Received: 14 March 2022 | Revised: 22 May 2024 | Accepted: 25 May 2024

DOI: 10.1002/smj.3648

RESEARCH ARTICLE

SMS Strategic Management Journal WILEY

Strategic restraint: When do human-capital-intensive companies choose (not) to use noncompete agreements?

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Abstract

Research Summary: Extant work in strategic management has focused on the role of noncompete agreements (NCAs)—a form of restrictive legal lever used by firms when managing human capital—and conceptualized them as being advantageous to firms. Challenging this notion, we highlight a novel downside of using NCAs and show how their use by some firms creates differentiation opportunities for rival firms. We analyze a unique survey dataset to examine the heterogeneity in the firms' actual use of NCAs conditional on industry and state. We find that the nonuse of NCAs is more common among firms that rely more heavily on talent and are also not the industry leaders, and such firms are more likely not to use NCAs with the goal of attracting skilled employees.

Managerial Summary: Noncompete agreements (NCAs) have long been regarded as effective tools for firms managing human capital. Our research challenges this conventional wisdom. We show that NCAs are not uniformly beneficial to all firms even when looking at competitors within the same industry. By analyzing a unique survey dataset, we find that firms relying heavily on talent and not leading their industries are more inclined to forgo NCAs. Their strategic intent? Attracting skilled employees. This study sheds light on the delicate balance between legal constraints and talent attraction and is particularly salient in the context of the policy efforts to ban NCAs.

KEYWORDS

employee mobility, knowledge spillovers, noncompete agreements, restrictive legal practices, strategic management of human capital

"*We want people who want to be here, not ones who feel trapped.*"

Daniel Hertzberg, CEO of CAD-design firm Onshape.

1 | INTRODUCTION

Exploring the role of restrictive legal levers in the management of knowledge and human capital is one of the traditional questions studied by scholars in strategic management. Firms often use patent enforcement and restrictive clauses in employment contracts to lower the risk of expropriation of their valuable knowledge by competitors (Agarwal et al., 2009; Kim & Marschke, 2005; Starr, Balasubramanian, & Sakakibara, 2018). Since employee mobility drives knowledge spillovers across firms (Fallick et al., 2006; Kim & Steensma, 2017; Rosenkopf & Almeida, 2003; Sevcenko & Ethiraj, 2018; Tzabbar, 2009; Tzabbar & Cirillo, 2020), management of knowledge outflows frequently focuses on human capital.

In this context, noncompete agreements (NCAs) have been studied extensively as a way to reduce mobility to rivals (Marx, 2011; Marx et al., 2009), lower the likelihood that employees found competing startups (Starr, Balasubramanian, & Sakakibara, 2018), reduce knowledge spillovers to competing firms (Marx et al., 2015), improve value appropriation (Starr et al., 2021; Starr, Ganco, & Campbell, 2018; Younge & Marx, 2016), and enhance collaboration between workers (Seo & Somaya, 2021).[1] Further, NCAs incentivize firms to invest in employees' human capital through training (Meccheri, 2009; Starr, 2019), share confidential information (Garmaise, 2011), and pursue riskier R&D projects (Conti, 2014). Given their practical relevance

[1]A NCA is a clause in an employment contract under which an employee agrees not to join a competitor or start a competing firm after exit from the focal employment, usually for a predetermined amount of time and over a geographical area (Conti, 2014; Garmaise, 2011; Rubin & Shedd, 1981; Samila & Sorenson, 2011; Starr, Balasubramanian, & Sakakibara, 2018a).

and theoretical interest, NCAs have become central to the literature on the management of knowledge flows through mobility.

While NCAs can be detrimental to employees because they restrict the employees' outside options, the value of NCAs for firms has been generally viewed as positive (Marx et al., 2009; Starr, Balasubramanian, & Sakakibara, 2018; Starr, Ganco, & Campbell, 2018; Younge & Marx, 2016). That is hardly surprising given that the laws that enable firms to use NCAs are intended to help firms retain their intellectual property (IP) and encourage investments associated with stronger property rights (Alchian & Demsetz, 1973; Ostrom & Hess, 2008). A question not addressed in prior work is, if NCAs are beneficial to firms, why don't all firms use them?[2] Do NCAs have downsides for some firms using them? Which firms choose not to use NCAs and why?

Our study aims to explore why firms choose to opt out of NCA use even when the NCAs are used within the focal industry. By doing so, we introduce a novel explanation of the heterogeneity of NCA use among competitors. There is emerging evidence about the heterogeneity of NCA use across workers. For instance, Starr et al. (2021) surveyed workers and found that many workers are not bound by NCAs even when such covenants are popular among firms in the focal industry and enforceable in the focal state. They also report that being bound by an NCA positively correlates with the worker's human capital and employer size.[3] However, together with the work examining the effects of state-level variation in the NCA legislation and its enforceability (Marx et al., 2009; Seo & Somaya, 2021; Starr et al., 2021; Starr, Balasubramanian, & Sakakibara, 2018; Starr, Ganco, & Campbell, 2018; Younge & Marx, 2016), these studies leave open the question of the reasons behind this firm-level heterogeneity.

We develop a theoretical framework describing when firms opt out of using NCAs. The core of our argument is that while NCAs may improve employee retention, they may also lower the firm's ability to attract workers. If a firm is less concerned about knowledge expropriation by exiting workers while it still needs to attract talented workers (e.g., because talent constitutes its core resource), it may decide not to use NCAs, even when NCAs are enforceable and used by competitors. Our theory posits that even within industries and states, there may be significant firm-level heterogeneity in NCA use due to the tension between talent attraction and retention.

We utilize a novel survey implemented in collaboration with PayScale, a US data and software company focusing on compensation analytics. PayScale routinely collects employment-related data from its client firms. We attached the NCA-related questions to their periodic firm-level survey (the respondents are primarily human resource [HR] managers and executives). The survey allowed us to observe the actual use of NCAs at the firm level and also ask questions about the reasons for opting out of NCAs.

Descriptively, our data reveal significant heterogeneity in the use of NCAs. On average, within industries, around 31% of the surveyed firms use NCAs for all workers, 40% for some workers, and 28% for none. We also find that among firms using NCAs for none or some of their workers, 15% of them report not using NCAs (at least for some workers) because doing so makes it harder to attract talented workers. This percentage increases to 30–35% in human capital-intensive industries such as "architecture and engineering" or "PR and marketing."

[2]There is limited evidence on the firm-level use of NCAs. Starr et al. (2021) estimated that around 18% of the entire US workforce is subject to NCAs.

[3]Other studies that focus on individuals are Colvin and Shierholz (2019), who provide descriptive information about the use of NCAs, and Johnson and Lipsitz (2022), who study NCA use in the context of hair salons.

In a regression analysis, where we condition on industry and state, firms that rank talent as the key resource differentiating them from competitors (relative to other resources) *and* are not the leading firms in their respective industries are more likely *not* to use NCAs.[4] These firms are more likely to report that they do not use NCAs precisely because they would hurt their ability to attract talented workers. In addition, we find that opting out of NCA use among firms that rely on talent is associated with easier filling of high-skill technical positions for non-leading firms relative to leaders. NCA use is, thus, more penalizing when attracting technical workers for non-leaders relative to leaders when their reliance on talent is high. Further, we observe that opting out of NCA use as a differentiation strategy is more pronounced in industries that rely less on patents, which further underscores knowledge leakage concerns as an underlying mechanism.

In a supplemental analysis, we show that firms opting out of NCAs are likely to use other practices to retain workers (Foss et al., 2015; Huselid, 1995). To assess the sensitivity of our results to alternative explanations, we employ a range of robustness tests, including recently developed tests for the sensitivity of regression estimates to omitted variable bias (Cinelli et al., 2020; Cinelli & Hazlett, 2020). We conclude from these tests that our findings result from firms making strategic choices as opposed to patterns previously reported across states, industries, or individuals (Marx et al., 2009; Starr, Balasubramanian, & Sakakibara, 2018; Starr, Ganco, & Campbell, 2018).

The study has theoretical, managerial, and policy implications. It implies that we may need a more refined theory of how mobility frictions interact with firm strategy. Specifically, the availability of frictions enables strategic differentiation contingent on firm characteristics. We contribute to the human capital literature on the use of legal levers (Agarwal et al., 2009; Starr, Ganco, & Campbell, 2018) by developing a framework highlighting the tension between the ability of firms to attract and to retain talent. By uncovering the firm-level heterogeneity, we also contribute to the literature on NCAs by complementing its focus on state-level enforceability (Conti, 2014; Starr, Balasubramanian, & Sakakibara, 2018) or worker-level heterogeneity (Rothstein & Starr, 2021; Starr et al., 2021). From a managerial perspective, our study may guide whether, when, and how managers should use NCAs. Our study is also highly relevant in the context of recent efforts by the federal government to ban NCAs due to their detrimental effect on workers.[5] Since NCAs are governed by state laws, and the proposed initiatives face significant pushback from some states, banning NCAs without a federal legislative overhaul may not be possible. However, the public discourse may make skilled workers more aware and proactive when dealing with NCAs. Such movement may, in turn, lead more firms to voluntarily opt out of using NCAs to attract skilled workers. Consequently, the mechanism that we describe in our study could play an important role in decreasing the extent to which NCAs are used by firms even when the national effort to explicitly ban NCAs fails.

[4]We conceptualize leading versus non-leading firms as a general proxy for within-industry differences in quality. Leading firms are more likely to have resources that are valuable to competitors and are subject to expropriation risks. These resources include knowledge or social capital embedded in employees. Similarly, we conceptualize the relative reliance on talent as a general proxy for reliance on skilled human capital relative to other resources. While these variables are based on survey questions, we employ validation and robustness tests using external datasets such as Compustat and CPS for a subsample of observations where a match is possible. The results hold irrespective of whether we control for firm size.

[5]https://www.ftc.gov/legal-library/browse/federal-register-notices/non-compete-clause-rulemaking.

2 | THEORETICAL BACKGROUND

A long-standing line of research has focused on examining the management of knowledge embodied in human capital (Carnahan et al., 2012; Coff, 1997; Kim & Steensma, 2017; Rosenkopf & Almeida, 2003; Sevcenko & Ethiraj, 2018; Singh & Agrawal, 2011; Tzabbar & Cirillo, 2020). The fundamental problem is that human capital is free to leave (Campbell, Ganco, et al., 2012; Coff, 1997; Raffiee, 2017). While the knowledge (such as trade secrets, IP, or client information) created by employees through employment generally belongs to the firm (Agarwal et al., 2009; Campbell, Coff, & Kryscynski, 2012; Klepper, 2001), knowledge is much harder to protect against expropriation than other resources (Arrow, 1962). Employers often utilize a variety of knowledge safeguards, such as patents or restrictive clauses in employment contracts to inhibit competitors' access to their valuable knowledge (Kim & Marschke, 2005; Starr, Balasubramanian, & Sakakibara, 2018). Since mobility represents a key channel through which knowledge spillovers and expropriation occur (Agarwal et al., 2009; Rosenkopf & Almeida, 2003), knowledge safeguards are often focused on improving retention (Ganco et al., 2015; Starr, Balasubramanian, & Sakakibara, 2018), deterring employees from joining competitors (Marx et al., 2009), or inhibiting knowledge use after departure (Agarwal et al., 2009).

