Bundling Postemployment Restrictive Covenants: When, Why, and How It Matters*

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Abstract

Many of a firm's most important informational or relational resources are at risk of diffusion to its competitors because they are embedded in the firm's human capital. Using novel firm- and worker-level data, we present descriptive evidence on the adoption of and outcomes associated with four post-employment restrictive covenants (PERCs) that limit the diffusion of such resources to competitors: non-disclosure agreements (NDA), non-solicitation agreements, non-recruitment agreements, and non-compete agreements. We find that firms tend to adopt these PERCs together, with just three combinations (no PERCs, only an NDA, all four) covering more than 82% of workers and 70% of firms. We examine two rationales for why firms might bundle PERCs together—value creation and *pure* value capture—and draw out and test their implications both for worker and firm outcomes and for adoption. Our results suggest that pure value capture is the likely rationale for bundling PERCs with the average worker, while value creation is more applicable to top managers. Finally, we document how studying just one PERC can be misleading when such PERCs are bundled.

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1. Introduction

For many firms, some of their most valuable resources—information, client relationships, and skills—are embedded in their workers' human capital. Because workers can move or otherwise share information, firms face the risk of such resources leaking to their competitors and losing any associated advantages (Agarwal, Gambardella, and Olson 2016). While prior research has emphasized several ways that firms reduce the risk of such leakage—including intellectual property protections, frictions, or development of firm-specific knowledge (Acemoglu and Pischke 1999; Hatch and Dyer 2004; Agarwal, Ganco, and Ziedonis 2009; Campbell, Coff, and Kryscynski 2012; Campbell et al. 2012; Luo and Mortimer 2017; Png 2017)—a key focus is on non-compete agreements (NCAs), which prohibit workers from joining some competitors altogether.[1]

However, NCAs are just one in a class of post-employment restrictive covenants (PERCs) that firms use to restrict what former employees can do. Other PERCs include non-disclosure agreements (NDAs), which prohibit workers from using or disclosing confidential information; non-solicitation agreements (NSAs), which prohibit workers from soliciting former clients; and non-recruitment agreements (NRAs), which prohibit workers from recruiting former co-workers. Despite recent calls to examine the "bundle" of PERCs firms deploy (Lobel 2020), the literature has not studied such PERCs, how they relate to NCAs, and how they matter for workers and firms. In this study, we fill these gaps by providing descriptive evidence on when firms deploy these four PERCs, whether and why firms bundle them together, how such bundling relates to value creation and capture, and how examining a single PERC without considering the bundle can be misleading.

[1] Most studies of NCAs examine state-level NCA *policies* (Bishara and Starr 2016). See Stuart and Sorenson (2003); Marx, Strumsky, and Fleming (2009); Garmaise (2009); Samila and Sorenson (2011); Conti (2014); Younge and Marx (2015); Starr, Balasubramanian, and Sakakibara (2018); Starr, Ganco, and Campbell (2018); Starr (2019); Balasubramanian et al. (2020); Jeffers (2020); Lavetti, Simon, and White (2020); Lipsitz and Starr (forthcoming); Kang and Fleming (2020); Young (2020). Studies examining NCA *use* include Johnson and Lipsitz (2020); Marx (2011); Lavetti, Simon, and White (2020); Sanga (2018); Starr, Prescott, and Bishara (forthcoming); Shi (2020); and Colvin and Shierholz (2019).

Leveraging two large-scale surveys—one of firms and the other of individuals—we find that NDAs are the most common among these PERCs, covering 57% of workers and 88% of firms (in our sample), while NSAs, NRAs, and NCAs cover 28%, 24%, and 22% of workers, respectively. We also find that of the 16 possible combinations of PERCs, just three cover 82% of workers and 71% of firms: "No PERCs" (38% of individuals, 22% of firms), "Only an NDA" (26% of individuals, 26% of firms) and "All" four PERCs (18% of individuals, 23% of firms). Thus, in practice, if we observe an NCA, NSA, or NRA, it is most likely bundled with the other three PERCs.

Building on prior research on NCAs and legal scholarship on the bundle of PERCs, we consider two rationales for why firms might bundle all four PERCs together: (1) value creation through the resolution of an investment hold-up problem, and (2) pure value capture by reducing turnover and wage growth. In contrast to prior research, which examines mostly how state NCA polices relate to worker or firm outcomes, we draw out the implications of each rationale for how bundling PERCs should relate to both firm and worker outcomes and for where firms should bundle PERCs in the first place (if each rationale is operative). The two rationales differ most prominently in their implications for investment and wages. In the value creation rationale, the resolution of the hold-up problem implies that bundling PERCs should be associated with more investment and non-negative wage growth. In contrast, the pure value capture rationale implies that firms bundle PERCs to reduce wage levels and growth—and that as a result they should be more likely to bundle PERCs in jobs with high expected wage growth in the first place.

Combining external data with our survey data, we find descriptive evidence supportive of both rationales for bundling PERCs. The results most consistent with the value creation rationale are that (1) firms that bundle PERCs are more likely to invest in training their workers (though the estimates are imprecise), (2) that top-management workers have higher wages when bound by all four PERCs, and (3) that firms are more likely to deploy all four PERCs in jobs where resolving a hold-up problem has higher value (i.e., in jobs with access to trade secrets and client information and in jobs with high turnover risk). In contrast, consistent with the pure value capture rationale, we find that (1) firms that use all four PERCs for all their workers are 6.5% less likely to report that they intend to increase wages relative to firms that deploy only an NDA, and (2) that firms are more likely to bundle PERCs in jobs with high wage growth. Using within-firm variation, we also find that the average worker is not compensated for giving up their postemployment freedoms. Rather, workers with all four PERCs earn on average 5.3% lower wages relative to workers with only an NDA, and such negative effects are concentrated among workers with low bargaining power.

Last, we estimate naïve models that ignore bundling and consider only one PERC. We find that examining each PERC in isolation yields the opposite sign of the bundling estimate with respect to either turnover or wages. We uncover evidence that these sign changes are either due to PERCs exhibiting differential effects when combined or due to differences in the comparison bundle (e.g., All four PERCs vs. No PERCs gives different results than All four PERCs vs. Only NDA).

Our work makes at least three contributions to the literature in management and economics on isolating mechanisms, labor market frictions, and competitive advantage generally, and to the literature on NCAs specifically (Dierickx and Cool 1989; Rumelt 1984; Campbell, Coff, and Kryscynski 2012; Mahoney and Qian 2013; Starr, Balasubramanian, and Sakakibara 2018; Manning 2021). While this prior literature has identified several ways that firms can help isolate valuable resources in the firm, our first contribution is to document the ubiquity of several unstudied PERCs designed to isolate valuable but otherwise fungible resources within the firm, all of which are more common than NCAs.

Second, we show that we cannot study these PERCs in isolation—since firms regularly bundle them together—and that such bundling creates unique theoretical and empirical challenges, which, to our knowledge, have not been highlighted in the literature. Indeed, our results highlight how estimates incorporating the bundle can reverse the sign of the estimate from a single PERC (as is common in the literature). In this regard, as we discuss later, our bundling results highlight a potential resolution to conflicting estimates in the extant literature of how NCAs relate to wages.[2]

Third, we distill key implications from potential value creation and pure value capture rationales for bundling PERCs, and provide (to our knowledge) the first empirical analysis of those implications. In this regard, a key novelty is to impute motives by simultaneously studying both the outcomes associated with bundling PERCs and the adoption of such bundling (in contrast to prior literature that has focused almost entirely on outcomes related to only NCAs). As we illustrate later, "backward inducting" from outcomes to adoption not only helps shed more light on the phenomenon but also provides greater confidence in the empirical results.

While our results should be interpreted as descriptive, they are consistent with firms bundling PERCs to limit turnover and wage growth, in addition to resolving a hold-up problem, though for different types of workers. In this regard, our results also contribute theoretically by providing evidence inconsistent with common "freedom to contract" arguments, which posit that firms will be unable to capture value from workers using PERCs because workers would not agree to them without a sufficiently large compensating differential (Callahan 1985; Friedman 1991). Our results are inconsistent with this view because low-bargaining-power workers bound by all four PERCs earn lower wages relative to those bound only by NDAs.

In what follows we provide background on PERCs, describe our data, and then highlight the adoption and bundling of four PERCs. We then draw out the implications of two likely rationales for why firms might bundle PERCs together, and then test those and related implications.

[2] More broadly, our study is also related to the literature on the bundling of organizational choices. That literature has focused on both the adoption and quality of multiple management practices (Bloom et al. 2014) and synergies across broad management domains (e.g., Rivkin and Siggelkow 2003; Ichniowski and Shaw 1999). In contrast, our findings highlight the importance of bundling even within narrow areas such as PERCs.

2. Background on Postemployment Restrictive Covenants

In this section, we provide a baseline understanding of PERCs and key institutional details. PERCs are a class of employment provisions that restrict what an employee can do following the cessation of a work relationship (Lobel 2020). These restrictions include not sharing information learned at a prior employer (NDA), not soliciting former clients or vendors (NSA), not recruiting former co-workers (NRA), or not moving to or starting a competitor (NCA).[3] While there are other PERCs (e.g.., non-disparagement agreements that prohibit workers from disparaging a former employer), our focus on these four PERCs stems from a recognition that information and relationships with clients and employees are of paramount importance to firm performance.

Notwithstanding the recent media attention around NDAs spurred by the #MeToo movement (Facchinei 2020), NCAs have historically received the most attention among academics and policymakers since they are the only PERC that directly prohibits the mobility of departing workers (U.S. Treasury 2016; Marx, Strumsky, and Fleming 2009). NCAs have three substantial limitations, however, which give firms incentives to bundle them together with other PERCs.

First, NCAs typically have a limited duration and apply only to a subset of the product market—often local competitors (Starr, Prescott, and Bishara 2020b). In contrast, NDAs may apply in perpetuity and without regard to whom the former employee might share information with (see Appendix Exhibit A1 for an example). NRAs and NSAs can also apply more broadly than NCAs across all industries and geographies (e.g., workers may join a non-competitor, but an NRA will still prohibit them from soliciting former co-workers), although they are also typically limited in duration (Graves 2021). Second, NCAs limit the flow of information and relationships to competitors only by limiting mobility. Thus, an NCA alone cannot protect against a worker leaving the proscribed area and sharing information or giving other firms leads on clients or co-workers. Third, NCAs can be

[3] Appendix Exhibit A1 provides examples of these postemployment restrictive covenants from *Cabela's v. Highby 2018*.

difficult or even impossible to enforce, depending on the policy of the state and the details of the case (Bishara 2011). In contrast, since NDAs, NRAs, and NSAs do not directly prohibit workers from joining another firm, courts have been more willing to enforce them. Given these limitations of NCAs, the other PERCs have value in protecting the firm, even if NCAs are otherwise effective.

It bears noting, however, that even though courts are more willing to enforce them, NDAs, NSAs, and NRAs can still be difficult to enforce because proving that a violation occurred can be difficult. For example, enforcement of an NDA requires the firm to prove that the worker misappropriated information, while enforcement of an NSA or NRA requires proof that the worker solicited former clients or co-workers. If these violations occurred secretly, then they may be hard to prove in court. Furthermore, in the case of solicitation, courts regularly debate what it means to solicit clients or co-workers (e.g., is changing employer on LinkedIn solicitation?) (Pepper 2017). Hence, NDAs, NSAs, and NRAs may offer the firm somewhat limited protection, and NCAs may therefore add an additional layer of protection.[4]

Finally, there are important details related to how NCAs are enforced that links these PERCs. Where NCAs are enforceable, a prerequisite for enforcing an NCA is that the firm has some legitimate interest to protect—e.g., trade secrets or client relationships. To enforce the NCA, the firm has to show the court that it is also trying to protect those interests through other means—e.g., by using an NDA, NSA, or NRA (Malsberger, Brock, and Pedowitz 2012). For this reason alone, NCAs are unlikely to be used in isolation.

Taken together, while these PERCs individually offer the firm protection by reducing the leakage of information, clients, and workers across firm boundaries, the associated limitations of

[4] Appendix Figure A1 reproduces a graphic from Beck Reed Riden, a leading law firm that litigates these PERCs, which documents the trade-off between the court's willingness to enforce each of these PERCs and the expected protection each PERC offers to the firm.

each PERC and the typical court enforcement process give firms strong baseline incentives to bundle them together.

3. Data

Our data derive from two large-scale surveys that were the result of a collaboration with an American compensation software and data company, Payscale.com ("Payscale"), in 2017. The first is a firm-level survey that Payscale deploys annually to build its key reports on organizational trends in compensation and related issues. The firm-level survey is deployed to HR professionals, executives, managers, and others in leading roles, constituting 7,700 global employers including both Fortune 500 companies and small and medium businesses. We limited our sample to private or public firms located in the United States (N=2,810) and further kept only those firms whose answers regarding the use of PERCs and key independent variables were non-missing (N=1,855). Appendix Table A1 shows the distribution of job characteristics for the individual who filled out the survey on behalf of the firm. Most of the time it was a "Manager" (36.6%) or "Director" (23.1%) whose job functions included "Human Resources" (54.8%). These facts are reassuring since human resource managers or directors are very likely to know the types of employment PERCs and practices used by the firm.

In Appendix Table A2, we compare the firm size distribution between our Payscale firm sample to data on the universe of US firms from the Census Bureau's County Business Patterns in 2017, and 2017 data from Compustat on publicly traded firms. The Payscale data are reflective neither of the average firm in the United States nor of the average firm in Compustat: 98% of US firms have between 1 and 99 employees, compared to 52.6% for Payscale firms and 20% for Compustat. The Payscale data more closely resemble publicly traded companies in Compustat, although the Payscale data also contain more small and mid-size firms. Given these large differences, we do not weight our data to be nationally representative of the population of firms.

The second dataset is an individual-level survey that Payscale deployed to individuals who visited the website between February 7, 2017, and August 28, 2017, and indicated their interest in knowing their earnings potential.[5] Overall, 66,942 individuals responded to the survey. To reach our final estimation sample, we limited it to those between 18 and 65 years old (4,509 observations dropped) who were working in for-profit or non-profit firms (6,462 dropped), not in educational service industries or public administrations (1,346 dropped), not in farming, fishing, or forestry occupations (59 dropped), and not independent contractors or government contractors (4,151 dropped). We further excluded those missing data on any of the four PERCs or key demographic variables (age, gender, income, for-profit vs. non-profit, firm size, industry, occupation, job level, and state; 16,778 dropped), which leads to our final simple of 33,637 individuals.

Since the sample of individuals visiting Payscale.com to take the survey is not likely to be random, we weight the individual data to match the US population by income, age, gender, and for-profit status of the worker.[6] Appendix Table A3 compares the weighted and unweighted individual data to the American Community Survey data for 2017 (Ruggles et al. 2020), which reflects the US population with nearly 1 million respondents. The table shows that on average our unweighted sample is younger, higher earning, and more likely to be in the non-profit sector, and our sample has more females. Weighting virtually eliminates these differences, however (though weighting does not necessarily remove differences between unobservable characteristics). Below, we report weighted results for the individual-level data, although the results are similar when unweighted.

[5] The survey was marketed as a "Salary Survey" and came with the tagline "Do you know what people like you are earning? Stop guessing." Thus, respondents have an incentive to respond accurately to the information, so that they can get accurate information on their earnings potential. To assuage concerns that the sample consists of reliable responses, a random sample of 10 job titles from the individual data includes: Strategic Account Manager, Insurance Broker, Purchasing Manager, Vice President (VP) Strategic Alliances, Clinical Dietitian, Marketing Director, Physical Therapist (PT), Human Resources (HR), Account Manager, and Painter Automotive.

[6] We used iterative proportional fitting ("raking") to create the weights. We matched on age (deciles), gender, income (quartiles), and whether the worker is for-profit or non-profit. We considered several alternative weighting schemes, but this set did the best in terms of matching overall fit without producing substantial imbalance in the weights.

In both surveys, we gathered information on NDAs, NSAs, NRAs, and NCAs. The precise wording and question structure for each survey is available in Appendix Figures A2 and A3.

4. Baseline Adoption Patterns on PERC Use and Bundling

Given the lack of evidence on the (joint) adoption of these PERCs, we begin by establishing two sets of stylized facts that emerge from both the individual- and firm-level data.

4.1 The Prevalence of Each PERC

Figures 1 and 2 show the distribution of each of the four PERCs (Appendix Figure A4 shows the unweighted individual-level results, and are similar). NDAs are the most common. In the individual-level data (Figure 1), approximately 57% of workers in the United States in 2017 were definitely or probably bound by an NDA, with 8.5% not knowing if they were bound or not.[7] Similarly, in the firm-level sample (Figure 2), 70.9% of firms use NDAs with all of their employees, while another 17.3% use NDAs with some but not all of their employees.

Following NDAs, NSAs are the next most common PERC—28.4% of workers report agreeing to or probably agreeing to one, while 40.9% of firms say they use NSAs with all workers and 28.5% more report using them with some workers. On the heels of NSAs are NRAs, which bind 24% of workers and cover all employees at 32.6% of firms and some employees at 24.2% of firms. Finally, although they have received the most attention in the literature, NCAs are the least common of these restrictions. In the individual data, NCAs cover 22.1% of workers, whereas 29.5% of firms report using them with all workers, and 37% report using them with some but not all workers. These NCA statistics are similar to prior estimates from the literature.[8]

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[7] Since workers may not know what they have agreed to, we allow for uncertainty by giving the workers in the individual survey the chance to assess whether they have definitely or probably signed, or whether they have no idea (see Figure A3). In general, when we report that a worker agrees, we group the definitely and probably agreed together.

[8] Starr, Prescott, and Bishara (2020b) find that in 2014 NCAs covered 18.1% of workers, and Colvin and Shierholz (2019) find that in 2017 31.8% of firms used NCAs with all employees, and 49.4% used them with all or some employees.

One question that the firm-level results raise is how to think about firms that indicate they use a PERC with "some" of their workers. What type of workers? And how much of the firm do they comprise? To shed some light on this point, the firm-level survey asked respondents who indicated that some of their workers were bound by NCAs a follow-up question regarding what percentage were bound by NCAs. Among firms that use NCAs with some workers, 62% report that 0–20% of their workers are bound by NCAs, while 15% report that 21–40% are bound by NCAs. A second follow-up question sought to ascertain how the firm determined which employees to ask to sign NCAs: 66.5% indicated that it was occupation-specific, and 9.3% noted it was related to earnings. When asked which occupations were asked to sign NCAs, respondents listed mostly occupations that included management, sales, or engineering. While there are no similar follow-up questions for the other three PERCs, these answers suggest that when firms respond that "some" of their workers are bound by these PERCs, it is likely that firms use them for a small proportion of workers in high-skill, sales, or managerial jobs.

In sum, the results in this section show that these four PERCs cover between 22% and 57% of the US workforce, with NDAs the most common and NCAs the least. What this analysis doesn't address, however, is the whether these PERCs are used in tandem. We now turn to that analysis.

4.2 The Joint Adoption of PERCs

Table 1 presents the distribution of all 16 combinations of PERCs at both the individual level and the firm level. Here, we exclude those reporting that they do not know about the use of a specific PERC because we cannot create bundles for them. Among the 16 combinations, column (1) indicates that just three combinations cover 82.3% of workers: 38.4% of workers have no PERCs, 25.9% have only an NDA, and 18% have all four. The firm-level data bear out a similar pattern: column (2) suggests that 70.6% of firms use just three of these bundles with all of their workers (22.2% use none, 25.7% use only an NDA with all workers, and 22.7% use all four PERCs with all workers). When we define adoption at the firm level to include "some or all workers" (column 3), the data suggest that 55.2% of firms use all four PERCs with some or all of their workers.

Importantly, these patterns are not random. As shown in Appendix Figure A5, the observed bundle distribution is very different from a simulated distribution if firms randomly chose which bundles to use (keeping the sample proportion of individual PERCs constant). Not surprisingly, a Kolmogorov-Smirnov test rejects the null that these observed and simulated distributions are the same with a p-value < 0.01 in both the individual- and firm-level data in 1,000 such simulations.

While Table 1 clearly shows that firms bundle these PERCs, it does not address the co-adoption patterns for individual PERCs. To that end, Table 2 presents pairwise adoption patterns for each PERC in both the firm- and individual-level data. Two aspects are apparent. First, Panel A shows that an individual who is bound by an NSA, an NRA, or an NCA has more than a 95% chance of also being bound by an NDA. Second, an individual who is bound by an NCA is very likely to be bound by an NSA (87.3%) and an NRA (77.7%), but the probability of being bound by an NCA if the individual is bound by an NSA or NRA is slightly lower (68–69%). These patterns are also borne out in the firm data. Finally, Table 2 shows that an individual who is bound by an NDA is not necessarily bound by the other three PERCs—rather, individuals have the highest likelihood of signing an NSA (50.1%), an NRA (43.9%), and then an NCA (38.6%). These patterns are also found at the firm level, regardless of how we define PERC adoption (Panels B and C).

