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RESEARCH ARTICLE

Strategic human capital management in the context of cross-industry and within-industry mobility frictions

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***Research Summary*:** We develop and test a theory examining how frictions that restrict mobility *across* industries and frictions constraining mobility *within* an industry can co-occur to effectively isolate individual human capital, ultimately changing the firm's make-versus-buy decision for human capital. Empirically, we demonstrate that when cross-industry frictions in the form of limited skill transferability and within-industry frictions in the form of noncompete enforceability are both present, employees exhibit longer tenures, firms hire workers with less initial experience, firms change the amount and nature of training provided, and wages marginally increase. These findings suggest that sufficiently strong and complementary mobility frictions shift the emphasis of firms' human capital management practices toward internal development of human capital relative to acquisition on the external market.

Managerial Summary: In the face of frictions to employee mobility both *within* and *across* industries, which we capture empirically using measures of noncompete enforceability and limited skill transferability across industries, firms tend to hire less experienced workers, such workers exhibit longer tenures, and firms invest more in their training, particularly in the development of new skills. Our findings imply that for firms operating under such complementary frictions, better hiring and internal development capabilities are particularly important for performance, while those firms without such capabilities may benefit from considering ways to circumvent the mobility frictions, including moving out of the focal state or lobbying for different noncompete laws.

KEYWORDS

employee mobility, industry-specific human capital, knowledge expropriation, labor market frictions, strategic human capital

1 | INTRODUCTION

Human capital has been identified as a critical source of competitive advantage in modern firms (Campbell, Ganco, Franco, & Agarwal, 2012; Castanias & Helfat, 1991; Hatch & Dyer, 2004; Helfat & Lieberman, 2002; Kor & Leblebici, 2005; Raffiee, 2017). Employees develop key innovations, hold the firm's trade secrets, translate physical capital into revenue, and develop valuable relationships with clients. Yet, employees can quit at will (Coff, 1997; LaVan, 2000), diffuse such knowledge to competitors (Singh & Agrawal, 2011), and expropriate investments in their human capital made by their employer (Starr, Prescott, & Bishara, 2018), posing a challenge to firms seeking competitive advantages. To address this challenge, research in strategic human capital has put primacy on frictions that create a wedge between the value that a worker creates at the focal firm relative to other firms (Campbell, Kryscynski, & Olson, 2017; Mahoney & Qian, 2013), thus supporting human capital-based competitive advantage (Barney & Wright, 1998; Campbell, Coff, & Kryscynski, 2012).

In a recent study, Mahoney and Qian (2013) developed a comprehensive framework connecting market frictions to firm heterogeneity in resources and capabilities, and associated heterogeneity in value creation, value appropriation, and cost minimization. Further, Mahoney and Qian emphasized the research opportunities provided by bridging multiple market frictions. While the strategic human capital literature has long recognized the importance of nonfungible human capital and other market frictions, the empirical studies in this literature have typically examined one market friction at a time. Prominent examples include firm-specific human capital, which is valuable only at the focal firm (Chatain & Meyer-Doyle, 2017; Frank & Obloj, 2014; Helfat, 1994; Kor & Leblebici, 2005; Morris, Alvarez, Barney, & Molloy, 2017; Raffiee & Coff, 2016; Wang, He, & Mahoney, 2009); industry-specific human capital, which constrains mobility across industries by imposing cross-industry opportunity costs (Harris & Helfat, 1997; Mayer, Somaya, & Williamson, 2012; Neal, 1995; Parent, 2000); and property rights-related frictions such as enforceable noncompete agreements, which make it costly to change jobs within the industry even when skills are transferable (Marx, Strumsky, & Fleming, 2009).

Drawing on Mahoney and Qian's (2013) insight that frictions do not exist in isolation, we focus on the notion that the complementary co-occurrence of labor market frictions may change how firms create and appropriate value from human capital. Specifically, we argue that some key frictions operate to constrain workers *across industries* (e.g., limited transferability of skills across industries), and other key frictions operate to constrain workers *within industries* (e.g., noncompete enforceability). These complementary frictions, which independently do not isolate human capital in the focal firm, can do so when combined. When these frictions co-occur, we predict that workers will exhibit longer tenures, firms will hire workers with less experience, and firms will invest more in internal development, particularly general and new skills training. We predict that these dynamics, in turn, will impact employee compensation levels because value creating investments will potentially offset value appropriation by the firm. Complementary frictions thus have the potential to shift the focus of the firm from "buying" human capital to "making" it internally (Mahoney & Qian, 2013).

Empirically, we use the matched monthly Current Population Survey (CPS), the March Supplement to the CPS, and the American Community Survey (ACS) to construct a number of novel measures that proxy for the extent to which an individual faces cross-industry mobility frictions. Additionally, we focus on the enforceability of covenants not to compete as a within-industry friction. We test our hypotheses on employee outcomes using data from the Survey of Income and Program Participation (SIPP), and find that when limited transferability of skills across industries and noncompete enforceability co-occur, employees exhibit longer tenures, firms hire employees with less experience, provide more firm-sponsored training, and provide relatively more novel skills training relative to basic skills training or training in company routines. Our analysis also shows that the effect of interacting frictions on tenure, overall training and the type of training is not simply driven by firms hiring less experienced workers. Further, in contrast to prior work that associated individual frictions such as noncompete agreements with lower wages (Garmaise, 2009; Starr, 2018), we find that the reinforcing frictions lead to (marginally) higher earnings. Thus, we find that the combination of within- and cross-industry mobility frictions induces firms to hire novice talent, make long-term investments in human capital, and share some of the returns with the employees.

The study makes multiple contributions. First, we answer the call of strategy scholars to examine "market frictions as fundamental building blocks for an organizational economics approach to strategic management" (Mahoney & Qian, 2013). Recognition of the role that market frictions play in firm strategies helps us understand how firms create and appropriate value from human capital. Second, we extend the strategic human capital literature (e.g., Chatain & Meyer-Doyle, 2017; Frank & Obloj, 2014; Harris & Helfat, 1997; Mawdsley & Somaya, 2016; Mayer et al., 2012) by highlighting that labor market frictions rarely occur in isolation and that by focusing on isolated and independent market frictions the extant literature does not fully capture the channels through which firms can isolate human capital and support competitive advantage. Additionally, by focusing on outcomes that are co-determined by individual and firm decisions, this approach supports a better understanding of the microfoundations of strategic human capital management.

Third, our study shows that complementary frictions fundamentally alter the calculus for human capital-based *make* or *buy* decisions. By constraining the labor markets for affected workers, complementary frictions make it challenging to acquire the human capital that the firm needs in the market, thereby shifting the firm's focus toward developing the skills it needs internally. Therefore, heterogeneity in internal human capital development capabilities are particularly important in generating performance heterogeneity. A variety of implications follow. For instance, firms without such capabilities may be more prone to lobby and exercise legislative pressure to remove mobility frictions (i.e., noncompetes) while firms with such capabilities will try to retain them. Similarly, firm location choices may be affected by how the capabilities relate to frictions in different locations.

Last, we contribute to the discussions on covenants-not-to-compete (Conti, 2014; Garmaise, 2009; Marx, 2011; Marx et al., 2009; Younge & Marx, 2016; Younge, Tong, & Fleming, 2015) by showing that the impact of noncompete enforceability varies according to the intensity of other market frictions that impact employees.

2 | THEORETICAL BACKGROUND AND HYPOTHESES

Under the assumption of perfect, frictionless labor markets, the ability of employees to move without costs across firms allows them to credibly threaten to leave their firm and extract the full value they generate (Becker, 1964; Williamson, 1975). As a result, employees pay for and reap the benefit of all general training, knowledge is homogeneous across firms, and firms never realize human capital-based competitive advantages. In contrast, the existing strategic human capital literature has focused on identifying mobility frictions that create a gap between how much value an employee can generate at a firm and how much value they can capture at an external employer. This creates quasi-appropriable rents that accrue to the employer who may then choose to share them with employees.

2.1 | Skill transferability and barriers to mobility

Given the challenge of capturing value from general human capital, the existing strategic human capital literature places an emphasis on the importance of firm-specific human capital because this component of an employee's human capital is fully isolated from the external labor market. Others have recognized that some skills may not be specific to the firm, but are transferable only within a certain context such as an occupation (Kambourov & Manovskii, 2009; Shaw, 1984), industry (Neal, 1995), task (Gibbons & Waldman, 2004), or relationship (Campbell, Saxton, & Banerjee, 2014).

Parallel to the developments in our understanding of the transferability of skills, extant research has highlighted the role of mobility barriers in labor markets (Campbell, Coff, & Kryscynski, 2012). For example, Marx et al. (2009) and Marx, Singh, and Fleming (2015) described the importance of noncompete enforceability in deterring and redirecting the mobility of patent holders. In contrast to skill transferability, noncompete enforceability does not change the value of skills in other jobs, but instead creates costs to acquiring those jobs in the first place. More broadly, the mobility barriers perspective holds that workers may be equally productive elsewhere, but the process of acquiring alternative jobs is costly, which prevents the easy movement of workers across firms.

While the literatures on mobility barriers and skill-transferability have largely proceeded in parallel, they both underscore the fact that a given individual can face various frictions when moving across firms. In some cases, these frictions could arise from the fact that a particular skillset is only valuable in certain contexts (e.g., an industry), thus causing workers to bear high opportunity costs were they to leave that context, or that various barriers in the market make it costlier to move to a job where their skills may be equally valued. While both classes of frictions reduce employee mobility, when we consider that some of these mobility frictions restrict employment options in other industries, and some operate to restrict opportunities within industries, the interaction of such complementary frictions may effectively isolate human capital.