Scholars studying the management of knowledge flows through mobility have often focused on the role of NCAs (Garmaise, 2011; Seo & Somaya, 2021; Starr, Balasubramanian, & Sakakibara, 2018; Starr, Ganco, & Campbell, 2018). NCAs belong to a group of post-employment restrictive covenants that employees may sign as part of their employment contract. NCAs restrict employees from joining or starting a competing firm (as defined by the NCA) after they leave within a specified geographical area and for a specified duration. While the allowed scope of NCAs varies, some form of the clause is enforceable in almost all US states, with the most notable exception being California (Gilson, 1999) and, very recently, New York.[6] However, NCAs have been shown to discourage mobility even when non-enforceable (Prescott & Starr, 2022).[7] Relative to the enforcement of patents and other forms of IP by litigation, NCAs represent an effective tool because they protect all knowledge that employees possess from use by rivals (Balasubramanian et al., 2022). Violations also tend to be readily observable, and, if enforceable, these violations may be easier to prove in the courts. Prior research has shown that NCAs improve employee retention (Balasubramanian et al., 2022; Lipsitz & Starr, 2022), are positively associated with employees' mobility to different states or different fields (Marx et al., 2009), and lower the likelihood of employees starting competing businesses (Starr, Balasubramanian, & Sakakibara, 2018). By increasing retention, NCAs also encourage employers to invest in human capital (Meccheri, 2009; Starr, Balasubramanian, & Sakakibara, 2018; Starr, Ganco, & Campbell, 2018).[8]

[6]https://ag.ny.gov/sites/default/files/non-competes.pdf accessed on July 23, 2023.

[7]Many firms include the NCA provision in contracts even in states where the NCAs are not enforceable (Starr, 2019). Not all employees may be informed about the enforceability of the NCAs in the state and signing this provision as part of the employment contract may be sufficient to discourage mobility (Prescott & Starr, 2022).

[8]Prior research has also shown mixed effects by NCAs on wages (Garmaise, 2011; Starr, 2019; Starr et al., 2018a). This is most likely driven by the presence of competing effects. While NCAs lower the value of employees' outside options, which allows the employer to appropriate more value in the form of lower wages, employers may be legally required to provide additional compensation for signing the NCA. Further, greater investments in human capital may make the individual better trained, increasing their value on the labor market even with the NCA in place. As a result, the wage effects of NCAs are ambiguous and prior work has shown mixed results (Garmaise, 2011; Starr, 2019; Starr et al., 2018a).

Despite the extensive study of NCAs, we lack an understanding of why some firms do *not* use NCAs, even in states where the practices are enforceable and in industries where they are common. It raises the possibility that the benefits of using NCAs may not be universal, and there may be downsides to including NCAs in employment contracts. Our key proposition is that while NCAs improve the ability to retain existing workers, they may worsen the ability of firms to attract talented prospective workers. Some firms may sacrifice an improved ability to retain workers in exchange for an improved ability to attract them. This logic also implies that making NCAs available to firms creates differentiation opportunities.

We rely on survey data to unpack such firm-level heterogeneity and propose a novel theoretical explanation for why competitors differ in their use of NCAs. The body of existing work was developed by examining the implications of state-level variation in the enforceability of NCAs. Complementing these studies, a smaller stream documents the variations in NCA use at the worker level. These studies rely on worker surveys representative of the US labor force (Rothstein & Starr, 2021; Starr et al., 2021) or specific groups of employees such as executives (Kini et al., 2021; Shi, 2021), physicians (Lavetti et al., 2020), or hair salon employees (Johnson & Lipsitz, 2022). Less is known, however, about firm-level heterogeneity in the use of NCAs and its drivers.[9]

We start by describing a general conceptual framework capturing how using NCAs affects a firm's ability to attract and retain talent and how such a mechanism depends on firm characteristics.[10] We examine the patterns observed in the data, including what predicts NCA use, how firms respond to the question of why firms do not use NCAs, and how the predictors of NCA use correlate with the hiring and retention of workers (when comparing firms that use and do not use NCAs). Finally, we discuss how the patterns relate to the conceptual grounding and how they inform prior work. We do not test specific predictions because our findings inform our theoretical framework. Consistent with several studies in the recent literature (Agarwal et al., 2021; Eesley & Lee, 2020), our approach to the analysis is abductive (Goldfarb & King, 2016; Heckman & Singer, 2017).

3 | NCAs AND THE ABILITY OF FIRMS TO RETAIN AND ATTRACT TALENT

By limiting mobility to competitors, NCAs can isolate firms' valuable resources by constraining their flow to competitors. However, the NCAs also significantly restrict workers' options for future employment, and some employees may be unwilling or hesitant to sign them (Balasubramanian et al., 2022; Rothstein & Starr, 2021; Rubin & Shedd, 1981). The "career-chilling" effect of NCAs may be more salient to workers who value career flexibility or to whom the restrictions may be particularly harmful, such as skilled workers. Using NCAs can thus be detrimental to firms that value skilled human capital. Using NCAs can enhance the retention

[9]Starr et al. (2021) report a positive correlation between firm size and NCA use. However, their focus is on the individual-level variation of NCA use and they do not explain or explore variation across firms, which is the subject of our study. The authors also do not identify the lower ability to attract talent as a potential downside of using NCAs. Further, we describe below that individual-level differences in NCA use as reported by Starr et al. (2021) could not explain our results. We thank an anonymous reviewer for helping us to delineate differences between our study and prior work.

[10]While we focus on NCAs when developing the theoretical arguments, the logic may apply to other restrictive practices as well. We revisit the potential differences in the discussion.

of current workers while lowering the ability to attract prospective workers. This creates tension for the focal firm.

How does such tension vary across firms, and how do firms decide to use or not use NCAs with their workers? Notably, the calculus related to the ability to attract and retain workers is separate from the explicit costs associated with NCAs. For instance, the explicit costs include compensating differentials in the form of higher wages that employees receive in return for signing an NCA. As discussed above, the extant empirical evidence shows that the effect on wages is null or ambiguous because signing an NCA also puts downward pressure on wages (Garmaise, 2011; Starr, Balasubramanian, & Sakakibara, 2018). Other costs are non-wage costs, such as those associated with drafting and incorporating the covenants into the employment contracts and enforcing the NCAs through litigation (enforcing an NCA is typically cheaper than enforcing a patent [Kesan & Ball, 2006]). Such direct costs likely apply to all rivals in a similar fashion.[11] Given our interest in explaining within-industry cross-firm heterogeneity in the use of NCAs, we focus on how the calculus with respect to the ability of firms to attract and retain workers varies with firms' competitive positions and key resources (i.e., within a state, which determines the NCA enforceability and applies to all firms in the state, and within an industry, which broadly defines the set of competitors).

We posit that the incentive to use NCAs is generally larger for industry leaders than for non-leaders for the following reasons. First, NCAs prevent the expropriation of valuable knowledge by competitors. The benefit of NCAs for the focal firm depends on the nature of skills and knowledge embedded in human capital that the firm needs to protect from expropriation. Knowledge residing in leading firms is likely more valuable to rivals than the knowledge from non-leader firms, as leaders may accumulate knowledge related to new technologies or valuable clients (McElheran, 2015). Rivals may desire to hire employees of leading firms because of the knowledge they possess or because they are likely to be more skilled and productive than those of their rivals (Campbell, Coff, & Kryscynski, 2012).[12] Even in less technologically intensive industries, employees of leaders may have more valuable social capital that may be expropriated by rivals (Phillips, 2005). The leading firms may invest more heavily in training their workers, and these investments cannot be realized if the workers leave. Consequently, using employment practices such as NCAs that improve retention and restrict knowledge outflows may be more critical for leaders.

It is helpful to note that, from the workers' perspective, working for leading firms may be attractive even if the firms ask them to sign NCAs.[13] This is because the leading firms may provide higher compensation, more opportunities for learning and careers, and higher status. Although the ability to attract talented workers is important for all firms, leading firms (relative to non-leaders) may be less concerned about the impact of NCAs on their ability to attract talent because leading firms may still be desirable places for workers despite NCAs.

[11]In our analysis, we also condition on firm size, which should serve as a proxy for resources that firms have available for the enforcement of NCAs. We also include a control for NCA prevalence among competitors, which serves as a proxy for whether NCAs are a common practice in the focal industry.

[12]Note that even leading firms that rely less on talent as their source of competitive advantage relative to other resources may attract more productive and skilled workers than competitors. Consequently, this argument is separate from the discussion of talent below.

[13]We can also think about the firm's decision to seek new hires as a demand side and workers' willingness to join as a supply side. For instance, our arguments imply that the supply is less sensitive to NCA use by leading firms (relative to non-leading firms) and that reliance on talent increases the demand.

From a non-leading firm's perspective, however, the impact of NCAs on the ability to attract external talent may be more critical than their impact on the retention of existing employees. Non-leaders generally have lower bargaining power in the labor market and may be unable to offer comparable compensation, status, and advanced learning opportunities relative to leading firms. Their ability to attract talented workers is likely lower than that of leading firms. Moreover, while employee exit is still detrimental to the human capital of non-leading firms, these firms likely worry less about the leakage of their knowledge to competitors. Their knowledge is more likely to represent the industry average rather than cutting-edge. Hence, non-leaders (relative to leaders) may face more difficulties when attracting skilled workers and be less concerned about knowledge leakage to rivals. Such calculus may favor opting out of NCA use for non-leaders relative to leaders.

From the standpoint of workers who value career flexibility, firms *not* requiring NCAs may become attractive. Thus, opting out of NCA use can be an effective differentiation strategy for non-leading firms. These differences between leader and non-leader firms are also in line with previous literature arguing that non-leaders may need to implement strategies that mitigate or neutralize the dominant firms' competitive advantages while avoiding head-on retaliation (Ito, 1997; Mascarenhas, 1986), and leaders are more likely to use strategies to prevent knowledge spillovers to competitors than non-leader firms (Albino et al., 1998; Boschma & Lambooy, 2002; Paniccia, 1998).

The differing emphasis on attracting versus retaining workers between leaders and non-leaders may be amplified by the extent to which firms rely on talented workers as a source of differentiation. Talented workers may likely be more critical in some industries than others, such as less capital-intensive and more service-based contexts. But their importance as a source of differentiation may also vary within industries. While leaders may have, on average, more productive workers and more valuable knowledge that rivals can expropriate, they may also hold other valuable resources such as brand and various capital-intensive assets. Thus, the relative importance of talent as a source of differentiation may not always be higher for leading firms. Consequently, it is meaningful to consider reliance on talent as a separate construct from a firm's leadership position. Extensive prior work in strategy has shown that firms, even within industries, vary in how they utilize resources to create competitive advantage (Barney et al., 2001; Porter, 1985). Importantly, how much firms rely on talent likely affects how NCAs affect their ability to attract versus retain talent.

When leading firms rely more heavily on talent relative to other resources, competitors' potential expropriation of their human capital becomes more threatening to their competitive advantage. Such threats increase their incentive to use NCAs. Talented workers may be willing to join these leading firms *despite* having to sign NCAs. Consequently, if human capital is more critical to their businesses relative to other resources, NCAs are more useful for leaders because potential knowledge leakage becomes more threatening and, at the same time, they may be less concerned about the negative impact of NCAs on their ability to attract new workers.

