Match to Grow

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Abstract

This study proposes a specific channel through which labor markets facilitate firm growth: the occupational alignment between an establishment's workforce and local skills. Using occupational employment statistics, we construct an index that compares each establishment's occupational mix to that of its local market. Establishments with higher alignment grow faster in sales and employment. This growth comes primarily through lower adjustment costs and higher capital investment. We also show that the effects are most pronounced in establishments with a higher share of skilled workers and industries with higher idiosyncratic cash flow risk. This employee–firm matching channel helps explain how local labor markets translate into competitive advantage.

JEL Classification: J24, D22, E22, J62

Keywords: Human Capital Allocation, Local Labor Markets, Intangible Capital, Establishment Growth

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1 Introduction

"(W)hen workers and firms can easily match and separate, it increases the average productivity of each job." – U.S. Department of the Treasury (2022)

U.S. local labor markets differ sharply in earnings, productivity, and firm dynamics. These facts raise important questions: why do some industries flourish while others falter, and why do firms choose high-cost locations despite mobile factors of production? For example, why would firms producing tradable goods choose to locate in areas like Silicon Valley, New York, or Boston, where labor and land costs are exorbitant, rather than in rural or less expensive cities with lower factor prices? We address these questions by proposing a novel mechanism of employee-firm alignment that links local skill supply to firm input choices and subsequent growth. By formalizing and quantifying this matching channel, we demonstrate that spatial variation in match efficiency rationalizes corporate location decisions and explains observed growth differentials.

In theory, efficient employee-firm matches facilitate the job turnover mechanism that firms use to correct hiring errors and lead to a better and more productive allocation of resources. From the perspective of firms, studies have shown that firms with better employee matches are more likely to invest in capital expenditures when they expect to find a replaceable workforce with similar quality (Acemoglu (1997))[1] and are less likely affected by adverse financial frictions, as the cost of replacement is lower in labor markets (Krugman (1991)). Employees, on the other hand, are more inclined to invest in their own skills when more

[1]Firms that commit to irreversible investments while facing the vacancy risk experience a diminished return on their ex-ante investment. This situation results in a lower capital-to-labor ratio and a decline in the quality of job offerings (Acemoglu and Shimer (1999)).

employers are hiring, recognizing that human capital investment will be valued and beneficial when transitioning to new job opportunities (Rotemberg and Saloner (2000); Lazear (2009); Moretti (2010)).[2]

Despite its intuitive appeal, empirical evidence that employee–firm matches benefit firms is limited. This is due, in part, to the fact that there is no standard measure of match efficiency. We develop an intuitive proxy for an establishment's labor matching efficiency (LME) relative to its local labor market using the Occupational Employment and Wage Statistics (OEWS) dataset published by the U.S. Bureau of Labor Statistics (BLS). The OEWS provides granular occupational distributions within each 6-digit NAICS industry classification and within a metropolitan area (MSA), allowing us to compute cosine similarities in the skill composition between an establishment's workforce and local labor supply. The unit of observation is the establishment level to avoid aggregation bias: public firms often span multiple segments and locations, making firm-level measures unreliable for inference.[3]

Our main finding is that establishments grow faster in regions characterized by greater labor matching efficiency. A one standard deviation increase in LME is associated with 2% increase in employment and 1.9% increase in sales. Our baseline specification includes establishments fixed effects, which reflects changes in growth within the establishment when

[2]Anecdotal evidence and industry reports point to the same fact: local workforce pool is central to firms' long-horizon choices. Tesla's selection of Berlin for its European Gigafactory illustrates the mechanism: the city offers an "expensive, but highly qualified" labor force (Murray (2019)). Sectoral evidence aligns with this view: wages have reached record levels, and firms are expanding benefits to compete for scarce talent (see Manufacturing Institute report at https://themanufacturinginstitute.org/how-manufacturers-compete-in-the-labor-market-14979/?stream=workforce-news).

[3]Manning and Petrongolo (2017) find that the attractiveness of jobs to workers sharply decreases with distance and conclude that labor markets are relatively local. We use MSAs as the logical geographic units for defining local labor markets, as the most granular OEWS data is measured at the MSA level. Our results are also robust to commuting zones as the geographic units, which include both metropolitan and non-metropolitan areas.

an establishment experiences a better match of the employee profile with local labor supply. This is particularly useful to account for any management style or unique production technology that are time-invariant. Hence, any cross-sectional difference in the "quality" or "type" of establishment is not driving the results.

We incorporate three time-varying fixed effects to control for industry trends, regional economic influences, and parent firm-level idiosyncratic corporate decisions, which could introduce bias. The inclusion of parent-by-year fixed effects is particularly helpful in addressing firm-wide policies or characteristics that might otherwise confound the results. Concerns regarding financial constraints, industry connections, and targeted expansion that are time-varying at the parent firm level are effectively mitigated. The estimated coefficients from the most rigorous specification are compared against establishments from the same parent company but located in regions with distinct local labor skill compositions.

Although our data allow for granular fixed effects, it is still possible that other time-varying unobservables impact both the *LME* and the growth trajectory. In an attempt to establish a likely causal relationship, we apply two strategies - an instrumental variable (IV) approach and an event study - and reassuringly both yield similar results. The first strategy exploits the broad (national) changes in an industry's occupational profile that typically spill over to each local market.[4] Leaving the focal MSA out and controlling for other time-varying factors, such as technology diffusion, production network spillovers, and cross-MSA labor mobility, we find a consistent positive relation between *LME* and establishment growth.

[4]The exclusion restriction requires that national industry-level *LME* be orthogonal to MSA labor-supply shocks, conditional on controls and fixed effects. This is plausible when industries are not highly concentrated within specific MSAs — a condition met in our data. Our IV approach follows Blanchard and Katz (1992) and is used by Acemoglu, Naidu, Restrepo, and Robinson (2019); Autor, Dorn, and Hanson (2013); and Borusyak, Hull, and Jaravel (2022).

Then we follow the literature that exploits Hurricane Katrina as an exogenous shock to the Houston area's labor supply (Ghaly, Anh Dang, and Stathopoulos (2017); McIntosh (2008)). We match establishments in the Houston metropolitan area with similar establishments not affected by Katrina, directly or indirectly. The event study yields quantitatively similar results to the IV approach.

We lean on theoretical predictions to test two economic mechanisms through which labor-matching efficiency increases establishment growth. For the first channel, we hypothesize that better matches and easier access to local labor supply can significantly reduce the labor adjustment costs, thus greatly improving an establishment's financial conditions. Consistent with this idea, we find that an increase in *LME* is associated with an increase in business credit score, measured by the Dun & Bradstreet Paydex score, and a lower likelihood of declaring bankruptcy. To further shed light on corporate restructuring activities - some of the most radical actions establishments can take in response to local labor market conditions - we find that establishments with higher *LME* are less likely to close or divest.

Building on this evidence, we next explore conditions under which the effect of *LME* is especially strong. When labor adjustment costs are high, the ability to hire productive workers quickly becomes more valuable. In such settings, *LME* should operate as a powerful recruitment advantage. To test this prediction, we exploit two sets of exogenous variations in the hiring frictions at the state level: the recognition of inevitable disclosure doctrine (*IDD*) (Klasa, Ortiz-Molina, Serfling, and Srinivasan (2018)) and changes in the enforceability of non-compete agreement (*NCA*) (Jeffers (2024)) to supplement the labor adjustment channel. Establishments in states that recognize *IDD*, or that recently experienced court rulings increasing *NCA* enforceability, face higher employee hiring costs. These shocks raise labor adjustment frictions, making labor matching efficiency more salient. Consistent with this view, the relation between *LME* and establishment growth is stronger when hiring costs are higher due to these state-level variations.

For the second channel, we hypothesize that an increase in labor matching efficiency reduces the "hold-up problem" in which irreversible capital investments must be made ex-ante of hiring. In a subsample of manufacturing establishments, which account for over 85% of our sample, we find a sizable increase in the industry-level capital expenditures and total factor productivity with *LME*. We then link our establishment sample with the COMPUSTAT universe. We find in a subsample of public subsidiaries that a one standard deviation increase in *LME* is associated with a 3% to 4% annual increase in capital expenditures relative to the mean value.

Finally, we examine cross-sectional heterogeneity related to the labor skill composition of workers and idiosyncratic cash flow shocks. We begin with the role of labor skill composition. Because high-skilled workers are more difficult and costly to replace, theory predicts that matching frictions will be particularly consequential in industries and establishments that rely heavily on such employees. Consistent with this view, we find that the positive effect of *LME* on growth is significantly stronger in establishments with a greater share of skilled labor. Next, we turn to financial risk. Public establishments facing higher idiosyncratic cash-flow volatility display a markedly larger sensitivity to *LME*. This pattern suggests that efficient employee–firm matching not only supports expansion, but also provides an insurance-like buffer: firms in volatile environments are better able to adjust and absorb shocks when their local labor markets offer a closer fit between workforce skills and firm needs.

Our paper contributes to the growing literature on the determinants of firm growth by highlighting the central role of employee-firm matches. While the literature agrees that human input is an important form of corporate resource (Belo, Gala, Salomao, and Vitorino (2022)), relatively little is known about how the efficiency of labor allocation across firms shapes growth outcomes. By constructing an intuitive measure of *LME* from industry occupation profiles and local labor pools, we show that better worker–firm matching translates into higher employment expansion and revenue growth. This extends the standard view of labor supply by establishing that the specificity of the employee-firm match is as critical to corporate expansion as the aggregate quantity of labor.

Second, our study complements research on human capital as an intangible asset. Existing work shows that financial frictions of labor adjustment (Klasa et al. (2018); Jeffers (2024)), intangible capital (Babina, Fedyk, He, and Hodson (2024); Edmans (2011)), and organizational capital (Eisfeldt and Papanikolaou (2013); Li, Qiu, and Shen (2018)) affect firm growth. We advance this literature by documenting that the external labor environment, not just internal incentives or governance, crucially shapes firm outcomes. In particular, our results suggest that access to a well-matched labor pool functions as a form of intangible capital that fosters firm scaling. In this sense, *LME* captures an external dimension of organizational capital, one that is market-wide and potentially subject to frictions beyond the control of individual firms.

Finally, we contribute to the finance literature on how local labor markets shape corporate outcomes. Building on Marshall (1890) agglomeration insight, prior work shows that geography influences capital structure (Almazan, De Motta, Titman, and Uysal (2010)), resilience during crises (Klasa, Ortiz-Molina, and Serfling (2025), and price efficiency (Engelberg, Ozoguz, and Wang (2018)). We extend the literature by proposing a measure of labor-matching efficiency that connects local labor market fit to establishment growth, offering a new lens on how geographic variation in workforce skills influences corporate outcomes. While recent studies have adopted parent firm-level variants of this measure (e.g. Jiang, John, Lee, and Xu (2025); Sabah and Thompson (2025); Ge, Qiao, and Zheng (2023)), their approach relies on segment-sales-weighted cosine similarities based on headquarters location and reported operating industries, which imposes strong assumptions about where firms actually hire and produce. By contrast, our establishment-level design links each plant to its own industry and local labor pool, and the empirical specification absorbs unobserved heterogeneity at the industry, location, and parent-firm levels. This approach delivers a cleaner test of how local labor market conditions shape establishment growth.