2.2 | The interaction of cross- and within-industry mobility frictions

Figure 1 contains an overview of the conceptualization of how cross-industry mobility frictions and within-industry mobility frictions interact. The lower right quadrant of the table represents employees who face few frictions when moving across and within industries. In this quadrant, employees are very mobile between industries. In the lower left quadrant, employees face difficulties transferring their skills across industries, but are free to move within their industry. The upper right quadrant contains employees that face significant within-industry barriers, but are fully mobile across industries. In the upper left quadrant, employees have difficulty transferring their skills to another industry and face barriers to moving within their industry: They are more strongly isolated from the market. The key takeaway from this figure is that when both classes of frictions are high, employees are more likely to be isolated at their employer.

Our central claim is that the interaction of cross- and within-industry mobility frictions effectively isolates the worker within the firm, which will change not only how long the worker stays at the firm,

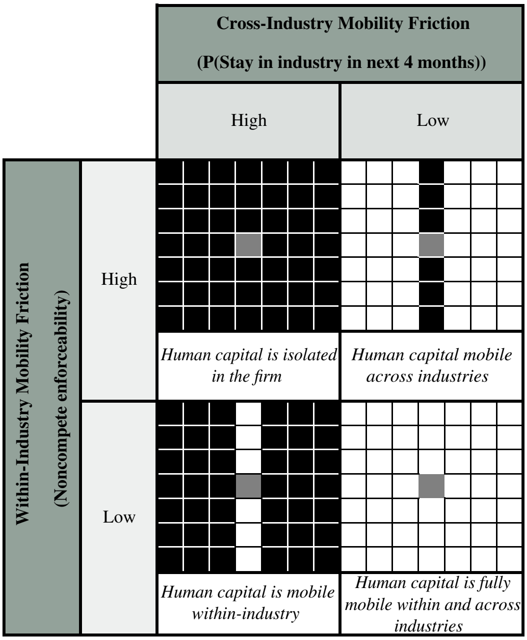

FIGURE 1 Interaction between within- and cross-industry mobility frictions.
Notes. Each column represents an industry, and each box represents a different firm. The table provides a stylized illustration of how within- and cross- industry frictions influence the mobility options of human capital

but also whom managers choose to hire in the first place, the amount and nature of investments the firm makes in the workers who are hired, and the wages that employees receive.

2.3 | Employee tenure and hiring

The predictions related to tenure and hiring provide a baseline for our arguments. Consider employees who have relatively few options in other industries, such as an aerospace engineer. Since their skills are primarily useful only in one industry, they may be unlikely to seek or consider jobs in other industries because aerospace engineers will be unable to generate, and thus, capture more value than they already do within their chosen industry. Similarly, firms from other industries would be less likely to spend time trying to recruit such workers since they could likely find engineers with more transferable skills who would thus be more likely to accept job offers. Further, suppose that the aerospace engineers were also bound by enforceable noncompetes.[1] The potential enforcement of noncompetes increases the expected cost of moving to a competitor (i.e., within the same industry), both for the poaching firm and for the worker since they may have to pay court costs, damages to the source firm, or otherwise wait until the contract expires. The result is that workers who have limited opportunities across industries and limited opportunities within their chosen industry are less likely to consider outside job offers and less likely to be recruited by other firms, thus increasing the likelihood that they stay at their current employer (see Fallick, Fleischman, & Rebitzer, 2006; Lavetti, Simon, & White, 2014; Marx et al., 2009; Starr, 2018). In other words, the marginal effect of increasing one of the frictions on tenure is higher when the complementary friction is also high because the focal friction reduces the remaining mobility options (as shown in Figure 1).

[1]Noncompetes are just one of many within-industry mobility frictions. Others include trade secret protections (Png, 2015), the inevitable disclosure doctrine (Contigiani, Hsu, & Barankay, 2018; Png & Samila, 2015), patent laws (Ganco, Ziedonis, & Agarwal, 2015), and restrictive covenants such as nondisclosure and nonsolicitation agreements.

The complementarity of cross- and within-industry mobility frictions thus constrains the worker, such that the tenure effects will be stronger than they would be in the presence of just one of these frictions. Consider website designers who work for an automotive company. Even if the website designers are bound by enforceable noncompetes, their skills are largely valuable in many other industries, and thus, it will be relatively easy for them to circumvent the within-industry prohibitions of the noncompete. Similarly, even though the skills of aerospace engineers are less useful outside of the aerospace industry, if the engineers are free to move within the industry, they will still have more options than if they were bound by an enforceable noncompete. Thus,

> **Hypothesis 1a (H1a)** *The interaction of limited transferability of skills across industries and noncompete enforceability is associated with longer employee tenure.*

The complementarity of cross- and within-industry mobility frictions also has implications for whom firms hire in the first place. When firms seek to hire an employee to fill an open position, they can hire from three sources: (a) experienced individuals within the industry, (b) experienced individuals from other industries, or (c) inexperienced, new labor market entrants.[2] To see how the interaction of cross- and within-industry mobility frictions will change whom firms hire, consider an airplane manufacturer that wants to hire an aerospace engineer to help with engine design. Given that the nature of the skills of an aerospace engineer are highly specific to the focal products, it is unlikely that the firm will be able to hire an experienced engineer from a different industry. If engineers within the field of aerospace engineering are bound by enforceable noncompetes, then firms will face additional costs trying to recruit them within the industry. Thus, in the face of both cross- and within-industry mobility frictions, the company will be more likely to hire from the pool of new industry entrants, for example, recent aerospace engineering graduates. This example highlights the intuition that when firms seek to hire for positions that require a high degree of industry-specific skills and when within-industry options are limited, it will be difficult for the firm to hire experienced employees from both outside and inside their industry, and thus, will be more likely to turn to less experienced workers.

Note that the interaction of cross- and within-industry mobility frictions will more strongly push the firm toward inexperienced workers than only cross-industry frictions or only within-industry frictions. For example, suppose that the firm is trying to hire a web designer, but that all the web designers who work for their competitors are bound by enforceable noncompetes. Because web designers have skills that are transferable across industries, the firm can easily hire an experienced web designer from another industry. Similarly, if the airplane manufacturer wishes to hire an engineer and noncompetes are unenforceable, then the company will be able to hire an experienced engineer from another firm within the industry. Thus,

> **Hypothesis 1b (H1b)** *The interaction of limited transferability of skills across industries and noncompete enforceability is associated with firms hiring less experienced employees.*

2.4 | Value creation and value capture

The interaction of cross- and within-industry mobility frictions has implications not only for whom firms hire and how long the employees stay, but also for the firm's choices regarding value creating

[2]Firms can also hire unemployed workers. Since our focus is on the length of prior work experience, we do not explicitly examine unemployment spells and their characteristics.

investments in human capital that increase worker productivity, and thus, willingness-to-pay. We maintain that the combination of within- and across-industry mobility frictions will affect (a) in whom the firm invests, (b) the nature of those investments, and (c) how the returns on those investments are shared.

There are two implications from the baseline hypotheses with regards to value-creating human capital investments. The first implication is that the tenure-enhancing effects of these complementary mobility frictions extend the time-horizon over which the firm can expect to receive benefits from these investments. Consequently, the firm has incentives to invest more, even in experienced workers. It is important to note that increased tenure enhances the incentives to invest only if there is a wedge between wages and marginal revenue product (Acemoglu & Pischke, 1999), such that the employee does not fully capture the value of the training, thereby allowing the firm to capture some share of the value created. Cross- and within-industry mobility frictions play an important role here because they increase the cost of job search for employees, constraining the ability of employees to bid up wages through the threat of mobility. This wedge creates an incentive for firms to invest in any training since firms can capture some of the training value, which is enhanced by the effect of longer tenure. The second implication is that if the interaction of within- and across-industry mobility frictions cause the firm to hire less experienced workers, then the firm will need to invest more in those workers for them to create value in their job. That is, because such workers come out of school with a broad, unspecialized set of skills, the firm will necessarily need to adapt those skills to the needs of the job. The resulting on-boarding training could be industry-specific, occupation-specific, task-specific, firm-specific, and so on, with the goal of increasing the value that the new hire generates and the value that the firm captures.

> **Hypothesis 2a (H2a)** *The interaction of limited transferability of skills across industries and noncompete enforceability is associated with employees receiving more firm-sponsored training.*

Importantly, the interaction of the complementary mobility frictions further impacts the firms' calculus regarding the *type* of training investments. We unpack the relationship in the previous hypothesis by focusing on training in four broad types of skills—basic skills, organizational policies and routines, training that upgrades existing skills, and new skills training. Basic skills are those that are required for the job and include training in office software, work routines and management practices. Organizational policies are a closely related category and include training of internal firm guidelines and required procedures. Firms likely provide the training of both basic skills and organizational policies irrespective of characteristics of a job, and thus, are more likely to be nondiscretionary. Training of new skills includes teaching an employee how to use new equipment, software, and machinery, or teaching other new procedures. Upgrading skills training expands on the skills that the employee already has. New skills and upgrading skills training may be more discretionary as they highlight commitment of the firm toward the employee.

