owner) and marketer. Since there is no overlap in the workforces (*HCR* = 0), the acquirer (barista) will not be able to layoff the accountant or generate the insurance benefit from having two marketers, and she may have to pay the marketer and accountant a higher wage to compensate for the additional complexity and duties of the merged business. The merger may still go through due to the complementarity between the barista and baker, but the lack of human capital relatedness should make it more costly and lower the benefits.

The two cases make several important points about how human capital relatedness is likely to influence merger decisions and outcomes. First, even if both cases result in the same postmerger employment (one barista, one baker, one marketer, and one accountant), the acquirer benefits more when *HCR* is high than when it is low. Thus, when *HCR* is high, the acquirer can reduce wages by laying off one of the accountants, and she can choose the higher quality marketer and pay him/her a lower wage for marketing services. Second, given the greater benefits to the acquirer when *HCR* is high, all else being equal, the likelihood of a merger should be increasing in *HCR*. Third, in comparison to premerger quantities, postmerger employment and wages are likely lower and labor productivity higher when *HCR* is high than when it is low. At the employee level, we see that high *HCR* is likely to lead to layoffs, and so one might argue that

HCR captures a substitution effect rather than complementarity. However, at the firm level (business level in our example), high *HCR* brings complementary human capital together under common ownership.

We formalize this discussion with the following testable hypotheses.

Hypothesis 1. The likelihood of two firms merging is increasing in the relatedness of their human capital.

Hypothesis 2. The gains from merger are increasing in the relatedness of merging firms' human capital.

Our tests measure merger gains using stock price reaction to the deal and postmerger operating performance. We discuss our measure of human capital relatedness in the next section. Lastly, the discussion suggests that key channels that drive higher postmerger performance are a leaner workforce, lower wages, and higher overall labor productivity. This leads to our third hypothesis.[9]

Hypothesis 3. Postmerger employment and wages are decreasing and labor productivity increasing in the relatedness of merging firms' human capital.

An important consideration is whether the type of merger and/or degree of product market relatedness influence the association between human capital relatedness and the likelihood and gains from merger. The discussion above implicitly focused on how human capital complementarities can be harvested from unrelated mergers because the coffee shop and bakery operate in different product markets. But what might we expect for a merger between firms with a high degree of human capital relatedness and product market relatedness, such as the merger of two coffee shops or two bakeries? Theoretical work by Fulghieri and Sevilir (2011) helps to answer this question.

[9] We thank the referee for suggesting that we test this hypothesis.

Fulghieri and Sevilir (2011) study how horizontal mergers between firms operating in similar product markets influence employee incentives to innovate and develop new products. From a human capital perspective, the benefit from combining merging firms' employees is that it increases the chances of producing innovations or allows the firm to winner-pick the best innovations. As such, when a merger takes place with a high degree of product market relatedness, it is almost always optimal for the postmerger firm to retain both firms' employees. This benefit of merging is offset, however, by a reduction in incentives to innovate due to a decrease in rewards from innovation. This happens because a merger between firms in the same product market reduces competition for human capital and allows the postmerger firm to extract greater rents from employees. The net result is that it can be optimal for firms competing in the same product market to remain as standalone firms, even if the merger reduces product market competition and thereby enhances profitability.

We can draw the following implications from the theoretical analysis in Fulghieri and Sevilir (2011). First, all else being the same, the likelihood of a merger should be decreasing (or at least not increasing) in human capital relatedness when product market relatedness is also high (e.g., when two firms have operations in overlapping industries, or when two firms operate in the same product space and a merger would be classified as horizontal). Second, we expect the gains from merger are lower when high human capital relatedness is accompanied by high product market relatedness.[10] Third, mergers between firms with high product and human capital relatedness would not be expected to lower total employment, as the postmerger firm more

[10] Fulghieri and Sevilir (2011, p. 2209) describe their result as follows: "This happens precisely because the merger has a negative effect on employee incentives to innovate. Hence, our article offers an explanation for why many mergers fail to create value, and why mergers might be bad for innovation and development of new products." Consistent with the idea that employee incentives are dampened after the merger of firms with high human and product market relatedness, Venkat (2016) finds that analyst forecast errors are significantly larger for up to two years following brokerage house mergers.

highly values the coinsurance provided by both firms' employees than the option to reduce wages by downsizing.[11]

3. Data and variables

3.1. Sample construction

We construct our sample from all US domestic mergers and acquisitions (M&A) reported in the Thompson Financial Securities Data Company (SDC) database over the period from 1997 to 2012. The sample ends in 2012 to allow for sufficient time after mergers occurring toward the end of the sample period to construct postmerger operating performance. We require that the deal is classified as a merger, an acquisition of majority interest, or an acquisition of assets. These requirements result in an initial sample of 29,305 M&A deals. We further require that both the acquirer and target have financial statement data reported in Compustat and stock returns available from the Center for Research in Security Prices (CRSP). This necessitates that both the acquirer and target are publicly traded firms, and reduces the sample to 1,474 M&A deals.

The analysis in Section 2 suggests that a key dimension of human capital complementarity is the degree to which merging firms have related human capital. To construct such a measure, at a minimum, we would like to have information on job titles, duties, wages, and a measure of the significance of each job title to the overall labor profile of merging firms (e.g., the fraction of employees performing a specific job). Unfortunately, there is a lack of publicly available data on workers at the firm level. We therefore use data from the OES program of the BLS to construct our human capital measure.

[11] We would also expect little change in employment and wages for (horizontal) mergers motivated by economies of scale.

The OES program surveys approximately 1.2 million nonfarm businesses in the US over three-year intervals (200,000 businesses every six months), collecting wage and employment data on over 800 occupations. The program reports this data at the aggregate level for the US by state, metropolitan area, and industry. We use the industry occupation data and the Compustat Industry Segment (CIS) database to construct a proxy for a firm's human capital profile based on the industries in which it operates. An important caveat is that our measure assumes the distribution of occupations at the industry level reasonably approximates the distribution of occupations for a firm in the industry. Our measure will not capture potentially important firm-specific diversity in human capital.

OES data is available from 1988. Prior to 1996, however, the OES program only collected occupation employment data for selected industries. This is the primary reason why we start our merger sample in 1997.[12] Industries are defined in the OES data using three-digit SIC codes up through 2001, and four-digit NAICS codes from 2002. The OES program collected number of employees and salary information for occupations based on the OES taxonomy of occupations prior to 1999. For years starting in 1999, the OES program switched to the more detailed Office of Management and Budget (OMB) Standard Occupational Classification (SOC) taxonomy of occupations. In comparison to the 258 occupations under the OES taxonomy, the SOC taxonomy has over 800 detailed occupations.[13] For mergers prior to 1999 (i.e., sample years

[12] Since we use lagged values in our multivariate analysis, and since OES data is missing in 1996, we use OES data in 1995 to construct human capital profiles for merging firms in 1997. Our results are unaffected if we start our merger sample in 1998.

[13] SOC classifies workers by major group, minor group, broad occupation, and detailed occupation. For example, in 2010, there were 23 major groups, 97 minor groups, 461 broad groups, and 840 detailed occupations. Each detailed occupation has a unique six-digit code with the first two digits indicating the major group, the first three digits indicating the minor group, and the first five digits indicating the broad group. For example, the detailed occupation Biochemist (19-1021), is in the major group life, physical, and social science occupations (19-0000), the minor group ife cientists (19-1000), and the broad group biological scientists (19-1020). Note that major group codes end in 0000, minor group codes end in 000, and broad groups end in 0. The dash after the first two digits is to make the numbers easier to read.

1997 and 1998), we use the OES taxonomy of occupations to construct acquirer and target human capital profiles. We use the detailed SOC taxonomy of occupations for all other merging firms in the sample.

In each sample year and for each three-digit SIC code before 2002 and four-digit NAICS code thereafter, we obtain an industry occupation profile vector from the OES program website (www.bls.gov/oes/) with elements equal to the proportion of total employment in the industry's occupations. Thus, for industry i in year t we obtain the vector $O_{it} = (O_{i1}, \ldots, O_{ik})_t$, where element O_{ij} is the proportion of the total number of workers in industry i assigned to occupation j. We use these industry occupation profile vectors and the industries in which a firm operates to compute a human capital profile, H, for each merging firm (acquirers and targets) in the sample in the year prior to the merger.

A firm's industries and the weight to attach to each industry are based on industry segment data from the CIS database. We first identify the number of industries, I, in which a firm operates and the number of unique occupations, N, across these industries. We then increase the number of occupations in each of the firm's industry profile vectors, O_i, to reflect the number of unique occupations, N. The augmented industry profile vectors, O_i', now have a common number of occupations (N) equal to the occupations in the industry, n_i, plus the additional occupations, $N - n_i$, in the firm's other industries, where the n_i elements are O_{ij} (i.e., the original employment proportions) and the $N - n_i$ elements are zeros. The firm's human capital profile vector, H, is then computed as $H = \sum_{i=1}^{I} w_i O_i'$, where the weights, w_i, are equal to segment sales to total segment sales.[14] For the 1,474 M&A deals with CRSP and Compustat

[14] We use industry segment information from SDC when a firm is not covered by CIS. The limitation is that the SDC dataset does not provide segment sales or any other information that could be used to weight a firm's industry

information, we can compute human capital profiles for 1,322 acquirer and target pairs (i.e., 2,644 firms) at the fiscal year-end immediately prior to the merger year. We lose 152 (1,474 – 1,322) deals because none of the industry segments of either the acquirer or target are covered by OES data.

3.2. Human capital relatedness

We construct a measure of human capital relatedness between merging firms A (acquirer) and T (target) using the angular separation (or uncentered correlation) of their human capital profile vectors H_A and H_T (see, e.g., Jaffe, 1986). Specifically, human capital relatedness, HCR, is computed as the scalar product of the merging firms' human capital profile vectors divided by the product of their lengths:[15]

$$HCR = \frac{H_A H_T'}{\sqrt{H_A H_A'}\sqrt{H_T H_T'}}. \tag{1}$$

HCR is bounded between zero and one; it is zero for merging firms whose human capital profile vectors are orthogonal and unity for merging firms whose human capital profile vectors are identical. Importantly, it is closer to unity for merging firms with more related human capital.

To illustrate the computation and interpretation of *HCR*, consider the acquisition of Summit American Television by E. W. Scripps Company. On December 19, 2003, an American media conglomerate, E. W. Scripps Company (EWS) announced plans to buy Summit America Television (SAT). As shown below, at the fiscal year-end 2002, EWS had four segments with different four-digit NAICS codes. The largest segment has a NAICS code of 5151 (radio and

occupation profiles. For this reason, when using SDC for industry segment information, we compute a firm's human capital profile, H, as the equally weighted average of its segments' industry occupation profiles.

[15] Obviously, the vectors H_A and H_T must have a common number of elements, N, to compute HCR. Similar to the construction of H discussed above, if $N_A \neq N_T$, we find the number of unique occupations across the merging firms, N, and we increase the size of H_A (H_T) by including zeros for the $N - N_A$ ($N - N_T$) occupations that are unique to the target (acquiring) firm.

television broadcasting), and its sales account for 47% of the firm's total sales. According to OES

Acquisition of Summit American Television by E. W. Scripps
Segment sales weights are based on industry segment data from the CIS database at the fiscal year-end 2002. The number of occupations by four-digit NAICS codes are from 2002 OES data. The merger was announced on December 19, 2003.

Acquirer: E. W. Scripps (EWS)			Target: Summit American TV (SAT)		
Segment NAICS	Sales weight	No. of occupations	Segment NAICS	Sales weight	No. of occupations
5151	47%	118	4541	100%	147
5111	44%	174			
5331	6%	80			
4541	3%	147			
Total	100%	221*	Total	100%	147

*This is the total number of unique occupations across the four industries.

data, this industry has 118 occupations. The next largest segment, NAICS code 5111 (newspaper, periodical, book, and directory publishers), accounts for 44% of total sales and has 174 occupations. The remaining segments, NAICS codes 5331 (lessors of nonfinancial intangible assets) and 4541 (electronic shopping and mail-order houses), account for only 6% and 3% of total firm sales and have 80 and 147 occupations, respectively.

The human capital profile of EWS, H_{EWS}, is a segment sales weighted average of its four industry segments' human capital profile vectors. Consider, for example, the occupation graphic designer in EWS's human capital profile vector.[16] The percentage of employees working in this occupation in EWS's industry segments (NAICS codes 5151, 5111, 5331, and 4541) are 0.38%, 3.03%, 0.88%, and 0.70%, respectively. Using segment sales weights, the graphic designer element in H_{EWS} is computed as (0.47)(0.38%) + (0.44)(3.03%) + (0.06)(0.88%) +

[16] In the SOC taxonomy, the broad occupation designers (27-1020) includes the detailed occupations commercial and industrial designers (27-1021), fashion designers (27-1022), floral designers (27-1023), graphic designers (27-1024), interior designers (27-1025), merchandise displayers and window trimmers (27-1026), set and exhibit designers (27-1027), and designers, all others (27-1029).

(0.03)(0.70%) = 1.59%. Other elements in H_{EWS} (i.e., the percentage of EWS's workers in other occupations) are similarly computed.

The target company, SAT, is a single-segment company. The firm's four-digit NAICS code 4541 has 147 different occupations. The firm's human capital profile vector, H_{SAT}, is the same as the human capital profile vector of NAICS industry 4541; however, we increase the size of the vector to 221 occupations to account for the 74 (221 − 147) occupations that are unique to the industries covered by EWS. These additional 74 occupations in H_{SAT} will have entries of zero.

The human capital relatedness (HCR) of EWS and SAT is the product of the merging firms' human capital profiles vectors scaled by the product of their lengths. The product is 93.11, and the lengths are 13.41 for EWS and 22.22 for SAT, so that $HCR = 0.31$. Note that the two firms share only one segment (NAICS 4541), and this segment represents only 3% of the acquirer's sales. Thus, although the two firms appear to have minimal product market relatedness, their human capital is nontrivially related. The reason, as illustrated in the graphic designer job title example above, is that different industries have considerable overlap in occupations.

