The Human Factor in Acquisitions:

Cross-industry Labor Mobility and Corporate Diversification*

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Current Version: August 2015

Abstract

Internal labor markets facilitate cross-industry worker reallocation and collaboration, and the resulting benefits are largest when the markets include industries that utilize similar worker skills. We construct a matrix of industry pair-wise human capital transferability using information obtained from more than 11 million job changes. We show that diversifying acquisitions occur more frequently among industry pairs with higher human capital transferability. Such acquisitions result in larger labor productivity gains and are less often undone in subsequent divestitures. Moreover, acquirers retain more high skill workers and they exploit the real option to move workers from the target firm to jobs in other industries inside the merged firm. Overall, our results identify human capital as a source of value from corporate diversification and provide an explanation for seemingly unrelated acquisitions.

JEL codes: G34, J24, J62, M51, M54.
Key words: Corporate Diversification, Mergers and Acquisitions, Internal Labor Markets, Worker Mobility, Human Capital Transferability

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* We thank Han Kim and seminar participants at the CSEF-EIEF-SITE Conference on Finance and Labor, Nova School of Business and Economics, CEMFI, Center for Economic Studies at the Census Bureau, SAIF, HKUST, and the University of Maryland for helpful suggestions. The research in this paper was conducted while the authors were Special Sworn Status researchers of the U.S. Census Bureau. This research uses data from the Census Bureau's Longitudinal Employer Household Dynamics Program, which was partially supported by the following National Science Foundation Grants SES-9978093, SES-0339191 and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

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1. Introduction

How important is human capital for determining the boundaries of the firm? The literature on incomplete contracts emphasizes the interaction between organizational form and workers' human capital investments (Grossman and Hart, 1986; Hart and Moore, 1990, Hart, 1995). Yet, the empirical literature has largely used industry classifications defined by firms' activity in product markets to define asset complementarity.[1] We consider how the transferability of human capital affects the decision to diversify into new industries by acquisition. We find that economy-wide patterns of labor migration between industries significantly predict the industry choices made by acquirers in diversifying deals. Consistent with a human capital channel, high skill workers are more likely to be retained and moved to new positions inside merged firms when there is greater human capital transferability between the industries in which the merging firms operate. Moreover, mergers of firms in high transferability industry pairs generate larger increases in productivity than other (diversifying) deals.

Merging firms can benefit from the internal labor markets created by the coownership of production processes in different industries. Internal labor markets lower the transaction costs of transferring human capital between industries. First, they can facilitate communication and collaboration between workers with similar skillsets in different divisions. For example, a scientist may find it less costly to solicit help from another scientist working in a different division of her firm than from a scientist with similar expertise in the external market. These collaborations can in turn improve worker productivity. Second, the ability to transfer workers within the internal labor market can enable the firm to bypass frictions in external labor markets—such as search, termination or training costs. This real option can be particularly valuable if the industries in which the firm operates are subject to different shocks, since the firm can more cheaply reallocate human capital towards industries with good opportunities and away from industries with weak opportunities than firms in the external market.

[1] See, e.g., Maksimovic and Phillips (2013, 2007) for surveys of the empirical literature on diversified firms and Betton, Eckbo, and Thorburn (2008) for a survey of the extensive empirical literature on corporate takeovers, including diversifying versus within-industry transactions. In all cases, diversification is measured based on the industries of the product markets in which firms sell their output.

The opportunities to change jobs within internal labor markets are also likely to feed back to worker incentives. For example, workers can exploit job rotation programs to increase their prospects for promotion (Carmichael and MacLeod, 1993). The resulting skill accumulation can also improve their productivity in their current positions; best practices from another division may be adapted to increase productivity in the worker's home division. Workers in focused firms have fewer opportunities and less incentive to acquire such skills. Thus, the resulting productivity gains are again unlikely to be available to firms operating independently in the same industries, creating a potential incentive for a diversifying merger. Moreover, the merger synergies from creating or expanding an internal labor market are likely to be the largest when the component industries use worker skills that are more closely related.

Given this discussion, we propose that firms may undertake diversifying acquisitions to reap the benefits of the internal labor markets created by jointly operating in multiple industries as part of the same firm. We test this hypothesis using data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program and Longitudinal Business Database (LBD). We use the LBD to identify firms involved in acquisitions and the timing of transactions. We use the LEHD data to link worker-level information to the acquiring and target firms, and to measure patterns of movement in U.S. labor markets over time.

To begin, we construct a measure of human capital transferability using observed cross-industry worker movement in the LEHD data. Year-by-year, we consider the sample of job changers over the prior five years. For each pair of industries, we measure the frequency with which job changers move between the two industries during the window as a fraction of the total number of job changers in the two industries. For pairs of distinct industries, a relatively high fraction of job changers provides a credible proxy for the overlap in (or relatedness of) the skillsets required of workers in the two industries. To isolate movement of workers whose human capital is likely to be scarce in the labor market, we also construct an alternative measure in which we restrict the sample of job changers to workers whose annual wages exceed $75,000.

We then use our measures of human capital transferability to predict the choices of industries into which firms diversify through acquisitions. Our identification strategy predicts industry level patterns in acquisitions using our measure of human capital transferability across industry pairs. Specifically, in each year and for each pair of distinct industries, we identify the total employment (or number of firms) from that industry pair that is part of a diversifying deal as a fraction of the total employment (or number of firms) that is part of an acquisition and regress it on the transferability of human capital within the pair. By doing so, we side-step firm- and deal-level sources of endogeneity in the decision to merge since these factors will net out when we aggregate to the industry level. We find that the mobility of workers between two industries over the prior five years has a significant positive effect on the fraction of diversifying deals that involve firms from those industries. The relation is strongest when we measure inter-industry transferability of human capital using only the job changes of high-wage workers. Moreover, the result is robust to several different approaches to control for product market linkages between the industries (i.e., input-output relations). Thus, firms choose industry configurations that maximize the ability to redeploy human capital inside the firm, consistent with a desire to establish or expand internal labor markets as a motivating factor for acquisition decisions.

Next, we test whether human capital transferability across industries leads to greater value synergies from combination using differences-in-differences specifications within an event study framework. First, we consider the rates at which the merged firms divest their new industries over time. We estimate a Cox proportional hazard model of the time at which divestiture occurs. We find that the likelihood of divestiture decreases as the transferability of human capital between the industries of the merging firms increases. Thus, transferability of the human capital employed in the industries of merging firms is associated with a greater realized fit between the merging firms over time. We also measure the change in labor productivity around acquisitions in our sample using the sales to employment ratio. We show that, among diversifying acquisitions, deals in which there is high transferability of human capital between the acquirer and target perform better: the change in labor productivity in a three-year window around the deal is about 18% higher. Again, the results are strongest when we measure human capital overlap using only high-skill workers who earn annual wages greater than $75,000. The results are robust to controls for the overall size of the merged firm as well as the relative size and industry overlap of the merging firms. We also include year fixed effects to capture systematic differences in the timing of the different types of transactions. Finally, we confirm that the results continue to hold when we measure the change in labor productivity as a function of payroll instead of employment. Thus, firms that diversify across industries with human capital overlap benefit even accounting for differences in the wage payments they must make to their workforces.

Next, we measure the effects of the transferability of human capital at the worker level. We measure worker outcomes four and eight quarters following the deal among workers who were employed in the target firm prior to an acquisition. Though there are many possible mechanisms through which firms can realize the benefits of human capital transferability following a deal, we focus on two readily observable worker-level outcomes: retention inside the merged firm and migration within the merged firm to a different industry. We find on average that firms retain fewer high-wage and high-tenure workers from the target firm following acquisitions. However, we see a significant deviation from this pattern in diversifying deals in which there is a high degree of human capital transferability. Relative to within-industry deals or diversifying deals with low transferability, there is a significantly higher retention rate of high-wage and long-tenured employees. One possible explanation for this pattern is that firms are more able to increase efficiency by cutting bloated labor costs in within-industry or low-transferability deals. However, we find the highest labor productivity gains among the high-transferability deals. Thus, our evidence is more consistent with the hypothesis that expanding internal labor markets creates value by increasing the ability of firms to retain valuable high-skill workers. Though we cannot directly measure all of the channels through which broader internal labor markets improve productivity (knowledge transfers, increased worker investments in human capital, etc.), we can observe worker job changes between target and acquiring firms. Consistent with our proposed mechanism, we find that high human capital transferability between the industries in a diversifying deal is associated with a higher likelihood that the firm will relocate workers from the target firm to a new industry in an establishment owned by the acquiring firm prior to the deal.

As a final step, we link human capital transferability to the industry configurations of diversified firms in the cross-section. We find that industries between which workers migrate more freely in external labor markets are also more likely to be collocated in diversified firms. Our result is again robust to controlling for vertical relatedness via input/output markets. Thus, human capital considerations seem to be a first-order consideration for understanding the organizational structure of established firms.

Overall, our results point to human capital as an important factor for merger decisions. Diversification can create value by allowing the firm to realize productivity gains in an internal labor market.

Our analysis builds on recent work that considers the link between finance and labor markets. Recent papers link the mobility of human capital to the prices of risk in financial markets (Donangelo, 2014, Eisfeldt and Papanikolaou, 2013). Unlike these papers, which model the firms from which human capital (may) exit, we consider variation in the transferability of human capital between industry pairs. By imposing this additional structure, we can link models of organization capital (Atkeson and Kehoe, 2005; Lustig and van Nieuwerburgh, 2011) with the decision to expand a firm's scope through acquisitions. Our approach builds on the analysis of Tate and Yang (2015), who show that diversified firms use internal labor markets to transfer workers towards the industries with the best opportunities at a higher rate than workers make those moves in the external labor market. They also find evidence that workers develop skills inside conglomerates that facilitate such moves. However, their analysis takes organizational structure as given and, thus, cannot address whether such benefits are an economically important factor in the decision to diversify or merely a side-effect of a decision made for other reasons. By focusing on the transferability of human capital and its effect on firm scope, our results complement the analysis of Ouimet and Zarutskie (2012), who show that some firms use takeover markets to expand the scale of their workforces. However, unlike Ouimet and Zarutskie, we do not argue that firms make acquisitions to obtain the services of particular workers. Instead, operations in multiple industries create internal labor market synergies regardless of the identities of the individual workers due to the transferability of skills between the industries. We also complement the findings of Custodio and Metzger (2013), who find that managers acquire assets in industries that they know but who do not consider the transferability of human capital between acquirers and targets, and Seru (forthcoming), who finds that diversification affects worker innovation but does not model the firm's decision to diversify.