These broad categories of skills vary along two key dimensions: the degree of firm-specificity and the time horizon for generating returns to the training. First, with regards to firm-specificity, organizational policies and some of the management practices and work routines are likely to be firm-specific. In contrast, building on the findings of Loewenstein and Spletzer (1999),[3] it is likely that a high proportion of new and upgraded skills will not be firm specific. Second, the time horizon

[3]Loewenstein and Spletzer (1999) found that among individuals who received firm-sponsored training in the last year, 63% reported that the skills learned through training are either fully or almost fully transferable to other employers, while only 11% reported that "less than half or none of the skills are useful at another employer."

of productivity gains resulting from a training investment may vary with the type of skills. While basic skills and organizational policies may be necessary to start the job, productivity gains from upgrading skills and training new skills may take longer to realize.

Both dimensions suggest that the increase in investments in human capital in response to isolating an employee will primarily come through the channel of new skills and skill upgrades. First, firms typically have stronger incentives to invest in firm-specific training than general training, so increasing isolation of human capital will have a smaller relative effect on firms' provision of firm-specific training. Additionally, firms are exposed to greater investment risks when providing general training: Employees can more easily walk out the door and take the training to a rival firm. So, in the absence of labor market frictions, firms would be relatively more hesitant to provide general training. If employees are isolated, however, this investment risk is mitigated, which strengthens firms' incentives to provide general training. As a result, the marginal impact of employee isolation on training will be much stronger for general training than for firm-specific training.

Second, isolating employees also provides a stronger incentive at the margin to invest in human capital that takes more time and resources to develop. For firms to invest in training, they need to expect to recoup the value of that investment over the anticipated tenure of the recipient. If training provides immediate gains and firms recoup their investment quickly, then extending the anticipated tenure of recipients does little to impact the incentives of firms to provide that type of training. However, if training takes a long time to pay off, firms will only provide that if they expect employees to remain with the firm for that duration. Consequently, when frictions extend the tenure of employees, there is a larger marginal impact on training such as the development of new skills or the upgrading of skills that likely takes a longer time to pay off.

Summarizing both mechanisms, when the focal worker faces significant within-industry mobility frictions *and* significant cross-industry mobility frictions, the firm has stronger incentives to invest in new and upgraded skill than in basic skills and organizational policies:

> **Hypothesis 2b (H2b)** *The interaction of limited transferability of skills across industries and noncompete enforceability is associated with employees receiving more firm-sponsored training in new skills and upgrading existing skills relative to training in basic skills and organizational policies.*

Our previous hypotheses suggest that in the presence of both cross- and within-industry mobility frictions, firms retain employees longer, hire less experienced workers, and provide more training, particularly training that develops new skills and upgrades existing skills. A firm's investments in human capital are driven by the firm's incentive to increase employee productivity given it can capture a portion of the additional value created. We next explore the impact of cross- and within-industry mobility frictions on the extent of the firm's ability to capture value through an examination of employees' wages. In exploring this relationship, we argue that cross- and within-industry mobility frictions may put both downward and upward pressure on wages, and thus, have contrasting effects on how the training gains are shared between firms and employees.

Focusing first on downward wage pressure, a natural result of the fact that such complementary mobility frictions isolate employees is that the firm likely faces less wage competition (Kim & Marschke, 2005). Because the joint frictions isolate employees, they cannot credibly threaten to leave, and thus, have less bargaining power. This allows the firm to capture more value from the employment relationship in the form of lower wages relative to an employee with comparable human capital not facing such frictions (Garmaise, 2009).

However, cross- and within-industry mobility frictions can also put upward pressure on wages. As previously argued, isolating human capital increases incentives of the firm to invest in employees' human capital, especially in skills that would create value in the long run. Such investments serve to increase productivity, which subsequently increases wages if productivity is, at least partially, tied to wages. The productivity gains could be tied to wages for several reasons even when a credible threat of mobility is lacking. For instance, the firm may be willing to share a portion of the productivity gains to provide incentives for subsequent productivity growth (Blinder, 1989; Hamilton, Nickerson, & Owan, 2003). Greater tenure associated with higher mobility constraints may also put the focal employee at higher likelihood of promotion (Tesluk & Jacobs, 1998). Hence, if greater isolation of human capital due to complementary frictions increases firm-sponsored investment and the resulting value creating capability of the employee, the effect on wages may be positive even though the firm appropriates more value than the employee creates. Additionally, sophisticated workers may anticipate such effects and demand higher initial wages to compensate for expected lower wage growth. Indeed, such bargaining frameworks are typically built into models of noncompetes (Garmaise, 2009; Posner, Triantis, & Triantis, 2004). This is likely to be stronger for employees who face greater cross-industry frictions because their incentive to negotiate is higher.

So, given that there are both upward and downward forces on wages when both classes' frictions are high and there are no a priori theoretical reasons to expect one to dominate, we propose competing hypotheses. If the downward wage pressure dominates, then:

> **Hypothesis 3a (H3a)** *The interaction of limited transferability of skills across industries and noncompete enforceability will be associated with lower wages.*

However, if the upward wage pressure dominates, then the opposite relationship holds:

> **Hypothesis 3b (H3b)** *The interaction of limited transferability of skills across industries and noncompete enforceability will be associated with higher wages.*

3 | DATA AND EMPIRICAL STRATEGY

To test our hypotheses, we require individual-level data on employee tenure, their level of experience when they were hired, the existence and type of training investments they receive, and their wages. We also require measures of cross-industry skill transferability and noncompete enforceability. The Survey of Income and Program Participation (SIPP), a public use Census data product, is a natural choice as it is nationally representative, contains detailed training data, measures of employee wages, dates of graduation from school, and employee tenure on their current job. The SIPP also tracks occupations and industries in consistent ways with other Census products, which is important for merging in our measure of skill transferability. We pool data from the 1996, 2001, 2004, and 2008 Wave 2 Topical Module of the SIPP and then restrict the sample to employees with one job.[4] We focus on workers aged 22 to 55 in business and STEM occupations in the for-profit sector.[5]

[4]The topical module is the one in which the training questions were asked. The SIPP tracks up to two occupations for each employee, and if the employee has multiple jobs, it is unclear in which occupation the reported outcomes occurred.

[5]The business occupations in our sample include Management (SOC code 11), Business and Financial Occupations (SOC code 13), Sales and Related Occupations (SOC code 41), and Office Support and Related Occupations (SOC code 43). Per the BLS, the STEM occupations (https://www.bls.gov/soc/Attachment_C_STEM.pdf) include Computer and Mathematical Occupations (SOC code 15); Architecture and Engineering (SOC code 17); Life, Physical and Social Sciences (SOC code 19); and Healthcare Practitioners and Technical Occupations (SOC code 29).

3.1 | Dependent variables

We construct our dependent variables from the individual-level data in the SIPP. To examine our tenure hypothesis, we utilize the employee's reported *Tenure* (in months) with the employer. To measure the *Postgraduation experience at hire* of the employee, we calculate the number of months between when the individual reports finishing his or her highest degree of education and when being hired into a job. In robustness checks, we also utilize the employee's *Potential experience at hire* by taking the respondent's reported age, subtracting tenure, years of schooling, and then five. The variable reflects the amount of time the respondent *could* have worked outside of all formal schooling. We also utilize a dummy for being hired within 12 months of finishing the highest educational degree, ***1****(Hired < 12 months after graduation).*

With regards to data on the receipt of individual training, the SIPP contains training data reflecting answers to the question: "During the past year, has [the respondent] received any kind of training intended to improve skill in one's current or most recent job?" For those who indicate that they have received skill-improving training in the last year, the SIPP asks a series of questions about the most recent training event, including who paid for it and what it included. For our training dependent variable, we utilize a dummy for whether the respondent reports the firm paying for the most recent training event, ***1****(Firm-sponsored Training).* For our training type variables, we use indicator variables equal to one if the respondent indicated that the training included *Basic skills, New skills, Upgraded skills,* and *Company policies.*[6]

With regards to wages, the SIPP asks respondents about their monthly earnings, which we convert to hourly wages by dividing reported monthly earnings by the product of reported hours worked per week and 4.33 (since there are 4.33 weeks in a month). As is standard in wage analyses, we use the *Log of the hourly wage* as the dependent variable, *Ln(Hourly Wage).*

3.2 | Explanatory variables: Limited transferability of skills across industries

To test our hypotheses, we require an empirical measure of the degree of cross-industry skill transferability faced by a given individual. The measures we develop build on the logic from prior literature that the skills associated with a *job* will be differentially transferable across industries (Bottazzi & Pirino, 2010; Bryce & Winter, 2009; Neffke & Henning, 2013). For instance, our measure will pick up the fact that website designers working in finance will be much more able to transfer their skills to another industry than aerospace engineers working in the aerospace industry. More specifically, we measure cross-industry transferability of skills based on the extent to which an individual *in a given job is likely to move across industries*, where we conceptualize a job as a combination of an *occupation* and an *industry.* In particular, we use the longitudinal nature of the Current Population Survey (CPS) to estimate *P(Stay in Industry in 4 Months)* which is the probability of that an individual will be in the same industry over a four-month period for every combination of occupations and industries (Flood, King, Ruggles, & Warren, 2017).[7] The logic underlying this measure is that workers in jobs that require or develop skills that have very limited skill transferability across industries will tend to stay in the same industry. Thus, the

[6]For each skill type, the SIPP lists a few examples. For basic skills, the examples are office software, work habits, or management practices. For new specific work skills, the examples are how to use equipment, machinery, or technical procedures. No examples are provided for upgrading skills. The examples for company policies include guidelines or requirements.

[7]The CPS is a monthly, nationally representative survey of roughly 65,000 households administered by the Bureau of Labor Statistics (BLS). For more information, please see https://cps.ipums.org.

