

# The Bright Side of Corporate Diversification: Evidence from Internal Labor Markets

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We document differences in human-capital deployment between diversified and focused firms. We find that diversified firms have higher labor productivity and that they redeploy labor to industries with better prospects in response to changing opportunities. The opportunities and incentives provided in internal labor markets in turn affect the development of workers' human capital. We find that workers more frequently transition to other industries in which their diversified firms operate and with smaller wage losses compared with workers in the open market, even when they leave their original firms. Overall, internal labor markets provide a bright side to corporate diversification. (JEL G34, J24, J31, J62, L22, L25, M51)

*The boundaryless company we envision will remove the barriers among engineering, manufacturing, marketing, sales, and customer service; it will recognize no distinctions between domestic and foreign operations... A boundaryless organization will ignore or erase group labels ..., which get in the way of people working together.*

—Jack Welch, CEO, GE 1989 Annual Report

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What are the benefits of corporate diversification? Traditional finance theory argues that broader internal capital markets can help diversified firms to overcome frictions in the external capital market. Yet, the empirical evidence on the efficiency of internal capital allocation in conglomerates is mixed.<sup>1</sup> Using novel worker-level data, we observe active internal labor markets in diversified firms: internal job changes occur more frequently than in focused firms and often involve cross-industry moves.

Adjusting labor inputs can be costly to the firm. Marginal hiring costs, which include search and training, are as high as 24 weeks of wage payments, and these costs increase with the skill requirements of the position (Blatter, Muehlemann, and Schenker 2012; Abowd and Kramarz 2003). Moreover, the costs of external hiring exceed the costs of internal promotions (Hamermesh 1995; Hamermesh and Pfann 1996). Diversification can provide firms with an advantage in responding to industry shocks: they can reallocate labor from divisions with weak prospects toward those with better opportunities, as they reallocate physical capital in models of internal capital markets (e.g., Stein 1997). The resulting internal labor markets, in turn, can affect the investments and prospects of individual workers. Experience gained in other industries within a diversified firm can facilitate workers' transitions to those industries in the future.<sup>2</sup> Moreover, the knowledge and skills to make such transitions are likely to be a portion of the human-capital investment made by workers in diversified firms. For example, promising young employees may take advantage of internal job rotation programs to acquire the broad organizational knowledge necessary to climb the corporate hierarchy.<sup>3</sup> This knowledge and transfer of ideas within the organization can further enhance productivity: a successful practice discovered in one division can be replicated and implemented in other divisions. Jack Welch initiated the well-known "Work-Out" program at GE in the 1990s, with the goal of cultivating such synergies through "integrated diversity."

We use newly available worker-firm matched panel data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program and the Longitudinal Business Database (LBD) to test this hypothesis at the firm and worker level. We begin by establishing a link between labor productivity and diversification. In each sample year, we match each segment of a diversified firm to focused firms of similar size and age from the same industry. We consider two measures of labor productivity: the ratio of sales to employment and the ratio of sales to payroll. We find that labor is more productive in diversified firms: output is 9% to 10% higher than predicted by the labor productivity

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<sup>1</sup> See Stein (2003) and Maksimovic and Phillips (2007) for surveys of the extensive literature on internal capital markets and diversification.

<sup>2</sup> Custodio, Ferreira, and Matos (2013) make a similar argument about skill accumulation over CEOs' careers.

<sup>3</sup> Wasmer (2006) constructs a model in which labor market frictions heighten the investments workers make in such firm-specific skills.

of comparable focused firms. Moreover, the productivity difference is most pronounced in industries that employ higher percentages of skilled workers.

Next, we test our prediction that diversified firms reallocate workers in response to changing opportunities at higher rates than those in the external market. A key identification concern is the endogeneity of job changes.<sup>4</sup> A job change can be initiated either by the worker or by the firm; moreover, the fraction of voluntary changes may differ across diversified and focused firms. To isolate firm-initiated worker reallocation, we adapt the approach of Gibbons and Katz (1991), constructing a sample of worker-establishment matched data that includes only involuntary job changes resulting from establishment closures. If workers from a multi-unit firm are retained and reallocated after an establishment closure, we can infer that the job change is desired by the firm.<sup>5</sup> Because workers have a choice to accept an offer to remain inside the firm or to seek a job outside the firm, our estimates provide a lower bound on the desired amount of internal labor reallocation in diversified firms.

We estimate a two-stage Heckman selection model on the sample of workers displaced from diversified firms. In the first stage, we model the diversified firm's choice to retain workers inside the firm; and, in the second stage, we model the choice to reallocate workers to a different industry (conditional on retaining them). We find that diversified firms retain more workers when growth opportunities in their remaining industries are high; and, they are more likely to redeploy workers to different industries when conditions in their former industries deteriorate. Moreover, we find that diversified firms are more likely to move workers to growing industries and to industries with the strongest growth opportunities in their portfolios, measured by Tobin's Q. We also find that the sensitivity of the rate of worker reallocation between industries to industry opportunities is higher in diversified firms than it is in the open market, and the difference in industry growth rates among workers who switch industries is significantly larger for workers who change jobs inside diversified firms. Thus, our evidence suggests that diversified firms use internal labor markets to allocate human capital more efficiently than the open market does.

We also test the worker-level implications of our hypothesis. We ask whether experience in a diversified firm allows workers to make easier transitions to the industries in which the firm operates. We consider two measures of cross-industry mobility. First, we consider wage changes. We again consider workers displaced from their jobs by establishment closure, to isolate involuntary job changes. We focus on workers who find jobs in new firms, to identify the

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<sup>4</sup> Note that we also consider the cross-section of organizational structure even though the structure of the firm is itself endogenous. Most diversified firms are large and mature. Because the decision to diversify typically occurred well in the past, it is unlikely to be influenced by current worker skills.

<sup>5</sup> Unionization could complicate this inference if unions are able to influence retention decisions following closure, and unions have a different effect in diversified and focused firms. We confirm the robustness of our findings to including controls for union membership at the industry level.

workers' outside options separately from potential inefficiencies in wage-setting practices inside conglomerates.<sup>6</sup> We find that workers from diversified firms who change industries (and firms), but move to a new industry in which their former firm operates, experience significantly smaller wage losses than other workers who switch between the same two industries. Second, we consider the frequency with which workers move to these "spanned" industries compared with workers in external markets. Workers from diversified firms are significantly more likely than other workers are to move between pairs of industries operated by the diversified firm.

We also provide evidence linking greater worker mobility across diversified firms' industries to skills attained inside the diversified firm. First, we show that the effects are concentrated among high-skill workers, measured at the worker or industry level. Second, we show that the effects increase with worker tenure inside the diversified firm. Finally, we show that the effects cannot be explained by worker experience in the firm's other industries prior to joining the diversified firm. We also address a number of alternative explanations for the evidence, including location and sorting effects.

Our analysis provides a new angle on corporate diversification. We identify benefits from internal markets for human capital. Just as diversified firms can use internal reallocation of resources to overcome frictions in capital markets, they can reallocate workers in the internal labor market in response to industry shocks, enhancing productivity. Unlike physical capital, workers can respond to the incentives provided by internal labor markets. Worker investments in human capital relevant to the firm's bundle of businesses can further enhance productivity relative to standalones. The desire to create these markets, then, may be an important determinant of the boundaries of the firm (Hart 1995).

Allowing a role for human capital also provides a way to reconcile existing results on productivity and capital allocation in conglomerates. Schoar (2002) finds that the manufacturing plants of diversified firms have higher total factor productivity than the establishments of focused firms in the cross-section. Moreover, Maksimovic and Phillips (2002) show that diversified firms achieve higher sales growth and adjust more easily to business cycles, particularly within core industries. Yet, other studies find less sensitivity of capital expenditures to industry Q among the business segments of diversified firms and argue that firms engage in "socialist" cross-subsidization of weak divisions at the expense of those with good opportunities (Ozbas and Scharfstein 2010; Lamont 1997; Shin and Stulz 1998; Rajan, Servaes, and Zingales 2000). Whited (2001) disputes this evidence based on error in the measurement of industry prospects. Maksimovic and Phillips (2008) use plant-level data and find that the manufacturing segments of diversified firms respond more aggressively than focused firms do to changing industry opportunities via

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<sup>6</sup> Schoar (2002) and Silva (2012), for example, propose that conglomerates pay inefficiently high wages.

acquisitions (though not with capital expenditures).<sup>7</sup> We provide an alternative reconciliation of the evidence. We identify human-capital investment as an important driver of increased productivity in diversified firms. Unlike focused firms, diversified firms are able to redeploy labor internally in response to changing industry conditions. If labor and capital are partial substitutes, and focused firms have less ability to adjust labor because of frictions in the external labor market, then we would expect to see a smaller elasticity of capital expenditures with respect to  $Q$  among diversified firms.

Finally, a large body of literature measures the effect of diversification on market valuations. Many studies find a “diversification discount”: diversified firms trade at a discount relative to portfolios of focused firms operating in the same industries using cash-flow-value multiples (Lang and Stulz 1994; Berger and Ofek 1995). Other studies dispute this evidence based on measurement or selection concerns (Villalonga 2004; Campa and Kedia 2002; Graham, Lemmon, and Wolf 2002). Our human-capital story can accommodate, but does not require such a discount. Diversified firms generate higher cash flows than focused firms do because of higher labor productivity. However, the human (or, organization) capital that improves relative efficiency can also generate additional risk. Recent literature argues that firms that invest more heavily in organization capital carry a risk premium because workers can leave the firm and transfer a portion of the capital to a new firm (Atkeson and Kehoe 2005; Lustig, Syverson, and Van Nieuwerburgh 2011; Eisfeldt and Papanikolaou 2013). If the risk effect dominates the cash-flow effect, then diversified firms will trade at a discount. However, the discount is a reflection of higher risk rather than inefficient operations.

## **1. Data**

We use worker-, firm-, and establishment-level data from the U.S. Census Bureau to test our hypotheses. We identify individual establishments and their ultimate owners (firm), geographic locations (state and county), and industries (4-digit Standard Industrial Classification system [SIC]), using the LBD. The LBD covers all nonfarm establishments with paid employees in the United States since 1976. It also provides information on employment, payroll, birth, and closure at the establishment level.

We retrieve individual worker-level information—including wage, gender, and age—from the LEHD program. The LEHD data are constructed using administrative records collected from the state unemployment insurance (UI) system and the associated ES-202 program. It covers 96% of total wage and salary civilian jobs in the United States and is generally comparable from state to state. Wages reported to the state UI system include bonuses, stock options,

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<sup>7</sup> See Maksimovic and Phillips (2013) for a survey of studies that find evidence of efficient allocation of physical capital within diversified firms.

profit distributions, the cash value of meals and lodging, tips and other gratuities in most of the states, and, in some states, employer contributions to certain deferred compensation plans such as 401(k) plans.<sup>8</sup> The data contain individual worker identifiers, as well as firm and unit identifiers. State laws require firms to file quarterly reports that link individual workers to each of their units. Thus, we can track workers and their wages dynamically within and across firms. We use employment records from 23 states provided by the Census Bureau through its Research Data Center (RDC).<sup>9</sup> In Figure 1, we provide a map of LEHD-covered states. The map does not reveal any obvious regional biases. Nevertheless, missing data from uncovered states impose some limitations on our analysis. First, we generally overstate unemployment rates in our sample: a worker may have a job in one quarter and not appear in the data the next because of either job loss or migration to an uncovered state. Second, we cannot observe the entire labor force or all internal-worker movement for firms that operate in both covered and uncovered states. Most of our analysis concerns changes in wages, rather than unemployment. As long as the factors affecting the decision of the state to opt into or out of the LEHD program are orthogonal to the determinants of (changes in) wages, our estimates should not suffer from selection bias.<sup>10</sup> Moreover, the within-sample rate of migration to a new covered state—even following establishment closure—is low (approximately 2%). Thus, the potential effect of unobserved migration on our analysis is likely to be small.

We use information from the LBD to measure firm-level diversification and labor productivity. We also use the LBD to identify establishment closures. Because our worker-level data are available through 2004, we consider closures through 2001 so that we can track the outcomes of workers for 3 years following a job change. We restrict the sample to establishments with at least 50 employees, to prevent our sample from being dominated by very small private ventures. We match workers from the LEHD data to establishments from the LBD using the internal bridge file provided by the Census at the Employer Identification Number (EIN), state, county, and 4-digit SIC code level. To achieve a unique match, we require that the LBD establishment is unique within this partition. We also require that both datasets recognize the closure within a seven-quarter window. Appendix A provides a detailed description of our data construction.

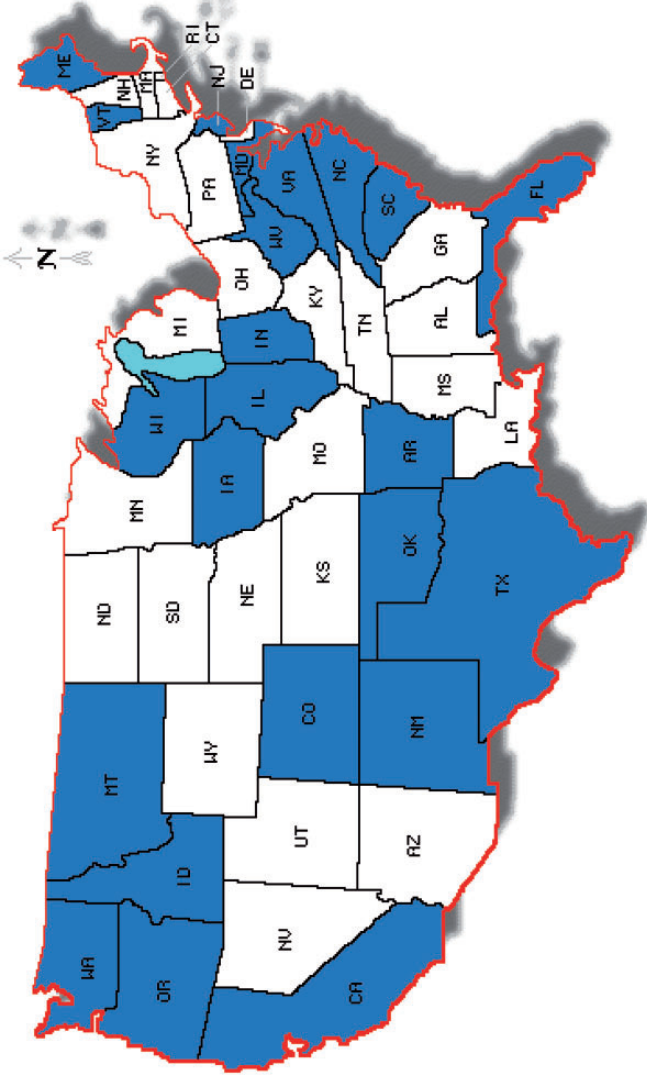
We adjust the reported wages for our analysis as follows. We use the quarterly consumer price index to compute real quarterly wages in beginning-of-1990

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<sup>8</sup> See <http://www.bls.gov/cew/cewfaq.htm> for additional details.

<sup>9</sup> All 50 states, the District of Columbia, Puerto Rico, and the U.S. Virgin Islands have been in the LEHD partnership since December 2010. However, not every state partner has passed through the experimental production phase. As of March 2011, only 23 states had data available for research purposes through the Census RDC, and the last year with available data was 2004.

<sup>10</sup> This is likely to be the case, as often the constraint that prevents the Census from making data available to researchers is preexisting state laws.