3.3. Product market relatedness

Hoberg and Phillips (2010) argue that product market relatedness between merging firms can lead to asset complementarity and the innovation of new products. As discussed in Section 2, product market relatedness, which should be linked to merger type (e.g., horizontal mergers), is predicted to influence the relation between human capital relatedness and merger likelihood and performance. We therefore include a measure of product market relatedness and the interaction between human and product market relatedness in our empirical tests.

We use the Hoberg and Phillips (2010, 2016) text-based measure of product market relatedness in our tests. Hoberg and Phillips analyze the relation between firms' product descriptions in 10-K annual filings in the Securities and Exchange Commission (SEC) Edgar database. Based on a comparison of key words in these descriptions, they compute product similarity scores between all pairs of firms with data in both CRSP and Compustat. The product similarity score between any two firms falls in the range from zero to one, with the score increasing as firms have more product description words in common. In an online data library, Hoberg and Phillips report firm pairs that have a product similarity score above a threshold.[17] We create a dummy variable, *PMR*, equal to one if merging firm pairs in our sample are classified by Hoberg and Phillips as having related product markets, and zero otherwise.

3.4. Control variables

We build on studies by Song and Walkling (1993), Harford (1999), Wang and Xie (2009), Ahern (2012), and Ishii and Xuan (2014) and control for many deal and merging firm characteristics in our multivariate tests. The deal characteristics we include are relative size of target to the acquirer, method of payment, type of merger (e.g., horizontal or conglomerate), and whether the deal has a termination fee. The bidder and target characteristics we include are firm size, market-to-book, leverage, free cash flow, cash holdings, sales growth, prior stock returns, and return on assets. All firm characteristics, except prior stock returns, are measured at the fiscal year-end immediately prior to the acquisition announcement date. Since our analysis examines the likelihood of acquisition, stock price reaction to merger announcement, and postmerger profitability, we defer discussion of the relations between the control variables and merger

[17] Hoberg and Phillips (2016) explain how the similarity score threshold is computed on page 1437. The online data library can be found at http://cwis.usc.edu/projects/industrydata/. We thank them for making this data available.

outcomes to Section 4. Appendix A contains the definitions of all variables that we use in our empirical tests.

3.5. Descriptive statistics

Panel A of Table 1 provides descriptive statistics for the sample of 1,322 mergers over the period from 1997 to 2012. All variables are winsorized at the 1st and 99th percentiles of their distributions except human capital relatedness (*HCR*), product market relatedness (*PMR*), and dummy variables. Thirty five percent of the merging firms in the sample have no industries in common, based on a comparison of three-digit SIC codes for the merging firms' segments. This includes 19% of the sample involving mergers between single segment firms in different industries (*MergerType*1) and 16% of the sample involving mergers where one or both acquirer and target have multiple segments (*MergerType*2). The remaining 65% of the sample has at least one segment in the same industry (*MergerType*3). Following the classification scheme developed by Fan and Goyal (2006), 12% of the acquisitions in our sample are vertical, 41% are horizontal, and 47% are conglomerate.

------- Insert Table 1 near here -------

Recalling that *HCR* is increasing in human capital relatedness and has a maximum value of one, the mean (median) *HCR* of 0.74 (0.84) suggests that the typical merger in our sample has high human capital relatedness. For comparison, we construct samples of randomly paired firms where each merger in the sample has up to ten nonmerging firm pairs in the same year as the merger. We find that the mean (median) *HCR* for the randomly paired samples never exceeds 25% (20%). The larger mean (median) *HCR* in our merger sample suggests that human capital relatedness is an important factor in mergers. Observe also that more than 50% of sample mergers have high product market relatedness (*PMR* = 1).

Average announcement returns (see Appendix A for computation details) are similar to those reported elsewhere.[18] Over the three-day period from one day before to one day after the announcement day, the mean acquiring firm excess return, *Acquirer CAR*, is negative (−1.23%), the mean target firm excess return, *Target CAR*, is positive (25.87%), and the weighted-average acquirer and target excess return, *Synergy*, is positive (1.48%). The later result indicates that acquisitions, on average, create wealth. The remainder of Panel A reports descriptive statistics of the deals and acquirer and target characteristics. More than 50% of the deals involve some stock financing, and the average (median) relative size of the target to the acquirer is 0.24 (0.10). In comparison to the target, the acquiring firm has larger mean and median market-to-book ratio, free cash flow, stock returns prior to the deal, and return on assets.

Panel B of Table 1 reports correlations between *HCR*, *PMR*, *Synergy*, *Acquirer CAR*, *Target CAR*, and all other deal and firm characteristics. The correlation between *HCR* and *PMR* is positive (0.26). This is intuitive, as a high degree of product similarity likely maps into many similar job titles. The correlations between *HCR* and *PMR* and merger types are consistently positive when merging firms have overlapping industries (i.e., *MergerType*3 and *Horizontal*) and negative when merging firms are in unrelated industries (i.e., *MergerType*1, *MergerType*2, *Vertical*, and *Conglomerate*). There is less evidence, however, that *HCR* and *PMR* are related to merger returns, since neither measure is related to acquirer or target returns, and the correlations with the combined return (*Synergy*) are positive, but quite modest.

4. Merger prediction and returns

4.1. Predicting mergers

[18] See Andrade, Mitchell, and Stafford (2001) and Betton, Eckbo, and Thorburn (2008) for surveys.

We test whether the likelihood of merger is increasing in the relatedness of firms' human capital (Hypothesis 1) in probit regressions estimated with our merger sample and a control sample of nonmerging firm pairs. In regressions reported in Table 2, each merging firm pair has one matching nonmerging firm pair (pseudo acquirer and pseudo target) having the same vertical relation, product similarity, number of segments, total assets, and market-to-book ratio. Appendix B (Control sample 1) describes the algorithm that we use to construct the nonmerging control sample.[19] The explanatory variables in the first three regressions are *HCR* (1), *HCR* and *PMR* (2), and *HCR*, *PMR*, and *HCR* × *PMR* (3). Regressions (4)–(6) are identical except they include all of the deal and firm characteristic control variables. All right-hand-side variables are lagged one year. Coefficients, *z*-statistics (in parenthesis), and economic significance are reported for each variable. Economic significance is the change in the probability of merger for a one standard deviation increase for continuous variables or a change from zero to one for dummy variables. Economic significance and standard errors for interactions (e.g., *HCR* × *PMR*) are computed using the methods in Ai and Norton (2003). The *z*-values are computed using robust standard errors clustered by year.

------- Insert Table 2 near here -------

Across all regressions reported in Table 2, the coefficient on *HCR* is significantly positive. However, notice that the estimates vary from a low of 0.314 in regression (2) to a high of 0.834 in regression (3). The cause of this instability is the addition of *PMR* in (2) and the further addition of the interaction between *HCR* and *PMR* in (3). The correlation between *HCR* and *PMR* in the sample is 0.26 (Panel B in Table 1), which although relatively high, is not

[19] We report in the online Internet Appendix probit regressions for the probability of merger that use two additional control samples of nonmerging firm pairs. Appendix B (Control samples 2 and 3) describes the algorithms that we use to construct these alternative control samples. The results using these control samples are very similar to those reported in Table 2.

suggestive of concerning multicollinearity. Additionally, the variance inflation factor (VIF) of *PMR* is below ten, a standard rule of thumb threshold for the detection of multicollinearity (e.g., Kennedy, 2003). Since theory strongly suggests that *PMR* (and its interaction with *HCR*) belongs in our models, excluding it can lead to specification error. To balance concern for specification error and multicollinearity, we will continue to report regressions in subsequent tests with and without *PMR*. Nevertheless, we will focus most of our attention on coefficient estimates in complete specifications with *PMR*, *HCR* × *PMR*, and deal and firm characteristics.

Overall, consistent with Hypothesis 1, the positive coefficients on *HCR* in Table 2 confirm that human capital relatedness increases the likelihood of merger. Although the economic significance of *HCR* varies across specifications, it is always substantial. For example, using the specification in regression (4), a one standard deviation increase in *HCR* increases the probability of merger by 8%.

Product market relatedness also contributes significantly to the likelihood of merger, as the coefficients on *PMR* in regressions (2), (3), (5), and (6) are positive and highly statistically and economically significant. Interestingly, the coefficients on *HCR* × *PMR* in regressions (3) and (6) are significantly negative, revealing that high product market relatedness (*PMR* = 1) mitigates the positive effect of *HCR* on the likelihood of merger. As discussed in Section 2, this is consistent with a prediction in Fulghieri and Sevilir (2011) who argue there is a decreased incentive to merge when both human capital relatedness and product market relatedness are high. The reason is that a merger between firms operating in the same product markets dampens employee incentives to innovate because the merger decreases competition for human capital, allowing the postmerger firm to offer lower rewards to employees.

Many of the control variables in regressions (4)–(6) are reliable predictors of mergers. Consistent with Song and Walkling (1993), Comment and Schwert (1995), and Harford (1999), acquisitions are more likely when acquirers are large and targets are small. The acquirer also tends to have high growth opportunities, as reflected in the reliably positive coefficient on the acquirer's market-to-book ratio and sales growth in all regressions. Consistent with results in Song and Walkling (1993) and Comment and Schwert (1995), however, there is little evidence that target growth opportunities predict takeovers. Lastly, higher free cash flow and lower cash balances and return on assets in acquirers and targets predict mergers. Our finding of negative effects of cash balances for acquirers and targets on the likelihood of merger is partially consistent with Harford's (1999) results. He finds that the likelihood of a firm being a target is negatively related to cash balances, and he conjectures that large cash balances help targets fight takeover attempts. In contrast, he finds that cash-rich firms are more likely to be bidders. Our finding that lower acquirer cash predicts mergers seems inconsistent with these results.

------- Insert Table 3 near here -------

Table 3 examines the influence of merger type on the relation between human capital relatedness and the probability of merger.[20] Columns (1)–(3) report probit regressions where *HCR* is interacted with merger-type dummy variables based on acquirer and target number of segments and industry overlap, and columns (4)–(6) report probit regressions where *HCR* is interacted with dummy variables, reflecting the vertical relation between merging firms. In regressions (1)–(3), *MergerType*1 is a dummy variable equal to one for single-segment acquirer and target in different industries, *MergerType*2 is a dummy variable equal to one when one or both acquirer and target are multi segment with no common industry segments, and

[20] The nonmerging firm control sample is the same one used in Table 2. We report in the online Internet Appendix Table 3 regressions using the two additional control samples discussed in Appendix B.

*MergerType*3 is a dummy variable equal to one when each of the merging firms is either single or multi segment and have at least one segment in the same industry. The dummy variables *Vertical*, *Horizontal*, and *Conglomerate* in regressions (4)–(6) are equal to one for vertical, horizontal, and conglomerate mergers, respectively, and they are constructed using the algorithm in Fan and Goyal (2006), which is based on the input-output table from the Bureau of Economic Analysis. The merger-type dummy variables in regressions (1)–(3) and the vertical relation dummy variables in regressions (4)–(6) are defined for both the merger sample and the control sample of nonmerging firm pairs (i.e., pseudo acquirers and pseudo targets). All regressions are estimated without an intercept, so the coefficients on *HCR* interacted with the merger-type dummy variables are the effects of *HCR* on the likelihood of merger for that merger type. Additionally, all regressions include the control variables used in Table 2, but we do not report coefficient estimates on control variables to save space.

We see in regressions (1)–(3) that the coefficients on the interactions of *HCR* and *MergerType*1 and *MergerType*2 are positive, while the coefficients on the interactions of *HCR* and *MergerType*3 are negative. The implication is that human capital relatedness predicts mergers of unrelated firms, but not related firms. A similar story emerges in regressions (4)–(6); the likelihood of vertical and conglomerate mergers is increasing in *HCR*, while the likelihood of horizontal mergers is decreasing in *HCR*. These findings are consistent with the negative effect of *HCR* × *PMR* on the likelihood of merger in Table 2. When firms are related along product market dimensions, human capital relatedness can discourage mergers because employee incentives are lower due to a decrease in competition for their services within the industry/product market. In effect, employees have fewer outside options, because the merger helps to consolidate the industry/product market among a smaller number of firms. This effect does not take place in unrelated mergers, since the merger has no influence on the number of competitors in the merging firms' product spaces and/or industries in which they compete.[21] Consistent with this interpretation, observe in regressions (3) and (6) that when *HCR* is interacted with merger type, the negative coefficients on *HCR* × *PMR* are smaller in absolute value (relative to regression (6) in Table 2) and are not significant (6) or marginally significant (3).[22]

4.2. Merger synergy

In this section, we test whether the gains from merger are increasing in the relatedness of firms' human capital (Hypothesis 2). We argue in Section 2 that human capital relatedness gives the postmerger firm greater bargaining power to extract wage concessions from employees and retain only the most productive components of the merged firms' workforces. The firm also has the option to keep related components of the merged firms' workforces intact and winner-pick the best ideas, innovations, and solutions to problems. Thus, human capital relatedness should allow for complementarities that create value in mergers.

We measure the gains from merger with the variable *Synergy*, which is computed as the weighted average of the cumulative abnormal returns of acquirer and target equity over days −1, 0, and +1, where day 0 is the merger announcement day. The weights are based on the market values of acquirer and target equity four days prior to the merger announcement day. Table 4 reports in columns (1)–(6), respectively, OLS regressions of *Synergy* on *HCR*, *HCR* and *PMR*,

[21] Fulghieri and Sevilir (2011) predict that if mergers do take place between firms operating in related product markets (e.g., a horizontal merger), we are unlikely to see a postmerger reduction in employment. They show that it is generally optimal to combine the two highly related work forces to capitalize on the coinsurance benefits (e.g., winner-picking) of having overlapping employee skills. We test this prediction in Section 5.