TABLE 1 Cross-industry skill transferability for selected occupations and industries

Two-digit NAICS industry	Three-digit census occupation	P(Stay in industry)
Panel A: Variation within marketing and sales managers		
Professional, scientific, and technical services	Marketing and sales managers	87.61
Wholesale trade	Marketing and sales managers	88.38
Retail trade	Marketing and sales managers	91.49
Manufacturing	Marketing and sales managers	91.56
Information	Marketing and sales managers	92.13
Finance and insurance	Marketing and sales managers	92.80
Panel B: Variation across selected occupations within professional, scientific, and technical services		
Professional, scientific, and technical services	Sales representatives, services	84.99
Professional, scientific, and technical services	Receptionists and information clerks	87.77
Professional, scientific, and technical services	Advertising sales agents	87.87
Professional, scientific, and technical services	Electrical and electronic engineers	89.00
Professional, scientific, and technical services	Computer programmers	89.12
Professional, scientific, and technical services	Engineers, all other	90.38
Professional, scientific, and technical services	Engineering technicians, except drafters	90.55
Professional, scientific, and technical services	Computer and info systems managers	90.63
Professional, scientific, and technical services	Computer software engineers	91.99
Professional, scientific, and technical services	Mechanical engineers	95.55
Panel C: Variation within the same two-digit SOC and two-digit NAICS codes		
Professional, scientific, and technical services	Electrical and electronic engineers	89.00
Professional, scientific, and technical services	Engineers, all other	90.38
Professional, scientific, and technical services	Engineering technicians, except drafters	90.55
Professional, scientific, and technical services	Civil engineers	92.45
Professional, scientific, and technical services	Drafters	93.38
Professional, scientific, and technical services	Surveying and mapping technicians	94.31
Professional, scientific, and technical services	Architects, except naval	95.05
Professional, scientific, and technical services	Mechanical engineers	95.55

Notes. P(Stay in industry) is calculated for each three-digit census occupation and two-digit NAICS industry as the probability of staying in the industry within four months multiplied by 100; these values are calculated using the merged monthly CPS from 1994 to 2010. All occupations shown are for 2003–2010 time period.

measure will indicate that an aerospace engineer in aerospace engineering will be less likely to switch industries than a website designer in finance.

The mean probability of staying in the industry is 89%, but there is significant variation both within occupations and industries. For example, Panel A of Table 1 shows that among sales and marketing managers, those in professional, scientific, and technical services have an 87.61% chance of staying in the industry compared to 92.80% in Finance and Insurance. In Panel B, within professional, scientific, and technical services, Mechanical Engineers have a 95.55% chance of staying in the industry, while Sales Representatives are on the lower end with an 84.99% chance. Table 1 provides evidence that skill transferability varies widely across jobs, even within fine-grained occupational categories and industries.[8]

[8]Our data set of cross-industry transferability of skills by occupations and industries is available at www.evanpstarr.com/research.

Prior research has documented a limitation in using the CPS to measure mobility: The CPS does not follow household members if they leave.[9] Thus, if an individual leaves the household because of a job change in month *t*, the individual may not be present in the data in month *t+3* to contribute to the estimate of the likelihood of changing industries. To address the fact that the CPS does not follow "movers," we create a similar index for robustness testing that exploits the unique design of the March Supplement to the CPS. In the March Supplement, individuals are asked about both their current job (in March) and their main job in the last calendar year *in the same interview*. As a result, data on both jobs are collected at the same point in time. Using this information to calculate industry changes, we similarly aggregate the data into the probability of staying in the industry for each three-digit Census occupation by two-digit (NAICS) industry cell, labeled *March CPS P(Stay in Industry).*

3.3 | A measure of cross-industry skill transferability using occupational concentration

A potential limitation of the prior measures is that if individual mobility decisions in the SIPP data are related to the probability of moving across industries in the CPS, then reverse causality could bias our results. While our Hypothesis 1a is about the interaction of cross- and within-industry frictions, and not the main effect, and our measures are derived from different datasets to limit this possibility, we nevertheless develop an alternative measure of skill transferability that relies on stocks as opposed to labor flows, labeled *Proportion of Occ. Employment in Industry.* The measure reflects the fact that some workers face limited skill transferability across industries because they have a high degree of occupation-specific human capital (Kambourov & Manovskii, 2009) and the stock of occupational employment is only found in their current industry. For example, salespeople in Professional Services will, if they want to stay in sales, be able to find many opportunities in other industries. In contrast, some occupations are almost entirely concentrated in one industry. For example, physicians are almost entirely consolidated in the medical industry, such that it would be unlikely for a physician to stay a physician but change industries.

To identify the degree of occupation-specific opportunities inside of an employee's focal industry, we use the American Community Survey (ACS) to calculate the proportion of occupational employment *inside* the focal industry (Ruggles, Genadek, Goeken, Grover, & Sobek, 2017).[10] If most of a given individual's occupational employment opportunities are in the industry in which they are already working, then they will face greater frictions to changing industries. Specifically, if a worker is in occupation *o* and industry *j*, and 10% of the employment in occupation *o* occurs *outside* of industry *j*, then our measure would calculate a value of 90%, suggesting that this focal worker faces few occupation-specific opportunities in other industries.

3.4 | Within-industry mobility frictions: Noncompete enforceability

While the literature on limited-skill transferability suggests that a focal worker's occupation and industry are strongly linked to the cross-industry frictions faced by an individual, it is unlikely that within-industry frictions would vary at the occupation and industry level because skills are likely to

[9] In 1994, the CPS adopted a dependent coding scheme that dramatically improved the reliability of employer moves and occupation coding over time. As a result, studies of mobility using the CPS utilize data after the change to dependent coding (e.g., Moscarini & Thomsson, 2007), and we do the same here. We only include occupation-industry combinations with at least 500 observations in the underlying CPS data to ensure our transition probabilities are well-measured. This 500 observations cutoff is also applied in the March CPS data and to the measure constructed from the American Community Survey. Additional, unreported testing suggests that the results are robust to different cutoffs.

[10] We use the American Community Survey because it is the largest sample of respondents in the United States every year (over 1 million) and is used for setting a variety of federal benchmarks.

be fully transferable within a given job type. Thus, we need to leverage some other characteristic to determine whether the worker faces within-industry frictions. One prominent within-industry friction is *noncompete enforceability*, which does not change the value of a given worker within the industry, but imposes costs to moving between competitors through the threat of litigation.

A growing literature on noncompetes has sought to measure the strength and effects of noncompete enforceability (Conti, 2014; Garmaise, 2009; Marx et al., 2009; Samila & Sorenson, 2011). The literature has typically exploited the fact that noncompetes are enforceable in some states, but not others. For example, noncompetes in Florida are broadly enforceable where courts do "not consider individualized economic or other hardship that might be caused to the person against whom enforcement is sought" (Florida Statutes §542.335). By contrast, noncompetes are unenforceable in California (Cal Business and Professions Code §16,600). The enforceability of noncompetes has been shown to reduce within-industry mobility (Balasubramanian, Chang, Sakakibara, Sivadasan, & Starr, 2018; Garmaise, 2009) and the incidence of within-industry spinouts (Starr, Balasubramanian, & Sakakibara, 2017).

To quantify the extent of cross-state variation in noncompete enforceability, previous studies have developed measures that attempt to classify states according to the strength of enforceability based on the treatises periodically updated by Malsberger (Bishara, 2011; Garmaise, 2009; Starr, 2018; Stuart & Sorenson, 2003). We use the measure developed in Starr (2018), which refines the measure used by Bishara (2011)[11] by using factor analysis on seven scores to generate less subjective weights.[12]

3.5 | Empirical approach

The ideal experiment to identify the effect of cross- and within-industry frictions would be to take individuals with the same skills and position and randomize the cross- and within-industry frictions they face. To approach this ideal experiment, we compare people who are broadly in the same job, but nevertheless differ in the probability they will stay in the industry and the extent to which they face enforceable noncompetes. We compare people with the same two-digit SOC code and two-digit NAICS code—the same broad occupation and industry categories—but with different likelihoods of staying in the industry because cross-industry frictions are calculated at a more disaggregated level of occupation coding (the three-digit Census level). For example, within the engineering occupation (two-digit SOC code 17) in professional, scientific, and technical services (two-digit NAICS code 54), as displayed in Panel C of Table 1, mechanical engineers are more likely to stay in the industry (95.55%) relative to electrical and electronics engineers (89.00%). This within-occupation-industry design ensures that we identify the effect of within- and across-industry frictions only on individuals who have chosen similar occupations and industries. We run variants of the following specification:

$$Y_{iojst} = \beta_0 + \beta_1 \text{ Cross–industry skill transferability}_{o3,j} \times \text{ Enforceability}_{st} \\ + \beta_2 \text{Cross–industry skill transferability}_{o3,j} + \alpha X_{ist} + \sum\nolimits_{o2,j} + \varphi_{s,t} + v_{io\,jst}, \quad (1)$$

where i indexes the individual, o the occupation, j the industry, s the state, and t indexes time. Because our key independent variables vary at the state and three-digit Census occupation by

[11]Bishara (2011) scored seven dimensions of noncompete enforceability for 1991 and 2009 from 0 to 10 and provides subjective weights to account for the importance of the various dimensions.

[12]Our results are robust to alternative measures of enforceability. Results are available from the authors on request.

two-digit NAICS by coding time period, we two-way cluster the standard errors at those levels (Moulton, 1990).

