The Human Factor in Acquisitions*

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Abstract

Why do firms diversify into unrelated product markets? Internal labor markets allow firms to reallocate workers in response to industry shocks. They also strengthen workers' incentives to invest in transferable, productivity-enhancing skills. Thus, the transferability of human capital can be a source of merger synergies. To test this hypothesis, we construct an index of human capital transferability using more than 11 million job changes. We show that diversifying acquisitions occur more frequently among industry pairs with higher transferability. The effect is roughly 1.7 times the size of the effect of product market relatedness. Diversifying acquisitions between industries with higher human capital transferability result in larger labor productivity gains and are less often undone in subsequent divestitures. Moreover, firms retain more high skill workers after acquiring new industries with high human capital transferability to their existing industries 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 the utilization of human capital as a source of value from corporate diversification.

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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1. Introduction

How important are human capital investments in 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 inputs affects the decision to diversify into new industries by acquisition. We find that cross-industry labor mobility significantly predicts the industry pairs of merging firms in diversifying deals. Consistent with a human capital channel, high skill workers are more likely to be retained and moved to new positions inside the merged firm when there is greater labor mobility between the industries of the merging firms. Moreover, mergers of firms in high mobility industry pairs generate larger increases in productivity than other (diversifying) deals.

Merging firms can benefit from coownership of production processes in different industries that use similar human capital. If industries are subject to different shocks, then firms that operate in multiple industries have the real option to reallocate human capital away from the ones hit by negative shocks and toward the ones hit by positive shocks (Tate and Yang, forthcoming). This option is particularly valuable when there are frictions in external labor markets—such as search, termination or training costs—that can be bypassed by reallocating labor internally. Moreover, common ownership increases the incentives of workers to make investments in acquiring and refining the skills that facilitate these transitions, for example, by exploiting job rotation programs (Carmichael and MacLeod, 1993). Doing so may increase the worker's prospects for promotion, but also their productivity in their current positions. For example, 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. Moreover, the exact bundles of skills that workers acquire over time in diversified firms

[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.

are likely to have a firm-specific component (Lazear, 2009). Thus, the resulting productivity gains are unlikely to be available to firms operating independently in the same industries. Mergers provide a way to increase value by maximizing the productivity of human capital, and the benefits may be strongest for deals that diversify across product markets because workers otherwise have little incentive to invest in skills that apply across industries.

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 inter-industry worker mobility from 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 overlap in 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 inter-industry labor mobility to predict the industry configurations that firms choose in diversifying deals. 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 deals. 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 mobility across the industries of firms involved in diversifying deals indeed leads to greater value synergies. First, we measure the change in labor productivity around all ownership changes in our sample. In years prior to the transaction, we measure labor productivity as the employment-weighted average of the ratio of firm sales to employment in the merging firms. For each transaction, we measure the change in labor productivity over several windows around the deal. We do not see significant differences-in-differences of labor productivity between within-industry deals and diversifying deals in which there is a low degree of mobility between the industries of the merging firms. However, we see significantly higher changes in labor productivity among firms involved in diversifying transactions between industries with high and low human capital transferability. 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.

As an alternative way to assess performance among the set of diversifying deals, 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. Our results are again robust to controlling for the overall size of the merged firm as well as the relative size of the merging firms, the number of industries in the acquiring firm prior to the transaction, and the timing of the deal. Thus, again, transferability of the human capital employed in the industries in which merging firms operate is associated with larger value synergies from combination.

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 the acquisition. And, we consider two 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-mobility deals. Thus, our evidence is overall more consistent with the hypothesis that expanding internal labor markets creates value by increasing the ability of firms to retain valuable high-skill workers. Consistent with our proposed mechanism, we find evidence 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 one of the establishments owned by the acquiring firm prior to the deal. The results are again robust to firm-level controls for the size and scope of operations as well as a battery of worker-level demographic characteristics including age, race, gender, and pre-deal wages.

