

Working paper series

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February 2023

<https://equitablegrowth.org/working-papers/new-evidence-on-employee-noncompete-no-poach-and-no-hire-agreements-in-the-franchise-sector/>

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New Evidence on Employee Noncompete, No Poach, and No Hire Agreements in the Franchise Sector

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February 16, 2023

Abstract

This paper presents new evidence about the prevalence, source, scope, content, and variety of anti-competitive behavior in the labor market. Drawing from a text corpus of 17,785 franchise disclosure filings, I find that 26% of filings from January 2011-August 2022 contained an employee noncompete clause that requires franchisees to bar employees from working for a competitor after leaving. Further, 44% contained a non-solicitation clause barring recruitment between firms, and 25% contain a no hire clause. Using new open-source, replicable methods to classify unstructured text, this paper also publicly releases: a document corpus, the software used to analyze the data, a knowledge base of rules to detect anti-competitive clauses, and an open-source machine learning classifier to detect no poach clauses. While prior evidence on anti-competitive practices largely draws from individual complaints, survey data, and limited hand-coded samples, this paper spotlights a large and representative sample of previously hidden inter-firm contracts that block employee mobility and describes tools that can automatically identify future unseen instances.

Keywords: Noncompete, non-solicitation, computational text analysis

JEL Classification: J08, J23, J41, J42, J47, J53, J62, and J63

¹ Loyola University Chicago, Quinlan School of Business, pnorlander@luc.edu. Comments are welcome. I am grateful for support from the Economic Security Project Anti-Monopoly Fund; Loyola Rule of Law Institute; Loyola Quinlan School of Business; and Loyola University Chicago. I thank: Patricia Tabarani, Chloe Clark, Kayleigh Currier, Zach Nelson, and Damian Orozco for research assistance; Laura Zbella, Angelica Vaca, and Denise DuVernay for research support; Kate Bahn, Michael Lipsitz, Ioana Marinescu, Eric Posner, Todd Sorensen, Evan Starr, Spencer Weber Waller, and David Weil for feedback on this work in progress and seminar participants at the 86th Midwest Economic Association Annual Meeting. All errors are mine. Under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License, CRAML software is at https://github.com/sjmeis/CRAML_Beta/, and the replication materials for the no poach analysis at <https://zenodo.org/record/7454758>. PDFs uploaded to DocumentCloud are available. The cleaned text and complete repository are embargoed.

Employers sometimes seek to bind workers to their current job by limiting their outside options. This may occur via agreements with other firms. For example, no poach clauses between two or more firms prevent one firm from proactively recruiting another's workers. No hire clauses bar one firm from employing another's current workers. In contrast, noncompete clauses are employer contracts with workers that bar the worker from taking a job at a competitor, either during or after their employment at the firm. No poach, no hire, and noncompete agreements are sometimes contrary to federal or state antitrust law. Recent efforts to end anti-competitive practices include the January 5, 2023 Federal Trade Commission's proposed rule to eliminate noncompete agreements imposed by firms on their employees.²

Considering the current proposal and debate over these clauses, this paper addresses a problem of knowledge: how do workers, citizens, and regulators learn about employer practices? This paper argues that regulators and scholars have been limited up to now in their ability to describe anti-competitive practices by a *streetlight effect*: looking where light already shines. For example, the noncompete clauses the FTC cites and would outlaw are sourced from individuals' public complaints: news reports, legal settlements, and court decisions. Harder to access sources of anti-competitive practices remain in the shadows: employer handbooks and individual employee contracts, and memoranda, e-mails, or contracts between firms.

This paper presents significant new information about the types of anti-competitive clauses found in inter-firm contracts in the franchise domain, including the first description of the widespread use of no hire clauses and noncompete clauses. Discoveries regarding no poach, no hire, and noncompete clauses in the franchise sector are drawn from a representative pool of 17,785 disclosure filings in the public domain. I find that 7,812 franchise filings (44%) had a suspected no

² See <https://www.ftc.gov/news-events/news/press-releases/2023/01/ftc-proposes-rule-ban-noncompete-clauses-which-hurt-workers-harm-competition>

poach clause. I describe these anti-competitive clauses with greater detail than prior hand-coded samples. There are 4,382 (25%) filings with a suspected “no hire” statement barring franchisees from hiring workers that have not been previously described in this context or at scale. These clauses effectively construct a noncompetition covenant between firms that the FTC rule might outlaw (but are not illustrated with examples in the proposed rule). In addition, 4,616 (26%) franchise filings had language that approves of or requires franchisee use of employee noncompete clauses. For both no poach and noncompete agreements, distinguishing the “naked” clauses with no limitations on their use from the “dressed” clauses that are limited with respect to “jurisdiction”, “narrow” application to subsets of employees, or statements about “limitations” on their enforceability against employees provides further definition to the concept of anti-competitive practices in labor markets. The analysis identifies 1,343 naked noncompetes and 3,994 naked no poach clauses, and a variety of other restrictive language around training repayment, liquidated damages for recruiting workers, post-term and during-term covenants not to compete, and trade secrets / confidential information that has previously not been illustrated.

Mining the mass of franchise disclosure text also yields new and significant information about the content and changes in the use anti-competitive language from January 2011 – August 2022. Following the 2017 release of a watershed 2017 working paper (published as Krueger and Ashenfelter 2022; hereafter referred to as KA) that revealed the use of no poach (also known as non-solicitation pacts) in franchise contracts, regulators in Washington state and elsewhere initiated efforts to ban the use of no poach clauses on low-wage workers. The percent of filings that contain suspected naked no poach clauses declined sharply after 2017, but continues into the present: from more than 25% in 2017 to under 10% in 2022. While a wave of firms abandoned their use of no poach clauses, regulatory actions have not eliminated anti-competitive practices. Because the Washington State addendum states that noncompetition covenants for workers earning over

\$100,000 are permissible, the appearance of language supporting the use of noncompetes for a narrow subset of workers actually increased from under 20% in 2017 to nearly 50% of all filings in 2022. Other language that “narrows” to a particular group of workers and sets a “jurisdiction” limit on the scope of a noncompete or no poach clause has also increased. Like a hydra, it is possible that regulatory focus on only one type of anti-competitive clause may give rise to other gradations or varieties of anti-competitive clause. Despite strong academic and public interest and regulatory actions, the details of this analysis suggest that there were thousands more no poach and noncompete clauses than previously understood, in a variety of anti-competitive language that was not previously understood and has not been illustrated, and that suspect naked no poach and noncompete agreements remain in effect in the franchise sector in full public view.

This paper represents recent advances in research methodology that may interest scholars in economics, management, and law who seek to conduct analysis of big data drawn from text. I build and release a knowledge base of rules to classify anti-competitive clauses and construct an open-source machine learning model to detect no poach clauses in any of the 151,708 documents contained within the 17,785 franchise disclosure filings. Applied researchers increasingly draw from the unstructured text of a large collection of documents (a “corpus”), but rely on third-parties, proprietary methods, proprietary data, and computational methods with major limitations (Meisenbacher and Norlander 2022). This is done at the peril of good science: many methods for building proprietary datasets from text involve trade secrets, and because access to the underlying text is difficult to access, and classification schemes are not transparent, results cannot be verified. This paper demonstrates the benefits of transparent, replicable, open-source data and methods for the analysis of unstructured text. The open-source knowledge tools described here can be used to exactly match and automatically detect a variety of anti-competitive clauses in the future and in contexts beyond franchise documents.

Section 2 of this paper motivates the analysis by describing the role of information in the operation of and search for anti-competitive practices, highlighting the need to look at inter-firm relationships and contract documents. Section 3 briefly summarizes the data and empirical framework. Section 4 describes the variety of anti-competitive clauses found. Section 5 illustrates time trends and compares machine learning results to rules-based results and KA's results. Section 6 discusses and Section 7 concludes. Appendix A provides methodological detail.