Our results provide a novel explanation for corporate diversification. A prominent strand of the finance literature identifies corporate diversification as a symptom of agency problems (e.g., Betton, Eckbo, and Thorburn (2008); Morck, Shleifer, and Vishny (1990)). Consistent with this notion, several studies find evidence of an empirical "diversification discount" (Lang and Stulz, 1994; Berger and Ofek, 1995). Many subsequent studies dispute the conclusion that diversification destroys value (Campa and Kedia, 2004; Villalonga, 2004; Arikan and Stulz, 2011). Yet, the mechanism by which diversification creates value is unclear. One possibility is that diversified firms allocate capital more efficiently than standalone firms. Maksimovic and Phillips (2002) find evidence consistent with this hypothesis, though Ozbas and Scharfstein (2010) take the opposite view. Another alternative is that traditional industry classifications (SIC/NAICS codes) are poor measures of the commonality of the product markets in which firms operate. Hoberg & Phillips (2012a,b) construct a pair-wise relatedness measure for public firms using textual analysis of product descriptions from 10K filings. Our results suggest a different form of industry misclassification: differences in the product markets in which firms operate may mask valuable synergies in human capital inputs.

A literature in strategy, starting from Wernerfelt (1984), also takes a resource-based view of diversification. A common approach in the literature is to measure resource relatedness using overlap in the occupations employed in different industries (Farjoun (1994, 1998)). We instead construct measures of cross-industry labor flows. Neffke and Henning (2013) take a similar approach using Swedish data, finding a correlation between labor flows and the industries into which firms diversify; however, they do not analyze deal performance or the micro-level labor allocation decisions of acquiring firms.

2. Data and Variable Definitions

We use data from the U.S. Census Bureau's Longitudinal Business Database (LBD) and Longitudinal Employer-Household Dynamics (LEHD) program to test our hypotheses. The LBD covers all non-farm establishments in the U.S. beginning in 1976 and contains information on plant ownership, location, status (active or inactive), industry, aggregate employment, and total payroll. We use the LBD to identify changes in ownership. We identify acquisitions as cases in which the firm identifier ("firmid") associated with all of a business's establishments changes from one year to the next. We also require that the new firmid existed in the data in the year prior to the change to separate changes in administrative records from true ownership changes, and we require that the old firmid transfers all of its operating assets to the new firm and disappears from the data following the change. The latter requirement eliminates partial asset sales from our data, but also reduces noise in merging the LBD to worker-level information in the LEHD data since all establishments in the firm (and, by implication, workers) experience the change. We also use the SIC code for the full sets of establishments of the merging firms to determine whether each ownership change is a diversifying or within-industry transaction. We identify an acquisition as diversifying if there is no overlap in the industries in which the acquiring and target firms operate prior to the transaction. This strict definition of diversification is necessary since otherwise acquirers could be motivated by a desire to expand their operations in the overlapping industries and not to take advantage of human capital synergies across industries. Throughout the analysis, we define industries using the 49 Fama-French industries.[2] We choose a broad definition of industries to ensure that there is a real distinction between the product markets and lines of business in which firms in different industries operate. Thus, our measures of job flows will differ from those constructed by Hyatt et. al. (2014) using NAICS classifications. Our final sample includes about 4000 diversifying acquisitions from 1995 to 2007.[3] Since the LBD covers both public and private firms, we are not restricted to transactions undertaken by public firms, as in most of the existing studies in the literature, and thus are able to analyze a substantially larger sample of deals.[4] Moreover, there should be less measurement error in our classification of diversification than in studies that classify

[2] See Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for industry definitions. Our results do not depend on this industry definition and hold, e.g., using 2-digit SIC codes to define industries. Throughout our analysis, we use data from 48 Fama-French industries and exclude the "Other" industry group.

[3] Here and elsewhere in the paper where we report sample sizes we round to a whole number. This is the current reporting convention for sample sizes in research using data from the Census Bureau's research data centers to minimize disclosure risk.

[4] For example, Mock, Shleifer and Vishny (1990) studies 326 diversifying acquisitions, Kaplan and Weisbach (1992) studies 123 diversifying acquisitions, and Chevalier (2000) has a sample of 215 diversifying acquisitions.

deals as diversifying using Compustat or CRSP since the LBD provides industry classifications for each of the firms' establishments and not just the firms' main industry code.

Our worker-level information comes from the LEHD data. The LEHD data contain worker-firm matched observations for 31 U.S. states.[5] In Figure 1, we provide a map of the states from which data is available. The earliest available data come from 1990, though the dates at which states enter the data vary. We observe quarterly data on workers' wages and the firm and unit in which they work. We also observe basic demographic characteristics including age, gender, and race.

We use the data for two purposes. First, we use the dynamic information on worker-firm matches to construct a measure of mobility between Fama-French industry groups, which we refer to as the human capital transferability (HCT) index. Using a 10% random sample of the data (about 11.5 million records), we identify the subset of workers in each quarter who accept a job in a new firm.[6] We observe the industry classification for each job at the reporting unit level.[7] We exclude workers with less than 1 year of tenure in their pre-job change firms to limit the effect of temporary workers on our analysis. We also exclude workers in counties with fewer than 10 industries so that we are more likely to capture industry changes that reflect workers' preferences and not location constraints. Using this information, we calculate for each industry the total number of job changers each quarter who move to each industry in the sample (including workers who remain in their original industries). We then aggregate across all quarters in a backward-looking five year window and scale by the total number of job changers in the industry. For each pair of industries in the sample, we then compute a non-directional measure of human capital transferability between the industries as the average of the fraction of workers from each industry that move to the other industry in the pair. It is important that our index is not directional since the transferability of human capital in either direction

[5] For our analysis, we use the 2008 "snapshot" of the LEHD data available to researchers in the U.S. Census Bureau's Research Data Center (RDC).

[6] We use the Census "firmid" to identify firms so that we restrict our sample only to external job changers. We exclude moves to another reporting unit within diversified firms to limit endogeneity concerns when we link our mobility measure to diversification choices. Our use of a 10% random sample is innocuous and is necessary for tractability since the full LEHD sample contains hundreds of millions of observations.

[7] Reporting units in the LEHD data are state employer identification numbers (SEINs). A single firm often operates many SEINs.

between industries could motivate a deal. We also construct an alternative version of the measure in which we first restrict the sample only to workers earning at least $75,000 in annual wages in their original jobs and a second version in which we restrict the sample to workers earning less than $25,000.[8] Throughout the paper, we use industry fixed effects to correct for differences in the absolute sizes of industries that could otherwise explain differences in the frequencies of cross-industry moves measured by the HCT index. Thus, we compare the frequency of job changes from an origin industry to a particular destination industry only to the frequency of job changes to that same destination industry from different original industries.

An alternative approach might be to construct a measure of worker mobility across industries that incorporated information on the wage changes workers experience upon making industry changes. However, we believe our approach introduces less noise into the measure. As long as workers make optimal choices between possible destination industries, our measure will correctly capture differences in transferability of their human capital to different industries regardless of the motive for the job change. Wage changes, however, are unlikely to be readily comparable across different types of job changes (e.g., voluntary versus involuntary moves).

We also use the LEHD data to measure the consequences of mergers at the worker level. Because both the LBD and the LEHD data contain employer identification numbers (EINs), it is straightforward to link firms in the LBD with quarterly information on their workers from the LEHD data for the firms involved in ownership changes in our sample.[9] We use the longitudinal information in the LEHD data to identify job changes after mergers for workers in the target firms as well as movement from the target firm to units owned by the acquirer prior to the deal.

Because the LEHD data only cover 31 states, we cannot observe all workers in firms involved in acquisitions. We cannot include workers from establishments in uncovered

[8] Wages reported in the LEHD data are quarterly. We annualize wages by taking the average quarterly wage over the prior four quarters and multiplying by four. We exclude the first and last quarters of workers' spells inside a firm to avoid bias from including wages earned over an unobserved portion of a quarter. We also adjust wages using the consumer price index so that the $75,000 ($25,000) threshold is consistent over time.

[9] Note again that this step would be more complex and could introduce measurement error if we included partial asset sales in our sample because not all workers linked to the target firm prior to the transaction would become part of the acquiring firm after the deal. Thus, we would need to partition the set of workers linked to the target firm in the LEHD data into those affected and those unaffected by the deal.

states. Moreover, we cannot distinguish between workers who leave the merged firm following the deal and workers who move to an establishment located in an uncovered state. A consequence is that we could understate worker retention and the amount of internal reallocation following mergers in our sample. To mitigate this problem, we exclude deals in which either the target or acquirer firm has establishments outside LEHD coverage (only) for our analysis of worker-level outcomes. A related concern is that our measures of human capital transferability draw only from the job choices of workers in 31 states. However, there are no obvious regional biases in the set of included states (see Figure 1). Moreover, the reason for inclusion in or exclusion from the set of states available to researchers is typically preexisting state laws, suggesting that it is appropriate to consider the available states to be a random sample.

In Table 1, we provide summary statistics of the data. In Panel A, we provide details on the sample of job changers from the LEHD data that we use to construct our measure of human capital transferability across industries. The data include over 11 million worker-quarters, in which the average annual wage is $24,990 and the average tenure in the pre-change firm is roughly 3 years. We also illustrate the industry distribution of the sample in Figure 2.

In Panel B of Table 1, we provide summary statistics of a subsample of merger deals for which we observe sales information for acquirer and target firms before the transaction and for the combined firm afterwards and, thus, can measure the change of labor productivity. The information on sales is obtained from the Business Register (SSEL) and is only available for a subset of firms. Our subsample with sales information includes 3,900 deals, 600 of which diversify the acquiring firm into an industry in which it operated no establishments prior to the deal. Acquiring firms are much larger than target firms on average, measured by employment: mean employment among acquirers is 13,588; mean employment among targets is 577. Labor productivity is similar among acquirers and targets, though it is significantly higher for acquirers than targets on average in the subset of diversifying deals, suggesting that diversifying acquirers operate relatively efficiently prior to the deal. We also observe that acquirers and targets in diversifying deals have smaller workforces than their counterparts in related deals. This difference is likely to be a consequence of defining diversification to include only deals in which there is zero overlap in the industry configurations of the acquiring and target firms.

Finally, in Panel C, we provide demographic information for the subsample in which we can cleanly identify workers from both acquirer and target firms before and after the transaction. Our subsample with worker records consists of 1.4 million workers from 3,700 transactions in which all involved establishments are in LEHD-covered sates (roughly 400 of which are diversifying). In this subsample, the average worker is 39 years old, with 3 years of tenure in the target firm and pre-deal annual wages of $30,350. Note that workers in target firms have higher mean wages than workers in the random sample in Panel A, consistent with the idea that some firms target human capital when making acquisitions. 72% of workers are white and 41% are women. We also provide separate summary statistics for the subsamples of workers from targets in diversifying and within-industry deals. If anything, workers in the targets of diversifying deals appear to have higher wages, though the difference is not significant, consistent with the idea that human capital may be an important factor for this type of transaction. The lone significant difference in demographics across the samples is for worker gender: we observe significantly more women in the targets of within-industry deals. We also observe higher worker retention rates following diversifying deals. It is worth noting that the two subsamples (from Panel B and Panel C) do not completely overlap – one is restricted by the availability of sales information and the other one is limited by the coverage of states in the LEHD data.

3. Human Capital Transferability and Corporate Diversification

We argue that diversification can create value when the human capital inputs used in different lines of business (or industries) are related. Employment in the same firm can lower the costs to employees of accessing the expertise of their colleagues, potentially increasing productivity and innovation. In addition, overlapping skillsets can create a valuable real option for the firm to reallocate workers across industries in response to shocks, particularly when there are frictions in external labor markets. Moreover, the opportunities provided by an internal labor market can increase the incentives of the firm’s workers to invest in productivity-enhancing skills, since those skills are also of greater value to their employing firm.