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. 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 results contribute to the growing literature that considers the effect of labor markets on corporate finance outcomes. Donangelo (2014) and Eisfeldt and Papanikolaou

(2013) develop models that link firm risk in asset markets to the mobility of human capital. We show that human capital mobility also has a bright side for the firm; increased labor productivity can justify the choice to employ and develop high mobility, high skilled workers. Our results also complement the analysis of Ouimet and Zarutskie (2012). They show that some firms use takeover markets as a way to grow their workforces. We focus on a more specific mechanism—the transferability of human capital between the acquiring and target firms—and use it to understand firm's decisions to expand the scope, rather than the scale of their operations.

Our results also shed new light on the motivation for corporate diversification. Traditionally, the finance literature identifies corporate diversification as a symptom of agency problems (e.g., Betton, Eckbo, and Thorburn (2008); Morck, Shleifer, and Vishny (1990)). However, in the cross-section, most of the largest and most successful U.S. corporations are diversified. We provide an alternative explanation for diversification: differences in the product markets in which firms operate may mask valuable synergies in human capital inputs.

Finally, our analysis relates to the strategy literature that builds on the resource-based view of diversification proposed by Wernerfelt (1984). One approach in the literature measures resource relatedness using overlap in the occupations employed in different industries (Farjoun (1994, 1998)). We instead construct explicit 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. Throughout the analysis, we define industries using the 49 Fama-French industries.[2]

Our worker-level information comes from the LEHD data. The LEHD data contain worker-firm matched observations for 31 U.S. states.[3] 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.[4] We observe the industry classification for each job at the reporting unit level.[5] We exclude workers with less than 1 year of tenure in

[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] 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).

[4] 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.

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

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 mobility 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 desire to move human capital in either direction 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.[6]

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.[7] 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 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

[6] 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.

[7] 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.

state. A consequence is that we may understate worker retention and the amount of internal reallocation following mergers in our sample. However, there is no obvious reason to suspect that these errors should be worse among within-industry deals (or deals between firms in industries with low human capital transferability). Moreover, the rate of cross-state migration within the LEHD data is small (approximately 2% annually), suggesting that this source of measurement error is unlikely to have a major effect on our analysis. 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 the sample of merger deals for which we observe sales information and, thus, can measure labor productivity. Our sample 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 workers in the target firms of sample deals. 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.

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. 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 49 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. In Panel B, we report the top 10 industry pairs by human capital mobility, 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.[8] 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 in each distinct industry group. We then scale by the total employment across all diversifying deals within the acquirer's

[8] All of our later regression results are robust to also considering any of these three samples.

(1)

industry in that year. Alternatively, we make the same computation, but using the number of firms instead of employment. We then estimate the following regression specification:

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

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*.[9] By conducting our tests at the industry level, we limit the ability of idiosyncratic firm-level variation or shocks to influence our estimates.

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 also allow these effects to vary by year to control for industry merger waves. 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

[9] While our HCT index is symmetric between industry i and j, the dependent variable is not.

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. 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. 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. 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.

Because we construct our measure of human capital transferability using worker job changes, a 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 measure the index. To address this concern, we reconstruct the HCT index from the job change sample after explicitly removing cases in which all workers from a firm-unit simultaneously change firm identifiers. Our results are unaffected. A second 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.

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. Labor Productivity

Because the synergies we propose operate through increases in worker productivity, we first consider differences in labor productivity as our measure of firm performance following a deal. We use sales, employment, and payroll information available from the Census Bureau's Business Register. We measure labor productivity using the ratio of firm sales to employment, as in, for example, Haltiwanger, Lane, and Spletzer (1999), Tate and Yang (forthcoming), and Giroud and Muller (2011). We cannot construct measures of total factor productivity on our sample because we include both

manufacturing and non-manufacturing firms (units) and data on capital inputs is available only for the subsample of manufacturing plants. It is 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. However, Foster, Haltiwanger, and Krizan (1998) show that labor productivity is highly correlated with total factor productivity in U.S. manufacturing firms.