2. The Role of Information in Anti-Competitive Practices in the Labor Market

Early economic theory suggested a tendency of employers toward collusion in the labor market, that such actions harmed workers' wages and opportunities, and that anti-competitive conduct is often hidden from market participants (Smith 1776). The hidden nature of anti-competitive conduct is important: employees may find it demoralizing to learn their employer is a party to such a conspiracy, and today, employers may be exposed to liability for engaging in such conduct, necessitating secrecy. Even so, Adam Smith describes anti-competitive practices as a "sort of tacit, but constant and uniform combination" that "[w]e seldom hear of because it is the usual, and one may say, it is the natural state of things, which nobody ever hears of" (qtd. In Krueger and Ashenfelter, 2022). Today, anti-competitive practices are also ordinary business practices – clauses that are anti-competitive in intent or in effect can be found in trainings on "how to write an employee handbook" training programs, for example. As this section shows, information plays a vital role in the enforcement and operation of anti-competitive practices. Such practices are memorialized and enforced via secret inter-firm e-mails or documents, or buried in masses of text available in the public domain, and while noncompete agreements are witnessed by employees who sign them, the text of these has previously been unobserved at scale.

The suggestion that research and policy have been subject to streetlight effects focused on the individual agreements as opposed to the inter-firm linkages is no way diminishes the conclusion that anti-competitive practices harm worker wages and opportunities. Significant evidence has already accumulated (see, e.g.: Garmaise 2011; Johnson, Lavetti, and Lipsitz 2020; Lipsitz and Starr 2021; Starr, Prescott and Bishara 2021; Rothstein and Starr 2021; Kini, Williams, and Yin 2021; Callaci et. al 2022; Balasubramanian et al. 2022). The theory of imperfect competition in labor markets (Robinson 1933) provides a general framework for these research findings, and for Smith’s insight that anti-competitive practices harm workers. Search and hiring frictions impair the flow of information that is essential to a well-functioning market (Burdett and Mortensen 1998; Manning 2003). A growing literature in economics uses models of imperfect competition to study the effects on wages of factors that limit labor market competition; for example, employer concentration also decreases wages (Azar et al. 2022; Benmelech, Bergman, and Kim 2022; Rinz 2022; Hershbein and Macaluso 2018; Gibbons et al. 2019; Qiu and Sojourner 2019; Kim and Pei 2022). Recent meta-analysis confirms that inter-firm employee mobility raises wages and that firms often have significant market (or monopsony) power (Sokolova and Sorensen 2021). For entry into the literature in economics, a recent special issue of the *Journal of Human Resources* is dedicated to the issue of labor market competition (Ashenfelter, Card, Farber, and Ransom 2022).

Anti-competitive practices aggravate information asymmetries in the labor market that make it difficult for workers to quit. This paper uses the term “anti-competitive clauses” to refer to “no poach,” “no hire,” and “noncompete” clauses that place downward pressure on wages through restricting employees’ opportunities in the labor market.³ “No poach” clauses are inter-firm

³ KA use the term “non-competitive clauses” to refer exclusively to “no poach” clauses. While my definition is broader than KA and intended to capture language that has as its primary purpose a restraint on employee mobility, it is narrower than the possible scope of all language that is anti-competitive in effect. As discussed in the FTC proposed rule, non-disclosure, training repayment, liquidated damages, no client solicitation, no business, and trade secret / confidential information language may also restrict labor market competition.

agreements not to solicit, recruit, and sometimes hire another firm's employees. "No hire" clauses are inter-firm agreements not to hire another firm's employees. Conversely, noncompete contracts between a firm and its workers ban the worker from joining a competitor during their term of employment or post-employment. While data is difficult to obtain, 18% of American workers believe that a noncompete they signed is currently in effect with respect to their current employer, and 38% report that they signed one at some point in their career (Starr, Prescott, and Bishara 2021). No poach clauses are typically kept secret from workers, by contrast, so no individual survey data can speak to their prevalence – for this reason, they are thought to affect fewer workers than noncompetes, and have received less attention.⁴ The literature and discussion of non-solicitation and noncompete clauses is often separated, but they are each a part of a broader class of anti-competitive practices in the labor market.

No poach agreements in the franchise sector were not widely known to exist by the research and policy community until the release of KA as a working paper in 2017. KA report that 58% of their sample of 156 large franchises contained a no poach clause in the year 2016. KA do not describe other types of anti-competitive practices in the franchise documents. In the franchise sector, only the largest and most visible franchises have been studied given the amount of effort and time hand-coding takes – 156 (KA) or 530 franchises (Callaci et. al 2022). In seeking representative evidence of noncompetes, only individual survey data has been used as an attempt to measure the prevalence of such contractual clauses (Starr, Prescott, and Bishara 2021). Even though entire written contracts containing explicit and possibly unlawful anti-competitive practices are available

⁴ For example, in recent reports on anti-competitive behavior in the labor market, simple word counts show that "no poach" appears 17 times in a U.S. Treasury Department report, compared to 87 times for "noncompete" while noncompete appears 187 times in a briefing from the Economic Innovation Group report compared to 30 for no-poach clauses (Starr 2019). For Treasury's report, see: https://home.treasury.gov/system/files/226/Non_Compete_Contracts_Economic_Effects_and_Policy_Implications_MAR2016.pdf

online for any member of the public to read, the sheer volume of documents compounds the problem of knowledge. No person could sift through hundreds of thousands of documents and no existing system for creating data from text could assist a researcher or regulator in rapidly identifying anti-competitive language. Despite advances in computational methods for text analysis, Larsen and Bong (2016) describe the technical challenge of detecting legal or other constructs in messy and large volumes of text as a “herculean task.”

In addition to knowing what clauses exist in the economy, knowing what is or is not legal, even under the FTC’s proposed rule, is challenging given that they are subject to different legal enforcement regimes and courts have yet to rule in many areas. For example, noncompete agreements are subject to a variety of state laws and because no direct federal law governs their use, noncompete agreements are often lawful.⁵ Generally state laws acknowledge employers may have reasonable or legitimate interests in protecting trade secrets, intellectual property, commercial / client relationships, recovering training costs, etc. Even as regulators have made attempts to address their use, “basic questions regarding the use and consequences of noncompetes remain either entirely unanswered or unsettled” (Bishara and Starr 2017). No poach clauses should be more clearly unlawful, but are not. Conspiracies between firms not to compete are generally illegal under The Sherman Antitrust Act of 1890, which states that: “Every contract, combination in the form of trust or otherwise, or conspiracy, in restraint of trade or commerce among the several States, or with foreign nations, is declared to be illegal.” Antitrust law applies to both labor and product markets and bans collusion by either buyers or sellers, but has been unevenly applied and failed to defend workers’ rights to quit a job and move freely to other firms hiring in the labor market (Posner 2021).

⁵ For this reason, there is understood to be significant heterogeneity in their use and enforceability across states. California bans the enforcement of noncompetes against employees completely, for example. See Malsberger (2022) and Bishara (2010) for greater detail.

No poach clauses are enforceable and lawful in certain circumstances – a court may deem them to be reasonable in cases such as a vertical relationship between firms. However, court cases and decisions about what is lawful or not become public only when individuals complain in court, and mandatory arbitration clauses that prohibit employees from seeking relief in a public court can also limit the information available about anti-competitive practices. Therefore, the publication of KA as a working paper in 2017 was a true watershed moment that catalyzed regulatory actions against no poach clauses under state antitrust laws. After KA’s publication, eleven state attorneys general issued a letter demanding the practice end.⁶ Many franchisors voluntarily ended the practice, and the State of Washington in 2018 first negotiated settlements with franchise companies in which many removed their no poach clauses.⁷

Even when such clauses are unenforceable due to state or federal law, anti-competitive clauses reduce employees’ job search and employer hiring through another problem of knowledge: *ad terrorem* effects – even unjustified fears that a firm will sue an individual ex-employee or a competitor firm for hiring the ex-employee reduces hiring (Starr, Prescott and Bishara 2020). Ambiguity and the threat of legal entanglement depresses workers’ wages, limits outside opportunities, and has multiple implications. In seeking to avert potentially financially crippling lawsuits, employees covered by a noncompete may refrain from starting new firms or seeking employment from competing firms (Lipsitz and Tremblay 2021). Inaccurate information about the extent and content of anti-competitive clauses impairs the ability of citizens, workers, and regulators to make wise economic decisions, and can lead to suboptimal uses of economic resources.