**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. No data are available for unshaded states.

dollars. We also aggregate quarterly wages into annual real wages. Because of annual bonuses and other predictable seasonal variation, quarterly wages may not provide an accurate reflection of the worker's earnings, and quarterly wage changes may not reflect real changes to the compensation contract. Thus, in any given quarter, we compute annual real wages for the preceding year as the mean real wage over the prior four quarters multiplied by four. We also require at least three consecutive quarters of wage data to include the quarter in the sample, and use only interior quarters in the computation. The latter restriction is necessary because the first or last quarter's wage reflects payment for an unobserved fraction of the quarter. Finally, we exclude workers younger than 16 or those who earn less than \$10,000 from our analysis. We identify the manager of the unit (firm) as the worker with the highest wage in the unit (firm).

To measure industry-level opportunities, we merge in additional data from Compustat. We define industry Q as the median among single-segment firms within each 2-digit SIC code of the market value of assets scaled by the book value of assets.<sup>11</sup>

In Table 1, we provide summary statistics of our establishment-level data. Panel A describes summary statistics for a 20% random sample of LBD establishments between 1993 and 2001.<sup>12</sup> The average establishment has 194 workers and a payroll of \$6.83 million. Of the establishments, 58% are part of multi-unit firms, and 42% are part of firms that operate in at least two distinct 2-digit SIC codes (diversified firms). In Panel B, we see that establishments from multi-unit firms do not have significantly larger employment (mean = 202), but do have larger payrolls (mean=\$7.59 million). Of the establishments, 55% come from the 23 states covered by the LEHD data.

We also consider the full sample of closing establishments from the LBD over the same period. Relative to the average establishment, closing establishments appear to be smaller (mean employment = 188) and to have smaller payrolls (mean = \$5.3 million). Only half come from multi-unit firms, but the fraction from diversified firms is similar to the overall sample (39%). There are no obvious regional patterns in closure rates, but we observe a clear spike in closures in the recession year of 2001.

Finally, we provide summary statistics for the subset of closing establishments we can match to individual workers in the LEHD data. In Appendix A, we detail the challenges of matching establishments across the two datasets. Because we can use only a fraction of closing establishments for our analysis, we must be cautious in extrapolating our results out of

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<sup>11</sup> Market value of assets is the book value of assets (at) plus the difference between market and book equity. Market equity is the fiscal year closing stock price (prec\_f) times common shares outstanding (csho). Book equity is common equity (ceq) plus deferred taxes (txdb).

<sup>12</sup> Throughout the study, we construct random samples by generating a uniform distribution over the entire sample and retaining observations with values less than the cutoff required to achieve the stated percentage, in this case 0.2. The choice of 20% is arbitrary.



**Table 1**  
**Summary statistics: Plant level**

	Panel A: All firms			Panel B: Multi-unit firms only		
	Random establishments in the LBD (N=655,929)	Closing establishments in the LBD (N=143,370)	Closing establishments in the LBD matched with the LEHD (N=12,439)	Random establishments in the LBD (N=383,238)	Closing establishments in the LBD (N=70,811)	Closing establishments in the LBD matched with the LEHD (N=1,850)
Plant employees	194 (514)	188 (647)	134 (292)	202 (473)	187 (565)	142 (224)
Firm employees	25,765 (83,464)	22,084 (57,124)	4,780 (26,992)	43,968 (105,480)	44,521 (74,912)	31,379 (63,789)
Annual payroll (\$000's)	\$6,830 (\$383,230)	\$5,299 (\$66,606)	\$2,333 (\$6,709)	\$7,590 (\$178,102)	\$6,676 (\$92,809)	\$3,703 (\$9,611)
% of Multi-unit firms	0.58	0.49	0.15			
% of diversified firms	0.42	0.39	0.10	0.71	0.79	0.69
Industry distribution						
SIC = 1	0.05	0.04	0.09	0.02	0.02	N/A
SIC = 2	0.08	0.08	0.08	0.09	0.08	N/A
SIC = 3	0.10	0.08	0.07	0.10	0.09	N/A
SIC = 4	0.06	0.07	0.05	0.08	0.08	N/A
SIC = 5	0.29	0.27	0.28	0.36	0.30	N/A
SIC = 6	0.06	0.09	0.04	0.07	0.10	N/A
SIC = 7	0.13	0.19	0.24	0.13	0.18	N/A
SIC = 8	0.21	0.16	0.13	0.15	0.13	N/A
Geographic distribution						
LEHD State	0.55	0.57	.	0.55	0.57	.
Region = NE	0.22	0.22	0.08	0.21	0.22	0.09
Region = MW	0.25	0.21	0.16	0.25	0.22	0.18
Region = S	0.23	0.24	0.23	0.24	0.24	0.26
Region = SW	0.12	0.13	0.19	0.12	0.12	0.19
Region = W	0.14	0.16	0.29	0.14	0.15	0.22
Region = RM	0.04	0.03	0.05	0.04	0.03	0.06
Yearly distribution						
Year = 1994	0.10	0.08	0.08	0.10	0.07	0.05
Year = 1995	0.11	0.08	0.10	0.10	0.08	0.07
Year = 1996	0.11	0.11	0.12	0.11	0.11	0.13
Year = 1997	0.11	0.10	0.09	0.11	0.10	0.07
Year = 1998	0.11	0.11	0.13	0.12	0.11	0.12
Year = 1999	0.12	0.12	0.12	0.12	0.14	0.10
Year = 2000	0.12	0.12	0.14	0.12	0.13	0.22
Year = 2001	0.12	0.21	0.14	0.12	0.17	0.17

Panel A reports summary statistics of a random sample of nonclosing establishments from the LBD, all closing establishments in the LBD, and the subsample of closing establishments from the LBD that we match with worker-level data from the LEHD program. The random sample of LBD establishments includes 20% of LBD establishments during the sample period 1993-2001. Panel B reports the corresponding statistics for the subsamples of establishments from multi-unit firms. We define multi-unit firms as firms that operate at least two distinct establishments. Standard deviations are reported in parantheses for continuous variables. N/A indicates industries that have a limited number of firms. Because of potential disclosure risk, we cannot report the industry distribution for these subsamples.

sample. In particular, worker-matched establishments are significantly less likely to be part of multi-unit firms (15%) relative to random closing establishments. Thus, we under sample large firms. Nevertheless, conditional on being part of a multi-unit firm, the fraction of establishments that are part of a diversified firm is 69%, which is similar to the overall LBD sample (71%) and only slightly lower than the LBD closure sample (79%).

**Table 2**  
**Summary statistics: Worker level**

Panel A: Random workers from the LEHD data

	Full sample (N = 251,440)	Single-unit firms (N = 63,173)	Multi-unit focused firms (N = 34,042)	Multi-unit diversified firms (N = 154,225)
Annual wage	\$34,999 (92,402)	\$30,613*** (64,364)	\$33,527*** (93,173)	\$37,121 (101,461)
Age	41.33 (11.10)	42.59*** (11.28)	40.06*** (11.30)	41.09 (10.94)
Tenure (in yrs)	3.36 (2.61)	3.49*** (2.68)	3.17*** (2.52)	3.34 (2.59)
Education (in yrs)	13.79 (2.60)	13.89*** (2.60)	13.73** (2.63)	13.76 (2.59)
% of Female	0.46	0.51***	0.49***	0.43
Race = Black	0.10	0.10**	0.10	0.10
Race = Asian	0.04	0.03***	0.04***	0.04
Race = Hispanic	0.09	0.10***	0.09***	0.08
Race = Other	0.05	0.05	0.06*	0.05
% of Foreigner	0.14	0.14*	0.15***	0.14

Panel B: Workers from the LEHD data matched to closing establishments from the LBD

	Full sample (N = 461,449)	Single-unit firms (N = 395,338)	Multi-unit focused firms (N = 15,947)	Multi-unit diversified firms (N = 50,137)
Annual wage	\$29,933 <sup>a</sup> (54,517)	\$29,751***, <sup>a</sup> (56,278)	\$28,642***, <sup>a</sup> (33,666)	\$31,781 <sup>a</sup> (44,897)
Age	39.68 <sup>a</sup> (11.43)	39.53***, <sup>a</sup> (11.47)	39.59***, <sup>a</sup> (11.53)	40.89 <sup>a</sup> (10.99)
Tenure (in yrs)	2.57 <sup>a</sup> (2.20)	2.52***, <sup>a</sup> (2.18)	2.69***, <sup>a</sup> (2.51)	2.96 <sup>a</sup> (2.17)
Education (in yrs)	13.66 <sup>a</sup> (2.66)	13.64***, <sup>a</sup> (2.67)	13.64***, <sup>a</sup> (2.60)	13.82 <sup>a</sup> (2.60)
% of Female	0.41 <sup>a</sup>	0.41*, <sup>a</sup>	0.42 <sup>a</sup>	0.41 <sup>a</sup>
Race = Black	0.10	0.10***	0.13***, <sup>a</sup>	0.11 <sup>a</sup>
Race = Asian	0.04 <sup>a</sup>	0.04***, <sup>a</sup>	0.05***, <sup>a</sup>	0.04
Race = Hispanic	0.12 <sup>a</sup>	0.13***, <sup>a</sup>	0.10***, <sup>a</sup>	0.09 <sup>a</sup>
Race = Other	0.06 <sup>a</sup>	0.06***, <sup>a</sup>	0.05*	0.05 <sup>a</sup>
% of Foreigner	0.19 <sup>a</sup>	0.19***, <sup>a</sup>	0.18***, <sup>a</sup>	0.15 <sup>a</sup>

Panel A reports summary statistics for a random sample of workers from the LEHD data. The random sample of the LEHD data includes 0.4% of workers during the sample period 1993-2001. Panel B reports summary statistics for workers matched to closing establishments in the LBD. We report statistics for the overall sample and for the subsamples of worker from single-unit firms, multi-unit focused firms, and multi-unit diversified firms. We define multi-unit firms as firms which operate at least two distinct establishments and diversified firms as firms which operate in more than one two-digit SIC code. Standard deviations are reported in parentheses for continuous variables. \*\*\*, \*\*, or \* indicate a significance of the difference in means between workers in the given column (single-unit or multi-unit focused firms) and workers in multi-unit diversified firms at the 1%, 5%, and 10% levels, respectively. a, b, or c in Panel B indicate significance of the cross-sample differences in means within groups between workers in the closing sample and workers from the random sample at the 1%, 5%, and 10% levels, respectively.

Matched establishments are also smaller than the typical LBD (closing) establishment, both among single- and multi-unit firms. In the full matched sample, mean employment is 134 and mean payroll is \$2.33 million. The matched sample also significantly under samples the Northeast, most likely because of the exclusion of New York from the LEHD universe. Surprisingly, we do not observe a large spike in closures in 2001, as in the random LBD sample.

In Table 2, we provide summary statistics at the worker level. In Panel A, we present statistics for a random sample of LEHD data worker-quarters.<sup>13</sup> The average worker is 41 years old, with 3.36 years of tenure in the establishment. Women make up 46% of the workforce; 10% of the workforce is black; 4% Asian; 9% Hispanic; and 5% other nonwhite. The mean annual wage is \$34,999. Workers in multi-unit firms earn higher mean wages, particularly in diversified firms (mean single unit = \$30,613; mean focused multi-unit = \$33,527; mean diversified = \$37,121).

In Panel B, we provide summary statistics for the workers in the LBD-LEHD matched sample of closing establishments. The mean worker is one year younger and women make up only 41% of the workforce. Most noticeably, mean wages are smaller (\$29,933), likely reflecting the smaller establishment size in the matched sample (Table 1). The pattern in mean wages across firms with different organizational structures is also less pronounced in this sample. Because we can only identify individual workers in “isolated” establishments, the multi-unit firms in our sample may be less diverse or complex compared with unmatched firms. If so, our results may understate the effect of such structures on the opportunity sets of workers and ongoing investment in human capital.

## **2. Diversification, Internal Labor Markets, and Productivity**

Our main hypothesis is that diversification confers benefits to the firm by enriching its internal labor market. Internal collaboration between workers in diverse ventures provides opportunities to improve efficiency. Moreover, workers in diversified firms invest in and develop skills with applications across the firms’ lines of business, in turn, providing the firm with the real option to reallocate its human-capital stock more aggressively in response to changing opportunities. We begin by testing the firm-level implications of this hypothesis: (1) Are workers in diversified firms more productive than their counterparts in focused firms are? and (2) are the internal labor markets in diversified firms a mechanism for reallocating human capital to its most productive use?

### **2.1 Diversification and labor productivity**

To estimate the effect of diversification on productivity, we consider the full set of diversified firms from the LBD. Our approach differs from most existing studies, which analyze only the subset of manufacturing firms (or the manufacturing segments of diversified firms). This distinction is important because the manufacturing sector is a relatively small and declining portion of the U.S. economy (<20%). We measure labor productivity in two ways: the

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<sup>13</sup> We take a 0.4% random sample of workers from the LEHD data to achieve a sample size comparable to the sample of workers in closing establishments in the LBD-LEHD matched data. As a robustness check, we draw repeated random samples of the same size and verify that there is no significant difference across various random samples in the statistics reported.

ratio of firm sales to employment and the ratio of firm sales to payroll. Our measures are similar to those in Haltiwanger, Lane, and Spletzer (1999).<sup>14</sup>

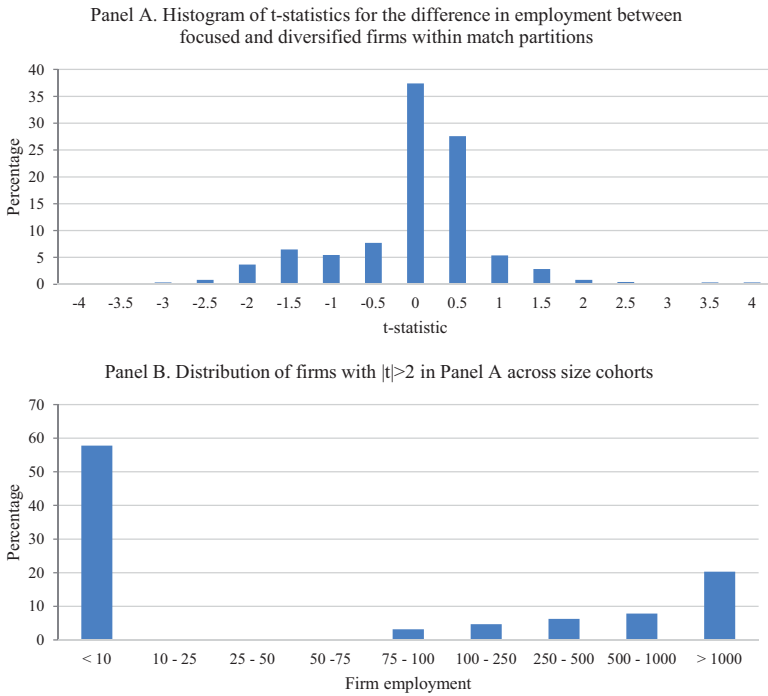
Production technology is likely to differ for firms of different sizes and across firms at different points in their life cycles. Thus, we construct a matching estimator, comparing the segments of diversified firms only to focused firms of similar size and age. In each sample year, we split the sample of focused firms into nine bins based on size (employment  $\leq 10$ , 10-25, 25-50, 50-75, 75-100, 100-250, 250-500, 500-1,000, or  $>1,000$ ), and five bins based on age (years of operation  $\leq 5$ , 5-10, 10-15, 15-20, or  $>20$ ). In both cases, we choose the cutoff values to create bins that are roughly equal in size. We then cross the two partitions, forming a set of 45 comparison samples defined by firm size and age. We match each segment of a diversified firm year-by-year with focused firms from the same industry (2-digit SIC code) in the same size-age partition. We exclude diversified firms if they operate a segment that cannot be matched to a set of focused firms or if they operate a segment with a one-digit SIC of 0 (agriculture), 4 (utilities), 6 (financials), or 9 (public sector).