2 Employee–Firm Matching and Firm Growth

The theoretical link between labor-matching efficiency and firm growth is grounded in the seminal work of the barter model by Diamond (1982). In his model, labor matches between workers and companies in a local economy generate multiple steady-state equilibria. Within each equilibrium, because workers and firms lack complete information about each other and cannot correctly predict the difficulty of matching, the equilibrium production is inefficient. To improve production efficiency, firms need to minimize labor–skill mismatches. In a wellfunctioning matching environment, an establishment can adjust its workforce until workers' skills are aligned with task requirements and generate the highest marginal product. Greater matching efficiency enables establishments to reallocate workers into better-suited roles more quickly, raising productivity and sustaining higher growth.

2.1 Costly Labor Adjustment

One implication of Diamond (1982) is that firms in environments with greater matching efficiency grow faster, as they face lower adjustment costs and fewer informational frictions in aligning workers with jobs. These frictions matter because labor turnover is costly: whenever a firm adjusts its workforce, it incurs expenses from firing, search, selection, hiring, and training (e.g., Oi (1962); Shapiro (1986)). Faced with such costs, a firm may rationally retain an unproductive worker whose wage exceeds their output or forego hiring a worker whose short-term productivity exceeds their wage (Blanchard and Portugal (2001)).

In addition to the direct turnover costs, empirical evidence suggests that firms also incur significant indirect costs of labor adjustment, such as reduced productivity (Autor, Kerr, and Kugler (2007)), costs of financial distress (Agrawal and Matsa (2013)), accumulation of precautionary cash (Ghaly et al. (2017)), and a high degree of operating leverage (Klasa et al. (2018)). Greater matching efficiency lowers the costs of labor adjustment. A competitive employer can fill vacancies quickly, reducing search and hiring expenses while minimizing production and financial losses. By easing these frictions, efficient matching directly supports faster firm growth.

2.2 Ex Ante Investment Hold Up

Information friction inevitably exists in a labor market because workers and firms lack complete information about each other to predict the probability of a successful job-worker match. This information friction creates a hold-up problem when irreversible capital investments must be made before hiring: workers are unwilling to invest in new skills when the wage premium depends on finding a firm with new technology, and firms are unwilling to invest in technology when the profitability depends on finding skilled labor to operate (Acemoglu (1997)). As a result, job vacancy risk can reduce the optimal investment return (Acemoglu (1998); Acemoglu and Shimer (1999)).

Higher matching efficiency also alleviates hold-up problems by improving information for both workers and firms about the likelihood of a successful match. In Acemoglu (1997)'s model, which assumes no technological externalities nor aggregate demand spillovers, firms are more likely to invest in technology where more workers are looking for a job, and workers are more likely to train for new skills where more employers are hiring (Rotemberg and Saloner (2000); Lazear (2009); Moretti (2010)). Thus, matching efficiency fosters growth not only by lowering adjustment costs but also by encouraging greater investment. Taken together, these mechanisms predict that a firm's labor-matching efficiency in its local market has a positive effect on growth.

3 Data and Methodology

3.1 Establishment Data: NETS

Our primary source for establishment-level data is the National Establishment Time-Series (NETS) database, maintained by Dun & Bradstreet. This comprehensive dataset provides detailed information, including addresses, for every U.S. establishment owned by public and private entities over the period of 1990 to 2020. More importantly, the dataset is free from survivorship bias and has a strong correlation with the U.S. Census data. We construct plant-level sales and employment from this dataset. We are also able to identify an extensive margin of corporate restructuring activities, such as plant closure and divestiture statuses. NETS includes unique parent- and establishment-level identifiers, allowing researchers to trace ownership information of establishments. It is important to mention a caveat that comes with the application of the NETS data. Crane and Decker (2020) find that, despite the strong correlation with the Current Employment Statistics (CES) and Quarterly Census of Employment and Wages (QCEW), NETS tends to oversample establishments with fewer than ten employees. Therefore, we exclude these small establishments to mitigate the bias.

3.2 Measurement of Labor Matching Efficiency (LME)

We aim to construct an empirical proxy for the likelihood that an establishment can recruit qualified workers from the local labor market. Intuitively, the relevant measure is likely to depend not only on the size of a metropolitan area, but also on the skill set required for the production function of the establishment. For instance, a software company may be more likely to find desired software engineers in the San Jose-Sunnyvale-Santa Clara MSA than in the Houston-The Woodlands-Sugar Land MSA, even though the latter is roughly 3.5 times larger in terms of the labor market size based on the 2020 census. We incorporate these considerations in our construction of the measure.

Our data source for labor matching efficiency is the Occupational Employment and Wage Statistics (OEWS) from the U.S. Bureau of Labor Statistics (BLS) for the period of 1999 to 2020. OEWS uses a standard occupational classification (SOC) system that includes 822 detailed occupational categories, covering near-universal job categories in the public, private, and military sectors. This data is released at various levels (e.g., national, state, industry, and MSA), and we use the revised categories whenever BLS makes those available. We began our sample in 1999, when the OEWS program started providing the most granular occupation definitions.[5]

We construct this measure in four steps: first, we use occupational data at industry level from the OEWS to construct an industry-level employee composition vector, $V_{i,t}$, for industry i in year t, where an element of $V_{i,t}$ is the proportion of labor in industry i assigned to occupation k.[6] We use 6-digit SIC codes up to 2001 and 6-digit NAICS codes from 2002 for industry classification. Because our unit of analysis is the establishment, we infer establishment-level occupational composition using NAICS industry-level data as the fine-grained industry classification mitigates concerns regarding the accuracy of labor matching inference.

[5]The OEWS adopted the SOC taxonomy in 1999, with 822 detailed occupational categories, compared to the 258 categories in the 1997–1998 OEWS taxonomy. Thus, we start our sample in 1999 for greater occupational granularity.

[6]By scaling occupational assignments by the total labor force, the "labor size" effect is effectively mitigated.

Second, we use the occupational data at the MSA level from the OEWS to construct a MSA-level employee composition vector, $V_{m,t}$ for the MSA m in year t, where an element of $V_{m,t}$ is the proportion of labor in the MSA m assigned to the occupation k. Third, we use the angular separation of the two vectors, $V_{i,t}$ and $V_{m,t}$, to calculate a cosine similarity between the labor-skill compositions of an industry and those of an MSA. Specifically, the cosine similarity is the scalar product of the two vectors divided by the product of their lengths:

$$Cosine\,Similarity_{i,m,t} = \frac{V_{i,t}V'_{m,t}}{\sqrt{V_{i,t}V'_{i,t}}\sqrt{V_{m,t}V'_{m,t}}} \tag{1}$$

Cosine Similarity in equation (1) is bounded between zero and one, where zero (one) means that the industry and MSA-level employee compositions have no (perfect) similarities. In our final step, we create the labor matching efficiency (*LME*) variable by standardizing the cosine similarity in equation (1) to simplify the interpretation of the results.[7] We explain the construction of the *Cosine Similarity* in Appendix B.

We assign the *LME* to each establishment based on its industry–MSA–year combination. Specifically, we map establishments' ZIP codes from the NETS to MSAs from the OEWS using the ZIP code–MSA crosswalk provided by the Office of Workers' Compensation Programs (OWCP) of the U.S. Department of Labor.[8]

[7]Every year, the cross-sectional mean and standard deviation of the *LME* measure are set to zero and one, respectively.

[8]While other studies (e.g., Ge et al. (2023), Jiang et al. (2025), Sabah and Thompson (2025)) use cosine similarity between industry and local labor market (e.g., MSA, commuting zone) to examine various corporate outcomes, they assign segment-sales-weighted cosine similarities to parent firms based on headquarters location and operating industries. Their approach relies on two key assumptions: (i) parent companies and their establishments operate in the same industry and are in the same local labor market, or in different markets with very similar employee composition; and (ii) for multi-industry firms, segment sales are proportional to segment employment. Our establishment-level measure relaxes both assumptions. We assign

3.3 Summary Statistics

Table 1 reports summary statistics. The sample in Panel A comprises 398,196 plant-year observations from 33,517 establishments and 21,268 parent corporations over the 1999 to 2020 period. On average, each parent firm operates 1.81 subsidiary establishments. The *Cosine Similarity* averages 0.26 (bounded between 0.10 and 0.55), implying that most establishments face partial but not perfect alignment with their local skill pool — exactly what one would expect in a frictional labor market. Establishments in higher-similarity terciles exhibit systematically larger employment and sales, higher Paydex scores, and lower bankruptcy incidence as shown in Panel D. For example, bankruptcy probability falls from 1.3% in the lowest tercile to 0.2% in the highest, while sales and employment rise monotonically.

Panel A of Figure 1 shows that manufacturing establishments account for the bulk of observations, a setting where workforce alignment is especially salient for studying how local labor markets shape firm outcomes. Panel B highlights that our proposed employee-firm match index exhibits meaningful time-series variation rather than being a sticky, slow-moving construct. This property is central to our identification strategy: if cosine similarity were largely fixed within industry–MSA pairs, any correlation with growth could be dismissed as reflecting permanent advantages or static firm sorting across locations. Instead, the observed evolution of *Cosine Similarity* over 1999–2020 indicates that local labor–firm fit responds

cosine similarity to each establishment based on its own industry and MSA, rather than the parent firm's primary industry and headquarters MSA. Moreover, we use establishment-level employment and sales data directly, avoiding the need to assume that an establishment's contribution to parent-firm sales is proportional to its share of total employment. By relaxing these assumptions, our approach is less likely to suffer from misclassification of establishment−labor market similarity, which potentially reduce measurement error and strengthen the reliability of the estimates. Additionally, we create an alternative *LME* based on commuting zone and find that our baseline results are comparable to those with MSA (results shown in columns (7) and (8) of Appendix Table C1).

systematically to shifts in occupational demand and supply.

4 *LME* and Establishment Growth

In this section, we first validate the *LME* and then present the primary findings. Additionally, we examine alternative specifications to address potential endogeneity concerns related to our results.

4.1 Validating the *LME*

We begin our analysis by investigating the relationship between our labor matching efficiency proxy and local business activity. Labor market theories posit that in regions with thick labor markets, firms experience faster growth and higher wages due to reduced labor adjustment costs, which are redistributed as higher wages to retain employees (Oi (1962)). If our measure effectively captures the alignment between establishment labor demand and local labor supply, we expect a positive association between labor matching efficiency and these outcomes.