As a first test of our hypothesis, we ask whether the transferability of human capital across industries affects the choices of industry configurations firms make in diversifying deals. We classify deals as diversifying if there are no establishments operating in the same Fama-French 48 industry group across the acquiring and target firms. We use the HCT index to measure the ease with which human capital transfers between the pairs of industries in each deal (See Section 2 for additional details of the index’s construction).

Before turning to our formal tests, we provide some additional statistics on the HCT index. In Table 2, we list pairs of industries between which we see a high frequency of worker movement under the HCT Index. In the left columns of Panel A, we report the top 10 industry pairs among the full sample of industry pair years. We see that several pairs include the Personal Services, Business Services, Wholesale, or Retail industry groups. It is not surprising that service-oriented industries rank high by worker mobility. Service-oriented firms may also benefit most from organizational structures that facilitate efficient deployment of human capital, since human capital is the primary production input. It is unlikely that such firms can achieve much value from reallocating physical capital. Since these industry groups rank among the highest by our measure, it eases concerns that our measures of human capital transferability might pick up synergies from capital reallocation. In Panel B, we report the top 10 industry pairs by human capital transferability, but excluding pairs that include these four industry groups. Among the remaining set are some industry pairs—such as Hardware and Chips—that may also be related through product market connections. As a final step, we report in Panel C the top 10 industry pairs by the HCT index, but excluding all pairs of industries in which more than 2.5% of industry output flows between the pair via input-output relations, using the input-output matrix available from the Bureau of Economic Analysis (BEA). Included are pairs like Medical Equipment and Drugs or Hardware and Laboratory Equipment in which movement of high-skill doctors or engineers is likely to drive the relation. However, we also see pairings such as Fun and Meals or Agriculture and Construction, in which low-skill workers may be responsible for most of the movement. On the right side of the table, we present the top 10 industry pairs using our second version of the HCT index, in which we restrict the sample to job changes by workers earning annual salaries of at least $75,000. We again consider the full sample and the same two restricted samples.[10] Focusing on Panel C, we find that some of the likely low-skill pairings remain on the list, though they tend to be lower in the ranking, suggesting that the skill overlap is not entirely driven by low-skill workers. We also see some additional pairs enter, such as Electrical Equipment and Chips, which are again likely to reflect job changes by highly-skilled engineers.

Next, we formally test whether acquirers are more likely to diversify into industries that have high human capital transferability with the industries in which they already operate establishments. We consider two dependent variables, both measured annually at the industry pair level. For each industry in which at least one acquiring firm operates, we aggregate the total employment acquired in all deals (both related and diversifying) in each distinct industry group. We then scale by the total employment across all diversifying deals within the acquirer's industry in that year. As such, the ratio we compute measures the absolute asset reallocation across industries and provides a fair comparison between industries. Alternatively, we make the same computation, but using the number of firms instead of employment.

There are many firm-specific factors that could affect the decision to make an acquisition or the likelihood of becoming a takeover target and that might also correlate with the transferability of human capital between merging firms' industries. To sidestep this source of endogeneity, we conduct our tests at the industry level. By aggregating to the industry level, idiosyncratic firm-level variation or shocks will net out and therefore will not influence our estimates or inferences. We estimate the following regression specification:

$$Y_{ijt} = \alpha + \beta HCT_{ij(t-5,t-1)} + \boldsymbol{X}'_{ijt}\boldsymbol{\gamma} + \varepsilon_{ijt} \quad (1)$$

where Y measures the intensity with which acquirers in industry i diversify into industry j (for i not equal to j) in sample year t, HCT is the human capital transferability index between industries i and j measured over a five year window ending at t-1, and $\boldsymbol{X}$ is a vector of controls in year t.[11] We include all of the 48 by 47 cross-industry pairs in the

[10] All of our later regression results are robust to also considering any of these three samples.
[11] While our HCT index is symmetric between industry i and j, the dependent variable is not.

period between 1995 and 2007 for which we can define the HCT index (i.e., we exclude cases in which we do not observe any industry changers from either industry in the pair and, therefore, the denominator is 0).

To control for product market linkages across industries, we include in $\boldsymbol{X}$ a measure of the input/output flows between the acquiring and target industries, defined using the BEA's input-output matrix. Similar to the construction of the HCT index (see Section 2), we compute the flows between two industries as the average of the flows in each direction. We include target industry fixed effects to control for time-invariant differences in the attractiveness of firms in different industries as takeover targets. Similarly, we include acquirer industry fixed effects to control for differences in acquisition propensities across industries, though such differences would only affect our analysis if increases in the propensity to acquire also affect the distribution of the industries into which acquirers diversify. In our main reported specification, we allow these effects to vary by year to control for industry merger waves. As we discussed in Section 2, the fixed effects also correct for differences in the sizes of industries that could contaminate the HCT index: we measure whether acquirers in a given industry are more likely to expand into industries with which they form high transferability pairs, adjusting for differences in the relative sizes of potential target industries.[12] Because expansion by acquiring firms across different industry groups is not independent in a given year, we cluster standard errors by acquirer industry year.

In Panel A of Table 3, we report the regression results using the dependent variable that measures the propensity for acquirers to diversify into other industries based on employment. In Column 1, we find that high human capital transferability between a target industry and an acquirer's existing industries, measured by the fraction of job changers over the prior five years who move between the two industries, predicts a significantly higher volume of diversification into that industry. Economically, a one standard deviation increase in the transferability of human capital would lead to a 58% increase in the fraction of employment moving between the industry pair in diversifying deals from its mean or, alternatively, 10% of a standard deviation. By comparison, a one

[12] Because including industry effects in the regression adjusts both the independent and dependent variables for industry-specific effects (including differences in size), this approach is better than adjusting the HCT index directly for these differences without a corresponding adjustment in the regressions.

standard deviation increase in industry relatedness measured by input-output links would lead to a 35% increase in the intensity of diversifying deals between the industry pair from its mean, or 5.5% of a standard deviation. Thus, the transferability of human capital appears to be a relatively more important factor in determining the industries firms target in diversifying deals—the marginal effect of the human capital factor is about 1.7 times as big as the effect from product market linkages.

In Column 2, we estimate equation (1) using an alternative version of the HCT index in which we measure human capital transferability using only job changes of high-wage workers, which we define as workers whose wages exceed $75,000 annually (high-skill HCT hereafter). We find that the magnitude of the effect is even stronger. Here a one standard deviation change in the index would increase the intensity of diversification activity between the industry pair by 94% from its mean, or 15% of a standard deviation. In Column 3, we use instead the index that defines human capital transferability based on the job changes of workers who make less than $25,000 in annual wages (low-skill HCT hereafter). We find that transferability of the human capital of low wage (or, low skill) workers has less predictive power for corporate diversification activity. This result could arise because the skills of low wage workers are not scarce, limiting the value of the redeployment option to the firm, or because the scope for productivity-enhancing investments in human capital among low skill workers is smaller. However, we still expect transferability of the skills of low wage workers to have some positive predictive power as long as there are frictions in external labor markets that can be avoided by redeploying workers internally in response to shocks. In Columns 4 to 6 of the table, we repeat the same estimations of equation (1), but replacing the dependent variable with the alternative version that defines the intensity of diversification into other industries based on the number of firms instead of employees involved in transactions. The employment-based measure better reflects the effect of the transactions on human capital allocation: deals involving more workers receive more weight. However, the results could conceivably be driven by a small number of very large deals. The firm-based measure instead equally weights transactions. Despite the differences, we find remarkably similar estimates of the effect of human capital transferability on diversification choices. Again, firms are significantly more likely to diversify into industries that have skill overlap with their existing portfolios of industries. The effect is largely driven by the transferability of the human capital of high wage workers. And, the effects are economically stronger than the effect of input-output relations between industry pairs.

A potential alternative explanation of our results is that they reflect firms' responses to changing industry opportunities. If workers migrate towards industries with better opportunities, then firms may also enter into those same industries. Moreover, those industries may be the ones with the strongest stocks of human capital. In our data, however, acquirers in diversifying deals have higher labor productivity on average than acquirers in within-industry deals and also higher labor productivity than target firms. Thus, acquirers do not appear to be struggling firms nor do target firms appear to be (relatively) thriving. Target firms are also an order of magnitude smaller on average than acquiring firms (See Table I). In Section 5, we provide additional evidence that the results instead reflect the transferability of human capital by estimating the direct effect of the HCT index on the likelihood that workers move from the target firm to the acquirer following a deal.

Because we construct our measure of human capital transferability using worker job changes, another concern is that our measure mixes firm ownership changes with worker job changes. If so, our results could simply reflect sequences of similar acquisitions within industries, even though we use job changes over a five year rolling window ending one year prior to each deal to construct the index. To address this concern, we reconstruct the HCT index from the job change sample after explicitly removing cases in which more than 10 workers from a firm-unit simultaneously change firm identifiers. Our results are unaffected. A third concern is that our linear control for the relatedness of industries based on traditional input-output links is insufficient. We consider a variety of ways to correct for these linkages, including a specification in which we simply exclude any industry pairs in which more than 2.5% of output flows between the two industries (Panel B, Table 3). Our results are never materially affected. Thus, we confirm the link between human capital that allows individual workers to make transitions between industry groups and the relative attractiveness of firms in different industries as takeover targets.

Our results link worker-level industry choices over long periods of time to subsequent industry choices acquirers make in diversifying deals, measured at the industry level.

Though this approach should insulate our analysis from reverse causality concerns and firm- or deal-specific sources of endogeneity, it does not provide direct, affirmative evidence for our human capital channel at the deal-level. In the remainder of the paper, we fill this gap, first measuring differences in the outcomes of high and low human capital transferability deals (Section 4) and then providing evidence for our proposed human capital allocation mechanism at the worker level (Section 5).

4. Human Capital Transferability and Acquisition Performance

Having established a relation between the frequency of diversification between different industries and the transferability of human capital employed in the industries, we examine the implications of human capital transferability on the ex post performance of acquirers following diversifying deals. Our story predicts that firms will experience greater gains in productivity following deals that diversify the firm into industries with human capital that is more related to the human capital already employed in the firm's existing industries.

4.1 Divestiture

We begin by examining a long-term measure of deal performance: the rate at which the new industries into which firms diversify are later divested. Maksimovic, Phillips and Prabhala (2011) show that following acquisitions only about half of all acquired plants are kept by the acquirer after three years. Kaplan and Weisbach (1992) shows that divestitures are almost four times more likely following diversifying acquisitions. Though we do not observe the terms on which divestiture occurs (and thus cannot make strong claims about its effect on profitability), we interpret divestiture as a revealed preference by the firm regarding the fit of the industry with the remainder of the firm's operations. Our theory predicts that firms that diversify into industries with high human capital transferability to their existing operations should be less likely to later divest those divisions. Instead, they should reap the productivity benefits of the human capital synergies created by their internal labor markets.