A potential concern is that diversified units are larger than focused units are, even after matching. To check the quality of the match, we compare the employment of diversified and focused units within each industry, size, age, and year partition. In Figure 2, we present a histogram of the t-statistics for a test of the null hypothesis that the difference in means between focused and diversified units equals zero. Roughly 4.5% of the t-statistics have an absolute value greater than two. In Panel B, we present the distribution of these cases across the nine size partitions. The majority of them (80%) occur among units with fewer than 10 or more than 1,000 workers; thus, we drop units in those categories to ensure that we have sufficient overlap of the distributions of treated and control observations. To compute the average treatment effect for the treated, we use the median sales to employment ratio of the matched group of focused firms, multiplied by the actual employment of the segment, to compute the predicted sales of the segment. We compute the predicted sales of a diversified firm as the sum of the predicted sales of all of its segments. We then compute the difference between the actual sales and predicted sales of each diversified firm, in natural logarithms. We drop observations in the 1% upper and lower tails of the distribution to limit the influence of outliers on our estimates. We find that sales in diversified firms are 9.1% higher than we would expect, given the contemporaneous labor productivity of similar-sized focused firms in the industry that are at the same point in their life cycle, an effect that is statistically significant at the 1% level.

We also conduct our test within a regression framework that allows for additional controls. Mirroring the literature on the diversification discount,

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<sup>14</sup> We cannot estimate total factor productivity because we do not restrict our sample to manufacturing firms (for which data on capital stocks is available). The tradeoff is that our sample is far more representative of the U.S. economy. Foster, Haltiwanger, and Krizan (1998) show that the sales-to-employment ratio is highly correlated with multifactor productivity in U.S. manufacturing firms.



**Figure 2**  
**Firm size within match cohorts**

In Panel A, we present a histogram of the t-statistics to test the null hypothesis that the difference in mean employment between focused and diversified firms in each match partition equals zero. Match partitions are all units in the same 2-digit SIC code in the same year that fall in the same firm-size and age grouping. Size groupings are based on employment (<10, 10-25, 25-50, 50-75, 75-100, 100-250, 250-500, 500-1000, and >1000). Age groupings are <5, 5-10, 10-15, 15-20, and >20. In Panel B, we consider the subset of match partitions in which the t-statistic from Panel A has an absolute value greater than 2. We present the distribution of these cases across the nine size bins, defined as above.

we compute our measure of excess sales for sample focused firms.<sup>15</sup> We then regress excess sales for all sample firms on an indicator for diversification. To correct any remaining biases in the estimates caused by the bunching of diversified and focused firms within the age and size bins, we include continuous controls for the natural logarithms of firm age and firm employment. We also include industry-year fixed effects and cluster standard errors at the industry-year level. We present the results in Column 1 of Table 3. We find that diversification is associated with excess sales of 26.5%, an effect that is again significant at the 1% level.

The ability to retain and reallocate talent internally is more valuable for firms that employ workers with skills that are scarce in the external

<sup>15</sup> To prevent very small firms from having a disproportionate effect on the estimates, we restrict the sample to firms with at least \$1 million in sales. However, the results are similar on the full sample.

**Table 3**  
**Productivity and cash flows in diversified firms**

	Panel A. Sales/employment		Panel B. Sales/payroll		Panel C. Manufacturing firms	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(firm age)	-0.079*** (0.004)	-0.079*** (0.004)	-0.032*** (0.002)	-0.032*** (0.002)	-0.025*** (0.003)	-0.024*** (0.003)
Ln(firm employment)	-0.196*** (0.004)	-0.196*** (0.004)	-0.083*** (0.002)	-0.083*** (0.002)	-0.088*** (0.004)	-0.088*** (0.004)
Ln(capital stock)					0.107*** (0.004)	0.107*** (0.004)
Ln(material and energy costs)					0.534*** (0.005)	0.534*** (0.005)
Diversified	<b>0.265***</b> (0.016)	<b>0.174***</b> (0.018)	<b>0.163***</b> (0.008)	<b>0.148***</b> (0.013)	<b>0.076***</b> (0.004)	<b>0.066***</b> (0.004)
% emp. in high-skill ind.		0.145*** (0.044)		-0.024 (0.040)		0.050*** (0.009)
Diversified × % emp. in high-skill ind		<b>0.275***</b> (0.022)		<b>0.044*</b> (0.023)		<b>0.025***</b> (0.008)
Industry × year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R <sup>2</sup>	0.135	0.135	0.035	0.035	0.771	0.771
N	3,601,677	3,601,677	3,601,677	3,601,677	418,848	418,848

The sample in Panels A and B consists of all firm-years for which we can match each individual segment (defined by 2-digit SIC codes) to a focused firm benchmark, excluding firms with a segment with a 1-digit SIC of 0 (agriculture), 4 (utilities), 6 (financials) or 9 (public sector). For each segment, we select matched focused firms based on 2-digit industry, year, size and age. The cutoffs to define size groups are <25, 25-50, 50-75, 75-100, 100-250, 250-500, and >500 employees, respectively; and the cutoffs to define age groups are <5, 5-10, 10-15, 15-20, and >20 years, respectively. In Panel A (B), we use the median sales employment (payroll) ratio of the matched group multiplied by the actual employment (payroll) of the segment to compute the predicted sales for the segment. Total predicted sales for a diversified firm is the sum of predicted sales of all segments. The dependent variable is the difference between actual sales and predicted sales in natural logarithms. In Panel C, the sample consists of plant-years for manufacturing plants from the Census Bureau's Longitudinal Research Database (LRD). The dependent variable is the natural logarithm of the ratio of total value of shipments to employment. Employment is the number of employees in the plant. Values for the capital stock are generated by the recursive perpetual inventory formula, accounting for capital expenditures and depreciation. See Schour (2002) for additional details. Material and energy costs are expenses for parts and intermediate goods, fuel, and energy purchased as well as inputs from contracted work. Diversified is an indicator variable equal to one if the firm operates establishments in at least two distinct 2-digit SIC codes. % Emp. in high-skill Ind. is the percentage of firm employment in 2-digit SIC codes in which the percentage of workers with 2-digit SOC codes less than 29 exceeds the median. The standard errors are clustered by industry-year and are reported in parentheses. \*, \*\*, and \*\*\* represent significance at 10%, 5%, and 1% level, respectively.

market. Moreover, workers in high-skill industries are likely to be able to make additional human-capital investments at lower cost than low-skill workers are, and the production externalities from bundling skills are likely to increase in skill levels. Thus, we predict that diversified firms should be particularly more productive in industries that employ high-skilled labor. To measure human capital use by industry, we collect information from the Bureau of Labor Statistics on the distribution of workers across Standard Occupational Classification (SOC) codes for each 2-digit SIC in our sample. We classify 2-digit SOC codes less than 29 as high-skill vocations. These groupings include, for example, management occupations, business and financial occupations, computer and mathematical science occupations, and architecture and engineering occupations. We group jobs with SOC codes higher than 29 as low-skill positions.<sup>16</sup> Examples in this category include food preparation and serving, office and administrative support, and construction positions. We then compute the percentages of workers in each 2-digit industry who work in high- and low-skill positions.<sup>17</sup> We classify industries in which the fraction of high-skill jobs is above the median as “high-skill” industries. In Appendix B, we list the ten industries with the highest and lowest percentages of workers in high-skill occupation codes. Many of the high-skill industries are in the services and financial sectors; many of the low-skill industries are in retail trade. Manufacturing industries are split fairly evenly, with industries that employ more engineers or scientists in the high-skill grouping.

To test our hypothesis, we add the percentage of the firm’s employment in high-skill industries and its interaction with the diversification indicator to the regression specification from Column 1 of Table 3. We report the results in Column 2. We find that excess sales among diversified firms significantly increase as the percentage of high-skill workers—for whom productivity is most likely to be enhanced by the cross-industry opportunities in diversified firms—increases. A one standard-deviation increase in the percentage of high-skill workers (0.49) would increase excess sales by roughly 13.5 percentage points.

In Columns 3 and 4 of Table 3, we repeat the exercise, but using the ratio of sales to payroll as our measure of labor productivity when computing excess sales. We find again that diversification is associated with significantly higher excess sales and that the effect is larger for firms operating more intensively in high-skill industries. The magnitude of returns to firms operating in high-skill industries is smaller than the estimate in Column 2 using sales to employment as the productivity measure: here, a one-standard-deviation increase in the

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<sup>16</sup> As a robustness check, we classify SOC codes in which the median worker salary is above the overall median wage as “high-skill industries.” The only meaningful change is that sales positions move from the low- to high-skill grouping. All of our results are qualitatively unchanged using this alternative definition of *high-skill vocations*.

<sup>17</sup> Ideally, we would classify individual workers based on the SOC codes of their positions; however, worker-level SOC codes are not available in any Census data accessible for research purposes. We only observe the fraction of workers with each SOC code at the 2-digit SIC level.

percentage of high-skill workers would increase excess sales by roughly two percentage points. Nevertheless, this result is expected because high-skill workers in diversified firms can extract some of the surplus from their higher productivity by demanding higher wages. The key result is that diversified firms enjoy increased cash flows, even net of the share that goes to workers.

Our estimates also suggest that diversified firms enjoy a productivity advantage in low-skill industries (we measure a significant level effect of diversification in Columns 2 and 4). Though we focus mainly on the role of skill accumulation in the remainder of the paper, a possible explanation is an “insurance effect” in wages. Low-skill workers do not have elevated outside options because their skills are not scarce, but they still enjoy the enhanced internal opportunities in diversified firms. Thus, payrolls for diversified firms in low-skill industries can be lower.<sup>18</sup> We provide direct evidence of this effect in Section 4.

A potential concern is the effectiveness of our matching procedure together with the regression controls in correcting for differences between diversified and focused firms along dimensions other than human-capital use. To correct for unobserved, time-invariant differences across firms, we reestimate the regressions in Table 3, including (separate) firm and year fixed effects. We continue to find that the intensity with which the firm operates in high-skill industries positively and significantly predicts excess sales in diversified firms. A more specific concern is that diversified firms employ more or better physical capital than do focused firms of the same age operating simultaneously in the same industry, in a way that varies over time. Unfortunately, the LBD does not provide information on physical capital. To address this concern, we consider the subsample of manufacturing establishments. On this sample, we can retrieve plant-level information on sales, labor and capital inputs, and expenditures for materials and energy from the Census’ Longitudinal Research Database (LRD). Thus, we can regress plant-level labor productivity, measured as the natural logarithm of the ratio of plant sales to employment, on an indicator for diversification, the intensity of the firm’s operations in high-skill industries, and the interaction of the two, controlling directly for the physical capital and materials used in the plant (in addition to plant age, employment, and industry-year fixed effects).<sup>19</sup> We report the estimates in Panel C of Table 3, again clustering standard errors at the industry-year level. We continue to find that the plants of diversified firms have higher labor productivity compared

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<sup>18</sup> Another possible mechanism that could generate a difference between the predicted sales using employment or payroll would be a higher fraction of part-time workers in diversified firms. Part-time workers are included in LBD aggregate employment, but our filters will drop them from our LEHD sample in most cases.

<sup>19</sup> See Schoar (2002) for a detailed description of the LRD database. Our regression specification and variable definitions are the same as Schoar (2002), with two exceptions. First, we use aggregate plant-level employment to measure labor inputs, as in Panels A and B, because labor hours are only available for production workers in the LRD. Second, we implement the model in one step, using industry-year fixed effects instead of first measuring TFP as a regression residual and then explaining it using diversification and, in our case, employee skill levels.



with plants of focused firms in the same industry-year and that the difference increases with the percentage of the firm's operations in high-skill industries. These results are reassuring because manufacturing firms are the firms in which our proposed human-capital allocation mechanism is likely to matter the least, and physical-capital allocation is likely to matter the most. Moreover, because we control for the value of physical capital in the plant, our results cannot be explained by differences in either the quantity or quality of the capital in diversified firms (assuming that quality is accurately reflected by prices).

Overall, we document excess productivity in the establishments of diversified firms and demonstrate that this excess productivity is significantly related to the skill level of the firm's workforce. Though our result cannot be explained by differences in the value of physical capital employed across plants, it is possible that physical capital is more productive in diversified plants, explaining a portion of the higher productivity levels that we observe. Thus, in the remainder of the study, we use worker-level data to provide direct evidence for the labor-allocation channel we propose.

## **2.2 Diversification and the redeployment option**

Next, we analyze one potential mechanism through which diversification can improve productivity: the ability to reallocate human capital in the internal labor market in response to changing conditions.<sup>20</sup> Our setting is analogous to studies that ask how diversified firms allocate scarce investment resources across divisions with differing opportunities, but focuses instead on labor allocation. If there are constraints on the ability to hire workers with appropriate skills in the external market, do diversified firms reallocate workers internally to the industries with the greatest opportunities in response to shocks? Moreover, does this reallocation exceed the reallocation of human capital across industries in the external market?

An immediate issue is the endogeneity of job changes. Worker allocation across jobs is the result of both a supply and a demand decision. Firms can decide which workers they prefer to employ, but workers can also choose to accept a job offer, to remain in their current jobs, or to quit and search for new employment. This is particularly problematic when comparing workers who change industries with workers who remain in their original industries. Workers may be more likely to accept jobs voluntarily within their industries than in new industries. We use establishment closures as a way to disentangle supply-and-demand-driven job changes. Workers displaced by establishment closure cannot remain in their current jobs, and the displacement is involuntary. Thus, we can isolate internal industry changes that are initiated by the firm and not the worker. Moreover, it is unlikely that displacement is related to the

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<sup>20</sup> We do not measure other mechanisms through which diversification may improve productivity, like the potential for improved innovation (e.g., by creating more interdisciplinary product improvements).

skill or performance of individual workers.<sup>21</sup> Of course, workers still have the choice to leave, even if they are offered a new job inside the firm. Therefore, our estimates provide a lower bound on the amount of reallocation desired by the firm.

Our main quantity of interest is the frequency with which the firm reallocates retained workers to new industries and how it depends on future opportunities in their existing and new industries. However, the choice of which workers to retain following closure is not random. Thus, we estimate a Heckman selection model on the sample of diversified firms. In a first-stage probit regression, we estimate the probability a displaced worker is retained inside the firm as a function of worker and firm characteristics. We include indicators for race (black, Hispanic, Asian, and other minority), gender, and managers, together with continuous controls for worker age, tenure, and preclosure wage. We also include a set of controls for firm size since larger firms may have a greater ability to retain workers: the number of establishments and the natural logarithms of establishment and firm employment. We include three additional controls to capture differences across workers in the costs of changing jobs or remaining in their home industries: the natural logarithms of the number of establishments in the same county and 2-digit SIC code as the worker's closing establishment and the total number of establishments in the county, as well as an indicator for whether the worker was born in the state in which the closing establishment is located. Finally, we include fixed effects for the year of establishment closure and for the worker's state and industry. We construct a measure of the firm's future opportunities by considering its industry portfolio. We compute a payroll-weighted average of industry Q across the industries in which the firm still operates in the year following the establishment closure.<sup>22</sup> To proxy for expected growth in the worker's current industry, we also include the realized difference in the natural logarithm of industry Q from year  $t + 1$  to year  $t + 3$ . Even though we use future values as an independent variable, reverse causality is not a major concern because the unit of observation is an individual worker, and we measure future performance at the industry level.