Taken together, Tables 1 and 2 document two main facts about the bundling of these four PERCs. First, NDAs are the baseline PERC. It is rare to see the other PERCs without an NDA. Second, while it is theoretically possible for firms to deploy 16 different combinations of these PERCs, most of the time workers agree to, or firms deploy, only three: nothing, only an NDA, or all four. That is, whenever a firm deploys an NCA, an NSA, or an NRA, they almost always come bundled together and with NDAs. These facts raise important questions: "Why do firms bundle these PERCs the way that they do?" And "what are the implications for firms and workers?" Before we turn to these questions, given that this is the first empirical investigation of these PERCs, we highlight other facts related to individual and firm characteristics that may be of general interest.

4.3 Bundling Patterns by Baseline Individual and Firm Characteristics

Table 3 provides a baseline analysis of demographic characteristics, including gender, age, worker class, income, job level, and firm size based on the individual data. Broadly, the statistics indicate that men and women are similarly likely to be bound by none or all of these PERCs, but women are somewhat more likely to be bound by only an NDA (27.6% vs. 24.5%). Similarly, while those above and below the median age level are equally likely to have none of these PERCs, older workers are more likely to be bound by only an NDA (27.8% vs 23.1%), while younger workers are more likely to be bound by all four PERCs (20.6% vs. 16.3%).

Workers in non-profits are 6.3 percentage points more likely to have none of these PERCs (37.8% vs. 44.1%), while workers in for-profit jobs are 9.4 percentage points more likely to be bound by all four PERCs (18.8% vs 9.4%). Workers in large firms (above median firm size) are less likely to have none of these PERCs (34.2% vs. 42.3%), more likely to have only an NDA (28.3% vs. 23.6%), and slightly more likely to have all four PERCs (18.4% vs. 17.7%). Appendix Figures A6–A8 present bundling patterns by firm size from both the individual- and firm-level data.

Finally, Table 3 shows that while those below the median income are much more likely to be bound by no PERCs (43.2% vs. 31.4%), higher earning workers appear only marginally more likely to be bound by all four PERCs (18.7% vs. 17.6%). Appendix Figure A9 breaks out the bundling patterns by income decile, revealing that as income rises, fewer individuals are bound by none of these PERCs, and more individuals are bound by NDAs. Surprisingly, however, low-wage workers appear similarly likely to be bound by all four PERCs as high-wage workers.

5. Guiding Theory on Why Firms Bundle PERCs

In this section, we consider some theoretical arguments about why firms might bundle all four PERCs. We compare two broad rationales: to facilitate value creation by the firm by alleviating a potential hold-up problem ("value creation rationale"), and purely as a device for the firm to extract value from workers' efforts ("pure value capture rationale").

To do so, we embrace recent legal scholarship that emphasizes PERC bundling and draw extensively from the literature on why firms might use NCAs (Blake 1960; Lobel 2020). In particular, since NCAs appear to be innately tied to the other three PERCs (as highlighted in Section 2), our broad approach is to consider some of the NCAs literature's main arguments and then apply those logics to the broader bundle of PERCs. Core to our argument (and contribution) is that prior literature has focused almost entirely on outcomes (related to NCAs), but that outcomes alone can tell us little about actual motives (since some outcomes may be unintended). We argue that to really understand why firms adopt a bundle of PERCs, we need to understand not only how they might create benefits for the firm in the future, but also to backward-induct to the adoption decision to examine whether firms adopt PERCs in situations where those benefits are most salient.

5.1 Value Creation Rationale

The first rationale for deploying PERCs, and perhaps the most common argument for why firms use NCAs, is to resolve investment hold-up problems (Rubin and Shedd 1981; Williamson 1975). In the typical setup, the firm would like to invest in developing valuable information, which would then be shared with the worker. However, if the firm does so, the worker can "hold up" the firm and appropriate the value of that investment, potentially at a competitor (who didn't pay for it). As a result, the firm will not invest in developing such information unless it can extract a credible promise that the worker won't compete. By solving this problem, NCAs incentivize firm investment (Barnett and Sichelman 2020; Conti 2014; Jeffers 2020; Posner, et al. 2004; Starr 2019).

A similar logic applies to the other PERCs. NDAs incentivize investment in the development of informational resources by prohibiting the disclosure of such information, NRAs motivate investment in worker- and team-specific human capital by barring the recruitment of co-workers, and NSAs encourage investments in developing relationships with clients by prohibiting workers from appropriating the firms' investments in such relationships. Thus, the value creation rationale implies that adopting PERCs, especially the bundle of all PERCs, should be associated with greater investment. With regard to wage levels and wage growth, the value creation rationale implies that they will be positively associated with adoption since PERC-induced investments will increase worker productivity, which will result in higher wages if wages are tied to productivity (or no association if wages are independent of productivity). Finally, this logic also implies that bundling of PERCs should be associated with reduced turnover, both because higher wages make other jobs less attractive, and because lower turnover (especially to competitors) mitigates the hold-up problem.

Taking this logic further, if firms bundle PERCs to resolve investment hold-up problems, then not only should we observe the aforementioned outcomes, but we should also observe bundling PERCs in situations where the hold-up problems are likely to be the most severe, especially because using PERCs is likely to come with some costs, including the direct costs of writing and implementing them and the indirect costs of possibly demotivating workers (Lobel and Amir 2013) in addition to possible litigation-related costs if workers violate these PERCs. Two possibilities arise naturally here. First, bundling PERCs may be beneficial only for workers with access to valuable information or relational resources. Second, high turnover risk is likely to exacerbate the hold-up problem because the risk of losing worker-specific investments and diffusion of valuable resources to competitors is higher.

Taken together, if firms bundle PERCs to resolve an investment hold-up problem, then such bundling should be associated with more investment, reduced turnover, and non-negative wage levels and growth. Moreover, firms should be more likely to bundle all four PERCs for workers that have access to valuable informational or relational resources or that have high turnover risk.

5.2 Pure Value Capture Rationale

While appealing, one challenge with this argument is that NCAs are often used in jobs where a strong hold-up logic is not apparent. Some examples include fast food sandwich workers (Jamieson 2014), temporarily employed Amazon packers (Woodman 2015), and doggy daycare sitters (Greenhouse 2014). Indeed, one prominent finding in our analysis in Section 4 is that many firms bundle all four PERCs for *all* employees, and that many low-income workers are bound by them. It is unlikely that such workers within the firm have access to (or might have access to in the future) the type of resources that would justify a hold-up rationale.

Building on these and other examples of seemingly overreaching NCAs, recent federal reports highlight that firms could use NCAs simply to benefit from (1) lower turnover, and (2) increased bargaining power over wages (McAdams 2019; White House 2016)—i.e., without any concomitant increase in investment. Similar logic extends to the other PERCs. Even though NDAs, NSAs, and NRAs are less restrictive than NCAs in that they do not prohibit a move, they can still affect bargaining power and mobility because they restrict the worker from taking their full set of human capital with them, and they can apply more broadly than to competitors. For example, Graves (2021) argues that NRAs are "salary suppression" devices, and a recent ruling in *TLS Management and Marketing Services LLC v. Rodriguez-Toledo et al.* found that broad NDAs can act as de facto NCAs.

Lobel (2020) further argues that these potential benefits are especially present when PERCs are bundled. She writes that employment "clauses should be examined on how they operate *together* to lock in talent and prevent [labor market] competition." She also posits that the "*effect* of multiple contractual clauses operating together is larger than their sum" because such bundling creates an "ironclad" legal challenge for any employee considering leaving, or any firm considering poaching. In this way, she argues, bundling "chills behavior" because it imposes a wide array of legal, reputational, and moral costs to workers considering breaking their contracts—and to the firms who wish to hire them.

This pure value capture rationale for bundling PERCs implies that bundling PERCs should be associated with both reduced turnover and reduced wage *growth* (without any significant investment effects), because firms use them to shield themselves from labor market competition. Note, however, that it's not clear that wage *levels* will be lower, because while bundling PERCs gives firms more bargaining power ex post, workers with ex ante bargaining power may demand a compensating differential to agree to such provisions. It's not clear that most workers have much bargaining power, however, especially if firms deploy PERCs after the worker has accepted the job (Marx 2011; Starr 2021). Not surprisingly, the literature on NCAs has found conflicting evidence on this point, with well-identified studies of NCA enforceability pointing to negative wage effects, and correlational studies of NCA use finding positive wage effects (Balasubramanian et al. 2020; Lipsitz and Starr forthcoming; Johnson, Lavetti, and Lipsitz 2020; Starr, Prescott, and Bishara 2020b; Lavetti, Simon, and White 2020; Kini, Williams, and Yin 2020; Rothstein and Starr 2021).

Nevertheless, if firms bundle PERCs to capture value via reduced turnover and wage growth, then we should observe not only that bundling PERCs is associated with lower turnover and wage growth, but also that firms are deploying such PERCs for workers who have a high likelihood of turnover and wage growth in the first place. That is, if workers are unlikely to leave or experience much wage growth, then it makes little sense to bundle PERCs for the purpose of limiting turnover or reducing wage growth.

Table 4 summarizes the value creation and pure value capture rationales for bundling PERCs and the attendant implications for how bundling PERCs should affect investment, turnover, and wage growth, and where firms would find the highest value for bundling PERCs.

6. Drivers of PERC Adoption

In this section we present descriptive analyses of the implications for where firms might bundle all four PERCs based on the two rationales described above. In theory, firms can decide whether to adopt PERCs for individual workers. Hence, one would ideally use matched employer-employee panel data with information about which individuals have PERCs in their employment contracts as well as some measure of their information access, likelihood of turnover, and expected wage growth. Because such detailed data are not available, however, we focus our adoption analysis on job-level (i.e., occupation-industry combinations) characteristics using the individual-level Payscale data combined with external data. The job-level analysis is also consistent with our survey evidence (see Section 4) that suggests firms tend to adopt PERCs for certain jobs (e.g., sales).

Furthermore, ideal tests of the adoption implications would require examining whether firms bundle all four PERCs in response to an exogenous increase in the value of informational or relational resources, turnover risk, and wage growth. Given the challenges inherent in identifying exogenous variation in cross-sectional data, and the extent to which it is difficult to shock one of these characteristics without affecting the others, our approach is necessarily descriptive. Table 5 summarizes the ideal experiments and our empirical approach.

To examine how information and relationships matter for bundling patterns, we leverage nationally representative data from the 2014 Noncompete Survey Project (Prescott, Bishara, and Starr 2016), which includes questions related to whether workers have access to trade secrets or client information, or work with clients directly. We aggregate that data to the occupation-industry level (two-digit SOC by two-digit NAICS) such that we estimate for each occupation and industry combination the proportions of workers with access to trade secrets and client information, and the proportion of workers who directly work with clients. We then merge this with the individual-level Payscale data at the occupation by industry level, and dichotomize each variable into high and low based on a median split (see Table A4 for the distribution). We then examine how the joint distribution of trade secrets, access to client information, or working with clients is associated with bundling all four PERCs.

To examine how bundling patterns relate to turnover risk and wage growth, we leverage data from the Current Population Survey (CPS), which surveys 60,000 individuals monthly (Flood et al. 2020). We use these data to calculate the likelihood of job mobility at the monthly level (based on questions about job transitions relative to the prior month) by each occupation and industry, and similarly annual wage growth for each occupation and industry combination.[9] We merge these measures with the Payscale individual-level data at the occupation by industry level.

Figure 3 presents our analyses examining job-level adoption, using binned scatterplots (Cattaneo et al. 2019). Each plot shows how the expected likelihood of bundling all four PERCs changes with job-level information and relationships (Panel A), turnover risk (Panel B), and wage growth (Panel C), holding fixed the other independent variables of interest and a set of controls (age, gender, class of the worker, log of firm size, and state fixed effects). The graphs also display 95% confidence intervals with standard errors clustered at the occupation-industry level (Abadie et al. 2017). In Table A5, we also deploy an identical multinomial logit model with the dependent variable as the bundle category. Those results are presented as marginal effects.

[9] To calculate the measures of mobility rates and wage growth, we limited the CPS to workers aged 18–70 in the private for-profit and non-profit sectors between 2000 and 2018. For the wage analysis, we limited our sample to workers who are working full time. Figure A10 and A11 in the Appendix show the heatmap of wage growth rate and job mobility rate for each occupation and industry.

The results broadly support the implications of both rationales. Panel A of Figure 3 shows that jobs that involve access to information on both trade secrets and clients are approximately 6 percentage points more likely to be bound by all four PERCs than jobs with no such access (and 12.3 percentage points less likely to be bound by none of these PERCs per Table A5).[10] In addition, Figure 3, Panel B, highlights that jobs with higher mobility risk are approximately 2 percentage points more likely to be bound by all four PERCs, while the highest wage growth jobs are 5 percentage points more likely to have all four PERCs relative to the lowest wage growth jobs.[11] Thus, these results suggest that firms are using all four PERCs for jobs characterized by high levels of access to information and relationships, and high levels of turnover risk and wage growth.

7. Bundle Adoption and Firm and Worker Outcomes

In this section, we consider the implications of the two rationales for how bundling PERCs relates to worker and firm outcomes: retention, training, and wages. Our theoretical arguments imply that the first-stage adoption implications for turnover and wage growth pose important selection challenges for studying the second-stage treatment effects in observational research designs. To study the causal effect of bundles of PERCs, one would need to randomly deploy employment contracts with the 16 possible combinations of PERCs. One could then isolate the treatment effect of each PERC alone in addition to the synergistic effects when various PERCs are combined. Relative to this ideal experiment, we have observational data on what firms have implemented. Accordingly, we face two significant challenges: First, how can we identify the individual effects of

[10] The bundling patterns by occupation and industry (Figure A12 and A13) show that the occupations and industries with the highest proportion of all four PERCs tend to be those in more technical jobs (i.e., computer and mathematical jobs) and that the professional, scientific, and technical services industry are the most likely to have all four PERCs. The results are similar in the firm-level survey (Figure A14). We note that the industry options in the firm-level survey are not standard SIC or NAICS codes. Table A6 in the Appendix shows the distribution of NDAs, NSAs, NRAs, and NCAs by industry and occupation.

[11] From Table A5, a one percentage point higher wage growth rate is associated with a 0.8 percentage point increase in being bound by all four PERCs, and a one percentage point rise in the likelihood of turnover is associated with an increase of 1.9 percentage points in the likelihood of being bound by all four PERCs.

each PERC and the cumulative effect of the bundle? Second, how can we separate (unobservable) factors that affect selection of the bundle and the treatment effect of the bundle itself?

Addressing the first question, our prior results suggest that there may in fact be no easily interpretable marginal effect of an NCA, an NSA, or an NRA because they are typically bundled together. While one could randomly assign, e.g., just NCAs to identify their effect on various outcomes, whatever effect one estimates may not reflect the appropriate parameter of interest in the population because the relevant population parameter reflects the effects of NCAs bundled with all three other PERCs. Accordingly, as a practical matter, we do not attempt to identify the marginal effect of each PERC. Nevertheless, in our empirical work below, we estimate the marginal effect of each PERC *as if* we had data only on that PERC, and compare those estimates to estimates that incorporate the bundle as a whole. This exercise illuminates how considering the bundle may change our perception of the relationship between individual PERCs and the outcomes of interest.

To resolve the second concern about separating the selection and treatment effects, absent an experiment one would have to identify 16 instruments that would cause firms to shift their use of each (set of) PERC(s), without affecting firm outcomes through any other path. Since anything that might cause firms to change their bundle will almost certainly change firm outcomes directly (or will cause firms to substitute between PERCs), identifying 16 such instruments will be challenging. To partially circumvent the issue of selection, while we examine PERC *adoption* analysis at the job level, we examine *outcomes* within and across firms (and jobs) using a novel differencing approach.

7.1 Empirical Approach

Without such instruments, our empirical approach relies on the argument that among the three bundle comparisons of interest—All vs. None, All vs. Only NDA, and Only NDA vs. None—the All vs. Only NDA comparison will likely difference out more unobserved selection than the All vs. None comparison. In particular, if the All bundle is similarly or more strongly related to unobservables than the Only NDA bundle,[12] then both the All (vs. None) estimate and the Only NDA (vs. None) estimate will be biased in the same direction, but the All (vs. None) estimate will be more biased such that differencing between them eliminates some of the additional bias due to selection.[13] In Appendix B we provide a simple econometric framework and Monte Carlo simulations that document this fact. The framework delivers an additional key result: in cases where the sign flips between the All vs. None and the All vs. Only NDA comparisons, it must be because the treatment effect dominates the selection effect.

To clarify the intuition behind this approach, consider a potential omitted variable bias driven by the unobserved value of informational resources that a worker has access to. Then, it is likely that workers with no or limited access to such resources are not bound by any PERCs while those with access to somewhat valuable resources are bound by only NDAs and those with access to the most valuable resources are bound by all PERCs. (Such a pattern would be consistent with the earlier evidence.) Since wages are likely to be higher for individuals with more valuable information, this unobserved variable will cause an upward bias in how All PERCs and only an NDA relate to wages (relative to no PERCs). However, because the bias will be higher for All PERCs than only an NDA, the difference between them will mitigate *some* of the omitted variable bias—specifically the bias will be reduced by the amount that the "only NDA" coefficient is biased upward.

In the individual-level wage analyses, we use this differencing approach while also controlling for firm fixed effects, which precludes fixed firm characteristics from biasing our results. Nevertheless, these approaches can only partially address concerns about omitted variables, and so

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[12] By stronger selection on unobservables, we mean that the covariance between the unobserved variable and the adoption of All is greater than the covariance between the unobserved variable and Only NDA.

[13] From a conceptual standpoint, our approach is similar to that of Altonji, Elder, and Taber (2005) and Oster (2019). In their approach, one compares the same coefficient across specifications with more controls. Under the assumption that those controls are reflective of the unobserved variables, these comparisons give us insight about the extent of selection on unobservables. In our approach, by contrast, we recognize that we can learn about selection on unobservables by differencing between two estimates that reflect some of the same relationships with unobservables.

we refrain from making any strong causal claims. In addition, this approach will not difference out unobservables that drive the choice of Only NDA vs. All, and it cannot resolve any concerns about reverse causality (i.e., if training workers more causes the firm to use all four PERCs). Accordingly, while we believe this differencing approach (and within-firm models) can highlight the role of selection to some extent, the results should be thought of as primarily descriptive. Table 5 presents a summary of our empirical approach to examining how adopting all four PERCs relates to outcomes.

When analyzing firm-level outcomes, we define firms as having adopted all four PERCs if they report using it for all their workers, and group firms that use PERCs for only some workers with firms who do not use such PERCs. This is consistent with earlier evidence that when firms adopt a PERC for only some workers, it is only for a small fraction of the workers. For the firm-level analyses, we use robust standard errors and control for firm size category and fixed effects for industry and state size. In the individual-level analyses, we cluster the standard errors by firm (consistent with the firm-level analyses) and control for age, gender, the class of the worker, firm size, and fixed effects for firm, industry, occupation, and state.[14]

7.2. Results on Firm and Worker Outcomes

In Figures 4-9, we examine how these PERCs and bundles relate to the outcomes of interest. Each figure reports results from two broad sets of specifications: the left panel considers four consecutive regressions each of which examines only one of the PERCs—as if we did not have data on the other three. The right panel considers a separate regression that incorporates the three different bundles (and an Other category, which is included in the regression but is not reported

[14] In models with firm fixed effects, observations with no within-firm variation are dropped, reducing the sample from 27,804 to 7,527. This drop includes about 8,000 individuals for whom we do not have a firm identifier. In analyses without firm fixed effects, we assume that these individuals work at different firms and give each a unique firm ID.

here) and reports the three comparisons described above: Only NDA vs. None, All vs. None, and All vs. Only NDA.[15]

To examine retention, we leverage a question in the firm-level survey asking the extent to which the firm agreed with the statement "Employee retention is a major concern for our company." We coded this as a dummy equal to one if the firm agreed or strongly agreed, which 60% did as a baseline. Figure 4 shows the results. The naïve regressions that consider each of the PERCs individually show little evidence of any relationship between the PERCs and retention, with the exception of NCAs. In contrast, once we incorporate the bundle, we find that firms that adopt only an NDA are 7.1 percentage points (12% of the mean) more likely to report that they consider retention a major concern (these results are reported in full in Table A7). Comparing the Only NDA vs. None estimate to the naïve NDA estimate strongly suggests that NDAs exhibit different effects when used alone, versus when they are combined with the other PERCs. Thus, this example highlights the importance of considering the bundle in the empirical analysis. Turning to the bundle of all four PERCs, our focal comparison suggests that firms that bundle all four PERCs are 7.7 percentage points (13% of the mean) less likely to perceive retention as a major problem relative to firms that use only an NDA.

With regard to investments, we examine if firms that use these PERCs are also more likely to spend one month or more on training their new hires (66.6% report that they are). Figure 5 presents the results. The naïve regressions show little relationship with training for any of the individual covenants. Incorporating the bundle, we see little differences in training for firms that use only an NDA vs. firms that use nothing, although we see larger differences between firms that use all PERCs and firms that use none or only NDAs. However, in most cases the estimates fail to reject

[15] In corresponding appendix tables, we also run models including each PERC in the model together (without any interactions). Interestingly, in these specifications different individual PERCs become statistically significant (perhaps due to collinearity; Kalnins 2018), even though the bundle is driving most of the effect.

the null of no effect with a *p*-value less than 5%. That is, firms that tend to use all PERCs provide, on average, more training than firms that do not use any of these PERCs or that use only an NDA, but the estimates are imprecise (results are reported in full in Table A8).

