

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

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Abstract

We estimate the labor market consequences of corporate diversification using novel worker-firm matched data from the U.S. Census Bureau. We find evidence that workers in diversified firms have more general skills than workers in focused firms. Displaced workers experience smaller wage losses when they switch jobs or industries internally and when they move to a new firm in a new industry in which their old firm also operates. We find a significant wage premium among workers in diversified firms, consistent with their more attractive outside options. We show that diversified firms exploit the option to redeploy workers internally: they redeploy workers from declining industries to expanding industries at a higher rate than the external market. Overall, our evidence suggests that internal labor markets provide a bright side to corporate diversification.

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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

What are the benefits of corporate diversification? The manufacturing plants of diversified firms have higher total factor productivity than the plants of focused firms in the cross-section (Schoar (2002)). They also achieve higher sales growth and adjust more easily to business cycles, particularly within core industries (Maksimovic and Phillips (2002)). A potential explanation is the existence of internal capital markets. To the extent that external capital markets are not efficient, firms operating multiple lines of business can generate value by re-allocating capital from divisions with excess cash to divisions with strong investment opportunities.¹ Yet, there is evidence suggesting instead that firms engage in “socialist” cross-subsidization of weak divisions at the expense of those with good opportunities (Lamont (1997); Rajan, Servaes and Zingales (2000); Ozbas and Scharfstein (2010)). We test a relatively unexplored alternative: diversification improves the productivity of labor relative to focused firms.

Since diversified firms operate in multiple industries, a potential source of synergies is the ability to develop and deploy “generalist” workers, whose skill sets span multiple tasks or industries.² A lawyer in a diversified firm might litigate cases for the firm’s finance and health care divisions, developing expertise and experience in both areas of the law. An engineer may develop technologies for units of the conglomerate which produce aircraft engines and home appliances. Workers may participate in joint ventures of different business segments. Or, promising young employees may take advantage of internal job rotation programs to acquire the broad organizational knowledge necessary to climb the corporate hierarchy. These opportunities, which are less common in focused firms, create value for the firm’s workers by increasing the scope and quality of their outside opportunities. GE-style integrated diversity also creates value for the firm by generating opportunities for innovation and the seamless

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

²Our notion of general skills has a natural relation to the “skill-weights” formalized by Lazear (2009).

transfer of “best practices” across the organization. For example, Jack Welch initiated the well-known “Work-Out” program at GE in the 1990s with the goal of cultivating such synergies. Moreover, an internal stock of “generalist” workers enables the firm to respond more effectively to industry shocks, redeploying workers – and not just physical capital – to lines of business with the best opportunities. This option may be particularly valuable when shocks create mismatches between employer needs and worker skills in the external labor market. Finally, the heightened external mobility of human capital in diversified firms can act as a source of risk that may carry a premium in financial markets. Thus, differences in the work forces of diversified and focused firms can provide a unified explanation for higher productivity, less sensitivity of physical capital investment to opportunities, and an equity market discount among diversified firms.

We use a novel worker-plant matched panel dataset to test several implications of this hypothesis. Our worker-firm matched data comes from the U.S. Census Bureau’s Longitudinal Employer Household Dynamics (LEHD) program. The newly developed LEHD data covers a broad cross-section of the U.S. economy and includes 96% of the workers from covered states.³ We use the Census Bureau’s Longitudinal Business Database (LBD) to identify the organizational structure within a firm and to measure firm diversification. We use the Business Register Bridge (BRB) to allocate workers to individual plants, where possible.

To measure differences in worker skills in diversified and focused firms, we compare the change in wages when workers change jobs or industries. A key identification concern is the endogeneity of the choice to change jobs. In particular, workers may be more likely to voluntarily accept a new job within their firm or industry. Since wage changes following voluntary job changes are likely to be censored below and wage changes following firing are likely to be censored above, this effect could immediately generate a pattern of better outcomes among internal movers. Moreover, the rates of voluntary versus forced job changes may differ across diversified and focused firms for reasons other than differences in worker skills or opportunities. To avoid these confounds, we adapt the approach of Gibbons and Katz (1991), constructing a sample of worker-plant matched data which includes only involuntary job changes due to plant

³Although the LEHD program covers 48 states in the U.S., only information from 23 states is available through the Census Research Data Center (RDC).

closures. We then compare outcomes for workers displaced from diversified and focused firms.

This strategy does not remove all sources of endogeneity from our analysis. In particular, workers may still choose whether or not to remain in a firm following displacement, conditional on their outside options and an offer from the firm. However, such differences are less problematic for our analysis. If higher quality workers choose to remain inside diversified firms than focused firms following displacement – conditional on the firm’s choice to extend an offer – that suggests an important labor market advantage to diversified firms. We also consider the cross-section of organizational structure and do not model directly the decision to diversify. Most diversified firms are large and mature. If the decision to diversify occurred well in the past, it is unlikely to have a direct relation with current workers skills.

We find evidence consistent with the hypothesis that workers in diversified firms possess more general skills than workers in focused firms. We find that workers fare significantly better when they change jobs in internal labor markets than in external markets. We find that the key source of wage losses in external labor markets is industry changes, consistent with Neal (1995). Displaced workers who change industries experience a 10.6 percentage point larger wage decline on average. However, we find that workers who change industries internally within a diversified firm do not experience the same wage losses. Moreover, workers from diversified firms who change industries, but move to a new industry in which their former firm operates experience significantly smaller wage losses. This result suggests that the better outcomes among workers who switch industries internally are not merely rent dissipation, since workers can obtain similar relative wage gains externally.

Our results hold across a variety of specifications. The effects are present comparing workers displaced from the same closing plants (plant fixed effects). Thus, our results are not due to (uncontrolled) differences in the plants from which industry-switchers originate. We also compare workers who switch between the same pair of 2-digit SIC codes (SIC pair fixed effects). Our results are not driven by differences in the pairs of industries between which workers from diversified and focused firms switch, though we do find some evidence of such differences. Our results also do not appear to be driven by sorting of better workers into diversified firms: displaced workers from diversified firms do not do better than their focused counterparts when they move to an industry that was not spanned by their previous firm or when they change

firms in the same industry. We also confirm that the results are not driven by workers with experience in their post-displacement industries prior to entering the diversified firm. Our results are also robust to the inclusion of a variety of controls, including measures of local job opportunities and the distance between the old and new employers. Moreover, the differences in outcomes persist for (at least) three years following plant closure.

Next, we test whether the effect of diversification on worker outcomes varies with worker skill. First, we use real annual worker wages prior to plant closure as a proxy for worker skill levels. We partition the sample into four wage groups (wage < \$25K; $25K \leq \text{wage} < 50K$; $50K \leq \text{wage} < 100K$; wage $\geq 100K$) and estimate the impact of changing industries separately within each group. For workers in the lowest wage group, the wage changes for industry switchers are the same regardless of whether the former employer operates in the new industry. However, as wage levels increase, the impact of exposure to the new industry in the old job increases monotonically. Second, we use information on the distribution of workers from different Standard Occupational Classification (SOC) codes to classify 2-digit industries by the importance of human capital, or high-skilled labor. We find that the importance of exposure to the new industry at the former employing firm is distinct to industries which employ high-skilled labor. Thus, the development of general skills appears to carry more of a premium among high-skill workers, whose skills are likely to be scarce in the marketplace and among whom human capital is a key driver of productivity.

Having established the worker-level impacts of diversification, we turn to the value implications to the diversified firm of employing generalist workers with heightened industry mobility. Consistent with higher productivity, we find higher average wages among diversified firms, controlling for worker and firm characteristics. We also show that worker flexibility provides an important real option to the firm. Diversified firms are more likely to retain workers following plant closure when growth opportunities in their remaining industries are high; and, they are more likely to redeploy workers to different industries when growth opportunities in their former industries are declining. We find that the effects are concentrated in industries which employ relatively more high-skill human capital, consistent with our earlier evidence on worker inter-industry mobility. Overall, our results suggest that the internal labor markets of diversified firms provide an advantage over focused firms: diversified firms are better able to

respond to changing conditions in their existing industries through the reallocation of human capital. These opportunities are particularly valuable if the skills firms require are scarce in the external labor market or if there are frictions in hiring workers from outside the firm.

As a final step, we examine the relation between worker mobility and the diversification discount. Consistent with a risk premium for human capital mobility, we find a significantly higher discount among firms that operate in high skill industries in which worker mobility is more pronounced. This interpretation is consistent with existing evidence that the change in excess value over time (or, realized returns) is higher among diversified firms (Hund, Monk, and Tice (2010)). If worker mobility is heightened during expansions, then our interpretation is also consistent with recent evidence suggesting a narrowing of the discount during recessions (Kuppuswamy and Villalonga (2010)). Our results suggest caution in interpreting the diversification discount as evidence of inefficient decision-making within conglomerates: diversified and focused firms are fundamentally different in terms of risk and, therefore, the cash flow-value relationship among focused firms does not provide an appropriate benchmark for valuing a segment of a diversified firm. It is unclear that disassembling conglomerates would create value, since they would lose cash flows from the “boundaryless” internal deployment of labor, yet would continue to employ labor with heightened external mobility.

Our analysis provides a new angle on the benefits of corporate diversification. Lang and Stulz (1994), among others, argue that diversified firms trade at a discount relative to a portfolio of focused firms in the same lines of business. Morck, Shleifer, and Vishny (1990) show that the market discounts firms which diversify by acquisition. Graham, Lemmon, and Wolf (1998) and Campa and Kedia (1999) dispute the interpretation of this evidence, arguing that diversified firms acquire units which are weak relative to the industry average, and that firms with lower value are more likely to diversify. Moreover, using data from the Census’ LBD, Villalonga (2000) argues that mis-classification of industries in the Compustat segment data may be responsible for findings of a diversification discount. Instead of focusing on the net benefit of diversification, we examine a particular unexplored mechanism by which diversification can create value: internal labor markets and the development of worker skills. In particular, the desire to facilitate human capital investment in skills with applications across industries may be an important determinant of the boundaries of the firm (Hart (1995)).

We build on recent work in asset pricing that identifies worker mobility as an important source of risk. Eisfeldt and Papanikolaou (2011) argue that firms that invest more in organizational capital carry an additional risk premium since key talent can transfer a fraction of that capital to a new firm and therefore demand wages that match their outside options. Consistent with this story, they show that firms with higher SG&A expenditures have higher expected returns. We provide insight into the nature of organizational capital and compare it across firms with different organizational structures. We show that diversified firms develop workers with general skills – increasing their value in the external labor market – and as a result pay higher wages. Thus, diversified firms may carry an additional risk premium, providing a way to reconcile the observed discount in equity markets with higher plant-level productivity. Donangelo (2011) also studies the relationship between worker mobility and firm risk, finding that firms in industries with more mobile workers command higher expected returns. We provide evidence that mobility is not exogenous and that diversified firms increase workers’ outside opportunities through their exposure to multiple industries.

Our analysis also suggests a novel interpretation of prior research on internal capital markets. Prior studies find less sensitivity of capital expenditures to industry Q among the business segments of diversified firms (e.g., Ozbas and Scharfstein (2010)). We find that workers in diversified firms are systematically different from workers in focused firms and that diversified firms are able to redeploy labor internally in response to changing industry conditions. If labor and capital are partial substitutes and diversified firms have flexibility to adjust both capital and labor inputs while focused firms have less ability to adjust labor due to 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.

The remainder of the paper is organized as follows. In Section I., we describe the data we use in our analysis and, in particular, the process by which we merge data across different Census products. In Section II., we measure the value consequences to workers of job changes in internal and external markets and within and across industries. In Section III., we examine whether and how diversified firms exercise their real option to redeploy workers across their business units. In Section IV., we link the presence of mobile skilled labor to the diversification discount. Finally, in Section V., we conclude.