[22] We find virtually identical results to those reported in Table 3 when we estimate probit regressions of the likelihood of merger by merger-type subsamples. These regressions are reported in the online Internet Appendix. There we report six probit regression specifications for each of six merger-type subsamples for each of the three different control samples discussed in Appendix B.

HCR, *PMR*, and *HCR* × *PMR*, and the corresponding regressions with control variables for deal and merging firm characteristics. Right-hand-side variables are measured at time $t-1$, except for relative size and the stock deal and termination fee dummy variables. All variables are defined in Appendix A, which also contains details on the computation of abnormal returns used to construct *Synergy*. We report *t*-statistics in parentheses below parameter estimates that are computed using robust standard errors clustered at the year level.

------- Insert Table 4 near here -------

The regressions in Table 4 show that *HCR* has a significantly positive effect on *Synergy*.[23] Similar to the probit regressions, however, the stability of the coefficients on *HCR* are sensitive to the inclusion of *PMR* and *HCR* × *PMR*. The VIF of both variables is below ten, so we are only mildly concerned about multicollinearity. Furthermore, the statistical significance of the coefficient estimate on *HCR* only takes a small hit when *PMR* is added to the specification and significantly improves when in turn *HCR* × *PMR* and the control variables are added to the specification. Concerning levels of multicollinearity typically increase the variance of the coefficient estimates, and the statistical significance of *HCR* should decrease rather than increase. Since we believe there are strong theoretical grounds to include *PMR* in the model, we are mindful of but willing to accept the consequences of some degree of multicollinearity. Overall, we think the regressions provide solid support for the prediction that human capital relatedness increases the synergy gains from merger.

Using the regression reported in column (6), the marginal effect of *HCR* on *Synergy* when *PMR* = 0 is positive, and a one standard deviation increase in *HCR* increases *Synergy* by approximately 42% of its mean. In contrast, the marginal effect of *HCR* on *Synergy* when *PMR* =

[23] Although not reported, the effects of *HCR* on the returns of acquirers and targets are positive, but not statistically significant.

1 is negative. This illustrates from a valuation perspective the result shown in the probit regressions that high human and product market relatedness discourages mergers because it has a negative effect on employee incentives. Our results show that the positive influence of *HCR* on the synergy gains from merger is completely wiped out when the merging firms are in related product markets. We investigate below how this negative effect of joint human and product market relatedness varies by whether merging firms are in related or unrelated industries.

The coefficients on the deal and firm characteristics are consistent with results reported in the literature for combined acquirer and target returns (see, e.g., Wang and Xie, 2009; Ahern, 2012; Ishii and Xuan, 2014). As expected, merger synergy is decreasing in the size of the acquirer, target market-to-book, target leverage, prior returns of the acquirer, and whether the deal is stock financed; merger synergy is increasing in the relative size of the target and acquirer leverage. The negative coefficient on target cash is consistent with the probit result that target cash decreases the likelihood of acquisition because a large cash stockpile allows the target to deter the acquisition. Lastly, we see that target termination fees have an insignificantly positive effect on merger synergy (consistent with Ahern, 2012), and acquirer termination fees significantly decrease merger synergy. To our knowledge, the significantly negative effect of acquirer termination fees on merger synergy is new to the literature, which finds that target and acquirer termination fees have no effect on target or bidder returns after controlling for other deal and firm characteristics (see, e.g., Bates and Lemmon, 2003; Officer, 2003).

------- Insert Table 5 near here -------

Table 5 reports merger synergy robustness regressions. In regression (1), we exclude mergers where the acquirer and target are single segment and from the same industry (i.e., mergers where *HCR* = 1). Excluding these observations has no effect on our results; the main effects of *HCR* and *PMR* are positive, and their interaction is negative. Regressions (2) and (3) are estimated, respectively, for the subsamples of mergers where *PMR* = 0 and *PMR* = 1. These subsample regressions confirm that the effect of *HCR* on *Synergy* is positive when *PMR* = 0 and zero when *PMR* = 1. Regression (4) is a robust regression that uses a two-step procedure to reduce the impact of outliers on the estimated coefficients. In the first step, we follow Bollen and Jackman (1990) and drop influential outliers with a Cook's D greater than 4/*N*, where *N* is the number of observations used to estimate the regression. In the second step, an iterative procedure following Li (2006) reduces the weight of observations with large absolute residuals. The coefficients on *HCR* and *PMR* are smaller—by 40% and 17%, respectively—but continue to be statistically and economically significant. Finally, in unreported regressions, our results are not sensitive to using a wider event window around the merger announcement to compute merger synergy (e.g., −2 to +2 and −3 to +3).

Table 6 examines the relation between *HCR* and *Synergy* for unrelated and related mergers. Columns (1)–(3) report OLS regressions when merging firms are grouped by single-segment acquirer and target in different industries (*MergerType*1), multi-segment acquirer and/or target in different industries (*MergerType*2), and multi-segment acquirer and/or target with industry overlap (*MergerType*3). We interact *HCR* with *MergerType*1–*MergerType*3 in regressions (1) and (2), and we use only the *MergerType*2 subsample in regression (3). Columns (4) and (5) report OLS regressions when the sample is grouped by *Vertical*, *Horizontal*, and *Conglomerate* mergers using the algorithm in Fan and Goyal (2006). We interact *HCR* with these merger indicator variables in regression (4), and we use only the *Conglomerate* subsample in regression (5).

------- Insert Table 6 near here -------

The coefficients on the interactions in regression (1) are positive, but only the one on *HCR* × *MergerType*2 is significant. Excluding mergers where *HCR* = 1 (i.e., single segment merging firms in the same industry) in regression (2) produces virtually identical results. In regressions using merger-type subsamples, we find that mergers classified as *MergerType*2 are the only ones with a significantly positive coefficient on *HCR* as reported in (3). The regressions in (4) and (5) similarly show that *HCR* has a significantly positive effect on *Synergy* only in unrelated (*Conglomerate*) mergers.

Overall, the results in Table 6 are consistent with the theory of Fulghieri and Sevilir (2011), which posits that human capital relatedness is less valuable in horizontal mergers or mergers between firms operating in similar product markets. The reason, as discussed above, is that mergers between firms operating in the same product market(s) decrease labor competition, which reduces the value of a worker's outside options and negatively effects wages and incentives. Fulghieri and Sevilir (2011) also show that in these types of mergers, it is almost always optimal for the postmerger firm to retain duplicate work forces and winner-pick. The implication is that postmerger employment in mergers between firms in overlapping industries or that operate in related product markets may not change from the sum of premerger levels. We examine postmerger changes in employment and wages in the next section.

5. Postmerger outcomes

5.1. Operating performance

We test whether human capital relatedness of merging firms influences postmerger operating performance (Hypothesis 2) in Table 7. Following Hoberg and Phillips (2010), operating performance is the change in postmerger industry-adjusted operating performance from year +1 to +2 and from year +1 to +3 (one- and two-year horizons, respectively). Operating performance is measured as the ratio of operating income before depreciation to total net sales.[24] Industry-adjusted operating performance is the difference between a firm's operating performance and the median operating performance of firms in the same three-digit SIC code. Panel A (B) reports regressions of postmerger operating performance on *HCR* (*HCR* conditioned by merger type). All regressions include controls for deal and firm characteristics (defined in Appendix A), which are measured at time $t-1$. We report t-statistics in parentheses below parameter estimates that are computed using robust standard errors clustered at the year level.

------- Insert Table 7 near here -------

The coefficients on *HCR* in Panel A are significantly positive, confirming that human capital relatedness predicts postmerger operating performance. The coefficients on *PMR* and the interaction between *HCR* and *PMR*, however, are never significantly different from zero. Analysis of merger type in Panel B confirms that the positive relation between *HCR* and postmerger operating performance is largely driven by unrelated acquisitions (*MergerType*2 and *Conglomerate*), consistent with the results in Section 4 showing that both the likelihood of merger and returns from merger are significantly higher for unrelated acquisitions. We next examine channels through which human capital relatedness can help explain improved postmerger operating performance.

5.2. Changes in employment, wages, and labor productivity

Our discussion in Section 2 suggests that key channels through which human capital relatedness influences postmerger operating performance are through a leaner workforce, lower wages, and higher overall labor productivity (Hypothesis 3). The prediction of postmerger

[24] Our results are similar if we scale by total assets.

reduction in employment, however, should be balanced against several considerations. First, labor market frictions can restrict the merged firm's ability to layoff redundant and/or low quality workers. For example, employment contracts can contain termination provisions that make it difficult, if not impossible, to layoff redundant employees without cause, or otherwise entitle the worker to a notice period and/or severance pay. Second, as discussed in Section 2, merging firms can have a strong incentive to keep the two workforces intact to maximize the ability to winner-pick. Although they do not examine the incentive to winner-pick in unrelated acquisitions, Fulgiheri and Sevilir (2011) argue that it is almost always optimal to do so in related acquisitions. This suggests that we can find little or no reduction in the merged firm's workforce in related acquisitions. Finally, it is possible that related acquisitions motivated by economies of scale show little or no decrease in employment because the larger postmerger scale of operations needs both firms' workforces.

Although data in Compustat on firm employment (EMP) is generally complete, there is a paucity of data on labor expense (XLR). The lack of labor expense data is especially severe in our merger sample, where only 14 out of our original sample of 1,322 deals have sufficient data to compute the change in labor expense around the merger. We therefore use selling, general, and administrative expense (SG&A) as a proxy for labor expense. Of the 215,960 firm-year observations in the Compustat Industrial Annual database between 1996 and 2012, 135,981 (63%) have SG&A, 49,723 (23%) have labor expense, and 26,442 (12.24%) have both SG&A and labor expense. The Pearson (Spearman rank) correlation coefficient between labor expense and SG&A is 0.82 (0.95), suggesting that SG&A is a reasonable proxy for labor expense. For our original sample of 1,322 deals from 1997 to 2012, 950 have employment data and 829 have SG&A for both acquirer and target in the year before the deal through two years after the deal.

------- Insert Table 8 near here -------

Table 8 reports regressions of the postmerger change in employment on *HCR*. The dependent variable is the average postmerger industry-adjusted number of employees in years +1 and +2 (or +1, +2, and +3) minus the premerger industry-adjusted number of employees in year –1, where year 0 is the merger announcement year. The premerger industry-adjusted number of employees is the sum of the acquirer and target industry-adjusted number of employees. Industry-adjusted number of employees is the difference between a firm's number of employees and the median number of employees for firms in the same three-digit SIC code. Panel A (B) reports regressions of postmerger change in employment on *HCR* (*HCR* conditioned by merger type). All regressions include controls for acquirer and target characteristics (defined in Appendix A) that are measured at time t–1. We report t-statistics in parentheses below parameter estimates that are computed using robust standard errors clustered at the year level.

Consistent with Hypothesis 3, the coefficient on *HCR* is significantly negative in all regressions reported in Panel A, indicating that human capital relatedness predicts lower post-merger employment. The negative relation is stronger when the regression includes *PMR* and when we exclude mergers where *HCR* = 1. In the regressions, the coefficient on *PMR* is also negative, and the coefficient on *HCR* × *PMR* is positive. Thus, product market relatedness also decreases postmerger employment, and the negative effect of human capital relatedness on postmerger employment is attenuated in mergers with a high degree of product market relatedness. The attenuating effect of product market relatedness is consistent with the prediction of Fulghieri and Sevilir (2011) that mergers between firms in related product markets will not see a reduction in employment because it is optimal for the postmerger firm to preserve the option to winner-pick.

This notion of winner-picking is bolstered in Panel B where we condition the influence of *HCR* on the change in employment by interacting *HCR* with merger-type indicator variables. As seen there, the negative effect of *HCR* on postmerger employment is significant only in unrelated acquisitions (i.e., *MergerType*1, *MergerType*2, and *Conglomerate* mergers). This negative effect is economically significant. For example, using model (4) in Panel B, we compute for conglomerate mergers (*Conglomerate* = 1) that a one standard deviation increase in *HCR* decreases postmerger industry-adjusted employment by approximately 6,500 jobs when *PMR* = 0 and 2,500 jobs when *PMR* = 1. In contrast, there is not a significant change in employment for related acquisitions (i.e., *MergerType*3, *Vertical*, and especially *Horizontal* mergers).

------- Insert Table 9 near here -------

Table 9 examines the influence of *HCR* on the postmerger change in industry-adjusted SG&A. Consistent with the negative effect of *HCR* on postmerger employment, we see in Panel A that *HCR* predicts lower postmerger labor expense. As shown in Panel B, this decrease in postmerger SG&A is primarily driven by unrelated mergers and appears to be highly economically significant. For example, using model (4) in Panel B, we compute for conglomerate mergers that a one standard deviation increase in *HCR* decreases postmerger industry-adjusted SG&A by 490 million for *PMR* = 0 and 250 million for *PMR* = 1.

Overall, the evidence in Tables 8 and 9 suggests that cost reductions through lower employment and wages are an important channel through which human capital relatedness enhances the performance of unrelated mergers. In contrast, there is no evidence that mergers between firms with a high degree of industry overlap and/or product market relatedness predict lower employment and wages. In the online Internet Appendix we report regressions that examine the relation between *HCR* and the postmerger change in labor productivity. Measuring labor productivity as the ratio of operating cash flow to employment or operating cash flow to SG&A, we find little reliable evidence that *HCR* influences labor productivity.