The situation is likely reversed for non-leading firms. Non-leaders relying on talent need to attract and retain high-quality workers, while the human capital may not be inherently more valuable to other firms. Thus, such firms may not need NCAs to prevent the leakage to rivals, while they may still worry about the impact of NCAs on their ability to attract skilled workers, which is amplified as talent becomes more critical for the firm. Consequently, non-leading firms relying heavily on talent may opt out of NCAs. Further, if NCAs are common among the leaders, non-leaders may advertise their opt-out in the labor market. For instance, Daniel

Hertzberg, the CEO of CAD-design firm Onshape,[14] argued in an article for *The Boston Globe* that, although using NCAs is a standard practice in Massachusetts, the company is following other tech firms, such as Acquia and RunKeeper (all non-leaders) that voluntarily eliminated NCAs for their workers. As we mention in the opening quote of our study, he claimed that "we want people who want to be here, not ones who feel trapped." Capturing the importance of being different, he also described that "we've been contacted by many talented people we'd like to hire but who are restricted by noncompete agreements. After they endure their waiting period, it would feel hypocritical to then ask them to sign the same kind of draconian agreement at my company."[15] This example illustrates that non-leading companies that need to attract talented workers may differentiate by opting out.

4 | EMPIRICAL ANALYSIS

4.1 | Data and sample

Our data are derived from an employer survey conducted in 2017 by PayScale, a US-based data analytics company focused on gathering information about HRs, mainly compensation practices. PayScale deployed the survey to HR managers and top executives during November and December 2016. Given that the data gained through the surveys constitute a core product for PayScale, they focus on achieving data quality, accuracy, and reliable sourcing of the data. The survey asked questions on hiring practices, compensation practices, and the use of post-employment restrictive covenants such as NCAs.[16]

The data contain responses from 7698 global employers participating in the survey. The respondent organizations are diverse, including private and public firms, public institutions, universities and schools, hospitals, and nonprofit organizations. We limit our sample to private and public firms (3610 observations dropped) headquartered and located in the United States (given large differences in the relevant legal frameworks outside the United States; 1278 observations removed). From the remaining 2810 firms, including both Fortune 500 companies and small and medium-sized businesses, we further remove respondents who were either unsure of their NCA use or chose not to answer the NCA questions (1007 observations removed).[17] The NCA questions are more likely to be missing for larger firms (which we condition out by controlling for firm size). To further mitigate the potential bias stemming from missing observations, we employ a robustness test that imputes missing NCA-use variables.

[14]According to an industry report by Enlyft tracking the use of various CAD products and technologies, Onshape has a non-leading market position with a market share of less than 5% in the Computer-aided Design & Engineering category and rank 71 out of 109 in the firms offering CAD products. https://enlyft.com/tech/computer-aided-design-engineering accessed on November 10, 2022.

[15]https://www.bostonglobe.com/opinion/2015/06/27/onshape-ceo-john-mceleney-noncompetes-hurt-workers-and-their-employers/6NbXbI5jhZpl5wyvc28FSI/story.html accessed on December 10, 2022.

[16]The full survey contains 125 questions. The survey focuses on compensation practices (data on compensation practices is the main product of PayScale) so most questions focus on how firms compensate their workers (why firms give pay raises, pay structure, incentives, administration of pay, how job classifications are created, pay grades and ranges, variable vs. fixed pay, compensation strategy, how firms measure performance, transparency of pay, performance reviews, payroll system, etc.).

[17]Appendix Table A1 compares firms that answered the NCA questions with those that did not answer them. In Table A1 Model 3, we include firm-level controls and industry and state fixed effects, and we do not find noticeable differences in our key independent variables ("non-leader" and "talent").

The restrictions imposed above result in a sample of 1803 observations.[18] In our regressions, the sample size varies across models with different dependent variables due to the varying extent of missing variables. The sample somewhat overrepresents larger firms compared to the US firm population (based on the 2017 County Business Patterns), but significantly less so than Compustat.[19] In addition to raw estimates, we use iterative proportional fitting to create weights to match our sample to the population along with size, industry, and state. Then, we reestimate our main specifications using weighted least squares.

4.2 | Variables

4.2.1 | NCA use

We create categorical and continuous variables capturing NCA use based on two survey questions. The first one is: "Which employees at your organization are subject to non-compete agreements (Prohibited from joining or starting a competing organization)?" The respondents chose from four categories: "All employees," "Some employees," "No employees," and "Don't know." For those who chose "Some employees," the survey provides a follow-up question: "To the best of your knowledge, what percentage of all employees within the organization have signed non-competes?" The respondents can select the answer from five choices: "1–20%," "21–40%," "41–60%," "61–80%," and "81–100%." The categorical NCA-use variable is a dummy coded as one if the response to the first survey question is "All employees," zero if "Some" or "No employees," and missing if "Don't know."[20] The continuous NCA-use variable is measured by the fraction of employees subject to NCAs using the follow-up survey question. We take the midpoint of each category (e.g., 10 for "1–20%") for those who chose "Some employees" and treat "All employees" as 100% and "No employees" as 0%.

4.2.2 | Industry leader/non-leader

This variable is constructed based on the response to the question: "Is your organization #1 in its industry?" The response can be "Yes," "No," or "I don't know." We construct a binary variable, *Non-leader*, coded as one if their choice is "No" and zero if their choice is "Yes." The choice of "I don't know" is treated as missing (26% of the sample). While this measure is subjective, most of the prior literature relies on secondary measures inferred from performance data.[21] For the subset of public firms, we match our sample with Compustat to examine the validity of

[18]In 99% of observations, a single person responded for each firm. In 1% of observations, more than one respondent submitted the survey because different establishments of the same firm were registered separately as clients with PayScale. The results are robust to the exclusion of either one or both observations for each of these firms. As shown in Appendix Table A2, 83.3% of respondents are in managerial or higher occupations, and over half (54.8%) have an HR-related job. The respondents likely have an accurate knowledge of their firms' NCA use.

[19]Appendix Table A3 compares the firm size distributions for PayScale, Compustat, and the County Business Patterns.

[20]In the robustness section, we assess the robustness of our results using several alternative operationalizations of the NCA use variables.

[21]For instance, measures based on the threshold values of R&D intensity (Berry, 2006), size, sales (Ito, 1997; Ito & Pucik, 1993; McElheran, 2015), or market share (Berry, 2006) have been used to proxy for industry leadership.

the survey-based leadership measure. The survey-based measure appears to be a reasonable proxy for the leadership position based on the Compustat sample.[22]

4.2.3 | Talent as the key differentiator from competitors

The variable is constructed based on the question: "Which of the following sets your company apart from competitors the most?" This single-selection question has six possible choices: "Larger client or customer lists," "Talented employees," "Innovative products," "Best-in-class service," "Better at improving employee skills," "Other (please specify)." For the main analysis, we construct a binary variable, *Talent*, coded as one if the response is "Talented employees" and zero if other choices. This aggregation is informed by the patterns observed in the data. We validate the measure using the Current Population Survey (CPS) in the robustness test section. It shows that the measure exhibits a strong correlation with skilled human capital intensity. In a robustness test, we also use a survey question capturing the amount of training new hires receive as a proxy for the importance of talent. While the results remain consistent, we suggest interpreting them with caution because the amount of training may depend on the use of NCAs (Starr, Ganco, & Campbell, 2018).

4.2.4 | NCA nonuse reason

To the respondents who answered that their organization either does not use NCAs at all or uses them only for some workers, the survey follows with a question about the reasons for not using NCAs (at least for some workers). The question is: "Why doesn't your organization use non-competes (multiple selections allowed)?" There are six possible answers to this question.[23] With our focus on attracting and retaining talent, we create a binary variable coded as one if the respondents chose "Non-competes make it hard to attract talented employees," and zero otherwise. We also construct another binary variable coded as one if "Loss of employees to competitors is not a big concern" was chosen, and zero otherwise.

4.2.5 | Ability to attract talent, ability to retain talent

To explore how the use of NCAs relates to the ability of firms to attract and retain talent, we rely on multiple survey questions. As a proxy for the ability to attract talent, we first use the question: "Do you have any positions that have been open for 6 months or more?" Companies that are better able to attract talent should have fewer vacant positions. We create a binary variable based on the response of "Yes" or "No." Among those responding "Yes," the survey follows with: "What kind of positions do you have a hard time filling? (check all that apply)." There are nine possible choices that are not mutually exclusive. As a proxy for higher knowledge

[22]Due to the smaller number of public firms, we are unable to examine the main analysis using this subsample and the Compustat variables. We discuss the validation of the measure in more detail in the robustness section.

[23]The possible choices consist of "Non-competes are not commonly used in the industry," "Non-competes make it hard to attract talented employees," "Loss of employees to competitors is not a big concern," "Not familiar with what non-competes are," "Non-competes are not legally enforceable in my state," and "Other (please specify)."

intensity, we focus on managerial jobs ("Management" and "Executive Level") and technical jobs ("IT" and "Engineering"), and create dummy variables based on each category.[24]

4.2.6 | Control variables

Our controls include variables identified in prior work as potentially driving NCA use. We utilize industry and state fixed effects for all analyses. Prior literature shows that NCAs tend to be more common in states that enforce them and for workers in technical sectors (Balasubramanian et al., 2022; Starr et al., 2021). In the robustness section, we employ subsample analyses based on states where NCAs are enforceable and in high-tech industries only. The PayScale uses 28 industry categories instead of standardized industry classes such as SIC or NAICS.[25] We include several additional control variables derived from survey questions: *firm size, NCAs common among competitors in local markets*, *primary deliverable*, the *share of low-wage employees*, and *the respondent job function*. *Firm size* is a categorical variable based on the question: "How many full-time employees are in your organization?" The respondents choose from: "1 to 99 employees," "100 to 749 employees," "750 to 4999 employees," and "Over 5,000 employees." Starr et al. (2021) report that individual workers in larger firms (over 5000 employees) are more likely to be bound by NCAs relative to smaller firms. Our results are robust to the inclusion or exclusion of firm size. *NCAs common among competitors in local markets*, which captures NCA use within the local labor market, is based on the response to the question: "To the best of your knowledge, how common are non-competes in your local market among competitors?" The respondents choose "Very uncommon," "Uncommon," "Common," or "Very common." We construct a binary variable coded as one if the response is "Very common" or "Common" and zero if "Very uncommon" or "Uncommon." *Primary deliverable* is based on the response to the question: "What is your organization's primary deliverable?" The possible choices consist of "a tangible product or products," "a service or services," "knowledge and information," or "something else (please specify)." The type of deliverable may correlate with differences in the human capital of the firm's employees. For *the share of low-wage employees* (who are less likely to be subject to NCAs [Starr et al., 2021]), we utilize the question: "What percentage of full-time employees in your organization earn less than $47,000 per year?" There are six choices: "None," "1–20%," "21–40%," "41–60%," "61–80%," and "81–100%." We create a continuous measure by taking the midpoint of each category and treating the "None" answer as zero. Finally, we control for the job function of the survey respondent, as the respondent's ability to answer specific details may vary with their position. The variable of the *respondent job function* is categorical based on the question: "What is your primary job function?" The functions are aggregated into three categories: "HR and compensation," "Executive (COO, CEO, etc.)," and "Others."[26]

[24]The other possible choices include "Customer Service," "Sales," "Marketing," "Finance," and "Other (please specify)."
[25]Twenty one percent of respondents did not select a specific industry from the list and entered "other." To reduce noise, we tried to assign firms to industries based on searching the company profiles. This reduced the proportion of firms in the "other" category to 8.9%. The results are robust to the exclusion of this category.
[26]The category "Others" includes "Finance/Accounting," "Sales," "Technology," "Marketing," "Operations," "Consultant," "Other (please specify)."