⁶ See <https://attorneysgeneral.org/wp-content/uploads/2019/02/2018.07.09-No-Poach-Agreements-Letter-Redacted.pdf>

⁷ As Ashenfelter wrote in the published epilogue to KA: “it is instructive that the mere revelation of collusive agreements, whether legal or not, has so quickly provoked a strong response from both the antitrust authorities and the franchisors whose agreements contained these no-poach clauses.”

State and federal regulators have taken significant steps in recent years to uncover and end the operation of anti-competitive practices in the labor market, but the number of cases to illustrate the problem of anti-competitive practices is limited. Again, mandatory arbitration clauses may move the cases to a non-public venue, and in certain cases, franchisors may require that franchisee employees sign mandatory arbitration clauses. The Department of Justice and the Federal Trade Commission in October 2016 issued guidance to Human Resource (HR) professionals announcing that naked no-poach agreements between labor market competitors violate antitrust law and that “allegations” would be investigated.⁸ In October 2016, a Council of Economic Advisors report offered a cohesive agenda to combat employer monopsony power.⁹ The Biden administration has placed a focus on competitive markets as vital to supporting workers’ freedom to quit.¹⁰ The FTC’s proposed rule to ban noncompete agreements is the strongest step taken yet. The plaintiff-side antitrust bar has taken few labor cases, and enforcement agencies may be reluctant to pursue cases in federal courts perceived as hostile to worker claims (Posner 2021). The FTC’s rule is likely to be subject to challenges and scrutiny in the courts.

In 2010, the Department of Justice uncovered and stopped a ring of no poach agreements between six major high-tech employers in Silicon Valley, a case which illustrates how limiting information about job opportunities injures a broad class of workers. The DOJ chose not to pursue criminal or civil penalties, and in exchange the companies agreed to drop their no poach agreements, but several employees at affected firms filed a class action lawsuit on behalf of all technical employees at these companies (*Haribaran v. Adobe Systems Inc., District Court, ND California, 2011*).

Expert testimony by Professor Edward Leamer estimated damages to Silicon Valley workers at over

⁸ See <https://www.justice.gov/atr/file/903511/download>

⁹ See https://obamawhitehouse.archives.gov/sites/default/files/page/files/20161025_monopsony_labor_mrkt_cea.pdf

¹⁰ See <https://www.whitehouse.gov/briefing-room/presidential-actions/2021/07/09/executive-order-on-promoting-competition-in-the-american-economy/>

\$1 billion. In seeking to quash the class action complaint, lawyers and economic experts for the defense argued that a class action requires all members of the class suffer damages. In ruling that the class action suit could go forward, the Court quoted heavily from an instructive lesson in UCLA Professor Edward E. Leamer's testimony on information economics:¹¹

Dr. Leamer hypothesized that, by restricting cold calling and other competition over employees, Defendants' anti-solicitation agreements impaired information flow about compensation and job offers. Defendants' inhibition of employees' ability to discover and obtain the competitive value of their services meant employees were afforded fewer opportunities to increase their salaries by moving between firms and deprived of information that could have been used to negotiate higher wages and benefits within a firm. In addition, by limiting the information available to employees, Defendants could avoid taking affirmative steps, such as offering their employees financial rewards and other forms of profit sharing, to retain employees with valuable firm-specific skills.

The class-action lawsuit settled for just over \$300 million and shed light on the strategic value, secretive operation, and mutual enforcement by multiple firms to enact anti-competitive conspiracies. For this reason, some materials revealed in discovery during the trial are instructive: in personal e-mail communications, Apple's CEO Steve Jobs threatened the Palm CEO with unrelated patent litigation for not joining the illegal conspiracy. When an Apple employee was poached, Jobs made "another irate phone call" to Google executive and co-founder Sergey Brin and warned Brin in writing that "if you hire a single one of these people that means war." Jobs also contacted Google Executive Chairman Eric Schmidt, who wanted to make a "public example" by swiftly firing a Google recruiter who had contacted an Apple employee about Google job opportunities. Schmidt wanted other Google participants in the conspiracy to enforce the agreement verbally "since I don't want to create a paper trail we can later be sued over?"¹²

¹¹ In *Hariharan v. Adobe Systems Inc.*, see: ORDER RE: DEFENDANTS' MOTIONS REGARDING DR. LEAMER AND DEFENDANTS' JOINT MOTION FOR SUMMARY JUDGMENT BASED ON MOTION TO EXCLUDE TESTIMONY OF DR. LEAMER

¹² The documents containing these quotations were covered in the press. See, e.g., <https://www.businessinsider.com/apple-google-recruitment-emails-lawsuit-2014-1>.

The first criminal indictments for no poach agreements brought by the Department of Justice were announced in early 2021 against a ring of companies offering dialysis treatment. In April 2022, a not guilty verdict was returned for the former CEO of DaVita Healthcare (*USA v. Davita Inc., Kent Thiry, U.S. District Court for Colorado, No 21-cr-00229-RBJ*). Some of the limitations of antitrust law as a tool to go after labor market concentration may be attributable to a shortage of plaintiff side lawyers who are expert and aggressive in pursuing the niche of antitrust and employment law cases, or a perception or reality that courts and juries might not convict (Posner 2021). There are signs that the plaintiffs' bar is paying attention: a class action lawsuit against DaVita went forward in September 2022 (*Outpatient Medical Center Employee Antitrust Litigation, U.S. District Court for the Northern District of Illinois, No. 1:21-cv-00305*), and there is additional litigation against other conspirators.

Perhaps the most significant barrier to antitrust enforcement has been a lack of information. The *streetlight effect* refers to the problem of searching for answers where the light is already shining. For the FTC's proposed rule, the resulting selection bias in the available anti-competitive language could lead to an inaccurate description of the source, scope, content, and variety of noncompetes and other anti-competitive language.¹³ In addition to promulgating rules, agencies such as the FTC, the Department of Justice, and the Washington and other state attorneys general can take specific cases only if aware of them. Information has so far come from individuals' complaints and limited samples of documents that are hand-coded only in part, but as the following section describes, inter-firm relationships are also important to consider when examining anti-competitive practices.

¹³ While illustrative, the FTC's documentation of noncompetes it would outlaw is not exhaustive in addressing a variety of clauses. The FTC rule does not illustrate the variety of other anti-competitive clauses, or state when their scope or content falls within or outside of the law. In particular, on pages 10-11, the FTC Rule discusses other provisions (without illustrative examples) including non-disclosure, non-solicitation, no hire, training repayment, no-business, and liquidated damages provisions, and states that: "[t]hese other types of restrictive employment covenants can sometimes be so broad in scope that they serve as de facto non-compete clauses." Regarding the source of noncompetes, the FTC ban would bar all firms from forcing individual workers to sign a noncompete, but the inter-firm agreements that are a source of noncompetes as discussed in this paper are not addressed directly by the rule.

2.a. Firm Boundaries and Anti-Competitive Practices

Restrictions on employee mobility are not only employer impositions on individual workers' freedom. They are also business-to-business agreements that are mutually agreed to, or they are imposed by a more powerful business on other businesses as a contractual condition of being a supplier or franchisee within a powerful firms' network. With the rise of networks of inter-firm relationships, no poach clauses can represent "vertical restraints" where independent firms have a supplier-buyer relationship, for example, or more legally suspect "horizontal restraints" on competition between firms that should be competitors in the labor market. Rising inter-firm inequality contributes to wage inequality (Song et al. 2018), and inter-firm power dynamics may influence the employment opportunities of workers throughout a network of firms. A network of firms that does not compete in the labor market has the same anti-competitive effects in the labor market as an individual employee noncompete. Either anti-competitive practice can distort the economic calculations in a firm's "make" vs. "buy" question central to outsourcing, franchising, and other business model decisions (Weil 2014). The extent and nature of firm boundaries are therefore important considerations for labor economists and labor market regulators evaluating anti-competitive practices.