6. Asset sales

Our measure of human capital relatedness appears to be an important determinant of merger gains. However, it would be valuable if we could design a falsification test of whether the associations we identify between *HCR* and merger performance are true or spurious. We can implement this test using asset sales. The idea is that the acquisition of an asset differs fundamentally from the merger of two firms in that human capital may not be transferred from the selling firm (parent) to the acquiring firm. Nevertheless, we can still compute *HCR* for the asset acquisition, since it measures the relatedness of the human capital associated with the asset and the acquiring firm regardless of whether human capital is actually transferred in the asset sale. Thus, we can conduct a falsification test in that the gains from merger are unlikely to be causally related to human capital relatedness if *HCR* predicts the gains to acquirers in asset sales when there is little or no transfer of employees.[25]

To implement this test, we collect all divestiture transactions in the US from the SDC Mergers and Acquisitions database during the period 1997 to 2013. Requiring that the seller is publicly traded, not from the financial industry, and that the transaction has a value of at least $75 million (as in Bates, 2005) gives us an initial sample of 2,553 asset sales. We then require that the seller (parent) and buyer (acquiring firm) have coverage in Compustat and CRSP for the data items in our analysis. This gives us our final sample of 500 asset acquisitions.

------- Insert Table 10 near here -------

[25] We thank the referee for suggesting this test.

Descriptive statistics for the sample are reported in Table 10. The mean (median) *HCR* is 0.655 (0.722), which is close to the mean (median) *HCR* for the merger sample reported in Table 1. The transaction value, relative transaction size, and parent and acquiring firm announcement returns are also close to those reported in the literature (e.g., Bates, 2005; Clayton and Reisel, 2013; Zhang and Wang, 2013). Importantly, the mean (median) relative transaction size of 29.82% (12.69%) suggests that asset acquisitions in our sample are significant transactions to the acquiring firm. The mean and median parent employment in the year after the transaction (year +1) are slightly higher than the mean and median parent employment in the year before the transaction (year −1), which suggests that the typical asset sale transfers few employees from the parent to the acquiring firm.

We report the results of the falsification test in Table 11. Panel A compares acquiring firm announcement returns by whether the change in parent employment is below or above a critical level, where the change in parent employment is computed as the absolute value of the difference between employment in year +1 minus employment in year −1, scaled by employment in year −1. We see in Panel A that for critical levels of the change in parent employment ranging from 1% to 5%, the acquiring firm announcement return is always significantly smaller (i.e., less positive) for the subsample below the critical level than for the subsample above the critical level. This supports rejection of falsification in that acquiring firm gains from asset acquisitions are economically and statistically smaller when there is not a significant human capital component to the transaction.

------- Insert Table 11 near here -------

We directly test falsification in Panel B, which reports regressions of acquiring firm abnormal returns on *HCR* for subsamples below and above a 3% change in parent firm employment. We use a 3% critical level to allow for a reasonable sample size in the below critical level change in employment subsample. Nevertheless, as reported in the online Internet Appendix, we find similar results to those in Panel B if instead we use a 1%, 2%, 4%, or 5% critical level.

The panel reports four sets of regressions for the below and above 3% subsamples. The first set regresses acquiring firm abnormal returns on *HCR* with no control variables or fixed effects. The second set includes year fixed effects, so the coefficients on *HCR* reflect the influence of within year variation of *HCR* on acquiring firm returns. The third and fourth sets add deal and acquiring firm controls to the first and second sets, respectively. The control variables include relative transaction size and the total assets, market-to-book, leverage, and prior returns of the acquirer.

As seen in Panel B, although the coefficients on *HCR* in the below 3% change in employment subsample are positive, they are not statistically significant. In contrast, the coefficients on *HCR* are significantly positive in the above 3% change in employment subsample, where there is more likely to be a nontrivial transfer of human capital in the asset sale. Overall, the results support rejection of the falsification hypothesis. There is, however, one important caveat. The lack of statistical significance in the below 3% subsample regressions—like the lack of statistical significance in the below 1%, 2%, 4%, and 5% subsample regressions reported in the online Internet Appendix—could reflect a lack of statistical power due to the relatively small number of observations.

7. Conclusions

We draw from the property rights theory of the firm and its extension to mergers by Rhodes-Kropf and Robinson (2008) to argue that human capital complementarities can motivate mergers and acquisitions. Developing a measure of the relatedness of firms' human capital, we test whether the likelihood of merger and the synergy benefits deriving from merger are increasing in the relatedness of merging firms' human capital. Consistent with our hypotheses, we find strong evidence that the likelihood of merger is increasing in human capital relatedness, and that announcement returns and postmerger operating performance are higher when merging firms have closely related human capital. Our analysis shows that the benefits from combining firms with complementary human capital accrue primarily to diversifying acquisitions. This is consistent with theoretical work by Fulghieri and Sevilir (2011) that shows that a merger between firms operating in similar product markets increases market power but harms incentives to innovate and develop new products. An investigation into the channels through which labor complementarities drive higher postmerger profitability finds that a merger of firms with high human capital relatedness predicts a reduction in postmerger employment and labor costs. Again, these post-merger outcomes largely accrue to diversifying acquisitions where the merging firms have high human capital complementarity.

Lastly, we examine the reliability of our measure of human capital relatedness with a falsification test. Using a sample of asset sales, we examine the relation between the acquiring firm's announcement return and our measure of human capital relatedness when little or no human capital is transferred from the parent to the acquiring firm. In these cases, we find little evidence that human capital relatedness influences acquiring firm returns, which supports rejection of falsification. Overall, our measure of human capital relatedness appears to reliability measure human capital synergy in mergers.

Appendix A. Variable definitions

Variable	Description
HCR	Human capital relatedness between merging firms in the fiscal year prior to the deal announcement date. For merging firms *i* and *j*, HCR_{ij} is computed as the scalar product of the firms' human capital profile vectors, H_i and H_j, divided by the product of their lengths, i.e., $$HCR_{ij} = \frac{H_i H_j'}{\sqrt{(H_i H_i')(H_j H_j')}}.$$ A firm's human capital profile vector is constructed as the weighted average of its industry segment occupation profile vectors where the weights are segment sales to total segment sales. Industry occupation profile vectors are from the Occupational Employment Statistics (OES) of the Bureau of Labor Statistics. For each three-digit SIC code for years 1989–2001 and four-digit NAICS code thereafter, OES reports an industry occupation profile vector where the elements are the number of industry workers assigned to an occupation divided by the total number of workers in the industry. The OES dataset includes 158 occupation titles based on the OES taxonomy up to 1998, and 444 occupation titles based on the Standard Occupational Classification (SOC) thereafter. When a firm does not have data in the Compustat segment database, we use industry segment information from the Securities Data Corporation (SDC) database. The SDC database reports SIC codes and NAIC codes for a firm's segments, but it does not provide segment sales. We therefore compute a firm's human capital profile vector as the equally weighted average of its segment OES occupation profile vectors. *HCR* is bounded between zero and one. It is unity for merging firms whose human capital profiles are identical and zero for merging firms whose human capital profiles are orthogonal.
PMR	Dummy variable equal to one if two firms are identified as product market related by Hoberg and Phillips (2010), and zero otherwise. Hoberg and Phillips compute product market similarity scores between firms using text-based analysis of 10-K product descriptions, and they define firms with similarity scores above a certain threshold as product market related.
Synergy	The weighted-average cumulative abnormal stock returns of acquirer and target from one day before to one day after the merger announcement date (i.e., days −1, 0, and +1, where day 0 is the merger announcement day). The weights are computed using the market values of equity of the merging firms four days before the merger announcement date. Using CRSP equally weighted market returns, we estimate market model parameters over the period from 210 days before to 11 days before the merger announcement date. Abnormal stock return is computed as a firm's raw stock return minus the predicted return from the market model.
Acquirer (target) CAR	Acquirer (target) firm cumulative abnormal stock returns from one day before to one day after the merger announcement date (i.e., days −1, 0, and +1, where day 0 is the merger announcement day). Using CRSP equally weighted market returns, we estimate market model parameters over the period from 210 days before to 11 days before the merger announcement date. Abnormal stock return is computed as a firm's raw stock return minus the predicted return from the market model.

(*continued*)

Appendix A – *continued*

Variable	Description
Parent CAR	Cumulative abnormal stock returns of the parent firm from one day before to one day after the announcement of the asset sale (i.e., days −1, 0, and +1, where day 0 is the asset sale announcement day). Using CRSP equally weighted market returns, we estimate market model parameters over the period from 210 days before to 11 days before the asset sale announcement date. Abnormal stock return is computed as a firm's raw stock return minus the predicted return from the market model.
Relative size	The ratio of the target firm's market value of equity to the acquiring firm's market value of equity four days before the merger announcement date.
Relative transaction size	The ratio of the asset sale transaction value (from SDC) to the acquiring firm's book value of total assets at the fiscal year-end immediately before the asset sale announcement date.
Stock deal dummy	Dummy variable equal to one if the deal is at least partially financed with stock, and zero otherwise.
*MergerType*1	Dummy variable equal to one for single-segment acquirer and target firms in different industries based on three-digit SIC (four-digit NAICS) code, and zero otherwise.
*MergerType*2	Dummy variable equal to one when one or both acquirer and target are multi-segment firms with no common industries based on three-digit SIC (four-digit NAICS) code, and zero otherwise.
*MergerType*3	Dummy variable equal to one when each of the merging firms is either single or multi segment and have at least one segment in the same industry based on three-digit SIC (four-digit NAICS) code, and zero otherwise.
Vertical	Dummy variable equal to one for a vertical merger, and zero otherwise. Vertical mergers are determined according to the algorithm described in Fan and Goyal (2006) based on the input-output table from the Bureau of Economic Analysis. Merging firms are vertically integrated if they are from different industries and if their vertical relatedness measure as defined by Fan and Goyal (2006) is greater than or equal to 1%.
Horizontal	Dummy variable equal to one for a horizontal merger, and zero otherwise. Horizontal mergers are determined according to the algorithm described in Fan and Goyal (2006) based on the input-output table from the Bureau of Economic Analysis. Horizontal mergers are mergers between firms in the same industry and exhibit no vertical relatedness (i.e., a Fan and Goyal (2006) vertical relatedness measure less than 1%).
Conglomerate	Dummy variable equal to one for a conglomerate merger, and zero otherwise. Conglomerate mergers are determined according to the algorithm described in Fan and Goyal (2006) based on the input-output table from the Bureau of Economic Analysis. Conglomerate mergers are mergers between firms in different industries and exhibit no vertical relatedness (i.e., a Fan and Goyal (2006) vertical relatedness measure less than 1%).
Total assets	Natural logarithm of total book assets (AT) at the fiscal year-end immediately prior to the merger (asset sale) announcement date.

(*continued*)

Appendix A – *continued*

Variable	Description
Market-to-book	The market-to-book ratio of a firm's assets at the fiscal year-end immediately prior to the merger (asset sale) announcement date, where the market value of assets is estimated as the book value of assets plus the difference between the market and book values of equity (AT + PRCC_F × CSHO − CEQ).
Leverage ratio	Ratio of long-term debt (DLTT) plus short-term debt (DLC) to total book assets (AT) at the fiscal year-end immediately prior to the merger (asset sale) announcement date.
Free cash flow	Ratio of operating income before depreciation (OIBDP) minus interest expense (XINT) minus income taxes (TXT) minus capital expenditures (CAPX) to total book assets (AT) at the fiscal year-end immediately prior to the merger (asset sale) announcement date.
Cash holdings	Ratio of cash equivalents (CHE) to total book assets (AT) at the fiscal year-end immediately prior to the merger (asset sale) announcement date.
Sales growth	Sales (SALE) in fiscal year t–1 minus sales in fiscal year t–2, scaled by sales in fiscal year t–2, where fiscal year t is the year of the merger announcement.
Prior returns	Buy-and-hold abnormal stock returns during the period from 210 days before to 11 days before the merger (asset sale) announcement date. Abnormal stock return is computed as the difference between a firm's raw stock return and the CRSP value-weighted market return.
Return on assets	Ratio of operating income before depreciation (OIBDP) to total book assets (AT) at the fiscal year-end immediately prior to the merger (asset sale) announcement date.
Termination fee	Dummy variable equal to one if the acquirer (target) termination fee reported by SDC is greater than zero, and zero otherwise.

Appendix B. Control samples for probit regressions

B.1. Control sample 1. Nonmerging firm pair—pseudo acquirer and pseudo target

The matching pair of nonmerging firms is based on vertical relation, product market similarity, number of segments, total assets, and market-to-book ratio according to the following steps.

Step 1. For each merging firm pair (real acquirer and real target) in year t, we use the Compustat segment database to identify all possible pairs of firms in year t in which the Fan and Goyal (2006) merger relation (i.e., vertical, horizontal, or conglomerate) between the pair is the same as that between the merging firms. Candidate pseudo merging firm pairs must not engage in M&A activity in years t–1 and t. (See Appendix A for descriptions of the Fan and Goyal (2006) merger relations vertical, horizontal, and conglomerate.)

Step 2. Among the candidate pseudo merging firm pairs, we identify pairs in which the pseudo acquirer (pseudo target) belongs to the same product market as the real acquirer (real target) according to the product market relatedness classification of Hoberg and Phillips (2010).

Step 3. Among the pseudo merger pairs, we identify five pairs that have the closest number of segments to the merging firm pair, where closest is defined by minimum Euclidean distance, computed as the square root of [(# segments real acquirer – # segments pseudo acquirer)^2 + (# segments real target – # segments pseudo target)^2].

Step 4. Among the five pairs, we identify the three pairs having the closest total assets to the merging firm pair, where closest is defined by minimum Euclidean distance, computed as the square root of [(total assets of real acquirer – total assets of pseudo acquirer)^2 + (total assets of real target – total assets of pseudo target)^2]

Step 5. Of these three pairs, we select the pair with the closest market-to-book ratio (M/B) to the merging firm pair, where closest is defined by minimum Euclidean distance, computed as the square root of [(M/B of real acquirer − M/B of pseudo acquirer)^2 + (M/B of real target − M/B of pseudo target)^2].

B.2. Control sample 2. Nonmerging firm pair—real acquirer and pseudo target

The matching pair of firms is based on vertical relation, product market similarity, number of segments, total assets, and market-to-book ratio according to the following steps.