5 | ESTIMATION METHOD

We employ a series of OLS regressions and linear probability models for ease of interpretation. Our claims are not causal, and the key objective of the analysis is to isolate the estimated relationships from alternative explanations unrelated to our conceptual framework. Throughout our specifications, we rely on industry and state fixed effects as well as the set of control variables to uncover the firm-level heterogeneity within industries and states. To corroborate our findings and validate our survey-based measure, we employ a series of robustness tests using different specifications and subsamples and external data sources such as Compustat, Glassdoor, and CPS. To further assess our results' sensitivity to alternative explanations, we employ recently developed sensitivity tests to assess how strongly omitted variables would need to be associated with our explanatory and outcome variables to overturn the results (Cinelli & Hazlett, 2020). In all our specifications, standard errors are clustered at the industry-by-state level. All results remain robust if we use two-way clustering on industry and state instead.[27]

6 | RESULTS

Table 1 reports the summary statistics and pairwise correlations for the variables we use in the analyses. The categorical variables are dichotomized for ease of interpretation. Table 2 describes the rate of NCA use for the key variables. In our sample, 71.7% of firms use NCAs for at least some of their employees, and 31.4% use them for all employees. Consistent with Starr et al. (2021), we observe that larger firms with 100 or more employees tend to adopt NCAs (77.4%) more often than smaller firms with 1–99 employees (66.7%), although the larger firms are likely using them only for some employees (53.0%). In contrast, smaller firms are more likely to use NCAs for all their employees (37.6%) rather than only some (29.1%). Unconditional adoption rates of NCAs for industry leaders are 73.7%, and for non-leaders, 70.9%. Firms reporting talented employees as what sets them apart from competitors are less likely to adopt NCAs (65.3%), compared to 73.1% of firms that report that factors other than talent set them apart from competitors. The prevalence of NCAs in local markets where firms operate is largely associated with the NCA use of focal firms. 90.3% of firms that report NCAs are common among their competitors in their local markets use NCAs for their workers, whereas only 44.7% of firms that report NCAs are uncommon among their competitors in their local markets use NCAs.

Table 3 summarizes the use of NCAs within and across industries. The highest prevalence of NCAs is in Marketing & PR, Technology, and Business & Management (40.3–63.2% of firms require NCAs from all workers), and the lowest prevalence is in Customer Service and Real Estate (48.5 and 59.3% of firms require no NCAs at all). Thus, industries that rely more on talented workers and clients (Marketing/PR, Business & Management) and technological knowledge (Technology, Biotech & Science) have a higher likelihood of firms using NCAs.[28] The

[27]The results using two-way clustering are available upon request.

[28]The knowledge intensive industries have, on average, somewhat higher rates of NCA use and the reliance on talent positively correlates with industry level of knowledge intensity (described in the robustness section). Note that this does not contradict the negative unconditional correlation between NCA use and the reliance on talent (Tables 1 and 2). This is because the unconditional correlation between NCA use and the reliance on talent depends on their correlation both within and across industries. The results on Table 4 show that, within industries, the correlation between NCA uses and the reliance on talent is negative and large for non-leaders.

TABLE 1 Summary statistics and pairwise correlations.

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	NCA use: a dummy for all employees	.31	.46	1													
2	NCA use: a dummy for all or some employees	.72	.45	.43	1												
3	NCA use: fraction of workers	.43	.44	.91	.63	1											
4	Non-leader	.69	.46	−.04	−.03	−.03	1										
5	Talent	.19	.39	−.02	−.07	−.01	.09	1									
6	Firm size: a dummy for 100 employees or more	.47	.50	−.14	.12	−.11	−.12	−.06	1								
7	NCA use is common in local market	.60	.49	.26	.50	.38	.00	−.01	.02	1							
8	Share of low-wage employees	.35	.27	−.11	−.05	−.13	.01	−.09	.02	−.10	1						
9	Respondent job function: HR and compensation	.28	.45	−.03	−.06	−.03	−.04	.05	−.16	−.02	.02	1					
10	Respondent job function: Executive	.13	.34	−.02	−.03	−.02	.02	.01	−.25	−.01	.03	−.25	1				
11	NCAs make it hard to attract talent	.15	.36		.03	−.03	.04	.00	.04	.02	−.06	.03	−.03	1			
12	Long-term vacant position	.31	.46	−.03	.00	−.02	.02	−.05	.11	.02	−.02	−.02	−.01	.08	1		
13	Difficulty in filling managerial jobs	.08	.28	.01	.04	.01	.04	−.03	.08	.01	−.05	.00	−.02	−.01	.46	1	
14	Difficulty in filling technical jobs	.14	.35	−.02	.06	.00	−.07	−.02	.18	.04	−.08	−.05	−.08	.06	.62	.33	1

TABLE 2 Propensity to use NCAs for no, some, and all employees.

	P (No emp.)	P (Some emp.)	P (All emp.)
All firms	28.3	40.3	31.4
Firm size: 1–99 employees	33.2	29.1	37.6
Firm size: 100 or more employees	22.6	53.0	24.4
Industry non-leader (non-leader = 1)	29.0	42.2	28.7
Industry leader (non-leader = 0)	26.3	40.9	32.8
Reliance on talent (talent = 1)	34.7	35.6	29.7
Reliance on other resources (talent = 0)	26.8	41.2	31.9
NCA use is common in local markets	9.8	48.6	41.7
NCA use is uncommon in local markets	55.2	28.1	16.6

Note: All variables in the table are either dummies or originally categorical but dichotomized.

table also reveals a significant heterogeneity within industries, including knowledge-intensive industries (the correlation between the reliance on talent and NCA use is negative within industries). For instance, in Accounting/Finance, 33.6% of firms require NCAs from all workers, while 53.8% do not require NCAs at all, or less than one-fifth of their workforce is required to sign them. A similar pattern is present in Medical/Healthcare: 22.4% of firms require all employees to sign, while 58.9% require no NCA or only less than one-fifth of their workforce.

The last column of Table 3 reports the reason for not using NCAs in the focal industry (or using them only for some workers): "NCAs make it hard to attract talent." The highest proportion of firms that list this reason for not using NCAs is in Architecture/Engineering and Marketing/PR (34.7 and 33.3% among firms not using NCAs at all or using them only for some workers), followed by Accounting/Finance (19.4%). This is consistent with our argument that some firms relying heavily on skilled workers choose *not* to use NCAs as a differentiation strategy, even in industries where many firms use NCAs heavily (as mentioned above, 63.2% of firms in Marketing/PR, 33.6% in Accounting/Finance, and 26.3% in Architecture/Engineering use NCAs for all workers).

We proceed by exploring what explains NCA use within each industry and state. Table 4 reports regression results where the dependent variables are NCA use (a dummy for all workers and the fraction of workers having NCAs), and the key independent variable of interest is the interaction between the industry non-leader status and the reliance on talent as a differentiator from competitors (i.e., "talent").[29] The table reporting the coefficients for all controls is in Appendix Table A5. The estimation sample is reduced from 1803 to 1232 (68.3%) due to missing survey responses on the independent variables.[30] We call the remaining 1232 observations *the NCA estimation sample*.[31]

[29]In Table A4, we report the number of observations in each cell defined by industry leader (vs. non-leader), talent (vs. non-talent), and the fraction of workers subject to NCAs.

[30]The largest reduction occurs due to the industry non-leader dummy. Removing observations with missing values or the values recorded as "I don't know" lowers the sample size by 483 observations (26.8% of the sample). The second largest reduction stems from the variable "*NCAs common among competitors in local markets*" (61 observations, or 3.3% of the sample). This is likely because some respondents lacked the knowledge to answer this question.

[31]In the analysis, for each dependent variable, we use the sample from the fully specified model (i.e., all variables are non-missing).

TABLE 3 NCA use and reasons for not using them across industries.

	Ratio of employees with NCAs (%)							HHI	*N*	"NCAs make it hard to attract talent" (ratio of firms not using NCAs at all or using them only for some workers)
	0	1–20	21–40	41–60	61–80	81–99	100			
Marketing & PR	18.4	10.5	2.6	5.3	0.0	0.0	63.2	0.447	38	33.3
Technology	20.1	13.4	4.0	4.0	1.3	3.6	53.6	0.350	224	14.8
Business & Management	24.7	16.9	3.9	6.5	6.5	1.3	40.3	0.262	77	19.4
Biotech & Science	24.4	17.1	7.3	0.0	7.3	4.9	39.0	0.254	41	5.0
Manufacturing	19.4	29.4	7.7	4.0	2.0	2.3	35.1	0.256	299	11.8
Accounting & Finance	31.1	22.7	4.2	2.5	4.2	1.7	33.6	0.266	119	17.2
Transportation	27.5	25.0	12.5	7.5	0.0	0.0	27.5	0.235	40	11.1
Energy/ Utilities	38.6	15.9	9.1	2.3	0.0	6.8	27.3	0.262	44	10.0
Architecture & Engineering	38.2	21.1	6.6	3.9	1.3	2.6	26.3	0.266	76	34.7
Other	35.3	23.5	5.9	6.5	1.3	2.0	25.5	0.253	153	17.0
Customer Service	48.5	15.2	6.1	0.0	3.0	3.0	24.2	0.322	33	14.3
Food, Beverage & Hospitality	36.4	34.8	1.5	0.0	3.0	0.0	24.2	0.314	66	12.2
Medical & Healthcare	27.1	31.8	9.9	4.2	1.0	3.6	22.4	0.237	192	8.7
Retail	38.3	28.4	6.2	2.5	1.2	2.5	21.0	0.276	81	15.1
Real Estate	59.3	20.4	3.7	1.9	0.0	0.0	14.8	0.416	54	13.2

Note: Among 1803 observations where NCA questions are not missing, only industries with over 30 non-missing observations are displayed. HHI is calculated based on the seven categories of employee ratios with NCAs. The industries are ordered by the average NCA use in descending order. The last column shows the percentage of firms that indicated talent attraction as the reason for not using NCAs among firms not using NCAs at all or using them only for some workers.

Based on Model 1 of Table 4, which only includes the main effects of talent and industry non-leaders, non-leaders are 3.6 percentage points less likely to use NCAs for all workers (p-value = .190), and firms that report talented employees as the key differentiator from the competition are 5.7 percentage points less likely to use NCAs for all workers (p-value = .081). As we will see in the following models, the negative coefficient on talent as a predictor for NCA use is driven by non-leading firms (i.e., it becomes positive for leading firms). Model 2 adds the key variable of interest, the interaction term of talent and industry non-leaders. Non-leader

TABLE 4 NCA use dependent on leadership and reliance on talent.