I. Data

We use worker-, firm-, and plant-level data from the U.S. Census Bureau to investigate differences in worker mobility and compensation across firms with different organizational structures. We identify individual plants and their ultimate owners (firm), geographic locations (state and county) and industries (4-digit SIC) using the Longitudinal Business Database (LBD). The LBD covers all non-farm establishments with paid employees in the U.S. since 1976. It also provides information on plant-level employment and payroll as well as information on plant birth or closure (if any).

We retrieve individual worker-level information – including wage, gender, and age – from the Longitudinal Employer Household Dynamics (LEHD) program. The LEHD data is 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 U.S. and is generally comparable from state to state. Wages reported to the state UI system include bonuses, stock options, 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.⁴ The data contain individual worker identifiers as well as firm and unit identifiers. Thus, we can track workers and their wages dynamically within and across firms. The Census Bureau currently provides access to employment records from 23 states through its Research Data Center (RDC).⁵ Missing data from uncovered states imposes 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 due either to job loss or to migration to an uncovered state. Second, we cannot observe the entire labor force or all internal worker movement for firms which 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

⁴See <http://www.bls.gov/cew/cewfaq.htm> for additional details.

⁵All 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 reasearch purposes through the Census RDC.

suffer from selection bias.⁶ Moreover, the within-sample rate of migration to a new covered state – even following plant closure – is low (approximately 2.5%). Thus, the potential impact of unobserved migration on our analysis is likely to be small.

We make several adjustments to the reported wages for our analysis. We use the quarterly consumer price index to compute real quarterly wages in beginning-of-1990 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 since the first or last quarter’s wage reflects payment for an unobserved fraction of the quarter. Finally, we exclude workers younger than 16 or who earn less than \$10,000 from our analysis. We identify the manager of the unit (firm) quarter-by-quarter as the worker with the highest wage in the unit (firm).

Within the LEHD data, we can identify firms using tax reporting units: federal employer identification numbers (EINs), state employer identification numbers (SEINs), and state reporting “units” (SEINUNITs). State laws require firms to file quarterly reports which link individual workers to each of their SEINs. Thus, we can track worker movement across SEINs over time. However, firms are only required to report aggregate employment and payroll information for SEINUNITs. Though it is possible to impute the SEINUNIT for each worker⁷, we conduct much of our analysis at the SEIN level to minimize measurement error.

We use plant-level information from the LBD to identify multi-unit firms (i.e., firms operating multiple plants) and to measure firm-level diversification. We construct a Herfindahl index of employment within all of the 2-digit SIC codes associated with the firm. We also use the LBD to identify plant closures. Since the LEHD data is available through the first quarter of

⁶This is likely to be the case as often the constraint which prevents the Census from making data available to researchers is pre-existing state laws.

⁷The Census Bureau has several imputation algorithms which make these assignments by, e.g., matching as closely as possible the sum of allocated workers and wages to the reported aggregates and by minimizing the distance between worker residence and work locations. We do not observe data on worker home addresses.

2004, we consider plant closures through 2001 so that we can track the outcomes of workers for (at least) 2 full years following a job change. We restrict the sample to plants with at least 50 employees to prevent our sample from being dominated by very small private ventures.

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 plants since the LEHD data report tax units and the LBD reports physical business establishments.⁸ 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 plant (from the LBD), we require that the LBD plant is unique within this partition.

To identify worker flows within and across firms, we use the firm identifiers provided in the LBD. Because workers in closing plants cannot remain in their original jobs, we can distinguish internal from external job changes by comparing the firm identifiers from the old and new jobs.⁹ If the firm identifier remains the same, then the worker changed jobs in the internal labor market.

When we turn to firm-level analysis in Sections III. and IV., we use additional data from Compustat. We define industry Q as the median of the market value of assets scaled by the book value of assets within each 2-digit SIC code.¹⁰ We also use Compustat segment data to compute the diversification discount for the subset of publicly traded firms. Following Lang and Stulz (1994), we measure the diversification discount among firms operating multiple business segments as the difference between the natural logarithms of the firm's imputed and actual market-to-book ratios.¹¹ Imputed market-to-book for each segment of a diversified firm

⁸The relation between the numbers of plants and tax reporting units for a particular firm is unclear. In some cases, the number of plants exceeds the number of tax reporting units; however, in other cases, the opposite is true.

⁹More generally, changes in firm identifiers can be hard to interpret due to administrative changes in the way the firm reports its information and/or corporate restructuring.

¹⁰Market value of assets is the book value of assets (data 6) plus the difference between market and book equity. Market equity is the fiscal year closing stock price (data 199) times common shares outstanding (data 25). Book equity is common equity (data 60) plus deferred taxes (data74).

¹¹Market value is measured as common shares outstanding (csho) times the fiscal year closing stock price

is the median market-to-book ratio among single-segment firms operating in the segment’s 3-digit SIC code. Imputed market-to-book for the firm is the asset-weighted average of the imputed market-to-book ratios for each of the firm’s segments. Finally, we use accounting data from Compustat to construct firm-level controls (for the subsample of public firms). We measure ROA as EBITDA (oibdp) scaled by beginning-of-fiscal-year assets (at). Tangibility is property, plants, and equipment (ppent); cash stock is cash and short term investments (che); investment is capital expenditures (capx). Tangibility, cash stock, and investment are all scaled by beginning-of-fiscal-year assets. Book leverage is long term debt (dltt) plus debt in current liabilities (dlc) divided by the numerator plus common equity (ceq). Finally, we construct an indicator variable equal to one for firms which pay a positive cash dividend (dv).

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

We also consider a random sample of closing plants from the LBD over the same time period. Relative to the average plant, closing plants appear to be smaller (mean employment = 188) and 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 plants we can match to individual workers in the LEHD data. Relative to random closing plants, worker-matched plants are significantly less likely to be part of multi-unit firms (15%). This difference occurs for two reasons. First, we only match plants which are unique within their firm, county, and 4-digit SIC and thus exclude cases in which multi-unit firms have more than one plant in this

(prcc_f) plus long term debt (dltt) plus debt in current liabilities (dlc) plus preferred stock (pstk). Book value is total assets (at).

partition. Second, for consistency, we require the LEHD data to record the “death” of the reporting unit within 8 quarters of the reported closing in the LBD. The LEHD data will often include imputed records based on the last filing for quarters in which a firm fails to file its tax information, until it is clear that the plant has closed. Imputed records are more common among multi-unit firms since the firm can continue to operate despite closing one or more plants. Because our goal is to track workers displaced by closure, these records create serious attenuation biases for our analysis and must be dropped. Conditional on being part of a multi-unit firm, the fraction of plants which 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%). Matched sample plants are also smaller than the typical LBD (closing) plant, both among single- and multi-unit firms.¹² In the full matched sample, mean employment is 134 and mean payroll is \$2.33 million. The matched sample also significantly undersamples the Northeast, most likely due to 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 II, we provide summary statistics at the worker level. In Panel A, we present statistics for a random sample of LEHD data worker-quarters. The average worker is 41 years old with 3.36 years of tenure in the SEIN. Women make up 46% of the workforce. 10% of the workforce is Black, 4% Asian, 9% Hispanic, and 5% other non-white. The mean annual wage is \$34,660. 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 plants. 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 plant size in the matched sample (Table I). 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” plants, the multi-unit firms in our sample may be less diverse or complex than unmatched firms. If so, our results may understate the impact of such structures on the opportunity sets of workers and on-going investment in human capital.

¹²This difference also arises due to our restriction to plants for which we observe closure in both the LEHD data and the LBD.

II. Diversification and the Transferability of Worker Skills

We propose that diversified firms enjoy an advantage over focused firms in developing “generalist” workers whose skills have value across industries. A direct implication of this hypothesis is that workers from diversified firms should make easier transitions across industries than their counterparts in focused firms. These industry changes can occur in the internal labor market of the diversified firm or in the external market by moving to a new firm. We measure the wage implications of both types of moves. Considering external moves has two advantages: (1) The new wage a worker receives in the external market is a clear measure of the worker’s outside option; and, (2), we can partition industry changes in the external market into cases in which workers move to new industries in which their former (diversified) firms also operate and cases in which they do not. This division tests a more subtle prediction: if internal exposure to tasks across industries develops the skills of workers in diversified firms, those skills should translate more readily to the particular industries in which the diversified firm operates.

An immediate issue in measuring wage changes for workers who switch jobs is the endogeneity of the job change decision. Worker allocation across jobs is the result of both a supply and 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 jobs in internal markets to workers who move to a new firm. Suppose, for example, that workers who move within the firm outperform workers who move between different firms. Such a result could arise mechanically if internal movement is largely voluntary and firm changes are due to firing. Wage changes in voluntary job changes are likely to be truncated below: workers will only change jobs if the new opportunity is more lucrative than their current job. However, wage changes for fired workers are likely to be truncated above.

We use plant closures as a way to disentangle supply- and demand-driven job changes. These workers have no option to remain in their current jobs and the displacement is involuntary. Moreover, it is unlikely that displacement is related to skill or performance of individual workers.¹³ Thus, measured differences in the outcomes of workers across diversified and focused

¹³This identifying assumption may fail for managers. Thus, we always include a control for managers in our regressions and confirm that our results are not driven by the very top of the wage distribution within the

firms should reflect differences in the opportunities or skills of those workers rather than differences in the endogenous choice to switch jobs. In addition, workers have limited bargaining power when displaced, so it is more likely that higher wages reflect higher outside options than the extraction of rents.

II.A. Internal Labor Markets and Wage Changes for Displaced Workers

To measure worker outcomes, we compute the change in the annual real wage from two quarters prior to plant closure to the fourth quarter following plant closure.¹⁴ This computation implicitly restricts our sample to displaced workers who find a new job within the first three quarters following the closure.¹⁵ Though this restriction potentially biases downward our estimates of the wage impact of plant 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.

In Table III, we measure the differences in the outcomes of workers who find new jobs in internal versus external labor markets and within versus outside their original industries. Because we are interested in the value consequences of changing jobs within the firm, we restrict our attention to workers from firms which only close a subset of their plants. Thus, it is possible for all sample workers to find a new position either within or outside their original firms. The sample consists of 42,354 workers across 697 firms. We control for a number of demographic factors which might affect worker opportunities in our regressions. 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 include the pre-job change wage level (in log form) to control for the impact of individual ability on wage changes. We assume that this wage level is a sufficient statistic for the unobserved component of ability uncorrelated with our demographic controls. We also control for variation at the plant and firm level. We include measures of plant and firm size: the natural logarithms of employment in the worker's plant and firm. We also include the number of plants in the

closing plant.

¹⁴We compute the annual real wage as defined in Section I. We winsorize the wage change at the 1% level to remove severe outliers.

¹⁵A worker re-employed 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 I. for details.

firm as a control for the availability of internal opportunities. And, we include an indicator variable for diversified firms (i.e., firms which operate in more than one 2-digit SIC code). All control variables are measured two quarters prior to plant closure. Finally, since firm size is an important determinant of wage levels (Oi and Idson (1999)), we control for the change in plant and firm size between the workers' old and new jobs. We include the differences in the natural logarithms of plant and firm employment and the difference in the number of plants between the old and new firms.

In Column 1, we measure the difference in wage changes between workers who move to a different plant within their original firms and workers who move to a new firm. The regression includes state, 2-digit industry, and year fixed effects. Here and throughout our analysis, standard errors are clustered by firm to correct for correlation in the residuals of workers displaced from the same firm. We estimate an 8.3 percentage point difference in wage changes, significant at the 1% level. The control variables also reveal interesting cross-group differences in displacement costs. We see that higher wage workers experience larger displacement costs, suggesting a larger loss of firm-specific capital. Consistent with this story, older workers and workers with longer tenure in the closing plant experience larger wage losses. We also see that women as well as Black and Hispanic workers lose more wages following involuntary job losses. In Column 2, we add plant fixed effects to the regression. We confirm that workers who move within the firm outperform those who change firms, even comparing workers who originate from the same closing plant and controlling for pre-closure wage levels.