Since 1980, employment has steadily moved outside of the scope of the vertically integrated firm, in part as a response to the rise of investor emphasis on firm core competencies (Applebaum and Batt 2014). The "fissuring" of the workplace implicates a network of inter-firm ties in the governance of the employment relationship (Weil 2014). Wages, working conditions, and the incidence of underpayment and wage theft may be substantially worse in franchisee or subcontractor firms compared to leading firms (Dube and Kaplan 2010; Ji and Weil 2015; DeVaro and Norlander 2021). Business models such as franchising, outsourcing, and gig work facilitate the movement of

the employment relationship outside of the leading firms and into a network of smaller firms. Sometimes, firms operating in these business models skirt antitrust laws to obtain the benefits of stable employment relationships, or skirt employment laws to avoid employee-employer relationships or joint employer liabilities.¹⁴ Anti-competitive practices may entrench these quasi-market or network structures of inter-firm relationships, protect incumbents, and prevent the growth of firms and vertical integration where it makes economic sense by making it difficult for more efficient firms to access a key input to production (labor).

These business models can separate workers from employment opportunities at firms that capture and generate much of the value in a service or production process, a phenomena referred to as the fissured workplace (Weil 2014). Historically, large, vertically integrated firms are a significant mechanism for structuring work and promoting economic and societal welfare (Chandler 1977). Through the employer-employee relationship, large bureaucratic firms can generate higher levels of efficiency through the promotion of firm-specific human capital investments, curbs on arbitrary management power, and contribute to macroeconomic stability through rationalization and stabilization of individuals' employment and income (Jacoby 2004). From a strategic management perspective, employees with rare and valuable skills who have long-term commitments are a resource that can contribute to sustainable competitive advantage for firms (Barney and Wright 1998). Transaction costs in the labor market may entrench market-like or network structures of inter-firm relationships and block vertical integration, even where it makes economic sense and where it would benefit workers by absorbing them in more efficient firms.

¹⁴ While avoiding employer responsibilities, even gig companies like Uber have found advantage from employment-like control over work process (Norlander, Jukic, Varma, and Nestorov 2021). While simultaneously claiming it does not exercise control over drivers and that they are independent business owners, Uber had also threatened to sue to block the City of Chicago from releasing lists of transportation network drivers that the City licenses, claiming that the list of city-issued licenses is their “closely guarded trade secret” whose release “would cause competitive harm specifically by allowing their competitors to target and ‘poach’ their drivers” (Eidelson 2019).

To zoom very far out on the question of how inter-firm relationships relate to anti-competitive practices in the labor market, Simon (1991) proposed that a Martian with a special pair of binoculars that illustrate economic activity would see nearly all transactions occurring within firms, with only sparse inter-firm exchanges. If a Martian who observed the economy in 1991 returned today, they might see more inter-firm transactions. However, if it is common for a dominant firm to exercise power over its suppliers' or franchisees' employment practices, and if no-poach clauses are widespread in these relationships, then our economic binoculars need to be refocused to clearly see the operational infrastructure behind the demise of the vertically integrated organizations and the operation of the markets or networks in question. There are scant descriptive facts about the existence of anti-competitive language in inter-firm contracts throughout the fissured workplace due to lack of access and methods for analysis of documents.

3. Empirical Framework

Obtaining accurate descriptive information for economic analysis from unstructured text is a non-trivial labor and a research methods contribution. In Appendix A, I describe the application of a novel method for building datasets for quantitative research from unstructured text in this context. While the method requires human labor, the result is tabular quantitative data indicating the existence of a particular concept, built either by the exact rules the user specifies, or a machine learning model trained according to data created by the rules. These rules and machine learning tools form a knowledge base that can be used to detect future, unseen instances. Compared to the alternative approaches to acquiring data from unstructured text, Context Rule Assisted Machine Learning (CRAML) returns results with high recall and accuracy in a transparent and replicable manner (Meisenbacher and Norlander 2022). CRAML is also accessible to lower-resource users, requiring only a desktop computer. While the process requires human intervention, significant

portions of the process are automated and enable a researcher to rapidly find their “needle” in any “haystack” of text.

For the data used in this paper, anyone can rerun the analysis and achieve the same result, or modify the rules according to their own ontological conceptions and achieve a different result. As part of the contribution of this work, and to enable replication and alternative interpretation, the replication materials include extracted data needed for the analysis here, the manually coded inputs that create the structured, labeled data output, the rules that create the training data for machine learning and that produce the rules-based classifications, and the training data ML classifier to detect suspect no poach clauses are stored on a Zenodo repository (see: <https://zenodo.org/record/7454758>). The software pipeline to complete the analysis from these replication files is Context Rule Assisted Machine Learning (CRAML) (see https://github.com/sjmeis/CRAML_Beta/). Appendix A provides additional description of the use of these computational tools in this context, and for a lengthier technical paper on computational methods for analyzing unstructured text, see Meisenbacher and Norlander (2022). Additionally, PDFs are now hosted on DocumentCloud, where they are text-searchable and available with stable links for inspection.¹⁵ The machine-readable text of all franchise documents studied here will be released to a repository upon publication.

Data and Descriptive Statistics

A corpus of Franchise Disclosure Documents (FDDs) from the California Department of Financial Protection and Innovation and the Minnesota Department of Commerce was built by scraping PDF documents from the public websites of these agencies. These records exclude companies that may be exempt from filing. Missing observations are due to PDF to text

¹⁵ Some PDFs could not be uploaded but could be analyzed locally due to different processing techniques and acceptable file format variations.

transcription errors, file corruptions, and scraping errors. Because these errors are related to computing errors, and occur mostly due to random timeout errors, the filings obtained are a representative sample of franchise filings. Each company filing contains one or more PDF attachments – exhibits, cover letters, disclosure documents, and ephemera – and with no a priori knowledge of which if any of those documents might contain anti-competitive language, each PDF is converted to plain text files that are linked to record-level metadata. The record contains the unique ID that the state assigns to multiple documents from a franchise on a particular date. Each document within a filing is traceable to a record with metadata that includes the name of the franchise, and the date of the filing (548 records out of 17785 are missing metadata due to processing errors while acquiring the data).

For pre-processing, Python's Tika performed an initial conversion to plain text, and ABBYY Fine Reader was used on difficult PDFs. The text is minimally cleaned – for example, text is converted to lower case, stripped of punctuations, common abbreviations are converted to words, and numbers are removed to enable human and computational reading across pagination. For California, 151,708 documents in 6.99 GB of cleaned machine-readable text that can be traced back to a total of 13,625 franchise records. For Minnesota, 5,493 documents in 1.64 GB of cleaned text that can be traced back to 4,201 franchise records were obtained. Due to incomplete data, I drop records before 2011, and focus on 17,785 records from January 2011- August 2022. Appendix Table 1 presents detailed year-by-tag count data, showing exactly how many documents each year contain combinations of tags. Figures below illustrate trends from 2013 onward, as California data is available only post 2013. First, however, I describe the variety of anti-competitive language seen and an effort to build a useful taxonomy and knowledge base.

4. The Language and the Law

Anti-competitive clauses come in a greater variety than has been previously described. Given the common effects of anti-competitive clauses, economic analysts may be less interested in fine-grained distinctions and definitions for anti-competitive clauses found in franchise contracts. Even so, there are many opportunities for further study suggested by the detail presented here. Regulators and lawyers may appreciate precision where much hinges upon whether or not a specific anti-competitive clause is “reasonable” – one may want to consider the application of a clause for a particular subset of employees, for example. This section offers definitions of terms used in the empirical analysis, provides examples of each term, and attempts to link each definition to the relevant legal distinctions.