Figure 6 examines how the bundling of all four PERCs relates to wage growth (results are reported in Table A9), leveraging a firm-level question about whether the firm intends to increase base pay (84% of the sample indicated that they would). Figure 6 shows that firms that use NCAs or NSAs with all workers are 4–5 percentage points less likely to offer base raises (5.4–6.4% of the mean). Incorporating the bundle, we find that the negative wage effects are driven by the All vs. Only NDA comparison (5.5 percentage points, or 6.5% of the mean).

While Figure 6 suggests that the use of all four PERCs allows firms to decrease wage *growth* by not offering raises, it does not necessarily imply that firms can capture more value, since workers could receive a compensating differential. Accordingly, Figure 7 examines wage *levels* in the individual data (full results in Table A10), using within-firm variation. This figure shows three important facts. First, NCAs on their own are positively associated with wages—a finding consistent with studies that have data only on NCAs (Lavetti et al. 2020; Starr, Prescott, and Bishara 2020b). Second, both the All PERCs and Only NDA bundles compared to No PERCs indicate strong positive associations with wages—however, comparing All PERCs to Only NDA, we find (in the most saturated specification) that those bound by all four PERCs have on average 5.3% lower wages than those bound only by an NDA. This result suggests that the positive wage effects on NCAs (and the All PERCs bundle) are due to selection, and that the true causal effect is likely more negative. Third, the results show the value of controls in reducing selection on unobservables (i.e., the coefficients on the All and Only NDA variables fall considerably when including the controls).

Lastly, we examine the heterogeneous wage effects of PERCs based on two proxies of bargaining power—whether a worker is part of the top management team (i.e., a chief executive, vice president, or director) and whether the worker is young. Top managers are likely to command much more power in contract negotiations, and may even have a legal team to review their contracts.[16] In addition, younger workers may be ill informed about PERCs or otherwise have less power to negotiate contract terms. Figure 8 shows the marginal effects of interest from our main specification with firm fixed effects, modified to include an interaction between PERC adoption and top managers. Specifically, it shows the marginal effects for both top managers and non-top managers (Table A12 reports the full regression results). Those that are not top managers have 7.7% lower earnings when they agree to all four PERCS (relative to only an NDA), while top managers have relatively higher earnings. Figure 9 shows similar patterns, this time using an interaction with whether the worker is above or below the median age: the negative wage effects of all four PERCs (vs. only NDAs) are disproportionately borne by the young, while older workers are relatively better off (Table A13 shows the full regression results). Both analyses show that the average negative wage effects of all four PERCs are being driven by workers with low bargaining power.[17]

8. Discussion and Conclusion

Our study is motivated by the lack of evidence on (1) a broad set of employment restrictions that firms use to control the diffusion of valuable and otherwise transferable resources, (2) the possibility that firms bundle these restrictions together, and (3) that such bundling may matter both for firms and workers and for prior research that studies just one restriction (e.g., NCAs). Based on two large-scale surveys, we show that NDAs, NSAs, and NRAs are more common than NCAs, and that the bundling of these PERCs is pervasive. We then consider why firms might bundle PERCs together, and we provide rich, descriptive evidence consistent with both value creation and pure value capture rationales. Last, we show that examining outcomes with data on just one PERC can be

[16] Table 3 indicates that top managers are somewhat more likely to be bound by all four PERCS, while Table A11 reports the coefficients from a multinomial logit model examining how bundling varies by job level.
[17] In unreported results, we found no statistically distinguishable effect for men versus women.

misleading without accounting for the bundle. In the rest of this section, we discuss our results in light of prior literature and highlight several directions for future research.

Our findings contribute to the literatures on isolating mechanisms, labor market frictions, and competitive advantage (Dierickx and Cool 1989; Rumelt 1984, Campbell, Coff, and Kryscynski 2012; Mahoney and Qian 2013; Starr, Ganco, and Campbell 2018; Manning 2021). Prior research in this domain has largely focused on how firms can isolate certain elements of human capital from the market—and thus benefit from the value derived from those resources—such as through intellectual property protections (i.e., patenting, trade secrecy, copyright) or by developing routines or skills that are difficult to emulate or are valuable only within the firm (Barney 1991; Hatch and Dyer 2004; Melero, Palomeras, and Wehrheim 2020). In contrast, we join a growing body of research that highlights that firms can use legally sanctioned employment restrictions to limit the diffusion of valuable resources. Thus far, this latter body of literature has focused entirely on NCAs. Here, we bring attention to the prevalence and bundling of several unstudied PERCs—NDAs, NSAs, and NRAs—that combined with NCAs directly limit the diffusion of informational or relational resources, thereby making such resources de facto firm-specific, even if they are otherwise fungible. While this study has focused on the bundle of PERCs, each of these PERCs (NDA, NSA, and NRA) is of independent interest (Carlson 2019, Graves 2021). Future research can examine where, how, and why each of these PERCs may matter to value creation and capture by firms (in this regard, bundling will pose important challenges, which we discuss later in this section). Further, future research can study other restrictions on workers, such as intellectual property (IP) assignment agreements, arbitration clauses, and non-disparagement clauses.

Our study also contributes to the literature by simultaneously studying adoption and outcomes related to the value creation and pure value capture rationales. While prior literature has discussed these two rationales, the focus of empirical analyses has been almost entirely on outcomes (especially in regard to changes in legal enforceability of NCAs). Extending the examination to adoption allows us to test additional implications and better identify the rationale involved. Furthermore, the fact that the patterns of adoption across jobs are consistent with the results about outcomes provides greater confidence in our results. For instance, the finding that firms bundle PERCs in jobs with high turnover and wage growth suggests that—as a result of selection—we might expect to find that PERCs are associated with *more* turnover and wage growth. However, by leveraging data at different levels of aggregation (including within-firm variation) and a novel differencing approach, our results show the opposite effects, thus likely overcoming the natural selection concern implied by our own adoption analyses.

Though our results are descriptive, they seem inconsistent with at least one prominent theory. Because these PERCs operate by contract, scholars have argued that it is not obvious whether firms can leverage them to capture value (Friedman 1991). Once signed, such PERCs give firms more bargaining power and incentives to invest, but ex ante negotiation by workers may extract all the value. Our results are inconsistent with such a theory, since the average worker appears to earn lower wages when bound by all four PERCs (relative to a worker bound only by an NDA). For top management jobs, however, these results reverse, in line with a value creation rationale, implying that workers with high bargaining power can be better off with such PERCs.

Finally, and perhaps most importantly, our study also highlights the importance of considering the bundle of organizational choices. Such bundling raises several theoretical and empirical challenges, including potential omitted variable issues, unmeasured synergies, and a multiplicity of potential counterfactuals. Indeed, the curse of dimensionality makes studying bundling nearly infeasible, even before one considers issues like selection and identification. Nevertheless, our research suggests that bundling even in narrow domains matters a good deal.

In the context of PERCs, our results suggest a need to carefully reconsider research studying just one PERC without incorporating bundling patterns. Since prior research has focused on NCAs, it is useful to consider how these challenges may affect inferences from previous studies of NCAs, which examine both the effects of NCA enforceability and the relationship between NCA use and various outcomes. Studies of NCA use are most likely to be affected by bundling because a comparison of a worker bound by an NCA and a worker not bound by an NCA is, based on our results, effectively a comparison between workers bound by all four PERCs to a weighted average of workers bound by only an NDA and workers not bound by any PERCs. In our context, we find that these different comparisons differ markedly when it comes to wages: workers with all PERCs are better off relative to a worker with no PERCs, but are worse off relative to workers with only an NDA. These findings also suggest that the average positive NCA wage effects estimated in the prior literature are likely due to selection into NCA use (Starr, Prescott, and Bishara 2020b), resolving an important discrepancy in the effects between studies of NCA use and NCA enforceability.

In contrast, the inferences from studies that focus on changes in the legal enforceability of NCAs (e.g., Balasubramanian et al. 2020; Lipsitz and Starr forthcoming; Johnson et al. 2020) are less likely to be affected by the bundle because they estimate only the aggregate effect of the policy (allowing for the endogenous substitution between PERCs). However, since these studies do not have data on the bundle, they cannot disentangle how such a policy change directly affects how a fixed bundle relates to the outcome of interest and the indirect effect through any substitution toward other PERCs. This is an important avenue for future research, especially as states continue to limit the enforceability of NCAs (Beck 2020).

Indeed, one possible policy objective may be that limiting the enforceability of one PERC—while making the others more prominent—is acceptable. To investigate whether firms do substitute across PERCs based on NCA enforceability, in Table A14 we examine bundling patterns in states where NCAs are per se unenforceable versus states where they are potentially enforceable (Arnow-Richman 2019). Both the firm- and individual-level data show little evidence of such substitution: when NCAs are unenforceable, workers are no less likely to be bound by all four PERCs, but they are *more* likely to be bound by only NDAs relative to where NCAs are enforceable.[18]

Our bundling results are also relevant for researchers, policymakers, and practitioners who are concerned about the efficacy of individual PERCs or bundles of PERCs. For example, setting aside the fact that we find little substitution between PERCs when NCAs are unenforceable, a common argument for banning NCAs is that other PERCs can protect firms without so bluntly restricting employee mobility (Silverman 2020). Examining this argument with observational data is challenging both because of selection issues, and because there are very few observations with all of these PERCs except NCAs. While our differencing approach helps deal with selection to a limited degree, the problem of missing combinations of PERCs is fundamentally unresolvable. Accordingly, our results suggest that (quasi)experimental research designs offer the most promising path forward for estimating causal effects of (sets of) individual PERCs, where the appropriate counterfactual can be properly specified. Such experimental work may also corroborate our observational results and test whether these PERCs do in fact synergize in important ways, as suggested by Lobel (2020).

Two additional limitations of our study are worth noting. First, our data are rich in several ways, in that they allow us to examine PERC adoption at the job level, and then how PERCs are associated with outcomes within and across firms and jobs. However, they also have several limitations since (1) we mostly have outcomes only in the firm-level data and (2) we cannot study workers within firms over time. Ideal data would include panel data on workers embedded within

[18] Examining why the use of NCAs is *not* lower where they are unenforceable is beyond the scope of this paper, but recent research has highlighted that unenforceable NCAs are still effective in reducing mobility (Starr, Prescott, and Bishara 2020a), that workers are largely unaware that their NCAs are unenforceable (Prescott and Starr 2021) and that firms can tie other provisions to unenforceable NCAs to make them de facto enforceable (Sanga 2018).

firms, where we would be able to measure, e.g., investments made in specific types of workers, or individual wage trajectories and mobility outcomes. The data would also ideally include measures of innovation, productivity, profitability, and related information. Analyses of such outcomes are infeasible given our data, and can be a productive line of future inquiry.

Last, it is important to note that since the PERCs we studied are often bundled, there may be other employment provisions that are also bundled but that we were unable to measure (e.g., IP assignment agreements). Accordingly, we refrain from making strong statements about this particular bundle of four PERCs, and we acknowledge that we should interpret the estimates in this study as reflecting a potentially broader bundle than we could capture. Future studies can examine the joint adoption of more such provisions, ideally using real contracts.

Limitations notwithstanding, our study represents an important first step toward improving our understanding of the bundling of PERCs, why firms adopt them, and how they matter for firms and workers. By highlighting some important stylized facts about this phenomenon, we hope our study sparks a deeper conversation about the role such mechanisms play in firm, worker, and other economic dynamics, and how the potential for bundling might cause us to reconsider the way we conduct research on these PERCs and other organizational choices moving forward.

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Figures

Figure 1. Incidence of PERCs in Payscale Individual-Level Data

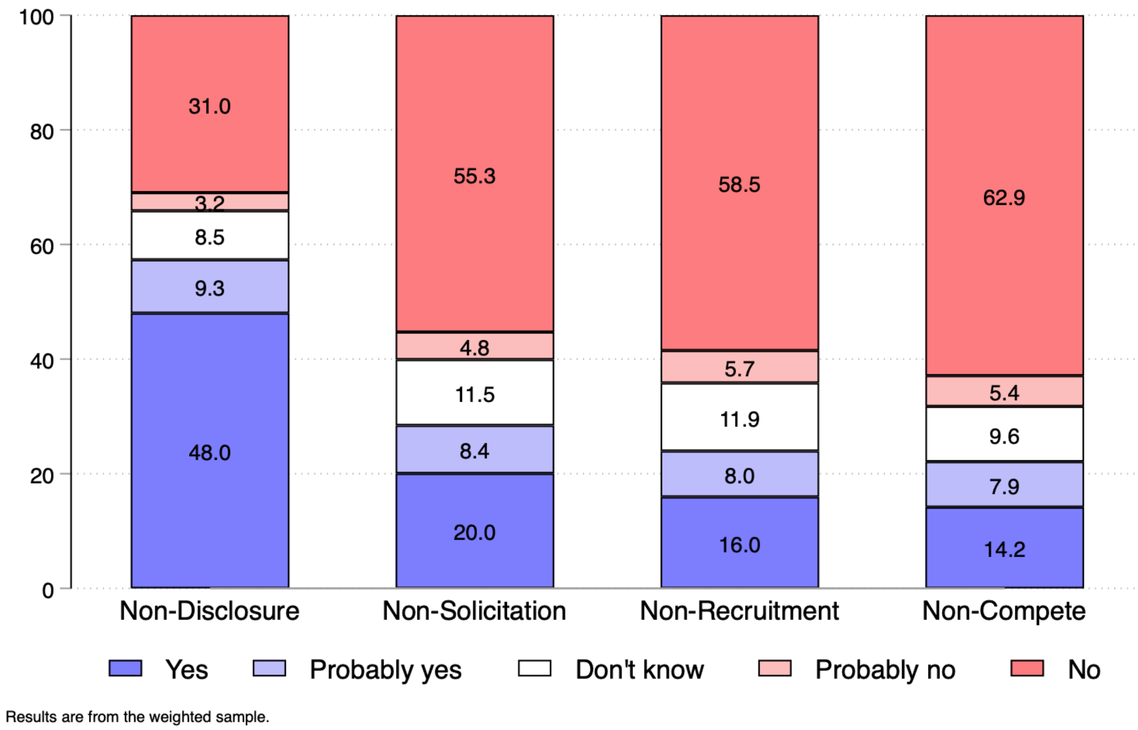


Figure 2. Incidence of PERCs in Payscale Firm-Level Data

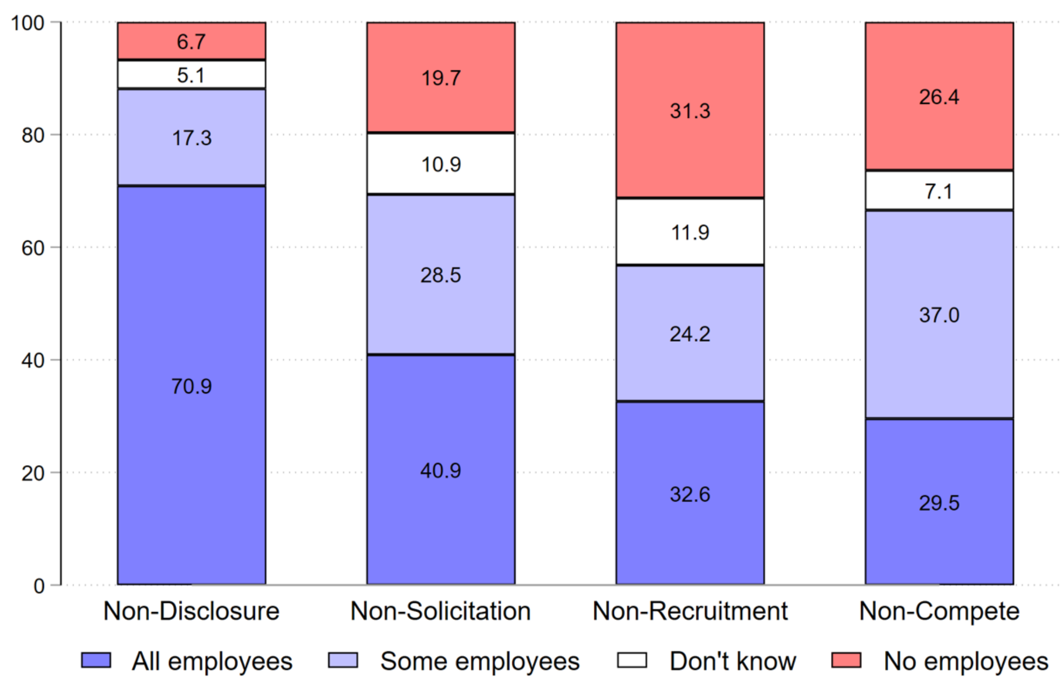
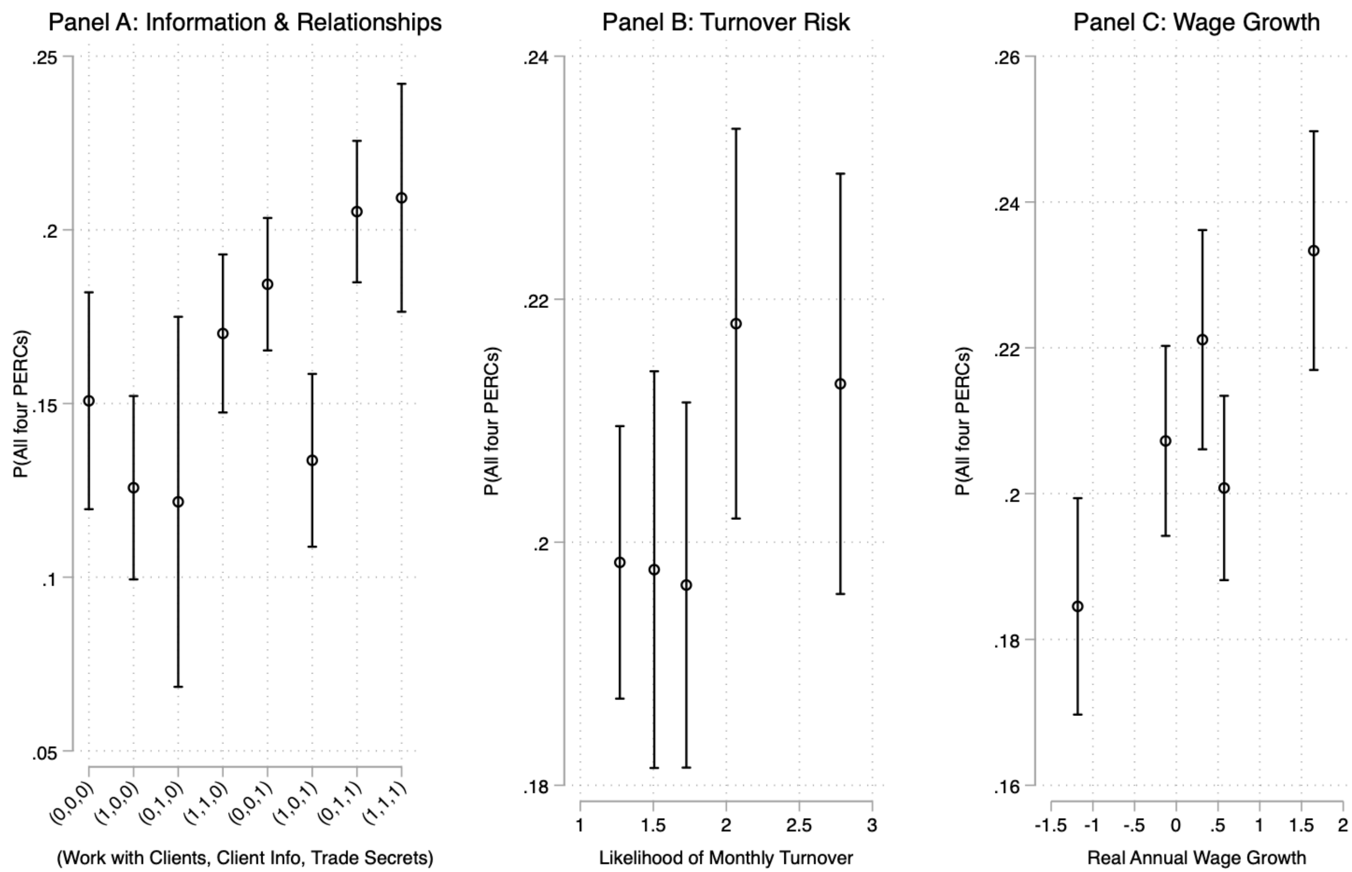


Figure 3. Adoption of All four PERCs, Information and Relationships, Turnover Risk, and Wage Growth



This figure shows binned scatterplots examining how the likelihood of adopting all four PERCs depends on three characteristics at the occupation-industry level: information and relationships (Panel A), the likelihood of monthly turnover (Panel B), and real annual wage growth (Panel C). Note that the turnover and wage growth measures are presented in percentages. Following Starr and Goldfarb (2020), we use "binsreg" in Stata to create these plots, which shows the expected likelihood of all four PERCs conditional on all the controls (and the other independent variables), and 95% confidence intervals, which reflect standard errors clustered at the occupation-industry level.