Our interest is in how labor productivity inside a firm changes following a deal in which there are labor market synergies. Though we can readily observe labor productivity year-by-year following deals, we must construct a benchmark for comparison prior to the deal. We compute the weighted average labor productivity for the acquiring and target firms annually for the three years preceding each merger in our sample, using annual employment shares as the weights. 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 over a symmetric 5 year window surrounding each deal:

$$Y_{it} = \alpha + \beta_1 After_{it} + \beta_2 After_{it} * 1_{75\%}\left(HCT_{i,-1}\right) + \boldsymbol{X_{it}}'\boldsymbol{\gamma} + \varepsilon_{it} \qquad (2)$$

where *Y* is the natural logarithm of the weighted average of labor productivity in years -2, -1, and 0 and of observed labor productivity of the merged firm in years 1, and 2; *After* is an indicator variable that takes the value 1 in years 1 and 2 following the deal; $1_{75\%}\left(HCT_{i,-1}\right)$ 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; and $\boldsymbol{X}$ is a vector of controls. Because acquiring and target firms can operate in multiple industries, we construct a deal-based HCT index by taking a weighted average of the HCT of each of the acquirer's industries with each of the target's industries, and then taking a second weighted average over all acquirer industries. We take this approach throughout Sections 4 and 5 of the paper (in all deal-level tests), though we often refer simply to the HCT index for ease of exposition.

We include the natural logarithm of total employment across the acquiring and target firms prior to the deal and in the merged firm after the deal as a control. We also include deal fixed effects. Thus, we do not need to include the level effect of $1_{75\%}\left(HCT_{i,-1}\right)$,

since it does not vary over time within a deal. Because the residuals are likely to be serially correlated within deals, we cluster standard errors at the deal level.

In Panel A of Table 4, we present the results from estimating equation (2). In Column 1, we find that the difference in labor productivity after a deal in which the acquiring firm diversifies into an industry with high human capital transferability to its existing industries is indeed significantly higher than the difference in productivity following other deals. The coefficient on *After** $1_{75\%}(HCT_{i,-1})$ is positive and statistically significant at the 5% level. Because the dependent variable is in log form, we can interpret the estimated difference as a percentage change. That is, firms that acquire targets with high human capital transferability experience a 20% increase in productivity relative to other acquirers. We also find lower labor productivity in firms that undertake deals involving more workers (coefficient estimate on total employment is negative and statistically significant). In Column 2, we repeat our estimation of equation (2), but use the alternative version of the HCT index constructed using only the job changes of high wage workers to define $1_{75\%}(HCT_{i,-1})$. Mirroring our results in Section 3, we find that the difference in differences between deals involving targets with high human capital transferability and other deals is larger in magnitude when we focus on a proxy for the relevance of the human capital of high skill workers, whose skills are more scarce in external markets and who are more likely to make productivity-enhancing investments in additional human capital following the deal.

In Columns 3 and 4 of Panel A, we repeat the same set of estimations, but replace the dependent variable with the natural logarithm of the ratio of firm sales to payroll. By scaling with payroll rather than aggregate employment, we can test whether the increases in sales that firms enjoy following a deal still provide the firm with additional cash flows after accounting for potential increases in the flows to labor through higher wages. We find that they do. Though the estimate of the difference in differences between deals with high human capital transferability and other deals is smaller in magnitude in all cases, it is still economically and statistically significant.

As a robustness check, we re-estimate the regressions in Panel A, 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.

In Panel B of Table 4, we report estimates of an alternative specification of the differences-in-differences strategy in which we include the change in labor productivity as the dependent variable. This specification allows us to hone in on the years immediately surrounding the event to identify cleanly the increment to productivity associated with the deal. In these regressions, the level effect of the indicator $1_{75\%}(HCT_{i,-1})$ captures the effect of interest. We also include several additional independent variables in the analysis. First, we add an additional 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 two additional variables to distinguish among the deals in the benchmark group. First, we add an indicator variable that takes the value 1 if the acquirer and target do not operate in any overlapping Fama-French 49 industry groups. Second, we add a continuous control for the degree of industry overlap between the acquirer and target firm. 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.[10] Since each deal appears only once in the estimation sample, we compute standard errors that are robust to heteroskedasticity, consistent with our approach in Panel A.