We rely on County Business Patterns (CBP), an annual series that provides local economic data by industry of the establishment. The CBP is constructed primarily from administrative records of the Internal Revenue Service (IRS) and the Social Security Administration (SSA), supplemented by Census Bureau surveys to ensure accuracy in establishment counts, employment, and payroll. The data are systematically validated and aggregated across multiple statistical units. A key advantage for our setting is that the CBP reports consistently at the industry–MSA level, which mitigates concerns that inference is confounded by establishment-specific heterogeneity and instead allows us to capture variation at the relevant local industry margin.

Table 2 presents the results. We use total employment and number of establishments as proxies for local business activities. Columns (1) and (2) indicate that *LME* is positively and significantly related to business growth at the industry–MSA level. The inclusion of MSA-by-year and industry-by-year fixed effects alleviate concerns that time-varying shocks at either the location or industry drive the estimates. Columns (4) and (5) show that these relations remain economically meaningful when outcomes are expressed in logarithms. A one–standard deviation increase in *LME* is associated with a 29.1% increase in total employment and a 17.3% increase in the number of establishments.[9]

An alternative interpretation to the above results is that our results may reflect the influence of dominant employers or industry clusters, rather than labor matching effect. In such cases, large firms or clusters could simultaneously drive both measured *LME* and local growth. To assess this possibility, columns (3) and (6) incorporate payroll-based outcomes. We find that *LME* is positively associated with average industry wages within an MSA. This pattern is inconsistent with the monopsony hypothesis, under which a dominant employer or concentrated set of firms would suppress wages below competitive levels due to limited worker outside options (Bhaskar, Manning, and To (2002); Berger, Herkenhoff, and Mongey (2022)).

Taken together, the evidence indicates that the positive relation between *LME* and local establishment growth is not an artifact of employer dominance or clustering. Rather, the

[9] The industry–MSA elasticity (29.1%) reflects both intensive margin growth and extensive margin of establishments entry.

results support the interpretation that *LME* captures genuine improvements in labor market efficiency, with economically meaningful implications for local growth.

4.2 OLS Results - Establishment Level

Next, we turn to our main analysis and use establishment-year panel data. Specifically, we estimate the following empirical equation using OLS regression:

$$Growth_{i,t+1} = \beta_0 + \beta_1 \times LME_{i,t} + \epsilon_{i,t+1} \tag{2}$$

where *Growth* is proxied by one of the following two variables: natural logarithm of employment, *log(emp)*, and natural logarithm of sales, *log(sales)*. The variable of interest, *LME*, is the standardized cosine similarity between establishments' operating industry and MSA.

Table 3 presents the regression results of equation (2). Columns (1) - (3) present the results with *log(emp)* and columns (4) - (6) present the results with *log(sales)* as the dependent variables. The coefficients across all columns are statistically significant and economically meaningful. For example, a one standard deviation increase in *LME* is associated with 2.0% increase in the employment and 1.9% increase in total revenues.

Our baseline results control for establishment fixed effects. Hence, any cross-sectional differences that are time invariant are not driving the results. We also account for local shocks, such as those caused by directed policy interference or economic fluctuations, by including a vector of MSA-by-year fixed effects in Columns (2) and (5) in addition to plant and industry-by-year fixed effects. We, therefore, estimate the effect of labor matching efficiency on establishment-level growth, conditional on the average effect of local shocks.

Finally, we control for parent firm-level shocks. For example, two establishments owned by the same parent firm may be subject to similar production functions, financial constraints, and business decisions at the parent level. We take advantage of this setting by interacting with a full set of parent-by-year fixed effects in Columns (3) and (6) in addition to plant, industry-by-year, and MSA-by-year fixed effects, so that the effect on establishment growth is relative to other establishments with the same parent.[10]

Overall, the findings reinforce the idea that access to quality employees is helpful for firm growth, particularly for businesses that depend significantly on labor in their production function.

4.3 Alternative Empirical Specifications

In this section, we substantiate the validity of our findings through a series of robustness tests. We also address potential omitted variable bias at the establishment level, which could confound the interpretation of *LME* as a driver of firm growth.

4.3.1 Does Initial Economic Condition Explain the Results?

Prior studies suggest that initial economic conditions signal firm quality and predict future performance (Maksimovic, Phillips, and Yang (2023); Guzman and Stern (2020)). Here, we would like to understand whether our baseline results stem from heterogeneous economic conditions across establishments within the same $MSA \times industry$ cells, which will be the level at which our *LME* measure varies.

[10]Prior research indicates labor market conditions may correlate with management practices, industry networks, and early technology adoption. Our stringent fixed effects control for these factors at the parent firm level, isolating the distinct effect of labor matching efficiency.

We include the initial size-MSA-year fixed effects in addition to establishment fixed effects, industry-by-year fixed effects, and parent-by-year fixed effects. The added fixed effects ensure that our analyses compare the effect of *LME* on establishment growth between establishments located in the same MSA that experience similar initial economic influence at the start of our sample but with different exposure to labor market pool. We measure initial establishment economic condition using total employment at the sample's inception.[11] The establishments are grouped into quintiles based on total employment.

Columns (1) and (2) of Table 4 report the results for *log(emp)* and *log(sales)*, respectively. The point estimates increase by approximately 30% (= 0.026/0.02 -1) relative to the baseline results. This pattern suggests that baseline estimates are attenuated by systematic differences in growth trajectories across establishment economic condition categories within local labor markets. Large and small establishments in the same MSA–year can face very different scaling constraints, such that larger establishments expand more slowly because they are closer to capacity, while smaller plants often grow more rapidly in the same booming local markets.

4.3.2 Do Large Establishments Explain the Results?

Very large employers or industry clusters may directly shape the occupational composition of the MSA, contaminating our proposed labor matching mechanism. Using CBP industry–MSA data, we show that *LME* is positively associated with industry wages within an MSA after absorbing MSA-by-year and industry-by-year shocks. This pattern is difficult to reconcile with a monopsony mechanism in which dominant employers depress wages; in-

[11] Total revenue yields nearly identical results. We report our estimates using total employments only.

stead, it is consistent with improved task matching and agglomeration rents being shared with workers. We provide further evidence that our results survive with alternative specifications at the establishment sample.

First, we remove the largest 20% of establishments with the highest employment at their inception. We report the estimates in columns (3) and (4) of Table 4 for *log(emp)* and *log(sales)* as the dependent variables, respectively and continue to find significant results in both columns. Importantly, the economic significance is 10% (0.022/0.02 -1 = 10%) to 42% (0.027/0.019 - 1 = 42%) greater compared to the baseline results, which indicates the access to labor is especially beneficial to smaller establishments as these firms tend to face steeper labor adjustment cost and have limited access to market capital (Garicano, Lelarge, and Van Reenen (2016); Moscarini and Postel-Vinay (2012)).[12]

Existing research also indicates that firm location significantly influences growth, with firms often situating within industry clusters to mitigate training costs and productivity shocks (Almazan et al. (2010)). We define *industry cluster* at the MSA level and remove observations with more than 10 establishments in the same 3-digit NAICS within an MSA. Then, we re-estimate the analysis in columns (5) and (6) with the restricted sample and find that the coefficients remain nearly identical to those in the main specification. The coefficient estimates are not sensitive to industry cluster definitions. We find similar results when using cutoffs of 5 to 20 establishments or NAICS classifications ranging from 2 to 6 digits.

[12]Our empirical results suggest that any "large employer" effects, if present, would likely bias against finding a positive relation.

4.3.3 Are Results Sensitive to Outliers and Skewed Distributions?

Another valid concern of the inference is that the growth in employments or sales may be systematically correlated with "super star" establishments. If unobserved variables simultaneously drive both *LME* and size, our inference can be biased as it does not apply to the majority of establishments we expect to cover.

We therefore transform outcome variables by ranking both employment and revenues into 10 equal-sized bins. By transforming outcomes into ranks ensures that results are not driven by a handful of establishments with extreme performance. It also helps to reduce the noise of outcome variables in levels (e.g. due to misreporting of employment or sales imputation), a potential issue identified by Crane and Decker (2020) in the NETS application.[13]

We report the estimates in columns (7) and (8) of Table 4. We find that the results are highly significant. One standard deviation increase in *LME* is associated with 1.7% rise in rank. Though modest at the establishment level, the systematic reallocation effects across thousands of establishments align with the aggregate productivity gains highlighted by the labor matching efficiency channel.

4.3.4 Is Growth Spuriously Correlated with *LME*?

Our final specification intends to create a placebo test. If the *LME* measure were pure noise or merely reflecting local trends that correlate with growth, reassigning values from other industries would still yield spurious correlation. Finding no effect in this placebo supports

[13]We take several steps to address potential shortcomings of the NETS sample. First, we restrict the analysis to establishments owned by publicly listed parents. Second, we exclude young firms in their first five years of operation, where reporting is noisier. Third, we focus on outcomes measured at lower frequency to reduce the influence of transitory shocks. These alternative specifications do not have a material effect on our findings. (See Appendix C1).

the idea that the true estimates are not a statistical artifact.

We construct a *placebo LME* by randomly permuting cosine similarity values across industries within each year, preserving the time structure but severing the true industry–MSA link. To ensure validity, we implement the permutation such that no industry retains its own value via re-draws until all self-matches are eliminated. This design maintains year fixed effects while eliminating any meaningful economic content, providing a falsification test of whether our results reflect genuine variation in labor matching efficiency rather than mechanical correlation or high-dimensional noise.

We report the results in columns (9) and (10) of Table 4. We find that none of the coefficients of *placebo LME* are statistically different from zero. The null results are consistent with the view that the baseline results are not driven by spurious correlation with time-specific shocks or mechanical features of the *LME* construction.

5 Toward a Causal Interpretation

By construction, the *LME* measure may capture the unobserved variables that are varying at the industry-MSA-year level. For instance, a sudden expansion of a local industry will simultaneously impact the matching proxy and the growth of establishments within the industry, as the industry becomes a larger share of the MSA. The overlap need not be confined to large establishments or industry clusters. As long as the "mechanical" feedback loop between local shocks and occupational alignment is retained, we still cannot rule out other alternative explanations.