To test our hypothesis, for all diversifying deals (about 4000 transactions in total), we track each firm created in a diversifying transaction for 10 years following the deal. For targets with multiple industries, we track the acquirer-new industry pairs. Our final sample has about 11,000 acquirer-new industry pairs.

We identify a divestiture in a firm year if the firm sells or closes all of its operations in the industry it acquired in the original diversifying deal (recall that we identify acquisitions as diversifying only if the acquirer and target had no operations in overlapping industries prior to the deal). We then estimate the effect of human capital transferability on later divestiture using a Cox (1972) proportional hazard model:

$$h_i(t) = h_0(t)e^{\beta HCT_i + \boldsymbol{X}_i{}'\boldsymbol{\gamma}} \qquad (2)$$

where $h(t)$ is the hazard in year t following a deal of divesting the acquired industry, $h_0(t)$ is the baseline hazard, *HCT* is a measure of the human capital transferability between the acquired industries and the industries already operated by the acquiring firm (in all cases calculated over a five year period ending one year prior to the deal), and $\boldsymbol{X}$ is a vector of control variables. As control variables, we include the natural logarithm of the total employment in the acquiring and target firms in the last available observation prior to the deal. We also include a measure of the relative size of the target and acquirer (the natural logarithm of the ratio of target employment to acquirer employment). We add a control for the number of industries in which the acquiring firm operates to capture differences in the baseline likelihood of divestiture between firms operating in many and few industries. Finally, we include fixed effects for the calendar year in which the deal occurred to capture differences in economic conditions at the time of the deal. We adjust standard errors for clustering at the deal level. We report coefficient estimates as hazard ratios so that an estimate less than (greater than) 1 indicates that the factor decreases (increases) the hazard for divestiture.

In Panel A of Table 4, we report the results of estimating the model using measures of human capital transferability based on the full sample of job changers. In Column 1, we include the continuous HCT index as the measure of human capital transferability. We find that higher human capital transferability indeed reduces the likelihood of divesting a newly acquired industry. Among the controls, we find that acquirers that already operate in more industries are less likely to divest newly acquired industries. This result could capture a selection effect: the firms that benefit most from diversification are also the least likely to undertake focusing divestitures. We also find that new industries that are larger relative to the acquirer are less likely to be divested and that deals involving a larger total set of employees are less likely to be undone. In Column 2, we replace the continuous HCT index with an indicator variable that takes the value 1 if the HCT index for the industries of the acquiring and target firms measured over the five year window ending one year prior to the deal is above the sample median. We again find that high human capital transferability between the acquiring firm's existing industries and the newly acquired industry reduces the hazard rate of divestiture. Here, the economic magnitude is straightforward to assess: the hazard for divestiture among deals with below-median transferability is roughly 22% higher compared to that for deals with human capital transferability above the median. We also further partition the sample by the HCT index in Column 3 of Table 5, including indicators for deals in which the HCT index between the industries operated by the acquirer and target are between the 25th percentile and sample median, between the sample median and the 75th percentile, and greater than the 75th percentile. The comparison group is deals with HCT index below the 25th percentile. We find a monotonic pattern in the coefficients: as human capital transferability increases, the likelihood of divesting the newly acquired industry decreases. We find the strongest effect among deals with human capital transferability greater than the 75th percentile, consistent with the estimates in Section 4.1.

In Panel B of Table 4 (Columns 4 to 6), we repeat the specifications from Panel A, but use the high-skill HCT index. We find the estimates very similar in magnitude, compared to the estimates in Panel A. Overall our findings suggest that human capital transferability significantly affects the likelihood of divestiture post acquisition – newly acquired industries for which the HCT index with the acquirer's existing industries is above the median have a survival rate that is 33% higher ten years following the acquisition.[13]

4.2. Labor Productivity

Because the synergies we propose operate through increases in worker productivity, we next examine changes in labor productivity as a measure of firm performance following a deal. We measure labor productivity using the ratio of firm sales to

[13] Our estimate predicts the survival rates for higher- and lower-than-median HCT industries are 25.9% and 19.5%, respectively (using the estimates in Column 2 of Panel A).

employment, as in, for example, Haltiwanger, Lane, and Spletzer (1999), Tate and Yang (2015), and Giroud and Mueller (2011). An alternative approach would be to use abnormal stock returns as a measure of value creation, however, our approach has two advantages. First, our outcome variable is a direct measure of labor productivity ("top-line" output per employee). Abnormal stock returns, by contrast, aggregate all value-relevant information about the firm and cannot be interpreted unless the researcher takes a stand on the appropriate measure of expected performance. Moreover, focusing on labor productivity allows us to study both public and private firms (which is one of the key advantages of Census data over traditional data sources).

To account for wage changes around acquisitions, we also consider the ratio of firm sales to payroll. Since we include both manufacturing and non-manufacturing firms (units) in our sample, we do not have enough information to calculate total factor productivity. However, Foster, Haltiwanger, and Krizan (1998) show that labor productivity is highly correlated with total factor productivity in U.S. manufacturing firms. It is also not appropriate to restrict our sample to manufacturing plants because our economic mechanism is likely to be strongest in non-manufacturing firms that rely more on human capital in production.

We construct our measures of labor productivity using firm-level sales information from the Census Bureau's Business Register (SSEL), and information on employment and payroll from the LBD. As discussed in Section 2, limits on the availability of sales data reduce our sample size for these tests. For both firm-level productivity measures, we adjust year-by-year for differences in productivity across industries by subtracting off the employee-weighted average of industry median productivity among single-segment firms in each of the industries in which the firm operates.. We compute changes in labor productivity around acquisitions over a three-year event window. We compute changes in productivity as the difference between the labor productivity of the combined firm one year after the transaction and the weighted average labor productivity of the acquiring and targets firms one year before the acquisition, using annual employment shares as the weights. Our final sample consists of roughly 3,900 deals for which we observe complete information on changes in labor productivity around acquisitions.

Because acquiring and target firms can operate in multiple industries, we compute a deal-level HCT index for diversifying deals as a double weighted average of the HCT index between each pair of the industries operated by the acquiring and target firms using the following formula:

$$HCT_{A,T} = \sum_{A_i} w_{A_i} \sum_{T_j} w_{T_j} HCT(A_i, T_j)$$

That is, for each acquirer-target industry pair in a diversifying deal, we first compute the weighted average HCT between each of acquiring firm's industries and each target firm industry using the industry-level employment in the target firm as weights. Then, we compute the weighted average across all acquirer industries using industry employment levels in the acquiring firm as weights. We take this approach throughout Sections 4.2 and 5 of the paper, though we often refer simply to the HCT index for ease of exposition.

Because labor productivity is a noisy measure, we do not estimate a linear relationship between productivity and human capital transferability, but instead test less parametrically whether productivity is high when relatedness is high. Specifically, we estimate the following regression specification:

$$\Delta_{t-1,t+1} Y_i = \alpha + \beta_1 Divers_i + \beta_2 Divers_i * High\_HCT_{i,t-1} + \boldsymbol{X_{it-1}}'\boldsymbol{\gamma} + \varepsilon_{it} \qquad (3)$$

where $\Delta_{t-1,t+1} Y_i$ is difference between the natural logarithm of observed labor productivity of the merged firm in year *t+1* and the natural logarithm of the weighted average of labor productivity across the target and acquirer firms in year *t-1*; *Divers* is an indicator variable that takes the value 1 for diversifying deals; $High\_HCT$ is an indicator variable equal to 1 if the value of the HCT index measured one year prior to the deal is in the top quartile in our sample; and $\boldsymbol{X}$ is a vector of controls. It is not necessary to include both $High\_HCT$ and it interaction with *Divers* in the regression because $High\_HCT$ is only defined among diversifying deals. Thus, the variables *Divers* and *Divers*High_HCT* allow us to compare deals across three groups: related deals (*Divers* = 0 and *Divers*High_HCT* = 0), diversifying deals with a low deal-level HCT index (*Divers* = 1 and *Divers*High_HCT* = 0), and diversifying deals with a high HCT index (*Divers* = 1 and *Divers*High_HCT* = 1).

In Table 5, we report estimates of the differences-in-differences in labor productivity between high and low human capital transferability deals, captured by the coefficient estimate on $Divers * High\_HCT_{i,t-1}$, or β_2. We also include several additional independent variables in the analysis. First, we add a control for the relative size of the acquiring and target firms (the natural logarithm of the ratio of target employment to acquirer employment) to correct for the possibility that high human capital transferability deals may be deals in which the target firm is smaller and thus more easily integrated. Second, we add an additional variable to distinguish among the deals in the benchmark group. *Divers* captures differences between deals in which the acquirer and target do not operate in any overlapping Fama-French 49 industry groups and other deals. We also add a continuous control for the degree of industry overlap between the acquirer and target firm (*Overlap*). Specifically, we include the ratio of the employment in industry groups operated by both the acquiring and target firms to the total employment in the acquiring firm. These variables allow us to compare the effect of human capital transferability on labor productivity to different benchmark groups of deals, depending on the degree of industry diversification.[14] Since each deal appears only once in the estimation sample, we compute standard errors that are robust to heteroskedasticity.

Among the controls, we find that both the relative size of the target to the acquirer and total employment across the acquiring and target firms have significant negative effects on the change in productivity around the deal, consistent with higher costs of integrating new workers in larger deals. Turning to the effects of interest, diversifying deals with a low HCT index result in a relative decline in labor productivity, compared to related deals, though the effect is not statistically significant. However, we find a positive and significant marginal effect of high human capital transferability on the change in labor productivity following an acquisition: we find an 18.4% relative increase in labor productivity among the high human capital transferability deals, relative to other diversifying deals. Taking together the coefficients on *Divers* and *Divers***High_HCT*, we estimate similar productivity changes between high human capital transferability diversifying deals and within-industry deals. Overall, the results (1) confirm that human capital transferability is associated with greater value creation among diversifying deals and (2) suggest that the relative productivity gains are of a similar magnitude to the relative benefits from acquiring a firm in the same product-market industry. We also

[14] None of these additional controls have a material effect on the estimates of interest.

consider how the effects evolve over time. We find that the negative level effect of diversification disappears and becomes slightly positive (though still insignificant) if we compute the change in productivity through the end of the second full year following the deal. The estimated effect of high human capital transferability is not similarly affected by this change and remains between 15 and 20%. Thus, over the extended horizon, high transferability diversifying deals appear to outperform even within-industry deals. This makes sense if the presence of workers with related skills in other industries in the firm creates synergies and increases human capital investments that boost productivity relative to workers in standalone firms, as in Tate and Yang (2015).

We also repeat the regression from Column 1, but measure $High\_HCT$ based on the human capital transferability index among job changers who earn at least $75,000 annually. We report the results in Column 2. We find that the magnitude of the coefficient of the HCT index is greater when we use the high-skill HCT index and consider workers whose human capital is likely to be more productive and scarce in the external market. Here the relative increase in productivity compared to low transferability diversifying deals is roughly 30%. Moreover, the estimate is statistically significant at the 1% level.