Figure 4. Firm "Agree[s] or Strongly Agree[s] That Retention Is a Major Concern"

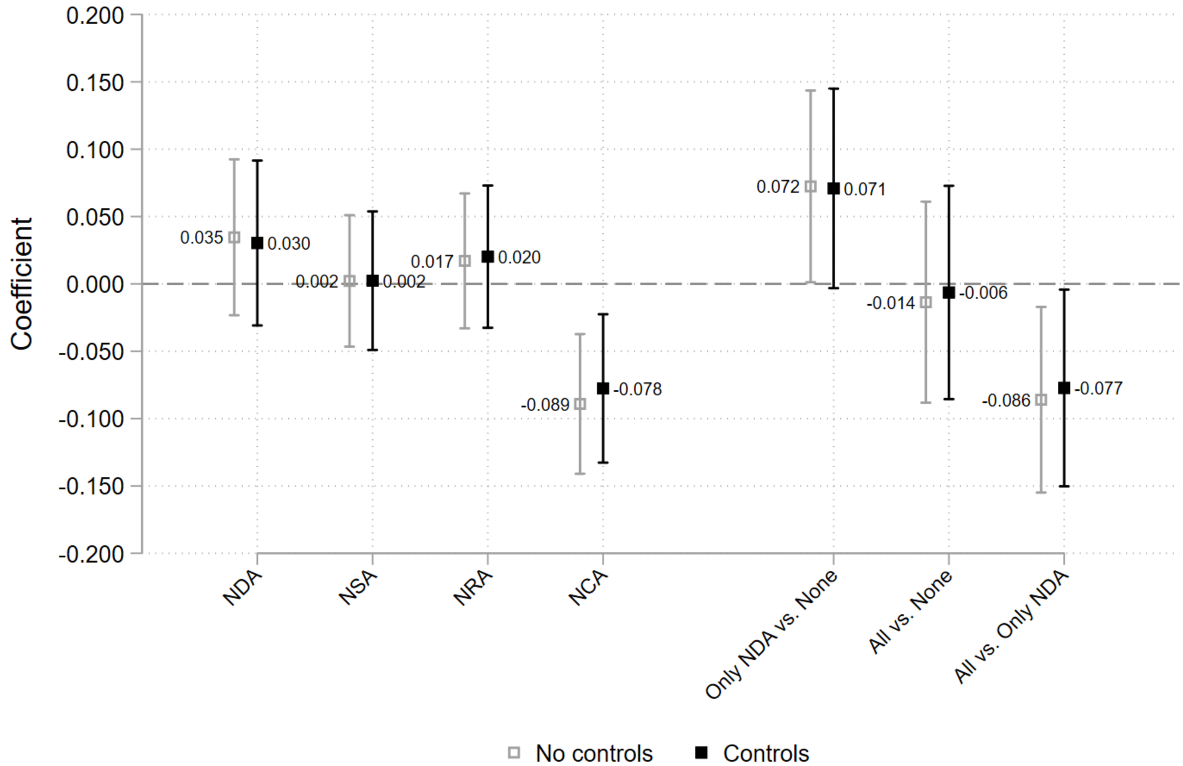


Figure 5. "Workers Spend One Month or More in Training When Initially Hired"

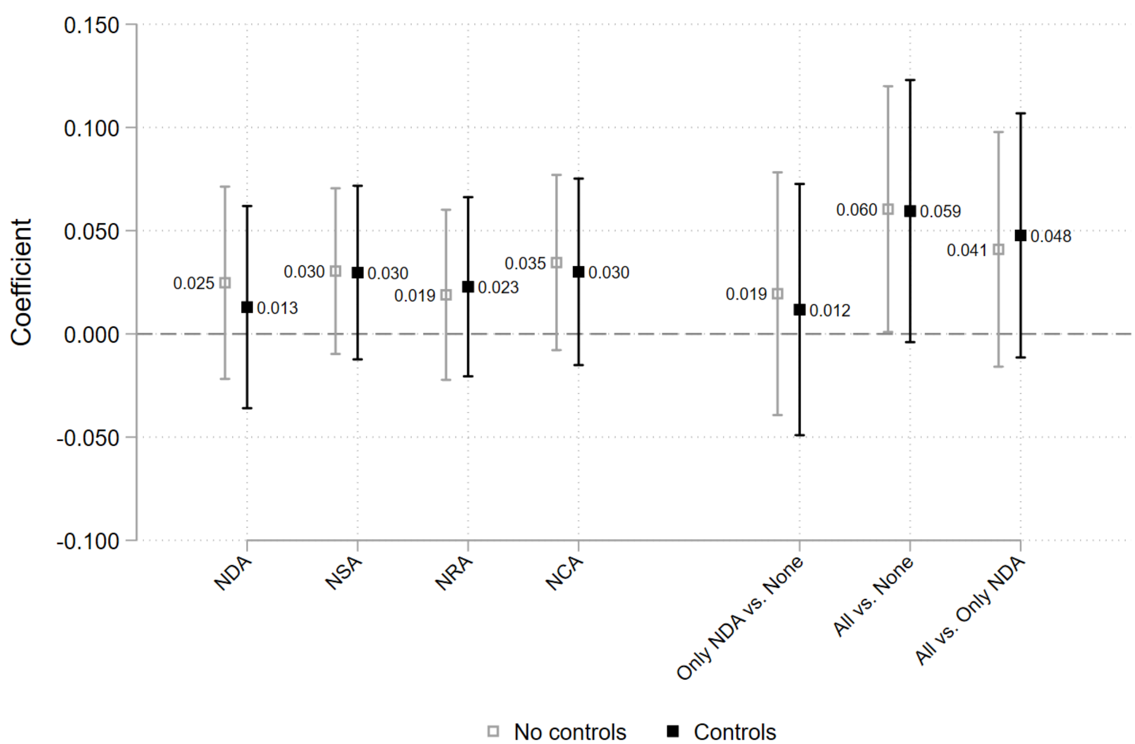


Figure 6. Likelihood Firm Intends to Increase Base Pay

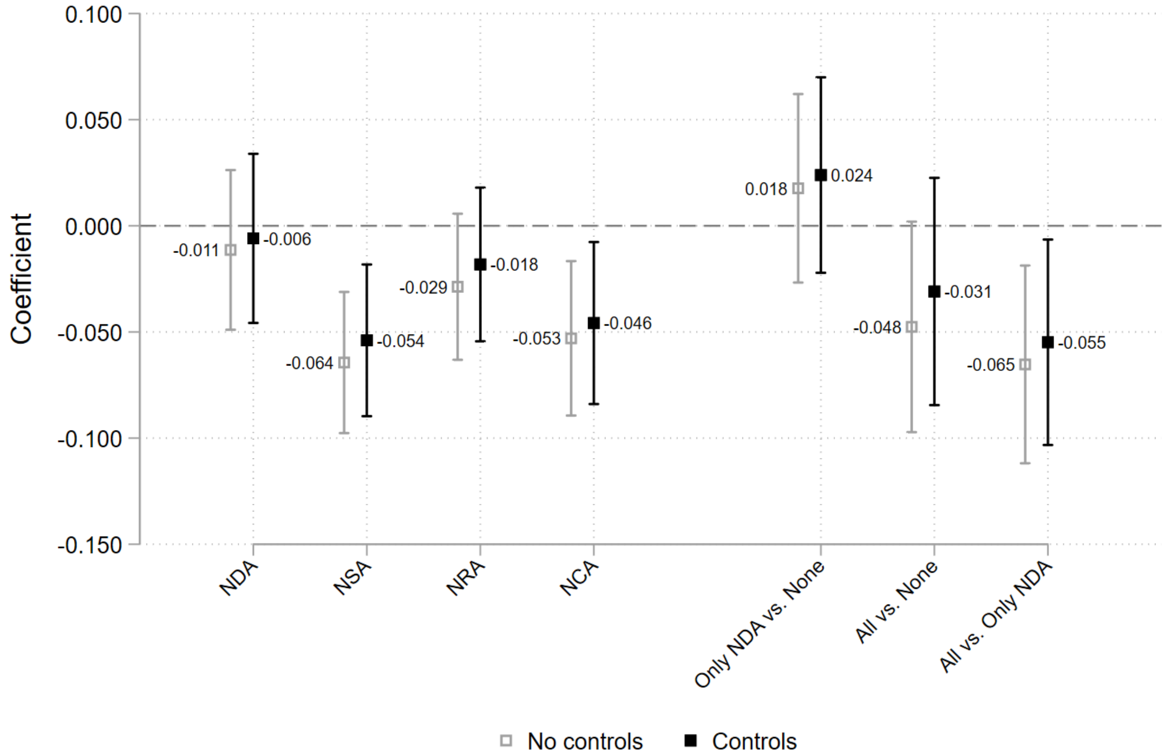


Figure 7. Log of Individual Earnings

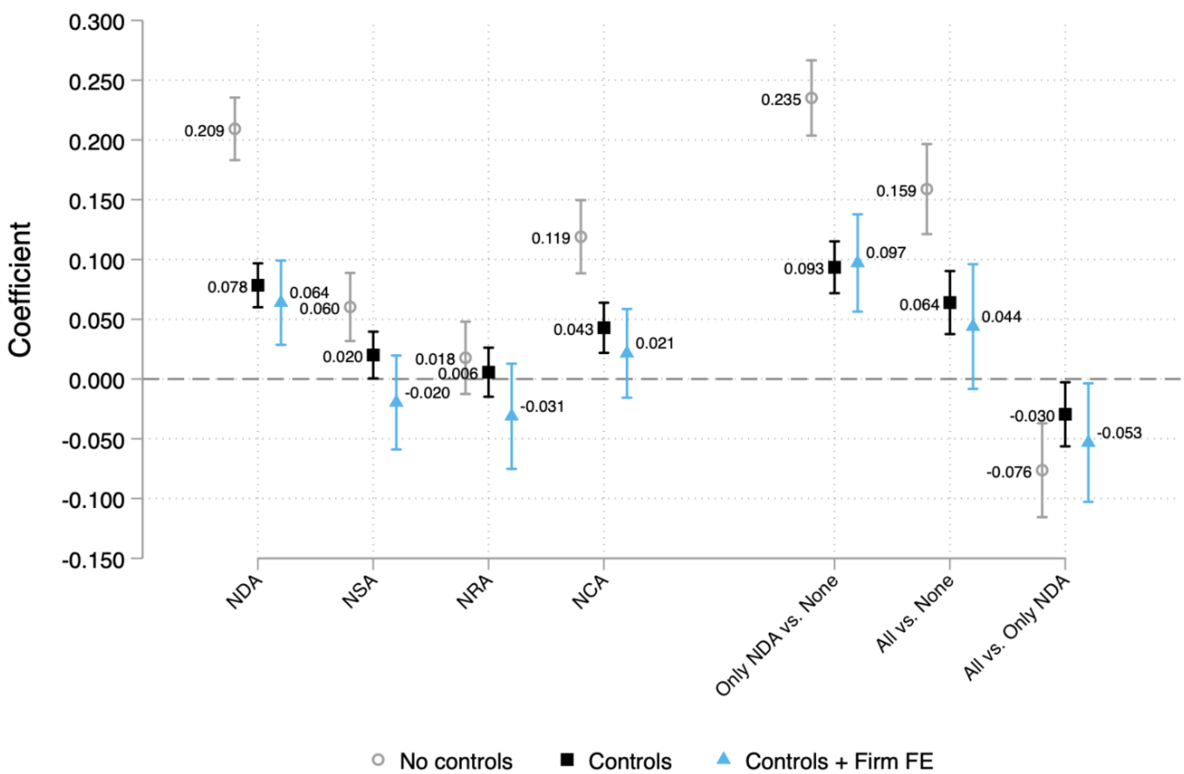


Figure 8. Log of Individual Earnings by Top Manager Status (with Controls + Firm FE)

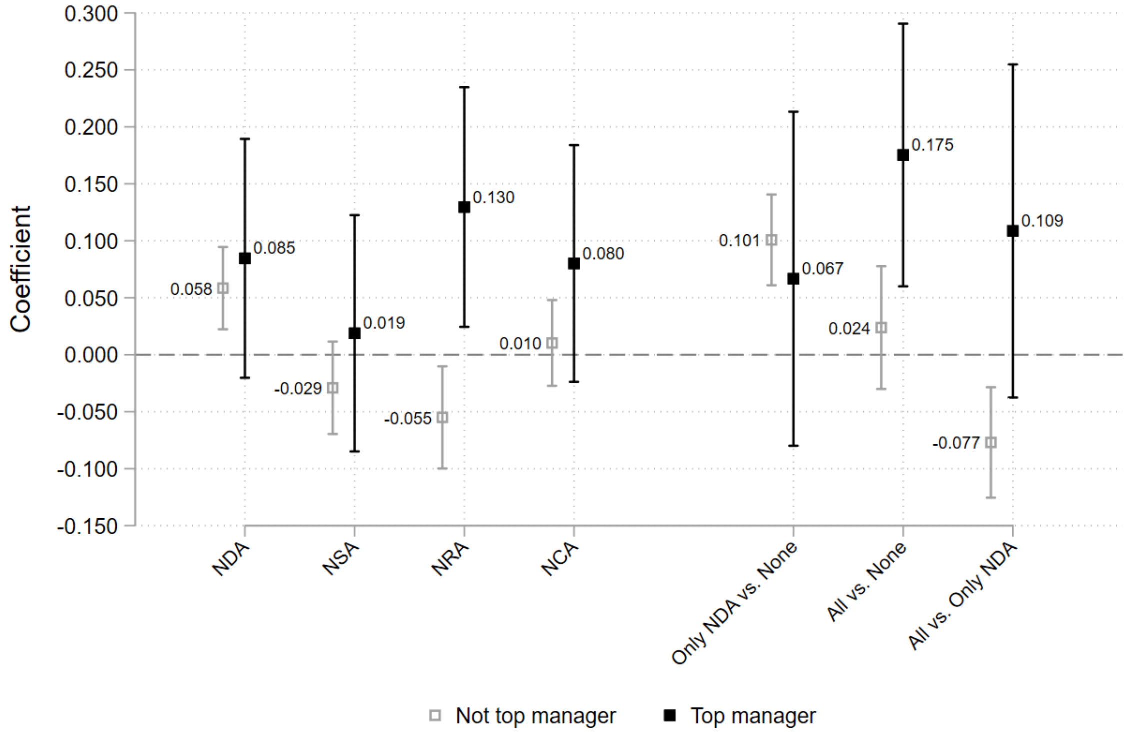
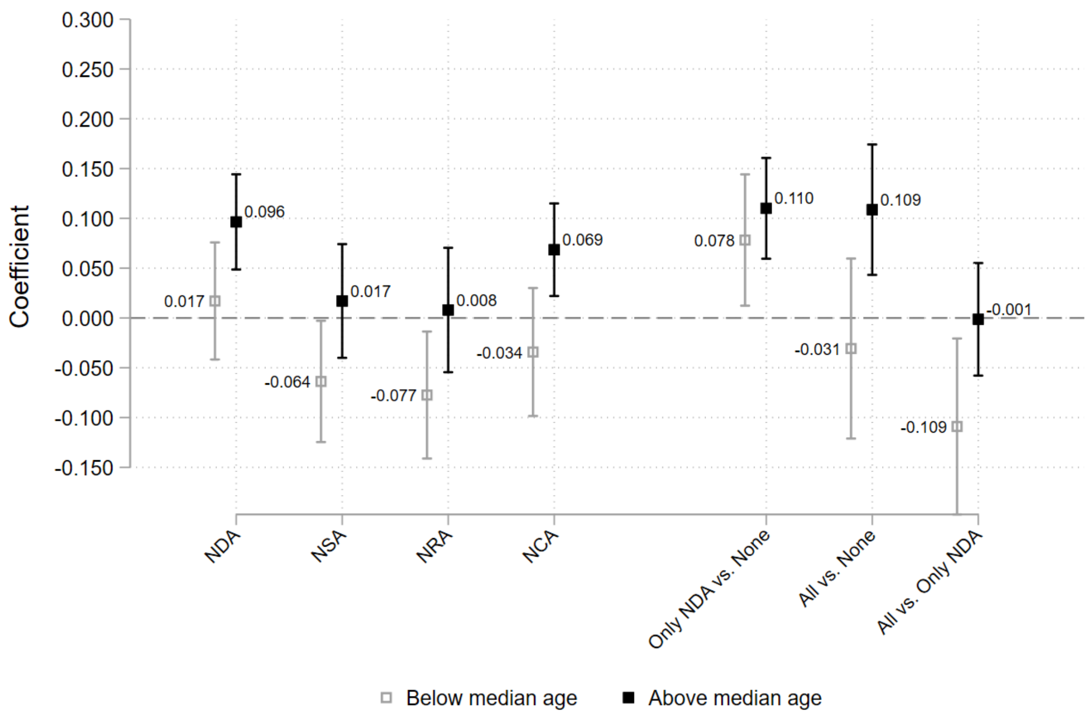


Figure 9. Log of Individual Earnings by Median Age (with Controls + Firm FE)



Tables

Table 1. Full Distribution of Contract Bundles

	Individual-Level Data	Firm-Level Data	
	(1)	(2)	(3)
Combination of contracts: (NDA, NSA, NRA, NCA)	1(Adopt)=Yes or Probably yes	1(Adopt)=All employees	1(Adopt)=All or some employees
(0,0,0,0)	38.4	22.2	5.2
(1,0,0,0)	25.9	25.7	10.9
(0,1,0,0)	0.3	1.0	0.2
(0,0,1,0)	0.1	0.5	0.1
(0,0,0,1)	0.6	0.7	0.9
(1,1,0,0)	3.1	4.5	3.2
(1,0,1,0)	1.6	1.6	0.5
(1,0,0,1)	2.0	3.0	3.8
(0,1,1,0)	0.3	0.7	0.1
(0,1,0,1)	0.2	0.3	0.7
(0,0,1,1)	0.1	0.0	0.0
(1,1,1,0)	6.2	11.5	7.8
(1,1,0,1)	2.6	5.0	10.0
(1,0,1,1)	0.5	0.5	1.2
(0,1,1,1)	0.2	0.1	0.2
(1,1,1,1)	18.0	22.7	55.2
Total	100.0	100.0	100.0

Notes: In column (1), adoption of each PERC includes those who indicate they agreed or probably agreed. In column (2), adoption of each PERC is equal to 1 if the firm uses that PERC for all employees. Column (3) considers firm-level adoption as 1 if the firm uses that PERC for all or some employees. "Don't know" responses are omitted.

Table 2. Pairwise Adoption of Restrictive Covenants

Panel A: Individual-Level Data (Adoption=Yes or Probably Yes)

	Unconditional probability	Probability conditional on:			
Contract type		NDA	NSA	NRA	NCA
Non-disclosure	59.9	-	96.7	97.5	95.6
Non-solicitation	31.0	50.1	-	91.7	87.3
Non-recruitment	26.9	43.9	79.7	-	77.7
Non-compete	24.2	38.6	68.0	69.7	-

Panel B: Firm-Level Data (Adoption=All employees)

	Unconditional probability	Probability conditional on:			
Contract type		NDA	NSA	NRA	NCA
Non-disclosure	74.6	-	95.6	96.7	97.0
Non-solicitation	45.8	58.7	-	93.0	87.2
Non-recruitment	37.6	48.8	76.4	-	72.4
Non-compete	32.2	41.8	61.3	61.9	-

Panel C: Firm-Level Data (Adoption=All or some employees)

	Unconditional probability	Probability conditional on:			
Contract type		NDA	NSA	NRA	NCA
Non-disclosure	92.7	-	98.4	99.4	97.5
Non-solicitation	77.5	82.3	-	97.3	91.9
Non-recruitment	65.1	69.8	81.7	-	78.6
Non-compete	72.0	75.8	85.4	86.9	-

Notes: This table documents the pairwise adoption patterns of each restrictive covenant. In Panel A, adoption of each PERC includes those who indicate they agreed or probably agreed. In Panel B, adoption of each PERC is equal to 1 if the firm uses that PERC for all employees. Panel C considers firm-level adoption as 1 if the firm uses that PERC for or all or some employees. "Don't know" responses are omitted.