In Column 1 of Table 4, we report the results of the first-stage estimation. We find that firms are significantly more likely to retain workers inside the firm when the firm's future opportunities (measured as the weighted average Q in its remaining industries, or "firm Q") are strong. Because the regression is nonlinear, we assess the economic significance of the effect in two ways. First,

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<sup>21</sup> In the absence of very large adjustment costs, the decision to close an establishment should depend on the NPV of operating the establishment efficiently and not the identities of its current workers: bad workers in a viable establishment can be fired and replaced, whereas good workers from a closing establishment can be retained and moved elsewhere within the firm.

<sup>22</sup> We restrict our attention to the firm's top-five industries by employment. These five industries contain more than 99.6% of the total firm payroll. For the subset of firms with more than 20 SIC codes, the percentage is roughly 84%. We use the median value of Q in the 2-digit SIC code among single-segment, publicly traded firms in the Compustat universe. Thus, we assume implicitly that industry Q as measured in public firms is an appropriate proxy for industry opportunities in both the public and private firms contained in our sample.

**Table 4**  
**Labor redeployment: Diversified firms**

Dependent variable	Heckman selection model	
	Same firm (1)	Industry change (2)
Ln(wage)	0.289*** (0.020)	0.095*** (0.010)
Ln(age)	0.011 (0.035)	0.003 (0.014)
Race = Black	0.044 (0.029)	-0.027** (0.011)
Race = Asian	0.216*** (0.045)	0.043*** (0.018)
Race = Hispanic	0.128*** (0.033)	0.016 (0.013)
Race = Other minorities	0.064 (0.042)	0.003 (0.017)
Female	0.140*** (0.021)	0.037*** (0.009)
Ln(tenure)	-0.018 (0.013)	0.000 (0.005)
Manager	-0.184** (0.088)	0.007 (0.037)
N_Estabs	0.009*** (0.002)	0.012*** (0.001)
Ln(EstabEmp)	0.231*** (0.014)	-0.007 (0.009)
Ln(FirmEmp)	-0.047*** (0.008)	-0.002 (0.004)
Native to state	-0.002 (0.020)	-0.026*** (0.008)
Ln(# of firms in CT & SIC2)	0.854*** (0.030)	0.263*** (0.023)
Ln(# of firms in CT)	-0.617*** (0.029)	-0.125*** (0.020)
Chg_Q	-0.452*** (0.071)	-0.387*** (0.037)
Firm_Q	0.680*** (0.033)	
State fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Lambda		0.389***
N	36,244	8,025

The sample contains one observation for each worker displaced from closing establishments of diversified firms. Column 1 presents coefficient estimates from a probit regression. Column 2 is the second stage of a Heckman selection model, with the regression in Column 1 serving as the first stage. The second stage is estimated as a linear probability model. The dependent variable is indicated in the column header. Same firm equals one if the worker remains in the same firm after the establishment closure and zero otherwise. Industry change equals one if the new job in quarter  $t + 4$  is in a different 2-digit SIC from the lost job. Ln(wage) is the natural log of the annualized wage. Ln(age) is the natural log of the worker's age. Race = "x" is an indicator variable that equals one for workers of race "x" and zero otherwise. Female is an indicator variable that equals one for female workers and zero otherwise. Ln(tenure) is the natural log of the number of quarters that a worker has spent in the SEIN. Manager is an indicator variable equal to one for the highest paid employee in the SEIN and zero otherwise. N\_Estabs is the number of establishments owned by the firm, divided by 100. Ln(EstabEmp) is the natural log of establishment employment. Ln(FirmEmp) is the natural log of aggregate firm employment. Native to State is an indicator variable which equals one if the worker was born in the state in which the closing establishment is located. Ln(# of firms in CT & SIC2) is the natural log of the number of establishments that operate in the same 2-digit SIC code and county as the closing establishment. Ln(# of firms in CT) is the natural log of the number of establishments that operate in the same county as the closing establishment. Chg\_Q is the change in industry-median Tobin's Q over the 2 years following plant closure. Firm\_Q is the payroll weighted average of industry-median Q for the remaining establishments of the firm. We use the two-step procedure from Heckman (1979) to compute consistent coefficient and standard error estimates. \*, \*\*, and \*\*\* represent significance at 10%, 5%, and 1% level, respectively.

we compute the marginal effect of a change in firm  $Q$  on the probability of staying in the firm at the mean of the continuous independent variables and at zero for discrete variables. We find that the marginal effect is 0.126. Second, we use the estimated probit function and the standard normal distribution function to evaluate the change in the probability of staying in the firm for a one-standard-deviation increase in firm  $Q$ , using the mean of the continuous variables (and zero for discrete variables) as the baseline. The baseline probability of staying in the firm is 0.11. A one-standard-deviation change in firm  $Q$  increases the probability of staying in the firm by 0.05, to roughly 0.16.

Next, we turn to the second stage regression, which estimates the likelihood the firm reallocates workers it chooses to retain to a different 2-digit industry. We include the same set of controls as in the first stage, with the exception of firm  $Q$ . Thus, our identifying assumption is that the firm's overall prospects determine its decision to retain a worker inside the firm but do not determine to which particular industry the firm allocates the worker. Our variable of interest in the second stage is expected growth in the worker's preclosure industry, which we measure using the realized difference in the natural logarithm of industry  $Q$  from year  $t + 1$  to year  $t + 3$ . If the firm's (remaining) establishments are already producing at the equilibrium level, then the firm should only move labor inputs internally toward (or away from) industry segments that experience shocks. We again assume that realized industry performance provides an appropriate proxy for the firm's expectations of these changes in industry conditions. We estimate the second stage as a linear-probability model; thus, we can interpret the coefficient estimate on the change in industry  $Q$  ("Chg\_Q") as a marginal effect. We find that a one-standard-deviation increase in Chg\_Q (0.22) decreases the probability of changing industries by 0.085.

Because we use variants of  $Q$  as an independent variable in our analysis, potential measurement error in  $Q$  can be a concern (Whited 2001). However, our hypotheses predict (and we find) statistically significant effects of firm  $Q$  (Chg\_Q) on worker retention (industry changes). Thus, if there is classical measurement error in our  $Q$  variables, our estimates understate the true effects. We also reestimate the Heckman model using an alternative measure of the expected growth rate in the worker's home industry, the vertical demand shock variable ("vdshock") from Maksimovic and Phillips (2001), as updated by Phillips and Zhdanov (2012).<sup>23</sup> Vdshock measures changes in industry opportunities using changes in shipments by downstream industries. We find similar results (see the Online Appendix).

We also ask whether the reallocation of workers out of a declining industry happens at a faster rate in diversified firms than in the external market. For this test, we consider the entire sample of displaced workers who found jobs by quarter  $t + 3$ , including workers from both single- and multi-unit firms. We

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<sup>23</sup> We thank Gordon Phillips for kindly sharing his data.

estimate a linear-probability model with a dependent variable indicating that the worker moved to a job in a new 2-digit SIC code in the year following job loss. We include indicator variables for multi-unit and diversified firms. The variable of interest is the interaction of the indicator for diversification with our measure of expected growth in the worker's current industry. Otherwise, we replicate the specification from Column 2 of Table 4.<sup>24</sup> We report the results in Table 5, with errors clustered at the firm level. We do not observe a significant relation between the expected trend in industry value and the likelihood that the worker switches industries in general. However, we see that workers in diversified firms are significantly more likely to switch industries when the expected growth rate of their current industry is low. The coefficient estimate on our main variable of interest ( $\text{Chg\_Q} * \text{Diversified}$ ) is  $-0.153$ , meaning that a one-standard-deviation increase in  $\text{Chg\_Q}$  in the worker's original industry (0.27) decreases the probability of changing industries by 4.1 percentage points for workers in diversified firms, relative to the near-zero effect in focused firms. In Column 2, we test whether the effect differs for workers who make job changes in the internal labor market. We find that it does not: workers from diversified firms are more sensitive to industry opportunities, whether they find new jobs inside or outside the firm. This result is consistent with our hypothesis that the human-capital investments made by workers in diversified firms are less specific to their home industries than the ones made in focused firms. Most importantly, we confirm that diversified firms move workers out of industries with relatively poor prospects at higher rates than we observe in the external market.

To determine whether the reallocation we observe is efficient, we ask next whether diversified firms move workers in the internal market to new industries with stronger prospects. As a benchmark, we consider the differences in the prospects of industries between which workers move in the external market following displacement. We again use realized changes in industry Q to proxy for expected growth. For each worker who changes industries following displacement, we compute the difference in the change in the natural logarithm of industry Q from year  $t + 1$  to year  $t + 3$  between the worker's post- and predisplacement industries. We then regress the difference on an indicator for diversification and an indicator for whether the industry change happened within the firm. The coefficient estimate on the latter variable captures job changes in the internal labor markets of diversified firms because only workers from diversified firms can change industries without leaving the firm. We also include a fixed effect for the worker's original industry to correct for the possibility that internal industry switchers originate in different industries from other industry switchers. We report the results in Table 6. In all cases, we cluster standard errors at the firm level. In Column 1, we find that the

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<sup>24</sup> The choice to estimate a linear probability model does not affect our conclusions; the coefficient of interest is even stronger statistically in a logit specification.

**Table 5**  
**Labor redeployment: All workers**

Dependent variable: Industry change	(1)	(2)
Ln(wage)	-0.045*** (0.007)	-0.044*** (0.006)
Ln(age)	-0.093*** (0.007)	-0.093*** (0.007)
Race = Black	0.007 (0.007)	0.008 (0.007)
Race = Asian	-0.009 (0.011)	-0.008 (0.011)
Race = Hispanic	-0.019*** (0.007)	-0.018*** (0.007)
Race = Other Minorities	-0.013*** (0.005)	-0.013*** (0.005)
Female	0.007 (0.004)	0.008* (0.004)
Ln(tenure)	-0.047*** (0.004)	-0.047*** (0.004)
Manager	0.037*** (0.009)	0.037*** (0.009)
Multi-unit	0.060** (0.029)	0.076** (0.029)
N_plants	0.003 (0.002)	0.002 (0.002)
Ln(EstabEmp)	-0.045*** (0.009)	-0.047*** (0.009)
Ln(FirmEmp)	0.008 (0.008)	0.010 (0.008)
Native to state	0.002 (0.003)	0.001 (0.003)
Ln(# of firms in CT & SIC2)	-0.062*** (0.011)	-0.060*** (0.011)
Ln(# of firms in CT)	0.062*** (0.010)	0.060*** (0.010)
Diversified	0.007 (0.037)	0.028 (0.038)
Chg_Q	<b>-0.012</b> (0.021)	<b>-0.014</b> (0.021)
Same firm		-0.198*** (0.048)
Chg_Q × Diversified	<b>-0.153*</b> (0.083)	<b>-0.184**</b> (0.082)
Divers × Same firm × Chg_Q		<b>0.040</b> (0.225)
State fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
R <sup>2</sup>	0.134	0.137
N	343,206	343,206

The sample contains one observation for each worker displaced from a closing establishment in our matched LBD-LEHD data. The estimates are from a linear probability model. The dependent variable, Industry change, equals one if the new job in quarter  $t + 4$  is in a different 2-digit SIC from the lost job. Ln(wage) is the natural log of the annualized wage. Ln(age) is the natural log of the worker's age. Race = "x" is an indicator variable that equals one for workers of race "x" and zero otherwise. Female is an indicator variable that equals one for female workers and zero otherwise. Ln(Tenure) is the natural log of the number of quarters that a worker has spent in the SEIN. Manager is an indicator variable equal to one for the highest paid employee in the SEIN and zero otherwise. Multi-unit is an indicator variable equal to one if the firm has more than one establishment and zero otherwise. N\_Estabs is the number of establishments owned by the firm, divided by 100. Ln(EstabEmp) is the natural log of establishment employment. Ln(FirmEmp) is the natural log of aggregate firm employment. Ln(# of firms in CT & SIC2) is the natural log of the number of establishments that operate in the same 2-digit SIC code and county as the closing establishment. Ln(# of firms in CT) is the natural log of the number of establishments that operate in the same county as the closing establishment. Native to state is an indicator variable which equals one if the worker was born in the state in which the closing establishment is located. Diversified is an indicator variable equal to one if the firm operates establishments in at least two distinct 2-digit SIC codes and zero otherwise. Same firm is an indicator variable equal to one if the worker is retained within the firm (firmid) and zero otherwise. Chg\_Q is the change in industry-median Tobin's q over the 2 years following establishment closure. Standard errors are clustered at the firm level and are reported in parentheses. \*, \*\*, and \*\*\* represent significance at 10%, 5%, and 1% level, respectively.

**Table 6**  
**Difference in expected growth (new-old industry)**

Dependent variable: Difference in change of Q	(1)	(2)	(3)
Same firm	0.074* (0.042)	0.074* (0.042)	0.074* (0.042)
Diversified	0.024 (0.017)	0.025 (0.017)	0.025 (0.017)
Lagged Q			-0.010 (0.020)
Industry fixed effect	Yes	Yes	Yes
Year fixed effect		Yes	Yes
R <sup>2</sup>	0.031	0.032	0.033
N	134,955	134,955	134,955

Table 6 presents estimates from an OLS model that examines the difference in growth rates between the new and original industries of displaced workers who make industry changes. The sample contains one observation for each worker (from focused or diversified firms) whose new job in quarter  $t + 4$  is in a different 2-digit SIC from their original job. The dependent variable is the difference in the change in industry-median Tobin's Q between the worker's new and original industries, where the change in Tobin's Q is measured from year  $t + 1$  to year  $t + 3$  and year  $t$  is the year of establishment closure. Same firm is an indicator variable equal to one if the worker is retained within the original firm (firmid) and zero otherwise. Diversified is an indicator variable equal to one if the firm operates establishments in at least two distinct 2-digit SIC codes. Lagged Q is industry-median Tobin's Q for the worker's original industry, measured at the end of the year prior to establishment closure. Standard errors are clustered at the firm level and are reported in parentheses. \*, \*\*, and \*\*\* represent significance at 10%, 5%, and 1% level, respectively.

difference-in-differences of industry prospects for workers displaced from diversified firms and workers displaced from focused firms is positive, though the estimate is not statistically significant. However, for workers who change industries in the internal labor market of a diversified firm, the difference-in-differences relative to workers from focused firms is positive and significant at the 10% level. The baseline difference in the prospects of the old and new industries among workers who make job changes in external markets is near zero. Thus, we conclude that diversified firms indeed reallocate workers toward industries with better future prospects, and they do so at a higher rate than the rate at which reallocation occurs in external markets. Economically, the difference in expected performance between the old and new industries of workers who change industries inside diversified firms is roughly 7.4 percentage points higher than the difference for industry switchers from focused firms. In Column 2, we also include a year fixed effect to correct for potential differences in the timing of industry switches in internal and external markets. Finally, in Column 3, we add a control for Tobin's Q in the original industry prior to the switch. In both cases, we continue to find that the average differences in the prospects of the former and new industries is significantly larger for workers who change industries in the internal labor markets of diversified firms.