In Column 3, we measure the importance of industry mobility as a factor in the better outcomes of workers who stay inside their firms. We add an indicator variable for workers who switch to a new 2-digit SIC in their new jobs and interact the indicator with the indicator for workers who remain within their original firms. Note that the ability to switch industries internally is a unique feature of the internal labor markets of diversified firms. We find that displaced workers who leave the firm and switch industries experience an 11.9 percentage point larger wage decline. On the other hand, workers who remain inside the firm and switch industries are no worse off than workers who stay inside both their original firm and industry. Moreover, seamless internal industry changes appear to explain nearly all of the advantage of internal job changes: workers who make internal job changes without changing industries do

only marginally better than workers who make external intra-industry job changes. In Column 4, we add plant fixed effects to the regression. We find similar results. Note that when we compare workers who originate in the same closing plant, there is no remaining effect of internal job changes relative to external changes for workers who remain in the same industry.

An important concern in interpreting these results is the possibility that workers who change industries in the internal labor markets of diversified firms switch between different pairs of industries than workers who change industries externally. Diversified firms may choose to operate in industries which are more inherently related and these synergies, rather than heightened portability of worker skills, might explain the smaller relative wage losses. To address this concern, we add fixed effects for each pair of old and new 2-digit SIC codes in the sample to the regression specification. Thus, we estimate the relative benefit of making an internal industry switch comparing only workers who switch internally and externally between the same two industries. We report the results in Column 5. By including these fixed effects, we can no longer estimate the level effect of changing industries on wages. However, our estimates of the same firm effect and the interaction of the same firm effect with the indicator for changing industries are virtually unchanged.

The evidence thus far is consistent with our theory: workers in diversified firms develop valuable general skills which make them more mobile across industries. A problem with interpreting differences in internal and external job changes, however, is that wages workers obtain in internal labor markets may be less disciplined by market forces than wages in the external market. To separate our skill-based story from this type of rent dissipation, we turn our attention exclusively to industry switches in external labor markets. In particular, we compare workers who move to a firm in a new industry in which their old firm also operates to workers who move to a new industry in which the old firm does not operate. If the better outcomes in internal labor markets are due to inefficient wage-setting practices, then displaced workers who move outside the firm should not enjoy the same advantages. This comparison also tests a more subtle prediction of our theory: if diversified workers enjoy labor market advantages due to the skills they obtain by working “across industries” in their diversified firms, then their skills should be most transferable to other firms in the industries in which their diversified firms operate. We present the results in Column 6 of Table III. Again we see that displaced

workers who move to a new firm in a different industry perform worse than workers who move to a new firm in their original industry. The relative loss is roughly 14.4 percentage points and is significant at the 1% level. On the other hand, moving to a firm in an industry in which the original (diversified) firm operates erases the vast majority of the relative wage loss. We observe a significant 10.9 percentage point difference in the wage changes between the two groups. In Column 7, we demonstrate the robustness of the results to comparing only workers who are displaced from the same plant. And, in Column 8, we add 2-digit SIC code pair fixed effects. We observe a decline in the magnitude of the difference, but we still find a significantly positive effect. Thus, the result cannot be explained solely by greater similarity of the industries in which diversified firms operate than between the typical industry pair between which workers switch in the external market. Instead, we find differences in the outcomes of workers from diversified firms who make the exact same industry switch as workers outside the firm.

Next, we test whether the relative advantage enjoyed by industry-switchers from diversified firms persists over time. We consider the two- and three-year wage changes around plant closure, re-estimating the regression specifications from Columns 6 to 8 of Table III. To avoid contamination by workers who make additional job changes, we restrict the sample to workers who stay in the same new job post-closure. So, for example, when we run our regression using the two-year wage change as the dependent variable, we restrict the sample only to workers who work in the same firm-unit four and eight quarters following plant closure. In Table IV, we present the results. We find that the difference in wage changes persists over the three years following involuntary job loss. However, we do not find evidence of any additional improvement in the relative positions of the displaced workers from diversified firms.

Overall, our analysis demonstrates distinct differences between labor in diversified and focused multi-unit firms. Diversified firms have richer internal labor markets than focused firms. These markets provide opportunities for workers to change jobs without experiencing the costs typical of job changes in external markets. This is particularly the case when workers switch industries. We find evidence that workers in diversified firms develop more general skills which are applicable across a wider range of industries. Relating our findings to the theory of Lazear (2009), firm-specific capital in diversified firms puts non-zero skill weights on skills applicable across the bundle of industries in which the firm operates.

II.B. Alternative Explanations

Next, we briefly consider several alternative explanations for the labor market advantage enjoyed by workers from diversified firms.

Worker Sorting. A potential explanation for better post-displacement outcomes among workers originating in diversified firms is that the workers in such firms are simply more skilled on average than their counterparts in focused firms, controlling for observable differences in characteristics and ex ante wages. If so, we should expect to see these workers outperform not only when they move to a new industry in which their former firm operates, but also when they move to a new firm in an industry in which their former firm does not operate (or to a new firm in the same industry). To address this possibility, we re-estimate our basic specifications from Columns 6 to 8 of Table III, allowing for a differences in the coefficients on D_DIFSIC and $Same_Firm$ for workers originating in diversified and focused firms. The interaction of diversification with the industry change indicator captures the difference between the wage changes of workers from focused firms who make industry changes and workers from diversified firms who move to a new industry in which their old firm does not operate. We find no evidence that workers from diversified firms outperform workers from focused firms. Moreover, we do not find evidence that they outperform workers from focused firms when they move to different firms within the industry (note the insignificant coefficients on the diversification indicator in Table III). Thus, the evidence is more consistent with workers in diversified firms possessing specific skills which are transferable across the specific industries in which their firms operate than with workers possessing a general higher ability.

Location Effects. Diversified firms may operate plants in systematically different geographic locations from focused firms. Suppose, for example, that diversified firms are more likely to operate in urban centers or in areas with more active local markets (at a finer level than the state, for which we have already controlled). Then, the better outcomes among workers who are displaced from diversified firms might reflect these better local opportunities and not broader skill sets obtained through work experience in the diversified firms. We test this hypothesis in two ways. First, we measure the distance between each displaced worker's old and new jobs. Since we know the county in which each job is located, we compute distance as the number of miles between the center of the two counties. We then re-estimate the regressions from Columns

6 to 8 of Table III, including the natural logarithm of the distance between the old and new jobs and its interactions with the indicators for internal job changes and industry changes as additional controls. In Panel A of Table V, we present the results. We find some evidence that workers who move greater distances to their new jobs experience relative wage losses, though the statistical significance of the estimate is weak. However, controlling for distance has almost no impact on our coefficient estimate of interest. We still find that workers who leave their firm, but move to a new industry in which their old firm operates experience significant relative wage gains.

Second, we introduce controls for the availability of jobs within the county in which the worker's closing plant operates. We again re-estimate the regressions from Columns 6 to 8 of Table III, but including as additional controls the natural logarithms of the total number of plants operating in the county, the number of plants in the worker's original SIC operating in the county, and the number of plants in the worker's SIC after displacement operating in the county. All three variables are measured in the year prior to the plant closure. We also interact all three measures of local opportunities with the indicators for internal job changes and industry changes. We report the results in Panel B of Table V. We again find little impact on the effect of interest. Across all three specifications, workers from diversified firms experience easier transitions to industries in which their diversified firms also operate. As a final robustness check, we re-estimate the regressions controlling for total employment, rather than the number of plants, in the county and old and new SICs (and interactions with the indicators for internal and industry changes). The results are qualitatively unchanged.

Information Effects. A second alternative explanation for our findings is that workers in diversified firms have better information about available opportunities in the industries in which their diversified firms operate. However, they do not have skills which are better suited for those industries than the typical worker who makes the same industry switch in the external market. In this case, workers in diversified firms should time their industry changes better than other workers. That is, the wage advantage relative to other workers who make the exact same change in industries in the external market comes from making the change when opportunities in the new industry are better (or, equivalently, opportunities in the old industry are worse). To test this hypothesis, we re-estimate the regression specification from Column 8 of Table III,

but interacting the industry pair fixed effects with the year fixed effects. Thus, we compare only the changes in wages for displaced workers who switch between the same two industries at the same time. Though our estimates are less powerful, the coefficient of interest has a roughly equal magnitude to the estimate in Column 8 of Table III (0.033, p -value = 0.109). Thus, better timing of the job change does not appear to explain our results.

Classification of Industries. Another possibility is that the meaning of particular industry classifications differs across focused and diversified firms. For example, consider a diversified firm which operates in SIC codes 24 (lumber and wood products) and 25 (furniture and fixtures). The firm's operations in SIC 24 may be more similar to the typical firm operating in SIC 25 than in 24 if there is an input-output relation between the two units. In this case, the workers classified in SIC 24 might be classified in SIC 25 were they not in the diversified firm, explaining their relative mobility to SIC code 25. Note, however, that this story also implies that intra-industry changes for workers from diversified firms are measured with error. In particular, we should see not only that workers from diversified firms perform better when they switch to industries in which the diversified firms operate, but also that they do worse when they move to a new firm operating in the same industry. We see no evidence of the latter effect in our data (Note again the insignificant coefficient estimate on the diversification indicator in Columns 6 to 8 of Table III). The mis-classification story also is most plausible for closely related industries. As another way to test the hypothesis, we re-estimate the regressions from Columns 6 to 8 of Table III, but considering only changes between 1-digit SIC codes. We present the results in Table VI. If anything, we find that our results are stronger using this more restrictive definition of industry changes. We continue to find a relative wage advantage among workers who move to a new firm in a different industry, but in which their old firm also operates.

Prior Experience and Worker-Firm Matching. An important alternative to the hypothesis that workers develop general skills and industry mobility within diversified firms is the possibility that workers already possess those traits before they are hired. Note in either case, our results identify important differences in the workforces of focused and diversified firms. To test this hypothesis, we consider the work histories of our sample of displaced workers prior to their employment in the closing plants. We define an indicator variable which takes the

value one if the worker ever worked in her new post-closure SIC prior to working in the closing plant. We then re-estimate the regressions from Columns 6 to 8 of Table III including the indicator and its interactions with the indicators for internal job changes and SIC changes as additional controls. We also allow for different effects of moving to a new industry in which the worker’s former firm operates depending on whether or not the worker has experience in the new SIC before joining the diversified firm. We report the results in Table VII. We find that prior experience in the new SIC is not responsible for our results. We do not see significant differences between the wage changes of workers who make a switch to an industry in which their former firm operates and who have or do not have prior experience in the SIC outside the diversified firm. We also do several robustness checks on this evidence. We allow for different effects depending on the amount of time the worker spent in the new SIC, with little impact on the results. We also consider the impact 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 post-closure SIC is roughly the same as in the overall sample (and, in fact, slightly larger). Thus, censoring does not seem to create an undersampling problem. Moreover, we continue to find that prior experience cannot explain the extra ease with which workers from diversified firms change industries on this reduced sample.

Overall, the evidence supports the hypothesis that diversified firms cultivate generalist workers. The “boundaryless” model of a conglomerate appears to pay dividends in terms of developing worker skills which are in high demand in the labor market. In Section III., we address more directly the value of such skills to the firm.

II.C. Wage Changes by Worker Skill Levels

Having explored competing explanations of our key findings, we next provide additional evidence on the role of skill in determining differences in the outcomes of workers from diversified and focused firms following job changes. Our hypothesis is that diversified firms facilitate worker investment in general human capital with applications across the firm’s business endeavors. To be of value to the firm (and to carry a wage premium when workers leave the firm),

these skills must be scarce in the marketplace. Thus, a natural implication is that our results should be strongest among workers of high ability, who contribute more to the firm’s stock of organizational capital and for whom high human capital is the main driver of productivity.