Table 3. Bundles by Demographic Characteristics in the Individual-Level Payscale Data

	(1) P(None)	(2) P(Only NDA)	(3) P(Other)	(4) P(All)
1(Male)	38.8	24.5	18.7	18.0
1(Female)	37.8	27.6	16.5	18.0
1(<Median Age)	38.1	23.1	18.2	20.6
1(≥Median Age)	38.6	27.8	17.4	16.3
1(<Median Income)	43.2	23.4	15.7	17.6
1(≥Median Income)	31.4	29.4	20.6	18.7
1(For Profit)	37.8	25.1	18.2	18.8
1(Not for Profit)	44.1	34.0	12.5	9.4
1(<Median firm size)	42.3	23.6	16.4	17.7
1(≥Median firm size)	34.2	28.3	19.0	18.4
1((wwc, ac ,ts) = (1,1,1))	32.2	25.6	21.4	20.9
1((wwc, ac ,ts) ≠ (1,1,1))	41.2	26.0	16.1	16.7
1(<Median wage growth in occ-ind)	42.9	25.2	15.8	16.1
1(≥Median wage growth in occ-ind)	32.8	26.7	20.0	20.4
1(<Median turnover rate in occ-ind)	37.1	29.1	16.8	17.0
1(≥Median turnover rate in occ-ind)	39.5	23.2	18.5	18.9
1(Top management)	31.5	28.8	20.5	19.3
1(Not top management)	39.1	25.6	17.4	17.9

Notes: This table presents the adoption patterns of the potential bundles of four restrictive covenants by basic demographic characteristics in the individual-level Payscale data. Each row adds to 100. "Don't know" responses are omitted. "wwc" is an indicator for working directly with clients; "ac" is an indicator for having access to client information (i.e., regardless of whether one works directly with client); "ts" is an indicator for the worker having knowledge of or access to company trade secrets. The client and trade secret variables are aggregated from the individual data in Starr, Prescott, and Bishara (2020b), merged into the Payscale data at the two-digit NAICS and two-digit SOC level, and then dichotomized by the median. Turnover rate and wage growth are calculated at the occupation and industry level in the Current Population Survey. The turnover rate is calculated as the likelihood that a worker in a given occupation and industry will change jobs next month. The wage growth variable is calculated as wage growth between year t and t+1 for occupation-industries in year t. Both turnover and wage growth are merged into the individual Payscale data at the occupation-industry level. Top management is chief executives, vice presidents, or directors. Not-top management is individual contributors or managers/supervisors.

Table 4. The Implications of the Two Rationales for Bundling PERCs

	Value Creation Rationale	Pure Value Capture Rationale
Logic	Firms bundle PERCs to resolve investment hold-up problems.	Firms bundle PERCs to limit turnover and reduce wage growth.
Outcomes	Bundling PERCs should be associated with: • More investment • Reduced turnover • Non-negative wage levels/growth	Bundling PERCs should be associated with: • Reduced turnover • Reduced wage growth
Adoption	Firms should bundle PERCs where the hold-up problem is most severe, including for workers • that require/have access to valuable information or relationships • with high turnover risk	Firms should bundle PERCs for workers that exhibit: • High turnover risk • High wage growth

Table 5. Ideal Experiments for Testing Competing Rationales vs. What We Do

Panel A. Outcomes	
Ideal Experiment:* Randomly deploy all four PERCs (to workers or firms) and examine whether firms	• Increase investment • Experience reduced turnover • Increase or lower wages
What we do: Examine whether, relative to firms that use only NDAs, firms that use all four PERCs are	• More likely to invest in worker training. • Less likely to see retention as a major concern. • More or less likely to report raising wages.
Panel B. Adoption	
Ideal Experiment: Examine whether firms bundle all four PERCs (for all workers or for certain jobs) when _______ exogenously increases.	• the value of information or relational resources in a firm (or in certain jobs) • turnover at the firm (or in certain jobs) • wage growth at the firm (or in certain jobs)
What we do: Examine whether occupation-industry combinations are more likely to have all four PERCs when they have	• access to more information and relationships • higher turnover risk • higher wage growth

Notes: In the outcome ideal experiments, it is not clear what the appropriate counterfactual is, since there are many possible counterfactuals of interest (i.e., "All four PERCs vs. None, or "All four PERCs vs. Only NDAs").

Online Appendix A

Exhibit A1. Actual Postemployment Restrictive Covenants from Cabela's v. Highby (2018)

1. Nondisclosure of Confidential Information.

(a) Access. Employee acknowledges that employment with Company or any of its affiliates necessarily has involved, and will involve, exposure to, familiarity with, and the opportunity to learn highly sensitive, confidential, and proprietary information of Company, which may include, without limitation, information about Company's products and services, markets, customers and prospective customers, the buying patterns and needs of customers and prospective customers, purchasing histories with vendors and suppliers, contact information for customers, prospective customers, vendors and suppliers, miscellaneous business relationships, investment products, pricing, quoting, costing systems, billing and collection procedures, proprietary software and the source code thereof, financial and accounting data, data processing and communications, technical data, marketing concepts and strategies, business plans, mergers and acquisitions, research and development of new or improved products and services, and general know-how regarding the business of Company and its products and services (collectively referred to herein as "Confidential Information"). Employee expressly acknowledges and agrees that Confidential Information may include, without limitation, confidential and proprietary information belonging to various third parties, such as Company's subsidiaries, affiliates, vendors, agents, or customers, but which has been and will be entrusted to Company for use by Company to conduct its business. The failure to mark or designate information as "confidential" or "proprietary" shall not prevent information that has been or will be accessed by or disclosed to Employee from being deemed Confidential Information under this Agreement.

(b) Valuable Asset. Employee further acknowledges that the Confidential Information is a valuable, special, and unique asset of Company, such that the unauthorized disclosure or use by Employee or persons or entities outside Company would cause irreparable damage to the business of Company. Accordingly, Employee agrees that, during and after Employee's employment with Company or any of its affiliates, Employee shall not directly or indirectly disclose to any person or entity or use for any purpose or permit the exploitation, copying, or summarizing of any Confidential Information of Company, except as specifically required in the proper performance of Employee's duties for Company. Employee represents and warrants that no such disclosure or use has occurred prior to the date hereof.

(c) Confidential Relationship. Company considers much of its Confidential Information to constitute trade secrets of Company which have independent value, provide Company with a competitive advantage over its competitors who do not know the trade secrets, and are protected from unauthorized disclosure under applicable law ("Trade Secrets"}. However, whether or not the Confidential Information constitutes Trade Secrets, Employee acknowledges and agrees that the Confidential Information is protected from unauthorized disclosure or use due to Employee's covenants under this Agreement and Employee's fiduciary duties as an employee of Company or any of its affiliates.

(d) Duties. Employee acknowledges that Company has instituted, and will continue to institute, update, and amend policies and procedures designed to protect the confidentiality and security of Company's Confidential Information, including, but not limited to, policies and procedures designed by Company to protect the status of Company's Trade Secrets. Employee agrees to take all appropriate action, whether by instruction, agreement or otherwise, to ensure the protection, confidentiality, and security of Company's Confidential Information, to protect the status of Company's Trade Secrets, and to satisfy Employee's obligations under this Agreement.

(e) Return of Documents. Employee acknowledges and agrees that the Confidential Information is and at all times shall remain the sole and exclusive property of Company. Upon the termination of Employee's employment with Company or any of its affiliates or upon request by Company at any time, Employee will promptly return to Company in good condition all Company property, including, without limitation, all documents, data, and records of any kind, whether in hard copy or electronic form, which contain any Confidential Information or which were prepared based on Confidential Information, including any and all copies thereof, as well as all such materials furnished to or acquired by Employee during the course of Employee's employment with Company or any of its affiliates.

(f) Use of Company's Computers. Employee is not authorized to access or use the Company's computers, email, or related computer systems to compete or to prepare to compete, or to otherwise compromise the Company's legitimate business interests, and unauthorized access to or use of the Company's computers in violation of this understanding may subject Employee to civil and/or criminal liability.

4. Nonsolicitation of Customers.

In order to prevent the improper use of Confidential Information and the resulting unfair competition and misappropriation of Goodwill and other proprietary interests, Employee agrees that while Employee is employed by Company or any of its affiliates and for a period of eighteen (18) months following the termination of Employee's employment for any reason whatsoever, whether such termination is voluntary or involuntary, and regardless of cause, Employee will not, directly or indirectly, on Employee's own behalf or by aiding any other individual or entity, call on, solicit the business of, sell to, service, or accept business from any of Company's customers (with whom Employee had personal contact and did business with during the eighteen (18) month period immediately prior to the termination of Employee's employment) for the purpose of providing said customers with products and/or services of the type or character typically provided to such customers by Company.

6. Nonsolicitation of Employees.

Employee agrees that while Employee is employed by Company or any of its affiliates and for a period of eighteen (18) months following the termination of Employee's employment for any reason whatsoever, whether such termination is voluntary or involuntary, and regardless of cause, Employee will not, directly or indirectly, on Employee's own behalf or by aiding any other individual or entity, hire·, employ, or solicit for employment any employee of Company with whom Employee had personal contact or about whom Employee received Confidential Information while employed by Company or any of its affiliates.

7. Noncompetition.

In order to prevent the improper use of Trade Secrets and Confidential Information and the resulting unfair competition and misappropriation of Goodwill and other proprietary interests, Employee agrees that while Employee is employed by Company or any of its affiliates and for a period of eighteen (18) months following the termination of Employee's employment for any reason whatsoever, whether such termination is voluntary or involuntary, and regardless of cause, Employee will not, directly or indirectly, perform services within the United States of America or Canada for Cornpetitor that are the same as or similar to the services Employee performed for Company during the eighteen (18) month period immediately prior to the termination of Employee's employment. For purposes of this Agreement, a "Competitor" of Company shall mean Bass Pro Shops, Gander Mountain, Sportsman's Warehouse, The Sportsman's Guide, Orvis, Dick's Sporting Goods, The Sport's Authority, Big 5 Sporting Goods, Scheels, L.L. Bean, Lands' End, REI, Academy, Amazon.com, Field & Stream, Wholesale Sports, Sail, Le Baron, Mountain Equipment Co-op, Canadian Tire, The Fishin' Hole, Northwest Company, or any other multi-state, multi-province, and/or multi- channel retailer engaged in the sale of products and/or services associated with hunting, fishing, or camping.

Figure A1. Enforceability vs. Protection of Various Restrictive Covenants

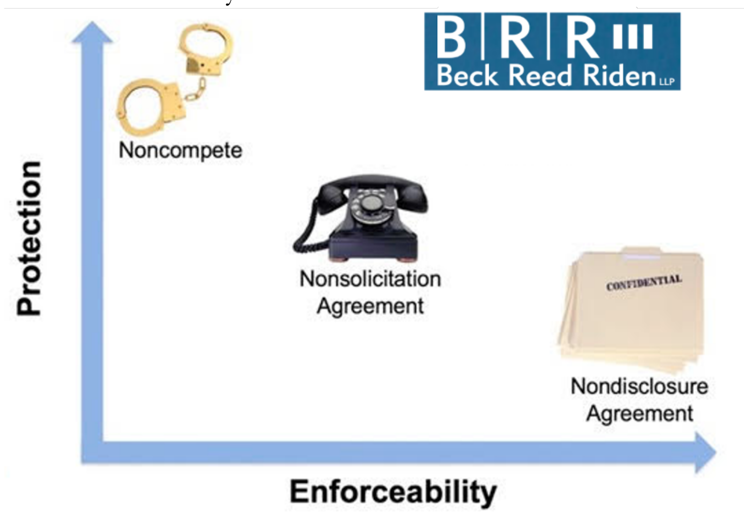


Figure A2. Firm Survey Postemployment Restrictive Covenant Questions

25. Which employees at your organization are subject to non-compete agreements (Prohibited from joining or starting a competing organization)?

All employees	Some employees	No employees	Don't Know
○	○	○	○

27. Which employees at your organization are subject to each of the following?

	All employees	Some employees	No employees	Don't Know
Non-solicitation of clients (Prohibited from leaving and soliciting former clients)	○	○	○	○
Non-poaching of co-workers (Prohibited from leaving and soliciting coworkers to join you)	○	○	○	○
Non-disclosure (Prohibited from leaving and sharing confidential information)	○	○	○	○

Figure A3. Individual Survey Postemployment Restrictive Covenant Questions

Sometimes employers try to restrict what employees can do after they leave.
In your current job did you agree that if you leave your employer you will:

Not join or start a competitor (non-compete)

- click to select -

Not solicit former clients (non-solicitation of clients)

- click to select -

Not solicit former co-workers (non-poaching of co-workers)

- click to select -

Not share your former employer's confidential information (non-disclosure agreement)

- click to select -

- click to select -
Yes, I definitely agreed
I'm not sure, but I probably agreed
I'm not sure, but I probably didn't agree
No, I definitely did not agree
I have no idea if I agreed or not

Figure A4. Unweighted Individual Survey Incidence of Each PERC

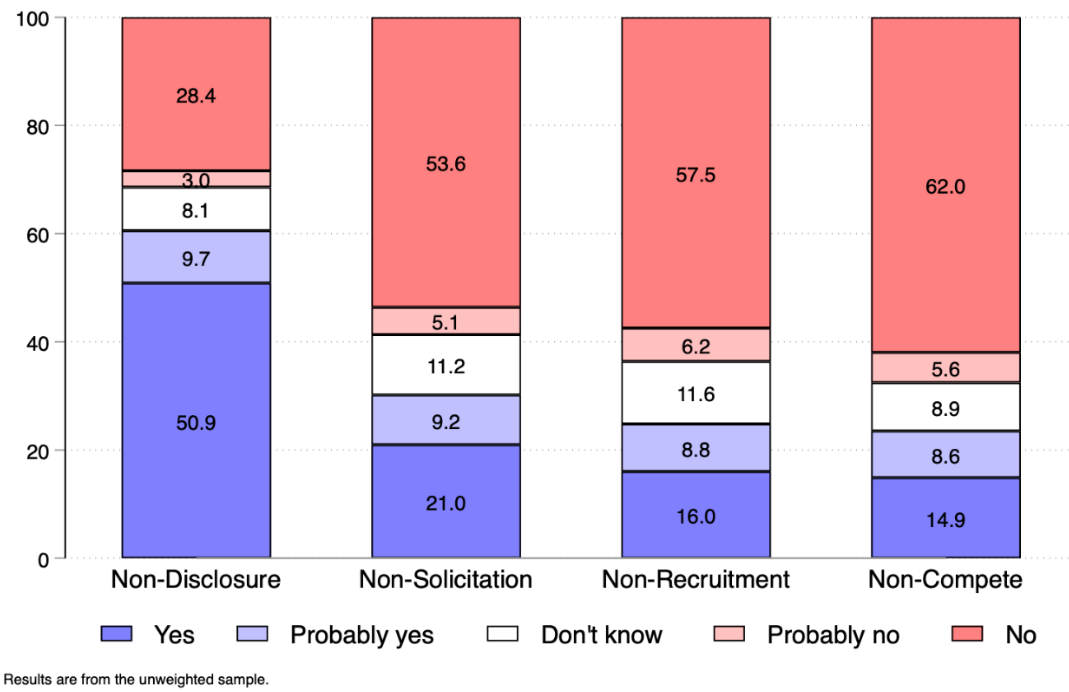
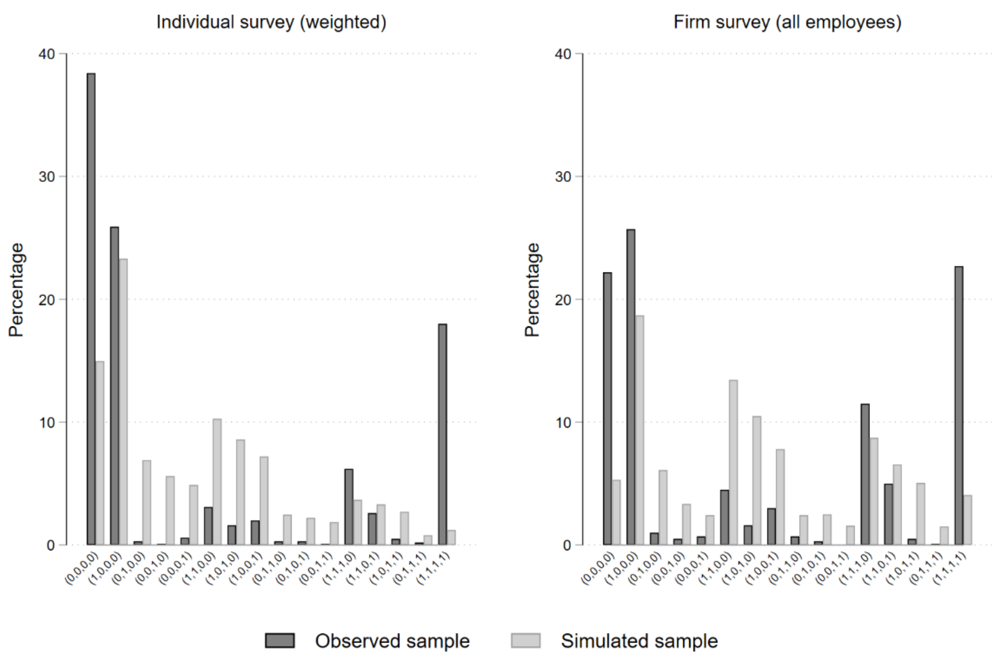


Figure A5. Bundling Distribution Simulation



Notes: Each figure compares the observed distribution of PERCs with the average of 1000 simulated distributions of PERCs we would observe if firms randomly chose which bundles to use, holding the marginal distribution of each PERC fixed at the overall sample proportion.

Figure A6. Firm Size Deciles and Bundling in Individual-Level Survey

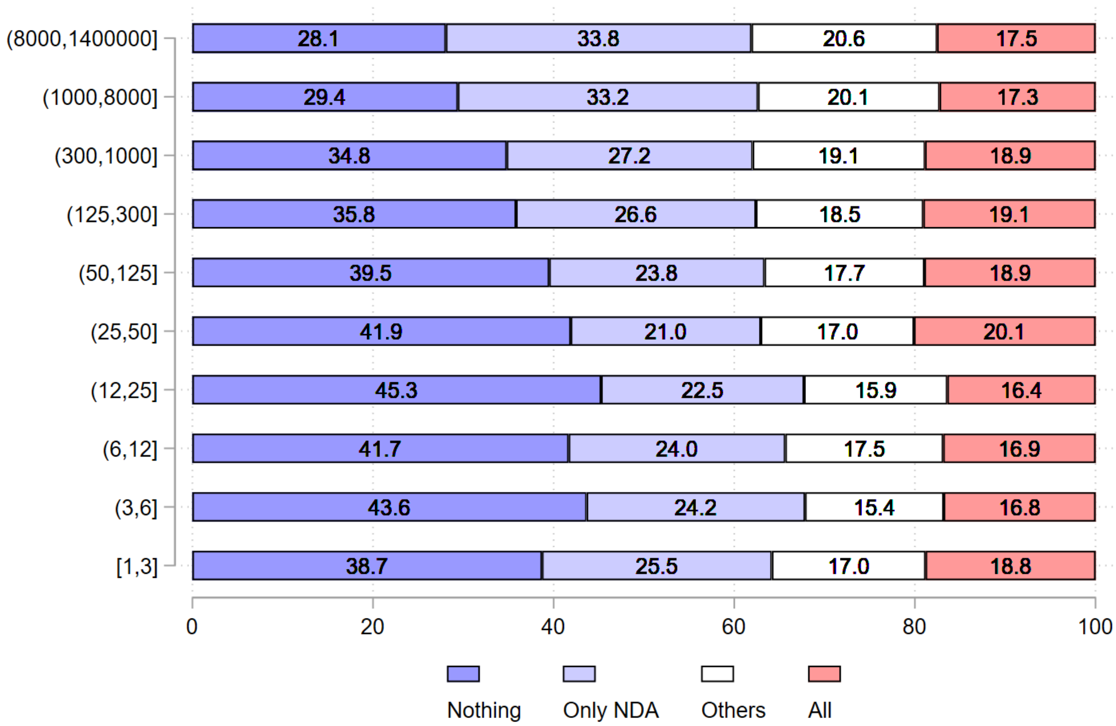


Figure A7. Firm Size and Bundling in Firm Survey (Adoption=All employees)

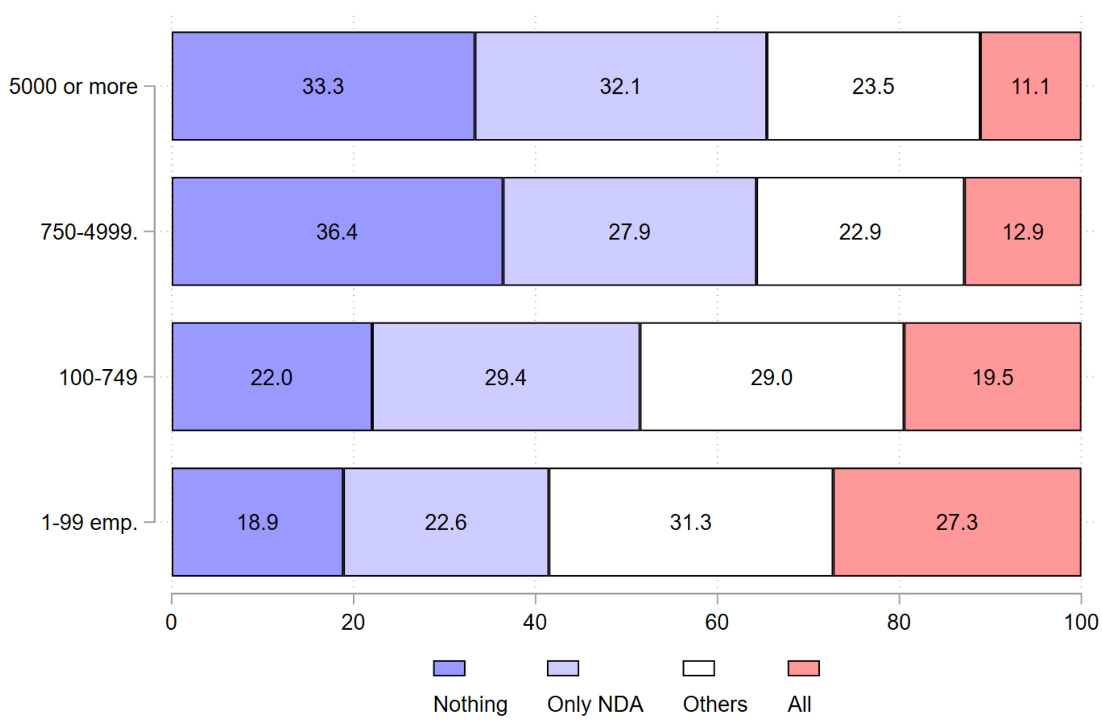


Figure A8. Firm Size and Bundling in Firm Survey (Adoption=All or some employees)