5.1 The Instrumental Variable Approach

To address these residual concerns, we rely on a strict leave-one-out (LOO) instrumental variable (IV) approach. This IV reconstructs the national occupational profile by excluding the focal MSA and then measures its alignment with other MSAs. By design, it removes the mechanical feedback between an establishment's own labor decisions and the *LME*, ensuring that local shocks do not enter the instrument. The identifying variation arises only from how the national skill-demand vector tilts when the focal unit is omitted, which is orthogonal to local industry–MSA–year shocks. Intuitively, when other MSAs' labor profiles shift in a way that moves the purged national vector closer to a focal MSA, cosine similarity rises—but this shift is driven entirely by conditions outside the focal market. The IV therefore addresses the simultaneity that neither fixed effects nor robustness checks can remove, delivering plausibly exogenous variation in national skill alignment. Our LOO is constructed in the following way:

$$Z_{i,m,t}^{\mathrm{LOO}} = \frac{1}{M-1} \sum_{m' \neq m} \cos(V_{i,t}^{-m}, V_{m',t}) \tag{3}$$

To satisfy the exclusion restriction, the industrial composition of MSAs must not disproportionately influence the purged national vector. This condition in turn will be true as long as sector is not concentrated in a particular MSA, a condition we verify at the two-digit NAICS level (Blanchard and Katz (1992))[14]. We assess sector concentration using the Herfindahl-Hirschman Index (*HHI*), computed across MSAs based on three proxies: *total*

[14] The identifying variation assumes that the influence of MSAs on the national level satisfies the"many-small-shock condition", as noted by Autor et al. (2013) and Borusyak et al. (2022).

establishments, *employment*, and *revenue*. As reported in Panel A of Table 5, the mean *HHI* ranges from 0.031 to 0.050, indicating that, on average, sector concentration is low (below 5%). This provides strong evidence that no single industry overwhelmingly drives labor demand within MSAs. Additionally, the median *HHI* ranges between 7 and 8 basis points, reinforcing the finding of limited concentration. While the 95$^{\text{th}}$ percentile of the distribution reveals some MSAs with higher concentration, these outliers are further excluded in our specifications.

Panel B of Table 5 reports the results of the IV estimation. The first-stage relationships are statistically strong across all specifications, with large F-statistics confirming instrument relevance for *LME*. The 2SLS estimates are both economically and statistically significant. In columns (1) and (2), using the full sample, a one–standard deviation increase in instrumented *LME* raises employment by 3.6% and revenues by 3.3%. To address potential concentration bias, we exclude the top 5$^{\text{th}}$ percentile of concentrated observations in columns (3) and (4). The results remain robust, with coefficients increasing by 19% and 9%, respectively, relative to the full-sample estimates. These larger effects mirror the OLS estimates from specifications that exclude the largest establishments, consistent with attenuation rather than identification hinging on a few dominant markets.

To test robustness to potential violations of the exclusion restriction, we add time-varying covariates that could confound the identifying variation. First, we construct a Bartik-style instrument, *Bartik IV Technology Adoption* using detailed capital input data from BEA/BLS integrated industry production accounts. This instrument interacts industry-level technological capital expenditures contributions to output growth with initial industry labor shares in each MSA, capturing heterogeneous exposure to technology diffusion. Similarly, we build *Bartik IV Input-Output Connection* (Menzly and Ozbas (2010)) and *Bartik IV Labor Mobility* (Donangelo (2014)) by interacting initial industry labor shares with supplier–customer linkages from BEA Benchmark I/O tables and industry-level labor mobility measures, respectively. These proxies account for potential confounding from production-network spillovers and cross-MSA labor flows. As reported in columns (5) to (10) of Panel B of Table 5, the 2SLS coefficients remain highly significant at the 5% level and are virtually unchanged across specifications, confirming that our results are robust to these alternative sources of variation and supporting the validity of the exclusion restriction.

In summary, our identification exploits plausibly exogenous variation in *LME* generated by national shifts in industry–occupation profiles driven by *other* MSAs. Using this source of variation, we find positive and significant effects of *LME* on growth. Reassuringly, the 2SLS estimates align with the OLS results, particularly regarding the heterogeneous effects of establishment size on growth.

5.2 A Natural Experiment - Hurricane Katrina

Our second identification strategy exploits the exogenous labor supply shock to Houston following Hurricane Katrina. The evacuation increased the population of the Houston MSA by roughly 3.1%, with most evacuees leaving the city within two years (McIntosh (2008); De Silva, McComb, Moh, Schiller, and Vargas (2010)). This sudden and unanticipated influx thickened Houston's labor market by expanding the pool of effective workers.

Following the methodology in McIntosh (2008) and Ghaly et al. (2017), we construct a *treatment* group of establishments located in the Houston MSA and a *control* group of propensity-score-matched establishments in nearby MSAs that were unaffected by Katrina. The *treatment* group consists of establishments located in the Houston metropolitan area (Houston–The Woodlands–Sugar Land, TX). The *control* group comprises propensity-score-matched establishments located in other metropolitan areas of Texas and neighboring states (Arkansas, New Mexico, and Oklahoma), excluding Louisiana. We drop MSAs directly struck by the storm as well as indirectly affected areas that experienced more than a 1% population increase due to evacuee migration. We match establishments by their 6-digit NAICS code. We define *post* as an indicator equal to one for the year following Hurricane Katrina and zero for the preceding year, as earlier evidence suggests that most evacuees returned within two years.

Columns (1) and (4) of Table 6 provide strong evidence that establishments in the Houston MSA experienced sizable increases in both employment and revenues following Hurricane Katrina. Using a short event window and the fixed effects effectively raises the bar for alternative explanations. Any alternative explanations must account for the observed growth in establishments located in the Houston MSAs relative to other geographically unaffected establishments, through channels that are not associated with the labor migration events.

One potential concern is that Hurricane Katrina did not directly shift our *LME* measure, but rather altered the composition of the local labor pool, implying heterogeneous shocks across industries depending on their occupational mix. In particular, low-skill, labor-intensive manufacturing sectors are more likely to have benefited from the influx, whereas high-skill industries may have experienced little improvement or even weaker matching

(De Silva et al. (2010)).

To address this concern, we first validate our identification strategy by employing a first-stage difference-in-differences test to confirm that Hurricane Katrina measurably impacted the *LME* variable. As shown in Appendix Table C2, we find that the hurricane-induced labor influx led to a significant increase in *LME* for Houston establishments.

While this concern is partially mitigated by the fact that manufacturing accounts for roughly 85% of our observations, we explicitly test for heterogeneity by reporting results separately for manufacturing and non-manufacturing establishments in columns (2) – (3) and (5) – (6) of Table 6. Consistent with the labor matching mechanism, the estimated effects are concentrated among manufacturing establishments, where occupational structures are more closely aligned with evacuee inflows. In contrast, the effects are essentially absent in the non-manufacturing subsample. Importantly, the 'first-stage' effect is also concentrated within the manufacturing sector (column (2) of Appendix Table C2), consistent with the sector-specific nature of the labor shock.

6 Mechanisms

In this section, we examine why local labor market conditions matter for establishment growth by considering two non-mutually exclusive channels. First, improved labor matching and greater access to local labor supply can foster growth by lowering labor adjustment costs, thereby strengthening establishments' financial positions. Second, higher matching efficiency mitigates investment hold-up problems by improving information flows for both workers and firms, which in turn supports greater levels of capital expenditures.

6.1 Labor Adjustment Costs

6.1.1 Financial Distress Costs

We examine credit risk and restructuring events as key indicators of financial distress. To measure credit risk, we use the *Paydex score* from NETS, which ranges from 0 to 100 and reflects a firm's trade credit performance. Prior research shows that the *Paydex score* is a strong predictor of business failure. Following Dun & Bradstreet guidelines, we also construct an indicator variable, $I_{\text{Paydex}\geq 80}$, which equals one if a plant's *Paydex score* is at least 80 and identifies low-risk establishments. Finally, we use the NETS bankruptcy flag, $I_{\text{Bankruptcy}}$, as a direct measure of financial distress.

To capture restructuring costs, we focus on plant closures and divestitures, which represent extensive-margin adjustments and constitute some of the most radical responses to adverse labor market conditions. Specifically, we classify an establishment as divested if it is sold to another firm in year t, and as closed if year t is its final year of existence in NETS.

Table 7 presents the results. Overall, we find that higher *LME* is associated with lower credit risk. In column (1), which includes plant and industry-by-year fixed effects, the *LME* coefficient is 0.329 and statistically significant at the 1% level. The coefficient remains statistically significant at the 5% level after MSA-by-year fixed effect is added. Columns (3) and (4) suggest that higher *LME* is associated with the likelihood of having a *Paydex score* of 80 or higher. In column (3), with establishment and industry-by-year fixed effects, the coefficient on *LME* is 0.011. Importantly, this estimate is virtually unchanged when MSA-by-year fixed effects are included in column (4). The economic magnitudes of the effect is non-trivial. A one standard deviation increase in *LME* corresponds to a 24% (=

0.011/0.0457) reduction in financial risk, that is, a higher likelihood of being classified as low risk relative to the mean.

Next, we examine the effect of labor matching efficiency on the likelihood that an establishment goes out of business. Column (5) includes plant and industry-by-year fixed effects, while column (6) further adds MSA-by-year fixed effects. In both specifications, the coefficients on *LME* are negative and statistically significant at the 1% level, indicating that higher labor matching efficiency reduces the probability of bankruptcy. Because bankruptcy events are rare in our sample (0.6% of plant-year observations), we interpret the economic magnitudes with caution. For example, in column (6), the coefficient of –0.002 implies that a one standard deviation increase in *LME* is associated with a 33% (= –0.002/0.006) reduction in the likelihood of plant bankruptcy relative to the mean, consistent with the economic magnitudes documented in Akey and Appel (2021).

Finally, columns (7) – (8) of Table 7 examine plant closure and divestiture. In column (7), the coefficient on *LME* is –0.004 and significant at the 1% level, implying that a one standard deviation increase in *LME* lowers the likelihood of plant closure by 9% (= –0.004/0.043) relative to the mean. Column (8) shows a similar effect for plant divestiture: the coefficient on *LME* is –0.002, indicating a 3.5% (= –0.002/0.056) decline in the likelihood of divestiture. These results reinforce the prediction that stronger labor matching reduces the probability of both closures and divestitures. Taken together, the evidence in Table 7 corroborates the theoretical prediction that enhanced employee–firm matching alleviates financial distress, thereby fostering greater stability in employment and revenue growth.

6.1.2 Hiring Frictions

We next examine the heterogeneous effects of local labor market exposures on growth conditional on labor adjustment costs. Our hypothesis is that the mitigating role of *LME* becomes more pronounced when hiring frictions are elevated. To test this prediction, first we exploit exogenous variation in hiring frictions arising from the staggered adoption (or rejection) of the Inevitable Disclosure Doctrine (*IDD*) by state courts. The *IDD* allows courts to restrict employee mobility when a new role is likely to lead to the disclosure of a former employer's trade secrets (Klasa et al. (2018)). If *LME* reduces labor adjustment costs by improving employee–firm matching, then its effect on establishment growth should be amplified in states and periods subject to *IDD*.

We extend our baseline specification by interacting *LME* with an *IDD* indicator in a difference-in-differences framework. In addition to plant and industry-by-year fixed effects, we estimate a specification with state-by-year fixed effects to absorb unobserved state-level shocks that may coincide with changes in courts' *IDD* positions and establishment growth. We incorporate parent-by-year fixed effects to control for unobserved heterogeneity within parent firms over time. To facilitate cross-state comparisons, we exclude MSA-by-year fixed effects and cluster standard errors at the state level. Motivated by the theoretical prediction in Section 2, these tests examine how the growth effects of *LME* vary with hiring frictions. By leveraging plausibly exogenous cross-state variation in *IDD*, the results strengthen the interpretation that *LME* mitigates labor adjustment costs, rather than capturing unobserved confounds.