Dependent variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	NCA use: a dummy for all employees				**NCA use: fraction of employees**			
Non-leader × Talent		**−0.151**	**−0.190**	**−0.189**		**−0.125**	**−0.174**	**−0.183**
		(0.080)	**(0.079)**	**(0.077)**		**(0.080)**	**(0.081)**	**(0.076)**
Non-leader	−0.036	−0.013	0.006	−0.015	−0.024	−0.006	0.015	−0.004
	(0.027)	(0.031)	(0.030)	(0.030)	(0.026)	(0.029)	(0.028)	(0.028)
Talent	−0.057	0.058	0.070	0.068	−0.057	0.038	0.071	0.085
	(0.033)	(0.069)	(0.069)	(0.068)	(0.033)	(0.069)	(0.070)	(0.066)
Constant	0.337	0.322	−0.013	−0.066	0.447	0.434	−0.017	−0.139
	(0.026)	(0.027)	(0.090)	(0.094)	(0.025)	(0.026)	(0.090)	(0.087)
Controls	No	No	No	Yes	No	No	No	Yes
Industry FE; state FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	1232	1232	1232	1232	1166	1166	1166	1166
R-squared	.004	.007	.112	.197	.003	.006	.131	.267
Mean of DV	0.302	0.302	0.302	0.302	0.419	0.419	0.419	0.419

Note: Linear probability models in Models 1–4 and OLS in Models 5–8. The dependent variable in Models 1–4 is based on: "Which employees at your organization are subject to non-compete agreements (prohibited from joining or starting a competing organization)?" It is coded as one for "All employees" and zero for "Some employees" or "No employees," while the "Don't know" answer is missing. In Models 5–8, we use the follow-up question: "To the best of your knowledge, what percentage of all employees within the organization have signed non-competes?" There are five possible choices: "1–20%," "21–40%," "41–60%," "61–80%," and "81–100%." We take the midpoint of each category for "Some employees" and treat "All employees" as 100% and "No employees" as 0%. Standard errors (in parentheses) are clustered at the industry-by-state level.

firms that report talent as the key differentiator from competition are 9.3 percentage points *less* likely to use NCAs than non-leaders relying on other resources, and the estimate on the interaction term is −0.151 (p-value = .060). In contrast, leader firms that report talent as the key differentiator from competition are 5.8 percentage points *more* likely to use NCAs than leaders that report other resources as the key differentiator, though the estimate is noisy (p-value = .404). Model 3 looks at the variation within industries and states. The coefficient on the interaction in Model 3 is not only consistent but larger in magnitude. Non-leaders relying heavily on talented employees are 12.0 percentage points less likely to use NCAs than non-leaders relying on other resources, and the coefficient on the interaction term is −0.190 (p-value = .017), whereas leader firms relying heavily on talented employees are 7.0 percentage points more likely to use NCAs relative to leader firms relying on other resources (p-value = .132). In Model 4, with additional controls, the corresponding coefficient on the interaction term is −0.189 (p-value = .015).[32] To illustrate the size of these estimates, panel a of Figure 1 plots the predicted likelihood of having all workers signing NCAs across leaders versus non-leaders and talent versus non-talent (based on Model 4 in Table 4). There is no significant

[32]The inclusion of non-leader, talent, and their interaction increases the R^2 of the model from .187 to .197.

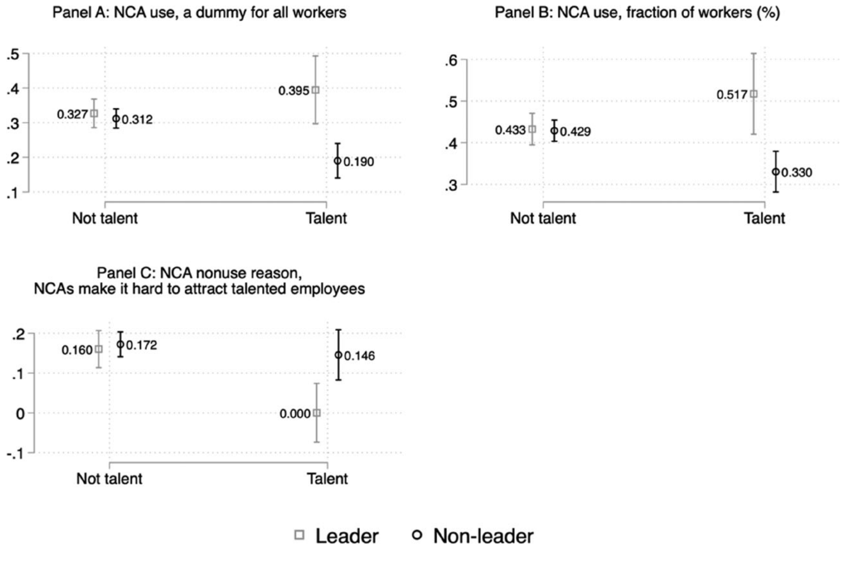

FIGURE 1 Predicted likelihood of NCA use and reasons for NCA nonuse. The regression models for calculating predicted likelihoods are based on Table 4 Model 4 (panel a), Model 8 (panel b), and Table 5 Model 4 (panel c).

difference across leaders versus non-leaders in the likelihood of using NCAs for all workers if they rely on something other than talent as the key differentiator. In contrast, if talent is the key differentiator from competition, then non-leader firms are 20.5 percentage points less likely than leader firms to use NCAs for all workers.[33]

Models 5–8 in Table 4 report the results using the fraction of employees subject to NCAs instead of a dummy for all workers with NCAs. Around 5% of the remaining respondents (66 observations) did not provide an answer for the NCA-use fractions, so the number of observations used here is 1166. Based on the most saturated model in Model 8, non-leaders relying on talent as the key differentiator are using NCAs for 9.8 percentage points *lower* proportion of workers relative to non-leaders relying on other resources. In contrast, leaders relying heavily on talent as the key differentiator are using NCAs for 8.5 percentage points *higher* proportion of workers relative to leaders relying on other resources (p-value = .198). The coefficient on the interaction term is estimated at −0.183 (p-value = .016).[34] Like above, panel b of Figure 1 shows that the difference in NCA use in terms of the fraction of workers subject to NCAs is only salient when firms rely on talented employees as the key differentiator.[35]

Among firms that do not use NCAs at all or use them only for some employees, we further explore their reasons for not using NCAs (at least for some workers). Specifically, we examine how firms' industry positions and the reliance on talent relate to their concerns about attracting talented employees as the reason for the NCA nonuse. Table 5 reports the regression results

[33]As we show in the robustness section, the results remain unchanged if we exclude the "Some" category or if we aggregate with the "All" category the firms that use NCAs for at least 50% of their workers. When we aggregate "Some" with "All" in the dependent variable or aggregate firms below the 50% threshold with "All," the coefficients on the interaction term continue to be negative but the errors become larger. This suggests that non-leader firms that opt-out of NCA use do so to differentiate themselves from leaders that use NCAs extensively.

[34]The inclusion of non-leader, talent, and their interaction increases the R^2 of the model from .260 to .268.

[35]Appendix Table A6 shows the disaggregated results of NCA-use for the full set of differentiating factors.

TABLE 5 Using NCAs makes it difficult to attract talent.

	Model 1	Model 2	Model 3	Model 4
Dependent variable	**Reason for NCAs nonuse: NCAs make it hard to attract talented employees**			
Non-leader × Talent		**0.149**	**0.134**	**0.135**
		(0.049)	**(0.068)**	**(0.069)**
Non-leader	0.040	0.019	0.014	0.012
	(0.030)	(0.034)	(0.034)	(0.034)
Talent	−0.030	−0.151	−0.154	−0.160
	(0.033)	(0.028)	(0.054)	(0.055)
Constant	0.137	0.151	0.380	0.435
	(0.026)	(0.028)	(0.200)	(0.197)
Controls	No	No	No	Yes
Industry FE; state FE	No	No	Yes	Yes
Observations	691	691	691	691
R-squared	.003	.007	.171	.182
Mean of DV	0.159	0.159	0.159	0.159

Note: Linear probability models. The sample only consists of the respondents who answered "Some employees" or "No employees" to the NCA-use question. The dependent variable is based on the question about the reasons for not using NCAs. The question is: "Why doesn't your organization use non-competes (multiple selections allowed)?" There are six possible answers to this question: "Non-competes are not commonly used in the industry," "Non-competes make it hard to attract talented employees," "Loss of employees to competitors is not a big concern," "Not familiar with what non-competes are," "Non-competes are not legally enforceable in my state," and "Other (please specify)." The dependent variable is coded as one if the respondents chose "non-competes make it hard to attract talented employees," and zero otherwise. Standard errors (in parentheses) are clustered at the industry-by-state level.

(coefficients on all controls are reported in Appendix Table A7). Here, we use a subsample of 691 respondents (56.1% of the NCA estimation sample) who do not use NCAs at all or use them only for some workers and responded to the questions about the reasons for the NCA nonuse. The dependent variable is a dummy for the response, "NCAs would make attracting talented workers difficult." In Model 1, only including non-leaders and talent, non-leaders are 4.0 percentage points more likely to report the ability to attract talent as the reason for not using NCAs than leaders, and firms relying heavily on talent are 3.0 percentage points less likely to do so than firms relying on other resources. In Model 2, adding the interaction term, industry leaders relying heavily on talented employees are 15.1 percentage points less likely to see the ability to attract talent as the reason for not using NCAs relative to leaders relying on other resources (p-value <.001). Thus, when leaders relying on talented employees do not use NCAs, their motivations likely stem from other reasons: NCAs are legally unenforceable, NCAs are not common among its industry members, or firms are not familiar with NCAs. For non-leaders, however, such associations reverse; among firms reporting talented workers as the key differentiator, industry non-leaders (relative to leaders) are 16.8 percentage points more likely to report that they do not use NCAs because the NCAs would make hiring talent difficult (p-value for the interaction term = .003; Model 2). The results remain consistent across specifications including industry and state fixed effects (Model 3) as well as other firm-level controls (Model 4).[36] Panel

[36]In Model 4, the inclusion of non-leader, talent, and their interaction increases the R^2 from .176 to .182.

c in Figure 1 displays the predicted likelihoods based on Model 4.[37] When we observe non-leaders that rely on talent not using NCAs, it is more likely because they worry about their ability to attract talented workers relative to leaders that rely on talent. These results provide evidence that some firms strategically opt out of using NCAs because they are concerned about their ability to attract talented workers.

Next, we explore whether and how the nonuse of NCAs is associated with a firm's actual ability to attract talent. In Table 6, we use the survey questions about whether firms face difficulty filling competitive job positions that are vacant for a longer period. Here, the sample consists of those who completed job position questions (832 respondents, or 67.5% of the NCA estimation sample). Our primary interest is in how the ease of filling vacancy positions differs across firms using and not using NCAs, depending on their industry positions and their reliance on various resources as a source of differentiation. For ease of interpretation, we first divide the sample based on the reliance on talented workers or other differentiators and then separately estimate the coefficients on the interaction for non-leaders and the fraction of workers *not* subject to NCAs (i.e., the extent of firms *not* using NCAs). This estimation is strictly correlational.[38]

In Table 6, Models 1–3 are based on the subsample of firms relying on talented workers as the critical differentiator, while Models 4–6 are based on the subsample of firms relying on other differentiators. All the models include the full set of controls and industry and state fixed effects. In Model 1, the coefficient on the interaction term for non-leaders and NCA nonuse fraction is estimated as a 19.0 percentage points decrease in the likelihood of firms having long-term vacancy positions in the talent-reliant sample (p-value = .418), while such a coefficient is estimated as 3.1 percentage points increase for the non-talent-reliant sample in Model 4 (p-value = .751). To get a sense of the estimate, Figure 2 panel a plots the estimated effects of NCA nonuse across the groups of leaders/non-leaders and talent/non-talent based on Models 1 and 4. Comparing those using NCAs for all workers and not using NCAs at all among non-leaders that rely heavily on talent, those not using NCAs at all are 9.5 percentage points *less* likely to have a long-term job opening, while the corresponding estimate for leaders is 11.9 percentage points *increase* in likelihood. These estimates are noisy, but the signs and magnitudes of the coefficients are consistent with our main arguments.

We further disaggregate the types of jobs that firms have difficulty filling. Models 2 and 5 show the results for the likelihood of having a long-term job opening for a managerial position, whereas Models 3 and 6 show the results for the likelihood of having a long-term job opening for a technical position. For both types of jobs, when talented workers are critical resources, industry non-leaders are less likely to encounter difficulty filling those vacant positions by opting out of NCAs. In particular, the coefficient on the interaction term in Model 3 represents 36.2 percentage points decrease in the likelihood of long-term vacancy in a technical job (p-value = .089), compared to the corresponding estimate of −0.061 in Model 6 (the

[37]In Appendix Table A8, we employ analogous regressions where the reason for not using NCAs is a lack of concern for losing talent. Our theory posits that fewer concerns about the expropriation of knowledge by competitors can be a reason for opting out of using NCAs. The dependent variable is a dummy for the "loss of employees is not a serious concern." The results are consistent with our theory. For instance, in Model 2, the coefficient on the interaction between non-leaders and talent is a 26.6 percentage points increase (p-value <.001). However, the interpretation is more difficult because lower concern about losing talent may be due to other reasons: the firm may have strong bargaining power in the labor markets, the labor supply may be abundant, or the risk of expropriation may be small. Appendix Table A9 shows the disaggregated results of NCA-non-use reasons for the full set of differentiating factors.