As a final step, we examine whether internal industry changers join relatively high-Q industries in their firms' portfolios. Here, the prediction is less clear: it may be efficient to reallocate a worker to an industry with relatively lower Q as long as that industry has a higher expected growth rate than the worker's previous industry. We find that 58% of workers move to a new industry ranked among the top half of the industries in the firm's portfolio. When we rank the

new industry only among the firm's industries in the same state, the result is stronger: 68% of workers move to an industry among the top-half industries with the best opportunities. If reallocation were purely random (i.e., reallocation did not depend on the prospects of the new industry), we would expect 50% of workers to make such moves.

Overall, the results confirm a key portion of our hypothesis: diversified firms reallocate workers internally from industries with relatively weak opportunities to industries with better opportunities at a higher rate than that found in the external market. Thus, firms use internal labor markets to mitigate labor market frictions in much the same way they can use internal capital markets to mitigate frictions in the market for physical capital.

### **3. Diversification and Worker Mobility**

Thus far, we have confirmed our main hypothesis at the firm level: diversified firms have higher labor productivity, in part because of their ability to adjust labor inputs more aggressively in their internal labor markets in response to changing opportunities across industries. Next, we test the implications of our hypothesis at the worker level.

#### **3.1 Diversification and job changes to “spanned” industries**

To begin, we ask whether the human capital in diversified firms differs from the human capital in focused firms. Internal labor markets may create value simply by removing barriers to the efficient allocation of human capital, even if human capital is identical across firms. However, another possibility is that workers in diversified firms have different human capital from workers in focused firms because of the differences in opportunities available inside the firm. Skillsets that put weight on skills used in multiple industries spanned by the firm create value by facilitating redeployment or internal collaboration. Thus, workers in diversified firms are likely to invest in additional skills outside their home industries. Because the resulting skillsets match best with the particular industry mix of the firm, workers are able to share in the value created by their additional skills and will bear the costs of attaining them, as in Lazear (2009). Thus, they become more mobile, both internally and externally, across those industries. We test this hypothesis using the worker-firm matched data described in Section 1.

To measure worker mobility across industries, we consider both the wage changes workers experience when changing industries and the frequency with which they make those changes. As in Section 2, an immediate obstacle is the endogeneity of job changes. Here, our focus on wage changes raises new challenges. Voluntary and involuntary job changes have different implications for wages: voluntary job changes are likely to result in outcomes that are more favorable for the worker than are involuntary changes. Moreover, the rates of voluntary and involuntary job changes may differ across diversified and focused



firms for reasons other than differences in worker skills or opportunities. To avoid these confounds, we again consider only the subset of involuntary job changes because of closures.

As a first test of our hypothesis, we compare the wage changes among displaced workers who move to a firm in a new industry in which their former firm also operates (“spanned industries”) with the wage changes among displaced workers who move to a new industry in which their former firm does not operate (“unspanned industries”). We propose that workers in diversified firms acquire skills that enhance their productivity in the set of spanned industries by direct experience in those industries inside the firm or because of human-capital investments that they make to improve their prospects in the firm. If so, then the wages those workers obtain when they move to a firm operating in spanned industries should exceed the wages obtained by workers moving to the same industries who have not acquired those skills.

In Table 7, we report estimates from regressions of the change in annual real wages (in log form) on an indicator for workers from diversified firms who find new jobs in “spanned industries” (“Different Industry \* Spanned Industry”) and a set of controls. Included among the controls to capture unobserved differences in skill levels is the log of the annual real wage prior to closure. Thus, the estimates of all other coefficients are equal to those we would obtain by regressing the ex post wage level on the same explanatory variables. We compute the change in the annual real wage from two quarters prior to closure to the fourth quarter following closure.<sup>25</sup> This computation implicitly restricts our sample to the roughly 77% of displaced workers who find a new job within the first three quarters following the closure.<sup>26</sup> Though this restriction potentially biases downward our estimates of the wage effect of establishment closure, our goal is not to measure the cost of displacement itself but simply to use displacement as a common cause of job changes for all sample workers.

As additional controls, we include a number of demographic factors that might affect wage changes and correlate with the types of job changes we observe. We include the natural logarithms of worker age and tenure, four separate race indicators (black, Hispanic, Asian, and other minority), and indicator variables for managers and women.

We also control for variation at the establishment and firm level. We include measures of establishment and firm size: the natural logarithms of employment in the worker’s establishment and firm. We also include the number of establishments in the firm as a control for the availability of internal opportunities. Moreover, we include an indicator variable for diversified firms (i.e., firms that operate in more than one 2-digit SIC code). All control variables

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<sup>25</sup> We compute the annual real wage as defined in Section 1. We winsorize the wage change at the 1% level to remove severe outliers.

<sup>26</sup> A worker reemployed in the fourth quarter following closure would not be included because we can compute the annual real wage starting only from the second quarter of employment. See Section 1 for details.

**Table 7**  
**Wage changes**

Dependent variable: $\Delta_{t+4,t-2}\ln(\text{wage})$	(1)	(2)	(3)
Ln(wage)	-0.111*** (0.009)	-0.137*** (0.009)	-0.120*** (0.008)
Ln(Age)	-0.118*** (0.010)	-0.097*** (0.009)	-0.105*** (0.009)
Race = Black	-0.040*** (0.008)	-0.045*** (0.006)	-0.035*** (0.007)
Race = Asian	0.003 (0.013)	0.001 (0.011)	-0.004 (0.014)
Race = Hispanic	-0.025*** (0.008)	-0.029*** (0.006)	-0.028*** (0.007)
Race = Other minorities	-0.015* (0.008)	-0.022*** (0.007)	-0.018** (0.007)
Female	-0.041*** (0.005)	-0.051*** (0.005)	-0.035*** (0.005)
Ln(tenure)	-0.021*** (0.005)	-0.018*** (0.004)	-0.020*** (0.004)
Manager	-0.001 (0.020)	0.045** (0.021)	0.009 (0.020)
N_Estabs	-0.003*** (0.001)		-0.003*** (0.001)
Ln(EstabEmp)	-0.003 (0.007)	0.012 (0.008)	-0.001 (0.006)
Ln(FirmEmp)	0.009** (0.004)		0.013*** (0.004)
Chg (N_Estabs)	-0.003*** (0.000)	-0.003*** (0.001)	-0.002*** (0.001)
Chg (EstabEmp)	-0.002 (0.003)	-0.006* (0.003)	0.000 (0.003)
Chg (FirmEmp)	0.017*** (0.002)	0.020*** (0.002)	0.016*** (0.003)
Diversified	-0.006 (0.013)		-0.019 (0.012)
Same_Firm	0.027* (0.016)	0.006 (0.023)	0.030* (0.016)
Different industry	<b>-0.144***</b> (0.017)	<b>-0.127***</b> (0.022)	
Same_Firm × Different industry	0.052* (0.030)	0.050 (0.042)	0.062 (0.039)
Different industry × Spanned industry	<b>0.109***</b> (0.015)	<b>0.104***</b> (0.016)	<b>0.038**</b> (0.015)
State fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes		
Year fixed effects	Yes	Yes	Yes
Establishment fixed effects		Yes	
SIC pair fixed effects			Yes
R <sup>2</sup>	0.112	0.200	0.260
N	42,354	42,354	42,354

The sample contains one observation for each worker displaced from a closing establishment of a multi-unit firm in our matched LBD-LEHD data. Coefficient estimates are from OLS regressions. The dependent variable is the change in the annual real wage from quarter (t - 2) to (t + 4). t is the quarter of the establishment closure. Ln(wage) is the natural log of the annual real wage. Ln(age) is the natural log of the worker's age. Race = "x" is an indicator variable that equals one for workers of race "x" and zero otherwise. Female is an indicator variable that equals one for female workers and zero otherwise. Ln(tenure) is the natural log of the number of quarters that a worker has spent in the SEIN. Manager is an indicator variable equal to one for the highest paid employee in the SEIN and zero otherwise. N\_Estabs is the number of establishments owned by the firm, divided by 100. Ln(EstabEmp) is the natural log of establishment employment. Ln(FirmEmp) is the natural log of aggregate firm employment. Chg(N\_Estabs), Chg(EstabEmp), and Chg(FirmEmp) are the differences between the old and new firm in N\_Estabs, establishment employment, and firm employment, respectively. Diversified is an indicator variable equal to one for firms that operate in at least two distinct 2-digit SIC codes. Same\_Firm is an indicator variable that equals one if the worker is retained within the firm (firmid) and zero otherwise. Different industry is an indicator variable that equals 1 if the job in quarter t + 4 has a different SIC than the job in quarter t - 2 and zero otherwise. Spanned industry is an indicator variable equal to one if the SIC of the (new) job in quarter t + 4 is an SIC in which the worker's quarter t - 2 firm operates excluding the worker's own industry and zero otherwise. All independent variables except Chg(N\_Estabs), Chg(EstabEmp), and Chg(FirmEmp) are measured at t - 2. All standard errors are clustered at the firm level and are reported in parentheses. \*, \*\*, and \*\*\* represent significance at 10%, 5%, and 1% level, respectively.

are measured two quarters prior to establishment closure. Finally, because firm size is an important determinant of wage levels (Oi and Idson 1999), we control for the change in establishment and firm size between the workers' old and new jobs. We include the differences in the natural logarithms of establishment and firm employment and the difference in the number of establishments between the old and new firms.

To control for the general effect of changing industries on wages (Neal 1995), we include an indicator for workers who change 2-digit SICs ("Different Industry"). We also distinguish between workers who change jobs in internal and external labor markets. Workers in diversified firms can make job changes to spanned industries without leaving the firm. However, wage changes when workers remain inside the firm may not reflect the workers' true outside options. A smaller wage loss might not reflect differences in human capital, but instead inefficiency in the wage-setting process (see, e.g., Silva 2012). Moreover, better workers may remain inside the firm following closure, making wage changes around internal and external moves difficult to compare. Thus, we include indicators for workers who remain in their original firms ("Same\_Firm") and workers who change industries in their original firms ("Same\_Firm \* Different Industry"), so that our main variable of interest isolates wage changes from external job changes to spanned industries. To ensure that all workers have the potential to find new jobs either inside or outside their original firms, we restrict our attention to firms that only close a subset of their establishments.<sup>27</sup> The resulting sample consists of 42,354 workers across 697 firms. We cluster standard errors by firm to correct for correlation in the residuals of workers displaced from the same firm.

We compare the wages obtained by workers from diversified firms who find jobs in new firms operating in spanned industries to three different benchmarks. In Column 1, we include state, 2-digit industry, and year fixed effects in addition to the controls described above. Thus, within industries, we can compare workers from diversified firms who moved to a new firm in a spanned industry with other workers who found jobs in a new firm and industry. We find that displaced workers who move to a new firm and industry experience a relative wage loss of roughly 14.4 percentage points (the baseline is workers from focused firms who find jobs in a new firm, but do not change industries). However, moving to a "spanned" industry erases the vast majority of the relative wage loss: the relative wage loss from changing industries is 10.9 percentage points smaller for these workers. Both effects are statistically significant at the 1% level.

A potential concern with this comparison is that different firms may close establishments at different times and under different circumstances. For example, diversified firms may have a lower threshold for closing

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<sup>27</sup> In the Online Appendix, we replicate all of the regressions we report below, without including this restriction, with no effect on our conclusions.

establishments than focused firms do because they can focus on their other remaining businesses. If so, workers moving to spanned industries may do better because they change jobs in better market conditions. In Column 2, we add establishment fixed effects to the regression. Thus, our second benchmark is workers from the same closing establishment who move to a new firm in a new unspanned industry. We find similar results. As a robustness check, we also restrict the analysis to a subset of establishments that closed during times of industry distress. This approach minimizes the effect of idiosyncratic differences in closure choices that might correlate with diversification and worker opportunities. To identify distressed industries, we follow an approach similar to Opler and Titman (1994). A drawback is that our sample occurs mainly during a protracted economic boom; for example, only the 2001 NBER recession lies within our sample period (and at the very end).<sup>28</sup> Despite the resulting lack of power, we find similar results: the estimate of the effect of moving to a spanned industry is 0.118, which is significant at the 1% level. The similarity of the estimates suggests that endogeneity of the firm's closure decision is unlikely to cloud our worker-level inferences.

A remaining concern is that the selection of industries inside a diversified firm is not random. Diversified firms may choose to operate in industries in which operations are more related. Then, these synergies, rather than differences in worker skills, might explain the smaller relative wage losses among workers who move to a new industry in which their former employing firm operates. In Column 3, we add fixed effects for each pair of pre- and postclosure 2-digit SIC codes in the sample to the regression specification. Thus, our final benchmark is workers who make the exact same industry change as workers in the treatment group, but for whom the new industry is not spanned by the initial employing firm. By including these fixed effects, we can no longer estimate the level effect of changing industries on wages. However, we again observe that moving to a spanned industry significantly reduces the wage losses associated with changing industries. Thus, we confirm our hypothesis using worker wages: workers from diversified firms obtain higher wages when moving to a spanned industry, even compared with other workers with the same preclosure wages who make the same industry change. We also confirm that the effect does not dissipate over the 2 or 3 years after they reenter the job market. We find no additional gains or losses in relative wages, but instead stable differences of the same magnitude as the estimates in Table 7 among workers who make no additional job changes. In the Online Appendix, we consider a number of alternative explanations for the wage evidence—worker sorting, location effects, information effects, and measurement error—finding that none can fully account for our results.

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<sup>28</sup> The Opler-Titman criteria to identify an industry shock are negative sales growth and stock returns less than -30%. Beyond 2001, these criteria identify only three industry shocks during our sample period: SICs 10, 13, and 33, all in 1998.

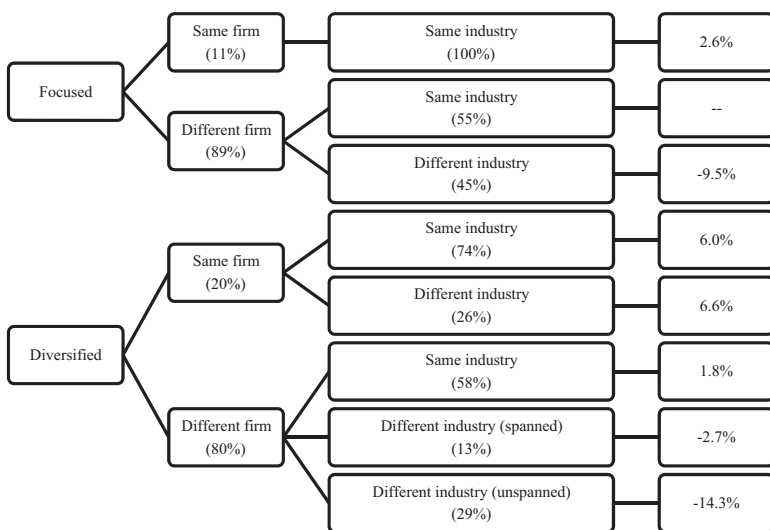
As a second test of our hypothesis, we examine the frequency with which workers from diversified firms move to “spanned” industries. To do so, we identify all of the possible employment outcomes for our sample of displaced workers four quarters following establishment closure and compare them across workers from diversified and focused firms. First, workers can be reemployed or unemployed. We find that 75.4% and 76.9% of workers from diversified firms and focused firms, respectively, find new jobs, a difference that is not statistically significant.<sup>29</sup> Thus, it does not appear that experience in a diversified firm has a significant effect on workers’ overall ability to find a new job. Next, we identify the possible types of job changes among workers who are reemployed one year following establishment closure. First, workers can find a new job in the internal or external job market. Second, workers can change industries or remain in their original industries. Workers from diversified firms who change industries can also move to a spanned or unspanned industry, but workers who remain in their original focused firm must also stay in the same industry. In Figure 3, we report the frequency of each type of job change among workers who are reemployed. The overall frequency of industry changes is nearly the same across workers who originate in focused and diversified firms (40% versus 39%, respectively), suggesting similar within-industry opportunities for the two types of worker. For workers from diversified firms, some of those industry changes occur in internal labor markets, resulting in a higher worker retention rate (20% versus 11%). Among industry changers who leave diversified firms, 31% move to “spanned” industries. The frequency with which workers from diversified firms change to spanned industries in new firms is significantly higher than the frequency with which workers from focused firms make changes between exactly the same industry pairs ( $p=0.024$ ). The effect is even stronger ( $p < 0.01$ ) when we include internal labor market moves.<sup>30</sup> Thus, again, the evidence supports our hypothesis that workers in diversified firms develop mobility between the industries in which their firms operate.