In Equation (1), the variable $Enforceability_{st}$ is the measure of noncompete enforceability proposed by Starr (2018), who provides a set of scores for both 1991 and 2009. Each set of scores is standardized to have a mean of zero and a standard deviation of one in a sample where each state has the same weight. We associate the 1991 enforceability scores with the SIPP data from 1996 and 2001, and the 2009 enforceability scores with the SIPP data from 2004 and 2008.[13]

Crucial to this specification is $\Sigma_{o_2,j}$, which represents two-digit SOC by two-digit NAICS fixed effects, and $\varphi_{s,t}$, which represents state-by-year fixed effects. The two-digit SOC by two-digit NAICS fixed effects ensure that the interaction of interest is identified by comparing individuals in the same broad occupation and industry. Similarly, the inclusion of state by year fixed effects, wipes out any common state-level differences or trends—the cost of this is that the main effect of noncompete enforceability is not identified. The key coefficient of interest is β_1, which is identified by comparing how within state-year differences between workers in jobs (in the same two-digit SOC and two-digit NAICS category) with high and low likelihoods of staying in the industry change as cross-sectional noncompete enforceability increases.

In addition to the above fixed effects, we also control for a host of individual characteristics in X_{ist}, including hours worked, the log of average weekly earnings in the three-digit Census occupation by two-digit industry, indicators for working in a metro area, having a bachelor's degree, having a graduate degree, gender, race, whether the employee is married, has children, and is unionized.

Table 2 provides descriptive statistics and correlations for the data. Across the sample, 24% of all respondents reported that their most recent training event was firm-sponsored. The average tenure is 82.3 months, and the average postgraduate experience when hired is 106 months. Average log real hourly wages are 3.02 (roughly $20 in 2008 wages). The sample is 46% male and 77% white.

4 | RESULTS

Table 3 contains the results on the relationship between the interaction of limited skill transferability across industries and noncompete enforceability and employee tenure, initial experience at hire, the incidence of firm-sponsored training, and wages. Model (1) shows that for a one percentage point increase in the likelihood of staying in the industry, a one standard deviation increase in noncompete enforceability is associated with an additional 0.23 months of tenure (p-value = 0.0177), thus supporting Hypothesis 1a. To provide some sense of the size of these estimates, in Panel A of Figure 2, we plot the effect of a one percentage point increase in the likelihood of staying in an industry on employee tenure for various levels of noncompete enforceability. One interpretation of interest is what will happen if an average enforcing state bans noncompetes (a move of four standard deviations). The estimates suggest that an employee with a 5% higher likelihood of staying in the industry would have an employee tenure that would be 4.6 months (= 0.23*5*4) lower (5.6% of the mean).[14]

Model (2) of Table 3 shows that the interaction of limited skill transferability across industries and noncompete enforceability is associated with individuals being hired with fewer months of postgraduate experience (p-value = 0.0335). For a one percentage point increase in the probability of staying in the industry, a one standard deviation increase in noncompete enforceability is associated

[13]Since the 1991 and 2009 scores are highly correlated, allocating enforceability scores to various SIPP years does not provide additional material information.

[14]All estimates are likely to be conservative, given that the effects will inevitably "average" over individuals who did and did not sign noncompetes. We revisit this in the following Limitations section.

TABLE 2 Summary statistics and correlation matrix

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1	P(Stay in industry in 4 months)	89.56	3.42	1.00											
2	March CPS P(Stay in industry)	85.40	4.12	0.77	1.00										
3	Proportion of occ. employment in industry	0.17	0.27	0.31	0.39	1.00									
4	Noncompete enforceability	−0.19	1.36	0.06	0.03	0.02	1.00								
5	Tenure (months)	82.38	85.83	0.12	0.12	−0.06	0.03	1.00							
6	Postgraduation experience at hire (months)	106.31	117.24	−0.05	−0.07	0.00	0.01	−0.32	1.00						
7	**1**(Hired < 12 months after graduation)	0.12	0.32	0.01	0.03	0.02	0.00	0.06	−0.32	1.00					
8	Potential experience at hire (months)	151.21	109.24	−0.04	−0.06	−0.01	0.00	−0.35	0.80	−0.28	1.00				
9	**1**(Firm-sponsored training)	0.24	0.43	0.03	0.08	0.01	0.03	0.04	−0.08	0.03	−0.07	1.00			
10	**1**(Basic skills)	0.08	0.26	0.04	0.03	0.00	0.02	0.01	−0.04	0.02	−0.03	0.50	1.00		
11	**1**(New skills)	0.10	0.30	0.05	0.06	0.01	0.02	0.01	−0.05	0.02	−0.04	0.59	0.42	1.00	
12	**1**(Upgrade skills)	0.18	0.38	0.05	0.08	0.01	0.03	0.03	−0.06	0.03	−0.05	0.82	0.37	0.46	1.00
13	**1**(New or upgrade skills)	0.21	0.41	0.04	0.08	0.01	0.02	0.03	−0.07	0.03	−0.06	0.90	0.39	0.65	0.91
14	**1**(Company policies)	0.06	0.24	0.05	0.05	0.02	0.02	0.02	−0.04	0.02	−0.03	0.45	0.43	0.40	0.43
15	Ln(Hourly wage)	3.02	0.66	0.21	0.32	−0.03	−0.04	0.22	−0.05	0.00	−0.08	0.14	0.04	0.07	0.13
16	Ln(Mean earnings in occupation-industry)	10.49	0.52	0.39	0.59	−0.02	0.01	0.16	−0.08	0.01	−0.10	0.14	0.03	0.07	0.13
17	**1**(Married)	0.64	0.48	0.07	0.10	−0.03	0.04	0.15	0.10	−0.08	0.09	0.02	0.00	0.02	0.02
18	**1**(Kids)	0.51	0.50	0.02	0.02	0.00	0.00	−0.02	−0.03	−0.03	−0.06	−0.01	−0.01	0.00	−0.01
19	**1**(Highest degree is Bachelor's)	0.27	0.45	0.07	0.14	0.00	0.01	−0.03	−0.07	0.06	−0.13	0.08	0.02	0.03	0.07
20	**1**(Highest degree is grad degree)	0.09	0.28	0.09	0.17	0.00	−0.01	0.00	−0.02	−0.02	−0.07	0.04	0.00	0.01	0.04
21	**1**(Metro area)	0.84	0.37	0.03	0.04	0.02	−0.05	−0.03	−0.01	0.00	−0.02	0.01	0.01	0.02	0.00
22	**1**(Male)	0.46	0.50	0.00	0.14	−0.04	−0.03	0.08	−0.05	0.02	−0.09	0.05	0.00	0.04	0.04
23	**1**(White)	0.77	0.42	0.04	0.06	−0.03	0.15	0.10	0.05	−0.01	0.04	0.07	0.02	0.04	0.07
24	Hours worked per week	41.48	9.94	0.11	0.18	−0.04	0.01	0.12	−0.04	−0.01	−0.05	0.13	0.04	0.05	0.12
25	**1**(Union)	0.04	0.20	−0.01	−0.01	0.03	−0.03	0.12	−0.04	0.01	−0.04	−0.02	−0.01	0.00	−0.02
26	Age (Years)	38.33	9.20	0.09	0.10	−0.05	0.03	0.42	0.50	−0.22	0.67	−0.01	−0.02	−0.02	0.00

TABLE 2 (Continued)

	Variable	13	14	15	16	17	18	19	20	21	22	23	24	25	26
13	**1**(New or upgrade skills)	1.00													
14	**1**(Company policies)	0.42	1.00												
15	Ln(Hourly wage)	0.13	0.05	1.00											
16	Ln(Mean earnings in occupation-industry)	0.14	0.06	0.55	1.00										
17	**1**(Married)	0.02	0.01	0.16	0.14	1.00									
18	**1**(Kids)	−0.01	−0.01	0.03	0.01	0.33	1.00								
19	**1**(Highest degree is Bachelor's)	0.07	0.03	0.25	0.26	0.03	−0.04	1.00							
20	**1**(Highest degree is grad degree)	0.04	0.00	0.29	0.29	0.07	0.01	−0.19	1.00						
21	**1**(Metro area)	0.01	0.00	0.14	0.09	−0.04	−0.01	0.08	0.07	1.00					
22	**1**(Male)	0.05	0.02	0.29	0.34	0.08	−0.02	0.14	0.13	0.05	1.00				
23	**1**(White)	0.07	0.03	0.11	0.13	0.11	−0.07	0.07	−0.01	−0.11	0.05	1.00			
24	Hours worked per week	0.12	0.06	0.20	0.36	0.03	−0.05	0.11	0.12	0.02	0.31	0.07	1.00		
25	**1**(Union)	−0.02	−0.01	0.00	−0.08	0.00	0.00	−0.06	−0.03	0.01	0.01	−0.04	−0.04	1.00	
26	Age (Years)	−0.01	−0.01	0.19	0.13	0.23	−0.07	−0.04	0.07	−0.02	0.02	0.13	0.08	0.04	1.00