We test this prediction in two ways. First, we partition the sample using workers’ pre-closure wages. We consider four groupings: 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. Workers in the lowest wage group are likely to hold low-skill positions; workers earning in excess of \$100,000 are likely to be high ability, white collar workers. We re-estimate our workhorse regressions from Columns 6 to 8 of Table III, including indicators for each wage group in lieu of the natural logarithm of the pre-closure wage. We also allow for a different impact of industry changes in each group. And, we estimate the impact of moving to a new industry in which the worker’s former firm also operates separately in each wage group. We present the results in Table VIII. Across all three specifications, we find that high-wage workers benefit the most when they move to a new industry in which their old firms operate. Interestingly, among low wage 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 post-closure 2-digit SIC pairs, the effect vanishes in this wage grouping. As we move to higher wage groupings, however, we see a monotonic increase in the benefit achieved by workers who move to a new industry in which their old firms operate, even relative only to workers who make a switch between the same industry pairs.

As a second test of our prediction, we construct a more direct measure of high- and low-skill vocations. We collect information from the Bureau of Labor Statistics on the frequencies 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.¹⁶ Examples in this category include food preparation and serving, office and administrative support, and construction

¹⁶As 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.

positions. We then compute the percentages of workers in each 2-digit industry who work in high and low skill positions.¹⁷ We classify industries in which the fraction of high-skill jobs is above the median as “high skill” industries. These industries employ 64% of our sample workers. Strongly represented in this grouping are services industries: among the top 10 industries by percentages of skilled jobs are engineering, accounting, research, management, and related services (SIC 87); legal services (SIC 81); and health services (SIC 80). Also represented in the top 10 are finance industries (insurance carriers (SIC 63) and holding and other investment offices (SIC 67)). At the opposite end of the spectrum, we find among the bottom 10 low skill industries food stores (SIC 54), automotive dealers and gasoline service stations (SIC 55), eating and drinking places (SIC 58), textile mill products (SIC 22), and apparel and other finished products made from fabrics and similar materials (SIC 23). While service industries tend to fall in the high skill grouping and retail trade industries in the low skill grouping, manufacturing industries are fairly split between the two categories. High skill manufacturing industries appear to be groupings with high proportions of engineering or natural science jobs; for example, electronic and other electrical equipment (SIC 36), industrial and commercial machinery and computer equipment (SIC 35), chemicals and allied products (SIC 28), and petroleum refining and related industries (SIC 29). Notably, our skill categories – and particularly the high skill group – appear to be absorbing states: only 26% of workers move from a high skill to a low skill position and 44% from low to high.

We re-estimate our three baseline regression specifications including an indicator for high skill industries interacted with the indicator for industry changes. As with the wage groupings above, we estimate separate effects of moving to a new industry in which the worker’s former firm operates for high skill and low skill industries. We report the estimates in Table IX. We find that workers benefit most from exposure to other industries in their diversified firms when they work in high skill industries. We also see a similar pattern to the one uncovered by the wage partition: the effect for workers in low skill industries disappears when we compare them only to other workers who switch between the same two industries. Thus, for low skill vocations, the benefit of diversification may derive more from synergies in production processes

¹⁷Ideally, 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 available for research purposes. We only observe the fraction of workers with each SOC code at the 2-digit SIC level.

– leading to non-random selection of which SIC codes are grouped together – than from human capital gains. On the other hand, the effect remains strong and significant for workers in high skill industries.¹⁸ 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 impact of moving to an industry in which the worker’s former firm operates for either type of transition by a worker who originates in a low skill job. On the other hand, workers who originate in high skill jobs benefit whether they move to another high skill or to a low skill position.

Overall, the evidence confirms a key prediction of our hypothesis: the impact of diversification on worker skills is most keenly felt among workers of high ability and in industries in which human capital is a key driver of productivity.

II.D. Diversification and Wage Levels

Thus far we have tested the predictions of our hypothesis for changes in worker wages upon displacement. The evidence is consistent with the workers in diversified firms developing general skills and, as a result, significantly higher outside options than workers in focused firms in their home industries. If wages are set through a bargaining process, then wage levels in diversified firms should also reflect these higher outside opportunities. However, it is important to note that workers cannot necessarily obtain the full rents from their heightened productivity in the diversified firm. If there is no other diversified firm with the same structure, then they can obtain the maximum wage among focused firms that operate in the industries in which they enjoy expertise. The residual cash flow remains with the firm. Thus, both the firm and worker receive rents from diversification.

When we consider wage levels (rather than job changes), focusing on workers in closing plants no longer provides an identification advantage. Thus, we test our hypothesis on the random sample of 251,440 worker-quarters described in Section I.¹⁹ We estimate a standard

¹⁸The between-group difference is marginally insignificant (p -value = 0.1093).

¹⁹As an additional robustness check, we also use this random sample to replicate our key regressions from Table III. We find qualitatively similar patterns, confirming the external validity of our estimates on the closure subsample.

wage regression. The dependent variable is the natural logarithm of the real annual wage. As independent variables, 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 include the number of plants in the firm, an indicator for multi-unit firms,²⁰ and the natural logarithms of employment in the worker’s SEIN (or, firm-unit) and employment in the firm. We include state, year, and 2-digit SIC code fixed effects and continue to cluster standard errors at the firm-level. The results in our sample – reported in Column 1 of Table X – conform to the usual patterns in the literature. More experienced workers earn higher wages (age, tenure). Workers in larger units and in firms with multiple plants also earn higher wages (Oi and Idson (1999)). We also estimate a significant gender wage gap of 28%. This estimate is in line with Altonji and Blank (1999) who report a 22% gap using data from the March 1996 Current Population Survey (which falls within our sample period).

In Column 2, we add an indicator for firm diversification to the regression. We find that workers in diversified firms earn a 2.1% premium over workers in other firms. In Column 3, we add the three indicators for degrees of diversification in lieu of the simple diversification indicator. More specifically, we construct a firm-level Herfindahl index of employment across the 2-digit SIC codes in which the firm operates. We then define three indicator variables to capture increasing degrees of diversification: (1) $0.75 \leq \text{Herfindahl} < 1$, (2) $0.5 \leq \text{Herfindahl} < 0.75$, and (3) $\text{Herfindahl} < 0.5$. Focused firms (the benchmark sample) have Herfindahl indices equal to 1. We find that worker wages appear to increase with diversification, even controlling for unit and firm size and the number of plants in the firm.

Given the correlation of diversification and firm size – most notably that all of the largest firms are diversified under the Column 2 definition – we take additional steps to separate the effects to the greatest degree possible. The reported estimates in Columns 2 and 3 appear to be the lower bounds of the effect of diversification: We find no additional loss of explanatory power if we include the square of firm size (as the sole additional control or in addition to the squares of the number of plants and plant size) or if we control for size less parametrically by

²⁰Both the multi-unit indicator and the number of plants are computed using information from the LBD. Plants are LBDNUM under the firm’s LBD firmid. Multi-unit firms have more than one plant.

including, for example, dummies for each decile of the size distribution. Thus, we conclude that workers in diversified firms indeed enjoy a wage premium relative to peers in focused firms.

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, like fringe benefits, can be attributed to rank-and-file workers. Our analysis demonstrates that workers in diversified firms indeed receive a wage premium over workers in focused firms throughout the wage distribution, even after including detailed controls for workforce composition (experience, race, gender, etc.). However, our results also suggest that diversification facilitates improvements in worker skills and opportunities. Thus, higher wage payments do not necessarily indicate rent dissipation, since workers in diversified firms can also obtain higher wages outside their firms.

III. Diversification and the Redeployment Option

Our evidence suggests that the opportunities and incentives to acquire general skills inside diversified firms provide benefits to the firms’ workers. Workers accrue human capital in diversified firms that is more valuable both internally and externally. Next, we ask whether this redeployment is likely to increase firm value. Rather than trying to tie worker characteristics directly to firm valuations, we test whether patterns of worker movement within the firm are consistent with value-maximizing re-deployment of workers. Our approach is analogous to studies which ask how diversified firms allocate scarce investment resources across divisions with differing opportunities. If there are constraints on the ability to hire workers with appropriate skills in the external market, do diversified firms re-allocate workers internally to the industries with the greatest opportunities in response to shocks?²¹

²¹It is important to note that this is only one mechanism through which the firm may benefit from cultivating generalist workers. For example, we do not measure directly the potential for improved innovation (e.g., by creating more interdisciplinary product improvements).

Before turning to our tests, we provide some summary evidence on the activity within internal labor markets. We consider a random sample of 89,099 workers who remain in the same multi-unit firm from the quarter of observation t to quarter $t + 6$.²² Of these workers, 3,964 (4.5%) move to a different unit (i.e., to a different SEIN within the same LBD firmid). This frequency understates the true degree of internal movement since SEINs can consist of many individual plants. We find that internal movement occurs with greater frequency in diversified firms and that movement to units in different 2-digit SIC codes accounts for just over 20% of the job changes in the internal labor markets of such firms. Thus, observable movement between the industries of diversified firms appears to be non-trivial, in addition to the opportunities for exposure to such industries through conduits like the “boundaryless” model of operations in GE.

Next we consider the timing of moves between industries. Are industry changes within diversified firms better timed to changing market conditions? To answer this question, it is important to isolate internal industry changes which are initiated by the firm and not the worker. Thus, we again focus our attention on the sample of workers displaced by plant closure. To begin, we estimate the impact of expected industry growth on the likelihood that displaced workers change industries. 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 estimate a logit regression 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 our typical worker-level controls for pre-closure wage, age, race, gender, and tenure as well as an indicator variable for the plant manager. We also control for the natural logarithms of firm and plant employment and include both an indicator for multi-unit firms and a control for the total number of plants. We include four additional controls to capture differences across workers in the costs of moving or switching industries: the natural logarithms of the number of plants in the same county and 2-digit SIC code as the worker’s closing plant, the total number of plants in the county, and the number of plants in the county in the worker’s quarter $t + 4$ SIC code as well as an indicator for whether the worker was born in the state in which the closing plant is located. To

²²This sample is a subsample of the sample of random workers from the LEHD data summarized in Table II, Panel A. We look at a six quarter window only to maintain consistency with the windows we used in our earlier analysis of workers displaced by plant closure. This choice has no impact on our conclusions.

proxy for expected growth in the worker’s current industry, we compute the realized difference in the natural logarithm of industry Q from year $t + 1$ to year $t + 3$.²³ Though we use future values as an independent variable, reverse causality is not a major concern since the unit of observation is an individual worker and we measure future performance at the industry level. Finally, we include an indicator variable for firm diversification (i.e., operations in at least two distinct 2-digit SIC codes) and its interaction with the expected industry growth rate of the worker’s current industry.

In Column 1 of Table XI, we report the results on the full sample. 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 ($Chg_Q * Diversified$) has a negative sign and is significant at the 5% level. Because the logit regression is nonlinear, the coefficient estimate on $Chg_Q * Diversified$ is not equal to the interaction effect. We compute the marginal effect of the interaction on the probability of switching industries at the mean of the independent variables to be a significant 0.19. Thus, it appears that diversified firms facilitate the movement of workers out of industries which are expected to decline. We also see some interesting patterns among the controls: Hispanic workers and “other minority workers” (excluding Black and Asian workers) are significantly less likely to switch industries. Older workers, high wage workers, and longer tenured workers are also less likely to switch industries. On the other hand, women and managers are particularly likely to switch industries. The latter effect is strong economically and statistically and runs counter to the general impact of higher wages.