A “naked no poach clause” is a pact between two firms that bans each from soliciting or recruiting worker of the other firm. While most no poach clauses are drafted to cover employees, some may also cover other workers such as independent contractors. A “naked no hire” clause restrains one firm from hiring or employing the workers of another firm. This is stronger than a “naked no-poach” as those prohibit solicitation, but an employee who applies to a job at the other firm unsolicited may still be hired under the language of the naked no poach clause. Naked no poach clauses are distinct from the dressed-up or “narrow no poach” clauses and “narrow no hire” clauses that apply only to soliciting or hiring certain employees, such as managers, those with proprietary or trade secret information, those who receive training, and those earning over a minimum salary amount. Because dressed-up clauses narrow application to a subset of workers, they are weaker than naked clauses.

Anti-competitive clauses also include “noncompete clauses” that bar workers from working for a competitor firm. These can also be naked or dressed to limit the scope. One limitation on no poach and noncompete clauses is their enforceability in certain jurisdictions. For this reason, I define “jurisdiction no poach clauses” and “jurisdiction noncompete clauses.” Table 1 presents a

summary of these anti-competitive clauses with examples drawn from the franchise corpus. Table 1 also introduces pro-competitive “yes poach” and “yes compete” clauses that state that these anti-competitive clauses cannot be enforced against workers and that workers are free to join any firm. I added both “yes poach” and “yes compete” clauses to a broader “limitations” tag highlighting all clauses that place limitations on the use of noncompete and no poach agreements. These come into existence in the corpus largely in the aftermath of KA and are related to regulatory efforts to enable worker mobility. While the Washington State Addendum includes “yes poach” and “yes compete” language, it also explicitly states that noncompete agreements for workers earning above \$100,000 are enforceable, so I include such statements when tracking limited, narrow, and jurisdictional noncompete clauses.

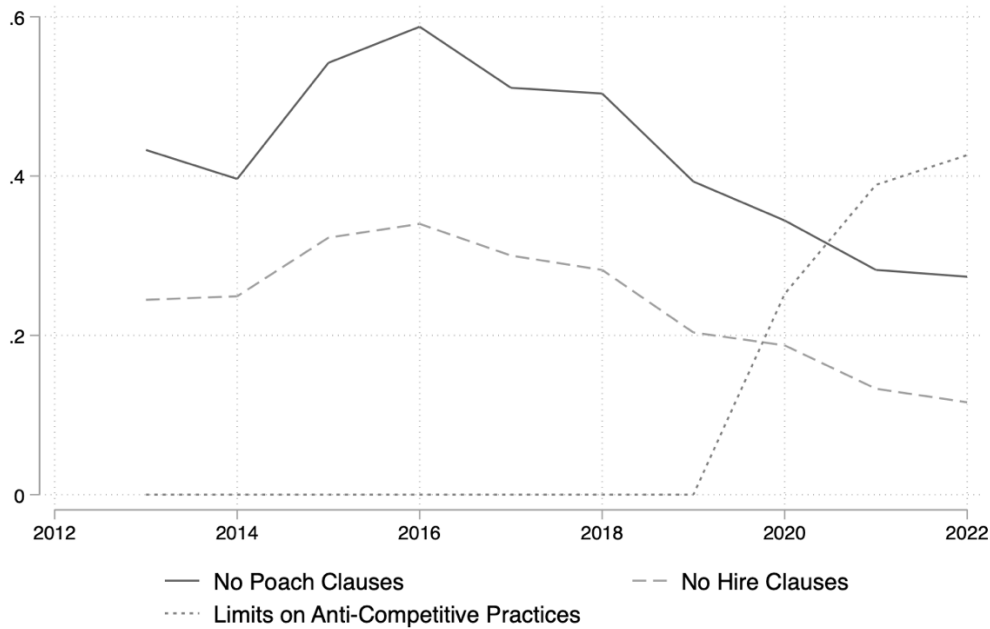
Table 1. The Variety of Anti-Competitive and Related Language in Franchise Documents

Clause	Example
“Naked No Poach”	“...you may not seek to employ or retain any employee or independent contractor who is at any time employed by us....”
“No Hire”	“... party shall not hire or solicit to hire any person employed then or within the preceding year by the other party....”
“Naked noncompete”	“...each of your employees must sign a non disclosure confidentiality and noncompetition agreement...” “...if franchisee has any reason to believe that any employee has violated the provisions of the confidentiality and noncompetition agreement...”
“Narrow clause”	“... managerial employees must sign the non competition ...” “... employees receiving training from us to execute non disclosure and non solicitation”... “...require your managers and supervisory personnel and other employees receiving training from us must execute covenants not to compete...” “... requiring employees who will have access to our confidential information to sign employment agreements containing non disclosure and non competition provisions...”
“Jurisdiction clause”	“... not affect the enforceability of the covenants not to compete in other jurisdictions... ”
“Yes Poach”	“... not restrict restrain or prohibit a franchisee from soliciting or hiring any employee....”
“Yes Compete”	“... covenant is void and unenforceable against an employee....”

5. Trends in Use of Anti-Competitive Language

Using the context rules alone, Figure 1 displays the percent of all suspected no poach, no hire, and limitations clauses within each year for each record filed from years 2013-2022 (with partial data for 2022). It illustrates that in 2016 over 60% of the records had “no poach” clauses and over 30% had “no hire” clauses, after which there was a decline. Beginning in 2019, “yes poach” and “yes compete” clauses that state limitations or bans on the use of anti-competitive practices increased from 0% to being included in over 40% of franchise documents. Interventions that followed the publication of KA decreased the prevalence of anti-competitive language in franchise documents.

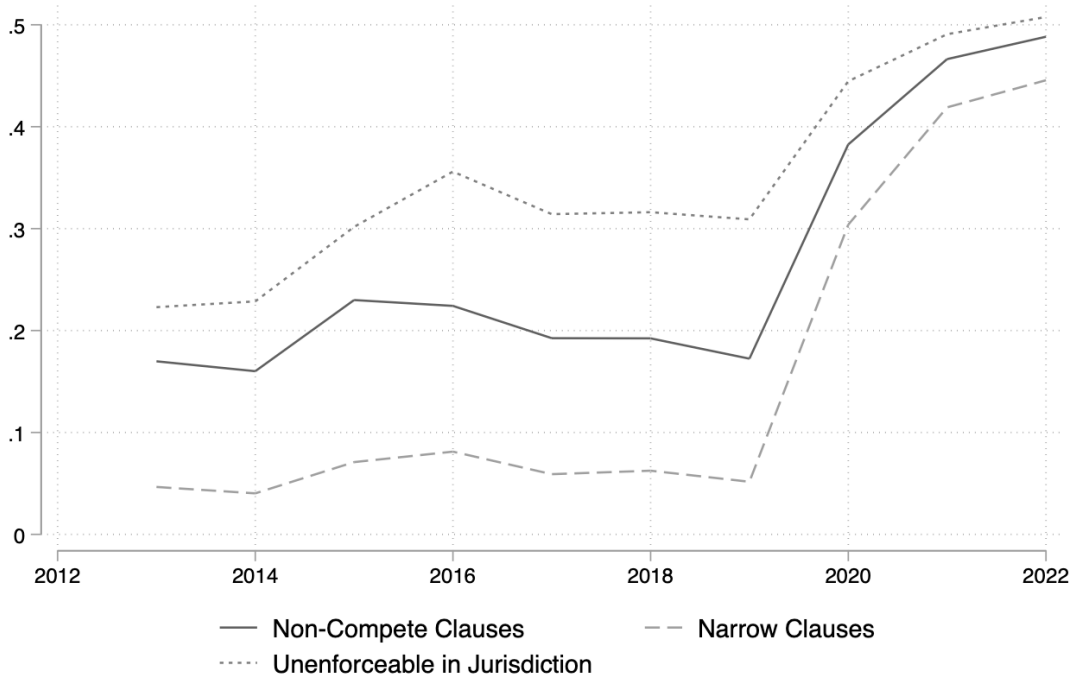
Figure 1. The Decline of No Poach Clauses and the Rise in Limitations on their Use



KA do not discuss noncompete clauses in franchise documents. The use of noncompetes increased since 2017. To reiterate, as the State of Washington Addendum includes a statement to the effect that noncompetes above \$100,000 are enforceable, this text within the Washington Addendum is treated like other anti-competitive clauses found in the text. This growth in noncompetes appears alongside growth in limitations placed on the use of no poach and noncompete clauses that appear in the Washington Addendum, as well as narrowing and

jurisdictional clauses. Figure 2 illustrates the growing appearance of noncompete, narrow, and jurisdictional clauses in the corpus since 2017.