Step 1. For each merging firm pair (real acquirer and real target) in year *t*, we use the Compustat segment database to identify all pairs of the real acquirer and firms in year *t* in which the Fan and Goyal (2006) merger relation (i.e., vertical, horizontal, or conglomerate) between the real acquirer and pseudo target is the same as that between the real merger pair. Candidate pseudo target firms must not engage in M&A activity in years *t*−1 and *t*. (See Appendix A for descriptions of the Fan and Goyal (2006) merger relations vertical, horizontal, and conglomerate.)

Step 2. Among the candidate merging firm pairs (real acquirer and pseudo targets), we identify pairs in which the pseudo target belongs to the same product market as the real target according to the product market relatedness classification of Hoberg and Phillips (2010).

Step 3. Among the real acquirer and pseudo target merger pairs, we identify five pairs where the pseudo target and real target have the same number of segments.

Step 4. Among the five pairs, we identify the three pairs where the total assets of the pseudo target are closest to the total assets of the real target.

Step 5. Of these three pairs, we select the pair where the market-to-book ratio of the pseudo target is closest to the real target.

B.3. Control sample 3. Nonmerging firm pair—random pair of firms

Each merging firm pair in year *t* has five randomly matched nonmerging firm pairs from the Compustat segment database in year *t*. We require the firms in the nonmerging firm pairs do not engage in M&A activity in years *t*–1 and *t*.

References

Agrawal, A.K., Matsa, D.A., 2013. Labor unemployment risk and corporate financing decisions. Journal of Financial Economics 108, 449–470.

Ahern, K.R., 2012. Bargaining power and industry dependence in mergers. Journal of Financial Economics 103, 530–550.

Ai, C., Norton, E.C., 2003. Interaction terms in logit and probit models. Economics Letters 80, 123–129.

Amess, K., Girma, S., Wright, M., 2014. The wage and employment consequences of ownership change. Managerial and Decision Economics 35, 161–171.

Andrade, G., Mitchell, M., Stafford, E., 2001. New evidence and perspectives on mergers. Journal of Economic Perspectives 15, 103–120.

Bates, T.W., 2005. Asset sales, investment opportunities, and the use of proceeds. Journal of Finance 60, 105–135.

Bates, T.W., Lemmon, M.L., 2003. Breaking up is hard to do? An analysis of termination fee provisions and merger outcomes. Journal of Financial Economics 69, 469–504.

Bena, J., Li, K., 2014. Corporate innovations and mergers and acquisitions. Journal of Finance 69, 1923–1960.

Berk, J., Stanton, R., Zechner, J., 2010. Human capital, bankruptcy and capital structure. Journal of Finance 65, 891–925.

Betton, S., Eckbo, B.E., Thorburn, K.S., 2008. Corporate takeovers. In: Eckbo, B.E. (Ed.), Handbook of Corporate Finance: Empirical Corporate Finance, Vol. 2. Handbooks in Finance Series. North-Holland, Amsterdam, pp. 291–430.

Bollen, K.A., Jackman, R.W., 1990. Regression diagnostics: an expository treatment of outliers and influential cases. In: Fox, J., Long, S.J. (Eds.), Modern Methods of Data Analysis. Thousand Oaks, pp. 257–291.

Brown, C., Medoff, J.L., 1988. The impact of firm acquisitions on labor. In: Auerbach, A.J. (Ed.), Corporate Takeovers: Causes and Consequences. Chicago, pp. 9–32.

Capron, L., Hulland, J., 1999. Redeployment of brands, sales forces, and general marketing management expertise following horizontal acquisitions: a resource-based view. Journal of Marketing 63, 41–54.

Chemmanur, T.J., Cheng, Y., Zhang, T., 2013. Human capital, capital structure, and employee pay: an empirical analysis. Journal of Financial Economics 110, 478–502.

Clayton, M.J., Reisel, N., 2013. Value creation from asset sales: new evidence from bond and stock markets. Journal of Corporate Finance 22, 1–15.

Comment, R., Schwert, G.W., 1995. Poison or placebo? Evidence on the deterrence and wealth effects of modern antitakeover measures. Journal of Financial Economics 39, 3–43.

Conyon, M.J., Girma, S., Thompson, S., Wright, P.W., 2002. The impact of mergers and acquisitions on company employment in the United Kingdom. European Economic Review 46, 31–49.

Donangelo, A., 2014. Labor mobility: Implications for asset pricing. Journal of Finance 69, 1321–1346.

Eisfeldt, A., Papanikolaou, D., 2013. Organization capital and the cross-section of expected returns. Journal of Finance 68, 1365–1406.

Fama, E.F., Schwert, G.W., 1977. Human capital and capital market equilibrium. Journal of Financial Economics 4, 115–146.

Fan, J.P., Goyal, V.K., 2006. On the patterns and wealth effects of vertical mergers. Journal of Business 79, 877–902.

Farjoun, M., 1994. Beyond industry boundaries: human expertise, diversification and resource-related industry groups. Organization Science 5, 185–199.

Farjoun, M., 1998. The independent and joint effects of the skill and physical bases of relatedness in diversification. Strategic Management Journal 19, 611–630.

Fulghieri, P., Sevilir, M., 2011. Mergers, spinoffs, and employee incentives. Review of Financial Studies 24, 2207–2241.

Gao, H., Ma, Y., 2016. Human capital driven acquisitions: evidence from inevitable disclosure doctrine. Unpublished working paper. Nanyang Technological University.

Grossman, S.J., Hart, O.D., 1986. The costs and benefits of ownership: a theory of vertical and lateral integration. Journal of Political Economy 94, 691–719.

Harford, J., 1999. Corporate cash reserves and acquisitions. Journal of Finance 54, 1969–1997.

Hart, O.D., 1995. Firms, Contracts, and Financial Structure. Oxford University Press, Oxford.

Hart, O.D., 1998. Residual rights of control. In: Newman, P. (Ed.), The New Palgrave Dictionary of Economics and Law. McMillan, New York, pp. 330–334.

Hart, O.D., Moore, J., 1990. Property rights and the nature of the firm. Journal Political Economy 98, 1119–1158.

Hoberg, G., Phillips, G., 2010. Product market synergies and competition in mergers and acquisitions: a text-based analysis. Review of Financial Studies 23, 3773–3811.

Hoberg, G., Phillips, G., 2016. Text-based network industries and endogenous product differentiation. Journal of Political Economy 124, 1423–1465.

Ishii, J., Xuan, Y., 2014. Acquirer-target social ties and merger outcomes. Journal of Financial Economics 112, 344–363.

Jaffe, A.B., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. American Economic Review 76, 984–1001.

John, K., Knyazeva, A., Knyazeva, D., 2015. Employee rights and acquisitions. Journal of Financial Economics 118, 49–69.

Kennedy, P., 2003. A Guide to Econometrics. The MIT Press, Cambridge.

Kole, S., Lehn, K.M., 2000. Workforce integration and the dissipation of value in mergers: the case of USAir's acquisition of Piedmont Aviation. In: Kaplan, S.N. (Ed.), Mergers and Productivity: NBER Conference Report Series. Chicago, pp. 239–279.

Krishnan, H.A., Hitt, M.A., Park, D., 2007. Acquisition premiums, subsequent workforce reductions and post-acquisition performance. Journal of Management Studies 44, 709–732.

Li, G., 2006. Robust regression. In: Hoeglin, D.C., Mosteller, C.F., Tukey, J.W. (Eds.), Exploring Data Tables, Trends, and Shapes. New York, 281–340.

Mayers, D., 1972. Nonmarketable assets and capital market equilibrium under uncertainty. In: Jensen, M.C. (Ed.), Studies in the Theory of Capital Markets. New York, pp. 223–248.

Mayers, D., 1973. Nonmarketable assets and the determination of capital asset prices in the absence of a riskless asset. Journal of Business 46, 258–267.

Neffke, F., Henning, M., 2013. Skill relatedness and firm diversification. Strategic Management Journal 34, 297–316.

Officer, M.S., 2003. Termination fees in mergers and acquisitions. Journal of Financial Economics 69, 431–467.

Ouimet, P., Zarutskie, R., 2016. Acquiring labor. Unpublished working paper. University of North Carolina and Federal Reserve Board.

Palacios, M., 2015. Human capital as an asset class implications from a general equilibrium model. Review of Financial Studies 28, 978–1023.

Rhodes-Kropf, M., Robinson, D.T., 2008. The market for mergers and the boundaries of the firm. Journal of Finance 63, 1169–1211.

Rosett, J.G., 1990. Do union wealth concessions explain takeover premiums? Journal of Financial Economics 27, 263–282.

Sheen, A., 2014. The real product market impact of mergers. Journal of Finance 69, 2651–2688.

Song, M.H., Walkling, R.A., 1993. The impact of managerial ownership on acquisition attempts and target shareholder wealth. Journal of Financial and Quantitative Analysis 28, 439–457.

Shleifer, A., Summers, L.H., 1988. Breach of trust in hostile takeovers. In: Auerbach, A.J. (Ed.), Corporate Takeovers: Causes and Consequences. Chicago, pp. 33–68.

Stein, J.C., 1997. Internal capital markets and the competition for corporate resources. Journal of Finance 52, 111–133.

Tate, G., Yang, L., 2015. The bright side of diversification: Evidence from internal labor markets. Review of Financial Studies 28, 2203–2249.

Tate, G., Yang, L., 2016. The human factor in acquisitions: cross-industry labor mobility and corporate diversification. Unpublished working paper. US Census Bureau for Economic Studies.

Teece, D.J., 1982. Towards an economic theory of the multiproduct firm. Journal of Economic Behavior and Organization 3, 39–63.

Teece, D.J., 1986. Profiting from technological innovation: implications for integration, collaboration, licensing and public policy. Research Policy 15, 285–305.

Tian, X., Wang, W., 2016. Hard marriage with heavy burdens: organized labor as takeover deterrents. Unpublished working paper. Kelley School of Business.

Wang, C., Xie, F., 2009. Corporate governance transfer and synergistic gains from mergers and acquisitions. Review of Financial Studies 22, 829–859.

Wernerfelt, B., 1984. A resource-based view of the firm. Strategic Management Journal 5, 171–181.

Venkat, P., 2016. The effect of mergers on human capital: evidence from sell-side analysts. Unpublished working paper. University of Texas, Austin.

Zhang, Y., Wang, S., 2013. Corporate restructuring and product market behavior. Applied Financial Economics 23, 603–617.

Table 1
Descriptive statistics and correlations for the merger sample.
The table reports descriptive statistics (Panel A) and Pearson correlation coefficients (Panel B) for the sample of mergers and acquisitions announced during the period 1997 to 2012. All variables are defined in Appendix A, and all variables are winsorized at the 1st and 99th percentiles of their distributions except *HCR*, *PMR*, and dummy variables. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Descriptive statistics

Variable	Mean	Std. dev.	25th Pctl.	Median	75th Pctl.	Obs.
Merger relatedness measures						
HCR	0.739	0.288	0.534	0.838	0.912	1,322
PMR	0.503					1,322
Merger returns (%)						
Synergy	1.477	7.594	−2.155	0.933	5.105	1,322
Acquirer CAR	−1.227	7.649	−5.272	−0.823	2.388	1,322
Target CAR	25.865	26.653	8.356	21.009	37.642	1,322
Deal characteristics						
Relative size	0.238	0.357	0.025	0.101	0.310	1,322
Stock deal dummy	0.519					1,322
*MergerType*1	0.191					1,322
*MergerType*2	0.160					1,322
*MergerType*3	0.649					1,322
Vertical	0.123					1,322
Horizontal	0.405					1,322
Conglomerate	0.472					1,322
Acquirer characteristics						
Total assets	7.709	2.016	6.256	7.700	9.287	1,235
Market-to-book	2.660	2.675	1.381	1.877	2.826	1,235
Leverage ratio	0.208	0.183	0.053	0.179	0.312	1,235
Free cash flow	0.023	0.158	0.007	0.055	0.092	1,252
Cash holdings	0.304	0.319	0.060	0.193	0.462	1,260
Sales growth	0.297	0.758	0.024	0.124	0.316	1,247
Prior returns	0.165	0.593	−0.154	0.044	0.297	1,322
Return on assets	0.108	0.137	0.077	0.122	0.171	1,133
Termination fee	0.222					1,322
Target characteristics						
Total assets	5.357	1.748	4.073	5.177	6.540	1,240
Market-to-book	2.139	1.747	1.159	1.562	2.385	1,241
Leverage ratio	0.208	0.235	0.003	0.138	0.344	1,240
Free cash flow	−0.070	0.258	−0.096	0.016	0.063	1,255
Cash holdings	0.418	0.418	0.058	0.279	0.698	1,264
Sales growth	0.314	0.822	−0.004	0.114	0.329	1,249
Prior returns	0.068	0.654	−0.329	−0.049	0.281	1,322
Return on assets	0.023	0.262	−0.020	0.098	0.160	1,255
Termination fee	0.688					1,322

(*continued*)