In Columns 2 and 3, we estimate the same regression specification, separately on the subsamples of workers who originate in high- and low-skill industries. To classify industries, we use the same SOC-based criteria as in Section II.C.. Consistent with our prior evidence, we find that the estimated sensitivity of industry changes to expected industry returns in diversified firms is higher for workers in high-skill industries. Thus, it is indeed high-ability workers who

²³We use the median value of Q in the 2-digit SIC code among publicly traded firms in the Compustat universe. Thus, we implicitly assume 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.

exit industries with poor opportunities at the highest rate. We also ask whether the effect is particularly strong among workers who switch industries within the diversified firm. Though the point estimate does indeed appear to be stronger among such workers, we do not estimate a statistically significant difference from the rate at which workers from diversified firms exit the declining industry in the external market. Nevertheless, the evidence confirms that diversified firms do redeploy workers internally away from declining industries.

Next, we ask whether diversified firms retain and re-deploy their workers when the returns to doing so are likely to be high. We consider only the subsample of displaced workers who originate in a diversified firm. We run a logit regression with a dependent variable indicating that the worker moved to a new job within the same diversified firm. As controls, we include our usual indicators for race, gender, and managers together with continuous controls for worker age, tenure and pre-closure wage. We also include our usual set of firm size controls: the number of plants and the natural logarithms of plant and firm employment. Finally, we include our four controls for local opportunities and moving costs. We construct a measure of the future opportunities within the firm by considering the firm's industry portfolio. We compute an employee-weighted average of industry Q across the industries in which the firm still operates in the year following the plant closure and include it as an independent variable.²⁴ In Column 4 of Table XI, we report the results. We find that firms are significantly more likely to retain workers inside the firm when their future opportunities are strong. We compute the marginal effect on the probability of staying in the firm at the mean of the independent variables, finding a significant estimate of 0.10. Mirroring Panel A, we re-estimate the regression separately for workers originating in high- and low-skill industries (Columns 5 and 6). We again find that the sensitivity of the choice to retain workers in the diversified firm to internal opportunities is stronger for high-ability workers. Such workers are likely both to have higher marginal productivity (i.e., generate more cash flows for the firm) and to be more scarce in the external market. Together with our findings from Panel A, our results suggest that diversified firms play an important role (relative to the external labor market) in re-deploying workers from declining to expanding industries. Moreover, this ability to adapt more easily to chang-

²⁴We 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%.

ing market conditions – as a result of the increased mobility of labor – is likely to generate significant value for the firm.

As a final step, we consider the impact of diversification on the allocation of workers across industries. We use the pattern of industry changes between 2-digit SIC codes among workers in focused firms as a benchmark. We consider only job changes in the external market. We then partition industry changes among workers in diversified firms into two groups: moves to industries in which the workers’ original firms operate and moves to industries not spanned by their original firms. We aggregate, industry by industry, the number of workers in the former group as a fraction of the total number of workers in diversified firms who switch industries. We then aggregate across industries in which the diversified firms operate the difference between the fraction of workers who moved to the industry and the focused firm benchmark. We also restrict our attention to industry transitions which occur for at least five workers. We find that for a given SIC pair, workers from diversified firms are more likely to make the transition compared to workers from focused firms if the new SIC is operated by the diversified firm, and the difference is statistically significant, with a t -statistic of 2.27 (Table XII, Panel A). Thus, diversified firms appear to shift the distribution of workers toward industries in which they operate (relative to the choices made by workers in focused firms). We also re-do the comparison, splitting the sample into workers who originate in high-skill 2-digit SIC codes (Panel B) and workers who originate in low-skill 2-digit SIC codes. Again, the industry skill classification is based on the distribution of SOC codes within the industry. We find that the result is more pronounced among high-skill workers who exit diversified firms; we find a significant difference between the industry changes among workers from diversified and focused firms only in this group. These results are consistent with our finding in Table III that workers suffer smaller wage losses when they move industries in which their former diversified firms operate and with heightened mobility as the underlying economic mechanism. We observe a spillover from the experience workers obtain in a diversified firm to their future career choices, even when those choices take them outside the diversified firm.

Overall, diversified firms not only re-deploy workers from declining to expanding industries internally, but also facilitate broader movements of workers to industries in which their labor has a higher marginal return.

IV. Worker Mobility and the Diversification Discount

Our analysis demonstrates that the labor stocks of diversified firms are significantly different from those of focused firms operating in the same industries. Workers from diversified firms have heightened cross-industry mobility – particularly among the set of industries in which their diversified firms operate – and, therefore, command extra compensation. The skills and expertise which underlie this mobility are a form of organization capital for the diversified firm. As such, it can carry a risk premium in financial markets and can generate a cross-sectional discount in the prices of publicly traded diversified firms relative to the median focused firms in their industries. Thus, the labor differences we identify are consistent with both higher productivity (or cash flows) among diversified firms and with a discount in equity markets.

As a final step, we test for a link between the diversification discount and worker mobility. To conduct this test, it is necessary to restrict our sample to publicly traded firms, for which we observe equity prices. We also require a measure which captures differences in the external mobility of workers across diversified firms. Because we only observe workers in the LEHD data for 23 U.S. states, we do not observe the full workforces among large diversified firms. Though this is not an impediment for our worker-level analyses, it could introduce serious biases in aggregating the individual worker-level data to create such a firm-level measure. As an alternative, we use our proxies for high- and low-skill industries from Section II.C. to capture differences across firms in worker mobility. In particular, we ask whether diversified firms that hold a higher proportion of their assets in business segments operating in high-skill industries have higher discounts than diversified firms that operate more intensively in low-skill industries.

In Column 1 of Table XIII, we report the average diversification discount among publicly-traded multi-segment firms during our sample period of 1992 to 2004. We find that such firms receive a discount of roughly 10%, significant at the 1% level. In Column 2, we add a continuous measure for the percentage of firm assets in high-skill industries. We find a coefficient estimate that is positive and significant at the 1% level. Economically, a firm operating 100% in high-skill industries would have a discount roughly twice as large as a firm operating 100% in low-skill industries. In Column 3, we add several firm-level controls to the regression. To control for differences in the discount driven by differences in profitability we include firm

ROA. We also include firm size, asset tangibility, investment, cash holdings, book leverage, and an indicator for dividend payers to capture differences in opportunities and the ability to access capital markets. Finally, we include year effects to capture macroeconomic patterns in firm composition and stock prices. We find little impact on the magnitude of our estimate of the effect of worker-skill on the discount. Finally, in Column 4, we eliminate all firms which operate a business segment in the financial industry (1-digit segment SIC = 6). Again, our results are virtually unchanged.

We perform a number of additional robustness checks on the evidence. We experiment with the definition of unrelated segments (i.e., total number of business segments vs. segments in different 3-digit SIC codes vs. segments in different 2-digit SIC codes) with little qualitative impact on the results. We also use sales based multiples rather than asset based multiples to measure the discount (following Berger and Ofek (1995)) and compute the percentage of sales from high-skill versus low-skill industries, again with little impact on the results.

Overall, we find that diversified firms that operate in industries that employ more high-skilled, highly mobile workers receive a larger discount in the cross-section (relative to the median stand-alone firm operating in their industries). Taken together, our results suggest that a diversification discount need not reflect inefficient operation of the diversified firm. To the contrary, diversified firms can generate higher cash flows, yet carry a risk premium due to larger stocks of organization capital. Thus, it does not follow that conglomerate firms would be worth more separated into their constituent parts than as a whole: the resulting firms would generate smaller cash flows by giving up the benefits of “boundaryless” operations, but would retain more mobile workers than the median firms in their industries (at least for as long as they retained their current workforces). In this case, they would continue to carry a risk premium. An interesting question, but beyond the scope of our cross-sectional analysis, is to consider the importance of these factors in the original decision to diversify.

V. Conclusion

We use a unique approach which combines worker-firm matched data from the U.S. Census Bureau’s LEHD program with plant- 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 workforces of diversified and focused firms. In particular, diversified firms cultivate general worker skills that increase worker mobility across industries. Diversified firms benefit from the resulting real option to redeploy labor to sectors with greater marginal returns in response to economic shocks.

We use plant 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 change jobs internally significantly outperform workers who leave their firms. We also find that workers change industries within diversified firms without a significant loss in wages, while the entirety of the wage losses from changing jobs externally accrues to workers who change industries. However, 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 workers who move to an entirely new industry. The latter result is consistent with the hypothesis that diversified firms encourage and benefit from 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 test an additional implication of our hypothesis. We find that the benefit of switching industries from a diversified firm accrues almost entirely to workers in high-skill vocations, measured using either pre-closure wage levels or Standard Occupational Classification codes.

Finally, we confirm that redeployment benefits not just the workers, but also the firm. We find that workers who switch industries in diversified firms are more likely to leave industries with declining opportunities. In addition, diversified firms are more likely to retain workers following plant closure when the future opportunities of their remaining segments are high.

Our results provide a potential reconciliation of several seemingly unrelated cross-sectional differences between diversified and focused firms. We offer an explanation for higher observed wage levels in diversified firms, even controlling for firm size and individual worker charac-

teristics. Diversified firms cultivate generalist workers with higher interindustry mobility and outside options. Thus, higher wages do not necessarily indicate rent dissipation since 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 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 towards struggling divisions. Yet, there is evidence in the literature that diversified firms are more productive than focused firms 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 towards industries with good opportunities does not necessarily indicate “socialistic redistribution” of resources in firms with higher labor mobility. An interesting avenue for future research is 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. However, the importance of this mechanism is difficult to evaluate by comparing the cross-section of diversified and focused firms. Moreover, 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. In ongoing research, we examine the labor market choices of firms which make diversifying acquisitions relative to firms which 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 impact of different organizational structures on the operations of the firm and, ultimately, what factors matter in determining firm boundaries.

References

- [1] Altonji, J. G. and R. M. Blank, 1999, Race and gender in the labor market in O. Ashenfelter and R. Layard, eds., *Handbook of Labor Economics*, Volume 3, 3143-3259.
- [2] Baker, G., M. Gibbs and B. Holmstrom, 1994a, The internal economics of the firm: Evidence from personnel data, *Quarterly Journal of Economics* 109, 881-919.
- [3] Baker, G., M. Gibbs and B. Holmstrom, 1994b, The wage policy of a firm, *Quarterly Journal of Economics* 109, 921-955.
- [4] Berger, P.G. and E. Ofek, 1995, Diversification's effect on firm value, *Journal of Financial Economics* 37, 39-65.
- [5] Campa, J. and S. Kedia, 2002, Explaining the diversification discount, *Journal of Finance* 57, 1731-1762.
- [6] Donangelo, A., 2011, Labor Mobility and the Cross-Section of Expected Returns, Mimeo.
- [7] Eisfeldt, A. and D. Papanikolaou, 2011, Organization capital and the cross-section of expected returns, Mimeo.
- [8] Gibbons, R. and L.F. Katz, 1991, Layoffs and lemons, *Journal of Labor Economics* 9, 351-380.
- [9] Giroud, X., 2010, Soft information and investment: Evidence from plant-level data, Mimeo.
- [10] Graham, J.R., M.L. Lemmon and J. Wolf, 2002, Does corporate diversification destroy value? *Journal of Finance* 57, 695-720.
- [11] Hart, O, 1995, *Firms, contracts, and financial structure*. London: Oxford University Press.
- [12] Hund, J., D. Monk and S. Tice, 2010, Uncertainty about average profitability and the diversification discount, *Journal of Financial Economics* 96, 463-484.
- [13] Kuppuswamy, V. and B. Villalonga, 2010, Does diversification create value in the presence of external financing constraints? Evidence from the 2007-2009 financial crisis, Working paper, Harvard University.
- [14] Lamont, O., 1997, Cash flow and investment: Evidence from internal capital markets, *Journal of Finance* 52, 83-109.
- [15] Lang, L. and R. Stulz, 1994, Tobin's Q, corporate diversification and firm performance, *Journal of Political Economy* 102, 1248-1280.
- [16] Lazear, E., 2009, Firm-specific human capital: A skill weights approach, *Journal of Political Economy* 117, 914-940.
- [17] Lazear, E. and P. Oyer, 2004a, Internal and external labor markets: A personnel economics approach, *Labour Economics* 11, 527-554.