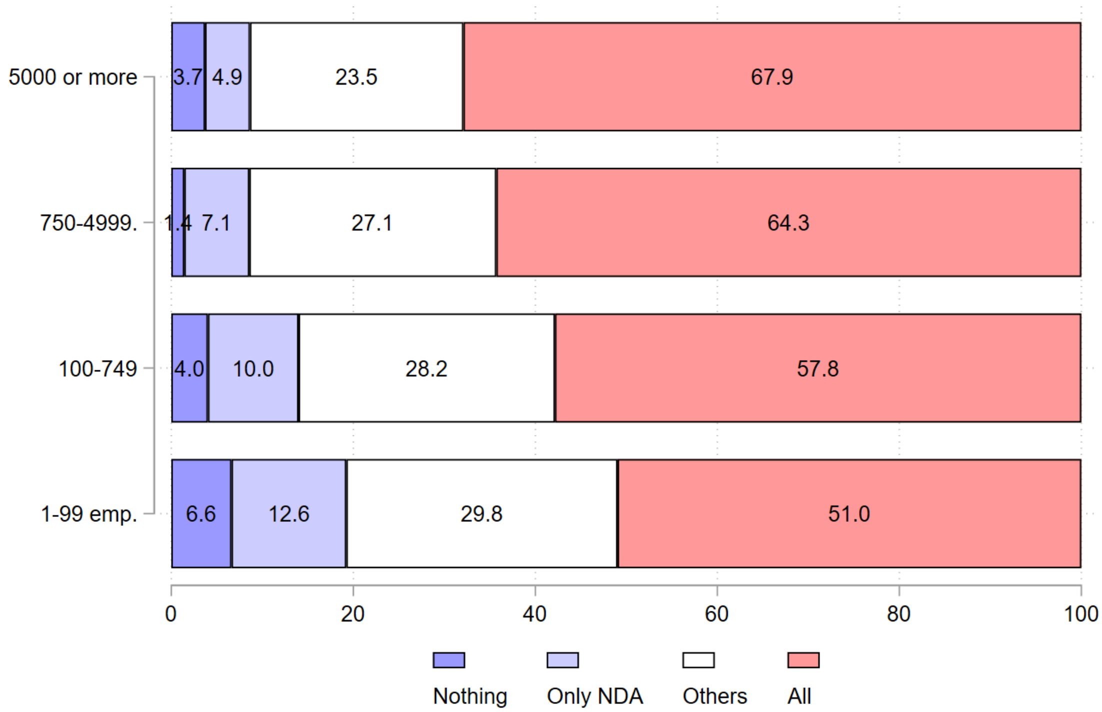


Figure A9. Bundling of Restrictive Covenants by Individual-Level Job Earnings

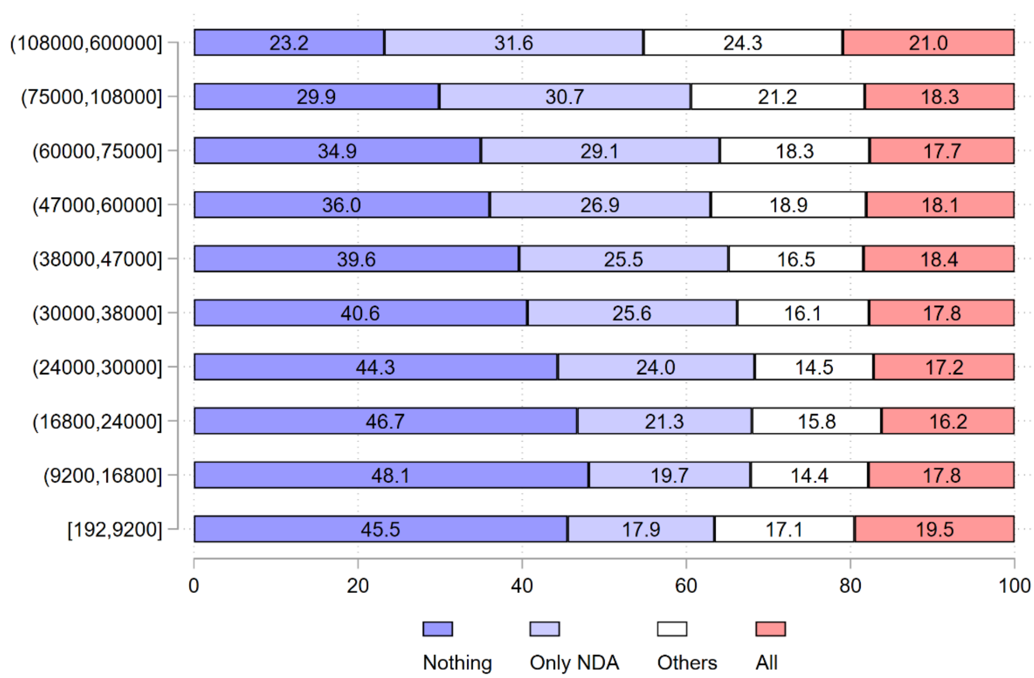


Figure A10: Heat Map Of Annual Wage Growth Rate By Occupation And Industry

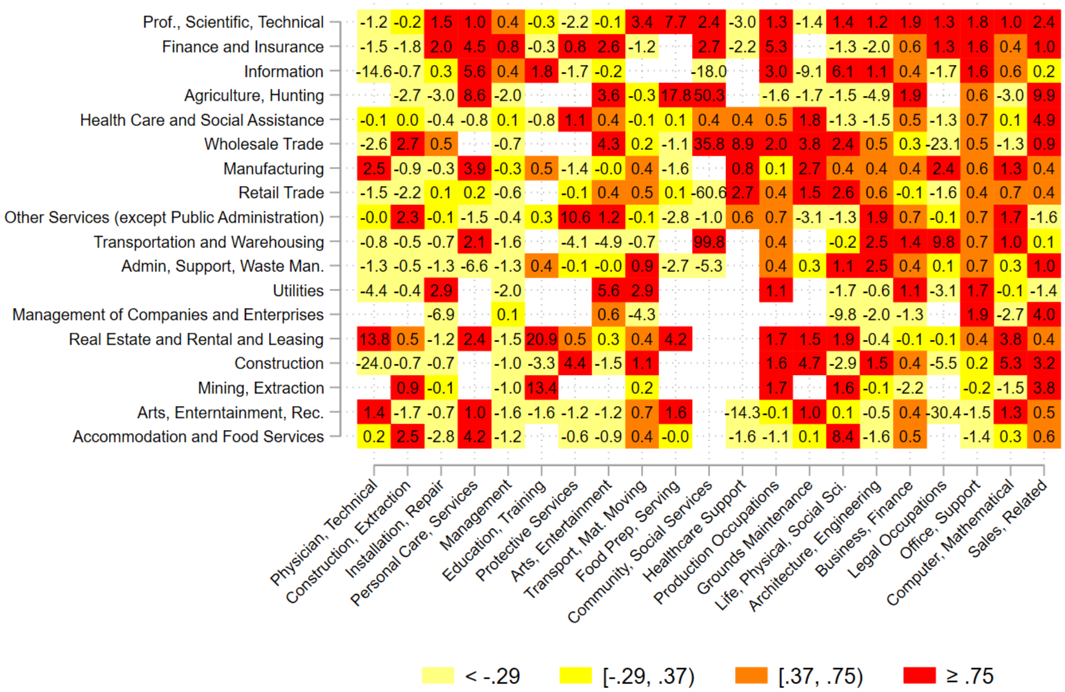


Figure A11: Heat Map Of Monthly Turnover Rate By Occupation And Industry

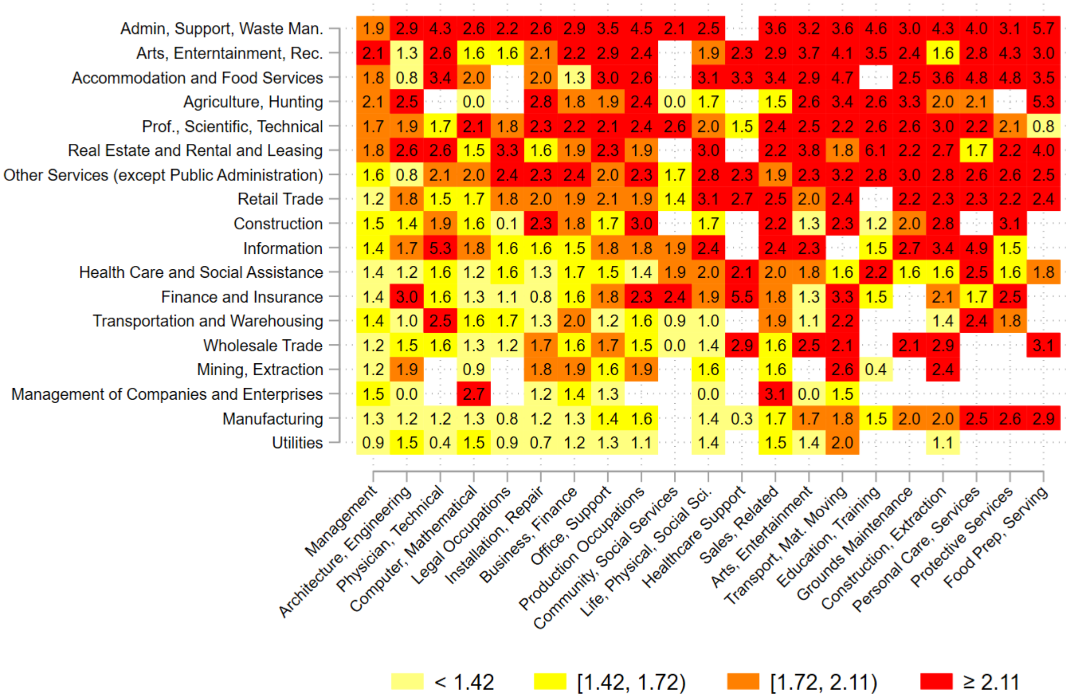


Figure A12. Occupation and Bundling from the Individual-Level Survey

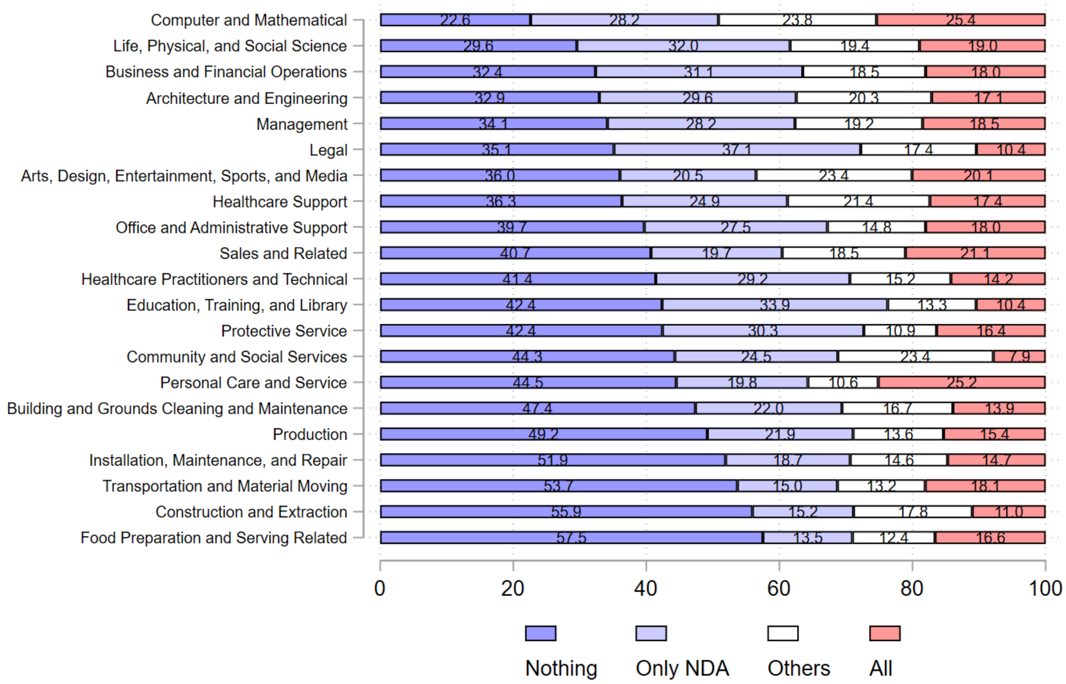


Figure A13. Industry and Bundling from the Individual-Level Survey

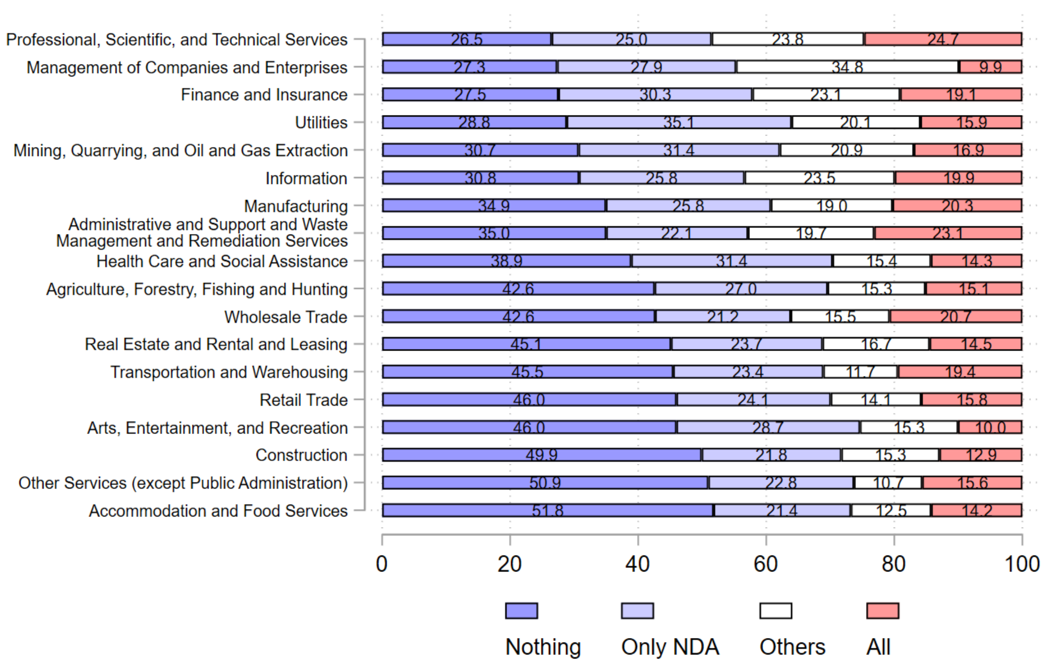
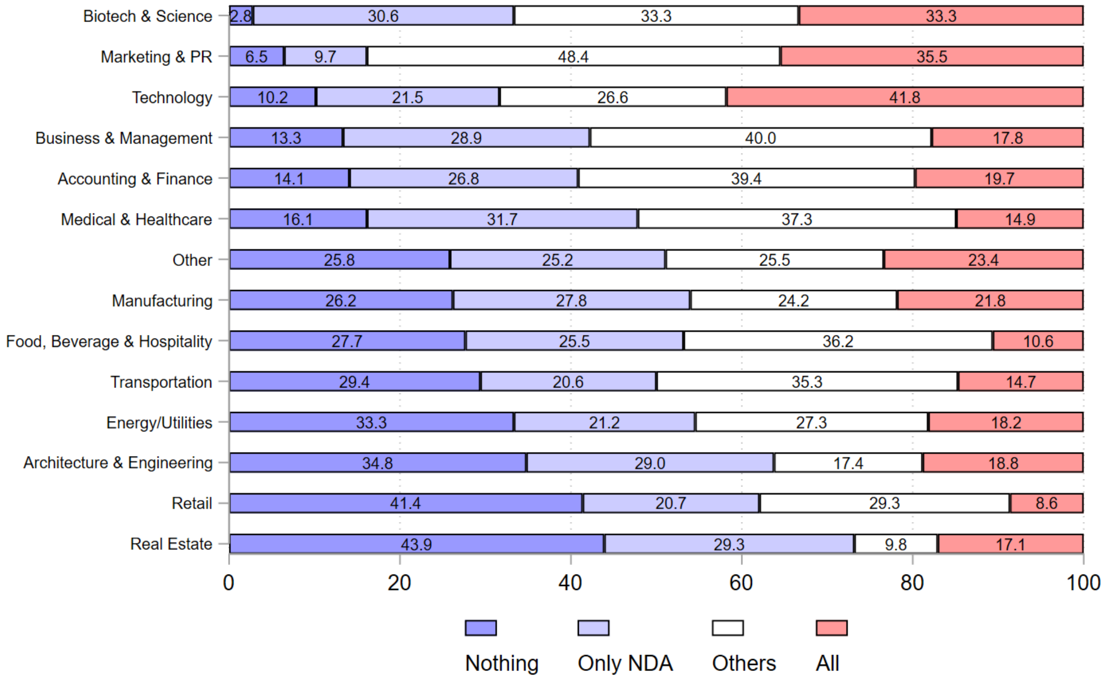


Figure A14. Industry and Bundling in Firm-Level Payscale Data (Adoption = All employees)



Only includes industries that have at least 30 observations.

Table A1. Job Characteristics of Survey-Taker in Firm-Level Payscale Survey

Panel A. Job Level

	N	%
C-Level	250	13.5
Vice President	161	8.69
Director	427	23.1
Manager	678	36.6
Individual Contributor	336	18.1
Total	1,852	100

Panel B. Job Function

	N	%
Compensation	83	4.48
Consultant	39	2.1
Executive (COO, CEO, etc.)	238	12.8
Finance/Accounting	122	6.58
Human Resources	1,015	54.8
Marketing	18	0.97
Operations	175	9.44
Sales	33	1.78
Technology	37	2
Other	94	5.07
Total	1,854	100

Notes: This table shows the job level and the job function of the individuals at the firm who took the Payscale Firm-Level Survey. The overall number of observations is slightly different because the individuals were not required to answer these questions.

Table A2. Comparison of Payscale Firm Data to Compustat and County Business Patterns

	Payscale	2017 County Business Patterns	Compustat
1-99 emp.	52.62	98.12	20.01
100-749 emp.	30.46	1.65	20.02
750-4,999 emp.	10.35	0.19	39.68
5,000 or more emp.	6.58	0.04	20.29
Total	100	100	100

Notes: This table shows the firm size distribution in the United States in 2017 comparing between the Payscale firm-level data, the 2017 County Business Patterns data from the US Census Bureau, and Compustat (which covers publicly traded companies).

Table A3: PayScale Individual Survey and 2017 American Community Survey

Variable	PayScale		ACS	PayScale - ACS Difference	
	Unweighted	Weighted		Unweighted	Weighted
Age	37.320	39.728	39.741	-2.421***	-0.013
	(11.077)	(12.880)	(12.986)	(0.139)	(0.118)
1(Female)	0.507	0.463	0.463	0.044***	0.000
	(0.500)	(0.499)	(0.499)	(0.006)	(0.006)
Annual Income	57721	50943	51,696	6,025***	-753
	(36097)	(40055)	(61,280)	(508)	(612)
1(Non-profit worker)	0.109	0.086	0.086	0.023***	0.000
	(0.312)	(0.280)	(0.280)	(0.005)	(0.004)
N	33,637	33,637	956,992		

Notes: The table shows the distributions of demographic characteristics in our sample data both weighted and unweighted and in data from the 2017 American Community Survey. The weights used in our samples are raking weights. *** p <.01, ** p<.05, * p<.1. Standard deviations (first three columns) and robust standard errors clustered at the state level (last two columns) are in parentheses.