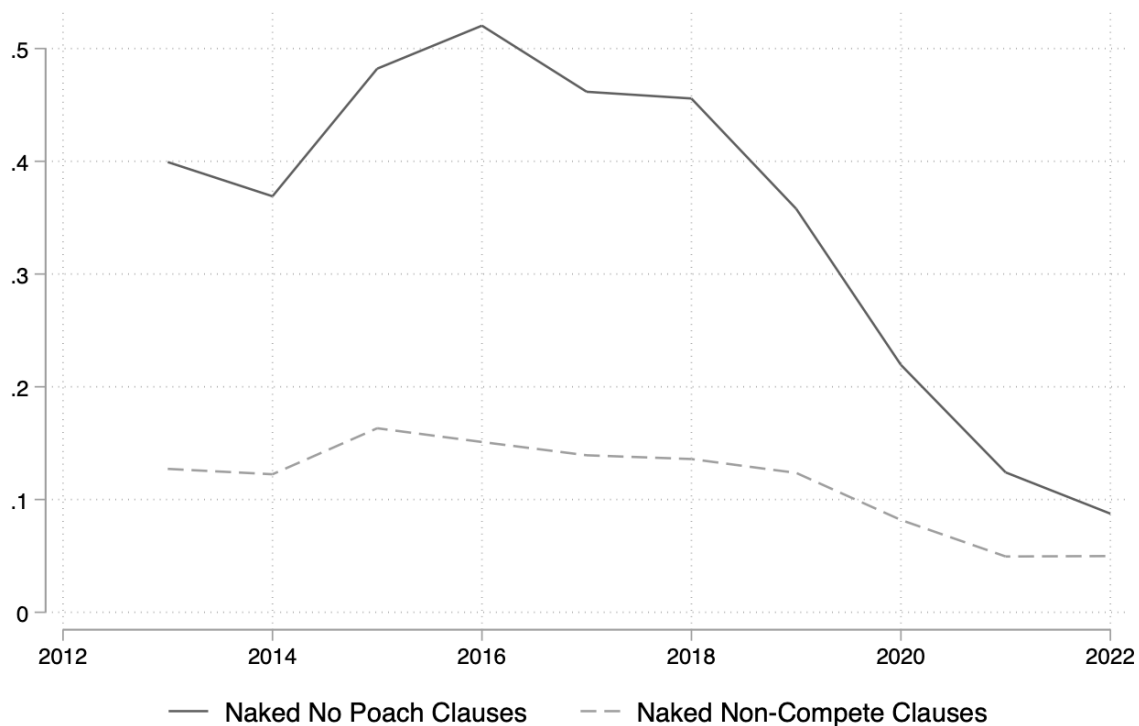
Figure 2. The Rise of Noncompete Clauses, Narrow, and Jurisdiction Clauses



Tags can be combined to create new variables that better correspond to complex constructs defined above. The appearance of noncompete clause language may be of lesser concern post-2017, as the noncompete language is accompanied by a limitation statement to the effect that the noncompete cannot be enforced against employees earning below a certain amount. For example, while Figure 1 showed a decline from over 60% to below 40% no poach clauses following 2017, a linear combination of tags provides trends for “naked” noncompetes and “naked” no poach agreements that apply broadly to all employees. These are noncompete and no poach clauses without limitations, jurisdictional language, or narrowing to a subset of employees. Figure 3 shows that naked no poach clauses declined from over 50% before 2017 to approximately 10% in 2022, and that the use of naked noncompete agreements has gradually declined since a peak in 2015. Post-

2017 regulatory actions have decreased the use of naked no poach and noncompete clauses. While the use of naked no poach clauses has declined sharply, these clauses continue into the present, and may be of particular interest to regulators as they are most likely to be run afoul of antitrust law.

Figure 3. The Near Extinction of the Naked No Poach and Noncompete Clause



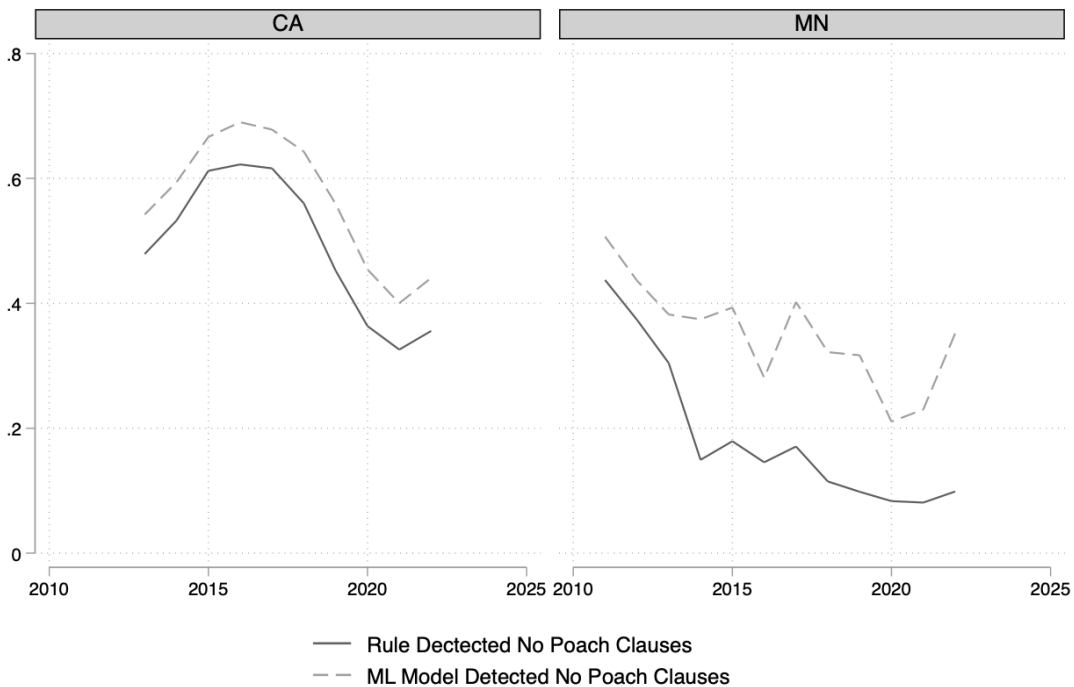
5.a. Machine Learning, Accuracy, and Transparency

The above analysis is based upon exact rule matching only. The rules that produce the results are available as replication materials and can be used to exactly replicate the above using CRAML software, or could be adjusted if another definition of the relevant text is desirable. A machine learning model to detect no poach clauses was also trained on the extracted data from the California corpus and used to identify suspect no poach clauses in the California and the Minnesota corpus. The above analysis is based upon the most recent download of the corpus from the web and is current through August 2022; the below analysis including machine learning results is based upon

a smaller subset 15,587 records obtained prior to the latest download. Figure 4 shows that the machine learning model detects more no poach clauses than the rule-based detection, and the Minnesota and California corpus have substantial differences but overall similar patterns.

The “no poach” classifier is built with training data from a 10% sample plus all the *no poach* tag== 1 observations in the full sample. This type of manual augmentation to training data was done because there are otherwise too few observations in the training data where *no poach* ==1. Using conventional statistics in machine learning to judge the model, the resulting model accuracy score is 0.99, precision of 0.97, recall of 0.96, and an overall F1-Score of 0.97 (the harmonic mean of precision and recall). These statistics are based upon a comparison between the ML output and the training dataset drawn from the rules. These statistics suggest a high level of accuracy and recall between the training dataset and results.