Next, we test whether the relative increase in sales among firms who diversify into industries with high human capital transferability suffices to cover any associated increases in payroll. In Columns 3 and 4, we present the results of repeating the regressions from Columns 1 and 2, but replacing the dependent variable with the difference in the natural logarithms of the ratio of sales to payroll before and after the deal. Not surprisingly, the magnitudes of the effects are slightly smaller—workers with scarce skills can share in some of the rents from those skills (Lazear, 2009). When we use the human capital transferability index among all workers (Column 3), the effect is also no longer statistically significant; however, it remains significant at the 5% level when we use the index defined for workers who make at least $75,000 annually.

As a robustness check, we re-estimate the regressions in Table 5, but with different thresholds for high human capital transferability deals. For example, we find broadly similar results if we use the median rather than the 75th percentile as the threshold. A difference is that the distinction between human capital transferability based on high wage workers and all workers is less pronounced. We also find a larger increase in the effect of human capital transferability on productivity changes from the first year to the second year following the deal. But, we continue to find that diversifying deals in which there is high human capital transferability outperform deals with low transferability. We also adjust the measured changes in productivity surrounding deals for pre-trends in productivity by subtracting off the weighted average growth rate in the acquiring and target industries, with no effect on our conclusions.

Overall, the estimates in Table 5 confirm our hypothesis that higher transferability of human capital between merging firms increases post-deal performance. The estimates in Table 5 capture benefits that merging firms are able to realize immediately following a deal. In Section 5, we analyze post-acquisition outcomes at the worker level to investigate the possible sources of these gains. However, it is important to note that firms are likely to reap additional benefits over time from the creation of internal labor markets relative to competitor firms that operate only in subsets of the industries spanned by the firm. The reason is that the additional continuing investments in human capital that workers make inside the diversified firm are likely to pay off only over time.

5. Human Capital Transferability and Worker Outcomes

Thus far, we have found evidence linking human capital transferability to enhanced labor productivity at the deal level. Next, we supplement the deal-level analysis by testing whether differences in the transferability of human capital between the industries in which acquiring and target firms operate affects post-deal outcomes at the worker level, confirming a human capital channel. The internal labor markets created in diversifying deals affect both labor supply and demand decisions. Workers may be more inclined to join or remain inside firms with more active internal labor markets because of the opportunities for advancement and skill development that they provide. Firms with broader internal labor markets may also be more willing and able to retain high-skill workers following negative shocks to their home industries due to the ability to reallocate them (at least temporarily) elsewhere within the firm. We test whether these effects are larger the more overlap there is between the human capital used in the industries operated by the firm. Of course, worker retention and reallocation decisions are only one mechanism through which human capital transferability can enhance productivity. Thus, we do not claim that differences in those choices are the sole source of the productivity gains we measure in Section 4. Factors like enhanced worker collaboration and ongoing human capital investments are also likely to explain some of the gains, though we cannot measure them directly in the data. These other channels are likely to be positively correlated with differences in job changes, suggesting that job changes may be a reasonable proxy for the larger set of worker-level outcomes.

To track employment status for workers in target firms following an acquisition, we combine our acquisition sample (identified from the LBD) with worker-level information from the LEHD data. Since the LEHD data only cover 31 states, we exclude deals in which either the target or acquiring firms have establishments outside the LEHD universe. We include workers who are employed by the target firm two quarters prior to the acquisition and require that they have worked at the target firm for at least one year.

5.1. Worker Retention

To begin, we test whether high-transferability acquirers are more likely to retain skilled workers following the deal. We compare the set of workers who are retained from the target firm following high transferability diversifying deals to the set of workers retained in other deals (within-industry or diversifying deals with low human capital transferability).

We estimate the following linear probability model on the full sample of workers employed by target firms two quarters prior to each deal in the sample:

$$\begin{aligned} Retain_i = \alpha + \beta_1 Divers_i + \beta_2 Divers_i * High\_HCT_{i,t-1} + \beta_3 Skill_i \\ + \beta_4 Skill_i * Divers_i + \beta_5 Skill_i * Divers_i * High\_HCT_{i,t-1} + \boldsymbol{X_i}'\boldsymbol{\gamma} + \boldsymbol{\varepsilon_i} \end{aligned}$$

where *Retain* is an indicator variable equal to 1 if the worker remains employed by the merged firm four quarters following the deal, *Divers* is an indicator variable equal to 1 if the acquirer and target do not operate in any common Fama-French industry groups prior to the acquisition, $High\_HCT_{i,t-1}$ is an indicator variable equal to 1 if the value of the HCT index measured one year prior to the deal is above the median, *Skill* is a proxy for worker skill level, and $\boldsymbol{X}$ is a vector of controls. We estimate a linear specification despite the binary dependent variable because we are interested in the coefficients on interaction terms (β_2, β_4, β_5), which are easier to interpret in a linear model.[15] Note again that it is unnecessary to include the level effect of our measure of high human capital transferability, $High\_HCT_{i,t-1}$, because it is defined only for diversifying deals and is therefore perfectly collinear with the interaction with *Divers*.

In the vector of controls $\boldsymbol{X}$, we include standard demographic controls: the natural logarithm of worker age and indicator variables for female workers, managers (measured as the highest paid worker in the reporting unit), and six race categories (with white workers as the omitted baseline). We also include the natural logarithm of worker tenure in the firm prior to the deal and the natural logarithm of the worker's annual wage measured over the window beginning five quarters and ending two quarters prior to the deal. We also include a number of firm- and deal-level controls. First, we include (separately) the natural logarithms of employment in the acquiring and target firms prior to the deal as a rough control for the availability of internal opportunities. Likewise, we include the number of different Fama-French industry groups in which the acquirer already operates prior to the deal and an indicator variable that equals 1 if the acquirer also operates in the state in which the target worker is employed prior to the deal. In addition, we include two controls to capture differences in the outcomes of workers from target firms that were already undergoing restructuring prior to the deal in our sample: the changes in the number of plants operated by the firm and total employment in the firm in the year prior to the acquisition.[16] Finally, we include deal year, state, and target firm industry fixed effects to capture differences in market conditions across years, states, and industries. We cluster standard errors at the deal level to correct for correlation of the residuals among workers who are part of the same deal.

In Panel A of Table 6, we present the results. We use an indicator for workers with annual wages higher than the within-firm 75th percentile as the measure of skilled workers (*Skill*).[17] In Column 1, we use the HCT index constructed from the full sample of job changers to define $High\_HCT$. Among the controls, we find, not surprisingly, that there is a general tendency towards retaining higher wage workers. However, managers

[15] We find similar results if we instead estimate logit specifications.
[16] These controls are potentially important for the worker-level tests because it is more difficult to accurately link workers to firms in cases of successive restructuring. We observe ownership changes in the LBD at an annual frequency, but worker information from the LEHD data at a quarterly frequency.
[17] The results are not sensitive to using this cutoff and, e.g., are similar using the median.

are unlikely to be retained. Also workers with more experience (age, tenure) are more likely to remain with the merged firm. Turning to the variables of interest, we find that the marginal effect of high human capital transferability on the likelihood of retaining high-skilled workers is positive and significant (coefficient on $Skill$*$Divers* \ High\_HCT$= 0.051). In Column 2, we replicate the regression from Column 1, but using the high-skill HCT index. Again, we find stronger results when we focus on the mobility of high-skilled workers' human capital, though the difference is not significant. Translating the marginal effects to differences in retention rates across acquisition types and using within-industry deals and low skill workers as the benchmark, we find that the relative retention rate of high skill workers is -4% among within-industry deals and -2.9% among diversifying deals with a low value of the HCT index, but is 2.2% among diversifying deals with a high HCT index. We see much smaller relative differences in the retention of low skill workers (the relative rate is 1.9% and 0.8% among diversifying deals with low and high HCT, respectively).

In Panel B, we reconsider the regressions from Panel A, but on the subsample of high-skill workers (i.e., workers who earn annual wages that exceed the within-firm 75th percentile). This specification addresses the possibility that the controls have different effects on retention among high and low skill workers without saturating the regression with interaction terms. In particular, it addresses the concern that our results could be driven by misspecification in the functional form of the wage control. We find, however, that the estimates of the effect of human capital transferability on retention—here measured by the estimated coefficient on $Divers* \ High\_HCT$—are largely the same. Again we find that acquirers that diversify into industries with high human capital transferability with their existing industry portfolios retain more skilled workers than acquirers who diversify into low transferability industries or who make within-industry acquisitions.

As a robustness check, we rerun the regressions reported in Table 6 using long tenure with the firm—specifically, tenure longer than 5 years—as an alternative proxy for skilled workers. Workers with longer tenure are likely to be higher skilled both because of selection (the firm will only retain workers who prove to be high skilled after information is revealed) and because of accumulated firm-specific human capital. We find qualitatively similar results: high human capital transferability has a positive effect on the likelihood of retaining skilled workers. We also extend the analysis of retention by considering the likelihood of remaining in the firm eight quarters following the deal. We again find patterns similar to those reported in Table 6: acquiring firms that diversify into industries with high human capital transferability to their existing operations are more likely to retain high-skilled workers, even two years following the deal.

A potential alternative explanation of the Table 6 results is that within-industry and low human capital transferability diversifying acquirers engage in more successful cost cutting following acquisitions by trimming experienced workers with bloated salaries. If this is the case, we should expect such deals to improve labor productivity relative to the high human capital overlap diversifying deals. Yet, in Section 4.2, we find the opposite. It is the high human capital transferability deals in which labor productivity increases most, even when measured relative to payroll. Our story, instead, does not rest on an assumption that the firms involved in either type of deal are operating inefficiently either before or after the deal. Diversifying deals with high human capital transferability simply have additional sources of synergies, including the real option for the acquirer to reallocate human capital.

5.2. Worker Internal Movement

Next, we test for direct evidence that acquirers who diversify into industries with which they have high human capital transferability benefit from the ability to reallocate human capital from the target elsewhere in the merged firm. Because we are interested in industry changes within internal labor markets, we only consider the subset of diversifying deals and compare deals depending on the transferability of human capital between the industries of the acquiring and target firms.

We estimate the following regression specification:

$$Move_i = \alpha + \beta \times High\_HCT_{i,t-1} + \boldsymbol{X_i}'\boldsymbol{\gamma} + \boldsymbol{\varepsilon_i} \tag{3}$$

where *Move* is an indicator variable equal to 1 if the worker moved to one of the acquirer's pre-deal reporting units after the acquisition, thereby changing industries. We measure *Move* at different frequencies following the deal and, in all cases, condition on the set of workers who worked for the firm at the time of the deal and who continue to work in the merged firm in the quarter we measure *Move*.[18] As before, $High\_HCT$ is an indicator variable equal to 1 if the value of the HCT index measured one year prior to the deal is above the median and $\boldsymbol{X}$ is a vector of controls. We include the same controls in $\boldsymbol{X}$ as we did in our estimation of worker retention probabilities in Table 6, including deal year, state, and target industry fixed effects. We also again report estimates of a linear regression model and adjust standard errors for deal-level clustering.[19]

We report the results of estimating equation (3) in Table 7. In Panel A, we use the human capital transferability index based on all workers' job changes to define $High\_HCT$. In Column 1, the dependent variable *Move* is defined by observing each target firm worker's employing unit four quarters following the acquisition. We find few robust predictors of internal industry changes among the control variables. An exception is the total number of employees in the target firm prior to the deal, which has a negative effect on the probability of changing jobs in the internal market. The strongest predictor is the independent variable of interest, the indicator for deals in which there is high human capital transferability between the industries of the acquirer and target. We find a 10.1 percentage point increment to the estimated probability of changing industries, an effect that is statistically significant at the 1% level. The sample mean frequency of changing industries is 7%, suggesting that the estimated effect is also economically large. In Column 2, we redefine the dependent variable *Move* by instead considering the workers' employing units eight quarters following the transaction. We find a stronger effect. Here, the probability of moving to a job in a new industry in the acquiring firm is roughly 12 percentage points higher when there is high human capital transferability between the acquirer and target.