- [18] Lazear, E. and P. Oyer, 2004b, The structure of wages and internal mobility, *AER Papers & Proceedings* 94, 212-216.
- [19] Maksimovic, V., and G.M. Phillips, 2002, Do conglomerate firms allocate resources inefficiently across industries? Theory and evidence, *Journal of Finance* 57, 721-767.
- [20] Maksimovic, V., and G.M. Phillips, 2007, Conglomerate firms and internal capital markets in Eckbo, B.E. (ed.), *Handbook of Corporate Finance: Empirical Corporate Finance*, Elsevier/North-Holland.
- [21] Morck, R., A. Shleifer and R.W. Vishny, 1990, Do managerial motives drive bad acquisitions? *Journal of Finance* 45, 31-48.
- [22] Neal, Derek, 1995, Industry-specific human capital: Evidence from displaced workers, *Journal of Labor Economics* 13, 653-677.
- [23] Oi, W.Y. and T.L. Idson, 1999, Firm size and wages in O. Ashenfelter and R. Layard, eds., *Handbook of Labor Economics*, Volume 3, 2165-2214.
- [24] Ozbas, O. and D. S. Scharfstein, 2010, Evidence on the dark side of internal capital markets, *Review of Financial Studies* 23, 581-599.
- [25] Rajan, R., H. Servaes, and L. Zingales, 2000, The cost of diversity: The diversification discount and inefficient investment, *Journal of Finance* 55, 35-80.
- [26] Scharfstein, D., and J. Stein, 2000, The dark side of internal capital markets: Divisional Rent-Seeking and Inefficient Investment, *Journal of Finance* 55, 3537-64
- [27] Schoar, A., 2002, Effects of corporate diversification on productivity, *Journal of Finance* 57, 2379-2403.
- [28] Stein, J., 1997, Internal capital markets and the competition for corporate resources, *Journal of Finance* 52, 111-33
- [29] Stein, J., 2003, Agency, information and corporate investment in Constantinides, G., M. Harris, and R. Stulz (eds.) *Handbook of the Economics of Finance*. Amsterdam: North Holland.
- [30] Villalonga, B., 2004, Diversification discount or premium? New evidence from the business information tracking series, *Journal of Finance* 59, 475-502.

Table I
Summary Statistics: Plant Level

Panel A reports summary statistics of a random sample of closing plants in the LBD, a random sample of non-closing plants from the LBD, and the subsample of closing plants from the LBD that we match with worker-level data from the LEHD program. Panel B reports the corresponding statistics for the subsamples of plants from multi-unit firms. We define multi-unit firms as firms which operate at least two distinct plants. Standard errors are reported in parentheses for continuous variables.

	Panel A: All Firms			Panel B: Multi-Unit Firms Only		
	Random Plants in the LBD (N=655,929)	Closing Plants in the LBD (N=143,370)	Closing Plants in the LBD Matched with the LEHD (N=12,439)	Random Plants in the LBD (N=383,238)	Closing Plants in the LBD (N=70,811)	Closing Plants 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	
SIC = 2	0.08	0.08	0.08	0.09	0.08	
SIC = 3	0.10	0.08	0.07	0.10	0.09	
SIC = 4	0.06	0.07	0.05	0.08	0.08	
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	
SIC = 7	0.13	0.19	0.24	0.13	0.18	
SIC = 8	0.21	0.16	0.13	0.15	0.13	
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

*Some industries have a limited number of firms. Due to potential disclosure risk, we cannot report the industry distribution for this subsample.

Table II
Summary Statistics: Worker Level

Panel A reports summary statistics for a random sample of workers from the LEHD data. Panel B reports summary statistics for workers matched to closing plants 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 plants and diversified firms as firms which operate in more than one two-digit SIC code. Standard errors are reported in parentheses for continuous variables.

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 Plants 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 (54,517)	\$29,751 (56,278)	\$28,642 (33,666)	\$31,781 (44,897)
Age	39.68 (11.43)	39.53 (11.47)	39.59 (11.53)	40.89 (10.99)
Tenure (in yrs)	2.57 (2.20)	2.52 (2.18)	2.69 (2.51)	2.96 (2.17)
Education (in yrs)	13.66 (2.66)	13.64 (2.67)	13.64 (2.60)	13.82 (2.60)
% of Female	0.41	0.41	0.42	0.41
Race = Black	0.10	0.10	0.13	0.11
Race = Asian	0.04	0.04	0.05	0.04
Race = Hispanic	0.12	0.13	0.10	0.09
Race = Other	0.06	0.06	0.05	0.05
% of Foreigner	0.19	0.19	0.18	0.15

Table IV
Wage Changes: Persistence

The table reports estimated coefficients from OLS regressions on a sample of workers in closing plants of multi-unit firms. Plant closures are identified using the LBD and the sample is restricted to closing plants which uniquely link to closing units in the LEHD data. The dependent variable is the change in the annual real wage from quarter (t-2) to (t+8) or from quarter (t-2) to (t+12), as indicated in the column header. t is the last quarter prior to plant closure. Ln(Wage) is the natural log of the annual real wage. Ln(Age) is the natural log of the worker's age. 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_plants is the number of plants owned by the firm, divided by 100. Ln(PlantEmp) is the natural log of plant employment. Ln(FirmEmp) is the natural log of aggregate firm employment. Chg(N_Plants), Chg(PlantEmp), and Chg(FirmEmp) are the differences between the old and new firm in N_plants, plant employment, and firm employment, respectively. Diversified is an indicator variable equal to one for firms that operate in at least two distinct two-digit SIC codes. Same_Firm is an indicator variable that equals one if the worker is retained within the firm (firmid) and zero otherwise. D_DIFSIC 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. Firm_SIC 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 and zero otherwise. All independent variables except Chg(N_Plants), Chg(PlantEmp), 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.

	$\Delta\text{Wage}_{t-2,t+8}$			$\Delta\text{Wage}_{t-2,t+12}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Wage)	-0.123 *** (0.009)	-0.145 *** (0.010)	-0.131 *** (0.009)	-0.137 *** (0.012)	-0.158 *** (0.015)	-0.149 *** (0.012)
Ln(Age)	-0.204 *** (0.011)	-0.182 *** (0.011)	-0.179 *** (0.011)	-0.246 *** (0.016)	-0.231 *** (0.017)	-0.220 *** (0.016)
Race = Black	-0.043 *** (0.008)	-0.044 *** (0.008)	-0.033 *** (0.008)	-0.039 *** (0.010)	-0.046 *** (0.009)	-0.037 *** (0.009)
Race = Asian	0.003 (0.014)	-0.007 (0.012)	-0.004 (0.015)	0.002 (0.021)	-0.019 (0.017)	-0.009 (0.021)
Race = Hispanic	-0.051 *** (0.008)	-0.042 *** (0.007)	-0.047 *** (0.008)	-0.043 *** (0.010)	-0.042 *** (0.009)	-0.045 *** (0.010)
Race = Other Minorities	-0.003 (0.008)	-0.009 (0.008)	-0.005 (0.008)	0.000 (0.011)	-0.006 (0.011)	-0.005 (0.010)
Female	-0.060 *** (0.008)	-0.066 *** (0.008)	-0.051 *** (0.006)	-0.052 *** (0.010)	-0.064 *** (0.010)	-0.043 *** (0.008)
Ln(Tenure)	-0.033 *** (0.005)	-0.030 *** (0.005)	-0.032 *** (0.005)	-0.044 *** (0.006)	-0.046 *** (0.006)	-0.042 *** (0.006)
Manager	0.012 (0.025)	0.052 * (0.027)	0.024 (0.025)	0.024 (0.036)	0.053 (0.040)	0.030 (0.036)
N_Plants	-0.002 *** (0.001)		-0.003 *** (0.001)	-0.001 (0.001)		0.000 (0.002)
Ln(PlantEmp)	-0.006 (0.008)	-0.008 (0.014)	-0.004 (0.006)	0.001 (0.007)	-0.013 * (0.008)	0.009 (0.008)
Ln(FirmEmp)	0.008 ** (0.004)		0.010 *** (0.004)	0.008 (0.005)		0.007 (0.006)
Chg (N_Plants)	-0.002 *** (0.001)	-0.002 *** (0.000)	-0.001 ** (0.000)	-0.001 (0.000)	-0.002 ** (0.000)	-0.001 (0.000)
Chg (PlantEmp)	0.002 (0.004)	-0.004 (0.004)	0.006 * (0.003)	-0.002 (0.004)	-0.010 *** (0.004)	0.001 (0.006)
Chg (FirmEmp)	0.015 *** (0.003)	0.020 *** (0.003)	0.010 *** (0.003)	0.017 *** (0.003)	0.024 *** (0.003)	0.013 *** (0.003)
Diversified	-0.004 (0.014)		-0.008 (0.014)	0.021 (0.017)		0.008 (0.017)
Same_Firm	0.017 (0.015)	-0.019 (0.025)	0.010 (0.015)	0.020 (0.019)	-0.013 (0.028)	0.005 (0.019)
D_DIFSIC	-0.116 *** (0.016)	-0.108 *** (0.020)		-0.097 *** (0.017)	-0.086 *** (0.021)	
Same_Firm * D_DIFSIC	0.029 (0.028)	0.035 (0.047)	0.057 (0.040)	-0.001 (0.034)	-0.011 (0.050)	0.055 (0.061)
D_DIFSIC * Firm_SIC	0.104 *** (0.015)	0.103 *** (0.015)	0.034 ** (0.017)	0.091 *** (0.020)	0.077 *** (0.022)	0.038 (0.024)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes			Yes		
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Plant Fixed Effects		Yes			Yes	
SIC Pair Fixed Effects			Yes			Yes
R ²	0.152	0.241	0.308	0.165	0.259	0.334
N	28,531	28,531	28,531	18,473	18,473	18,473

Table VI
Alternative Explanations: Industry Classification

The table reports estimated coefficients from OLS regressions on a sample of workers in closing plants of multi-unit firms. Plant closures are identified using the LBD and the sample is restricted to closing plants which uniquely link to closing units in the LEHD data. The dependent variable is the change in the annual real wage from quarter (t-2) to (t+4). t is the last quarter prior to plant closure. Ln(Wage) is the natural log of the annual real wage. Ln(Age) is the natural log of the worker's age. 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_plants is the number of plants owned by the firm, divided by 100. Ln(PlantEmp) is the natural log of plant employment. Ln(FirmEmp) is the natural log of aggregate firm employment. Chg(N_Plants), Chg(PlantEmp), and Chg(FirmEmp) are the differences between the old and new firm in N_plants, plant employment, and firm employment, respectively. Diversified is an indicator variable equal to one for firms that operate in at least two distinct two-digit SIC codes. Same_Firm is an indicator variable that equals one if the worker is retained within the firm (firmid) and zero otherwise. D_DIFSIC_1 is an indicator variable that equals 1 if the job in quarter t+4 has a different 1-digit SIC than the job in quarter t-2 and zero otherwise. Firm_SIC 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 and zero otherwise. All independent variables except Chg(N_Plants), Chg(PlantEmp), 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.