Table 1 – *continued*

Panel B. Pearson correlation coefficients

Variable	*HCR*	*PMR*	Synergy	Acquirer CAR	Target CAR
HCR	1.000				
PMR	0.259***	1.000			
Synergy	0.031	0.046*	1.000		
Acquirer CAR	–0.015	–0.003	0.845***	1.000	
Target CAR	0.008	–0.028	0.280***	0.122***	1.000
Relative size	0.058**	0.068***	0.165***	–0.020	–0.262***
Stock deal dummy	0.064**	0.072***	–0.190***	–0.242***	–0.226***
*MergerType*1	–0.467***	–0.038	–0.037	–0.020	0.013
*MergerType*2	–0.398***	–0.201***	0.003	0.037	0.008
*MergerType*3	0.691***	0.185***	0.028	–0.012	–0.017
Vertical	–0.095***	–0.085***	–0.014	–0.002	0.071***
Horizontal	0.423***	0.303***	0.024	–0.030	–0.062**
Conglomerate	–0.353***	–0.242***	–0.015	0.031	0.014
Acquirer total assets	–0.056**	–0.173***	–0.082***	0.028	0.067**
Acquirer market-to-book	0.087***	0.031	–0.137***	–0.079***	–0.019
Acquirer leverage ratio	–0.019	–0.047*	0.094***	0.061**	–0.053*
Acquirer free cash flow	–0.054*	–0.011	0.033	0.075***	0.071***
Acquirer cash holdings	0.118***	0.110***	–0.106***	–0.105***	0.022
Acquirer sales growth	0.057**	0.015	–0.106***	–0.096***	–0.108***
Acquirer prior returns	0.030	0.001	–0.145***	–0.112***	–0.066**
Acquirer return on assets	–0.009	–0.064**	0.039	0.121***	0.037
Acquirer term. fee	0.021	0.079***	0.010	–0.106***	–0.155***
Target total assets	0.090***	0.070***	0.029	–0.084***	–0.137***
Target market-to-book	0.030	–0.015	–0.152***	–0.112***	–0.110***
Target leverage ratio	0.040	0.044	0.040	0.033	–0.071***
Target free cash flow	–0.034	–0.045	0.046	–0.023	–0.063**
Target cash holdings	0.078***	0.026	–0.154***	–0.103***	0.055**
Target sales growth	0.049*	–0.014	–0.057**	–0.040	–0.046*
Target prior returns	0.030	0.042	–0.047*	–0.024	–0.063**
Target return on assets	0.010	–0.039	0.061**	–0.007	–0.091***
Target term. fee	0.021	0.004	0.062**	0.039	–0.020

Table 2
The effect of human capital relatedness on the probability of merger.
The table reports the results of probit regressions of the probability of merger. The sample includes merging firm pairs (acquirer and target) announced during the period from 1997 to 2012 and nonmerging control firm pairs. Columns (1), (2), and (3) report results for the effects of human capital relatedness (*HCR*) and product market relatedness (*PMR*) on the probability of merger when the regression does not include control variables, and columns (4), (5), and (6) report the corresponding regressions with control variables. All variables are defined in Appendix A. Each merging firm pair has one matching nonmerging control firm pair. The algorithm used to construct the nonmerging control firm pair is described in Appendix B (Control sample 1). All independent variables are lagged one year. Coefficients, *z*-statistics (in parenthesis), and economic significance are reported. Economic significance is the marginal effect on the probability of merger for a one standard deviation change for a continuous independent variable or for a change from zero to one for a dummy variable, holding all other variables at their means. Marginal effects and standard errors for interactions are computed using the methods in Ai and Norton (2003). The *z*-statistics are computed using robust standard errors clustered at the year level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
HCR	0.594***	0.314***	0.834***	0.808***	0.399***	0.767***
	(6.71)	(3.21)	(6.45)	(6.87)	(3.07)	(4.36)
	0.075	0.049	0.102	0.080	0.058	0.084
PMR		0.441***	1.373***		0.752***	1.362***
		(7.02)	(8.47)		(8.79)	(6.42)
		0.169	0.206		0.164	0.169
HCR × *PMR*			–1.276***			–0.840***
			(–6.28)			(–3.17)
			–0.126			–0.079
Total assets of acquirer				0.199***	0.241***	0.245***
				(8.23)	(9.47)	(9.56)
				0.092	0.106	0.107
Total assets of target				–0.038***	–0.144***	–0.141***
				(–3.37)	(–4.94)	(–4.81)
				–0.038	–0.055	–0.053
Market-to-book of acquirer				0.161***	0.168***	0.171***
				(6.90)	(6.95)	(7.04)
				0.099	0.098	0.099
Market-to-book of target				–0.037	–0.037	–0.040*
				(–1.63)	(–1.56)	(–1.70)
				–0.015	–0.014	–0.015
Leverage ratio of acquirer				–0.532**	–0.597***	–0.573**
				(–2.40)	(–2.61)	(–2.50)
				–0.022	–0.024	–0.023
Leverage ratio of target				0.383*	0.287	0.294
				(1.82)	(1.33)	(1.36)
				0.021	0.015	0.015
Free cash flow of acquirer				9.635***	9.839***	9.774***
				(16.00)	(15.96)	(15.83)
				0.352	0.339	0.335
Free cash flow of target				5.920***	5.931***	5.840***
				(13.20)	(13.00)	(12.79)
				0.352	0.333	0.326

(*continued*)

Table 2 – *continued*

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Cash holdings of acquirer				−0.558***	−0.667***	−0.649***
				(−3.68)	(−4.22)	(−4.08)
				−0.041	−0.046	−0.045
Cash holdings of target				−0.807***	−0.853***	−0.839***
				(−6.67)	(−6.87)	(−6.73)
				−0.078	−0.078	−0.076
Sales growth of acquirer				0.136**	0.127**	0.130**
				(2.29)	(2.08)	(2.10)
				0.024	0.021	0.021
Sales growth of target				0.044	0.066	0.063
				(0.92)	(1.34)	(1.28)
				0.008	0.012	0.011
Return on assets of acquirer				−10.904***	−11.182***	−11.091***
				(−19.17)	(−19.14)	(−18.92)
				−0.344	−0.333	−0.328
Return on assets of target				−6.101***	−6.008***	−5.916***
				(−13.54)	(−13.13)	(−12.91)
				−0.369	−0.343	−0.336
Intercept	−0.419***	−0.453***	−0.753***	−0.466**	−0.543**	−0.833***
	(−6.09)	(−6.51)	(−8.74)	(−2.20)	(−2.50)	(−3.50)
Pseudo R-squared	0.02	0.05	0.07	0.45	0.47	0.48
Observed prob. merger	0.50	0.50	0.50	0.50	0.50	0.50
Predicted prob. merger	0.50	0.50	0.50	0.49	0.49	0.51
No. of observations	1,978	1,978	1,978	1,978	1,978	1,978

Table 3
The influence of merger type on the effect of human capital relatedness on the probability of merger.
The table reports the results of probit regressions of the probability of merger. The sample includes merging firm pairs (acquirer and target) announced during the period from 1997 to 2012 and nonmerging control firm pairs. Columns (1) and (2) interact human capital relatedness (*HCR*) with merger-type dummy variables, *MergerType*1-*MergerType*3, based on acquirer and target firm number of segments and industry overlap, and columns (3) and (4) interact human capital relatedness (*HCR*) with dummy variables for whether the merger is vertical (*Vertical*), horizontal (*Horizontal*), or conglomerate (*Conglomerate*). *MergerType*1 is a dummy variable equal to one for single-segment acquirer and target in different industries, *MergerType*2 is a dummy variable equal to one when one or both acquirer and target are multi segment with no common industry segments, and *MergerType*3 is a dummy variable equal to one when each of the merging firms is either single or multi segment and have at least one segment in the same industry. The dummy variables *Vertical*, *Horizontal*, and *Conglomerate* are equal to one for vertical, horizontal, and conglomerate mergers, respectively, and they are constructed using the algorithm in Fan and Goyal (2006). All regressions are estimated without an intercept so there is not a left out or baseline merger group. All variables are defined in Appendix A. Each merging firm pair has one matching nonmerging firm pair. The algorithm used to construct the nonmerging control firm pairs is described in Appendix B (Control sample 1). All independent variables are lagged one year. Coefficients, *z*-statistics (in parenthesis), and economic significance are reported. Economic significance is the marginal effect on the probability of merger for a one standard deviation change for a continuous independent variable or for a change from zero to one for a dummy variable, holding all other variables at their means. Marginal effects and standard errors for interactions are computed using the methods in Ai and Norton (2003). The *z*-statistics are computed using robust standard errors clustered at the year level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
HCR × *MergerType*1	1.164***	0.977***	1.129***			
	(3.91)	(3.12)	(3.48)			
	0.115	0.097	0.108			
HCR × *MergerType*2	0.842***	0.807**	0.942***			
	(2.62)	(2.44)	(2.77)			
	0.091	0.086	0.095			
HCR × *MergerType*3	−0.404	−0.907***	−0.570			
	(−1.33)	(−2.84)	(−1.57)			
	−0.059	−0.092	−0.069			
HCR × *Vertical*				1.495***	1.241***	1.343***
				(3.99)	(3.15)	(3.27)
				0.138	0.115	0.122
HCR × *Horizontal*				−0.997***	−1.173***	−0.965**
				(−3.26)	(−3.73)	(−2.51)
				−0.102	−0.110	−0.096
HCR × *Conglomerate*				1.247***	0.981***	1.061***
				(6.67)	(5.03)	(4.98)
				0.120	0.097	0.103
PMR		0.762***	1.149***		0.761***	0.956***
		(8.63)	(5.27)		(8.57)	(4.26)
		0.162	0.243		0.161	0.202
HCR × *PMR*			−0.541*			−0.271
			(−1.95)			(−0.95)
			−0.037			−0.019

(*continued*)

Table 3 – *continued*

Variable	(1)	(2)	(3)	(4)	(5)	(6)
*MergerType*1	−0.493**	−0.671***	−0.829***			
	(−2.02)	(−2.65)	(−3.10)			
	−0.111	−0.143	−0.176			
*MergerType*2	−0.830***	−0.993***	−1.134***			
	(−3.19)	(−3.69)	(−4.05)			
	−0.186	−0.211	−0.240			
*MergerType*3	0.664*	0.639*	0.372			
	(1.87)	(1.74)	(0.95)			
	0.149	0.136	0.079			
Vertical				−1.017***	−1.153***	−1.239***
				(−3.16)	(−3.45)	(−3.56)
				−0.227	−0.244	−0.262
Horizontal				1.149***	0.790**	0.622
				(3.36)	(2.24)	(1.58)
				0.257	0.167	0.132
Conglomerate				−0.772***	−0.871***	−0.943***
				(−3.40)	(−3.73)	(−3.83)
				−0.173	−0.184	−0.199
Intercept	No	No	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo *R*-squared	0.46	0.48	0.48	0.46	0.48	0.48
Observed prob. merger	0.50	0.50	0.50	0.50	0.50	0.50
Predicted prob. merger	0.51	0.51	0.51	0.51	0.51	0.51
No. of observations	1,978	1,978	1,978	1,978	1,978	1,978

Table 4

The effect of human capital relatedness on the gains from merger.

The table reports regressions of merger announcement returns on human capital relatedness (*HCR*), product market relatedness (*PMR*), and the interaction between the two. The sample includes deals announced during the period 1997–2012. The dependent variable, *Synergy*, is the weighted average of the cumulative abnormal returns of acquirer and target firms over days −1, 0, and +1, where day 0 is the merger announcement day. The weights are based on the market values of equity of acquirer and target four days prior to the merger announcement day. All variables are defined in Appendix A, and all variables are winsorized at the 1st and 99th percentiles except *HCR*, *PMR*, and dummy variables. We report *t*-statistics in parentheses below parameter estimates that are computed using robust standard errors clustered at the year level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
HCR	1.155**	0.773*	2.173**	1.164***	0.893**	2.164***
	(1.98)	(1.70)	(2.15)	(2.78)	(2.02)	(3.40)
PMR		0.765*	2.854**		0.652	2.580**
		(1.82)	(2.35)		(1.40)	(2.00)
HCR × *PMR*			−2.838**			−2.615*
			(−2.06)			(−1.95)
Relative size				2.686***	2.682***	2.747***
				(3.51)	(3.54)	(3.62)
Stock deal dummy				−2.757***	−2.772***	−2.802***
				(−4.74)	(−4.82)	(−4.95)
Total assets of acquirer				−0.711***	−0.668**	−0.654**
				(−2.77)	(−2.43)	(−2.38)
Total assets of target				0.225	0.188	0.191
				(1.12)	(0.89)	(0.90)
Market-to-book of acquirer				0.165	0.166	0.169
				(1.00)	(1.01)	(1.03)
Market-to-book of target				−0.370***	−0.371***	−0.386***
				(−3.46)	(−3.43)	(−3.67)
Leverage ratio of acquirer				3.335**	3.370**	3.429**
				(1.97)	(1.99)	(2.00)
Leverage ratio of target				−1.803*	−1.902*	−1.810*
				(−1.70)	(−1.82)	(−1.75)
Free cash flow of acquirer				0.400	0.345	0.444
				(0.28)	(0.24)	(0.30)
Free cash flow of target				−1.339	−1.233	−1.242
				(−1.18)	(−1.09)	(−1.09)
Cash holdings of acquirer				−1.662	−1.733*	−1.634
				(−1.63)	(−1.65)	(−1.57)
Cash holdings of target				−1.839**	−1.878**	−1.813**
				(−2.29)	(−2.33)	(−2.24)

(*continued*)

Table 4 – *continued*

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Sales growth of acquirer				–0.671	–0.667	–0.674
				(–1.19)	(–1.19)	(–1.21)
Sales growth of target				0.274	0.279	0.294
				(0.72)	(0.73)	(0.76)
Prior returns of acquirer				–1.114**	–1.105**	–1.055**
				(–2.04)	(–2.01)	(–1.98)
Prior returns of target				–0.038	–0.053	–0.073
				(–0.12)	(–0.17)	(–0.23)
Termination fee for acquirer				–1.036**	–1.072**	–1.104**
				(–2.02)	(–2.11)	(–2.08)
Termination fee for target				0.409	0.421	0.467
				(0.74)	(0.76)	(0.81)
Intercept	4.409***	4.247***	3.310***	9.775***	9.514***	8.394***
	(9.49)	(8.82)	(4.35)	(7.59)	(6.66)	(4.89)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.04	0.04	0.05	0.16	0.16	0.16
No. of observations	1,127	1,127	1,127	1,127	1,127	1,127

Table 5
Robustness regressions of the effect of human capital relatedness on the gains from merger.
The table reports regressions of merger announcement returns on human capital relatedness (*HCR*), product market relatedness (*PMR*), and the interaction between the two. The sample includes deals announced during the period 1997–2012. The dependent variable, *Synergy*, is the weighted average of the cumulative abnormal returns of acquirer and target firms over days −1, 0, and +1, where day 0 is the merger announcement day. The weights are based on the market values of equity of acquirer and target four days prior to the merger announcement day. Model (4) is a robust regression that uses a two-step procedure to reduce the impact of outliers in the OLS regression. In the first step, we follow Bollen and Jackman (1990) and drop influential outliers with a Cook's D greater than 4/*N*, where *N* is the number of observations used to estimate the regression. In the second step, an iterative procedure following Li (2006) reduces the weight of observations with large absolute residuals. All variables are defined in Appendix A, and all variables are winsorized at the 1st and 99th percentiles except *HCR*, *PMR*, and dummy variables. We report *t*-statistics in parentheses below parameter estimates that are computed using robust standard errors clustered at the year level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Excluding *HCR* = 1 (1)	Only *PMR* = 0 (2)	Only *PMR* = 1 (3)	Robust regression (4)
HCR	2.317***	2.263***	0.014	1.384***
	(3.11)	(3.42)	(0.01)	(3.62)
PMR	2.519**			2.100***
	(2.12)			(3.51)
HCR × *PMR*	−2.249*			−2.051***
	(−1.74)			(−3.57)
Intercept	7.693***	2.886	14.807***	5.079***
	(5.19)	(1.23)	(7.60)	(4.87)
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Adjusted *R*-squared	0.16	0.22	0.16	0.37
No. of observations	827	493	634	885

Table 6

The influence of merger type on the effect of human capital relatedness on the gains from merger.