In Panel B, we report the results of estimating equation (3) using the human capital transferability index based on the job changes of workers who make more than $75,000 annually to define $High\_HCT$. We report the results from estimating the probability of moving to the acquirer four (Column 3) and eight (Column 4) quarters following the deal. The estimates are not materially different from those we report in Panel A. Again, it is the

[18] If we do not condition on retention, the magnitude of our estimates is smaller (by construction), since a worker who is not retained cannot be working anywhere inside the merged firm. However, our results are qualitatively unchanged. All the estimates of interest continue to have the same signs and significance.
[19] Again, the results are unaffected by instead estimating a logit specification.

workers from targets with high human capital transferability with the industries operated by the acquiring firm that are more likely to move to the acquirer's units following the merger. In untabulated regressions, we also include interactions of the human capital transferability variable with the proxies for worker skill from Table 6. We do not find that the probability of moving to the acquirer in a high transferability deal differs for low and high skill workers using either measure. While the benefits to the firm from the mobility of high skill workers may be larger—explaining the larger productivity differences and predictive power for the decision to merge—these results suggest that the firm exercises (and likely profits from) the ability to redeploy workers of all types.

Overall, we find evidence at the worker level for the human capital synergies we propose as motivation for diversifying deals. When there is high transferability of human capital between the industries operated by merging firms, the merged firm is better able to retain high skill workers following the deal. Moreover, the firm is more likely to reallocate the acquired workers to its own units operating in different industries.

6. Human Capital Transferability and Firm Composition

The main objective of our study is to investigate the role human capital mobility plays in explaining merger choices and, specifically, the decisions of firms to expand the scope of their operations. As a result, our analysis thus far consists of a variety of event studies around mergers, comparing the outcomes of deals with high and low human capital transferability between the acquirers and targets. As the final step in our analysis, however, we abstract from merger events. We test whether the industry composition of diversified firms in the cross-section corresponds to our measures of human capital transferability. This test provides one way to evaluate the economic significance of the human capital channel we propose. If human capital mobility is a first order consideration for firms in choosing how to expand the scope of their operations, then it should show up as a predictor of firm composition.

To conduct our test, we reconsider equation (1) from Section 3. However, instead of defining the dependent variable using diversifying acquisitions within industry pairs, we instead measure the frequency with which each industry pair is jointly operated by diversifying firms. Specifically, for each diversifying firm in the LBD, year-by-year, we identify industry segments that make up at least 10% of total employment. Then, for each Fama-French industry, we define the dependent variable as the fraction of diversified firms operating in that industry that also operate a segment in each of the other distinct Fama-French industries. Thus, the unit of observation is again an industry pair year. We again include the percentage of output that flows between the two industries, measured using the BEA's input-output matrix, as a control for relatedness of the products produced by the industries. We also include year fixed effects and industry fixed effects and adjust the standard errors for clustering by industry.

We report the results in Table 8. In Column 1, we include the HCT index defined using all workers' job changes over a five year rolling window ending one year prior to the year in which we measure the industry composition of the diversified firm. We find a strong and significant positive effect of human capital transferability on the industries that are jointly operated by diversified firms. As in Section 3, we find that human capital transferability has far more explanatory power for the composition of diversified firms than the product market relatedness of the industries. The coefficient estimate on the HCT index is more than twenty times the size of the estimate on input-output relatedness, even though a standard deviation of the HCT index is only roughly 40% of a standard deviation of input-output relatedness. In Column 2, we repeat the estimation, but using the HCT index defined using only job changes of workers who make at least $75,000 annually. The results are essentially unchanged.

An immediate concern in interpreting these results could be that the job changes on which we base our measure of human capital transferability are simply job changes within diversified firms in the sample, inducing reverse causality. However, recall that we use only job changes in which workers exit their original employing firm to construct our indices, ruling out this possibility. Moreover, we confirm that the results are robust if we consider only job changes in which some, but not all of the workers from a firm change jobs in a given quarter. This restriction prevents changes in firm identifiers due to mergers from contaminating our sample of job changes. Thus, our tests indeed isolate a tendency for diversified firms to operate in sets of industries between which individual workers find their skills to be more transferable. Moreover, the existence of the association between this transferability and firm composition in the cross-section—and its relative strength compared to traditional product market measures of industry relatedness—suggests that human capital transferability is a first-order determinant of firm scope.

7. Conclusion

We identify the transferability of human capital as a primary motivation for diversifying acquisitions. We use worker-firm matched data from 31 states available from the LEHD program to construct a measure of this transferability using the frequency of worker job changes between industries. We find that human capital transferability not only predicts the intensity with which firms from an industry diversify into other industries, but also predicts it more strongly than measures of product market relatedness. Moreover, the transferability of human capital between industries is a strong predictor of the industry composition of diversified firms in the cross-section.

We also find that firms reap tangible benefits from diversifying into new industries into which their existing workers' human capital more easily transfers. Firms that acquire industries with greater human capital transferability with their existing industries enjoy larger increases in labor productivity than other acquirers and are less likely to subsequently divest their newly acquired industries.

Finally, we find evidence consistent with the human capital channel at the worker level. Acquiring firms that diversify into industries with high human capital transferability with their existing operations are more likely to retain skilled workers following the deal. They also appear to quickly take advantage of the real option to transfer workers from the target firm to other industries in the merged firm. This sort of reallocation occurs at a significantly higher rate when there is greater human capital transferability between the industries that are joined by the deal.

Our results challenge the view that diversification across product markets destroys value or is a manifestation of agency problems. Instead we identify realized synergies from diversification based on the mobility of human capital across industries. Moreover, our theory does not require that acquirer, target, or merged firms are operating inefficiently to justify the transactions. Thus it is likely to be a mistake to equate diversification with a failure of governance. Though we do not claim that all diversifying deals create value or that there is no role for agency models in explaining observed merger activity, our results can help to understand why diversifying deals are common and why the majority of the largest, most successful firms in U.S. markets are diversified.

Our results also have implications for how we think about firm groupings, like industries, in finance and economics. Traditionally, researchers have focused exclusively on product market considerations to group firms. An industry consists of firms that sell similar products. Similarly, industries are related if the products produced by one industry are used as inputs for the other. We instead identify human capital as an important common factor across firms. Recent asset pricing research argues that this commonality is a risk factor in equity markets (Eisfeldt and Papanikoloau, 2013; Donangelo, 2014). We argue that it also is an important determinant of firm boundaries. An interesting avenue for future research is to build on this evidence, considering the implications of shocks to human capital for corporate outcomes in much the same way traditional corporate finance considers product market industry shocks.

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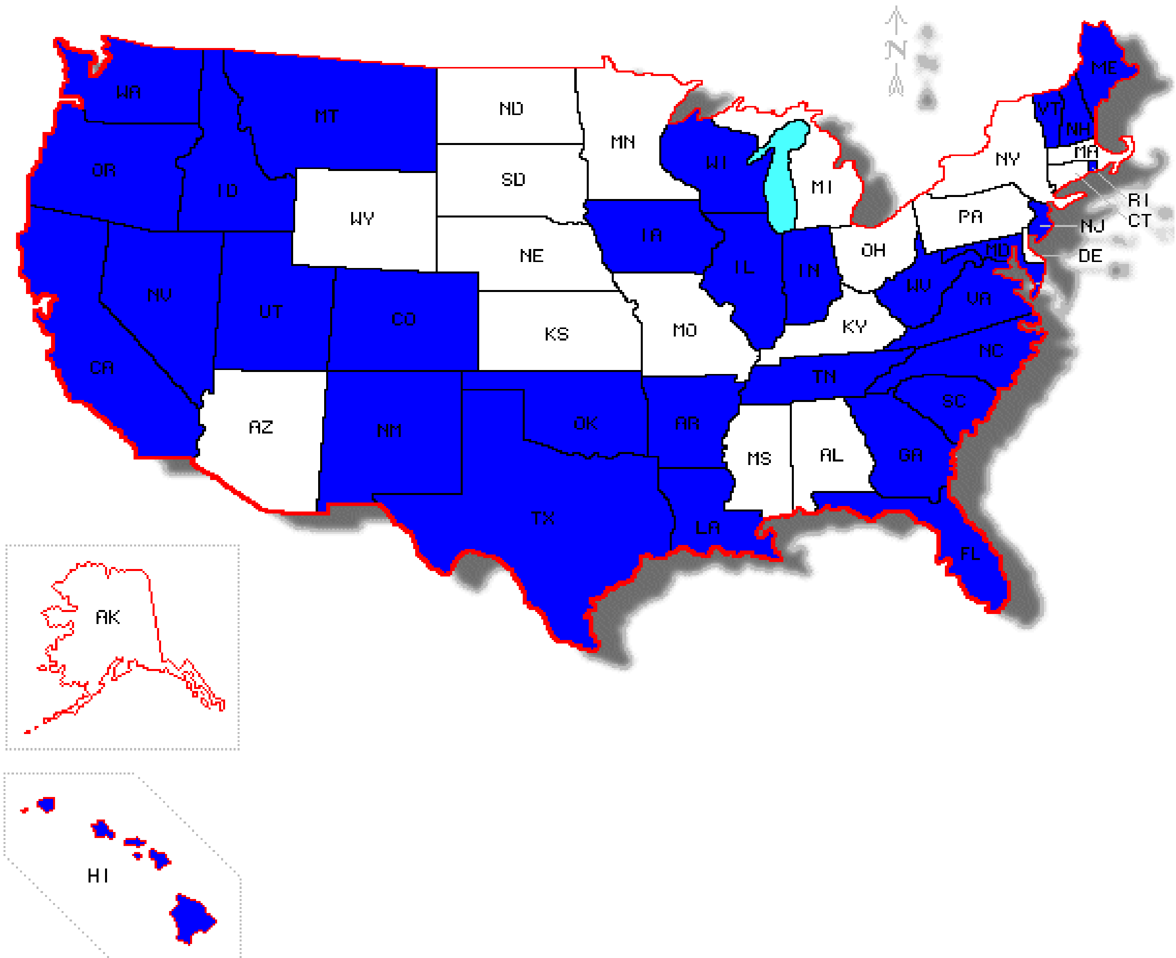

Figure 1

States covered in the Longitudinal Employer-Household Dynamics (LEHD) data

The map shows states for which worker-firm matched panel data are available through the U.S. Census Bureau's LEHD program in our sample. No data are available for states in white.