[38]Further, because NCA use is endogenous, as we show that it depends on the industry non-leader and talent variables, the estimated coefficient of the interaction term does not represent simple derivatives of the two individual terms.

TABLE 6 Ability to fill vacant positions.

Subsample	Model 1 Firms relying on talent as the key differentiator (Talent = 1)	Model 2	Model 3	Model 4 Firms relying on other resources as the key differentiator (Talent = 0)	Model 5	Model 6
Dependent variables	**Long-term vacant position**	**Difficulty filling managerial jobs**	**Difficulty filling technical jobs**	**Long-term vacant position**	**Difficulty filling managerial jobs**	**Difficulty filling technical jobs**
Non-leader × NCA nonuse percentage	**−0.190**	**−0.148**	**−0.362**	**0.031**	**0.024**	**−0.061**
	(0.234)	**(0.180)**	**(0.211)**	**(0.096)**	**(0.061)**	**(0.078)**
Non-leader	0.412	0.245	0.357	0.016	0.019	−0.019
	(0.179)	(0.121)	(0.169)	(0.068)	(0.043)	(0.049)
NCA nonuse percentage	−0.006	−0.055	0.253	−0.005	−0.024	0.062
	(0.211)	(0.155)	(0.171)	(0.077)	(0.047)	(0.064)
Constant	0.133	−0.186	−0.179	0.194	−0.012	0.220
	(0.417)	(0.165)	(0.466)	(0.336)	(0.096)	(0.285)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE; state FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	147	147	147	685	685	685
R-squared	.506	.433	0.547	0.116	0.100	0.157
Mean of DV	0.252	0.075	0.129	0.317	0.083	0.152

Note: Linear probability models. Controls include firm size, the dummy for the prevalence of NCAs in local labor market, primary deliverable, share of low-wage employees, and the respondents' job functions. In Models 1 and 4, the dependent variable is based on the response of "Yes" or "No" to the question: "Do you have any positions that have been open for six months or more?" Among those responding "Yes," the survey follows with: "What kind of positions do you have a hard time filling? (check all that apply)." There are nine possible choices that are not mutually exclusive: "Management," "IT," "Customer Service," "Sales," "Executive Level," "Marketing," "Engineering," "Finance," and "Other (please specify)." The dependent variable in Models 2 and 5 is based on the choice for managerial jobs ("Management" and "Executive Level"), while the dependent variable in Models 3 and 6 is based on the choice for technical jobs ("IT" and "Engineering"). Standard errors (in parentheses) are clustered at the industry-by-state level.

non-talent sample; *p*-value = .435). panel b (and c) in Figure 2 illustrate the differences in the likelihoods between firm groups, indicating that non-leaders relying heavily on talent are 9.9 (13.1) percentage points less likely to have a managerial (technical) long-term job opening if they do not use NCAs at all (compared to those using NCAs for all workers), whereas those relationships reverse for industry leaders. In sum, though correlational and suggestive, the regression results from Table 6 and the plots in Figure 2 do not contradict the key arguments. Opting out of NCA use appears to be associated with easier filling of high-skill positions (conditional on relying on talented workers). NCA use is, thus, more penalizing when attracting workers for non-leaders relative to leaders.

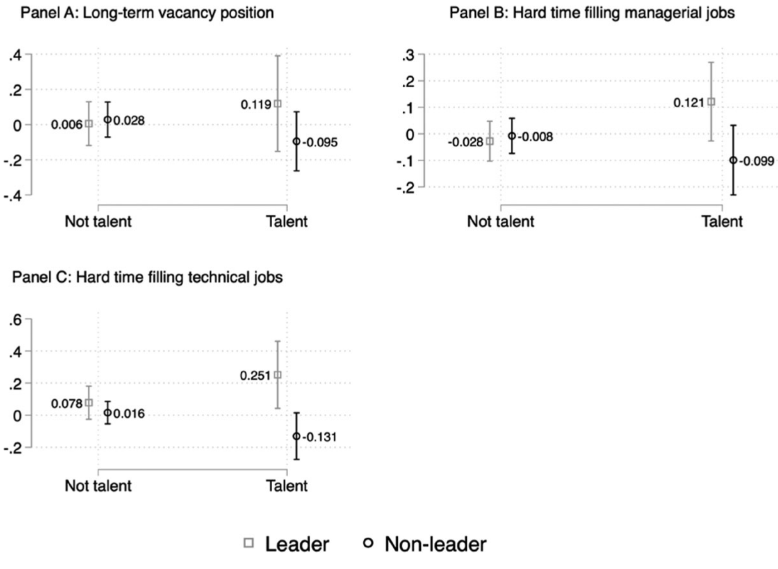

FIGURE 2 Marginal effects of NCA nonuse on the ability to attract talent. The regression models for calculating predicted likelihoods are based on Table 6 Models 1 and 4 for panel a, Models 2 and 5 for panel b, and Models 3 and 6 for panel c.

We also implement a supplementary analysis of how firms' decision *not* to use NCAs to attract talent is associated with differences in organizational climate (Schneider et al., 2011). We use the survey question: "Rate your level of agreement with the following statements," which has six different items. Each answer is based on a five-point Likert scale ("Strongly disagree," "Disagree," "Neither agree nor disagree," "Agree," "Strongly agree"). We focus on two items (most others focus on compensation), "There is frequent, two-way communication between managers and employees" and "Employees at my organization feel appreciated at work."[39] Since the reasons for the NCA nonuse are only available for respondents who answered that their organization either does not use NCAs at all or uses them only for some workers, we restrict the sample to these firms. Table A10 shows the regression results where the dependent variables are respondents' evaluations of frequent communication with top management and employees' general job satisfaction. Panels a and b in Figure A1 display the corresponding predicted likelihoods. Overall, these results suggest that when firms do not use NCAs at all, and the reason for not using NCAs is their ability to attract talent, respondents rate communication with managers and job satisfaction higher relative to other firms.[40] These

[39]The other four items consist of: "Compensation drives employee engagement at my organization," "Employees at my organization feel they are paid fairly," "My organization has a transparent pay process," and "Employees at my organization have a great relationship with their direct managers."

[40]We also explore various types of incentives such as individual/team incentive bonuses, retention bonuses, hiring bonuses, and other available metrics such as the extent to which compensation drives employees' engagement, and the extent to which employees feel they are paid fairly. The regression results for incentives are reported in Appendix Table A11, and those for other items related to work environments in the same survey question as Table A10 are reported in the Appendix Table A12. The only result representing sizeable associations is team incentive bonuses (Models 3 and 4 in Table A11), which weakly suggests that team-based incentive schemes may effectively reduce individual-level turnover, and thus be used for retention when NCAs are not used. However, as mentioned earlier, the effects of NCAs on compensation are notoriously difficult to estimate and interpret so this result needs to be taken with caution.

results may imply that firms that opt out of using NCAs because they are concerned that NCAs would inhibit their ability to attract talent may resort to alternative ways of retention such as improving the work environment.

Finally, we examine how the estimated effects vary with the IP environment. If our patterns are partly driven by concerns about knowledge leakage, as we argue theoretically, we should observe the associations to be more pronounced when the ability to protect IP through alternative means, such as the availability of patent protection, is weaker. This is because the risk of knowledge leakage is likely larger when firms lack other potential means of protecting knowledge, such as patents. To examine this, we explore the heterogeneity in NCA use and the reason for the NCA nonuse as they vary with the patenting intensity of the industry. We rely on the DISCERN database (Arora et al., 2021) that links the USPTO patents between 1980 and 2015 to Compustat, to calculate industry-level patent intensity (based on two-digit NAICS). Then, we interact the patent intensity variable with the non-leader and talent variables to estimate how the effects (reported in Tables 4 and 5) vary with patent intensity. In Table A13, we use a dummy for high versus low patent-intensive industries by equally dividing the industries into both categories. In Table A14, we use a continuous measure of patent intensity, the log-transformed patent stock. We lose some statistical power in the estimations, likely due to noisy matching between the 2-digit NAICS codes and the PayScale industry classifications. Still, the results are consistent with the argument that the relationships between our key independent variable (the interaction between non-leader and talent) and NCA use are attenuated in high patent-intensive industries relative to low patent-intensive industries. For instance, in Table A13 Model 2, in low patent-intensive industries and where talent is a critical resource, non-leaders are 32.7 percentage points less likely to use NCAs for all workers relative to leaders. In high patent-intensive industries, this difference decreases to 15.3 percentage points. Further, in low patent-intensive industries, a lack of concern about retaining talent is more likely to be reported by non-leaders as a major reason for not using NCAs relative to leaders (34.5 percentage points difference, Model 8). This difference decreases to 6.5 percentage points in high patent-intensive industries. Similar attenuations are observed when we use a continuous measure of industry-level patent intensity (Appendix Table A14). The concerns about knowledge leakage are likely critical for leaders when they lack alternatives to protect IP and help to drive differences in NCA use by leaders versus non-leaders.

6.1 | Robustness tests: Alternative specifications

We perform additional analyses to assess the robustness of the results. We employ weighted regressions on firm size, industries, and states, use alternative operationalization of NCA and talent variables, and assess the robustness of the regression estimates in different subsamples. We also assess the sensitivity of our regression estimates to potential confounders.

First, we assess how the representativeness of the survey sample affects our main findings. We use iterative proportional fitting ("raking") to create the weights based on firm size, industry, and state (Kalton & Flores-Cervantes, 2003). The weighting answers the question of how the estimates may change if the survey sample is perfectly representative of the population of US firms in terms of size, industry, and state.[41] The analysis is in the Appendix and the results are reported in Appendix Table A15. The findings reported in Tables 4 and 5, as well as the

[41]We obtain the data from the 2017 County Business Patterns for the population of US firms.

findings from Table 6 related to technical occupations remain robust and consistent in the weighted regressions.

Next, we examine the robustness of our main findings to using alternative measures of NCA use (using different aggregation for the binary variable and different cutoffs for the continuous variable), an alternative proxy for talent (investments in training of new hires), subsample analysis (knowledge-intensive sectors and excluding states with unenforceable NCAs), and analysis using multiple imputations of missing variables. The analysis and the results are described in the Appendix (Appendix Tables A16-A20). The results remain consistent.

Finally, we conduct the sensitivity analysis proposed by Cinelli and Hazlett (2020). The gist of the approach is to estimate how strongly any potential confounders need to be associated with both treatment and outcome to negate the observed relationships. The analysis is described in the Appendix and reported in Appendix Table A21. Based on this analysis, we conclude that potential confounders, such as unobserved individual characteristics, would need to explain far more variation in the dependent variable than observed firm-level characteristics, such as firm size, to overturn our NCA results. A similar conclusion can be derived for NCA use measured by the fraction of workers and the NCA nonuse reason. Consequently, we conclude that omitted variables are unlikely to drive our findings.

6.2 | Validation of key explanatory variables and further mechanism checks

Since our key variables rely on subjective evaluations by responding managers, we examine the validity of the variables using external sources: Glassdoor, CPS, and Compustat.