The table reports regressions of merger announcement returns on human capital relatedness (*HCR*) interacted with merger type, product market relatedness (*PMR*), and the interaction between *HCR* and *PMR*. The sample includes deals announced during the period 1997–2012. The dependent variable, *Synergy*, is the weighted average of the cumulative abnormal returns of acquirer and target firms over days −1, 0, and +1, where day 0 is the merger announcement day. The weights are based on the market values of equity of acquirer and target four days prior to the announcement day. *MergerType*1 is a dummy variable equal to one for single-segment acquirer and target in different industries, *MergerType*2 is a dummy variable equal to one when one or both acquirer and target are multi segment with no common industry segments, and *MergerType*3 is a dummy variable equal to one when each of the merging firms is either single or multi segment and have at least one segment in the same industry. The dummy variables *Vertical*, *Horizontal*, and *Conglomerate* are equal to one for vertical, horizontal, and conglomerate mergers, respectively, and they are constructed using the algorithm in Fan and Goyal (2006). Regressions (1), (2), and (4) are estimated without an intercept, so there is not a left out or baseline group. Regressions (3) and (5) are estimated, respectively, using type two and conglomerate mergers only. All variables are defined in Appendix A, and all variables are winsorized at the 1st and 99th percentiles except *HCR*, *PMR*, and dummy variables. We report *t*-statistics in parentheses below parameter estimates that are computed using robust standard errors clustered at the year level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Full sample (1)	Excluding *HCR* = 1 (2)	Only *MergerType*2 (3)	Full sample (4)	Only *Conglomerate* (5)
HCR × *MergerType*1	1.537	1.571			
	(0.77)	(0.78)			
HCR × *MergerType*2	2.388*	2.535*	4.831***		
	(1.67)	(1.73)	(3.03)		
HCR × *MergerType*3	2.269	2.510			
	(1.36)	(1.46)			
HCR × *Vertical*				1.029	
				(0.69)	
HCR × *Horizontal*				1.195	
				(0.57)	
HCR × *Conglomerate*				2.653***	2.877***
				(3.25)	(2.84)
PMR	2.652**	2.580**	5.672**	2.348*	3.364**
	(1.99)	(2.03)	(2.55)	(1.69)	(2.53)
HCR × *PMR*	–2.702*	–2.297	–7.499**	–2.301	–3.196**
	(–1.88)	(–1.54)	(–2.45)	(–1.51)	(–1.97)
*MergerType*1	8.559***	7.852***			
	(4.33)	(4.29)			
*MergerType*2	8.460***	7.970***			
	(4.91)	(5.64)			
*MergerType*3	8.375***	7.725***			
	(3.40)	(2.96)			
Vertical				8.765***	
				(5.08)	
Horizontal				9.279***	
				(3.62)	
Conglomerate				8.291***	
				(4.78)	
Intercept	No	No	7.341***	No	3.824**
			(2.74)		(2.03)
Controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Adjusted *R*-squared	0.20	0.20	0.32	0.20	0.17
No. of observations	1,127	827	175	1,127	525

Table 7
The effect of human capital relatedness on postmerger operating performance.
The table examines the effect of human capital relatedness (*HCR*) on postmerger operating performance. The sample includes deals announced during the period 1997–2012. The dependent variable is the change in postmerger industry-adjusted operating performance from year +1 to +2 and from year +1 to +3 (one- and two-year horizons), where year 0 is the merger announcement year. Operating performance is measured as the ratio of operating income before depreciation to total net sales. Industry-adjusted operating performance is the difference between a firm's operating performance and the median operating performance for firms in the same three-digit SIC code. Panel A regressions do not condition *HCR* by type of merger. Regressions (3) and (6) exclude mergers between single segment firms in the same industry (i.e., cases in which *HCR* = 1). Panel B regressions condition *HCR* by type of merger. *MergerType*1 is a dummy variable equal to one for single-segment acquirer and target in different industries, *MergerType*2 is a dummy variable equal to one when one or both acquirer and target are multi segment with no common industry segments, and *MergerType*3 is a dummy variable equal to one when each of the merging firms is either single or multi segment and have at least one segment in the same industry. The dummy variables *Vertical*, *Horizontal*, and *Conglomerate* are equal to one for vertical, horizontal, and conglomerate mergers, respectively, and they are constructed using the algorithm in Fan and Goyal (2006). In panel B, regressions (1), (2), (4), (6), (7), and (9) are estimated without an intercept, regressions (2) and (7) exclude mergers between single segment firms in the same industry (i.e., cases in which *HCR* = 1), regressions (3) and (8) are estimated using type two mergers only, and regressions (5) and (10) are estimated using conglomerate mergers only. The control variables are those used in Panel A. All variables are defined in Appendix A, and all variables are winsorized at the 1st and 99th percentiles except *HCR* and *PMR*. We report *t*-statistics in parentheses below parameter estimates that are computed using robust standard errors clustered at the year level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. All merger types

	Dependent variable is change in postmerger industry-adjusted operating performance					
	From year +1 to +2			From year +1 to +3		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
HCR	0.027*	0.026**	0.041***	0.017	0.017*	0.028**
	(1.90)	(2.00)	(3.11)	(1.37)	(1.67)	(2.49)
PMR	0.018	0.009	0.015	0.022	0.016	0.001
	(0.74)	(0.41)	(0.65)	(0.71)	(0.55)	(0.03)
HCR × PMR	–0.022	–0.016	–0.040	–0.019	–0.024	–0.005
	(–0.81)	(–0.64)	(–1.42)	(–0.59)	(–0.80)	(–0.13)
Relative size		0.006	0.004		0.012	0.004
		(0.97)	(0.93)		(1.42)	(1.04)
Total assets of acquirer		–0.005	–0.007*		–0.002	–0.008
		(–1.41)	(–1.68)		(–0.47)	(–1.52)
Total assets of target		0.003	0.005		0.001	0.002
		(0.94)	(1.61)		(0.27)	(0.66)
Market-to-book of acquirer		–0.006***	–0.008***		–0.004**	–0.005
		(–5.34)	(–3.04)		(–2.41)	(–1.54)
Market-to-book of target		0.001	–0.001		–0.002	–0.002
		(0.53)	(–0.42)		(–1.09)	(–0.57)
Leverage ratio of acquirer		0.008	0.016		0.033	0.047
		(0.22)	(0.39)		(1.17)	(1.38)
Leverage ratio of target		–0.006	–0.002		0.039	0.042
		(–0.27)	(–0.10)		(1.55)	(1.44)
Cash holdings of acquirer		0.015	0.032		0.077**	0.097***
		(0.39)	(0.82)		(2.06)	(2.70)
Cash holdings of target		0.008	0.027		0.017	0.038
		(0.53)	(1.14)		(0.62)	(1.16)
Intercept	–0.029***	0.001	–0.003	–0.026*	–0.039	–0.016
	(–2.70)	(0.03)	(–0.12)	(–1.74)	(–1.27)	(–0.50)
Adjusted *R*-squared	0.002	0.03	0.04	0.001	0.04	0.07
No. of observations	964	964	709	878	878	642

Table 7 – *continued*

Panel B. Mergers grouped by type

	Dependent variable is change in postmerger industry-adjusted operating performance									
	From year +1 to +2					From year +1 to +3				
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HCR × *MergerType*1	0.051	0.061				0.005	−0.010			
	(0.95)	(1.08)				(0.07)	(−0.15)			
HCR × *MergerType*2	0.066**	0.073**	0.080***			0.065**	0.060*	0.083***		
	(2.03)	(2.22)	(2.77)			(1.99)	(1.79)	(2.98)		
HCR × *MergerType*3	0.018	0.027				−0.008	0.005			
	(0.80)	(1.19)				(−0.25)	(0.17)			
HCR × *Vertical*				−0.034					0.022	
				(−0.91)					(0.44)	
HCR × *Horizontal*				0.051*					0.057	
				(1.87)					(1.44)	
HCR × *Conglomerate*				0.027**	0.042***				0.015	0.032**
				(2.03)	(3.17)				(1.02)	(2.41)
PMR	0.003	0.012	0.045*	0.012	0.039	0.011	−0.002	0.045**	0.022	0.036
	(0.15)	(0.49)	(1.67)	(0.56)	(1.39)	(0.38)	(−0.05)	(2.40)	(0.71)	(0.86)
HCR × *PMR*	−0.008	−0.035	−0.091**	−0.022	−0.065**	−0.016	0.000	−0.090***	−0.030	−0.068
	(−0.29)	(−1.18)	(−2.34)	(−0.87)	(−2.27)	(−0.53)	(0.01)	(−2.79)	(−0.93)	(−1.61)
*MergerType*1	−0.001	−0.006				−0.032	−0.005			
	(−0.03)	(−0.17)				(−0.83)	(−0.11)			
*MergerType*2	−0.031	−0.031				−0.057	−0.019			
	(−0.98)	(−1.02)				(−1.64)	(−0.50)			
*MergerType*3	−0.002	−0.004				−0.017	0.010			
	(−0.06)	(−0.10)				(−0.37)	(0.21)			
Vertical				0.041					−0.025	
				(0.99)					(−0.60)	
Horizontal				−0.016					−0.079*	
				(−0.48)					(−1.68)	
Conglomerate				−0.001					−0.035	
				(−0.04)					(−1.15)	
Intercept	No	No	−0.028	No	0.009	No	No	−0.037	No	0.018
			(−0.72)		(0.42)			(−1.18)		(0.92)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted *R*-squared	0.04	0.05	0.19	0.04	0.09	0.04	0.08	0.24	0.05	0.10
No. of observations	964	709	150	964	446	878	642	137	878	415

Table 8

The effect of human capital relatedness on postmerger change in employment.

The table reports regressions of the change in number of employees on human capital relatedness (*HCR*), product market relatedness (*PMR*), and the interaction between *HCR* and *PMR*. The sample includes deals announced during the period 1997–2012. The dependent variable is the average postmerger industry-adjusted number of employees in years + 1 and +2 (or +1, +2, and +3) minus the premerger industry-adjusted number of employees in year −1, where year 0 is the merger announcement year. The premerger industry-adjusted number of employees is the sum of the acquirer and target industry-adjusted number of employees. Industry-adjusted number of employees is the difference between a firm's number of employees and the median number of employees for firms in the same three-digit SIC code. Panel A regressions do not condition *HCR* by type of merger. Regressions (3), (4), (7), and (8) exclude mergers between single segment firms in the same industry (i.e., cases in which *HCR* = 1). Panel B regressions condition *HCR* by type of merger. *MergerType*1 is a dummy variable equal to one for single-segment acquirer and target in different industries, *MergerType*2 is a dummy variable equal to one when one or both acquirer and target are multi segment with no common industry segments, and *MergerType*3 is a dummy variable equal to one when each of the merging firms is either single or multi segment and have at least one segment in the same industry. The dummy variables *Vertical*, *Horizontal*, and *Conglomerate* are equal to one for vertical, horizontal, and conglomerate mergers, respectively, and they are constructed using the algorithm in Fan and Goyal (2006). In panel B, regressions (1), (2), (4), (6), (7), and (9) are estimated without an intercept, regressions (2) and (7) exclude mergers between single segment firms in the same industry (i.e., cases in which *HCR* = 1), regressions (3) and (8) are estimated using type two mergers only, and regressions (5) and (10) are estimated using conglomerate mergers only. The control variables are those used in Tables 4–6. All variables are defined in Appendix A, and all variables are winsorized at the 1st and 99th percentiles except *HCR* and *PMR*. We report *t*-statistics in parentheses below parameter estimates that are computed using robust standard errors clustered at the year level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable is average postmerger industry-adjusted employment minus premerger industry-adjusted employment							
	Average of years +1 and +2 versus −1				Average of years +1, +2, and +3 versus −1			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. All merger types								
HCR	−7.039*	−17.883**	−13.168***	−23.662***	−7.364*	−20.496**	−13.823**	−27.201***
	(−1.77)	(−2.29)	(−2.63)	(−2.77)	(−1.66)	(−2.49)	(−2.28)	(−3.19)
PMR		−10.830**		−12.661**		−12.272**		−15.472***
		(−2.30)		(−2.27)		(−2.41)		(−2.90)
HCR × *PMR*		19.375**		22.446**		23.052***		28.839***
		(2.44)		(2.14)		(3.03)		(3.42)
Intercept	33.328***	39.459***	42.046***	48.694***	34.759***	41.725***	43.397***	51.778***
	(3.14)	(3.16)	(3.45)	(3.53)	(2.97)	(3.07)	(3.31)	(3.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted *R*-squared	0.08	0.08	0.10	0.11	0.07	0.09	0.10	0.11
No. of observations	921	921	676	676	838	838	614	614