In Column 1 of Panel B, we present the results measuring the change in productivity over a symmetric three year window beginning one year prior to the deal and ending one year after the deal (in natural logarithms). 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. We also

[10] None of these additional controls have a material effect on the estimates of interest in the specifications that use the change in labor productivity as the dependent variable.

continue to find a positive marginal effect of high human capital transferability on the change in labor productivity following an acquisition. Even with the additional controls, we again find a roughly 20% relative increase in labor productivity among the high human capital overlap deals. In general, diversifying deals (with low human capital transferability) appear to result in a relative decline in labor productivity; however, the effect is not statistically significant. Moreover, we find that this effect 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.[11] High human capital transferability deals result in similar and, if anything, slightly larger productivity changes than within-industry deals. This result supports our hypothesis that the overlap in inputs between merging firms could be as important as or even more important than the relatedness of the product markets in which they operate to determining deal success. Given our findings in Panel A, we repeat the regression from Column 1, but measure $1_{75\%}(HCT_{i,-1})$ based on the human capital transferability index among job changers who earn at least $75,000 annually. We report the results in Column 2. As in Panel A, we find that the magnitude of the human capital effect is stronger when we consider workers whose human capital is likely to be more productive and scarce in the external market.

Mirroring Panel A, we next 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 replicating 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 over the same horizon. We find broadly similar results. Not surprisingly, the magnitudes of the effects are slightly smaller—workers with scarce skills can share in some of the rents from those skills. 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.

[11] 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.

Overall, the estimates in Table 4 confirm our hypothesis that higher transferability of human capital between merging firms increases post-deal performance. Comparing the results in Panels A and B, it appears that our estimates 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. Tate and Yang (forthcoming) provide evidence on cross-sectional differences in labor productivity between diversified and focused firms that is consistent with this channel.

4.2 Divestiture

We also consider a second, longer-term measure of deal performance: the rate at which the new industries into which firms diversify are later divested. 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, we track each firm created in a diversifying transaction for 10 years following the deal. 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 overlap between the industries in which the acquiring and target firms in the deal operate on the hazard rate of divestiture using a Cox (1972) proportional hazard model:

$$h_i(t) = h_0(t)e^{\beta HCT_i + \boldsymbol{X_i}'\boldsymbol{\gamma}}$$

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 in Section 4.1, we include in $\boldsymbol{X}$ 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 our measure of the relative size of the target and acquirer (the natural logarithm of the ratio of target employment to acquirer employment). Here, we also add an additional 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 times when deals occurred. We again 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 5, 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 overlap 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 is roughly 78% as high among deals with human capital transferability above the median as it is among deals with below-median human capital overlap. We also further partition the sample by the HCT index in

Column 3 of Table 5, including indicators for deals in which the human capital overlap 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 human capital transferability below the 25th percentile. Though the estimates are not significantly different from each other, we find that all three indicators have negative and statistically significant effects on the likelihood of divestiture. Moreover, we find a monotonic pattern in the coefficients: as human capital transferability increases, the likelihood of divesting the 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 5 (Columns 4 to 6), we repeat the specifications from Panel A, but define the human capital transferability index using only the job changes of workers who make at least $75,000 annually. Though some of the estimates are more significant statistically, we do not see differences in the economic magnitude of the effects of human capital transferability, compared to the estimates in Panel A. On this dimension, our results differ from the labor productivity results in Section 4.1. However, taken together, the results imply that firms benefit more from the transferability of human capital among high-wage (or, high-skill) workers. Human capital transferability appears to affect divestiture similarly whether measured based on the mobility of high or low wage workers, perhaps because divestiture of an entire industry is an extreme measure of deal failure. However, merged firms reap greater cash flow benefits from the overlap in skills of high wage workers. Overall, we again establish a strong positive relation between human capital transferability and post-acquisition performance.