First, we check our firm size measure in PayScale using Glassdoor.[42] We scraped the information on employment from the Glassdoor website and merged it with the PayScale dataset by matching a company name, headquarter state, and industry. 92.7% of companies in PayScale with employer names are matched with Glassdoor. Appendix Table A22 examines the correlation between the size measures in PayScale and Glassdoor. It suggests that the PayScale size measure broadly aligns with the Glassdoor size measure, as one additional employee in PayScale is associated with a 1.25 increase in size in Glassdoor.

Next, we examine how our talent measure is associated with the average levels of workers' human capital for each industry and state. The test is inherently noisy, but a positive correlation provides an additional validation check. We link our data with the CPS in the periods 2007–2016 to obtain workers' education levels at the industry level (2-digit NAICS) and the industry-by-state level. The CPS sample was pooled across periods, and the education variables were aggregated to produce three measures: a dummy for a bachelor's degree or higher, a dummy for a master's degree or higher, and a continuous measure of years of education. Regression results are reported in Appendix Table A23. In panel a, the three measures of industry-level human capital—the ratio of workers with bachelor's degrees or higher, the ratio of workers with master's degrees or higher, and the years of education—are all strongly positively correlated with our talent measure. Similar results are derived when the education level is measured at the industry-state level (in panel b).

[42]Glassdoor is an employer review and recruiting website where both current and former employees voluntarily and anonymously review their companies. The employees are incentivized to leave reviews through a "give-to-get" policy, whereby contributors gain access to the information submitted by others.

To examine whether the subjective evaluation of industry leaders and non-leaders in the survey aligns with the objective measures of industry leadership, we match the firm names in our sample with Compustat.[43] From 1803 observations in the survey, we identify 119 Compustat matches (112 unique firms). We then perform regressions where the independent variable is the industry leader dummy, and the dependent variables are the dummies for the top 10%, top 5%, and top 5 firms in the number of employees, total assets, sales, and net income within the industries defined by 4-digit SICs. The results are reported in Appendix Table A24. Due to its subjective nature, the loosely defined industries and markets, and the small size of the matched sample, our industry leadership measure is not perfectly aligned with the objective financial performance. Still, we find that, for instance, industry leaders are 9.7–11.7 percentage points more likely to be top five firms in any of the metrics within the same 4-digit SIC industries (panel c).

Finally, it is useful to note that our arguments hinge on the assumption that prospective workers are aware and sensitive to the firms' use of NCAs. We assume that at least some talented prospective workers pay attention to whether a firm uses NCA and, if it does, prefer to select another employment opportunity. While we cannot validate this assumption in the context of our survey, there is emerging evidence in the literature supporting this notion. For instance, Prescott and Starr (2022) report that about 70% of workers in knowledge-intensive industries who are subject to NCAs are aware of the implications of what they signed. More recently, Cowgill et al. (2024) implemented a large-scale randomized field experiment with knowledge workers while randomizing whether the NCA clause is present in the employment contract (and how salient it is). Their findings appear consistent with our assumptions. For instance, they find that for highly skilled workers (defined as those making $40/hour), the presence of an NCA in an employment contract leads to a 7% lower likelihood of accepting a job offer (if the NCA is non-salient). This increases to 17% for a more salient NCA. They also track how much time prospective workers spend on reading each section of the employment contract and find that about 70% of highly skilled workers do not skip reading the section with the NCA (in the non-salient version), supporting the notion that such workers are aware and paying attention to NCAs.

7 | DISCUSSION AND CONCLUSION

While extensive prior literature has conceptualized NCAs as beneficial for firms (Marx et al., 2015; Starr, Ganco, & Campbell, 2018), there may be downsides to using NCAs for some firms. Our study examines why some firms may opt out of using NCAs, even if they are available and are used by their competitors. We provide a conceptual explanation highlighting the tension between the ability to attract and retain talent, leading to firm-level heterogeneity in using or not using NCAs.

We find that non-leaders that rely more heavily on talent are less likely to use NCAs (relative to leaders that rely on talent). Importantly, these firms are more likely to respond that they opt out of NCAs because NCAs can lower their ability to attract talented workers. Further, by opting out of NCAs, the focal firms are better able to fill vacant skilled positions such as engineers. We also find that firms opting out of NCAs due to their need for talent are likely to have

[43]We employed fuzzy matching of company names using the STATA command *matchit*, followed by manual checks to detect false positives.

workers who are more satisfied and communicate better with managers. Finally, the patterns are more pronounced in less patent-intensive industries, underscoring that concerns about knowledge leakage may drive the results.

Our theoretical framework developed above aligns with these findings. In a competitive context, for non-leading firms, acquiring highly skilled employees may be more important than protecting their existing knowledge from expropriation. For firms that report talent as the key differentiator, attracting a highly skilled and motivated workforce may be particularly critical. To the extent that NCAs diminish the attractiveness of these firms, NCAs undercut the firms' key advantage. While talent may be essential for non-leaders, leading firms may rely on valuable complementary resources such as brands, dominant distribution channels, or client relationships in addition to skilled workers. Relative to non-leaders, leading firms may have cutting-edge knowledge and IP and, thus, may worry more about the diffusion of such knowledge to their competitors. Consequently, for leading firms, retaining workers may be more critical, and such firms may opt for more extensive NCA use. Our analysis indicates that opting out of NCAs to attract talent correlates with a work environment where workers are more satisfied and communicate better with management. This may imply that opting out of NCAs is part of a broader human capital strategy oriented toward the attraction and retention of skilled employees. The firms that implement such strategies may be seen as creating a work climate where employees prefer to stay relative to competitors that employ legal levers to retain their workers.

While the explanation of our findings applies to NCAs, it may be useful to discuss several broader implications. Our logic may apply to other restrictive practices that are widespread, effective, and require firm commitment (e.g., non-poaching or non-solicitation agreements [Balasubramanian et al., 2023]). In contrast, it may be more difficult for some firms to opt out of patent enforcement as a differentiation strategy. Patent litigation results from a potential ex-post infringement instead of a violation of an employment contract. Thus, the opt-out strategy may be seen as "cheap talk" as it does not require commitment at the time of hiring. We leave the investigation of how our results extend to other restrictive clauses for future work. Further, our findings indicate that non-leader firms primarily differentiate from leading firms that use NCAs very aggressively and use NCAs for all or most of their workers (see Appendix Table A17). This may be because such leading firms are highly visible, and it may be easier to draw a contrast with such firms when recruiting talent. Such dynamics may extend to other restrictive practices.

Our study has several limitations that open avenues for future work. The usual tradeoffs stem from our use of survey data. In order to achieve a high level of granularity and detail, some of the data may reflect subjective assessments of the respondents. For example, whether a firm is an industry leader or not may be open to interpretation by respondents, leading to noise or bias. While the fact that most of the survey respondents were in managerial positions or HR jobs (see Appendix Table A1) may partially alleviate this concern, we sought to validate our leadership measure by matching the public firms in our sample with Compustat. We generally found a good correspondence between our proxy and other measures of industry leadership (see Appendix Table A24). Still, it will be helpful for future work to replicate our results using a broader range of measures.

The survey-based focus may affect the sample's representativeness and the generalizability of the results. While PayScale sent their survey to a representative cross section of firms in terms of size and industry, it is possible that the response rate may be a function of some variables of interest in our model. We have used raking weights matching on size, industry, and states, and imputation methods for missing NCA questions to mitigate potential biases stemming from the selection in the survey participation and the absence of observations (Appendix Tables A15, A19, and A20). However, it is still possible that failing and low-performing firms may be less likely to respond to the PayScale survey. Those firms may face severe difficulties attracting talented workers whether they use NCAs or not. Given the low benefits of not using NCAs to attract talented workers, failing firms may opt for using NCAs and settle for less competitive workers. Considering this possibility, our results may not be generalizable to low-performing and failing firms, and future work should examine this population in more detail.

Further, the objective of our analysis was primarily descriptive while focusing on ruling out alternative explanations and spurious patterns. Our core objective is to explain the variation in strategic behavior (i.e., opting out of NCAs). An ideal design would require strict exogeneity of a firm's leadership position, how much it relies on skilled human capital, and of the matching between human capital and firms. Implementing such a design in the context of our data is impossible. For instance, one may be concerned that a firm's choice to use or not use NCAs may be driven by the level of human capital it possesses. Non-leaders may tend to use NCAs less simply because they can hire only lower-level human capital. While our finding that firms choose not to use NCAs due to the lower ability to attract workers mitigates this concern, future studies could consider the quality of human capital the firms can acquire.

Our analysis is also cross-sectional in nature. Future work may focus on the temporal aspects of NCA use. For instance, it would be useful to examine how firms create and develop their NCA strategies over time. Such an approach would also open avenues for incorporating other theoretical perspectives that deviate from our rational choice framework such as the behavioral theory of the firm.[44] Future work may also examine the interaction between the state-level variation in NCA enforceability and the firm-level NCA use.

Our study provides one of the first investigations of firm-level heterogeneity in NCA use, and we make several contributions to the literature. We contribute to the literature on strategic human capital and mobility frictions by developing a novel explanation for the firm-level heterogeneity in the use of NCAs within industries. Relatedly, it is useful to connect our findings to the broader discussions in the field on the specificity of human capital (Campbell, Coff, & Kryscynski, 2012). Prior work has emphasized that mobility frictions allow firms to lock employees into their organizations, improving both the value creation and value appropriation associated with human capital (Starr, Balasubramanian, & Sakakibara, 2018). Our study presents an important complementary view. Improving value appropriation and "de facto" firm-specificity of human capital may be at the expense of the quality of talent that firms can hire. In the context of frictions, we should focus more on examining the impacts of frictions on hiring and not only on knowledge expropriation and existing workers.

We also contribute to the literature on NCAs. Most of the existing work examined the relationship between the state-level differences in the enforceability of NCAs and various individual- and firm-level outcomes. We shift attention to a more granular analysis at the firm level and highlight the importance of NCA nonuse. We show that such a shift has important ramifications by revealing significant heterogeneity in firms' actual use of NCAs. Examining firm-level behaviors more directly will reduce the impact of confounding factors and potentially improve the reliability of analyses in future studies. Future work on NCAs may collect more

[44]We note that such analysis would focus on the within-firm differences using firm fixed effects. Using firm fixed effects is not relevant in our context because it would remove the primary source of heterogeneity.

granular data and go beyond examining legislative changes at the state level only. We hope to stimulate more research in this fruitful and important area.

ACKNOWLEDGMENTS

The authors would like to thank the editor Raffaele Conti and two anonymous reviewers for their helpful comments during the revision process. The authors would also like to thank Rajshree Agarwal, Natarajan Balasubramanian, Serguey Braguinsky, and Evan Starr for helpful comments on earlier versions of the paper. The paper was presented at Purdue University, University of Texas at Austin, University of Wisconsin-Madison, 2022 Academy of Management Annual Conference, and 2022 Strategic Management Society Annual Conference. The authors appreciate helpful comments from these seminar and conference participants.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from PayScale, Inc. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of PayScale, Inc.

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REFERENCES

Agarwal, R., Ganco, M., & Raffiee, J. (2021). Immigrant entrepreneurship: The effect of early career immigration constraints on new venture formation. *Organization Science*, *33*(4), 1372–1395.

Agarwal, R., Ganco, M., & Ziedonis, R. H. (2009). Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. *Strategic Management Journal*, *30*(13), 1349–1374.

Albino, V., Garavelli, A. C., & Schiuma, G. (1998). Knowledge transfer and inter-firm relationships in industrial districts: The role of the leader firm. *Technovation*, *19*(1), 53–63.