(*continued*)

Table 8 – *continued*

	Dependent variable is average postmerger industry-adjusted employment minus premerger industry-adjusted employment									
	Average of years +1 and +2 versus −1					Average of years +1, +2, and +3 versus −1				
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel B. Mergers grouped by type										
HCR × *MergerType*1	−10.001*	−11.991*				−13.025**	−17.106***			
	(−1.83)	(−1.65)				(−2.35)	(−2.62)			
HCR × *MergerType*2	−71.429**	−71.813***	−61.692***			−74.582**	−75.333***	−63.384***		
	(−2.48)	(−2.63)	(−2.61)			(−2.44)	(−2.62)	(−2.70)		
HCR × *MergerType*3	−13.636	−20.953				−18.240	−26.415*			
	(−1.27)	(−1.57)				(−1.59)	(−1.88)			
HCR × *Vertical*				−24.367					−21.344	
				(−1.23)					(−0.87)	
HCR × *Horizontal*				−5.081					−9.176	
				(−0.83)					(−1.60)	
HCR × *Conglomerate*				−23.170***	−30.867***				−26.763***	−34.046***
				(−2.59)	(−2.76)				(−2.85)	(−2.91)
PMR	−8.959	−11.304*	−15.292	−8.049*	−17.983***	−9.971*	−13.801**	−12.318	−9.426**	−19.675***
	(−1.63)	(−1.75)	(−1.22)	(−1.91)	(−2.98)	(−1.67)	(−2.08)	(−0.94)	(−2.07)	(−3.18)
HCR × *PMR*	14.707	18.448	11.982	14.677*	33.986***	17.862*	24.611**	10.676	18.285**	36.979***
	(1.54)	(1.48)	(0.39)	(1.93)	(3.21)	(1.84)	(2.12)	(0.34)	(2.53)	(3.52)
*MergerType*1	35.699***	44.979***				37.876***	47.434***			
	(3.98)	(4.40)				(3.98)	(4.74)			
*MergerType*2	57.943***	66.929***				59.708***	65.989***			
	(3.25)	(3.66)				(3.11)	(3.64)			
*MergerType*3	39.329***	52.660***				43.657***	52.504***			
	(3.51)	(4.23)				(3.47)	(4.23)			
Vertical				46.178**					45.670**	
				(2.57)					(2.17)	
Horizontal				31.310***					34.703***	
				(3.20)					(3.21)	
Conglomerate				41.068***					43.154***	
				(3.29)					(3.20)	
Intercept	No	No	104.415***	No	55.672***	No	No	108.540***	No	63.203***
			(3.16)		(3.50)			(3.33)		(4.23)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted *R*-squared	0.13	0.15	0.30	0.10	0.14	0.13	0.16	0.33	0.10	0.16
No. of observations	921	676	140	921	424	838	614	128	838	391

Table 9

The effect of human capital relatedness on postmerger change in selling, general, and administrative expense.

The table reports regressions of the change in selling, general, and administrative expense (SG&A) on human capital relatedness (*HCR*), product market relatedness (*PMR*), and the interaction between *HCR* and *PMR*. The sample includes deals announced during the period 1997–2012. The dependent variable is the average postmerger industry-adjusted SG&A in years + 1 and +2 (or +1, +2, and +3) minus the premerger industry-adjusted SG&A in year −1, where year 0 is the merger announcement year. The premerger industry-adjusted SG&A is the sum of the acquirer and target industry-adjusted SG&A. Industry-adjusted SG&A is the difference between a firm's SG&A and the median SG&A for firms in the same three-digit SIC code. Panel A regressions do not condition *HCR* by type of merger. Regressions (3), (4), (7), and (8) exclude mergers between single segment firms in the same industry (i.e., cases in which *HCR* = 1). Panel B regressions condition *HCR* by type of merger. *MergerType*1 is a dummy variable equal to one for single-segment acquirer and target in different industries, *MergerType*2 is a dummy variable equal to one when one or both acquirer and target are multi segment with no common industry segments, and *MergerType*3 is a dummy variable equal to one when each of the merging firms is either single or multi segment and have at least one segment in the same industry. The dummy variables *Vertical*, *Horizontal*, and *Conglomerate* are equal to one for vertical, horizontal, and conglomerate mergers, respectively, and they are constructed using the algorithm in Fan and Goyal (2006). In panel B, regressions (1), (2), (4), (6), (7), and (9) are estimated without an intercept, regressions (2) and (7) exclude mergers between single segment firms in the same industry (i.e., cases in which *HCR* = 1), regressions (3) and (8) are estimated using type two mergers only, and regressions (5) and (10) are estimated using conglomerate mergers only. The control variables are those used in Tables 4–6. All variables are defined in Appendix A, and all variables are winsorized at the 1st and 99th percentiles except *HCR* and *PMR*. We report *t*-statistics in parentheses below parameter estimates that are computed using robust standard errors clustered at the year level. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable is average postmerger industry-adjusted SG&A minus premerger industry-adjusted SG&A							
	Average of years +1 and +2 versus −1				Average of years +1, +2, and +3 versus −1			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. All merger types								
HCR	−0.722***	−1.393***	−0.962***	−1.703***	−0.758***	−1.508***	−1.079***	−1.880***
	(−2.82)	(−2.58)	(−2.91)	(−2.63)	(−2.77)	(−2.78)	(−3.18)	(−3.05)
PMR		−0.591		−0.743		−0.604		−0.781
		(−1.42)		(−1.59)		(−1.29)		(−1.52)
HCR × *PMR*		1.158*		1.510**		1.266**		1.645**
		(1.94)		(2.00)		(2.07)		(2.22)
Intercept	2.882***	3.213***	3.095***	3.505***	2.638***	2.995***	2.921***	3.380***
	(3.88)	(3.65)	(3.67)	(3.52)	(3.50)	(3.33)	(3.62)	(3.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted *R*-squared	0.09	0.09	0.10	0.11	0.07	0.08	0.09	0.10
No. of observations	798	798	592	592	729	729	537	537

(*continued*)

Table 9 – *continued*

	Dependent variable is average postmerger industry-adjusted SG&A minus premerger industry-adjusted SG&A									
	Average of years +1 and +2 versus –1					Average of years +1, +2, and +3 versus –1				
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel B. Mergers grouped by type										
HCR × *MergerType*1	–0.779	–0.906				–0.965*	–1.175*			
	(–1.51)	(–1.43)				(–1.79)	(–1.81)			
HCR × *MergerType*2	–5.634**	–5.648**	–4.647**			–5.575**	–5.571**	–4.048**		
	(–2.35)	(–2.47)	(–2.45)			(–2.32)	(–2.44)	(–2.23)		
HCR × *MergerType*3	–1.419*	–1.523				–1.658**	–1.983			
	(–1.76)	(–1.27)				(–2.00)	(–1.62)			
HCR × *Vertical*				–1.592					–1.580	
				(–1.17)					(–1.01)	
HCR × *Horizontal*				–0.479					–0.641	
				(–0.95)					(–1.21)	
HCR × *Conglomerate*				–1.718***	–2.111***				–1.894***	–2.241***
				(–3.16)	(–3.53)				(–3.36)	(–3.68)
PMR	–0.549	–0.670	–1.257	–0.397	–0.339	–0.574	–0.747	–0.610	–0.421	–0.344
	(–1.54)	(–1.57)	(–1.12)	(–0.90)	(–0.61)	(–1.48)	(–1.66)	(–0.54)	(–0.85)	(–0.58)
HCR × *PMR*	0.881	1.152	0.968	0.851	1.489**	1.016*	1.369*	–0.094	0.951	1.552**
	(1.61)	(1.49)	(0.33)	(1.38)	(2.14)	(1.84)	(1.84)	(–0.03)	(1.50)	(2.27)
*MergerType*1	3.028***	3.370***				2.821***	3.261***			
	(4.41)	(4.29)				(4.09)	(4.44)			
*MergerType*2	4.250***	4.491***				3.929***	4.265***			
	(3.47)	(3.62)				(3.20)	(3.63)			
*MergerType*3	3.464***	3.749***				3.343***	3.870***			
	(4.18)	(3.57)				(3.93)	(3.51)			
Vertical				3.183**					2.866*	
				(2.40)					(1.96)	
Horizontal				2.572***					2.432**	
				(2.73)					(2.49)	
Conglomerate				3.331***					3.133***	
				(4.00)					(3.75)	
Intercept	No	No	10.768***	No	3.571***	No	No	10.000***	No	3.563***
			(4.31)		(3.53)			(4.53)		(3.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.15	0.17	0.35	0.10	0.11	0.13	0.16	0.36	0.09	0.11
No. of observations	798	592	119	798	383	729	537	110	729	354

Table 10
Descriptive Statistics for the asset sale sample.
The table reports descriptive statistics for the sample of asset sales announced during the period 1997 to 2013. All variables are defined in Appendix A, and all variables are winsorized at the 1st and 99th percentiles of their distributions except *HCR*.

Variable	Mean	Std. dev.	25th Pctl.	Median	75th Pctl.	Obs.
HCR	0.655	0.246	0.491	0.722	0.842	500
Parent CAR (−1, +1) (%)	1.876	7.207	−1.444	0.599	3.399	500
Acquirer CAR (−1, +1) (%)	2.194	5.539	−0.945	1.342	4.569	500
Transaction value ($millions)	632.312	1,242.140	125.000	225.500	536.000	500
Relative transaction size (% acquirer's assets)	29.816	41.109	4.150	12.687	36.249	483
Parent presale employees (1,000s)	50.450	72.238	5.488	17.160	70.600	500
Parent postsale employees (1,000s)	50.859	73.478	5.068	18.300	71.000	500
Total assets of acquirer	7.800	1.507	6.718	7.694	8.815	483
Market-to-book ratio of acquirer	1.813	0.800	1.234	1.540	2.145	470
Leverage ratio of acquirer	0.292	0.187	0.146	0.282	0.417	483
Prior return of acquirer (%)	8.202	30.657	−12.703	4.541	25.800	500

Table 11
Acquirer returns in asset sales and parent employee transfer.
The table reports acquirer returns in assets sales conditioned on the change in employment for the selling firm (parent) from before to after the asset sale. Panel A reports acquirer cumulative abnormal returns by whether the change in parent employment is below or above a critical level from 1% to 5%. The percentage change in parent employment is the absolute value of employment in year +1 minus employment in year −1 scaled by employment in year −1, where year 0 is the asset sale announcement year. Acquirer cumulative abnormal returns are the sum of abnormal returns from day −1 to day +1, where day 0 is the asset sale announcement day. Panel B reports regressions of acquirer cumulative abnormal returns on human capital relatedness (*HCR*) between the acquirer and asset acquired for subsamples of acquirers where the percentage change in parent employment is below and above 3%. All variables are defined in Appendix A, and all variables are winsorized at the 1st and 99th percentiles of their distributions except *HCR*. The *t*-statistics for the difference in acquirer mean abnormal returns in Panel A are bootstrapped based on 1,000 samples with replacement from the below and above critical level groups in proportion to their sample sizes. The *t*-statistics in Panel B (in parentheses below parameter estimates) are computed using robust standard errors clustered at the year-level. We use ***, **, * to denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Acquirer CAR (%) for change in parent employment around asset sale below and above a critical value

Critical level of change in parent empl.	Change in parent employment is: Below critical level			Above critical level				
	Mean (%)	*t*-stat	Obs.	Mean (%)	*t*-stat	Obs.	Difference (%)	*t*-stat
1%	0.344	0.45	30	2.312	8.96***	470	1.968	2.24**
2%	0.483	0.74	52	2.393	9.05***	448	1.910	2.75***
3%	0.900	1.58	73	2.416	8.88***	427	1.516	2.33**
4%	1.323	2.79***	102	2.418	8.47***	398	1.095	1.72*
5%	1.411	3.11***	113	2.423	8.34***	387	1.012	1.82*

Panel B. Regressions of acquirer CAR on HCR for subsamples below and above a 3% change in parent employment

	(1)		(2)		(3)		(4)	
Variable	Below	Above	Below	Above	Below	Above	Below	Above
HCR	1.159	2.510***	0.429	2.118**	1.303	2.354**	1.947	1.820*
	(0.77)	(3.03)	(0.13)	(2.57)	(0.68)	(2.17)	(0.65)	(1.86)
Relative transaction size					−1.403	2.633***	−1.352	2.633**
					(−0.63)	(2.65)	(−0.55)	(2.43)
Total assets of acquirer					−0.337	−0.534**	−0.626	−0.526**
					(−0.78)	(−2.22)	(−1.12)	(−2.08)
Market-to-book of acquirer					−1.254*	−0.695**	−1.894**	−0.529
					(−1.78)	(−2.38)	(−2.23)	(−1.51)
Leverage of acquirer					4.722	1.260	4.025	1.361
					(1.27)	(0.91)	(0.94)	(0.90)
Prior returns of acquirer					0.543	0.086	0.098	−0.110
					(0.21)	(0.09)	(0.03)	(−0.11)
Intercept	0.185	0.756	−0.614	0.701	4.242	5.016**	6.606	4.921**
	(0.18)	(1.13)	(−0.29)	(1.18)	(1.06)	(2.46)	(1.32)	(2.30)
Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Adjusted *R*-squared	0.004	0.01	0.25	0.06	0.13	0.10	0.38	0.13
No. of observations	73	427	73	427	69	401	69	401