TABLE 3 Cross- and within-industry constraints and employee management

Estimation method: OLS	Dependent variable			
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
	Tenure (months)	**Postgrad experience at hire (months)**	**1(Firm-sponsored training)**	**Ln(Hourly wage)**
Enforceability*P(Stay in industry)	0.2275	−0.2042	0.0013	0.0007
	(0.0177)	(0.0335)	(0.0076)	(0.0894)
P(Stay in industry)	2.4489	−2.3879	0.0038	0.0034
	(0.0000)	(0.0000)	(0.1208)	(0.1744)
Ln(Occupation-industry earnings)	9.3991	−4.9972	0.0270	0.424
	(0.0131)	(0.3698)	(0.2398)	(0.0000)
1(Married)	8.1019	1.7906	0.0035	0.0531
	(0.0000)	(0.2540)	(0.4915)	(0.0000)
1(Kids)	0.0011	2.1017	−0.0119	0.0231
	(0.9988)	(0.1391)	(0.0451)	0.0018)
1(Bachelor's degree)	−11.5981	−6.3308	0.0356	0.2314
	(0.0000)	(0.0039)	(0.0001)	(0.0000)
1(Grad degree)	−22.0995	−8.4004	0.0096	0.3934
	(0.0000)	(0.0046)	(0.4210)	(0.0000)
1(Metro)	−2.7203	1.6668	0.0178	0.1388
	(0.0980)	(0.3822)	(0.1437)	(0.0000)
1(Male)	4.2259	−2.9284	−0.0128	0.1616
	(0.0065)	(0.1344)	(0.0354)	(0.0000)
1(White)	2.1207	2.4369	0.0449	0.083
	(0.2167)	(0.1339)	(0.0000)	(0.0000)
1(Hours)	0.4228	−0.4051	0.004	−0.0009
	(0.0000)	(0.0000)	(0.0000)	(0.2402)
1(Unionized)	44.4157	−37.6041	−0.0150	0.1068
	(0.0000)	(0.0000)	(0.3405)	(0.0000)
Age	1.6541	6.5236	0.0061	0.0404
	(0.0030)	(0.0000)	(0.0200)	(0.0000)
Age*age	0.0241	0.0034	−0.0001	−0.0004
	(0.0021)	(0.7029)	(0.0058)	(0.0000)
Observations	28,721	28,721	28,726	28,726
R-squared	0.2492	0.3064	0.0852	0.4174
State-year FE	Yes	Yes	Yes	Yes
Two-digit SOC by two-digit NAICS FE	Yes	Yes	Yes	Yes

Notes. Robust *p*-values are in parentheses, two-way clustered at the state and three-digit census occupation by two-digit NAICS industry by time period. P(Stay in Industry) is calculated for each three-digit census occupation and two-digit NAICS industry as the probability of staying in the industry within four months multiplied by 100; these values are calculated using the merged monthly CPS from 1994 to 2010.

with an additional 0.204 fewer months of experience. Panel B of Figure 2 plots the marginal effect of a one percentage point increase in the probability of staying in the industry on postgraduate experience at hire for different levels of noncompete enforceability. The results imply that if an employee

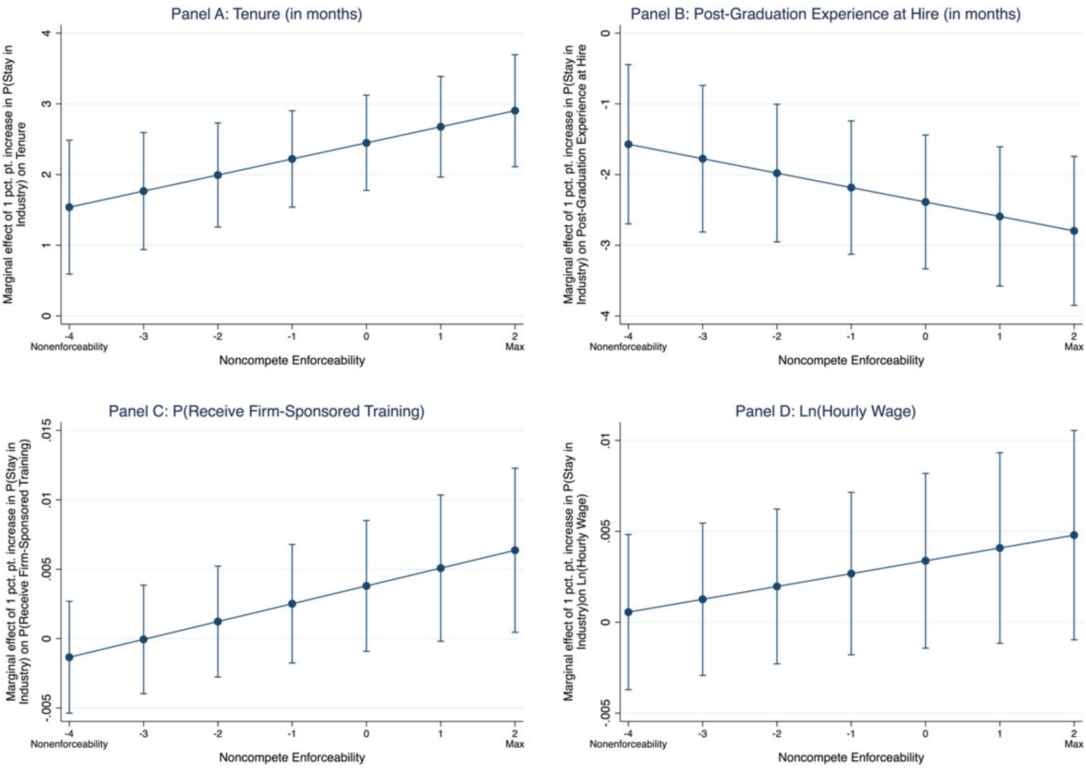

FIGURE 2 Marginal effects of 1 percentage point increase in P(Stay in industry) by levels of noncompete enforceability

had a five percentage point higher likelihood of staying in the industry, they would be hired with 4.1 (=0.204*5*4) fewer months of postgraduate experience in an average enforcing state versus a non-enforcing state, which is 4% of the sample average of initial experience. Thus, Hypothesis 1b is supported.

Model (3) of Table 3 reports the firm-sponsored training results. For a one percentage point increase in probability of staying in the industry, a one standard deviation increase in noncompete enforceability increases the likelihood of receiving firm-sponsored training by an additional 0.13 percentage points (p-value = 0.0076), supporting Hypothesis 2a. These results are plotted graphically in Panel C of Figure 2. For a five percentage point increase in the probability of staying in the industry, these results suggest that the employee will experience a 2.6 (= 0.0013*5*4) percentage point increase in the likelihood of receiving training in an average enforcing versus a non-enforcing state; this represents a 10.8% increase relative to the mean.

Table 4 reports the results from testing the training *type* hypotheses. The top part of the table reports the coefficients on the interaction of noncompete enforceability and the probability of staying in the industry for each training type. The bottom half of the table uses seemingly unrelated regression to compare the point estimates across the models, reporting the p-value for the test of equality of the coefficient on the interaction of noncompete enforceability and the probability of staying in the industry.[15] The raw coefficient sizes suggest that the interaction of noncompete enforceability and limited skill transferability across industries has a stronger effect on new skill training and upgrade

[15]Note that seemingly unrelated regression only allows the standard errors to be clustered on one dimension. We chose state as it seemed to be the more conservative number of clusters and thus has lower power to identify an effect.

TABLE 4 Content of the most recent training event

Estimation method: OLS	Dependent variable					
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
	1(New skills training)	**1(Upgrading skills training)**	**1(Upgrade or new skills training)**	**1(Basic skills training)**	**1(Company policies)**	**1(Basic skills or company policies)**
Enforceability*P(Stay in industry)	0.0009	0.0007	0.0012	0.0004	0.0002	0.0004
	(0.0060)	(0.0790)	(0.0108)	(0.1427)	(0.2947)	(0.1737)
P(Stay in industry)	0.0014	0.0014	0.0028	0.0021	−0.0001	0.0019
	(0.2073)	(0.4295)	(0.1927)	(0.0940)	(0.8745)	(0.1751)
Observations	28,726	28,726	28,726	28,726	28,726	28,726
R-squared	0.0343	0.0624	0.0716	0.0244	0.0274	0.0327
State-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Two-digit SOC by two-digit NAICS FE	Yes	Yes	Yes	Yes	Yes	Yes
P-*value of cross-model test of equality of coefficient on Enforceability*P(Stay in Industry) for each Training Type* versus *the same coefficient for:*						
Company policies	0.0255	0.2050	0.0265	0.4485		
Basic skills	0.0115	0.3106	0.0279		0.4485	
Basic skills or company policies	0.0325	0.2900	0.0288			

Notes. Robust *p*-values are in parentheses, two-way clustered at the state and three-digit census occupation by two-digit NAICS industry by time period. All models include the same set of controls as in Table 1. P(Stay in Industry) is calculated for each three-digit census occupation and two-digit NAICS industry as the probability of staying in the industry within four months multiplied by 100; these values are calculated using the merged monthly CPS from 1994 to 2010. Dependent variables are indicator variables equal to one if the individual's most recent training included receiving new skills training (Model 1), training that upgraded existing skills (Model 2), training that provided either new or existing skills (Model 3), receiving basic skills training (Model 4), introducing company policies (Model 5), or receiving basic skill training or introducing company policies (Model 6).

skill training (both individually and jointly) than on basic skill training and company policy training (both individually and jointly). These differences are borne out in the cross-model tests, where the coefficient on new skills (0.09 percentage points) and new or upgrade skills (0.12 percentage points) are greater than the coefficients on basic skills, company policies, and the combination or basic skills or company policies.[16]

Column (4) of Table 3 reports our results on the value appropriation hypothesis. We find that the interaction of noncompete enforceability and limited skill transferability across industries is marginally positively associated with wages (p-value = 0.0894), which is broadly consistent with Hypothesis 3b. These interaction effects are plotted in Figure 2, Panel D.