Figure 4: Suspect No Poach Clauses: Comparison of Method and State



Model performance statistics above are at the “chunk” level – a 13 word string of text containing a keyword. The record or filing of a franchise is a perhaps more relevant to an applied researcher or regulator. At the record level, the no poach classifier closely matches the rule-generated results with respect to accuracy, but ML results suggest more records require inspection (recall) than suggested by rules alone. Comparing machine learning and rules-based classification in this context requires further investigation. If the rules-based results are taken to be perfect, Table 2 demonstrates that precision of the ML model is high at the record level: 0.899 (7736 / 8607), where precision is the number of true positives (6,823+913) out of true positive plus false positives (672+199). Accuracy, or the true positives (6,823+913) divided by the true positives and false negatives (22+54), is very high: 0.99.

Table 2. Rules versus Machine Learning Model Classification

		Rules-Based Classification			
		<i>California</i>		<i>Minnesota</i>	
		<i>Nopoach ==0</i>	<i>Nopoach ==1</i>	<i>Nopoach ==0</i>	<i>Nopoach ==1</i>
<i>ML-Based Classification</i>	<i>Nopoach ==0</i>	5,405	22	1,499	54
	<i>Nopoach ==1</i>	672	6,823	199	913

5.b. Comparison to Hand-Coded KA Results

It would be ideal to compare results between CRAML and the analysis in KA that was based upon a manual inspection of records by experts at FRANdata. However, KA is non-replicable because the text data used are not available. KA do report in an appendix a list of large franchise companies that in 2016 filings did or did not contain no poach clauses. Based upon this list, I compare their results to the results I was able to obtain and match for 103 companies. Companies may be missing from the text corpus analyzed here because the data was not obtainable online, and filings for the year 2016 may also be missing. In Table 3, I compare whether a firm had a no poach

clause in 2016 according to KA to whether a firm ever had a no poach clause according to the rules-based and the ML based classification from CRAML.

Table 3. Firm-Level Comparison of KA Result to Rule-Based and ML Model from CRAML

		KA Results	
		<i>Nopoach</i> ==0	<i>Nopoach</i> ==1
CRAML Results		39	64
<i>ML-Based Classification</i>	<i>Nopoach</i> ==0	31	8
	<i>Nopoach</i> ==1	8	56
<i>Rules-Based Classification</i>	<i>Nopoach</i> ==0	33	16
	<i>Nopoach</i> ==1	6	48

If KA results are taken to be true, then rules-based classification has precision of 0.88 and recall of 0.75, and ML classification has precision of 0.875 and recall of 0.875. ML results may be preferred given their higher recall: given the PDF to text process, and extremely messy text, the machine learning results may have picked up additional no poach clauses that exact matches do not – a speck of dust on a scanner could confuse Optical Character Recognition software and render the exact match wrong, but the predictive ML model right.¹⁶ Unfortunately, without access to the KA data or greater detail on the classification scheme used to detect no poach clauses in that paper, this tells us little about the accuracy of KA or the rules-based and ML based results from CRAML.

However, because CRAML’s rule-based classification returns the exact chunk matched to a specific rule that assigns a value of 1, it is possible to demonstrate what triggered the assignment of a tag *nopoach* ==1 in CRAML for the subset of firms where CRAML appears to give a false positive compared to KA. Table 4 lists several examples where I believe CRAML is correctly classifying a no poach clause existing in a company that KA do not identify in their paper (suggesting possible

¹⁶ Consider the following text from an Anytime Fitness franchise document that was not classified as a no poach clause by either machine learning or exact matching: “vour ai ipie fitness center operates for the purpose of soliciting their fimplovges tq yowf anytime fitness center.” This example is chosen because KA’s data provider identified Anytime Fitness as having a no poach clause, but it was not found using computational methods used here. While ML may catch more examples that contain typographical errors, this is an example of an unseen instance unclassified by rules or ML.

recall errors in the hand-coding by FRANData). Of course, this does not mean anything in KA is incorrect. These firms may not have had a no poach clause in 2016, and so this may be a comparison of different underlying text. No determinate conclusions can be drawn about the accuracy of the KA results because the underlying text was not accessible (presumably even to the paper authors that received a cleaned dataset). No one knows the rules that determined whether the documents for KA are classified as having a no poach or not – even the expert who classified the documents would presumably have used a “I know it when I see it” rule for judging if a document has a no poach clause, and not have built a knowledge base to classify future unseen instances.

Table 4. Rule-Based Classification for Cases where CRAML Positively IDs a No Poach Clause and KA Do Not

Franchise	Excerpted Text and Rule (bolded) that Led CRAML to Assign Nopoach ==1
Great Food & Friends	<i>“...you will not solicit for employment or employ any employees of us...”</i>
Midas Intl Corp	<i>“... interference with employment relations during the term of this agreement term and for the twelve consecutive ...”</i>
Miracle Ear	<i>“...indirectly solicit or induce such person to leave his or her employment...”</i> Rule: REGEX::^(?=.*\binduce)(?=.*\bleave.*employ).*\$
Supershuttle	<i>“...will not induce or attempt to induce the franchisee employees to leave their employment with the franchisee...”</i> Rule: REGEX::^(?=.*\binduce)(?=.*\bleave.*employ).*\$

The results of CRAML are highly accurate and fully traceable to choices made in the construction of a rule set for the no poach classifier. The no poach clause identified in the Miracle Ear contract in Table 4, for example, if seen in its broader context, is a vertical restraint and possibly not unlawful. Still, for economic analysis and to understand the scope of no poach clauses, I thought it useful to maintain a broad definition of no poach rather than to further pursue a separate classification scheme that distinguished vertical and horizontal restraints. It might be desirable to build a classifier focused on identification of only the naked no poach construct, and with the data

made public in this research project and CRAML software tools, it would be possible to do so.

Users can “steer learning” and achieve almost any intra-subjectively consistent desired classification scheme by changing rule sets and thus re-shaping the training data.

6. Discussion

Streetlight effects may lead researchers and regulators to rely on only readily available examples and cleaned datasets ready for analysis, which can lead to wrong conclusions if the right information is buried in a pile of text waiting for discovery. Given the reality of the *ad terrorem* effects that any language that permits a restraint on employee mobility creates one, and the inevitability of misperception and ambiguity about what is lawful, a federal rule may be preferred over state-by-state rules. However, such rules should be thorough in describing the legality of the variety of clauses that could potentially run afoul of the law. In addition to the revelation that there are many noncompete clauses in the franchise sector, there are also many no hire clauses. Illustrative examples of other clauses found in the corpus include damages clauses, training repayment, no business agreements, client non-solicitation, and non-disclosure agreements that “can sometimes be so broad in scope that they serve as de facto non-compete clauses” (FTC, pg. 10).

The core finding that there are thousands more no poach and noncompete clauses in franchise documents and a greater variety of them than previously known suggests there is much more to understand about restraints on competition that apply to employees, as well as clauses that apply to franchise owners. It might be particularly interesting to examine non-competition clauses in contexts such as franchises that fall under an umbrella franchise group or in a particular sector (E.g., fitness, health care, home repair, child care, etc.). The FTC may also wish to promulgate additional rules for inter-firm contracts with clauses that restrain employee mobility, and/or describe narrower circumstances where trade secrets can be a legitimate reason for imposing what is effectively a non-

competition clause on a worker.¹⁷ Machine learning tools and the knowledge base of the variety of language that creates anti-competitive barriers could be particularly useful for future efforts by regulators in detecting no poach language and anti-competitive practices. Open-source and transparent ML models that detect language that creates or enforces no poach clauses could be implemented within companies as a compliance tool, for example. Such text classification models are also useful for research: a follow-up project uses the knowledge base built here to detect anti-competitive language occurring within a much larger corpus of procurement contracts from state and local governments.

7. Conclusion

The results presented in this paper should be of interest to both academics and regulators. Using a new set of “binoculars,” this paper demonstrates for the first time that inter-firm contracts impose noncompete agreements upon employees of firms inside a leading firms’ network. Further, more than just containing non-solicitation pacts between firms, these documents contain numerous “no hire” and other types of clauses that the FTC rule may deem unlawful. With subtle variations in language and no pre-existing knowledge base for how to identify these clauses, the knowledge tools described here can automate the classification of future unseen instances of anti-competitive clauses that are truly diamonds in the rough: a few sentences in hundreds of thousands of documents that contain millions of pages.