Alchian, A. A., & Demsetz, H. (1973). The property right paradigm. *The Journal of Economic History*, *33*(1), 16–27.

Arora, A., Belenzon, S., & Sheer, L. (2021). Knowledge spillovers and corporate investment in scientific research. *American Economic Review*, *111*(3), 871–898.

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In *The rate and direction of inventive activity: Economic and social factors* (pp. 609–626). Princeton University Press.

Balasubramanian, N., Chang, J. W., Sakakibara, M., Sivadasan, J., & Starr, E. (2022). Locked in? The enforceability of covenants not to compete and the careers of high-tech workers. *Journal of Human Resources*, *57*(S), S349–S396.

Balasubramanian, N., Starr, E., & Yamaguchi, S. (2023). Employment restrictions on resource transferability and value appropriation from employees. Available at SSRN. Retrieved from https://ssrn.com/abstract=3814403 https://doi.org/10.2139/ssrn.3814403

Barney, J., Wright, M., & Ketchen, D. J., Jr. (2001). The resource-based view of the firm: Ten years after 1991. *Journal of Management*, *27*(6), 625–641.

Berry, H. (2006). Leaders, laggards, and the pursuit of foreign knowledge. *Strategic Management Journal*, *27*(2), 151–168.

Boschma, R. A., & Lambooy, J. G. (2002). Knowledge, market structure, and economic coordination: Dynamics of industrial districts. *Growth and Change*, *33*(3), 291–311.

Campbell, B. A., Coff, R., & Kryscynski, D. (2012). Re-thinking competitive advantage from human capital: How the concept of firm-specificity has led strategy theorists astray. *Academy of Management Review*, *37*(3), 376–395.

Campbell, B. A., Ganco, M., Franco, A. M., & Agarwal, R. (2012). Whole leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal*, *33*(1), 65–87.

Carnahan, S., Agarwal, R., & Campbell, B. A. (2012). Heterogeneity in turnover: The effect of relative compensation dispersion of firms on the mobility and entrepreneurship of extreme performers. *Strategic Management Journal*, *33*(12), 1411–1430.

Cinelli, C., Ferwerda, J., & Hazlett, C. (2020). Sensemakr: Sensitivity analysis tools for OLS in R and stata. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3588978

Cinelli, C., & Hazlett, C. (2020). Making sense of sensitivity: Extending omitted variable bias. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *82*(1), 39–67.

Coff, R. (1997). Human assets and management dilemmas: Coping with hazards on the road to resource-based theory. *Academy of Management Review*, *22*(2), 374–402.

Colvin, A., & Shierholz, H. (2019). *Noncompete agreements: Ubiquitous, harmful to wages and to competition, and part of a growing trend of employers requiring workers to sign away their rights*. Economic Policy Institute. Retrieved from https://policycommons.net/artifacts/1409606/noncompete-agreements/2023868/

Conti, R. (2014). Do non-competition agreements lead firms to pursue risky R&D projects? *Strategic Management Journal*, *35*(8), 1230–1248.

Cowgill, B., Freiberg, B., & Starr, E. (2024). Clause and effect: A field experiment on noncompete clauses, knowledge flows, job mobility, and wages. Working Paper.

Eesley, C. E., & Lee, Y. S. (2020). Do university entrepreneurship programs promote entrepreneurship? *Strategic Management Journal*, *42*(4), 833–861.

Fallick, B., Fleischman, C. A., & Rebitzer, J. B. (2006). Job-hopping in Silicon Valley: Some evidence concerning the microfoundations of a high-technology cluster. *The Review of Economics and Statistics*, *88*(3), 472–481.

Foss, N. J., Pedersen, T., Reinholt Fosgaard, M., & Stea, D. (2015). Why complementary HRM practices impact performance: The case of rewards, job design, and work climate in a knowledge-sharing context. *Human Resource Management*, *54*(6), 955–976.

Ganco, M., Ziedonis, R. H., & Agarwal, R. (2015). More stars stay, but the brightest ones still leave: Job hopping in the shadow of patent enforcement. *Strategic Management Journal*, *36*(5), 659–685.

Garmaise, M. J. (2011). Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment. *The Journal of Law, Economics, and Organization*, *27*(2), 376–425.

Gilson, R. J. (1999). The legal infrastructure of high technology industrial districts: Silicon Valley, route 128, and covenants not to compete. *New York University Law Review*, *74*, 575.

Goldfarb, B., & King, A. A. (2016). Scientific apophenia in strategic management research: Significance tests & mistaken inference. *Strategic Management Journal*, *37*(1), 167–176.

Heckman, J. J., & Singer, B. (2017). Abducting economics. *American Economic Review*, *107*(5), 298–302.

Huselid, M. A. (1995). The impact of human resource management practices on turnover, productivity, and corporate financial performance. *Academy of Management Journal*, *38*(3), 635–672.

Ito, K. (1997). Domestic competitive position and export strategy of Japanese manufacturing firms: 1971–1985. *Management Science*, *43*(5), 610–622.

Ito, K., & Pucik, V. (1993). R&D spending, domestic competition, and export performance of Japanese manufacturing firms. *Strategic Management Journal*, *14*(1), 61–75.

Johnson, M. S., & Lipsitz, M. (2022). Why are low-wage workers signing noncompete agreements? *Journal of Human Resources*, *57*(3), 689–724.

Kalton, G., & Flores-Cervantes, I. (2003). Weighting methods. *Journal of Official Statistics*, *19*(2), 81–97.

Kesan, J., & Ball, G. G. (2006). How are patent cases resolved-an empirical examination of the adjudication and settlement of patent disputes. *Washington University Law Review*, *84*, 237–310.

Kim, J., & Marschke, G. (2005). Labor mobility of scientists, technological diffusion, and the firm's patenting decision. *RAND Journal of Economics*, *36*(2), 298–317.

Kim, J. Y., & Steensma, H. K. (2017). Employee mobility, spin-outs, and knowledge spill-in: How incumbent firms can learn from new ventures. *Strategic Management Journal*, *38*(8), 1626–1645.

Kini, O., Williams, R., & Yin, S. (2021). CEO noncompete agreements, job risk, and compensation. *The Review of Financial Studies*, *34*(10), 4701–4744.

Klepper, S. (2001). Employee startups in high-tech industries. *Industrial and Corporate Change*, *10*(3), 639–674.

Lavetti, K., Simon, C., & White, W. D. (2020). The impacts of restricting mobility of skilled service workers evidence from physicians. *Journal of Human Resources*, *55*(3), 1025–1067.

Lipsitz, M., & Starr, E. (2022). Low-wage workers and the enforceability of noncompete agreements. *Management Science*, *68*(1), 143–170.

Marx, M. (2011). The firm strikes back: Non-compete agreements and the mobility of technical professionals. *American Sociological Review*, *76*(5), 695–712.

Marx, M., Singh, J., & Fleming, L. (2015). Regional disadvantage? Employee non-compete agreements and brain drain. *Research Policy*, *44*(2), 394–404.

Marx, M., Strumsky, D., & Fleming, L. (2009). Mobility, skills, and the Michigan non-compete experiment. *Management Science*, *55*(6), 875–889.

Mascarenhas, B. (1986). International strategies of non-dominant firms. *Journal of International Business Studies*, *17*(1), 1–25.

McElheran, K. (2015). Do market leaders lead in business process innovation? The case (s) of e-business adoption. *Management Science*, *61*(6), 1197–1216.

Meccheri, N. (2009). A note on noncompetes, bargaining and training by firms. *Economics Letters*, *102*(3), 198–200.

Ostrom, E., & Hess, C. (2008). Private and common property rights. In *Encyclopedia of law & economics*. Edward Elgar. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1304699

Paniccia, I. (1998). One, a hundred, thousands of industrial districts. Organizational variety in local networks of small and medium-sized enterprises. *Organization Studies*, *19*(4), 667–699.

Phillips, D. J. (2005). Organizational genealogies and the persistence of gender inequality: The case of Silicon Valley law firms. *Administrative Science Quarterly*, *50*(3), 440–472.

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining competitive advantage*. Free Press.

Prescott, J., & Starr, E. (2022). Subjective beliefs about contract enforceability. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3873638#

Raffiee, J. (2017). Employee mobility and interfirm relationship transfer: Evidence from the mobility and client attachments of United States federal lobbyists, 1998–2014. *Strategic Management Journal*, *38*(10), 2019–2040.

Rosenkopf, L., & Almeida, P. (2003). Overcoming local search through alliances and mobility. *Management Science*, *49*(6), 751–766.

Rothstein, D. S., & Starr, E. (2021). Mobility restrictions, bargaining, and wages: Evidence from the National Longitudinal Survey of Youth 1997. Retrieved from https://ssrn.com/abstract=3974897 https://doi.org/10.2139/ssrn.3974897

Rubin, P. H., & Shedd, P. (1981). Human capital and covenants not to compete. *The Journal of Legal Studies*, *10*(1), 93–110.

Samila, S., & Sorenson, O. (2011). Noncompete covenants: Incentives to innovate or impediments to growth. *Management Science*, *57*(3), 425–438.

Schneider, B., Ehrhart, M. G., & Macey, W. H. (2011). Perspectives on organizational climate and culture. In S. Zedeck (Ed.), *APA handbook of industrial and organizational psychology. Building and developing the organization* (Vol. 1, pp. 373–414). American Psychological Association. https://doi.org/10.1037/12169-012

Seo, E., & Somaya, D. (2021). Living it up at the hotel California: Employee mobility barriers and collaborativeness in firms' innovation. *Organization Science*, *33*(2), 766–784.

Sevcenko, V., & Ethiraj, S. (2018). How do firms appropriate value from employees with transferable skills? A study of the appropriation puzzle in actively managed mutual funds. *Organization Science*, *29*(5), 775–795.

Shi, L. (2021). The macro impact of noncompete contracts (No. 2103). Einaudi Institute for Economics and Finance (EIEF). Retrieved from http://www.eief.it/eief/images/WP_21.03.pdf

Singh, J., & Agrawal, A. (2011). Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science*, *57*(1), 129–150.

Starr, E. (2019). Consider this: Training, wages, and the enforceability of covenants not to compete. *ILR Review*, *72*(4), 783–817.

Starr, E., Balasubramanian, N., & Sakakibara, M. (2018). Screening spinouts? How noncompete enforceability affects the creation, growth, and survival of new firms. *Management Science*, *64*(2), 552–572.

Starr, E., Ganco, M., & Campbell, B. A. (2018). Strategic human capital management in the context of cross-industry and within-industry mobility frictions. *Strategic Management Journal*, *39*(8), 2226–2254.

Starr, E., Prescott, J. J., & Bishara, N. D. (2021). Noncompete agreements in the US labor force. *The Journal of Law and Economics*, *64*(1), 53–84.

Tzabbar, D. (2009). When does scientist recruitment affect technological repositioning? *Academy of Management Journal*, *52*(5), 873–896.

Tzabbar, D., & Cirillo, B. (2020). Introduction: An integrated perspective of employee intra- and inter-firm mobility. In D. Tzabbar & B. Cirillo (Eds.), *Employee inter- and intra-firm mobility* (Vol. 41, pp. 1–11). Emerald Publishing Limited.

Younge, K. A., & Marx, M. (2016). The value of employee retention: Evidence from a natural experiment. *Journal of Economics & Management Strategy*, *25*(3), 652–677.

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Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Ganco, M., Liu, J., Wang, H., & Yamaguchi, S. (2024). Strategic restraint: When do human-capital-intensive companies choose (not) to use noncompete agreements? *Strategic Management Journal*, *45*(13), 2696–2726. https://doi.org/10.1002/smj.3648