5. Human Capital Transferability and Worker Outcomes

Next, we investigate the sources of the productivity gains we identified in Section 4 by measuring the movement of the acquired human capital following diversifying deals. We argue that 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. These effects will be larger the more overlap there is between the human capital used in the industries operated by the firm. Arguably, some of the largest benefits of internal labor markets may accrue only over time: the match between workers and the firm improves over time due to the ongoing human capital investments of the workers, creating rents for both the workers and the firm. However, in this section, we focus on testing the short-term predictions of the theory at the worker level.

To begin, 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 test whether high-overlap acquirers are more likely to retain skilled workers following the deal. 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:

$$Retain_i = \alpha + \beta_1 Divers_i + \beta_2 Divers_i * 1_{50\%}(HCT_{i,-1}) + \beta_3 Skill_i + \beta_4 Skill_i * Divers_i + \beta_5 Skill_i * Divers_i * 1_{50\%}(HCT_{i,-1}) + \boldsymbol{X_i}'\boldsymbol{\gamma} + \boldsymbol{\varepsilon_i}$$

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, $1_{50\%}(HCT_{i,-1})$ 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 ($\beta_2, \beta_4, \beta_5$), which are easier to interpret in a linear model.[12] Note also that it is unnecessary to include the level effect of our measure of high human capital transferability, $1_{50\%}(HCT_{i,-1})$, 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

[12] We find similar results if we instead estimate logit specifications.

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 change in the number of plants operated by the firm and total employment in the firm in the year prior to the acquisition.[13] 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*).[14] In Column 1, we use the HCT index constructed from the full sample of job changers to define $1_{50\%}(HCT_{i,-1})$. Among the controls, we find, not surprisingly, that there is a general tendency towards retaining higher wage workers. However, managers 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** $1_{50\%}(HCT_{i,-1})$ = 0.051). In Column 2, we replicate the regression from Column 1, but using only job changes by workers earning at least $75,000 annually to define the human

[13] 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.
[14] The results are not sensitive to using this cutoff and, e.g., are similar using the median.

capital transferability index. Again, we find stronger results when we focus on the mobility of high-skilled workers' human capital, though the difference is not significant.

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 75^{th} 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*$* 1_{50\%}(HCT_{i,-1})$—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 4.1, 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 overlap simply have additional sources of synergies, including the real option for the acquirer to reallocate human capital.

Next, we test for direct evidence that acquirers who diversify into industries with which they have high human capital overlap benefit immediately 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 consider the subset of diversifying deals and compare deals depending on the overlap of human capital between the industries of the acquiring and target firms. We estimate the following regression specification:

$$Move_i = \alpha + \beta 1_{50\%}\left(HCT_{i,-1}\right) + \boldsymbol{X_i}'\boldsymbol{\gamma} + \boldsymbol{\varepsilon_i} \quad (3)$$

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*.[15] As before, $1_{50\%}\left(HCT_{i,-1}\right)$ 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.[16]

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 $1_{50\%}\left(HCT_{i,-1}\right)$. 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

[15] 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.
[16] Again, the results are unaffected by instead estimating a logit specification.