	(1)	(2)	(3)
Ln(Wage)	-0.109 *** (0.009)	-0.137 *** (0.010)	-0.121 *** (0.008)
Ln(Age)	-0.116 *** (0.010)	-0.096 *** (0.009)	-0.104 *** (0.009)
Race = Black	-0.039 *** (0.008)	-0.044 *** (0.006)	-0.035 *** (0.007)
Race = Asian	0.002 (0.014)	0.002 (0.011)	-0.003 (0.014)
Race = Hispanic	-0.023 *** (0.008)	-0.029 *** (0.006)	-0.028 *** (0.007)
Race = Other Minorities	-0.016 ** (0.008)	-0.023 *** (0.007)	-0.018 ** (0.007)
Female	-0.040 *** (0.005)	-0.050 *** (0.005)	-0.035 *** (0.005)
Ln(Tenure)	-0.020 *** (0.005)	-0.017 *** (0.004)	-0.020 *** (0.004)
Manager	-0.002 (0.021)	0.044 ** (0.021)	0.010 (0.020)
N_Plants	-0.003 *** (0.001)		-0.003 *** (0.001)
Ln(PlantEmp)	-0.004 (0.008)	0.012 * (0.007)	-0.001 (0.006)
Ln(FirmEmp)	0.011 *** (0.004)		0.013 *** (0.004)
Chg (N_Plants)	-0.003 *** (0.000)	-0.003 *** (0.000)	-0.002 *** (0.000)
Chg (PlantEmp)	-0.003 (0.003)	-0.006 * (0.004)	0.000 (0.003)
Chg (FirmEmp)	0.018 *** (0.002)	0.020 *** (0.002)	0.016 *** (0.003)
Diversified	-0.002 (0.013)		-0.018 (0.012)
Same_Firm	0.037 *** (0.014)	0.017 (0.020)	0.031 * (0.016)
D_DIFSIC_1	-0.140 *** (0.016)	-0.122 *** (0.019)	
Same_Firm * D_DIFSIC_1	0.069 ** (0.035)	0.062 (0.044)	0.083 ** (0.041)
D_DIFSIC_1 * Firm_SIC	0.100 *** (0.019)	0.092 *** (0.019)	0.047 *** (0.018)
State Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes		
Year Fixed Effects	Yes	Yes	Yes
Plant Fixed Effects		Yes	
SIC Pair Fixed Effects			Yes
R ²	0.115	0.204	0.260
N	42,354	42,354	42,354

Table VII
Alternative Explanations: Prior Industry Experience

The table reports estimated coefficients from OLS regressions on a sample of workers in closing plants of multi-unit firms. Plant closures are identified using the LBD and the sample is restricted to closing plants which uniquely link to closing units in the LEHD data. The dependent variable is the change in the annual real wage from quarter (t-2) to (t+4). t is the last quarter prior to plant closure. Ln(Wage) is the natural log of the annual real wage. Ln(Age) is the natural log of the worker's age. 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_plants is the number of plants owned by the firm, divided by 100. Ln(PlantEmp) is the natural log of plant employment. Ln(FirmEmp) is the natural log of aggregate firm employment. Chg(N_Plants), Chg(PlantEmp), and Chg(FirmEmp) are the differences between the old and new firm in N_plants, plant employment, and firm employment, respectively. Diversified is an indicator variable equal to one for firms that operate in at least two distinct two-digit SIC codes. Same_Firm is an indicator variable that equals one if the worker is retained within the firm (firmid) and zero otherwise. D_DIFSIC 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. Firm_SIC 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 and zero otherwise. Prior Experience is an indicator variable equal to one if the worker changed industries between quarters t-2 and t+4, but had experience working in the new industry prior to joining the t-2 employer. All independent variables except Chg(N_Plants), Chg(PlantEmp), 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.

	(1)	(2)	(3)
Ln(Wage)	-0.111 *** (0.009)	-0.138 *** (0.009)	-0.121 *** (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	-0.024 *** (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)
Female	-0.041 *** (0.005)	-0.051 *** (0.005)	-0.035 *** (0.005)
Ln(Tenure)	-0.021 *** (0.005)	-0.019 *** (0.004)	-0.021 *** (0.004)
Manager	-0.001 (0.021)	0.045 ** (0.021)	0.009 (0.020)
N_Plants	-0.003 *** (0.001)		-0.003 *** (0.001)
Ln(PlantEmp)	-0.003 (0.007)	0.013 * (0.008)	-0.001 (0.006)
Ln(FirmEmp)	0.009 ** (0.004)		0.013 *** (0.004)
Chg (N_Plants)	-0.003 *** (0.000)	-0.003 *** (0.001)	-0.002 *** (0.000)
Chg (PlantEmp)	-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	0.028 * (0.016)	0.006 (0.023)	0.031 * (0.016)
D_DIFSIC	-0.139 *** (0.017)	-0.120 *** (0.022)	
Same_Firm * D_DIFSIC	0.040 (0.031)	0.062 (0.043)	0.066 * (0.036)
D_DIFSIC * Firm_SIC	0.113 *** (0.015)	0.106 *** (0.015)	0.039 ** (0.016)
Prior Experience	-0.033 ** (0.015)	-0.039 *** (0.013)	-0.013 (0.014)
Same_Firm * Prior Experience	0.068 (0.056)	-0.030 (0.039)	-0.010 (0.046)
D_DIF_SIC * Firm_SIC * Prior Experience	-0.017 (0.030)	-0.011 (0.027)	-0.010 (0.023)
State Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes		
Year Fixed Effects	Yes	Yes	Yes
Plant Fixed Effects		Yes	
SIC Pair Fixed Effects			Yes
R ²	0.115	0.204	0.260
N	42,354	42,354	42,354

Table VIII
Worker Skill: Wage Splits

The table reports estimated coefficients from OLS regressions on a sample of workers in closing plants of multi-unit firms. Plant closures are identified using the LBD and the sample is restricted to closing plants which uniquely link to closing units in the LEHD data. The dependent variable is the change in the annual real wage from quarter (t-2) to (t+4). t is the last quarter prior to plant closure. Variable definitions for demographic and firm controls are presented on Table III. $x \leq y$ are indicator variables equal to 1 if the worker's real annual wage in quarter t-2 falls in the indicated range. D_DIFSIC 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. Firm_SIC 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 and zero otherwise. All independent variables except Chg(N_Plants), Chg(PlantEmp), 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.

	(1)	(2)	(3)
Wage < 25K	0.091 *** (0.012)	0.307 *** (0.033)	0.097 *** (0.011)
25K ≤ Wage < 50K	0.035 *** (0.008)	0.250 *** (0.031)	0.032 *** (0.008)
Wage ≥ 100K	-0.193 *** (0.030)		-0.187 *** (0.030)
Ln(Age)	-0.126 *** (0.010)	-0.109 *** (0.009)	-0.114 *** (0.009)
Race = Black	-0.030 *** (0.008)	-0.033 *** (0.006)	-0.024 *** (0.007)
Race = Asian	0.008 (0.013)	0.008 (0.010)	0.002 (0.014)
Race = Hispanic	-0.014 * (0.008)	-0.016 ** (0.006)	-0.017 ** (0.007)
Race = Other Minorities	-0.015 * (0.008)	-0.020 *** (0.007)	-0.018 ** (0.007)
Female	-0.032 *** (0.005)	-0.039 *** (0.005)	-0.024 *** (0.005)
Ln(Tenure)	-0.023 *** (0.005)	-0.023 *** (0.004)	-0.023 *** (0.004)
Manager	-0.014 (0.020)	0.021 (0.021)	-0.010 (0.020)
N_Plants	-0.003 *** (0.001)		-0.003 *** (0.001)
Ln(PlantEmp)	-0.002 (0.007)	0.020 *** (0.008)	0.000 (0.006)
Ln(FirmEmp)	0.010 ** (0.004)		0.013 *** (0.004)
Chg (N_Plants)	-0.003 *** (0.000)	-0.003 *** (0.001)	-0.002 *** (0.000)
Chg (PlantEmp)	-0.002 (0.003)	-0.006 * (0.003)	0.000 (0.003)
Chg (FirmEmp)	0.017 *** (0.002)	0.019 *** (0.002)	0.016 *** (0.002)
Diversified	-0.009 (0.012)		-0.022 * (0.012)
Same_Firm	0.024 (0.015)	0.007 (0.023)	0.026 (0.016)
Same_Firm * D_DIFSIC	0.050 * (0.030)	0.048 (0.041)	0.059 (0.038)
D_DIFSIC * (Wage < 25K)	-0.128 *** (0.013)	-0.103 *** (0.015)	0.024 (0.065)
D_DIFSIC * (25K ≤ Wage < 50K)	-0.163 *** (0.027)	-0.147 *** (0.032)	0.000 (0.065)
D_DIFSIC * (50K ≤ Wage < 100K)	-0.134 *** (0.022)	-0.144 *** (0.028)	-0.021 (0.068)
D_DIFSIC * (Wage ≥ 100K)	-0.134 ** (0.063)	-0.181 *** (0.067)	
D_DIFSIC * (Wage < 25K) * Firm_SIC	0.097 *** (0.017)	0.083 *** (0.018)	0.017 (0.017)
D_DIFSIC * (25K ≤ Wage < 50K) * Firm_SIC	0.117 *** (0.025)	0.117 *** (0.024)	0.041 * (0.022)
D_DIFSIC * (50K ≤ Wage < 100K) * Firm_SIC	0.094 *** (0.028)	0.127 *** (0.025)	0.068 ** (0.031)
D_DIFSIC * (Wage ≥ 100K) * Firm_SIC	0.159 ** (0.075)	0.210 *** (0.077)	0.109 (0.082)
State Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes		
Year Fixed Effects	Yes	Yes	Yes
Plant Fixed Effects		Yes	
SIC Pair Fixed Effects			Yes
R ²	0.112	0.197	0.253
N	42,354	42,354	42,354

Table IX
Worker Skill: Occupational Codes

The table reports estimated coefficients from OLS regressions on a sample of workers in closing plants of multi-unit firms. Plant closures are identified using the LBD and the sample is restricted to closing plants which uniquely link to closing units in the LEHD data. The dependent variable is the change in the annual real wage from quarter (t-2) to (t+4). t is the last quarter prior to plant closure. Ln(Wage) is the natural log of the annual real wage. Ln(Age) is the natural log of the worker's age. 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_plants is the number of plants owned by the firm, divided by 100. Ln(PlantEmp) is the natural log of plant employment. Ln(FirmEmp) is the natural log of aggregate firm employment. Chg(N_Plants), Chg(PlantEmp), and Chg(FirmEmp) are the differences between the old and new firm in N_plants, plant employment, and firm employment, respectively. Diversified is an indicator variable equal to one for firms that operate in at least two distinct two-digit SIC codes. Same_Firm is an indicator variable that equals one if the worker is retained within the firm (firmid) and zero otherwise. D_DIFSIC 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. Firm_SIC 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 and zero otherwise. 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. Low_Skill is the complement of High_Skill. All independent variables except Chg(N_Plants), Chg(PlantEmp), 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.