Before turning to our remaining hypotheses, we use the taxonomy of job changes from Figure 3 to provide a more complete picture of the wage outcomes of workers following displacement. Taking workers from focused firms who find new jobs outside the firm in their original industries as the baseline, we estimate the relative wage losses for the other seven categories. To do

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<sup>29</sup> We reexamine the evidence on reemployment rates in the Online Appendix, estimating logit regressions that control for other firm and worker characteristics. We find positive, but near-zero effects of diversification. We also test for differences in the length of unemployment spells for workers displaced from diversified and focused firms. We find that the unemployment spells of workers from diversified firms are shorter on average, although the difference tends to be statistically insignificant. A caveat to these analyses is that workers we measure as unemployed may have obtained new employment in states that are not part of our LEHD data sample.

<sup>30</sup> Nevertheless, workers from diversified firms making changes to a “spanned” industry are typically outnumbered by workers from focused firms making the same changes because there are more workers from focused firms in the sample (they are 78% of the sample). Therefore, we do not need to worry that the comparison group in Column 3 of Table 7 is too small to be meaningful.



**Figure 3**  
**Worker wage changes by job-change category**

The sample is workers displaced from closing establishments who are reemployed by the third quarter following the closure. The baseline job-change category is workers displaced from focused firms who find new jobs in the external market, but remain in their original industries. The figure reports wage losses for the remaining seven job-type categories relative to the baseline. The relative losses are inferred from a linear-regression mirroring the specification in Column 1 of Table 7, but including additional marginal effects for workers from diversified firms who remain inside their original firm and workers from diversified firms who change industries. All worker and firm characteristics are included. The full regression estimates are available in the Online Appendix. At each node, we report in parentheses the percentage of workers who make each possible type of job change.

so, we replicate the regression specification from Column 1 of Table 7, but include additional indicators for workers from diversified firms who remain in their original firms and who change industries.<sup>31</sup> In Figure 3, we report the wage changes, net of the firm and worker controls. We include the full estimates in the Online Appendix. Our main result remains apparent: workers from diversified firms who move to spanned industries experience smaller relative wage losses than workers from either diversified or focused firms who change industries in external markets do. Workers from diversified firms who change industries internally do better still, although, as noted above, this pattern is more difficult to interpret. Our story does not make robust predictions for all of the cross-group comparisons. Nevertheless, the figure reveals some interesting patterns. First, workers from diversified and focused firms who find jobs in their original industries in the external market experience roughly the same relative wage losses. This suggests that workers in diversified firms are not relatively overpaid and that the skills workers develop in spanned

<sup>31</sup> We do not report an estimate of the wage loss in the baseline job-change category because the model includes fixed effects for industries and years, making the estimate dependent on which industry and year categories we (arbitrarily) choose as the baseline.

industries do not come at the expense of weaker domain-specific skills in their home industries. We also find that workers from diversified firms that move to unspanned industries experience larger relative losses than workers from focused firms who change industries do; however, the effect is not robust to controlling for industry-pair effects. Here, industry-pair fixed effects correct for the possibility that the pairs of unspanned industries between which workers from diversified firms switch are less related than the pairs of industries between which workers from focused firms switch. We provide additional analysis and discussion of this effect in the Online Appendix. The overall average wage losses experienced by workers from diversified and focused firms are similar, although they are slightly smaller for workers from diversified firms. Finally, we find that workers who remain in diversified firms in their original industries do well relative to workers who remain in focused firms, even though the magnitude of the difference is roughly half the difference between workers who move to spanned industries and industry changers from focused firms.

Consistent with our hypothesis, workers in diversified firms display a greater mobility between the industries in which their firms operate than do other workers in the external market. Our analysis does not immediately imply, however, that a job in a diversified firm strictly dominates a job in a focused firm *ex ante*. Workers must pay a cost to invest in the human capital that facilitates such transitions. They are willing to pay these costs because of the benefits we identify. In equilibrium, the costs and benefits of working in a diversified firm may balance to make workers indifferent between accepting a job in a diversified or a focused firm. Instead, our analysis highlights a difference between the human capital of diversified and focused firms and a particular instance in which it confers an advantage to the worker from the diversified firm: when making a job change to a “spanned” industry.

### **3.2 Diversification and worker skills**

As a final step, we provide evidence to tighten the link between the smaller wage losses experienced by workers from diversified firms who move to spanned industries and worker skills. For workers to enjoy a share of the rents from the human capital they accumulate in diversified firms, they must have bargaining power *vis-a-vis* the firm. This, in turn, requires that their skills are scarce in the marketplace. We use the skill level of the worker as a proxy for this scarcity. In Section 2.1, we found that the relative labor-productivity advantage of diversified firms is stronger for firms operating in high-skill industries. Here, we begin by testing whether workers in these high-skill industries also earn higher relative wages when they move to spanned industries.

Following the approach in Section 2.1, we use the frequency of high-skill SOC codes within each 2-digit SIC in our sample to classify industries as high- and low-skill. We estimate separate effects of moving to a spanned industry for workers who originate in high- and low-skill industries. We report the

**Table 8**  
**Wage changes in high- and low-skill industries**

Dependent variable: $\Delta_{t+4,t-2}\ln(\text{wage})$	(1)	(2)	(3)
Ln(wage)	-0.111*** (0.009)	-0.137*** (0.009)	-0.120*** (0.008)
Ln(age)	-0.118*** (0.010)	-0.097*** (0.009)	-0.105*** (0.009)
Race = Black	-0.039*** (0.008)	-0.045*** (0.006)	-0.034*** (0.007)
Race = Asian	0.003 (0.013)	0.001 (0.011)	-0.003 (0.014)
Race = Hispanic	-0.024*** (0.008)	-0.029*** (0.006)	-0.028*** (0.007)
Race = Other minorities	-0.015* (0.008)	-0.022*** (0.007)	-0.018** (0.007)
Female	-0.041*** (0.005)	-0.051*** (0.005)	-0.035*** (0.005)
Ln(Tenure)	-0.020*** (0.005)	-0.018*** (0.004)	-0.020*** (0.004)
Manager	0.000 (0.021)	0.045** (0.021)	0.010 (0.020)
N_Estabs	-0.003*** (0.001)		-0.003*** (0.001)
Ln(EstabEmp)	-0.003 (0.007)	0.012 (0.008)	-0.001 (0.006)
Ln(FirmEmp)	0.009** (0.004)		0.013*** (0.004)
Chg (N_Estabs)	-0.003*** (0.000)	-0.003*** (0.001)	-0.002*** (0.000)
Chg (EstabEmp)	-0.002 (0.003)	-0.006* (0.003)	0.000 (0.003)
Chg (FirmEmp)	0.017*** (0.002)	0.020*** (0.002)	0.016*** (0.003)

(continued)

estimates in Table 8. We find that workers benefit most from exposure to other industries in their diversified firms when they work in high-skill industries, although the cross-group difference is not significant. Interestingly, among low-skill workers the effect appears to be driven by differences in the pairs of industries between which workers switch: When we include fixed effects for pre- and postclosure 2-digit SIC pairs, the effect vanishes for low-skill workers, but it remains strong and significant for high-skill workers.<sup>32</sup> In this specification, high-skill workers from diversified firms who move to spanned industries experience a 5.5 percentage point smaller wage loss than do workers who change industries; however, low-skill workers from diversified firms enjoy no such relative advantage.

We also estimate a specification in which we subdivide the outcomes for workers who originate in high- and low-skill jobs depending on whether their new position belongs to a high- or low-skill group. Focusing on the specification with SIC-pair fixed effects, we do not see an effect of moving to a spanned industry for either type of transition by a worker who originates in a low-skill

<sup>32</sup> The between-group difference is marginally insignificant ( $p$ -value = 0.1093).



**Table 8**  
**Continued**

Dependent variable: $\Delta_{t+4,t-2}\ln(\text{wage})$	(1)	(2)	(3)
Diversified	-0.006 (0.013)		-0.019 (0.012)
Same_Firm	0.028* (0.016)	0.006 (0.023)	0.030* (0.016)
Different industry	<b>-0.146***</b> (0.015)	<b>-0.121***</b> (0.013)	
Same_Firm × Different industry	0.050* (0.030)	0.048 (0.041)	0.058 (0.039)
High_Skill × Different industry	0.004 (0.026)	-0.010 (0.034)	
High_Skill × Diff. industry × Spanned industry	<b>0.117***</b> (0.021)	<b>0.114***</b> (0.022)	<b>0.055***</b> (0.019)
Low_Skill × Diff. industry × Spanned industry	<b>0.091***</b> (0.022)	<b>0.084***</b> (0.022)	<b>-0.002</b> (0.029)
State fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes		
Year fixed effects	Yes	Yes	Yes
Establishment fixed effects		Yes	
SIC pair fixed effects			Yes
R <sup>2</sup>	0.118	0.205	0.260
N	42,354	42,354	42,354

The sample contains one observation for each worker displaced from a closing establishment of a multi-unit firm in our matched LBD-LEHD data. Coefficient estimates are from OLS regressions. The dependent variable is the change in the annual real wage from quarter  $(t - 2)$  to  $(t + 4)$ .  $t$  is the quarter of establishment closure.  $\ln(\text{wage})$  is the natural log of the annual real wage.  $\ln(\text{age})$  is the natural log of the worker's age.  $\text{Race} = "x"$  is an indicator variable that equals one for workers of race "x" and zero otherwise.  $\text{Female}$  is an indicator variable that equals one for female workers and zero otherwise.  $\ln(\text{tenure})$  is the natural log of the number of quarters that a worker has spent in the SEIN.  $\text{Manager}$  is an indicator variable equal to one for the highest paid employee in the SEIN and zero otherwise.  $N\_Estabs$  is the number of establishments owned by the firm, divided by 100.  $\ln(\text{EstabEmp})$  is the natural log of establishment employment.  $\ln(\text{FirmEmp})$  is the natural log of aggregate firm employment.  $\text{Chg}(N\_Estabs)$ ,  $\text{Chg}(\text{EstabEmp})$ , and  $\text{Chg}(\text{FirmEmp})$  are the differences between the old and new firm in  $N\_Estabs$ , establishment employment, and firm employment, respectively.  $\text{Diversified}$  is an indicator variable equal to one for firms that operate in at least two distinct 2-digit SIC codes.  $\text{Same\_Firm}$  is an indicator variable that equals one if the worker is retained within the firm (firmid) and zero otherwise.  $\text{Different Industry}$  is an indicator variable that equals 1 if the job in quarter  $t + 4$  has a different SIC than the job in quarter  $t - 2$  and zero otherwise.  $\text{Spanned Industry}$  is an indicator variable equal to one if the SIC of the (new) job in quarter  $t + 4$  is an SIC in which the worker's quarter  $t - 2$  firm operates excluding the worker's own industry and zero otherwise.  $\text{High\_Skill}$  is an indicator variable equal to one if the percentage of workers in the 2-digit SIC in occupations with 2-digit SOC codes less than 29 exceeds the median.  $\text{Low\_Skill}$  is the complement of  $\text{High\_Skill}$ . All independent variables except  $\text{Chg}(N\_Estabs)$ ,  $\text{Chg}(\text{EstabEmp})$ , and  $\text{Chg}(\text{FirmEmp})$  are measured at  $t - 2$ . All standard errors are clustered at the firm level and are reported in parentheses. \*, \*\*, and \*\*\* represent significance at 10%, 5%, and 1% level, respectively.

job. However, workers who originate in high-skill jobs benefit whether they move to another high-skill or to a low-skill position.

As an alternative to SOC codes, we use preclosure wages as a worker-level proxy for skill, partitioning the sample into four groups.<sup>33</sup> We find similar results. Including industry-pair fixed effects, we find no effect among low-skill workers. However, the effect of exposure to the new SIC in the original employing firm increases monotonically across the wage groupings.

<sup>33</sup> We define the groups as follows: workers who earn less than \$25,000 in real annual wages, workers who earn \$25,000 to \$50,000, workers who earn \$50,000 to \$100,000, and workers whose wages exceed \$100,000. We provide the full estimates in the Online Appendix.

Next, we explore the origins of the differences in human capital we observe between diversified and focused firms. Our hypothesis is that workers invest in and develop these skills inside the firm. However, another possibility is that workers with preexisting skill sets that allow them to be productive in different industries within the set spanned by the firm select into diversified firms (ex ante matching). To distinguish between these alternatives, first, we examine the relation between the workers' mobility across the industries spanned by the firm and their tenure inside the firm. We reestimate the regression models from Section 3.1, but allowing the estimate among workers who move to a new firm in a "spanned" industry to differ for workers who have worked more or less than 2 years in the original diversified firm. This split roughly corresponds to splitting the sample at the median of tenure in the preclosure firm. We also allow the control for workers who change industries to vary by tenure. We report the results in Table 9. In general, we find a significantly larger positive effect of experience in a diversified firm that operates in the new industry among workers with long tenure in the diversified firm prior to displacement. Focusing on the specification with industry-pair fixed effects, workers with more than 2 years of experience in a diversified firm prior to displacement experience a six-percentage point smaller wage loss when they move to a spanned industry than other displaced workers who move between the same two industries do. Workers with less than 2 years of tenure who move to spanned industries, however, do not experience significant gains relative to other industry switchers.<sup>34</sup> The results are qualitatively similar if we vary the threshold for long tenure in the diversified firm.

We also take a second approach to distinguish ex ante matching from internal skill accumulation. We consider the work histories of our sample of displaced workers prior to their employment in the closing establishments. We define an indicator variable, which takes the value one if the worker ever worked in her new postclosure SIC prior to working in the firm that owns the closing establishment. We then reestimate the regression models from Section 3.1 but allow for different effects of moving to a spanned industry depending on whether or not the worker has experience in the new SIC before joining the diversified firm.<sup>35</sup> We report the results in Columns 1 to 3 of Table 10. We do not see significant differences between the wage changes of workers who make a switch to a spanned industry and who have or do not have prior experience in the SIC outside the diversified firm in any specification.

Surprisingly, it appears that experience in the postdisplacement new industry before entering the firm from which the worker is displaced does not provide a wage benefit similar to experience within a diversified firm that spans the

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<sup>34</sup> The estimates in Columns 1 and 2 suggest a relative gain even to low-tenure workers, but the difference between low- and high-tenure workers is nearly constant across specifications.