Table A4. Occupation by Industry Classification of Working with Clients, Access to Client Information, and Trade Secrets

	Management	Business and Financial	Computer and Mathematical	Architecture and Engineering	Life, Physical, and Social Science	Community and Social Services	Legal	Education, Training, and Library	Arts, Design, Entertainment, Sports, and Media	Healthcare Practitioners and Technical	Healthcare Support
Accomodation and Food Services	(1,0,1)	(1,1,1)	(0,0,1)	(0,0,0)					(1,0,1)		(1,0,0)
Administrative and Support and Waste Management and Remediation Services	(1,1,1)	(0,1,1)	(0,0,0)		(0,0,0)	(1,0,0)	(1,1,0)	(1,1,1)		(1,0,0)	
Agriculture, Forestry, Fishing and Hunting	(1,1,1)	(0,1,1)	(0,1,1)	(0,1,1)					(0,0,1)		
Arts, Entertainment, and Recreation	(0,1,1)	(1,0,0)	(1,1,1)		(1,0,0)			(0,0,0)	(1,0,1)		
Construction	(1,1,1)	(0,1,1)	(0,0,1)	(1,1,1)			(0,1,1)	(0,0,0)	(1,0,0)		
Finance and Insurance	(0,1,1)	(1,1,1)	(0,1,1)	(1,1,1)		(1,1,0)	(0,1,1)		(1,1,1)	(1,0,1)	(0,1,1)
Health Care and Social Assistance	(0,1,1)	(0,1,1)	(0,1,0)	(0,1,1)	(1,1,0)	(1,1,0)	(0,0,0)	(1,1,0)	(0,0,0)	(1,1,0)	(1,1,0)
Information	(0,1,1)	(1,1,1)	(0,1,1)	(1,1,1)	(1,1,0)			(1,0,0)	(0,1,1)		
Management of Companies and Enterprises	(1,1,1)										
Manufacturing	(0,1,1)	(0,1,1)	(0,0,1)	(0,1,1)	(0,0,1)		(0,0,0)	(1,0,0)	(0,1,1)	(0,0,0)	(0,0,1)
Mining, Quarrying, and Oil and Gas Extraction	(1,1,1)	(0,1,1)	(1,1,1)	(0,1,0)	(1,1,0)			(0,0,0)			
Other Services (except Public Administration)	(1,1,1)	(1,1,1)	(0,1,1)	(1,0,0)	(1,1,1)	(1,0,0)	(0,0,0)	(1,1,0)	(1,0,0)	(1,1,1)	(1,0,0)
Professional, Scientific, and Technical Services	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(0,1,1)		(1,1,1)	(0,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
Real Estate and Rental and Leasing	(1,1,1)	(1,1,1)	(1,0,0)				(1,0,0)		(1,1,1)		
Retail Trade	(1,1,1)	(1,0,1)	(0,1,1)	(1,1,0)	(0,0,0)	(0,0,1)	(0,1,1)		(0,0,0)	(1,1,0)	(1,0,0)
Transportation and Warehousing	(1,1,1)	(0,1,1)	(0,1,1)	(0,0,1)							
Utilities	(0,1,1)	(0,0,1)	(0,0,0)	(0,0,0)	(1,1,1)						
Wholesale Trade	(0,1,1)	(0,1,1)	(0,1,1)	(1,1,1)			(0,0,0)		(0,1,1)		(0,0,1)

	Protective Service	Food Preparation and Serving	Building and Grounds Cleaning and Maintenance	Personal Care and Service	Sales and Related	Office and Administrative Support	Construction and Extraction	Installation, Maintenance, and Repair	Production	Transportation and Material Moving
Accomodation and Food Services	(1,0,0)	(1,0,0)	(0,0,0)	(0,0,0)	(1,0,0)	(1,1,0)		(0,0,0)	(0,1,0)	(0,1,1)
Administrative and Support and Waste Management and Remediation Services	(1,0,0)	(1,0,0)	(0,0,0)	(1,1,1)	(1,1,1)	(1,1,0)	(1,0,0)	(0,1,1)	(0,0,1)	(1,0,0)
Agriculture, Forestry, Fishing and Hunting		(1,0,0)	(0,0,0)		(1,1,1)	(1,0,1)		(1,0,0)	(0,0,0)	(1,0,0)
Arts, Entertainment, and Recreation	(0,1,0)	(1,0,0)	(0,0,0)	(1,0,0)	(1,0,0)	(0,1,1)		(0,1,1)	(1,0,1)	
Construction	(0,1,0)		(0,0,0)		(1,1,1)	(0,1,1)	(0,0,0)	(1,1,0)	(0,1,0)	(0,0,0)
Finance and Insurance	(1,1,1)				(1,1,1)	(1,1,1)				(1,0,0)
Health Care and Social Assistance	(1,0,0)	(1,1,0)	(0,0,0)	(1,1,0)	(1,0,0)	(1,1,0)	(0,0,0)	(0,1,1)	(1,0,0)	(1,1,0)
Information				(1,0,0)	(1,1,1)	(0,1,1)		(1,0,1)	(0,1,0)	
Management of Companies and Enterprises						(1,1,0)				
Manufacturing	(0,0,0)	(0,0,1)	(0,0,0)		(1,1,1)	(0,1,1)	(0,0,0)	(0,0,1)	(0,0,1)	(0,0,1)
Mining, Quarrying, and Oil and Gas Extraction					(1,1,0)	(1,1,1)	(0,1,1)	(0,1,0)	(0,1,1)	(0,0,1)
Other Services (except Public Administration)	(1,0,0)	(0,0,0)	(0,0,0)	(1,1,0)	(0,1,0)	(0,1,1)	(1,1,0)	(0,0,1)	(0,0,1)	(1,0,0)
Professional, Scientific, and Technical Services			(1,0,0)	(0,0,0)	(1,1,1)	(1,1,1)	(1,1,1)	(1,0,1)	(0,0,1)	
Real Estate and Rental and Leasing	(1,1,0)		(0,0,0)	(1,1,1)	(1,1,1)	(1,1,1)		(0,0,0)	(1,0,0)	(0,0,0)
Retail Trade	(1,1,1)	(1,0,1)	(0,0,0)	(0,0,0)	(1,0,0)	(0,0,0)		(1,1,1)	(0,0,1)	(0,0,1)
Transportation and Warehousing	(1,0,0)				(1,1,1)	(1,1,0)		(0,0,1)	(0,0,0)	(0,0,0)
Utilities					(1,0,1)	(0,0,0)	(0,0,0)	(0,0,0)	(0,0,0)	(1,1,1)
Wholesale Trade		(1,0,0)	(0,0,0)		(1,1,1)	(0,1,1)		(1,0,1)	(0,0,1)	(0,1,1)

Notes: This table shows work characteristics by occupations and industries as to whether workers work with clients directly, have access to client information or trade secrets. The data are from the individual Payscale survey and includes 27,476 observations. Each cell represents the scores for (wwc, ac, ts), where "wwc" is an indicator for working directly with clients; "ac" is an indicator for having access to client information (i.e., regardless of whether one works directly with client); "ts" is an indicator for the worker having knowledge of or access to company trade secrets. The client and trade secret variables are aggregated from the individual data in Starr et al. (2021), merged into the Payscale data at the 2 digit NAICS and 2 digit SOC level, and then dichotomized by the median.

Table A5. Bundling Patterns by Wage Growth, Turnover Risk, Relationships, and Trade Secrets

	(1) P(None)	(2) P(Only NDA)	(3) P(Other)	(4) P(All)
Information and Relationships				
(wwc,ac,ts) = (1,0,0)	0.030	-0.004	-0.002	-0.023
	(0.035)	(0.020)	(0.021)	(0.017)
(wwc,ac,ts) = (0,1,0)	0.011	0.043	-0.024	-0.030
	(0.047)	(0.038)	(0.027)	(0.027)
(wwc,ac,ts) = (1,1,0)	-0.058*	0.016	0.026	0.016
	(0.030)	(0.021)	(0.022)	(0.018)
(wwc,ac,ts) = (0,0,1)	0.006	-0.014	-0.022	0.030*
	(0.032)	(0.024)	(0.014)	(0.018)
(wwc,ac,ts) = (1,0,1)	-0.032	0.035	0.015	-0.019
	(0.031)	(0.025)	(0.014)	(0.019)
(wwc,ac,ts) = (0,1,1)	-0.100***	0.023	0.024*	0.053***
	(0.028)	(0.019)	(0.014)	(0.018)
(wwc,ac,ts) = (1,1,1)	-0.123***	0.015	0.054***	0.055***
	(0.033)	(0.019)	(0.015)	(0.021)
Wage Growth and Turnover Rates				
Annual wage growth rate	-0.021**	0.003	0.010**	0.008*
	(0.008)	(0.005)	(0.005)	(0.004)
Monthly turnover rate	0.037**	-0.045***	-0.011	0.019*
	(0.015)	(0.011)	(0.010)	(0.010)

Notes: The data are from the individual survey and comprise 27,476 observations. "wwc" is an indicator for working directly with clients; "ac" is an indicator for having access to client information (i.e., regardless of whether one works directly with client); "ts" is an indicator for the worker having knowledge of or access to company trade secrets. The client and trade secret variables are aggregated from the individual data in Starr et al. (2021) to the occupation by industry level (2 digit NAICS and 2 digit SOC codes) and then merged into the individual Payscale data. Turnover rate and wage growth are calculated at the occupation and industry level in the Current Population Survey. The turnover rate is calculated as the likelihood that a worker in a given occupation and industry will change jobs next month. The wage growth variable is calculated as wage growth between year t and t+1 for occupation-industries in year t. Both turnover and wage growth are merged into the individual Payscale data at the occupation-industry level. The results are from a multinomial logit model, and have been converted into marginal effects such that each row must add up to 0 (i.e., if having trade secrets makes one 5 percentage points more likely to be in the All category relative to somebody without trade secrets, then that individual must be 5 percentage points likely to be in the other categories). Controls include age, gender, class of worker, log(firm size), state FE. Standard errors in parentheses are clustered at the occupation by industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6. Distribution of PERCs by Occupation and Industry

Panel A: Incidence by Industry	NDA	NSA	NRA	NCA
Agriculture, Hunting	54.7	23.8	18.0	20.8
Mining, Extraction	63.5	26.4	26.4	21.5
Utilities	67.0	26.2	22.9	23.9
Construction	46.1	24.9	21.2	15.6
Manufacturing	60.5	29.5	24.2	28.7
Wholesale Trade	53.0	27.2	23.5	27.3
Retail Trade	49.9	22.2	20.8	17.6
Transportation, Warehousing	52.5	25.2	22.2	21.4
Information	65.1	33.2	25.8	27.0
Finance, Insurance	68.5	36.7	29.2	22.2
Real Estate	51.4	25.5	24.9	15.9
Prof., Scientific, Technical	69.2	39.7	31.3	30.9
Management of Companies	65.1	23.2	19.7	23.2
Admin, Support, Waste Man.	59.8	35.4	27.5	27.3
Health Care, Social Assistance	55.9	24.2	20.5	15.2
Arts, Entertainment, Rec.	52.1	19.8	21.1	12.7
Accommodation, Food Services	44.1	19.5	19.3	17.2
Other Services	47.6	23.3	20.7	18.5

Panel B: Incidence by Occupations	NDA	NSA	NRA	NCA
Management	62.8	29.8	25.2	25.4
Business and Financial Operations	64.0	30.0	24.4	22.3
Computer and Mathematical	72.8	37.9	31.1	32.7
Architecture and Engineering	61.7	26.7	22.2	24.0
Life, Physical, and Social Science	64.2	30.3	22.4	25.2
Community and Social Services	50.3	28.2	22.1	8.0
Legal	61.5	25.4	21.3	11.7
Education, Training, and Library	55.7	21.3	19.7	13.7
Arts, Design, Entertainment, Sports, and Media	57.4	33.0	27.4	25.5
Healthcare Practitioners and Technical	54.5	23.5	19.3	15.4
Healthcare Support	55.7	30.4	24.4	15.4
Protective Service	55.9	24.4	18.5	16.7
Food Preparation and Serving Related	39.5	22.6	20.7	16.9
Building and Grounds Cleaning and Maintenance	44.6	23.6	22.7	18.6
Personal Care and Service	55.3	33.0	27.3	22.8
Sales and Related	54.0	30.8	26.4	26.2
Office and Administrative Support	56.8	27.1	23.0	20.3
Construction and Extraction	37.8	25.0	20.2	13.6
Installation, Maintenance, and Repair	44.3	24.4	22.2	17.6
Production	45.5	22.0	19.4	18.1
Transportation and Material Moving	42.0	25.2	21.8	19.7

Notes: This table shows the incidence of non-disclosure agreements (NDAs), non-solicitation agreements (NSAs), non-recruitment agreements (NRAs), and non-compete agreements (NCAs) measures are calculated from the 2017 Individual-Level Payscale data. An individual is recorded as agreeing to one of these PERCs if they definitely or probably agreed.

Table A7. Retention is a major concern

Model: OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DV: 1(Agree or Strongly Agree that Retention is a major concern)												
NDA	0.035	0.030							0.055	0.045		
	(0.035)	(0.037)							(0.039)	(0.041)		
NSA			0.002	0.002					0.028	0.018		
			(0.030)	(0.031)					(0.048)	(0.050)		
NRA					0.017	0.020			0.047	0.049		
					(0.030)	(0.032)			(0.046)	(0.047)		
NCA							-0.089***	-0.078**	-0.146***	-0.124***		
							(0.031)	(0.033)	(0.038)	(0.040)		
Only NDA vs. Nothing											0.072*	0.071
											(0.043)	(0.045)
All vs. Nothing											-0.014	-0.005
											(0.045)	(0.048)
All vs. Only NDA											-0.086**	-0.077*
											(0.042)	(0.044)
Constant	0.576***	0.783***	0.601***	0.816***	0.596***	0.808***	0.632***	0.833***	0.579***	0.760***	0.568***	0.755***
	(0.031)	(0.199)	(0.020)	(0.195)	(0.019)	(0.198)	(0.018)	(0.182)	(0.031)	(0.189)	(0.033)	(0.188)
Observations	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099	1,099
R-squared	0.001	0.088	0.000	0.087	0.000	0.088	0.007	0.092	0.014	0.097	0.013	0.098
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is 1 if a respondent agrees or strongly agrees that 'employee retention is a major concern for its company', and 0 otherwise. The mean of the dependent variable is 60%. Controls include firm size (four categories), industry FEs, state FEs. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A8. Training For More Than One Month When Hired

Model: OLS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DV: 1(New hire training over one month)												
NDA	0.025	0.013							0.010	-0.003		
	(0.028)	(0.030)							(0.032)	(0.033)		
NSA			0.030	0.030					0.023	0.022		
			(0.024)	(0.026)					(0.038)	(0.039)		
NRA					0.019	0.023			-0.013	-0.001		
					(0.025)	(0.026)			(0.037)	(0.039)		
NCA							0.035	0.030	0.024	0.019		
							(0.026)	(0.027)	(0.032)	(0.034)		
Only NDA vs. Nothing											0.019	0.012
											(0.036)	(0.037)
All vs. Nothing											0.060*	0.059
											(0.036)	(0.039)
All vs. Only NDA											0.041	0.048
											(0.035)	(0.036)
Constant	0.648***	0.658***	0.653***	0.653***	0.660***	0.658***	0.656***	0.664***	0.646***	0.657***	0.645***	0.660***
	(0.025)	(0.192)	(0.017)	(0.188)	(0.016)	(0.188)	(0.015)	(0.189)	(0.025)	(0.189)	(0.026)	(0.194)
Observations	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500	1,500
R-squared	0.001	0.059	0.001	0.060	0.000	0.060	0.001	0.060	0.002	0.060	0.003	0.062
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is 1 if 'the typical workers spend one month or more in training when they are initially hired', and 0 otherwise. The mean of the dependent variable is 66.7%. Controls include firm size (four categories), industry FEs, state FEs. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9. Firm Intentions To Increase Base Pay

Model: OLS DV = 1(Firm intends to increase base pay)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NDA	-0.011	-0.006							0.026	0.022		
	(0.023)	(0.024)							(0.025)	(0.026)		
NSA			-0.064***	-0.054**					-0.091***	-0.080**		
			(0.020)	(0.022)					(0.034)	(0.034)		
NRA					-0.029	-0.018			0.044	0.047		
					(0.021)	(0.022)			(0.033)	(0.034)		
NCA							-0.053**	-0.046**	-0.028	-0.027		
							(0.022)	(0.023)	(0.027)	(0.028)		
Only NDA vs. Nothing											0.018	0.024
											(0.027)	(0.028)
All vs. Nothing											-0.048	-0.031
											(0.030)	(0.033)
All vs. Only NDA											-0.065**	-0.055*
											(0.028)	(0.029)
Constant	0.849***	0.648***	0.870***	0.665***	0.851***	0.652***	0.858***	0.648***	0.855***	0.639***	0.859***	0.648***
	(0.020)	(0.173)	(0.013)	(0.177)	(0.012)	(0.175)	(0.012)	(0.175)	(0.020)	(0.175)	(0.020)	(0.179)
Observations	1,347	1,347	1,347	1,347	1,347	1,347	1,347	1,347	1,347	1,347	1,347	1,347
R-squared	0.000	0.090	0.008	0.095	0.001	0.090	0.005	0.093	0.011	0.097	0.006	0.093
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is 1 if a respondent answers yes for 'do you plan to give base pay increases in 2017?', and 0 otherwise. The mean of the dependent variable is 84%. Controls include firm size (four categories), industry FEs, state FEs. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A10. Log(Wage) from the Individual Data

Model: OLS DV: Log(Wage)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NDA	0.209***	0.078***	0.064***									
	(0.016)	(0.011)	(0.021)									
NSA				0.060***	0.020*	-0.020						
				(0.017)	(0.012)	(0.024)						
NRA							0.018	0.006	-0.031			
							(0.018)	(0.012)	(0.027)			
NCA										0.119***	0.043***	0.021
										(0.019)	(0.013)	(0.023)
Constant	10.495***	9.816***	10.169***	10.602***	9.851***	10.210***	10.615***	9.855***	10.213***	10.591***	9.845***	10.203***
	(0.013)	(0.052)	(0.158)	(0.011)	(0.052)	(0.159)	(0.010)	(0.052)	(0.158)	(0.010)	(0.052)	(0.159)
Observations	27,804	27,804	7,527	27,804	27,804	7,527	27,804	27,804	7,527	27,804	27,804	7,527
R-squared	0.019	0.510	0.826	0.001	0.507	0.826	0.000	0.507	0.826	0.005	0.508	0.826
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Controls include age, gender, class of worker, log(firm size), industry FEs, occupation FEs, state FEs. Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A10 Continued. Log(Wage) from the Individual Data

Model: OLS DV: Log(Wage)	(13)	(14)	(15)	(16)	(17)	(18)
NDA	0.245***	0.093***	0.091***			
	(0.018)	(0.012)	(0.023)			
NSA	-0.026	-0.014	-0.038			
	(0.030)	(0.019)	(0.032)			
NRA	-0.174***	-0.062***	-0.079**			
	(0.030)	(0.020)	(0.037)			
NCA	0.139***	0.052***	0.066**			
	(0.024)	(0.017)	(0.033)			
Only NDA vs. Nothing				0.235***	0.093***	0.097***
				(0.019)	(0.013)	(0.025)
All vs. Nothing				0.159***	0.064***	0.044
				(0.023)	(0.016)	(0.032)
All vs. Only NDA				-0.076***	-0.030*	-0.053*
				(0.024)	(0.016)	(0.030)
Constant	10.495***	9.816***	10.163***	10.489***	9.815***	10.159***
	(0.013)	(0.052)	(0.157)	(0.013)	(0.052)	(0.156)
Observations	27,804	27,804	7,527	27,804	27,804	7,527
R-squared	0.026	0.511	0.827	0.021	0.510	0.827
Controls	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes

Notes: Controls include age, gender, class of worker, log(firm size), industry FEs, occupation FEs, state FEs. Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A11. Job Level and Bundling Patterns

VARIABLES	(1) P(None)	(2) P(Only NDA)	(3) P(Other)	(4) P(All)
Job Level (base: individual contributor)				
Chief executive	-0.100***	-0.021	0.033*	0.088***
	(0.035)	(0.021)	(0.019)	(0.034)
Vice president	-0.109***	0.006	0.053**	0.050
	(0.037)	(0.031)	(0.025)	(0.035)
Director	-0.061*	0.033**	0.019	0.009
	(0.032)	(0.014)	(0.022)	(0.021)
Manager or supervisor	0.017	0.006	-0.015**	-0.008
	(0.013)	(0.008)	(0.007)	(0.010)

Notes: The data are from the individual survey and comprise 27,804 observations. For the job-level results, the base level comparison is an "individual contributor." These titles were self-selected by individuals in the Payscale survey. The results are from a multinomial logit model, and have been converted into marginal effects such that each row must add up to 0 (i.e., if having trade secrets makes one 5 percentage points more likely to be in the All category relative to somebody without trade secrets, then that individual must be 5 percentage points likely to be in the other categories). Controls include age, gender, class of worker, log(firm size), state FE. Standard errors in parentheses are clustered at the occupation by industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table A12: Log(Wage) from the Individual-Level Data by Top Manager Status

Model: OLS DV: Log(Wage)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
TM	0.555***	0.391***	0.354***	0.570***	0.388***	0.361***	0.564***	0.388***	0.320***	0.579***	0.392***	0.357***
	(0.019)	(0.029)	(0.052)	(0.014)	(0.022)	(0.050)	(0.013)	(0.021)	(0.048)	(0.013)	(0.021)	(0.047)
NDA	0.123***	0.069***	0.058***									
	(0.007)	(0.012)	(0.022)									
NDA x TM	0.051**	0.039	0.026									
	(0.024)	(0.033)	(0.065)									
NSA				0.032***	0.005	-0.029						
				(0.007)	(0.012)	(0.025)						
NSA x TM				0.069***	0.096***	0.048						
				(0.023)	(0.030)	(0.065)						
NRA							0.018**	-0.013	-0.055**			
							(0.008)	(0.013)	(0.027)			
NRA x TM							0.104***	0.115***	0.185***			
							(0.024)	(0.032)	(0.064)			
NCA										0.068***	0.028**	0.010
										(0.008)	(0.013)	(0.023)
NCA x TM										0.052**	0.100***	0.070
										(0.024)	(0.031)	(0.066)
Constant	10.694***	9.720***	10.121***	10.761***	9.754***	10.161***	10.767***	9.758***	10.171***	10.755***	9.746***	10.155***
	(0.006)	(0.051)	(0.157)	(0.005)	(0.051)	(0.157)	(0.005)	(0.051)	(0.157)	(0.005)	(0.051)	(0.157)
Observations	27,804	27,804	7,527	27,804	27,804	7,527	27,804	27,804	7,527	27,804	27,804	7,527
R-squared	0.118	0.531	0.833	0.107	0.529	0.832	0.107	0.529	0.833	0.109	0.529	0.832
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: TM is an indicator for "Top Management", which includes executives, vice presidents, and directors. Controls include age, gender, class of worker, log(firm size), industry FEs, occupation FEs, state FEs. Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1