Table 1
Summary Statistics

This table presents summary statistics for samples used in the paper. Panel A describes the sample of job changers used to construct our measure of human capital transferability between industries (HCT Index). Panel B provides summary statistics of acquisitions by type, and Panel C provides summary statistics for workers employed by the target firms in acquisitions. Relative Size is defined as the log of the ratio of target employment to acquirer employment. Overlap is the percentage of employment in the acquiring firm in industries operated by the target firm. ***, **, or * indicate a significance of the difference in means between related and diversifying deals at the 1%, 5%, and 10% levels, respectively.

Panel A: Sample of Workers Used to Construct Human Capital Transferability (HCT) Index

Tenure	Percent	Wage		Percent
1-2 yrs	39.7	< $10K		24.2
2-3 yrs	20.9	$10 - $25K		42.4
3-4 yrs	12.7	$25 - 50K		24.6
4-5 yrs	8.4	$50 - 75K		5.5
>5 yrs	18.3	> $75K		3.3
N =	115,219,000			
Mean	12.67	Mean	$	24,990
Std. Dev.	9.87	Std. Dev.	$	92,385

Panel B: Sample of Acquisitions

	All	Related	Diversifying	
Number of Deals	3900	3300	600	
Acquirer's Employment	13588	14877	6638	***
	(27002)	(28169)	(18038)	
Target's Employment	577	629	296	***
	(2205)	(2381)	(648)	
Relative Size	-2.81	-2.91	-2.25	***
	(1.85)	(1.83)	(1.89)	
Overlap	0.59	0.70	0	
	(0.42)	(0.36)	—	
Acquirer: Sales/Emp	165.56	152.99	234.02	***
	(266.87)	(245.46)	(353.57)	
Target: Sales/Emp	170.65	169.60	176.29	
	(219.56)	(218.52)	(225.16)	
Acquirer: Sales/Payroll	4.11	3.90	5.27	***
	(5.47)	(5.17)	(6.76)	
Target: Sales/Payroll	4.70	4.76	4.39	
	(5.11)	(5.12)	(5.02)	

Panel C: Workers in Our Acquisition Sample

	All	Related	Diversifying	
Number of Deals	3700	3300	400	
Tenure	12.18	12.18	12.13	
	(6.11)	(6.11)	(6.11)	
Wage	30350	30201	31545	
	(23990)	(24696)	(17318)	
Age	39.48	39.45	39.72	
	(4.74)	(4.78)	(4.37)	
White	0.72	0.72	0.73	
	(0.21)	(0.21)	(0.22)	
Female	0.41	0.42	0.37	***
	(0.25)	(0.25)	(0.22)	
Retain(t=4)	0.61	0.60	0.64	***
	(0.21)	(0.22)	(0.19)	
Retain(t=8)	0.45	0.45	0.48	**
	(0.25)	(0.48)	(0.25)	

Table 2

Summary of Industry Pairs based on Human Capital Transferability Index

This table lists the top 10 industries based on the Human Capital Transferability (HCT) Index. We define industries using the Fama-French 49 industry classification. The HCT index is the average within each industry pair of the percentage of job changers from each industry who move to the other industry in the pair. We compute the HCT index annually from 1990 to 2007 and use the average over all years to rank industries. For each panel, we report the list based on versions of the HCT index using all workers (left panel) and workers with wages > $75,000 (right panel). In Panel C, we exclude industry pairs if the average industry output flows between the industries exceed 2.5% using the I/O matrix from the Bureau of Economic Analysis (BEA).

Panel A: All Industry Pairs

All Workers					Workers with Wage >$75K				
Ind1	Ind2	Ind1_Des	Ind2_Des	HCT Index	Ind1	Ind2	Ind1_Des	Ind2_Des	HCT Index
11	33	Hlth	Persv	8.88%	34	42	Bussv	Whlsl	12.44%
34	42	Bussv	Whlsl	8.64%	11	33	Hlth	Persv	8.58%
43	44	Retail	Meals	8.27%	45	48	Banks	Fin	8.48%
33	43	Persv	Retail	8.06%	42	43	Whlsl	Retail	5.98%
33	34	Persv	Bussv	7.69%	35	37	Hardw	Chips	5.72%
42	43	Whlsl	Retail	7.58%	34	37	Bussv	Chips	5.32%
34	43	Bussv	Retail	7.09%	37	42	Chips	Whlsl	5.28%
11	34	Hlth	Bussv	6.47%	18	47	Constr	RlEst	5.20%
18	34	Constr	Bussv	5.56%	33	34	Persv	Bussv	4.94%
34	44	Bussv	Meals	5.34%	32	34	Telcm	Bussv	4.81%

Panel B: Industry Pairs Excluding Personal Services, Business Services, Wholesale and Retail

All Workers					Workers with Wage >$75K				
Ind1	Ind2	Ind1_Des	Ind2_Des	HCT Index	Ind1	Ind2	Ind1_Des	Ind2_Des	HCT Index
45	48	Banks	Fin	4.38%	45	48	Banks	Fin	8.48%
7	44	Fun	Meals	4.02%	35	37	Hardw	Chips	5.72%
35	37	Hardw	Chips	3.94%	18	47	Constr	RlEst	5.20%
17	21	BldMtl	Mach	3.72%	35	36	Hardw	Softw	4.50%
1	2	Agri	Food	3.57%	12	13	MedEq	Drug	4.05%
20	21	FabPr	Mach	3.53%	37	38	Chips	LabEq	3.44%
17	18	BldMtl	Constr	3.50%	46	48	Insur	Fin	3.29%
45	46	Banks	Insur	3.35%	36	37	Softw	Chips	3.00%
11	44	Hlth	Meals	3.01%	18	44	Constr	Meals	2.97%
37	38	Chips	LabEq	3.00%	21	38	Mach	LabEq	2.94%

Panel C: Industry Pairs Excluding Personal Services, Business Services, Wholesale and Retail, and Pairs with Linkage through I/O Markets

All Workers					Workers with Wage >$75K				
Ind1	Ind2	Ind1_Des	Ind2_Des	HCT Index	Ind1	Ind2	Ind1_Des	Ind2_Des	HCT Index
7	44	Fun	Meals	4.02%	12	13	MedEq	Drug	4.05%
45	46	Banks	Insur	3.35%	18	44	Constr	Meals	2.97%
11	44	Hlth	Meals	3.01%	21	38	Mach	LabEq	2.94%
1	18	Agri	Constr	2.81%	35	38	Hardw	LabEq	2.71%
12	13	MedEq	Drug	2.69%	45	46	Banks	Insur	2.57%
18	44	Constr	Meals	2.62%	11	46	Hlth	Insur	2.52%
10	16	Clths	Txtls	2.51%	1	18	Agri	Constr	2.27%
35	38	Hardw	LabEq	2.40%	1	44	Agri	Meals	2.17%
11	46	Hlth	Insur	2.35%	47	48	RlEst	Fin	2.09%
41	44	Trans	Meals	2.25%	22	37	ElcEq	Chips	1.95%

Table 3

HCT Index and Diversifying Acquisitions

The sample in Panel A contains all industry pairs by year and the sample in Panel B excludes industry pairs in which more than 2.5% of industry output flows between the pair using the I/O matrix from the Bureau of Economic Analysis (BEA). The table reports coefficient estimates from OLS estimation of equation (1). The dependent variable is the intentisty with which acquirers in industry i diversify into industry j (for i ≠ j) in year t. HCT Index is the human capital transferability index between industry i and j measured over a five year window ending at t-1. The column header provides the (sub-)sample of job changers we use to compute the index used as an independent variable in that column. Pct_Related measures the average output flows (in percentage) between industry i and j in year t-1. For both panels, Columns (1) to (3) measure the propensity for acquirers to diversify into other industries using the employment in target firms and Columns (4) to (6) use instead the number of target firms. Standard errors are clustered by acquirer industry-year. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: All Industry Pairs

Dependent Variable	PCT_EMP			PCT_NFIRMS		
	All Workers	>$75K	<$25K	All Workers	>$75K	<$25K
	(1)	(2)	(3)	(4)	(5)	(6)
HCT Index	***0.432 ******	***0.685 ******	***0.274 ******	***0.465 ******	***0.703 ******	***0.289 ******
	(0.064)	(0.106)	(0.056)	(0.054)	(0.100)	(0.043)
Pct_Related	0.098 ***	0.050 ***	0.120 ***	0.108 ***	0.061 ***	0.132 ***
	(0.017)	(0.019)	(0.018)	(0.015)	(0.017)	(0.016)
Acq. Ind.-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Target Ind. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.063	0.073	0.060	0.098	0.11	0.094
N	27,800	27,800	27,800	27,800	27,800	27,800

Panel B: Excluding Industry Pairs That Are Related Through I/O Market

Dependent Variable	PCT_EMP			PCT_NFIRMS		
	All Workers	>$75K	<$25K	All Workers	>$75K	<$25K
	(1)	(2)	(3)	(4)	(5)	(6)
HCT Index	***0.440 ******	***0.767 ******	***0.308 ******	***0.472 ******	***0.796 ******	***0.326 ******
	(0.071)	(0.190)	(0.052)	(0.064)	(0.187)	(0.042)
Acq. Ind.-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Target Ind. Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.044	0.054	0.042	0.072	0.085	0.069
N	23,600	23,600	23,600	23,600	23,600	23,600

Table 4
Human Capital Transferability and Subsequent Industry Divestitures

This table presents estimates from a Cox Proportional Hazard Model. We follow acquirers for 10 years following diversifying acquisitions and identify failure events as the cases in which the acquirer exited the new industry it acquired in the transaction. HCT Index is the Human Capital Transferability Index. Columns (1) to (3) use the index constructed using all workers in the sample and Columns (4) to (6) use the index based on workers with wages greater than $75K. Acq_#ofInds is the number of industries in which the acquirer operates prior to the transaction. HCT>Median is an indicator variable that equals 1 if the HCT Index is higher than the median among all diversifiying acquisitions. HCT_Q2, HCT_Q3, HCT_Q4 are indicator variables that equal 1 if the HCT index is in the 2nd, 3rd or 4th quartile among all diversifying acquisitions in the sample. Standard errors are clustered by deal. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	Panel A. HCT Using All Workers			Panel B. High-Skill HCT		
	(1)	(2)	(3)	(4)	(5)	(6)
HCT Index	***0.944 ****			***0.954 ****		
	(-12.42)			(-10.23)		
Acq_#ofInds	0.855 ***	0.858 ***	0.856 ***	0.86 ***	0.859 ***	0.857 ***
	(-20.95)	(-20.74)	(-20.77)	(-20.44)	(-20.56)	(-20.67)
Relative_Size	0.871 ***	0.868 ***	0.869 ***	0.869 ***	0.869 ***	0.87 ***
	(-19.17)	(-19.54)	(-19.40)	(-19.55)	(-19.37)	(-19.34)
Ln(Employment)	0.969 ***	0.964 ***	0.966 ***	0.962 ***	0.963 ***	0.966 ***
	(-3.42)	(-4.03)	(-3.76)	(-4.27)	(-4.15)	(-3.76)
HCT > Median		***0.777 ****			***0.807 ****	
		(-12.93)			(-10.98)	
HCT_Q2			***0.955 **			***0.933 ****
			(-1.77)			(-2.65)
HCT_Q3			***0.785 ****			***0.823 ****
			(-8.98)			(-7.26)
HCT_Q4			***0.733 ****			***0.733 ****
			(-11.19)			(-11.09)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.016	0.016	0.016	0.015	0.015	0.016
N	27,000	27,000	27,000	27,000	27,000	27,000
N Failures	8,617	8,617	8,617	8,617	8,617	8,617