<sup>35</sup> Here we cannot also allow the effect of industry changes to vary by prior experience in the new industry because having prior experience in the new industry already implicitly indicates that the worker has changed industries.

**Table 9**  
**Worker tenure in the diversified firm**

Dependent variable: $\Delta_{t+4,t-2}\ln(\text{Wage})$	(1)	(2)	(3)
Ln(wage)	-0.112*** (0.009)	-0.138*** (0.009)	-0.121*** (0.008)
Ln(age)	-0.117*** (0.010)	-0.098*** (0.009)	-0.104*** (0.009)
Race = Black	-0.040*** (0.008)	-0.045*** (0.006)	-0.035*** (0.007)
Race = Asian	0.002 (0.013)	0.001 (0.011)	-0.005 (0.015)
Race = Hispanic	-0.026*** (0.008)	-0.029*** (0.006)	-0.028*** (0.007)
Race = Other minorities	-0.015* (0.008)	-0.022*** (0.007)	-0.018** (0.007)
Female	-0.041*** (0.006)	-0.050*** (0.005)	-0.035*** (0.005)
Ln(Tenure)	-0.026*** (0.008)	-0.012* (0.006)	-0.024*** (0.008)
Manager	0.000 (0.020)	0.044** (0.021)	0.009 (0.020)
N_Estabs	-0.003*** (0.001)		-0.003*** (0.001)
Ln(EstabEmp)	-0.003 (0.007)	0.013 (0.008)	0.000 (0.006)
Ln(FirmEmp)	0.008** (0.004)		0.011*** (0.004)
Chg (N_Estabs)	-0.003*** (0.000)	-0.003*** (0.001)	-0.002*** (0.001)
Chg (EstabEmp)	-0.002 (0.003)	-0.006* (0.003)	0.000 (0.003)
Chg (FirmEmp)	0.016*** (0.002)	0.019*** (0.002)	0.015*** (0.003)

(continued)

industry (the level effect of prior experience is negative). However, as with experience within a diversified firm, the length of time the worker spent in the postdisplacement industry turns out to matter. In Columns 4 to 6 of Table 10, we allow for a difference in the effect of prior experience in the postdisplacement industry when the worker's tenure in the industry was greater than or less than four years. For workers with longer spells, we uncover a positive relation between prior experience in the new industry outside the displacing firm and the wage change following displacement.<sup>36</sup> We also consider the effect of data censoring on our conclusions. Because our worker data begins in 1991, we do not observe full worker histories for all workers in the sample. When we consider only the subsample of workers who were 18 or younger in 1991, we find that the frequency of prior experience in the postclosure SIC is roughly the same as the overall sample (in fact, slightly larger). Thus, censoring does not seem to create an undersampling problem. Moreover, we continue to find that

<sup>36</sup> We also estimate models including a continuous measure of the length of the worker's experience in the postdisplacement industry. We find that each quarter of experience reduces the postdisplacement wage loss by 40 to 50 basis points, depending on the specification.

**Table 9**  
**Continued**

Dependent variable: $\Delta_{t+4,t-2}\ln(\text{Wage})$	(1)	(2)	(3)
Diversified	-0.006 (0.013)	-0.019	(0.012)
Same_Firm	0.043*** (0.015)	0.019 (0.020)	0.045*** (0.015)
Different industry	-0.173*** (0.024)	-0.155*** (0.032)	
Same_Firm × Different industry	0.053** (0.026)	0.065* (0.038)	0.073** (0.036)
Different Industry × Spanned industry	0.132*** (0.024)	0.125*** (0.024)	0.060*** (0.021)
Low_Tenure	-0.032** (0.013)	-0.004 (0.011)	-0.022* (0.011)
Low_Tenure × Different industry	0.063*** (0.021)	0.059** (0.025)	0.050*** (0.013)
Low_Tenure × Different industry × Spanned industry	-0.058** (0.025)	-0.050** (0.025)	-0.050** (0.022)
State fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes		
Year fixed effects	Yes	Yes	Yes
Establishment fixed effects		Yes	
SIC pair fixed effects			Yes
R <sup>2</sup>	0.119	0.190	0.222
N	42,354	42,354	42,354

The sample contains one observation for each worker displaced from a closing establishment of a multi-unit firm in our matched LBD-LEHD data. Coefficient estimates are from OLS regressions. The dependent variable is the change in the annual real wage from quarter  $(t - 2)$  to  $(t + 4)$ ,  $t$  is the quarter of establishment closure.  $\ln(\text{wage})$  is the natural log of the annual real wage.  $\ln(\text{age})$  is the natural log of the worker's age.  $\text{Race} = "x"$  is an indicator variable that equals one for workers of race "x" and zero otherwise.  $\text{Female}$  is an indicator variable that equals one for female workers and zero otherwise.  $\ln(\text{tenure})$  is the natural log of the number of quarters that a worker has spent in the SEIN.  $\text{Manager}$  is an indicator variable equal to one for the highest paid employee in the SEIN and zero otherwise.  $N\_Estabs$  is the number of establishments owned by the firm, divided by 100.  $\ln(\text{EstabEmp})$  is the natural log of establishment employment.  $\ln(\text{FirmEmp})$  is the natural log of aggregate firm employment.  $\text{Chg}(N\_Estabs)$ ,  $\text{Chg}(\text{EstabEmp})$ , and  $\text{Chg}(\text{FirmEmp})$  are the differences between the old and new firm in  $N\_Estabs$ , establishment employment, and firm employment, respectively.  $\text{Diversified}$  is an indicator variable equal to one for firms that operate in at least two distinct 2-digit SIC codes.  $\text{Same\_Firm}$  is an indicator variable that equals one if the worker is retained within the firm ( $\text{firmid}$ ) and zero otherwise.  $\text{Different industry}$  is an indicator variable that equals 1 if the job in quarter  $t + 4$  has a different SIC than the job in quarter  $t - 2$  and zero otherwise.  $\text{Spanned Industry}$  is an indicator variable equal to one if the SIC of the (new) job in quarter  $t + 4$  is a SIC in which the worker's quarter  $t - 2$  firm operates excluding the worker's own industry and zero otherwise.  $\text{Low\_Tenure}$  is an indicator variable that equals one for workers who have spent two years or less in the closing establishment. All independent variables except  $\text{Chg}(N\_Estabs)$ ,  $\text{Chg}(\text{EstabEmp})$ , and  $\text{Chg}(\text{FirmEmp})$  are measured at  $t - 2$ . All standard errors are clustered at the firm level and are reported in parentheses. \*, \*\*, and \*\*\* represent significance at 10%, 5%, and 1% level, respectively.

prior experience cannot explain the ease with which workers from diversified firms change industries on this reduced sample.

Overall, we confirm the link between worker skill and the ability to move between the spanned industries of a diversified firm with lower relative wage losses. We also provide evidence that these skills develop inside the diversified firm. Diversified firms may attract workers whose ex ante skills are well suited to their particular business combination, but the match between worker skills and the firm's lines of business improves over time. This in turn increases the value of the firm's real option to redeploy workers as industry opportunities change.

**Table 10**  
**Prior experience in the post-displacement new industry**

Dependent Variable: $\Delta_{t+4,t-2}\ln(\text{Wage})$	(1)	(2)	(3)	(4)	(5)	(6)
Ln(wage)	-0.112*** (0.009)	-0.138*** (0.009)	-0.121*** (0.008)	-0.112*** (0.009)	-0.138*** (0.009)	-0.122*** (0.008)
Ln(age)	-0.117*** (0.010)	-0.097*** (0.009)	-0.104*** (0.009)	-0.118*** (0.010)	-0.098*** (0.009)	-0.105*** (0.009)
Race = Black	-0.040*** (0.008)	-0.045*** (0.006)	-0.035*** (0.007)	-0.040*** (0.008)	-0.045*** (0.006)	-0.034*** (0.007)
Race = Asian	0.003 (0.013)	0.001 (0.011)	-0.004 (0.015)	0.003 (0.013)	0.001 (0.011)	-0.004 (0.014)
Race = Hispanic	-0.025*** (0.008)	-0.029*** (0.006)	-0.028*** (0.007)	-0.025*** (0.008)	-0.029*** (0.006)	-0.028*** (0.007)
Race = Other minorities	-0.016** (0.008)	-0.023*** (0.007)	-0.019** (0.007)	-0.016** (0.008)	-0.023*** (0.007)	-0.019** (0.007)
Female	-0.042*** (0.006)	-0.051*** (0.005)	-0.035*** (0.005)	-0.042*** (0.006)	-0.051*** (0.005)	-0.035*** (0.005)
Ln(Tenure)	-0.021*** (0.005)	-0.019*** (0.004)	-0.020*** (0.004)	-0.020*** (0.005)	-0.019*** (0.004)	-0.020*** (0.004)
Manager	-0.001 (0.020)	0.044** (0.021)	0.009 (0.020)	-0.001 (0.020)	0.044** (0.021)	0.009 (0.020)
N_Estabs	-0.003*** (0.001)		-0.003*** (0.001)	-0.003*** (0.001)		-0.003*** (0.001)
Ln(EstabEmp)	-0.002 (0.007)	0.013 (0.008)	0.000 (0.006)	-0.002 (0.007)	0.013 (0.008)	0.000 (0.006)
Ln(FirmEmp)	0.007** (0.004)		0.011*** (0.004)	0.007** (0.004)		0.011*** (0.004)
Chg (N_Estabs)	-0.003*** (0.000)	-0.003*** (0.001)	-0.002*** (0.000)	-0.003*** (0.000)	-0.003*** (0.001)	-0.002*** (0.000)
Chg (EstabEmp)	-0.002 (0.003)	-0.006* (0.003)	0.000 (0.003)	-0.002 (0.003)	-0.006* (0.003)	0.000 (0.003)
Chg (FirmEmp)	0.016*** (0.002)	0.019*** (0.002)	0.015*** (0.003)	0.016*** (0.002)	0.019*** (0.002)	0.015*** (0.003)
Diversified	-0.006 (0.013)		-0.019 (0.012)	-0.006 (0.013)		-0.018 (0.012)
Same_Firm	0.043*** (0.015)	0.017 (0.021)	0.045*** (0.015)	0.042*** (0.015)	0.016 (0.021)	0.045*** (0.015)
Different industry	<b>-0.137***</b> (0.018)	<b>-0.118***</b> (0.023)		<b>-0.137***</b> (0.017)	<b>-0.118***</b> (0.023)	
Same_Firm × Different industry	0.050* (0.026)	0.070* (0.038)	0.073** (0.035)	0.052** (0.027)	0.072* (0.038)	0.075** (0.035)
Different industry × Spanned industry	<b>0.103***</b> (0.016)	<b>0.102***</b> (0.015)	<b>0.035**</b> (0.017)	<b>0.102***</b> (0.016)	<b>0.102***</b> (0.015)	<b>0.035**</b> (0.017)
Prior experience	-0.030** (0.015)	-0.040*** (0.013)	-0.014 (0.014)	-0.042*** (0.015)	-0.052*** (0.013)	-0.027* (0.014)
Prior exp × Diff. ind. × Span. ind.	<b>0.000</b> (0.031)	<b>-0.016</b> (0.027)	<b>-0.016</b> (0.024)	<b>0.000</b> (0.034)	<b>-0.014</b> (0.029)	<b>-0.011</b> (0.025)

(continued)

#### 4. Discussion

Our analysis documents an important difference between diversified and focused firms. The internal labor markets of diversified firms facilitate the reallocation of human capital to its most productive uses. They also encourage workers to develop skills that translate across the firms' portfolios of industries. These forces contribute to higher labor productivity among workers in diversified firms compared with matched focused peers in the same industries. Although there is a large amount of existing literature on corporate diversification, few studies account for differences in human capital

**Table 10**  
**Continued**

Dependent Variable: $\Delta_{t+4,t-2}\ln(\text{Wage})$	(1)	(2)	(3)	(4)	(5)	(6)
Long prior experience				<b>0.060*</b> (0.032)	<b>0.049</b> (0.032)	<b>0.081***</b> (0.028)
Long prior exp. $\times$ Diff ind. $\times$ Span. ind.				-0.026 (0.053)	-0.050 (0.053)	-0.066 (0.049)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes			Yes		
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Fixed Effects		Yes			Yes	
SIC Pair Fixed Effects			Yes			Yes
R <sup>2</sup>	0.117	0.190	0.221	0.118	0.190	0.222
N	42,354	42,354	42,354	42,354	42,354	42,354

The sample contains one observation for each worker displaced from a closing establishment of a multi-unit firm in our matched LBD-LEHD data. Coefficient estimates are from OLS regressions. The dependent variable is the change in the annual real wage from quarter  $(t - 2)$  to  $(t + 4)$ .  $t$  is the quarter of establishment closure.  $\ln(\text{wage})$  is the natural log of the annual real wage.  $\ln(\text{age})$  is the natural log of the worker's age.  $\text{Race} = "x"$  is an indicator variable that equals one for workers of race "x" and zero otherwise.  $\text{Female}$  is an indicator variable that equals one for female workers and zero otherwise.  $\ln(\text{tenure})$  is the natural log of the number of quarters that a worker has spent in the SEIN.  $\text{Manager}$  is an indicator variable equal to one for the highest paid employee in the SEIN and zero otherwise.  $N\_Estabs$  is the number of establishments owned by the firm, divided by 100.  $\ln(\text{EstabEmp})$  is the natural log of establishment employment.  $\ln(\text{FirmEmp})$  is the natural log of aggregate firm employment.  $\text{Chg}(N\_Estabs)$ ,  $\text{Chg}(\text{EstabEmp})$ , and  $\text{Chg}(\text{FirmEmp})$  are the differences between the old and new firm in  $N\_Estabs$ , establishment employment, and firm employment, respectively.  $\text{Diversified}$  is an indicator variable equal to one for firms that operate in at least two distinct 2-digit SIC codes.  $\text{Same\_Firm}$  is an indicator variable that equals one if the worker is retained within the firm (firmid) and zero otherwise.  $\text{Different industry}$  is an indicator variable that equals 1 if the job in quarter  $t + 4$  has a different SIC than the job in quarter  $t - 2$  and zero otherwise.  $\text{Spanned industry}$  is an indicator variable equal to one if the SIC of the (new) job in quarter  $t + 4$  is an SIC in which the worker's quarter  $t - 2$  firm operates excluding the worker's own industry and zero otherwise.  $\text{Prior experience}$  is an indicator equal to one for workers who change industries and who have experience in the quarter  $t + 4$  SIC code before entering their quarter  $t - 2$  employing firm.  $\text{Long prior experience}$  is an indicator variable equal to one for workers with  $\text{Prior Experience}$  equal to 1 and at least 4 years of experience in the  $t + 4$  SIC code before entering their quarter  $t - 2$  employing firm. All independent variables except  $\text{Chg}(N\_Estabs)$ ,  $\text{Chg}(\text{EstabEmp})$ , and  $\text{Chg}(\text{FirmEmp})$  are measured at  $t - 2$ . All standard errors are clustered at the firm level and are reported in parentheses. \*, \*\*, and \*\*\* represent significance at 10%, 5%, and 1% level, respectively.

use in such firms. As a final step to our analysis, we discuss the implications of our hypothesis for three findings in the existing literature. Our dataset is less suited to allow causal statements in these settings (it was designed to identify the effects of internal labor markets, as described in prior sections). Nevertheless, we offer suggestive evidence that a broader view of corporate diversification that encompasses human capital may provide useful insights. We provide additional details and tables in the Online Appendix.