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. 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 $1_{50\%}(HCT_{i,-1})$. 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 workers from targets with high human capital overlap 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 overlap 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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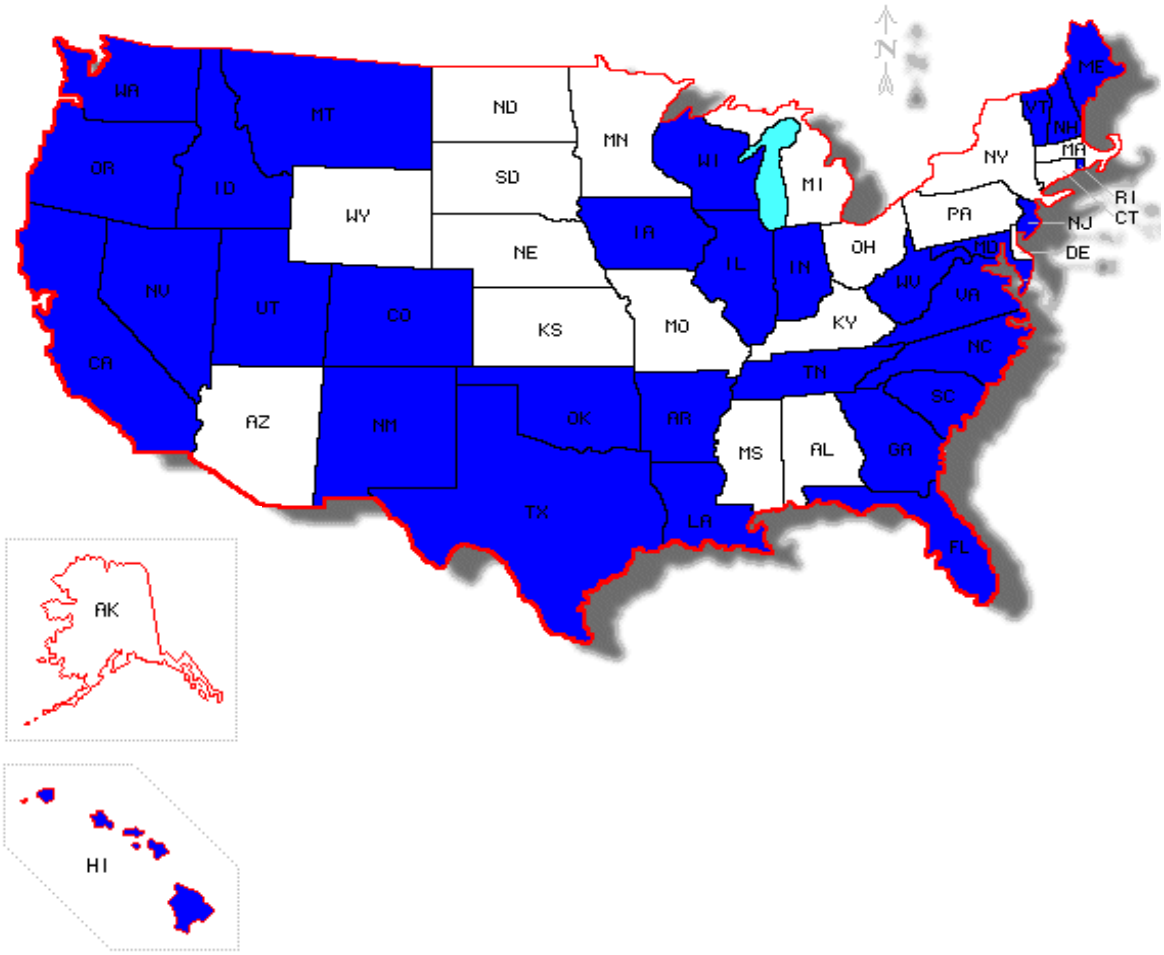

Figure 1

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.