4.1 | Robustness and sensitivity analysis

In this section, we establish the robustness of our results to a variety of potential concerns, including the measurement of initial experience, controlling for initial experience, using different measures of cross-industry transferability, and including additional sets of fixed effects. In Panel A of Table 5, we begin by examining a more direct test of whether firms hire individuals directly out of school. We use a dependent variable for initial experience that is equal to one if the individual was hired into

[16]The *p*-values range between 0.01 and 0.033.

TABLE 5 Different measures of initial experience and controlling for initial experience

Estimation method: OLS	Panel A: Different measures of initial experience at hire		Panel B: Controlling for postgraduate experience at hire				
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
	1(Hired < 1 year after most recent degree)	Potential experience at hire (months)	Tenure (months)	1(Firm-sponsored training)	1(Upgrade or new skills training)	1(Basic skills or company policies)	Ln (Hourly wage)
Enforceability*P(Stay in industry)	0.0006	−0.2077	0.121	0.0012	0.0011	0.0003	0.0006
	(0.0434)	(0.0196)	(0.0660)	(0.0084)	(0.0112)	(0.1889)	(0.1263)
P(Stay in industry)	0.0020	−2.3207	1.2028	0.0033	0.0023	0.0017	0.0022
	(0.0223)	(0.0000)	(0.0000)	(0.1683)	(0.2620)	(0.2144)	(0.3596)
Postgrad experience at hire (months)			−0.5218	−0.0002	−0.0002	−0.0001	−0.0005
			(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Observations	28,726	28,721	28,721	28,721	28,721	28,721	28,721
R-squared	0.0812	0.5289	0.6020	0.0877	0.0735	0.0333	0.4225
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Two-digit SOC by Two-digit NAICS FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-*value of cross-model test of equality of coefficient on Enforceability*P(Stay in Industry) for Upgrade or New Skills Training Type* versus *the same coefficient for:*							
Basic skills or company policies					0.0299		

Notes. Robust p-values are in parentheses, two-way clustered at the state and three-digit census occupation by two-digit NAICS industry by time period. All models include the same set of controls as in Table 1. P(Stay in industry) is calculated for each three-digit census occupation and two-digit NAICS industry as the probability of staying in the industry within four months multiplied by 100; these values are calculated using the merged monthly CPS from 1994 to 2010.

TABLE 6 Different measures of cross-industry frictions

Estimation method: OLS	Dependent variable									
	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**	**Model (10)**
	Tenure (months)	**Experience when hired (months)**	**1(Firm-sponsored training)**	**Type of training**						**Ln (Hourly wage)**
Measures of industry specificity:				**1(New skills)**	**1(Upgrading skills)**	**1(Upgrade or new skills)**	**1(Basic skills)**	**1(Company policies)**	**1(Basic skills or company policies)**	
Panel A: March CPS measure of probability of staying in the industry										
Enforceability*March CPS P(Stay in industry)	0.2373 (0.0543)	−0.4121 (0.0005)	0.0018 (0.0000)	0.0008 (0.0066)	0.0012 (0.0009)	0.0013 (0.0009)	0.0002 (0.4380)	0.0003 (0.1572)	0.0004 (0.1042)	0.0010 (0.0671)
March CPS P(Stay in industry)	1.9784 (0.0002)	−2.2555 (0.0005)	0.0044 (0.0474)	0.0025 (0.0286)	0.0028 (0.1184)	0.0036 (0.0740)	0.0017 (0.1356)	0.0016 (0.0312)	0.0024 (0.0648)	−0.0002 (0.9379)
P-*value of cross-model test of equality of coefficient on Enforceability P(Stay in Industry) for each Training Type* versus *the same coefficient for:*										
Company policies				0.0046	0.0021	0.0004	0.6304			
Basic skills				0.0000	0.0001	0.0000		0.6304		
Basic skills or company policies				0.0028	0.0042	0.0005				
Panel B: Proportion of employment in focal occupation within the focal industry (POI) from American community survey										
Enforceability*POI	1.2289	−2.4628	0.0136	0.0147	0.0056	0.011	0.0035	0.0083	0.0086	0.0167
	(0.0116)	(0.0054)	(0.0001)	(0.0001)	(0.0423)	(0.0001)	(0.2904)	(0.0112)	(0.0368)	(0.0025)
POI	−0.5291	1.7909	0.0283	0.0269	0.0247	0.0301	0.0054	0.0145	0.0181	−0.0021
	(0.8855)	(0.6712)	(0.0337)	(0.0117)	(0.0256)	(0.0250)	(0.4971)	(0.0506)	(0.0834)	(0.9234)
P-*value of cross-model test of equality of coefficient on Enforceability P(Stay in Industry) for each Training Type* versus *the same coefficient for:*										
Company policies				0.0198	0.3368	0.4164	0.0293			
Basic skills				0.0001	0.4332	0.0130		0.0293		
Basic skills or company policies				0.0222	0.2197	0.3749				

Notes. Robust p-values are in parentheses, two-way clustered at the state and three-digit Census occupation by two-digit NAICS industry by time period. All models include the same set of controls as in Table 3. P(Stay in Industry) in Panel A is calculated for each three-digit Census occupation and two-digit NAICS industry as the probability of staying in the industry of the job in the last calendar year and in March of this year, multiplied by 100; these values are calculated using the March Supplement to the CPS from 1994 to 2010. In Panel B, the measure of industry specificity (POI) is calculated using the American Community Survey, as the proportion of individuals in a given occupation (three-digit Census Code) that are in the focal industry (three-digit Census Code).

their job within one year of finishing their highest degree. The results show that the interaction of noncompete enforceability and the likelihood of staying in the industry is positively related to hiring individuals within one year of graduating from school (p-value = 0.043). Using a different measure of experience in Model (2) of Panel A of Table 5—potential experience at hire, which is the amount of potential work experience the individual could have had by the time they were hired into their job—we find the same pattern.

In Panel B of Table 5, we examine how our results change when initial experience is added as a control.[17] The rationale for including initial experience as a control is that in a cross-section where we control for age, individuals hired at an earlier age will naturally have longer tenures.[18] Similarly, less experienced individuals will necessarily need more training. Thus, we want to examine if our results are driven by differential hiring patterns or whether the effects of interaction of these frictions extend beyond the experience of the employee hired. Model (3) shows that the tenure effect falls by half (0.23 to 0.12), with a p-value of 0.066 when controlling for initial experience. Model (4) shows that the training effect is marginally reduced (from 0.13 percentage points to 0.12) with a p-value of 0.008. Models (5) and (6) shows that even after controlling for initial experience, noncompete enforceability and limited cross-industry skill transferability still have stronger effects on new skill and upgrading training relative to basic skills and company policies (p-value = 0.029). In Model (7), we find that the interaction effect on wages falls slightly, but remains positive while the p-value rises to 0.126.

In Table 6, we replicate all the models with our two different measures of cross-industry skill transferability. Panel A uses the measure derived from the March CPS in which industry transitions are captured within the same interview for the job in March and the main job in the last year. The results are replicated in each specification. The main distinction between these results and our main results is that the effect on upgrading skills training appears to be much larger and statistically different from the effect on basic skills training and company policies training. In Panel B, we utilize the measure derived from the American Community Survey that reflects the proportion of occupational employment within the focal industry. Again, the results on the interaction of noncompete enforceability and the likelihood of staying in the industry are largely consistent across all models. The only discrepancies in this model are company policies, which pick up a larger coefficient and a smaller p-value, while upgrading skills has a smaller coefficient in absolute value. Nevertheless, we still find that the effects on new skills that are stronger than the other coefficients.

In unreported results, we also re-ran our analyses using occupation by industry by year fixed effects and found the results to be robust. We also used a higher cutoff of 2,000 observations required to be in the CPS when calculating the probability of staying in the industry measure and found substantively similar effects. We also re-ran our main specifications with alternative measures of noncompete enforceability from Bishara (2011) and Garmaise (2009) as well as with additional state controls. The results, available from the authors, remain robust.

Potential sorting of workers into occupation-industry categories is also worth noting. While our design ensures that the effects are identified by comparing individuals in the same occupation and industry, the fact that people choose their job causes concern that an unobserved variable might drive both job decisions and the outcome of interest. The most natural confounder is expected earnings in each job: If jobs with a high degree of cross-industry frictions and a high degree of within-industry frictions have higher earnings on average, then they might also be associated with longer tenures and higher earnings. Because we are concerned about separating treatment from selection, we control for

[17]We also explored polynomials in initial experience, and all results were robust. Results are available from the authors.

[18]In unreported robustness checks, we also dropped age as a control and found that all the results persist.

		Cross-Industry Mobility Friction	
		High	Low
Within-Industry Mobility Friction	High	*Human capital is isolated in the firm.* Firms cannot buy experienced employees on the market. Given the inability to hire experienced employees on the external market, heterogeneity in performance will likely be determined by firms' advantages in both recruiting high quality, inexperienced workers and providing general and specific training.	*Human capital is fungible between industries but not within industries.* Firms can buy general human capital on the market, but not industry-specific human capital. Relative to high-high, performance heterogeneity is more likely to come from advantages in the ability to select and attract easily trained new employees and experienced employees from other industries and from advantages in delivering industry-specific development.
	Low	*Human capital is fungible within industries but not between industries.* Firms can buy industry-specific human capital on the market. Relative to high-high, performance heterogeneity is more likely to come from advantages in the ability to select and attract high quality, experienced, within-industry talent. There is less primacy on internal development relative to high-high because workers with industry-specific skills are available.	*Human capital is broadly fungible.* Firms can buy desired human capital on the market and workers are able to capture a larger portion of their rents. Given the absence of other labor market frictions, relative to high-high, firm-specific inducements likely play a key role in creating Human Capital-related performance heterogeneity and competitive advantage.