Table A12 Continued: Log(Wage) from the Individual-Level Data by Top Manager Status

Model: OLS	(13)	(14)	(15)	(16)	(17)	(18)
DV: Log(Wage)	Base = No PERCs			Base = Only NDA		
Top Management	0.826***	0.390***	0.359***	0.720***	0.345***	0.324***
	(0.040)	(0.030)	(0.049)	(0.045)	(0.034)	(0.083)
Only NDA	0.223***	0.095***	0.101***			
	(0.019)	(0.014)	(0.024)			
All	0.127***	0.044***	0.024	-0.096***	-0.051***	-0.077***
	(0.023)	(0.017)	(0.033)	(0.024)	(0.017)	(0.029)
Only NDA x Top Management	-0.106*	-0.045	-0.034			
	(0.060)	(0.043)	(0.089)			
All x Top Management	0.113*	0.114***	0.151**	0.219***	0.159***	0.186**
	(0.060)	(0.043)	(0.073)	(0.059)	(0.044)	(0.088)
Constant	10.423***	9.721***	10.112***	10.646***	9.816***	10.213***
	(0.013)	(0.051)	(0.155)	(0.015)	(0.052)	(0.157)
Observations	27,804	27,804	7,527	27,804	27,804	7,527
R-squared	0.135	0.531	0.833	0.135	0.531	0.833
Controls	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes

Notes: Columns (16), (17), and (18) are the same regression as in columns (13), (14), and (15), but change the base category from No PERCs to Only an NDA. Controls include age, gender, class of worker, log(firm size), industry FEs, occupation FEs, state FEs. Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Log(Wage) from the Individual-Level Data by Age

Model: OLS DV: Log(Wage)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
High Age	0.221***	0.029	-0.019	0.222***	0.046**	0.009	0.221***	0.042**	0.011	0.222***	0.046**	0.011
	(0.011)	(0.024)	(0.044)	(0.008)	(0.021)	(0.037)	(0.008)	(0.021)	(0.036)	(0.008)	(0.021)	(0.038)
NDA	0.134***	0.047***	0.017									
	(0.009)	(0.017)	(0.036)									
NDA x HA	0.020	0.053**	0.079									
	(0.014)	(0.022)	(0.048)									
NSA				0.044***	-0.008	-0.064*						
				(0.009)	(0.018)	(0.037)						
NSA x HA				0.039***	0.049**	0.081						
				(0.015)	(0.024)	(0.053)						
NPA							0.030***	-0.035*	-0.077**			
							(0.010)	(0.019)	(0.039)			
NPA x HA							0.048***	0.073***	0.085			
							(0.015)	(0.025)	(0.055)			
NCA										0.071***	0.005	-0.034
										(0.010)	(0.020)	(0.039)
NCA x HA										0.052***	0.066***	0.103**
										(0.015)	(0.025)	(0.050)
Constant	10.630***	9.876***	10.218***	10.700***	9.902***	10.240***	10.707***	9.909***	10.242***	10.696***	9.896***	10.232***
	(0.008)	(0.054)	(0.154)	(0.006)	(0.054)	(0.155)	(0.006)	(0.054)	(0.155)	(0.006)	(0.054)	(0.156)
Observations	27,804	27,804	7,527	27,804	27,804	7,527	27,804	27,804	7,527	27,804	27,804	7,527
R-squared	0.059	0.511	0.827	0.046	0.508	0.826	0.046	0.508	0.826	0.049	0.509	0.826
Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: High Age (HA) is an indicator if the individual is above the median age (36). Controls include age, gender, class of worker, log(firm size), industry FEs, occupation FEs, state FEs. Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1

Table A13 Continued: Log(Wage) from the Individual-Level Data by Age

Model: OLS	(13)	(14)	(15)	(16)	(17)	(18)
DV: Log(Wage)	Base = No PERCs			Base = Only NDA		
High Age	0.425***	0.030	-0.020	0.407***	0.056**	0.012
	(0.024)	(0.024)	(0.045)	(0.029)	(0.026)	(0.046)
Only NDA	0.229***	0.078***	0.078*			
	(0.029)	(0.021)	(0.040)			
All	0.144***	0.013	-0.031	-0.085**	-0.065**	-0.109**
	(0.032)	(0.025)	(0.055)	(0.035)	(0.026)	(0.054)
Only NDA x High Age	-0.018	0.025	0.032			
	(0.037)	(0.027)	(0.049)			
All x High Age	0.076*	0.092***	0.139**	0.094**	0.066**	0.108
	(0.043)	(0.032)	(0.071)	(0.046)	(0.033)	(0.066)
Constant	10.234***	9.874***	10.194***	10.463***	9.952***	10.273***
	(0.018)	(0.054)	(0.152)	(0.023)	(0.057)	(0.156)
Observations	27,804	27,804	7,527	27,804	27,804	7,527
R-squared	0.105	0.511	0.827	0.105	0.511	0.827
Controls	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes

Notes: Columns (16), (17), and (18) are the same regression as in columns (13), (14), and (15), but change the base category from No PERCs to Only an NDA. Controls include age, gender, class of worker, log(firm size), industry FEs, occupation FEs, state FEs. Standard errors in parentheses, clustered by firm. *** p<0.01, ** p<0.05, * p<0.1.

Table A14. Bundles by NCA Enforceability

Panel A: Bundles by NCA enforceability

Contract Bundle	Individual Survey (1) NCAs not enforceable	Individual Survey (2) NCAs enforceable	Firm Survey (3) NCAs not enforceable	Firm Survey (4) NCAs enforceable
Nothing	33.8	38.9	16.4	23.5
Only NDA	28.1	25.6	30.2	24.7
Other	20.3	17.4	30.6	29.1
All	17.8	18.1	22.8	22.7

Panel B: Bundles by PERC type and NCA enforceability

Bundle types	Individual Survey (1) NCAs not enforceable	Individual Survey (2) NCAs enforceable	Firm Survey (3) NCAs not enforceable	Firm Survey (4) NCAs enforceable
Nothing	33.8	38.9	16.4	23.5
Has NCAs	23.2	24.3	32.8	32.1
No NCA but ≥ one other PERC	43.1	36.8	50.7	44.5
No NCA but has NDA	42.3	36.1	49.3	42.2
No NCA but has NSA	12.7	9.6	19.0	17.5
No NCA but has NRA	11.0	7.8	14.2	14.4

Panel C. Individual-level survey multinomial logit

	(1) P(Nothing)	(2) P(Only NDA)	(3) P(Other)	(4) P(All)
1(Noncompete Not Enforceable)	-0.043***	0.028***	0.023***	-0.008
	(0.005)	(0.005)	(0.004)	(0.005)

Panel D. Firm-level survey multinomial logit

	(1) P(Nothing)	(2) P(Only NDA)	(3) P(Other)	(4) P(All)
1(Noncompete Not Enforceable)	-0.054***	0.067***	0.01	-0.022
	(0.019)	(0.011)	(0.023)	(0.017)

Notes: States that do not enforce noncompetes are CA, OK, ND; all other states in 2017 enforce them in at least some circumstances (Beck 2019). In Panel A and B, columns (1) and (2) refer to the individual-level data, whereas columns (3) and (4) refer to the firm-level data. In columns (3) and (4), a PERC is considered adopted only the firm uses the PERC with all employees. Panel C and D are multinomial logit results of NCA enforceability. Panel C uses individual-level survey data with 27,804 observations, while Panel D uses firm-level data (where bundle adoption is based on using the PERC for all workers) with 1,525 observations. Controls in Panel C include age, gender, class of worker, log(firm size), state fixed effects, and occupation and industry fixed effects. Controls in Panel D include firm size (four categories) and industry fixed effects. In both panels, standard errors in parentheses are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix B. Differencing between All vs. Only NDA to Address Omitted Variables

Suppose that there is just one unobserved variable *w*,[19] and that the choice of bundle is constrained to three options {Nothing, NDA, All}, where we will use NDA for shorthand to refer to "Only NDA" so that the options are mutually exclusive. Also suppose that the data generating process for *y* is:[20]

$$(1) \quad y_i = \beta_0 + \beta_1 All_i + \beta_2 NDA_i + \beta_3 w_i + \epsilon_i$$

where ϵ_i is uncorrelated with All_i, NDA_i, and w_i. However, because we cannot observe w_i, the model we estimate is: $y_i = \alpha_0 + \alpha_1 All_i + \alpha_2 NDA_i + e_i$, where $e_i = \beta_3 w_i + \epsilon_i$. Estimating this equation via ordinary least squares,[21] the bias in $\widehat{\alpha_1}$ (comparing All to None) takes the form:

$$(2) \quad Bias_{\widehat{\alpha_1}} = E[\widehat{\alpha_1}] - \beta_1 = \frac{\beta_3\big(p_{NDA}(1-p_{NDA})cov(All,w) + p_{NDA}p_{All}cov(NDA,w)\big)}{p_{NDA}p_{All}(1-p_{All}-p_{NDA})}$$

where $Probability(NDA) = p_{NDA}$ and $Probability(All) = p_{All}$, and we've incorporated the fact that {Nothing, NDA, All} are drawn from a multinomial distribution.[22] A symmetric expression reflects the bias in $\widehat{\alpha_2}$ (comparing only NDA to None):

$$(3) \quad Bias_{\widehat{\alpha_2}} = E[\widehat{\alpha_2}] - \beta_2 = \frac{\beta_3\big(p_{All}(1-p_{All})cov(NDA,w) + p_{NDA}p_{All}cov(All,w)\big)}{p_{NDA}p_{All}(1-p_{All}-p_{NDA})}$$

In both cases, $cov(NDA,w) \neq 0$ and $cov(w,All) \neq 0$ cause bias in the estimate as long as $\beta_3 \neq 0$ (that is, the omitted variable actually influences the outcome). Further, if $\beta_3 > 0$, $cov(NDA,w) > 0$, and $cov(w,All) > 0$ then both $\widehat{\alpha_1}$ and $\widehat{\alpha_2}$ will be biased upwards.

The core assumption we consider is that omitted variables could covary to similar degrees with the choice to adopt only an NDA or All four PERCs. If anything, it seems natural that the choice to adopt all PERCs is more strongly related to unobservables than the choice to adopt only

[19] It is straightforward to extend this to a vector of unobservables, as in Oster 2017.

[20] Using the Frisch-Waugh-Lovell theorem it is straightforward to extend our results to models with other covariates.

[21] If $y_i = \alpha_0 + \alpha_1 x_i + \alpha_2 z_i + e_i$, OLS yields $\widehat{\alpha_1} = \frac{cov(x,y)var(z) - cov(z,y)cov(x,z)}{var(x)var(z) - cov(x,z)^2}$. The estimate for $\widehat{\alpha_2}$ is symmetric.

[22] This implies that $var(All) = p_{All}(1-p_{All})$ and that $cov(All,NDA) = -p_{All}p_{NDA}$.

an NDA. For example, if w reflects the unobserved value of firm assets, then it seems natural that firms with more (unobservably) valuable assets would be more likely to use all PERCs. This implies that $cov(All, w) \geq cov(NDA, w) \geq 0$.

Under this assumption, we examine the conditions under which the absolute value of the bias in the comparison between All vs. Only NDA is lower than the bias from the All vs. None comparison. That is, under what conditions will $|Bias_{\widehat{a_1}-\widehat{a_2}}| < |Bias_{\widehat{a_1}}|$?[23] Leveraging equations (2) and (3), assuming that $cov(All, w) \geq cov(NDA, w) \geq 0$, and incorporating that in the data $p_{NDA} > p_{All}$ it is straightforward to show that the All vs. Only NDA comparison is less biased than the All vs. None comparison (i.e., that $|Bias_{\widehat{a_1}-\widehat{a_2}}| < |Bias_{\widehat{a_1}}|$).[24] The intuition is that under these assumptions the All vs. None comparison will be more biased than the Only NDA vs. None comparison, but that since both are biased in the same direction differencing between them reduces the size of the bias for All vs. Only NDA.[25]

We demonstrate this fact via Monte Carlo simulations. We model the first stage relationship between w and the bundle choices directly using a latent variable framework. Let $b^* = w + u$, where u and w are independent normal random variables with mean zero and variance of one; b^* is an unobserved latent index that determines the bundling patterns based on the following cutoff rules: the firm adopts "None" if $b^* \leq b^*_{none}$, "Only NDA" if $b^*_{nda} \geq b^* > b^*_{none}$, and "All" if $b^* > b^*_{nda}$. This structure necessarily implies that $cov(All, w) \geq cov(NDA, w)$ because when w is larger there will be a greater chance that $b^* > b^*_{nda}$.

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[23] Note that $|Bias_{\widehat{a_1}-\widehat{a_2}}| = |Bias_{\widehat{a_1}} - Bias_{\widehat{a_2}}|$.

[24] Simplification of the algebra leads to the condition that $|Bias_{\widehat{a_1}-\widehat{a_2}}| < |Bias_{\widehat{a_1}}|$ when $\frac{cov(w,All)}{cov(w,NDA)} > \frac{p_{All}}{p_{NDA}}$, which is true based on the observed data and the assumption that $cov(w, All) > cov(w, NDA)$.

[25] A numerical example may help clarify the logic. Suppose that the causal effect of All vs. None is 3 and that the causal effect of Only NDA vs. None is 1, such that causal effect of All vs. Only NDA is 2. Suppose further that under selection on unobservables the Only NDA vs. None estimate is positively biased by 3 units to 4, while the All vs. None estimate is positively biased by 5 units to 8. As a result the All vs. Only NDA estimate becomes 4 (=8-4), which makes it biased by 2 units, which is lower than bias in the All vs. None coefficient (5). This finding holds true as long as there is some upward bias in the Only NDA vs. None comparison (assuming again that Only NDA will be less biased upward than All). No bias in the All vs. No NDA comparison is differenced out when the Only NDA vs. None actually estimates the causal effect.

Define $G(b^*)$ as the cumulative distribution of b^*. Then $p_{none} = G(b^*_{none})$, $p_{nda} = G(b^*_{nda}) - G(b^*_{none})$ and $p_{All} = 1 - G(b^*_{nda})$. When we simulate this distribution we define the thresholds b^*_{nda} and b^*_{none} by requiring the overall distribution of bundles to match distribution observed in the data, thereby fixing p_{none}, p_{All}, and p_{NDA} at their sample levels.

The second stage data generating process is $y = 1 - 4All - NDA + 5w + \epsilon$ where $\epsilon \sim N(0,1)$. However, since we cannot observe w the model we actually estimate is $y = \alpha_0 + \alpha_1 All + \alpha_2 NDA + e$. Note that we are assuming that the "All" bundle has a stronger negative effect than the "Only NDA" bundle, but that the omitted variable is going to bias estimates of $\widehat{\alpha_1}$ and $\widehat{\alpha_2}$ upward because $cov(w, All) \geq 0$, $cov(w, NDA) \geq 0$, and $cov(w, y) \geq 0$.

Since we are holding fixed the proportion in each bundle,[26] the only way to vary the extent of selection on unobservables across these bundles is to vary the extent to which b^* is driven by changes in w versus changes in u. Intuitively, when variation in u explains all the variation in b^* then the bundle choice is effectively random and our estimates will be unbiased since $cov(w, All) = cov(w, NDA) = 0$. However, when variation in w explains all the variation in b^* then the bundling choice is driven entirely by unobservables and our estimates will be seriously biased. The key result, however, is that even in the face of pure selection on unobservables, our differencing approach will mitigate the bias from omitted variables to at least some extent. Moreover, when the result flips signs as a result of this differencing framework it is because the treatment effect has now overpowered the selection effect.

We simulate this data generation process 100 times, drawing 1000 observations each time, and then repeat the process varying the variance of u such that the proportion of variance in b^* explained by variance in w is {0%, 33%, 66%, 100%}. Figure B1 displays the estimates of our three comparisons (All vs. None, Only NDA vs. None, and All vs. Only NDA) while Figure B2 shows the bias for the three separate comparisons (i.e., comparing the estimate to the true causal effect),

[26] That is, $cov(All, w)$ is not independent of p_{All} because $cov(All, w) = (E[w|All = 1] - E[w|All = 0])p_{all}(1 - p_{all})$ by definition.

for varying degrees of selection on unobservables. The top row of Figures B1 and B2 show that when choices are effectively random, we recover unbiased causal effects on average. However, when bundle choices are driven entirely by unobserved factors (in the bottom row), we can see that the "All vs. None" estimate is the most biased (with these parameters we estimate a coefficient of 7, on average, which is 11 units more than the true causal effect), while the Only NDA vs. None estimate is less biased (upward by 6 units), and the least biased estimate is All vs. Only NDA (biased upwards by 5 units). Indeed, Figure B2 shows that for all levels of selection on unobservables, the All vs. Only NDA comparison is the least biased of these comparisons.

In addition, Figure B1 highlights a second key result related to sign switching which derives from the fact that selection causes upward bias in these estimates when in fact the causal effects are negative. When selection on unobservables is sufficiently strong, even though the treatment effects of All and Only NDA are negative, the selection effect overwhelms the treatment effect such that the resulting estimates (including All vs. Only NDA) are all positive. We see this in Figure B1 when the variance of the latent term explained by the omitted variable is 66% or higher. In contrast, when there is no selection, then all estimates are negative and unbiased. However, for moderate amounts of selection, even though the All vs. None and Only NDA vs. None comparisons are both biased upwards to the point where they are positive, because the All vs. Only NDA differences out *additional* selection the All vs. Only NDA comparison can be negative. This is what we see in Figure B1 when the proportion of variance explained by the omitted variable is 33%. From an econometric perspective, in these moderate ranges of selection, the treatment effect is becoming sufficiently strong relative to the selection effect such that the sign reverses. This finding is important because it is precisely what we find in the case of individual wages, which suggests that the true effect of All vs. Only NDA and All vs. None is even lower than the 3% lower wages we estimate (since there is still positive selection remaining).

Figure B1. Estimates from varying selection on unobservables

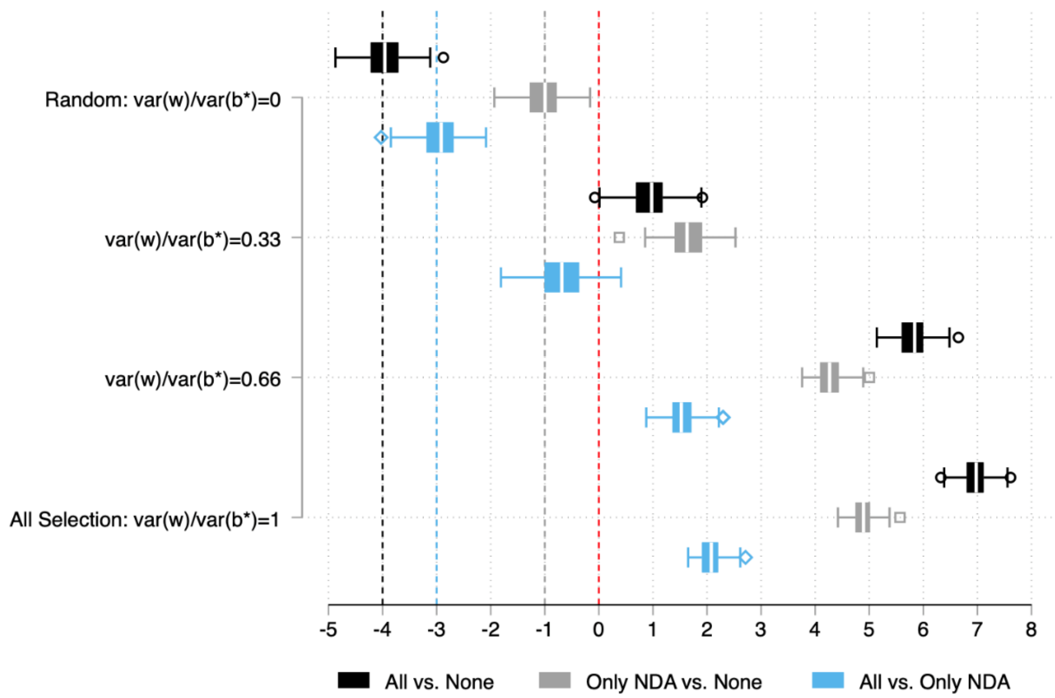

Figure B2. Difference in bias from three comparisons under selection on unobservables