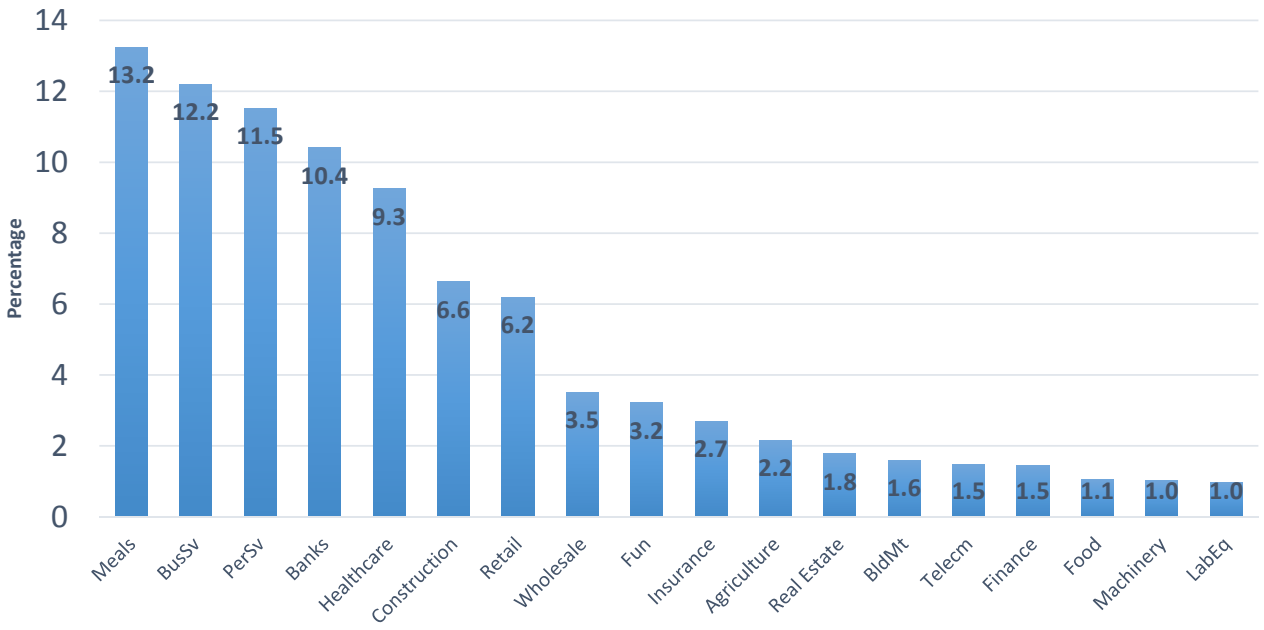

Figure 2
Distribution of job changers in our sample
This figure shows the distribution of job changers in our sample by industries (Fama-French 49 industries). We only show industries that account for at least 1 percent of our sample.

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	39.72	< $10K	24.2
2-3 yrs	20.85	$10 - $25K	42.44
3-4 yrs	12.72	$25 - 50K	24.63
4-5 yrs	8.41	$50 - 75K	5.45
>5 yrs	18.3	> $75K	3.28
N =	115,219,000		
Mean	12.67	Mean	$ 24,990
STDEV	9.87	STDEV	$ 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)	(2496)	(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 $i \neq j$) 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 Performance

This table estimates the change of performance around acquisitions. In Panel A, we estimate equation (2) over a symmetric five-year window surrounding each deal excluding the transaction year. The dependent variable is the natural logarithm of (weighted average) labor productivity. After is an indicator variable that equals 1 for year 1 and 2 following the deal. High_HCT and High_HCT(>$75) 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. Ln(Employment) is the natural logarithm of the total employment of the acquirer and target firms. 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. In Panel B, the dependent variable is the change in labor productivity for the combined firm around acqusitions. We use a three-year event window surrounding each deal. DIVERS is an indicator variable that equals 1 if the transaction is diversifying. 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. Columns (1) and (2) measure labor productivity using the sales-employment ratio and columns (3) and (4) measure labor productivity using the sales-payroll ratio. Standard errors are clustered by deal in Panel A and are robust to heteroskedasticity in Panel B. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

Panel A: Labor Productivity

Dependent Variable	Sales/Emp		Sales/Payroll	
	(1)	(2)	(3)	(4)
After	-0.048	-0.052	-0.066	-0.070 *
	(0.043)	(0.043)	(0.042)	(0.042)
After x High HCT	***0.208 *****		***0.180 *****	
	(0.087)		***(0.090)***	
After x High_HCT(>$75K)		***0.325 ******		***0.290 ******
		(0.083)		***(0.088)***
Ln(Employment)	-0.263 ***	-0.263 ***	-0.205 ***	-0.205 ***
	(0.034)	(0.034)	(0.034)	(0.033)
Constant	6.235 ***	6.233 ***	2.408 ***	2.407 ***
	-0.290	-0.289	-0.282	-0.281
Deal Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.063	0.064	0.074	0.074
N	13,900	13,900	13,900	13,900

Panel B: Changes of Labor Productivity

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 5
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. HCT Using Workers with Wage>$75K		
	(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 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	HCT for W > $75K	HCT	HCT for W > $75K
	(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. HCT Using Workers with Wage>$75K	
	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	HCT for W > $75K
	(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