FIGURE 3 Implications for heterogeneity in firm performance

average job level earnings at the three-digit SOC code and two-digit NAICS code level in all specifications.

Last, because cross-industry skill transferability is necessarily an individual phenomenon and we capture it at the job-level, some measurement error will inevitably occur. It is not obvious to us that the measurement error will be anything other than classical error, which attenuates our results.

5 | DISCUSSION

We explore how cross-industry mobility frictions in the form of cross-industry skill transferability interact with within-industry frictions in the form of noncompete enforceability to affect firms' human capital practices. Specifically, we hypothesize and find that in the face of both cross- and within-industry mobility frictions, firms hire workers with less prior experience, provide them with more training generally, and more training in new and upgrading skills relative to basic skills specifically. Workers also exhibit longer tenures, and wages rise marginally. These results are robust to different measures of initial experience, different measures of cross-industry frictions, different measures of noncompete enforceability, and different specifications. That the results are robust to controlling for initial experience indicates that the observed effects are not driven by simply having to educate less experienced workers (e.g., new graduates), suggesting that isolation of human capital drives a fundamental change in how firms invest in and manage their employees.

We now turn to the question of what these results mean for firm heterogeneity and the development of human capital-based competitive advantage. Broadly, firms can either develop strategically-relevant human capital internally or buy such human capital on the external market. In line with Mahoney and Qian (2013), we suggest that market frictions have important implications for firms' human capital make-or-buy decisions, and consequently, firm heterogeneity. To understand how interacting complementary labor market frictions are likely to drive firm heterogeneity, we provide the "2 × 2" displayed in Figure 3. Through the following discussion, we hope to stimulate future research on how specific human capital management strategies and practices can support performance heterogeneity in the face of different labor market frictions.

When a given worker in an industry faces high within- and cross-industry frictions in a labor market (top left quadrant in Figure 3), the worker's human capital is isolated. This presents a double-edged sword for firms. On one hand, this means that labor market rivals cannot bid up the wages of important employees. On the other hand, firms cannot hire targeted employees away from rival firms. As a result, firms can develop human capital-based competitive advantages through two primary channels: advantages in internal development of strategically valuable employees and advantages in hiring in the market for inexperienced workers.

If firms cannot acquire experienced workers with the relevant skills from the external market, they must forecast what human capital they will need in the future and implement training systems that provide the right human capital to the firm at the right time. The human capital strategies must thus emphasize a longer-term view of development and compensation of employees while maximizing value (Wright, Dunford, & Snell, 2001). Firms that are unable to do so will have a mismatch of their human capital and what the current business conditions require. Thus, paths toward developing human capital-based competitive advantages spawn from both advantages in forecasting human capital needs and advantages in cost-effective training. On the hiring side, the market for inexperienced workers is fraught with uncertainty on employee quality and preferences, and other sources of information asymmetries between employers and potential employees. As a result, the firms that are better able to identify and develop inexperienced talent are likely to have superior performance. To the extent that firms vary in these capabilities, this variation will be a source of performance heterogeneity.

In contrast, when both within- and cross-industry frictions are low (bottom right quadrant of Figure 3), sustaining human capital-based performance advantages will be difficult since workers can easily bid up wages. Relative to the high-high context, advantages in inexperienced human capital acquisition are potentially less salient as firms can hire experienced talent away from other firms diminishing the benefits of navigating the uncertainty associated with inexperienced workers. Similarly, advantages in internal development are also less salient because firms can hire desired general and industry-specific human capital on the market. In this context, the firm's ability to develop firm-specific human capital or firm-specific incentives (as well as potential complementarities with other resources at the firm) will play a more important role in creating performance heterogeneity.

The other two cases reflect some combination of these extremes. When workers can flow within industries but not across (i.e., bottom left quadrant in Figure 3), then there is less emphasis on the firm's internal development because firms can hire experienced workers with desired industry-specific human capital (i.e., "buy") from competitors in the same industry. When workers can flow across, but not within industries (i.e., top right quadrant in Figure 3), heterogeneity in firm performance is likely to be driven by the firm's ability to hire experienced workers from outside the industry who have relevant general human capital or for whom the marginal cost of training is low. In this case, firms can safely invest in industry-specific skills since those skills are effectively isolated. This study thus contributes to our understanding of the implications of interdependent frictions on firm heterogeneity generally and on human capital-based competitive advantages more specifically.

Additionally, with regards to the literature on mobility (Marx et al., 2015; Singh & Agrawal, 2011) and covenants not to compete (Conti, 2014; Garmaise, 2009; Marx, 2011; Marx et al., 2009; Younge et al., 2015; Younge & Marx, 2016), our findings build on prior work that explores the interactions of noncompetes and other worker or regional characteristics. Marx et al. (2009) hypothesized that the effect of enforceability on the movement of inventors will be stronger if the inventors are specialized, and Garmaise (2009) examined how the extent of local competition moderates the impact of noncompete enforceability. Our theoretical and empirical focus on the cross- and within-industry frictions provides a more general framework that relates the interaction of these frictions to not only retention, but also hiring behavior, the amount and type of investment, and wages. Furthermore, our results suggest that some types of employees with valuable knowledge (e.g., mechanical engineers) face high cross-industry frictions and are among the most impacted by the interaction with noncompete enforceability. This has implications for their ability to diffuse knowledge across firm boundaries (Almeida & Kogut, 1999) and innovation (Samila & Sorenson, 2011).

From a policy perspective, the differential effect of noncompete enforceability across jobs highlights an inherent inequity in one-size-fits-all regulatory approaches. If the goal of noncompete law is to be equally impactful across jobs, then the design of the laws must be job-specific.

From a managerial perspective, while our empirical analysis offered insights into value creation and appropriation from workers conditional on the existence of complementary frictions, firms may have some control over which frictions they face. If the friction is geographic in nature (e.g., noncompete enforceability is a state choice), then a firm can move to a location with policies that better suit its capabilities or lobby for desired policies. For example, firms that lack strong internal development capabilities may desire to move to a place where noncompetes are not enforceable, so that they may be able to hire experienced, within-industry talent. This may contribute to reasons for why startups thrive in states that do not enforce noncompetes such as California (Saxenian, 1996).

5.1 | Limitations and additional avenues for future research

Given the nature of the data, it is not possible to identify the specific mechanisms that underpin the cross-industry skill specificity of human capital. For simplicity, our theory development revolved around the ability of employees' skills to be valuable in multiple industries. If there are systematic differences in the boundaries of employees' personal and professional networks across industries, and social networks play an important role matching employees and employers (Castilla, 2005), then this mechanism may contribute to the observed results. For example, if mechanical engineers only have professional and personal networks with other large machinery mechanical engineers, then their social capital could contribute to cross-industry mobility frictions—even if their human capital component was theoretically transferable to other industries. Similarly, human capital pipelines (Brymer, Molloy, & Gilbert, 2014) could drive cross-industry frictions. If some firms only hire from feeder firms in the same industry, for example, from firms with similar organizational structure (Karim & Williams, 2012), and there are systematic differences across industries, then this mechanism could also contribute to the observed results. However, the general logic in the theory development accommodates these alternative mechanisms and other unobserved within industry movement frictions. Research exploring the roots of cross-industry skill transferability would provide a valuable contribution in understanding the source of mobility frictions.

Additionally, cross-industry skill transferability and firm specificity are potentially related. A high level of firm specificity is likely to result in long tenure on the job (Hashimoto, 1981; Jovanovic, 1979), and thus, a low probability of changing firms. If an employee has a low probability of changing firms, then the employee may also have a low probability of changing industries. Consequently, our conceptualization of cross-industry frictions might absorb some degree of firm specificity.

However, we measure cross-industry skill transferability at the occupation-industry level, and firm specificity is likely heterogeneous within these categories (i.e., the effect of firm specificity is attenuated because jobs with varying degree of firm specificity are included). In general, we leave an analysis explicitly comparing firm specificity with cross-industry frictions for future work.

Further, noncompete enforceability might only create within-industry frictions within the focal state (depending on the extent to which other states will enforce contracts signed in other states). If so, for those on the border, noncompete enforceability may be less effective in constraining workers than for those in the middle of the state. Unfortunately, the SIPP data do not have any county or city information and so a border county analysis is infeasible in this case.

A final data limitation is that it is not possible to identify exactly which employees are asked to sign noncompetes nor whether they are enforced for specific individuals. This limits the ability to make claims on individual micro-mechanisms: we can only address average outcomes and our results likely underestimate the magnitude of the effect sizes for individuals who did sign noncompetes. Thus, a clear path for future research is to better understand these micro-level effects of actual noncompetes to better understand the impact of within-industry mobility frictions.

6 | CONCLUSION

We develop and test a theory examining how frictions that restrict mobility across industries and frictions constraining mobility within an industry can co-occur to effectively isolate individual human capital, which ultimately impacts how firms create and appropriate value from human capital. Our findings indicate that sufficiently strong and complementary mobility frictions shift the emphasis of firms' human capital management practices toward internal development of human capital relative to acquisition on the external market. These results have implications for how labor market frictions may explain human capital-based firm heterogeneity in performance.

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