Panel A of Table 8 shows that higher *LME* has a stronger effect on establishment growth when labor adjustment costs are high. The $LME \times IDD$ coefficients are positive and economically significant: a one standard deviation increase in *LME* in an *IDD* state is associated with an additional 1.5% increase in employment growth (column (3)) and 1.8% increase in sales growth (column (6)) relative to the mean, compared with a non-*IDD* state. These findings suggest that *LME* mitigates the adverse impact of *IDD* on establishment growth, supporting the hypothesis that improved employee–firm matching reduces labor adjustment costs and amplifies the growth-enhancing effect of *LME* under hiring frictions.

Next, we exploit state-level changes in non-compete (NC) enforcement between 2009 and 2013 as another plausibly exogenous source of variation in hiring frictions, following Jeffers (2024). These shocks were identified by reviewing practitioner blogs and annual 50-state surveys of NC enforceability, and consist of seven state Supreme Court rulings, one Appellate Court ruling, and one legislative change. All cases were verified using Westlaw. We define *NCA* as equal to 1 in years following an increase in NC enforceability, –1 following a decrease, and 0 otherwise.[15]

Consistent with the *IDD* specification, we interact *LME* with *NCA* in a difference-in-differences setting. Panel B of Table 8 reports the results. We find that the effect of *LME* on establishment growth is stronger when states increase non-compete enforcement. Across all six specifications, the interaction terms are positive and significant. Economically, a one standard deviation increase in *LME* is associated with an additional 2.1% increase in both employment growth and sales growth (columns (3) and (6)) relative to the mean, compared with states that did not change enforcement. This evidence is consistent with the

[15]Our results are robust to alternative event windows, including (–5, +5) and (–3, +3) around the shocks.

mechanism that better matching lowers labor adjustment costs and amplifies growth when mobility restrictions heighten frictions.

6.2 Investment Hold-Up

A second channel through which labor matching efficiency may promote establishment growth is by mitigating investment hold-up problems. In thin labor markets, firms face greater uncertainty about retaining skilled workers, which discourages irreversible investments in capital and technology. By mitigating the uncertainty surrounding unobserved match quality and curbing the risk of costly separation, tighter labor market alignment incentivizes firm level capital deepening.

We empirically test this channel using the NBER CES manufacturing industry data. A key strength of the CES dataset is its inclusion of both expenditure data and industry-level total factor productivity (TFP), enabling us to evaluate the scale of capital and labor inputs as well as their efficiency in driving output. Additionally, manufacturing industry accounts for more than 85% of our sample (Figure 1). To construct our key explanatory variable, we compute a weighted average of cosine similarity across MSAs. Because the CES dataset reports only three-digit NAICS codes prior to 2017, we aggregate our measures accordingly, and the dependent variable is also defined at the three-digit NAICS level.

We construct two proxies for industry-level investment following Giroud (2013): total capital expenditures scaled by capital stock ($CAPEX/CS$) and TFP. The latter captures the relative productivity of an establishment within its industry and is defined as the difference between actual and predicted output, where predicted output reflects the expected output given an establishment's input mix. Using industry-year panel data, we then estimate the following regression:

$$Investments_{j,t+1} = \beta_0 + \beta_1 \times LME_{j,t} + \epsilon_{i,t+1} \quad (4)$$

where $Investments_{j,t+1}$ is *CAPEX/CS* or *TFP* for industry j in year *t+1*. $LME_{j,t}$ is the industry-level cosine similarity for industry j in year t. All regressions include year and industry fixed effects, with standard errors clustered at the industry level.

Panel A of Table 9 presents the results from equation (4). Columns (1) – (3) use *CAPEX/CS* as the dependent variable, while columns (4) – (6) use *TFP*. Across all specifications, higher *LME* is associated with greater industry-level investment, with all coefficients statistically significant and economically meaningful. For example, a one standard deviation increase in *LME* corresponds to roughly an 18% increase in *CAPEX/CS* (column (3)) and an 8% increase in *TFP* (column (6)) relative to their respective standard deviations.

To assess whether the industry-level relationship extends to publicly listed firms, we turn to COMPUSTAT, where we link plant-level activity to parent company financial fundamentals using the cross-walk file provided by NETS. We also manually verify the match to ensure accuracy. Establishments are matched to their public parent firms using GVKEY, six-digit NAICS codes, and plant names. We restrict the sample to observations with positive capital expenditures, sales, and assets, yielding 33,459 firm-year observations. The dependent variables are (1) total capital expenditures scaled by total assets (*CAPEX/TA*) and (2) total capital expenditures scaled by lagged PP&E (*CAPEX/PPE*).

Panel B of Table 9 reports the estimates. Across all four specifications, the coefficients on *LME* are positive and significant, indicating a robust association between labor matching efficiency and investment at the parent-firm level. For example, in column (1), a one standard deviation increase in *LME* corresponds to a 1.9% (= 0.001/0.054) increase in *CAPEX/TA* relative to its mean, while column (4) suggests similar positive effect of 2.8% (=0.005/0.179) for *CAPEX/PPE*. Taken together, these findings support the mechanism that improved labor matching fosters capital formation and enhances the efficiency of capital and labor inputs.

7 Cross-Sectional Heterogeneity

In this section, we study heterogeneity in the growth response to labor matching. Because skilled labor is costly to adjust, firms that rely more heavily on it face higher adjustment costs and greater exposure to cash flow shocks (Oi, 1962; Shapiro, 1986; Ghaly et al., 2017). If *LME* mitigates labor adjustment frictions, its growth effects should be stronger both in skill-intensive firms and in firms more exposed to idiosyncratic cash flow risk.

7.1 Skilled Labor

First, we examine whether the growth effects of *LME* are stronger for firms that rely more heavily on skilled labor. To capture this dimension, we construct a Labor Skill Index (*LSI*) following Ghaly et al. (2017), which measures an industry's dependence on skilled workers. The *LSI* is calculated as the weighted average skill level of occupations within the industry, on a scale from one to five. Lower values indicate that most jobs require minimal skill, whereas higher values reflect a workforce with greater reliance on advanced skills. We use an establishment's industry membership, defined by the three-digit SIC code pre-2002 or the four-digit NAICS code from 2002 onward, to match the establishment with a corresponding *LSI* score. The *LSI* score is then standardized to have mean zero and unit standard deviation to facilitate the interpretation. We extend our baseline regression by interacting *LME* with *LSI*, estimating specifications with various combinations of plant-, industry-by-year, MSA-by-year, and parent-by-year fixed effects, and clustering standard errors at the MSA level.

Panel A of Table 10 presents the results. Columns (1) – (4) use *log(emp)* as the dependent variable, and columns (5) – (8) use *log(sales)*. Across specifications with plant-, industry-by-year, and MSA-by-year fixed effects, the interactions between *LME* and *LSI* are positive and statistically significant. Economically, a one standard deviation increase in *LSI* for a given *LME* is associated with 0.7% higher employment growth and 0.8% higher sales growth relative to their means. However, the estimates lose statistical significance once parent-by-year fixed effects are included in columns (3) and (7). Note that parent-by-year fixed effects restrict identification to within-parent-year comparisons. Since sister establishments of a parent often operate in similar industries, their *LSI* values and *LME* exposures show little variation, leaving the $LME \times LSI$ interaction weakly identified. The loss of significance therefore likely reflects limited variation rather than a reversal of the effect. To strengthen the statistical power of our tests in the presence of parent-by-year fixed effects, we further restrict the sample to establishments with at least three observations within a given firm-year. This restriction ensures sufficient variation in the interaction term to identify heterogeneous effects. Accordingly, we find that the interaction terms become positive and statistically significant in columns (4) and (8), where sufficient variation arises at the industry-MSA level from comparisons among establishments within the same parent firm.

7.2 Idiosyncratic Cash Flow Volatility

We next examine whether the effects of *LME* are stronger for firms facing higher cash flow risk. If *LME* mitigates labor adjustment frictions, its growth effects should be amplified among firms more exposed to idiosyncratic cash flow shocks. We construct idiosyncratic cash flow volatility (*Idio_CF_Vol*) as the variance of the residual from regressing a firm's cash flow volatility on its industry's cash flow volatility over the past three years. The measure is constructed at the public firm level and is standardized to have mean zero and unit standard deviation. Owing to data limitations, this measure is available only for public firms with non-missing cash flow variables. We then extend our baseline regression by interacting *LME* with *Idio_CF_Vol* and report the results in Panel B of Table 10.

Columns (1) – (3) report results with *log(emp)* as the dependent variable, and columns (4) – (6) use *log(sales)*. First, as expected, the coefficients of *LME* display positive signs and *Idio_CF_Vol* display negative signs and are statistically significant. The negative relation between establishment growth and idiosyncratic cash flow volatility aligns with the previous findings that firms facing more firm-specific uncertainty invest less and grow more slowly due to costly external finance (Minton and Schrand (1999)), precautionary saving motive (Bates, Kahle, and Stulz (2009)), and heightened product market competition (Irvine and Pontiff (2008)).

Search-and-matching models with costly adjustment predict larger returns to efficient employee–firm matching when establishments face more frequent idiosyncratic cash flow shocks.

In high-volatility environments, efficient matching lowers expected separation, vacancy, and retraining costs and accelerates reallocation. Consistent with this prediction, we find that *LME* is associated with stronger subsequent employment and sales growth among firms with higher idiosyncratic cash flow volatility as shown in columns (3) and (6). Economically, a one standard deviation increase in *Idio_CF_Vol* for a given *LME* is associated with a 0.6% increase in employment and a 0.7% increase in revenues relative to the means. Overall, the benefits of matching are amplified when firms in volatile environments are better able to adjust and absorb shocks when their local labor markets offer a closer fit between workforce skills and firm needs.

8 Conclusion

We show that efficient employee–firm matching is a key determinant of establishment outcomes. Establishments more closely aligned with local labor markets expand faster in sales and employment, exhibit higher productivity, and face lower risks of closure or divestiture. These effects remain robust across extensive fixed effects, alternative specifications, and two identification strategies—a leave-one-out IV and the Hurricane Katrina natural experiment. Establishments in high-*LME* environments also enjoy stronger credit profiles and lower bankruptcy risk, highlighting the role of matching in supporting corporate resilience.

Mechanism tests reveal that *LME* reduces labor adjustment costs and mitigates investment hold-up. Its effects are amplified when mobility restrictions increase hiring frictions, in industries with greater reliance on skilled labor, and in firms facing high idiosyncratic cash-flow volatility. At both the firm and industry levels, higher *LME* spurs capital investment and raises productivity. Our findings highlight labor–firm matching as an external form of organizational capital that bridges finance and labor economics. Together, the results position workforce alignment as a fundamental driver of competitive advantage across firms and locations.