	(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_Plants	-0.003 *** (0.001)		-0.003 *** (0.001)
Ln(PlantEmp)	-0.003 (0.007)	0.012 (0.008)	-0.001 (0.006)
Ln(FirmEmp)	0.009 ** (0.004)		0.013 *** (0.004)
Chg (N_Plants)	-0.003 *** (0.000)	-0.003 *** (0.001)	-0.002 *** (0.000)
Chg (PlantEmp)	-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	0.028 * (0.016)	0.006 (0.023)	0.030 * (0.016)
D_DIFSIC	-0.146 *** (0.015)	-0.121 *** (0.013)	
Same_Firm * D_DIFSIC	0.050 * (0.030)	0.048 (0.041)	0.058 (0.039)
High_Skill * D_DIFSIC	0.004 (0.026)	-0.010 (0.034)	
High_Skill * D_DIFSIC * Firm_SIC	0.117 *** (0.021)	0.114 *** (0.022)	0.055 *** (0.019)
Low_Skill * D_DIFSIC * Firm_SIC	0.091 *** (0.022)	0.084 *** (0.022)	-0.002 (0.029)
State Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes		
Year Fixed Effects	Yes	Yes	Yes
Plant Fixed Effects		Yes	
SIC Pair Fixed Effects			Yes
R ²	0.118	0.205	0.260
N	42,354	42,354	42,354

Table X
Wages in Focused and Diversified Firms

OLS regressions on a random sample of workers from the LEHD data. The dependent variable is the natural log of the annual real wage. Ln(Age) is the natural log of the worker's age. 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_plants is the number of plants owned by the firm, divided by 100. Ln(PlantEmp) is the natural log of aggregate SEIN employment. Ln(FirmEmp) is the natural log of aggregate firm employment. Diversified is an indicator variable equal to one for firms that operate in at least two distinct two-digit SIC codes. Diversified_1, Diversified_2 and Diversified_3 are indicator variables equal to one for firms with Herfindahl indices of employment across two-digit SICs greater than 0.75, between 0.5 and 0.75, and less than 0.5, respectively. All standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Ln(Age)	0.311 *** (0.009)	0.311 *** (0.009)	0.309 *** (0.009)
Race = Black	-0.216 *** (0.005)	-0.216 *** (0.005)	-0.215 *** (0.005)
Race = Asian	-0.068 *** (0.009)	-0.067 *** (0.009)	-0.067 *** (0.009)
Race = Hispanic	-0.304 *** (0.006)	-0.304 *** (0.006)	-0.303 *** (0.006)
Race = Others	-0.046 *** (0.007)	-0.046 *** (0.007)	-0.045 *** (0.007)
Female	-0.280 *** (0.005)	-0.279 *** (0.005)	-0.279 *** (0.005)
Ln(Tenure)	0.080 *** (0.003)	0.080 *** (0.003)	0.080 *** (0.003)
Manager	1.023 *** (0.027)	1.024 *** (0.027)	1.029 *** (0.026)
N_Plants	0.000 ** (0.000)	0.000 ** (0.000)	0.000 ** (0.000)
Ln(PlantEmp)	0.016 *** (0.003)	0.017 *** (0.003)	0.021 *** (0.003)
Ln(FirmEmp)	0.027 *** (0.003)	0.025 *** (0.003)	0.020 *** (0.003)
Multi-Unit	0.018 *** (0.007)	0.006 (0.008)	0.005 (0.008)
Diversified		<i>0.021 **</i> (0.009)	
Diversified_1			<i>0.001</i> (0.010)
Diversified_2			<i>0.042 ***</i> (0.011)
Diversified_3			<i>0.079 ***</i> (0.013)
State Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R ²	0.300	0.300	0.302
N	251,440	251,440	251,440

Table XI
Labor Redeployment

Logit regressions with coefficient estimates presented as log odds ratios. In Panel A, the sample consists of workers in closing plants and the dependent variable is an indicator variable (D_DIFSIC) which equals one if the new job in quarter t+4 is in a different two-digit SIC from the lost job. Plant closures are identified using the LBD and the sample is restricted to closing plants which uniquely link to the LEHD data. In Panel B, the sample consists only of workers in closing plants that are part of a diversified firm. The dependent variable is an indicator variable (Same_Firm) which equals one if the worker remains in the same firm after the plant closure and zero otherwise. Ln(Wage) is the natural log of the annualized wage. Ln(Age) is the natural log of the worker's age. 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_plants is the number of plants owned by the firm, divided by 100. Ln(PlantEmp) is the natural log of aggregate plant employment. Ln(FirmEmp) is the natural log of aggregate firm employment. Diversified is an indicator variable equal to one for firms that operate in at least two distinct two-digit SIC codes. Chg_Q is the change in industry-median Tobin's q over the two years following plant closure. Firm_Q is the payroll weighted average of industry-median q for the remaining plants of the firm. Ln(# of Firms in CT & SIC2) is the natural log of the number of plants that operate in the same 2-digit SIC code and county as the closing plant. Native to State is an indicator variable which equals one if the worker was born in the state in which the closing plant is located. High-skill Industries are industries in which the percentage of workers in the 2-digit SIC in occupations with 2-digit SOC codes less than 29 exceeds the median. Low-skill Industries are the remaining 2-digit SIC codes not classified as High-skill. The standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	Panel A. Industry Changes			Panel B. Internal Job Changes		
	(1)	High-skill Industries (2)	Low-skill Industries (3)	(4)	High-skill Industries (5)	Low-skill Industries (6)
Ln(Wage)	-0.241 *** (0.038)	-0.190 *** (0.049)	-0.354 *** (0.046)	0.411 *** (0.146)	0.360 ** (0.170)	0.255 (0.215)
Ln(Age)	-0.475 *** (0.036)	-0.506 *** (0.051)	-0.437 *** (0.046)	0.302 ** (0.135)	0.188 (0.187)	0.649 *** (0.202)
Race = Black	0.031 (0.036)	0.014 (0.048)	0.066 (0.051)	0.020 (0.148)	-0.138 (0.200)	0.295 (0.179)
Race = Asian	-0.057 (0.054)	-0.080 (0.072)	-0.038 (0.073)	0.408 ** (0.179)	0.292 * (0.151)	0.816 (0.581)
Race = Hispanic	-0.104 *** (0.033)	-0.088 * (0.046)	-0.081 ** (0.041)	0.184 * (0.103)	0.040 (0.151)	0.298 ** (0.120)
Race = Other Minorities	-0.082 *** (0.026)	-0.046 (0.035)	-0.146 *** (0.036)	0.193 ** (0.096)	0.039 (0.128)	0.389 *** (0.128)
Female	0.042 * (0.023)	0.010 (0.032)	0.105 *** (0.029)	0.177 ** (0.077)	0.097 (0.092)	0.270 * (0.140)
Ln(Tenure)	-0.239 *** (0.020)	-0.264 *** (0.028)	-0.196 *** (0.026)	0.073 (0.097)	0.047 (0.121)	0.466 *** (0.143)
Manager	0.204 *** (0.047)	0.199 *** (0.065)	0.245 *** (0.062)	-0.116 (0.307)	-0.058 (0.398)	0.781 (0.550)
N_Plants	0.014 (0.010)	-0.001 (0.011)	0.038 *** (0.013)	0.006 (0.022)	0.002 (0.055)	0.062 ** (0.030)
Ln(PlantEmp)	-0.248 *** (0.048)	-0.23 *** (0.065)	-0.314 *** (0.063)	0.546 *** (0.151)	0.454 ** (0.178)	0.652 * (0.363)
Ln(FirmEmp)	0.026 (0.041)	0.038 (0.056)	0.009 (0.060)	-0.090 (0.105)	-0.168 (0.147)	0.611 *** (0.220)
Multi-Unit	0.319 ** (0.139)	0.086 (0.168)	0.626 *** (0.214)			
Diversified	0.069 (0.180)	0.446 * (0.243)	-0.381 (0.241)			
Native to State	0.005 (0.016)	0.002 (0.022)	0.001 (0.022)	-0.090 (0.063)	-0.022 (0.065)	-0.208 ** (0.097)
Ln(# of Firms in CT & SIC2)	-0.223 *** (0.059)	-0.198 * (0.117)	-0.477 *** (0.071)	2.148 *** (0.395)	2.061 *** (0.460)	2.913 *** (0.848)
Ln(# of Firms in CT)	0.322 *** (0.055)	0.613 *** (0.123)	0.153 ** (0.059)	-1.412 *** (0.367)	-1.402 *** (0.454)	-1.495 ** (0.694)
Ln(# of Firms in CT & SIC _{t+4})	-0.101 ** (0.041)	-0.370 *** (0.066)	0.287 *** (0.049)	-0.369 *** (0.108)	-0.319 ** (0.128)	-0.568 *** (0.169)
Chg_Q	0.072 (0.127)	0.083 (0.152)	0.244 (0.257)			
Chg_Q * Diversified	-1.040 ** (0.452)	-1.031 * (0.578)	-0.793 (0.689)			
Firm_Q				1.361 ** (0.681)	1.504 ** (0.640)	1.204 (1.281)
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R ²	0.117	0.173	0.087	0.421	0.463	0.527
N	342,477	198,952	143,525	24,974	17,821	7,113

Table XII
Industry Migration

This table presents the results of t-tests comparing industry migration patterns for workers in closing plants. We use the subsample of workers who move to a different industry (based on 2-digit SIC) following plant closure. Within a diversified firm (i.e., operating in multiple industries based on 2-digit SIC codes), we calculate the percentage of workers moving from their previous industry to all other industries in which the firm operates (Pct_Diversified). Then, we compute the percentage of the same combination for workers from focused firms (Pct_Focused). We only include observations (Firm * Old SIC * New SIC) if there are more than five workers in the Firm * Old SIC combination. Panel A presents t-tests for the overall sample. N is the number of Old SIC - New SIC combinations included in the computation. The diversified sample in Panel A includes all workers who move to new firms. In Panel B (C), it includes the subsample from Panel A who originate in high-skill (low-skill) industries. High-skill Industries are industries in which the percentage of workers in the 2-digit SIC in occupations with 2-digit SOC codes less than 29 exceeds the median. Low-skill Industries are the remaining 2-digit SIC codes not classified as High-skill.

Panel A: All External Job Changes

	Mean	Std. Error	N
Pct_Diversified	8.01%	0.61%	562
Pct_Focused	6.69%	0.36%	562
Difference	1.32%		
<i>t</i> -statistic	2.268		
<i>p</i> -value	(0.024)		

Panel B: External Job Changes from High-skill Industries

	Mean	Std. Error	N
Pct_Diversified	8.87%	0.83%	347
Pct_Focused	6.90%	0.44%	347
Difference	1.96%		
<i>t</i> -statistic	2.412		
<i>p</i> -value	(0.016)		

Panel C: External Job Changes from Low-skill Industries

	Mean	Std. Error	N
Pct_Diversified	7.56%	0.89%	227
Pct_Focused	6.36%	0.60%	227
Difference	1.19%		
<i>t</i> -statistic	1.258		
<i>p</i> -value	(0.105)		

Table XIII
Worker Skill and the Diversification Discount

The table reports estimated coefficients from OLS regressions for the sample of firms which report multiple business segments (diversified firms). The dependent variable is the diversification discount, measured as the natural logarithm of the ratio of the imputed market-to-book ratio to the firm's actual market-to-book ratio. The imputed market-to-book ratio is the asset-weighted average of the median market-to-book ratio among single-segment firms operating in each of the diversified firms 3-digit SIC codes. % Assets in High Skill Ind. is the percentage of the firms assets in segments which operate in 2-digit SIC codes in which the percentage of workers with 2-digit SOC codes less than 29 exceeds the median. Firm Size is the natural logarithm of assets. ROA is operating income before depreciation scaled by beginning-of-fiscal-year assets. Asset Tangibility is net property, plants, and equipment scaled by beginning-of-fiscal-year assets. Investment is capital expenditures. Investment and Cash are scaled by beginning-of-fiscal-year assets. Dividend Payer is an indicator variable equal to 1 if the firm paid a positive dividend during the fiscal year. Book leverage is long term debt plus the current portion of long term debt scaled by the numerator plus common equity. Finance Companies are any firm with a business segment that has a 1-digit SIC code of 6. The standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** represent significance at 10%, 5%, and 1% level, respectively.

	Full Sample (1)	Full Sample (2)	Full Sample (3)	No Finance Firms (4)
% Assets in High Skill Ind.		<i>0.072</i> *** (0.020)	<i>0.073</i> *** (0.020)	<i>0.072</i> *** (0.021)
Firm Size			-0.006 (0.005)	-0.014 *** (0.005)
ROA			-0.006 (0.005)	0.006 * (0.003)
Asset Tangibility			0.004 *** (0.001)	0.020 *** (0.006)
Investment			-0.008 (0.005)	-0.079 *** (0.025)
Cash			-0.011 ** (0.005)	-0.058 *** (0.021)
Dividend Payer			-0.050 *** (0.017)	-0.061 *** (0.018)
Book Leverage			0.009 * (0.005)	0.009 (0.006)
Constant	0.108 *** (0.008)	0.056 *** (0.016)		
Year Fixed Effects			yes	yes
R ²	0.000	0.003	0.013	0.023
N	18,397	18,397	17,367	14,207
N Firms	3,977	3,977	3,804	3,191