Table 5
Human Capital Transferability and Productivity Changes

This table estimates the change of performance around acquisitions. The dependent variable is the change in labor productivity for the combined firm around acqusitions. Columns (1) to (3) measure labor productivity using the sales-employment ratio and Columns (4) to (6) measure labor productivity using the sales-payroll ratio. We use a three-year event window surrounding each deal. DIVERS is an indicator variable that equals 1 if the transaction is diversifying. High_HCT and High_HCT(>$75K) are indicator variables that takes the value of 1 if the value of the human capital transferability (HCT) index based on all workers and workers with annual wages greater than $75K, respectively, measured one year prior to the transaction is in the top quartile among all transactions. Relative Size is defined as the natural logarithm of the ratio of target employment to acquirer employment. Overlap is the percentage of employment in the acquiring firm in industries operated by the target firm. Ln(Employment) is the natural logarithm of the total employment of the acquirer and target firms. Standard errors are clustered by deal in and are robust to heteroskedasticity in Panel B. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Dependent Variable	Sales/Emp		Sales/Payroll	
	(1)	(2)	(3)	(4)
DIVERS	-0.139	-0.280 *	-0.113	-0.231
	(0.164)	(0.162)	(0.165)	(0.165)
DIVERS x High_HCT	***0.184 ****		***0.159***	
	(0.107)		***(0.109)***	
DIVERS x High_HCT(>$75K)		***0.299 ******		***0.255 *****
		(0.105)		***(0.110)***
Relative Size	-0.047 **	-0.048 ***	-0.042 **	-0.042 **
	(0.019)	(0.019)	(0.018)	(0.018)
Overlap	-0.024	-0.022	-0.022	-0.02
	(0.075)	(0.075)	(0.074)	(0.074)
Ln(Employment)	-0.057 ***	-0.057 ***	-0.059 ***	-0.059 ***
	(0.021)	(0.021)	(0.021)	(0.021)
Constant	0.633 ***	0.632 ***	0.605 ***	0.604 ***
	(0.177)	(0.177)	(0.177)	(0.177)
Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.046	0.047	0.045	0.046
N	3,900	3,900	3,900	3,900

Table 6
Human Capital Transferability and Worker Retention

The table estimates linear probability modelson the sample of workers employed by target firms in acquisitions. The dependent variable equals 1 if the worker is retained following the deal and zero otherwise. Columns (1) and (2) include all target firm workers and Columns (3) and (4) include the subsample of skilled workers. We define skilled workers as workers whose wage is higher than the within-firm 75th percentile. Ln(Wage) is the natural logarithm of the worker's annual wage prior to transaction. Female is an indicator variable equal to 1 for female workers and zero otherwise. Manager is an indicator variable equal to one for the highest paid employee in the SEIN and zero otherwise. Divers is an indicator variable equal to one for diversifying acquisitions and zero otherwise. Low_HCT (High_HCT) is an indictor variable that equals 1 if the transaction has a HCT index that is below (above) the median. Skilled worker is an indicator that equals 1 for workers whose wage is higher than the within-firm 75th percentile and zero otherwsie. Ln(Age) is the natural logarithm of worker age. Ln(Tenure) is the natural logarithm of the number of quarters that a worker has spent in the SEIN. Ln(Target_Emp) is the natural logarithm of emploment in the target firm. Chg(N_Estabs) and Chg(FirmEmp) are the changes in N_Estabs and firm employment, respectively, in the target firm in the year prior to the acquisition. Acq_#ofInds is the number of industries in which the acquirer operated prior to the transaction. Ln(Acq_Emp) is the natural log of acquirer employment. Same_State is an indicator variable that equals 1 if the worker is born in the same state as the target firm. We include six indicator variables for race categories (coefficient estimates not reported). Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	Panel A. All Workers		Panel B. High-Skill Workers Only	
	HCT	High-Skill HCT	HCT	High-Skill HCT
	(1)	(2)	(3)	(4)
Ln(Wage)	0.106 ***	0.106 ***	0.014	0.014
	(0.007)	(0.007)	(0.010)	(0.010)
Female	0.021 ***	0.021 ***	0.002	0.002
	(0.004)	(0.004)	(0.007)	(0.007)
Manager	-0.179 ***	-0.179 ***	-0.045 ***	-0.045 ***
	(0.014)	(0.014)	(0.016)	(0.016)
Divers x Low_HCT	0.032	0.019	0.039	0.019
	(0.020)	(0.020)	(0.024)	(0.027)
Divers x High_HCT	-0.002	0.008	***0.040 ****	***0.054 *****
	(0.025)	(0.025)	***(0.021)***	***(0.019)***
Skilled Worker	-0.040 ***	-0.040 ***		
	(0.006)	(0.006)		
Skilled Worker x Divers x Low_HCT	-0.004	-0.008		
	(0.024)	(0.024)		
Skilled Worker x Divers x High_HCT	***0.051 *****	***0.054 *****		
	(0.024)	***(0.023)***		
Ln(Age)	0.139 ***	0.139 ***	0.082 ***	0.083 ***
	(0.010)	(0.010)	(0.013)	(0.013)
Ln(Tenure)	0.093 ***	0.093 ***	0.096 ***	0.096 ***
	(0.004)	(0.004)	(0.006)	(0.006)
Ln(Target_Emp)	0.012 ***	0.012 ***	0.015 ***	0.015 ***
	(0.004)	(0.004)	(0.005)	(0.005)
Chg(N_Estabs)	0.039	0.040	0.05	0.051
	(0.038)	(0.038)	(0.043)	(0.043)
Chg(FirmEmp)	-0.039	-0.038	-0.046 *	-0.046 *
	(0.024)	(0.024)	(0.027)	(0.027)
Acq_#ofInds	0.006 ***	0.006 ***	0.006 **	0.006 **
	(0.002)	(0.002)	(0.002)	(0.002)
Ln(Acq_Emp)	-0.004	-0.003	-0.006	-0.006
	(0.004)	(0.004)	(0.005)	(0.005)
Same_State	-0.027 *	-0.027 *	-0.032 *	-0.033 *
	(0.016)	(0.016)	(0.018)	(0.018)
Year Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Target Industry Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.144	0.144	0.091	0.091
N	1,400,700	1,400,700	353,500	353,500

Table 7
Human Capital Transferability and Worker Movement

The sample includes all workers from target firms who were retained following diversifying acquisitions. The table reports estimates of linear probability models in which the dependent variable equals 1 if the worker moves to a new industry within the merged firm and zero otherwise. Columns (1) and (2) use the human capital transferability (HCT) index based on all workers and Columns (3) and (4) use the HCT index based on workers with wages greater than $75K. We measure worker outcomes four quarters (Columns (1) and (3)) and eight quarters (Column (2) and (4)) after the transaction. Ln(Wage) is the natural logarithm of the worker's annual wage prior to transaction. Female is an indicator variable equal to 1 for female workers and zero otherwise. Manager is an indicator variable equal to one for the highest paid employee in the SEIN and zero otherwise. High_HCT is an indictor variable that equals 1 if the transaction has a HCT index that is above the median. Ln(Age) is the natural logarithm of worker age. Ln(Tenure) is the natural logarithm of the number of quarters that a worker has spent in the SEIN. Ln(Target_Emp) is the natural logarithm of emploment in the target firm. Chg(N_Estabs) and Chg(FirmEmp) are the changes in N_Estabs and firm employment, respectively, in the target firm in the year prior to the acquisition. Acq_#ofInds is the number of industries in which the acquirer operated prior to the transaction. Ln(Acq_Emp) is the natural log of acquirer employment. Same_State is an indicator variable that equals 1 if the worker is born in the same state as the target firm. We include six indicator variables for race categories (coefficient estimates not reported). Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	Panel A. HCT Using All Workers		Panel B. High-Skill HCT	
	t + 4	t + 8	t + 4	t + 8
	(1)	(2)	(3)	(4)
High HCT	***0.101*** ***	***0.123*** ***	***0.097*** ***	***0.128*** ***
	(0.031)	(0.039)	(0.033)	(0.039)
Ln(Wage)	0.000	0.003	-0.001	0.002
	(0.008)	(0.011)	(0.008)	(0.011)
Female	0.006	0.004	0.006	0.005
	(0.010)	(0.012)	(0.010)	(0.012)
Manager	0.003	-0.005	0.007	0.001
	(0.017)	(0.026)	(0.018)	(0.026)
Ln(Age)	-0.010	-0.001	-0.008	0.002
	(0.008)	(0.011)	(0.008)	(0.011)
Ln(Tenure)	0.008	0.009	0.009	0.009
	(0.007)	(0.009)	(0.007)	(0.009)
Ln(Target_Emp)	-0.035 **	-0.05 **	-0.034 **	-0.048 **
	(0.014)	(0.020)	(0.014)	(0.020)
Chg(N_Estabs)	-0.160 *	-0.168 **	-0.165 *	-0.179
	(0.084)	(0.080)	(0.086)	(0.083)
Chg(FirmEmp)	-0.029	-0.028	-0.012	-0.005
	(0.039)	(0.045)	(0.038)	(0.045)
Acq_#ofInds	-0.003	-0.007	-0.001	-0.005
	(0.006)	(0.009)	(0.006)	(0.009)
Ln(Acq_Emp)	-0.003	-0.014	-0.005	-0.018
	(0.009)	(0.014)	(0.009)	(0.014)
Same_State	0.007	0.017	0.010	0.021
	(0.031)	(0.040)	(0.031)	(0.041)
Year Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Target Industry Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.351	0.328	0.348	0.327
N	67,200	53,700	67,200	53,700

Table 8
HCT Index and Industry Portfolio in Diversified Firms

The sample contains all industry pairs by year. The dependent variable is the intentisty with which a firm operating in industry i also operate in industry j (for i ≠ j) in year t. HCT Index is the human capital transferability index between industry i and j measured over a five year window ending at t-1. We use the HCT index based on all workers in Column (1) and the HCT index based on workers with wages greater than $75K in Column (2). Pct_Related measures the average output flows (in percentage) between industry i and j in year t-1. For all specifications, we include acquirer industry-year fixed effects and target industry fixed effects. Standard errors are clustered by industry. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	HCT	High-Skill HCT
	(1)	(2)
HCT Index	***2.661 ****	***2.428 ****
	(0.298)	(0.348)
Pct_Related	0.119 **	0.102 *
	(0.045)	(0.019)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Adjusted R^2	0.334	0.305
N	27,800	27,800