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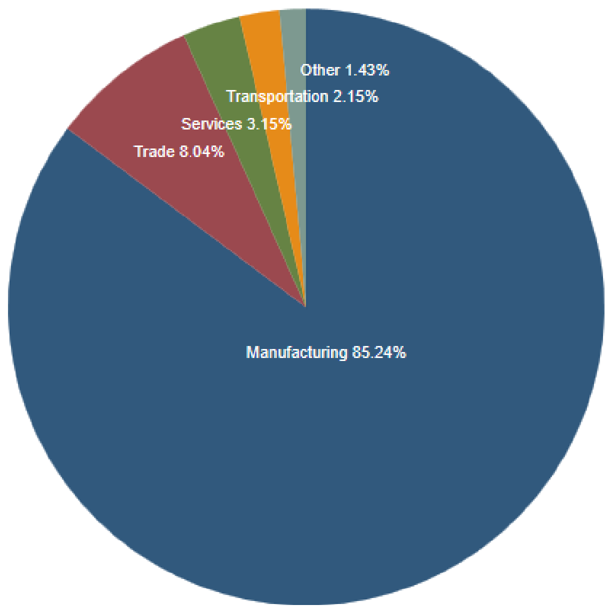
Figure 1: Establishment-Level Sector Shares and Time-Series Variation in *Cosine Similarity*, 1999–2020

The figure displays sectoral composition and time-series patterns of the NETS sample. Panel A reports establishment-level sector shares, while Panel B plots the time-series variation in *Cosine Similarity*. Both private and public establishments are included. The sample covers 1999–2020, with sectors defined by two-digit NAICS industry classifications.

(a) Sector Distribution



(b) Time-Series Variation of *Cosine Similarity*

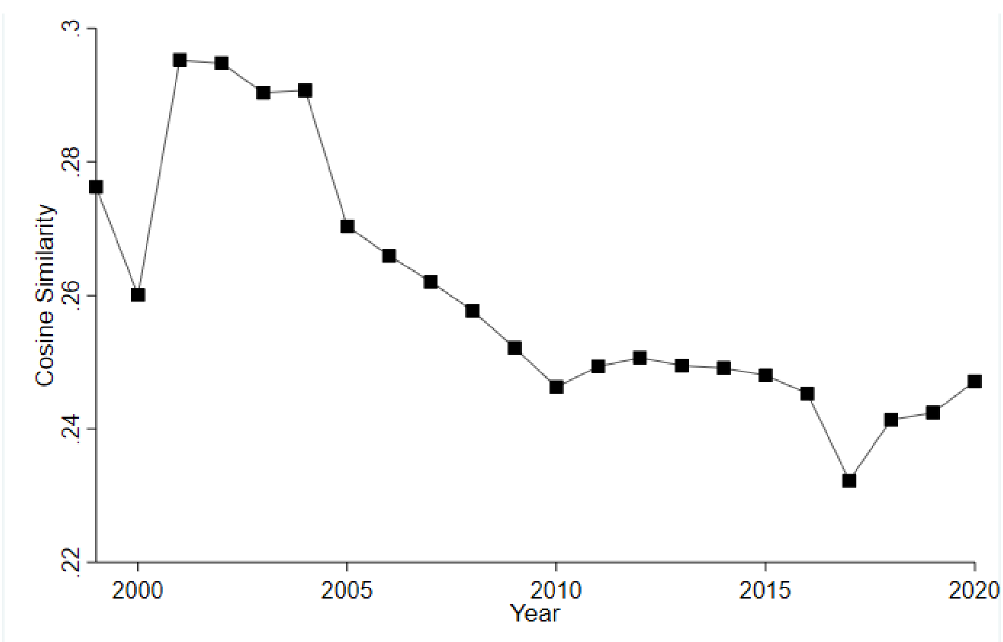


Table 1: Summary Statistics

This table reports summary statistics. Panel A presents the full sample of 398,196 establishment-year observations from 1999 to 2020, comprising 33,517 distinct establishments and 21,268 parent firms. We winsorize *Employment* and *Sales* at the 1st and 99th percentiles before taking logarithms to mitigate the influence of extreme values. Panel B reports the manufacturing industry subsample, covering 21 industries. Panel C presents the COMPUSTAT sample of 33,459 firm-year observations, comprising 890 unique public firms. Panel D reports the distribution of key variables across *LME* terciles.

Panel A: Establishment-Level Sample	Obs.	Mean	Median	Standard Deviation	Min	Max
Cosine Similarity	398,196	0.262	0.244	0.097	0.096	0.553
LME	398,196	0	-0.187	1	-1.717	3.010
Employment	398,196	187.792	80	434.541	10	19000
Log(Emp)	398,196	4.443	4.394	1.158	2.303	7.433
Sales ($ millions)	398,196	42.630	14.026	155.980	0.865	6845.119
Log(Sales)	398,196	16.500	16.456	1.395	11.800	20.047
Paydex	360,431	67.346	69	10.322	0	99
Bankruptcy	398,196	0.006	0	0.077	0	1
Closure	398,196	0.043	0	0.204	0	1
Divestiture	398,196	0.056	0	0.229	0	1

Panel B: NBER-CES Manufacture Sample	Obs.	Mean	Median	Standard Deviation	Min	Max
CAPEX/CS	378	0.067	0.066	0.022	0.022	0.128
TFP	378	-0.0004	0.003	0.037	-0.115	0.104

Panel C: COMPUSTAT Sample	Obs.	Mean	Median	Standard Deviation	Min	Max
CAPEX/TA	33,459	0.054	0.043	0.046	0.004	0.284
CAPEX/PPE	33,459	0.179	0.081	0.275	0.004	1.688

Panel D: Univariate Distribution of Key Variables Sorted by LME Terciles

LME	Log(Emp)	Log(Sales)	Paydex	Bankruptcy
T1 (Low)	4.403	16.423	66.920	0.013
T2	4.432	16.522	67.339	0.003
T3 (High)	4.495	16.555	67.781	0.002

Table 2: Validation Using County Business Patterns Sample

This table reports MSA-Industry level OLS estimates using County Business Patterns (CBP) data. The dependent variables are *Total Employees*, *Total Number of Establishments*, *Total Annual Payroll ($1,000)*, *Log Total Employees*, *Log Total Number of Establishments*, and *Log Total Annual Payroll*, in columns (1) - (6), respectively. The independent variable is the labor matching efficiency (*LME*), which is the standardized cosine similarity between the employment profile of a plant's industry and that of the local supply at the MSA. The CBP data use three-digit NAICS codes to aggregate industry figures, so we construct the *LME* at the same level. All ratio variables are winsorized at the first and 99th percentile. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the MSA level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Total Employees	Total Number of Establishments	Total Annual Payroll ($1,000)	Log Total Employees	Log Total Number of Establishments	Log Total Annual Payroll
	(1)	(2)	(3)	(4)	(5)	(6)
LME	5036.815***	172.823**	481805.8***	0.291***	0.173***	0.331***
	(1364.16)	(75.69)	(11503.8)	(0.026)	(0.016)	(0.030)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	24,834	24,834	24,834	24,834	24,834	24,834
Adjusted R^2	0.472	0.433	0.339	0.818	0.942	0.788
Mean of Dep	24,600.82	1,586.28	1,297,069	8.82	5.67	12.65

Table 3: OLS Panel Regression

This table reports reduced form OLS panel regression results studying the effect of labor matching efficiency on establishment growth. The dependent variables are establishment-level log employment in columns (1) - (3), and log sales in columns (4) - (6). The sample consists of 398,196 plant-year observations. The independent variable is the labor matching efficiency (*LME*), which is the standardized cosine similarity between the employment profile of a plant's industry and that of the local supply at the MSA. All ratio variables are winsorized at the first and 99th percentile. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the MSA level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Emp)			Log(Sales)		
	(1)	(2)	(3)	(4)	(5)	(6)
LME	0.019***	0.019***	0.020**	0.021***	0.019***	0.019*
	(0.004)	(0.005)	(0.010)	(0.004)	(0.006)	(0.010)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year	No	Yes	Yes	No	Yes	Yes
Parent-Year	No	No	Yes	No	No	Yes
Obs.	398,196	398,196	398,196	398,196	398,196	398,196
Adjusted R^2	0.924	0.925	0.931	0.927	0.928	0.943

Table 4: OLS - Alternative Specification

This table reports the results of alternative empirical specifications studying the effect of labor matching efficiency (*LME*) on firm growth. The dependent variables are establishment-level log employment in odd columns and log sales in even columns. The independent variable is the labor matching efficiency (*LME*), which is the standardized cosine similarity between the employment profile of a plant's industry and that of the local supply at the MSA. Columns (1) - (2) control for initial size-MSA-year fixed effects in addition to establishment fixed effects, industry-by-year fixed effects, and parent-by-year fixed effects. Columns (3) - (4) exclude the largest 20% establishments based on employment at the inception. Columns (5) - (6) exclude the largest establishments based on industry clusters. We define *industry cluster* at the MSA level and remove observations with more than 10 establishments in the same 3-digit NAICS within an MSA. Columns (7) - (8) report the results where the dependent variables are employment and sales ranks based on 10 equal-sized bins. Columns (9) - (10) report the results with a placebo *LME* where we assign *LME* values randomly across industries within each year, preserving the time structure but severing the true industry–MSA link. All ratio variables are winsorized at the first and 99th percentile. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the MSA level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Initial Size-MSA-Year FE		Excluding largest 20% plants		Excluding industry cluster		Rank based on 10 deciles		Randomly Assigned LME	
	Log(Emp)	Log(Sales)	Log(Emp)	Log(Sales)	Log(Emp)	Log(Sales)	Rank of Emp	Rank of Sales	Log(Emp)	Log(Sales)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LME	0.026***	0.025**	0.022***	0.027***	0.017***	0.019***	0.017**	0.015**	-0.007	-0.007
	(0.010)	(0.010)	(0.008)	(0.010)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)	(0.009)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Initial Size-MSA-Year FE	Yes	Yes								
Obs	398,196	398,196	318,594	318,594	319,826	319,826	398,196	398,196	398,196	398,196
Adjusted R^2	0.934	0.945	0.943	0.956	0.933	0.943	0.932	0.937	0.931	0.943

Table 5: Instrumental Variable Estimation

This table reports the results of the instrumental variable approach. Panel A presents summary statistics of sectoral concentration across MSAs, measured using the Herfindahl-Hirschman Index (HHI) at the two-digit NAICS level. Panel B reports the results of the IV estimation. The dependent variables are establishment-level log employment in odd columns and log sales in even columns. Leave-one-out (LOO) *LME* is computed by rebuilding the national occupational profile excluding the focal MSA. *Bartik IV Technology Adoption* is computed using detailed capital input data from BEA/BLS integrated industry production accounts. *Bartik IV Input-Output Connection* is computed following Menzly and Ozbas (2010) and *Bartik IV Labor Mobility* is computed from Donangelo (2014) by interacting initial industry labor shares with supplier–customer linkages from BEA Benchmark I/O tables and industry-level labor mobility measures, respectively. Columns (1) - (2) present the full sample and columns (3) - (10) exclude top 5% industry concentration. All ratio variables are winsorized at the first and 99th percentile. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the MSA level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Sector Concentration in MSAs (2-digits SIC)