### 4.1 Wages

Schoar (2002) proposes rent dissipation through higher wage payments to workers as a value-destroying consequence of corporate diversification. She provides evidence of larger aggregate wage bills in diversified firms and, in particular, higher "supplementary labor costs." However, she does not have worker-level data, making it difficult to control for worker heterogeneity across firms. Moreover, it is unclear to what degree the estimates of supplementary labor costs, such as fringe benefits, can be attributed to rank-and-file workers.

Our analysis suggests an alternative channel to explain higher wage payments in diversified firms: workers in diversified firms accumulate additional skills

that allow them to extract rents in the labor market. We reexamine the link between diversification and wages using the random sample of worker-quarters described in Section 1. We run a standard wage regression, including controls for worker and firm characteristics and state, year, and 2-digit-SIC-code fixed effects. We find that workers in diversified firms earn a 2.1% premium over workers in other firms on average; however, the average masks large differences depending on worker skill (Online Appendix Table OA12). Using industry-level variation in SOC codes to define high- and low-skill industries (as defined in Section 2.1), we find higher wages among diversified firms operating more intensively in high-skill industries. The level effect of diversification turns negative once we include the interaction of the diversification indicator with the fraction of workers in high-skill industries. Thus, a diversified firm with only low-skill workers can pay lower wages than a focused firm can. In this case, workers command a smaller wage premium (because they do not have scarce skills) and may accept a discount because of the “insurance effect” provided by the internal labor market of the diversified firm. Higher wages on average, then, need not reflect inefficient rent dissipation, but may instead be a simple reflection of the mix of (properly compensated) high- and low-skill employees in the firm.

#### **4.2 Internal capital allocation**

Many studies find that segment investment within diversified firms is less sensitive to industry opportunities than investment in focused firms, interpreting the result as evidence of inefficient corporate socialism (see, e.g., Ozbas and Scharfstein 2010). However, these studies assume implicitly that there are no frictions in labor markets (or, at least, that any frictions equally affect diversified and focused firms) so that capital allocation can be interpreted independently from labor allocation. We find that diversified firms adjust their labor inputs more aggressively in response to changing industry opportunities compared with focused firms (Section 2.2). If labor and capital are partial substitutes, this suggests that less-aggressive adjustment of capital inputs in diversified firms might be an optimal response.

#### **4.3 Diversification discount**

Many researchers find that diversified firms trade at a discount relative to focused firms in equity markets (e.g., Lang and Stulz 1994; Berger and Ofek 1995), interpreting the result as evidence that diversified firms operate less efficiently than focused firms do. Our analysis demonstrates that the human capital of diversified firms is significantly different from that of focused firms operating in the same industries. Workers from diversified firms have heightened mobility across the set of industries in which their diversified firms operate and, therefore, command extra compensation. The skills and expertise that underlie this mobility are a form of organization capital for the diversified firm. In addition to increasing cash flows through higher labor productivity,

they also increase firms' risk because workers can leave the firm taking a portion of the organization capital with them. New firms that enter in response to technology shocks may pay a premium for such workers, introducing a systematic component to the risk (Eisfeldt and Papanikolaou 2013). Thus, diversified firms may face a higher discount rate relative to focused firms in their industries. In this case, the documented diversification discount may reflect higher risk, instead of inefficient operations.

We use Compustat segment data over our 1992–2004 sample period to test for a link between the diversification discount and human capital. In Section 3, we show that workers from diversified firms who work in high-skill industries benefit from the internal labor market by developing greater mobility across the firm's spanned industries, even in the external labor market. Thus, we use the percentage of firm sales (or assets) in high-skill industries as a proxy for the organization capital workers develop in diversified firms that could command a risk premium in the market. We measure the diversification discount using the methodology of Berger and Ofek (1995). We find a baseline valuation discount of 17% (28%) among diversified firms relative to focused firms operating in the same industries using asset (sales) multiples. We also find substantial cross-sectional variation in the discount related to the intensity of the firm's operations in high-skill industries. As the percentage of firm assets (or sales) in high-skill industries increases, the discount also significantly increases (Online Appendix Table OA 13). Economically, a firm operating 100% in high-skill industries would have a valuation discount two to three times as large as that of a firm operating 100% in low-skill industries.

It is important to recognize the limitations of this analysis. The percentage of operations in high-skill industries is a noisy proxy for organization capital. For example, it could also capture differences in other firm characteristics such as growth rates or investment. To address this concern, we add a variety of controls to try to isolate the effect driven by our human-capital channel—including lagged return on assets, asset tangibility, and investment—with little effect on the results. However, we do not claim that organization capital is the sole driver of the discount or that we isolate a causal link. Notably, we do not have a valid instrument to address the endogeneity of the diversification decision. Moreover, we do not claim, nor does the theory predict, that human-capital investment in diversified firms will always be associated with a valuation discount. We find evidence in Section 2.1 that the human capital in diversified firms generates higher cash flows. Thus, it can lead to a premium or discount depending on whether the cash flow or risk effect dominates. This in turn can depend on macroeconomic conditions. Our sample period contains a major technology shock and economic boom, which could explain why the risk effect dominates (many new entrants operating new technologies compete for diversified firms' stocks of high-skill workers). A risk-based channel can also help to explain recent evidence that the change in excess value over time (or, realized returns)



is higher among diversified firms (Lamont and Polk 2001; Hund, Monk, and Tice 2010) and that the discount narrows during recessions (Kuppuswamy and Villalonga 2010), given that worker mobility is heightened during expansions (Jovanovic and Moffitt 1990). However, a more comprehensive analysis of these tradeoffs is beyond the scope of this study.

Overall, we find suggestive evidence that differences in human capital have the potential to resolve a number of puzzling empirical patterns from the literature on conglomerates. Our analysis challenges the view that diversified firms are operating suboptimally.

## **5. Conclusion**

We use a unique approach that combines worker-firm matched data from the U.S. Census Bureau's LEHD program with establishment- and firm-level data from the LBD and valuation data from Compustat to look inside the black box of internal labor markets. We find significant differences between the human capital employed in diversified and focused firms. In particular, workers in diversified firms develop skills suited for the set of industries in which the firm operates. Diversified firms enjoy higher productivity and benefit from the resulting real option to redeploy labor to sectors with greater marginal returns in response to economic shocks.

We use establishment closures as a way to separate voluntary from involuntary job changes and to compare credibly the outcomes of workers who make job changes. We find that workers who leave a diversified firm but move to a new industry in which their former firm operates experience only a modest wage loss, significantly less than do workers who move to an entirely new industry. When changing industries, they are also more likely to move to the set of industries spanned by the firm than workers from focused firms are. These results are consistent with the hypothesis that diversified firms foster the skills workers develop by working synergistically across the firms' lines of business.

We address several competing explanations of our evidence: differences in the local markets in which diversified and focused firm operate, differences in the information available to workers in diversified firms about cross-industry opportunities, differences in industry classifications across diversified and focused firms, and differences in the work histories of workers prior to joining diversified and focused firms. We also find that the benefit of switching industries from a diversified firm accrues almost entirely to workers in high-skill vocations and that the benefits increase with worker tenure inside the diversified firm.

We find that the development of human capital in diversified firms benefits not only the workers but also the firm. Diversified firms are more likely to retain workers following establishment closure when the future opportunities of their remaining segments are high. Moreover, they are more likely to move workers

out of industries with declining opportunities and into the industries with the strongest opportunities. Even though they pay higher wages—reflecting the higher outside opportunities of their workers—diversified firms also receive higher productivity in return, even measured with respect to payroll.

Our results provide a potential reconciliation of several cross-sectional differences between diversified and focused firms. We offer an explanation for higher observed wage levels in diversified firms, controlling for firm size and individual worker characteristics. Diversified firms cultivate workers with higher inter-industry mobility and outside options. Thus, higher wages do not necessarily indicate rent dissipation because workers can also achieve those higher wages outside the firm. Moreover, the firm also benefits from resulting productivity gains and the ability to redeploy these workers internally. In addition, the greater dependence on human capital and heightened worker mobility in diversified firms may require a higher risk premium, which can reconcile a diversification discount with higher observed productivity.

We also suggest a different interpretation of existing research on the internal capital markets of diversified firms. A substantial body of research suggests that “dark side” theories of internal capital markets dominate empirically: diversified firms appear to engage in socialistic allocation of capital toward struggling divisions. Yet, there is evidence in the literature that diversified firms are more productive than focused firms are in the cross-section. Our results provide one possible reconciliation of these results. Diversification can improve productivity through worker skill development and the ability to redeploy workers internally to their most productive use. Smaller capital reallocations toward industries with good opportunities do not necessarily indicate “socialistic redistribution” of resources in firms with higher labor mobility. Moreover, by focusing exclusively on manufacturing firms, existing studies may have excluded precisely the service-oriented firms that benefit most from diversification. An interesting avenue for future research would be to study the interactions of internal capital and labor allocation in a unified framework.

Finally, the labor-related benefits we identify may provide a motivation for firms to pursue diversification. Variation in the importance of human capital and the opportunities for developing synergistic skills may be an important determinant of the industry configurations that firms choose. However, the importance of this mechanism is difficult to evaluate by comparing the cross-section of diversified and focused firms. In ongoing research, we examine the labor market choices of firms that make diversifying acquisitions, relative to firms that make focused acquisitions or choose not to grow by acquisition. An added advantage of this context is that the acquisition event—at least for public acquirers—provides the opportunity for direct measurement of the value consequences of different strategies for the firms in question. Evidence along these lines may help to deepen our understanding of the effect of different

organizational structures on the operations of the firm and, ultimately, what factors matter in determining firm boundaries.

## Appendix A. Details on Merge of LBD to the LEHD Data

Our analysis requires us to merge closing establishments identified within the Census's Longitudinal Business Database (LBD) with worker data from the Longitudinal Employer-Household Dynamics (LEHD) program. Because both Census data sources include firms' EINs, it is relatively straightforward to merge firm-level information from the LBD to the worker-level information in the LEHD data for single-unit firms. For multi-unit firms, however, it is not generally possible to assign individual workers uniquely to LBD establishments because the LEHD data report tax units (State EINs, or SEINs) and the LBD reports physical business establishments.<sup>37</sup> The internal bridge file at the Census, the LEHD Business Register Bridge (BRB), provides a link between the LEHD data and the LBD at various levels of aggregation. Its finest partition is at the EIN, state, county, and four-digit-SIC-code level. Thus, to achieve a match of workers (from the LEHD data) to a unique establishment (from the LBD), we require that the LBD establishment is unique within this partition. We also require that the SEINUNIT(s) to which we match the closing establishment disappear within a seven-quarter window centered on the reporting quarter in which we observe the closure in the LBD.

When we match the LEHD data to the LBD, the number of closing establishments in our sample declines from 143,370 to 12,439 (Table 1). In the table below, we list the reasons for the attrition. The steps are ordered, and the percentages in Column 3 are conditional. For example, we lose 42% of the closing establishments because there is no link between the establishment identifier and an EIN in the Business Register, conditional on the closing establishment being among the 55% of the sample located in an LEHD-covered state. Notice that the first four items are unavoidable restrictions imposed on our analysis by the data. If any one of these conditions fails, it is impossible to link workers from the LEHD data to the closing establishment in the LBD. Imposing these four restrictions takes the number of closing establishments to 21,953, with the greatest loss coming from closing establishments located in states not covered by the LEHD data. Even though we lose many closing establishments, we have no reason to believe that these restrictions introduce any bias into our analysis. The most potentially troubling item is the restriction to LEHD-covered states, which we discuss in Section 1.

	Restriction	% Included
<i>Restrictions imposed by the Census:</i>	Closing LBD establishment is located in an LEHD state	55%
	Firm/EIN link exists in the Business Register	58%
	EIN/SEIN link exists in LEHD files	64%
	LBDNUM can be linked using the Business Register Bridge at the firm, county, and 4-digit-SIC-code level	75%
<i>Restrictions imposed by us:</i>	Closing LBD establishment exits the LEHD data in a 7-quarter window around the LBD closure quarter	62%
	Closing LBD establishment is unique within its firm, county, and 4-digit SIC code	91%

<sup>37</sup> The relation between the numbers of establishments and tax-reporting units for a particular firm is unclear. In some cases, the number of establishments exceeds the number of tax-reporting units; however, in other cases, the opposite is true.

The final two items are restrictions we impose. They are not the main drivers of the sample attrition (they result in the loss of the final 9,517 closing establishments), and they are necessary. For our analysis, it is crucial to know which of a firm’s workers are employed in a closing establishment. If there are multiple establishments within the EIN, state, county, and 4-digit-SIC-code partition, we cannot distinguish workers who were displaced by the closure but moved to a new job in the firm’s internal labor market from workers who were not employed in the closing establishment. Similarly, if we do not observe closure of the unit in the LEHD data, we cannot distinguish workers who obtained a new job in the firm’s internal labor market from workers who were displaced by the closure and remained unemployed. “Ghost records” in the LEHD data are more common among multi-unit firms, because multi-unit firms often continue operating despite closing a subset of their establishments. Thus, both restrictions disproportionately affect multi-unit firms, resulting in the smaller fraction of multi-units in the matched sample (15% versus 49% among all closing LBD establishments). Our main analyses condition on the closing establishment being operated by a multi-unit firm. Notice that among closing establishments from multi-unit firms in the matched sample, the fraction of establishments operated by diversified firms is 69%, which is similar to the fraction of establishments from diversified firms in the closing (79%) and overall (71%) samples. Thus, the selection imposed on the sample by our match appears unlikely to affect our key results. Nevertheless, we consider regressions with establishment fixed effects in part to address remaining selection concerns.

### Appendix B. High- and Low-Skill Industry Classifications

For each 2-digit SIC code, we calculate the percentage of workers in high-skill occupations. High-skill occupations have Standard Occupation Classifications less than 29 in the U.S. Bureau of Labor Statistics’ classifications. In Panel A, we list the 10 2-digit SIC codes with the highest percentages of high-skill workers and the percentages of high-skill occupations in the industry. In Panel B, we list the 10 2-digit SIC codes with the lowest percentages of high-skill workers and the corresponding percentages.

2-digit SIC code	Industry name	% of workers in high-skill occupation codes
Panel A: Top-10 industries by worker skill		
82	Educational services	72.10
87	Engineering, accounting, research, management, and related services	64.82
89	Miscellaneous services	64.52
81	Legal services	53.09
80	Health services	49.69
83	Social services	49.23
67	Holding and other investment offices	46.68
63	Insurance carriers	45.54
38	Measuring, analyzing, and controlling instruments; photographic, medical, and optical goods; watches and clocks	40.47
86	Membership organizations	38.79

2-digit SIC code	Industry name	% of workers in high-skill occupation codes
Panel B: Bottom-10 industries by worker skill		
56	Apparel and accessory stores	7.29
45	Transportation by air	7.28
22	Textile mill products	7.20
70	Hotels, rooming houses, camps, and other lodging places	7.14
42	Motor freight transportation and warehousing	7.04
23	Apparel and other finished products made from fabrics and similar materials	7.00
55	Automotive dealers and gasoline service stations	6.83
53	General merchandise stores	6.09
58	Eating and drinking places	5.56
54	Food stores	5.08

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