Variables	Mean	5th Percentile	25th Percentile	50th Percentile	75th Percentile	95th Percentile
Sector HHI (Establishments)	0.031	0.000006	0.0001	0.0008	0.007	0.111
Sector HHI (EMP)	0.045	0.000004	0.0001	0.0007	0.006	0.165
Sector HHI (SALES)	0.050	0.000003	0.0001	0.0007	0.006	0.231

Panel B: First and Second stage IV estimates

Dependent Variable	Full Sample		Exclude Top 5% Concentration							
	Log(Emp)	Log(Sales)	Log(Emp)	Log(Sales)	Log(Emp)	Log(Sales)	Log(Emp)	Log(Sales)	Log(Emp)	Log(Sales)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2SLS Estimates with Fixed Effects									
Instrumented LME	0.036**	0.033*	0.043**	0.036**	0.043**	0.036**	0.044***	0.036**	0.043**	0.036**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Bartik IV Technology Adoption					0.050	0.111				
					(0.073)	(0.099)				
Bartik IV Input-Output Connection							-0.080	-0.025		
							(0.058)	(0.079)		
Bartik IV Labor Mobility									0.011	-0.0001
									(0.010)	(0.014)
	First Stage Estimates									
LOO LME	0.254***	0.254***	0.257***	0.257***	0.257***	0.257***	0.257***	0.257***	0.257***	0.257***
	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Kleibergen-Paap F-statistic	151.35	151.35	161.03	161.03	162.88	162.88	161.68	161.68	161.10	161.10
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parent-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	398,196	398,196	378,286	378,286	378,286	378,286	378,286	378,286	378,286	378,286

Table 6: Hurricane Katrina Shock

This table reports the results from a difference-in-difference regression setting, using the Hurricane Katrina shock to the labor supply resulting from labor migration from New Orleans to Houston. The dependent variables are establishment-level log employment in columns (1) - (3) and log sales in columns (4) - (6). Columns (1) and (4) present the full sample specification. Columns (2) and (5) present the manufacturing industry only and columns (3) and (6) report all other industries. *Treat* is an indicator variable taking one for establishments located in the Houston metropolitan area and zero for matched establishments located in neighboring metropolitan areas that were not affected by Katrina, either directly or indirectly following Ghaly et al. (2017). *Post* is an indicator variable taking one for the year following Katrina and zero for the year preceding it. We match establishments at the six-digit NAICS level. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the MSA level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Log(Emp)			Log(Sales)		
	Full Sample	Manufacturing Only	Others	Full Sample	Manufacturing Only	Others
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.044***	0.050***	0.023	0.046***	0.059***	0.003
	(0.014)	(0.014)	(0.042)	(0.015)	(0.015)	(0.044)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,447	3,529	918	4,447	3,529	918
Adjusted R^2	0.979	0.980	0.969	0.981	0.983	0.970

Table 7: Financial Distress Costs

This table investigates why the local labor market matters for a plant's growth by studying the effect of labor matching efficiency (*LME*) on a plant's financial distress costs. Plant's financial distress costs are proxied by credit risk and corporate restructuring. We measure credit risk by a continuous paydex score in columns (1) - (2), an indicator of a paydex score greater than or equal to 80 ($I_{Paydex>=80}$) in columns (3) - (4), and the likelihood that a subsidiary goes out of business ($I_{Bankruptcy}$) in columns (5) - (6). Columns (7) - (8) examine the effect of *LME* on corporate restructuring activities at the plant level, where the dependent variable is plant closure in column (7) and plant divestiture in column (8). All ratio variables are winsorized at the first and 99th percentile. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the MSA level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Credit Risk						Corporate Restructuring	
	Paydex Score		$I_{Paydex>=80}$		$I_{Bankruptcy}$		Plant Closure	Plant Divestiture
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LME	0.329***	0.187**	0.011***	0.011***	-0.003***	-0.002***	-0.004***	-0.002**
	(0.067)	(0.083)	(0.001)	(0.002)	(0.0004)	(0.0005)	(0.001)	(0.001)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year FE	No	Yes	No	Yes	No	Yes	Yes	Yes
Observations	360,431	360,431	360,431	360,431	398,196	398,196	398,196	398,196
Adjusted R^2	0.416	0.422	0.245	0.248	0.059	0.064	0.157	0.022

Table 8: Labor Adjustment Costs

This table investigates why the local labor market matters for a plant's growth by studying the effect of labor matching efficiency (*LME*) on a plant's labor adjustment costs. Panel A studies the effect of the staggered implementation of state-level Inevitable Disclosure Doctrine (*IDD*). Panel B studies the effect of the changes in enforceability of non-compete agreements (*NCA*) at the state-level. The dependent variables are establishment-level log employment in columns (1) - (3) and log sales in columns (4) - (6). *LME* is standardized the cosine similarity between the employment profile of a plant's industry and that of the local supply at the MSA. *IDD* is an indicator variable taking the value of one for states with an active Inevitable Disclosure Doctrine in year t and zero otherwise. *NCA* is the changes in enforceability of the state-level non-compete agreements from Jeffers (2024), which equals 1 for increase, -1 for decrease, and zero otherwise. All ratio variables are winsorized at the first and 99th percentile. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the state level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Inevitable Disclosure Doctrine (IDD)

	Log(Emp)			Log(Sales)		
	(1)	(2)	(3)	(4)	(5)	(6)
LME	0.011**	0.014***	0.010	0.012**	0.014***	0.007
	(0.005)	(0.005)	(0.009)	(0.005)	(0.005)	(0.009)
IDD	−0.015*			−0.018*		
	(0.009)			(0.010)		
LME × IDD	0.019***	0.013**	0.015*	0.018***	0.010*	0.018*
	(0.005)	(0.005)	(0.009)	(0.005)	(0.006)	(0.009)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	No	Yes	Yes	No	Yes	Yes
Parent-Year FE	No	No	Yes	No	No	Yes
Observations	398,196	398,196	398,196	398,196	398,196	398,196
Adjusted R^2	0.924	0.925	0.931	0.927	0.928	0.943

Panel B: Changes in Enforcement of Non-Compete Agreement (NCA)

	Log(Emp)			Log(Sales)		
	(1)	(2)	(3)	(4)	(5)	(6)
LME	0.020***	0.018***	0.016**	0.021***	0.019***	0.016**
	(0.004)	(0.005)	(0.008)	(0.004)	(0.005)	(0.008)
NCA	−0.010*			−0.008		
	(0.006)			(0.005)		
LME × NCA	0.018***	0.017**	0.021*	0.012**	0.010*	0.021*
	(0.007)	(0.007)	(0.012)	(0.005)	(0.005)	(0.012)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	No	Yes	Yes	No	Yes	Yes
Parent-Year FE	No	No	Yes	No	No	Yes
Observations	398,196	398,196	398,196	398,196	398,196	398,196
Adjusted R^2	0.924	0.925	0.931	0.927	0.928	0.943

Table 9: Investments

This table investigates investments as one of the channels through which labor matching efficiency (*LME*) affects firm growth. Panel A reports the industry-level investment of manufacturing firms using the NBER-CES Manufacturing sample. Panel B reports the results of the establishments that belong to public subsidiaries of the COMPUSTAT sample. The dependent variables are capital expenditures scaled by capital stock (*CAPEX/CS*) and total factor productivity (*TFP*) in Panel A, and capital expenditures scaled by total assets (*CAPEX/TA*) and capital expenditures scaled by lagged PP&E (*CAPEX/PPE*) in Panel B. *LME* is the standardized cosine similarity between the employment profile of a plant's industry and that of the local supply at the MSA. All ratio variables are winsorized at the first and 99th percentile. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the industry level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Weighted By Industry Share at MSA

	CAPEX/CS			TFP		
	(1)	(2)	(3)	(4)	(5)	(6)
LME	0.005*	0.005*	0.004***	0.004**	0.003**	0.003**
	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Observations	378	378	378	378	378	378
Adjusted R^2	0.054	0.118	0.502	0.008	0.465	0.466

Panel B: COMPUSTAT Sample

	CAPEX/TA		CAPEX/PPE	
	(1)	(2)	(3)	(4)
LME	0.001**	0.002***	0.008**	0.005***
	(0.0004)	(0.001)	(0.003)	(0.002)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Observations	33,459	33,459	33,459	33,459
Adjusted R^2	0.399	0.589	0.559	0.719

Table 10: Skilled Labor and Idiosyncratic Cash Flow Volatility

This table investigates how *LME* drives firm growth conditional on workers' skill sets and firms' cash flow shocks. Panel A presents the results with skilled labor. We construct a labor skill index (*LSI*) following Ghaly et al. (2017)) that measures a firm's dependence on skilled workers. *LSI* is designed as an industry-level index that calculates the weighted average skill level of occupations in an industry, on a scale from one to five. The conditional variable, *LSI*, is standardized to have mean zero and unit standard deviation within each year. Panel B presents the results with firms' cash flow risks. We construct idiosyncratic cash flow risk (*Idio_CF_Vol*) as the variance of the error term when regressing a firm's cash flow volatility on the industry's cash flow volatility of the past three years. Due to data limitations, this variable is calculated for public firms only. The conditional variable, *Idio_CF_Vol*, is standardized to have mean zero and unit standard deviation within each year. The dependent variables are establishment-level log employment and log sales. *LME* is the standardized cosine similarity between the employment profile of a plant's industry and that of the local supply at the MSA. All ratio variables are winsorized at the first and 99th percentile. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the MSA level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Skilled Labor

	Log(Emp)				Log(Sales)			
	Full Sample			≥ 3 plants per firm	Full Sample			≥ 3 plants per firm
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LME	0.021***	0.021***	0.020**	0.020***	0.023***	0.021***	0.021**	0.019**
	(0.004)	(0.006)	(0.010)	(0.005)	(0.004)	(0.006)	(0.010)	(0.008)
LME × LSI	0.008***	0.007**	0.001	0.006*	0.010***	0.008**	0.007	0.013***
	(0.003)	(0.003)	(0.007)	(0.003)	(0.004)	(0.004)	(0.007)	(0.005)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Parent-Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	398,196	398,196	398,196	158,782	398,196	398,196	398,196	158,782
Adjusted R^2	0.924	0.925	0.931	0.938	0.927	0.928	0.942	0.942

Panel B: Idiosyncratic Cash Flow Volatility

	Log(Emp)			Log(Sales)		
	(1)	(2)	(3)	(4)	(5)	(6)
LME	0.016***	0.026***	0.035***	0.018***	0.026***	0.033***
	(0.006)	(0.009)	(0.011)	(0.006)	(0.010)	(0.012)
Idio_CF_Vol	-0.011***	-0.010***		-0.010***	-0.009**	
	(0.003)	(0.003)		(0.004)	(0.004)	
LME × Idio_CF_Vol	0.008***	0.009***	0.006*	0.008***	0.010***	0.007*
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year FE	No	Yes	Yes	No	Yes	Yes
Parent-Year FE	No	No	Yes	No	No	Yes
Observations	99,214	99,214	99,214	99,214	99,214	99,214
Adjusted R^2	0.914	0.916	0.931	0.911	0.913	0.936

Internet Appendix A

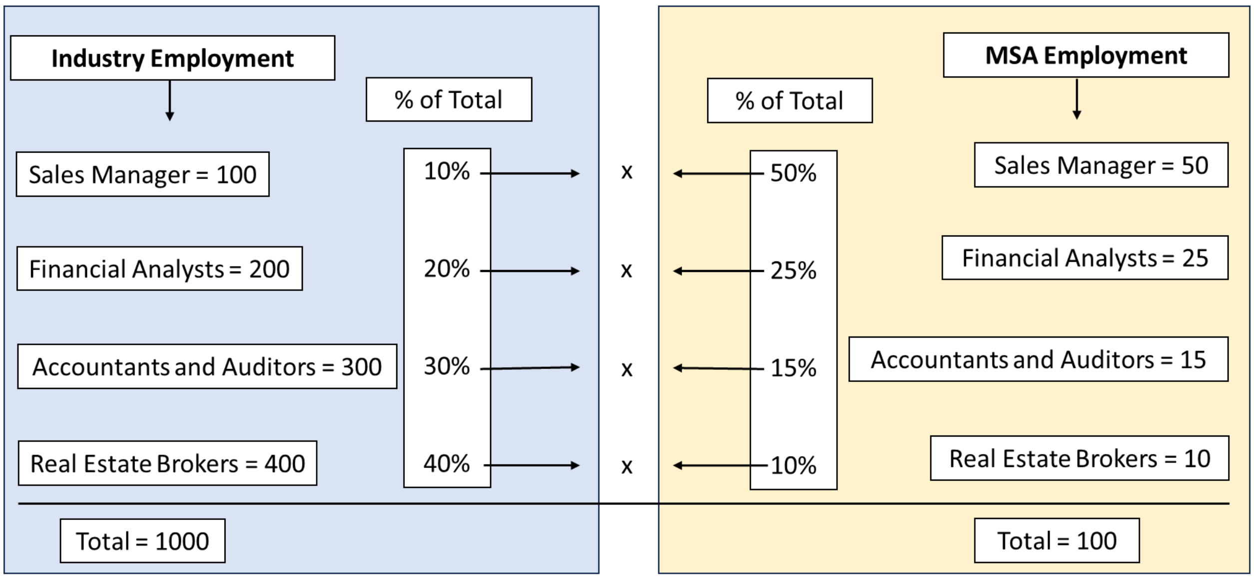
Variable Definition

Variables	Definitions
Cosine similarity	The Cosine similarity between an establishment's employee composition vector and that of its metropolitan statistical area (MSA).
LME	Standardized cosine similarity to have mean zero and unit standard deviation within each year.
Log(Emp)	Natural logarithm of the total employment, winsorized at the 1^{st} and 99^{th} percentiles.
Log(Sales)	Natural logarithm of the total revenues in dollars, winsorized at the 1^{st} and 99^{th} percentiles.
Treat	An indicator variable taking one for plants located in Houston–The Woodlands–Sugar Land MSA and zero for matching plants in adjacent MSAs.
Post	An indicator variable taking zero years before Hurricane Katrina (including 2005) and one thereafter.
Paydex	The business credit score from Dun & Bradstreet. The score ranges from 0 to 100.
$I_{Paydex>=80}$	An indicator variable for Paydex score ≥ 80.
$I_{Bankruptcy}$	An indicator variable within NETS to identify bankruptcy at the establishment level.
Plant Closure	An indicator variable that takes the value of one if a plant is in its last year of existence in NETS, and is set to zero otherwise.
Plant Divestiture	An indicator variable that is equal to one if a plant is sold to another firm in year t, and zero otherwise.
IDD	An indicator variable taking the value of one for states with an active Inevitable Disclosure Doctrine (IDD) in year t and zero otherwise.
NCA	Changes in enforceability of the state-level non-compete agreements from Jeffers (2024). Takes 1 for increase, -1 for decrease, and zero otherwise.
CAPEX/CS	Total capital expenditures scaled by capital stocks. Capital stock is computed using the perpetual inventory formula.
TFP	Total factor productivity, defined as the difference between actual and predicted output. The predicted output is the plant's expected output for a given level of inputs using a log-linear Cobb-Douglas production function.
CAPEX/TA	Total capital expenditures scaled by total assets.
CAPEX/PPE	Total capital expenditures scaled by lagged PP&E .
Labor Skill Index (LSI)	A firm's reliance on skilled labor, from Ghaly et al. (2017), calculated as the weighted average skill level of occupations in an industry, on a scale from one (minimum skills) to five (advanced skills).
Idio_CF_Vol	Variance of residuals from a three-year rolling regression of a firm's annual cash flow on contemporaneous three-digit NAICS industry cash flow, where residuals are taken at the firm level.

Internet Appendix B

Figure B1: An illustration of *Cosine Similarity*

This diagram illustrates the construction of the *Cosine Similarity* for each industry-MSA pair.



$$Cosine\,Similarity = \frac{(10\% \times 50\% + 20\% \times 25\% + 30\% \times 15\% + 40\% \times 10\%)}{\sqrt{(10\%^2 + 20\%^2 + 30\%^2 + 40\%^2)(50\%^2 + 25\%^2 + 15\%^2 + 10\%^2)}} = 0.58$$

Construction of *LME*

Our *LME* measure is the standardized version of the *Cosine Similarity* between an establishment's employee composition vector and that of its metropolitan statistical area (MSA). Cosine similarity is a widely used measure in various fields, including labor economics, to assess the degree of similarity between two vectors. In the context of constructing a labor match proxy for industry and Metropolitan Statistical Area (MSA) labor profiles, cosine similarity can be instrumental in quantifying the alignment between an establishment's labor demand (industry profile) and the available labor supply within a given MSA. The mechanism operates by representing both the industry's labor requirements and the MSA's labor force characteristics as multidimensional vectors, where each dimension corresponds to specific occupations and skills. The cosine similarity is calculated as the cosine of the angle between these two vectors, ranging from 0 to 1, where 1 indicates perfect alignment (or similarity), and 0 denotes no alignment. This metric captures not only the presence or absence of specific labor characteristics but also the relative importance or prevalence of these traits within the industry and the MSA labor pool.

There are a couple of advantages of cosine similarity particularly in the context of matching multidimensional data (there are over 800 occupations in a given labor market). One of the primary advantages is its in-variance to the magnitude of the vectors. This means it measures the orientation similarity between two vectors, regardless of their length. This property is particularly useful in labor market analysis as it allows for the comparison of the profile alignment between industries and MSAs based on the structure or pattern of the labor characteristics, rather than being influenced by the absolute quantities of labor resources or demands. This can be especially relevant when comparing labor markets of different sizes and remain a robust and interpretable measure as the dimensionality of the data increases. In many cases, labor market data can be sparse, with many zeros indicating the absence of certain skills or occupations in particular industries or MSAs. Cosine similarity can handle such sparsity effectively, as it focuses on the non-zero dimensions where data is present, making it a robust choice for analyzing labor markets with incomplete or uneven data distributions.

By employing cosine similarity in this manner, the measure effectively captures an establishment's potential to attract the local labor force by quantifying how well the skills and qualifications demanded by the industry align with those available in the local labor market. A high cosine similarity score suggests that the local labor force possesses the skills and qualifications that are in demand by the industry, indicating a favorable labor match. Conversely, a low score may imply a mismatch, suggesting that the establishment may face challenges in attracting suitable local labor. This intuitive approach allows us to assess labor market matches, analyzing labor market fit, provide insights into the compatibility between industry labor demands and the available labor force within MSAs that can be challenging to measure ex ante.

Internet Appendix C

Table C1: NETS Data Remediation and Alternative *LME*

This table reports the main results after addressing the limitation of the NETS data and using an alternative *LME*. Following Crane and Decker (2020), we adopt three suggestions. First, we use only COMPUSTAT firms to define the business universe to address biasing towards small establishments. We report these results in columns (1) - (2). Second, we drop young establishments with less than 5 years of history to address the limitation that young firms may have inaccurate measurements in the NETS data. These results are reported in columns (3) - (4). Third, we measure the dependent variables as three-year changes in sales and employment to address the limitation that the NETS sales data may be inaccurate due to imputation. We report these results in columns (5) - (6). Finally, we construct an alternative measure of labor matching efficiency (LME_{czone}) based on commuting zones instead of MSAs. We report the main results using the LME_{czone} in columns (7) - (8). The dependent variables are firm-level log employment and log sales except in columns (5) - (6) where the dependent variable is three-year change in employment and sales. Standard error estimates are adjusted for clustering at the MSA (or commuting zone in columns (7) - (8)) level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	NETS Data Remediation						Alternative LME	
	Suggestion 1: Use COMPUSTAT Firms		Suggestion 2: Drop young firms		Suggestion 3: Focus on low-frequency dynamics		Commuting Zone	
	Log(Emp)	Log(Sales)	Log(Emp)	Log(Sales)	% Change in Emp Growth	% Change in Sales Growth	Log(Emp)	Log(Sales)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LME	0.028***	0.028**	0.019**	0.018*	0.002***	0.001***		
	(0.011)	(0.011)	(0.010)	(0.01)	(0.001)	(0.0003)		
LME_{czone}							0.018***	0.018***
							(0.005)	(0.005)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA-Year FE	Yes	Yes	Yes	Yes	Yes	Yes		
CZONE-Year FE							Yes	Yes
Parent-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104,991	104,991	382,947	382,947	302,929	302,929	392,778	392,778
Adjusted R^2	0.931	0.936	0.934	0.945	0.177	0.189	0.931	0.943

Table C2: Hurricane Katrina Shock - First Stage Test of Katrina on *LME*

This table reports the first stage regression results from a difference-in-difference regression setting, using the Hurricane Katrina shock to *LME* measure resulting from labor migration from New Orleans to Houston. The dependent variable is the cosine similarity (*LME*). Column (1) presents the full sample specification. Column (2) presents the manufacturing industry only and column (3) reports all other industries. *Treat* is an indicator variable taking one for establishments located in the Houston metropolitan area and zero for matched establishments located in neighboring metropolitan areas that were not affected by Katrina, either directly or indirectly following Ghaly et al. (2017). *Post* is an indicator variable taking one for the year following Katrina and zero for the year preceding it. We match establishments at the six-digit NAICS level. Fixed effects are indicated in the table. Standard error estimates are adjusted for clustering at the MSA level and are reported in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	LME	LME	LME
	Full Sample	Manufacturing Only	Others
	(1)	(2)	(3)
Treat*Post	0.036***	0.053***	-0.035
	(0.008)	(0.008)	(0.025)
Plant FE	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Observations	4,447	3,529	918
Adjusted R^2	0.976	0.970	0.962