¹⁷ Trade secret law arises from the common law and protects employee rights to practice their profession, or use their general knowledge, skill, and experience in other firms. Courts, however, often misapply and misunderstand trade secret doctrine in protecting “company secrets” that rightfully belong to an employee as “skills, talents, or abilities developed by employees in their employment even though they may be developed at the expense of the employer” (jury instructions qtd. in Hrdy 2019). Non-disclosure agreements, trade secret, confidential and proprietary information clauses can effectively create a non-competition agreement that blocks employees from transferring their skills to another firm.

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Appendix Table 1. The frequency of different clauses in the franchise document corpus

No Poach	No Hire	Noncompete	Jurisdictional	Narrow	Limitations	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Total
0	0	0	0	0	0	364	84	676	585	811	441	652	645	801	597	719	413	6,788
0	0	0	1	0	0	80	23	90	58	148	104	110	102	183	101	62	24	1,085
0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	1	1	3
0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	1	2
0	0	1	0	0	0	74	24	53	26	82	36	43	29	32	29	26	8	462
0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1
0	0	1	0	1	0	6	0	17	13	23	15	8	15	14	14	23	3	151
0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	15	11	2	28
0	0	1	1	0	0	25	3	26	21	24	18	14	18	25	16	11	12	213
0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	2	1	3
0	0	1	1	1	0	3	0	3	2	3	6	9	9	15	20	12	2	84
0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	231	422	247	900
1	0	0	0	0	0	100	17	155	80	206	151	153	138	135	60	51	19	1,265
1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1
1	0	0	0	1	0	0	0	1	1	6	4	3	2	0	1	0	2	20
1	0	0	1	0	0	48	8	58	41	136	109	104	127	101	47	28	12	819
1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	3	3	0	6
1	0	0	1	1	0	0	0	0	0	1	3	0	3	0	0	1	0	8
1	0	1	0	0	0	27	6	40	24	59	26	27	26	35	11	6	3	290
1	0	1	0	1	0	6	0	6	7	23	10	7	6	7	5	0	0	77
1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	4	2	0	6

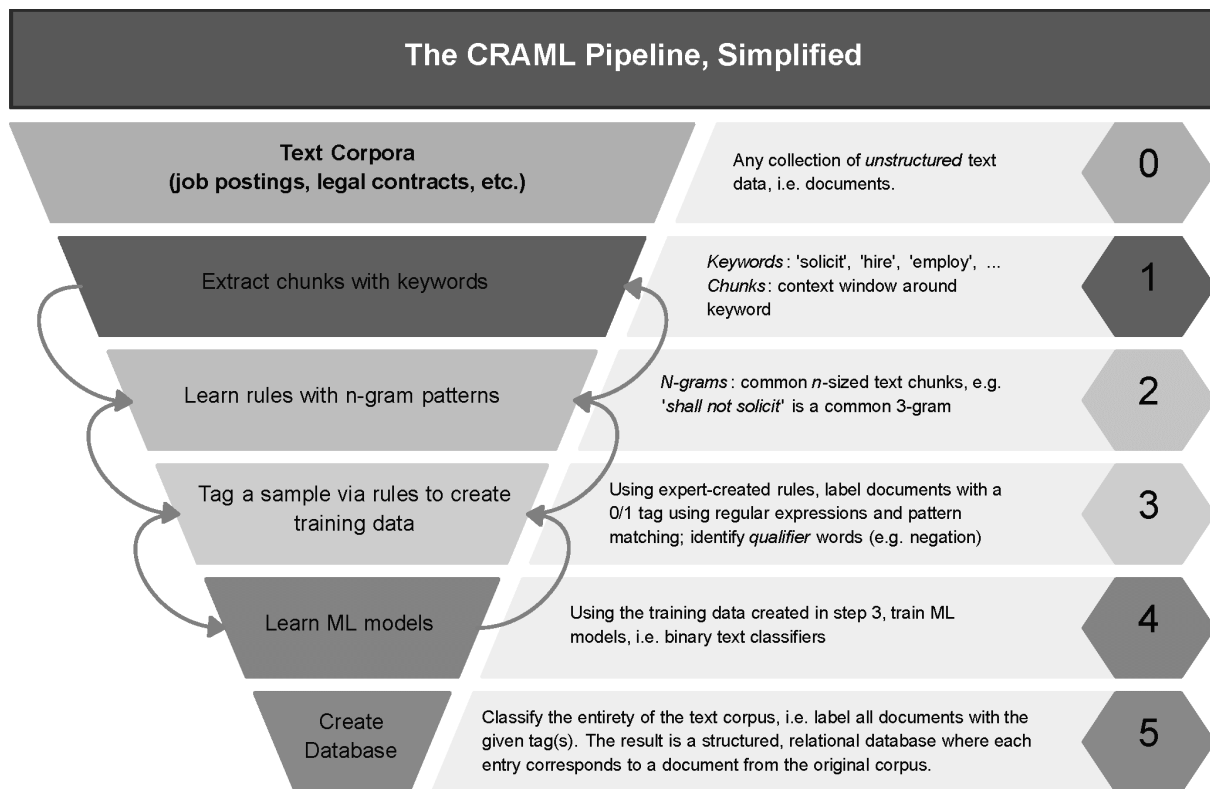
1	0	1	1	0	0	15	4	23	15	70	57	51	47	44	24	16	7	373
1	0	1	1	1	0	4	0	4	4	22	12	15	16	12	12	9	3	113
1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	78	151	109	338
1	1	0	0	0	0	108	19	187	133	325	203	208	183	131	82	50	18	1,647
1	1	0	0	1	0	2	0	4	2	2	3	3	3	3	4	2	3	31
1	1	0	1	0	0	61	13	94	81	199	146	143	126	103	69	40	9	1,084
1	1	0	1	1	0	0	0	1	0	1	2	4	2	2	0	0	1	13
1	1	1	0	0	0	22	6	26	24	83	48	51	59	43	30	18	11	421
1	1	1	0	1	0	8	2	20	6	44	31	17	21	17	13	5	2	186
1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	2	1	0	3
1	1	1	1	0	0	24	5	26	33	71	42	52	45	39	15	10	7	369
1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	2	0	0	2
1	1	1	1	1	0	4	0	15	12	44	36	35	26	21	19	9	5	226
1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	57	104	58	219
Total						981	214	1,525	1,168	2,383	1,503	1,709	1,648	1,763	1,563	1,797	983	17,237

Note: 548 records dropped due to missing year in the metadata. No hire clauses are similar to no poach agreements but include no hire language. Jurisdictional language restricts applicability of clauses in California, Washington, etc. Narrow language restricts no poach or noncompete clauses to a subset of employees. Limitations are language that requires a franchisor not restrict or prohibit a franchisee from soliciting or hiring OR bans noncompetes.

Appendix A - Methods

Figure 1 illustrates the pipeline of tools in CRAML. Step 0 begins with a researcher acquiring a text corpus. While metadata is not required in CRAML and pseudo-metadata can be created for a collection of text documents, good metadata is invaluable as the result of CRAML is to merge newly created classifiers with the original metadata and produce a document or record-level dataset for further analyses.

Figure 1. The CRAML process.



Step 1 reduces the volume of text and narrows the scope of the potential analysis for the user. An user selects keywords and a context window of *n* words or sentences surrounding each keyword to extract from the corpus. CRAML takes as input a keywords.json file and extracts keyword-containing chunks of text from the corpus, saving the result in a CSV file. Extraction can take place for the entire corpus, or a sub-sample. Each keyword is a set of words belonging to a tag, which is a label that the user wants to place on each chunk of text. Each project in CRAML can

involve multiple tags in a tag set. Step 1 and all steps in CRAML are necessarily iterative: the user manipulates tags and keywords and studies the extracted results until satisfied that all the plausibly relevant text is contained in the CSV.

Listing 1 displays the *keywords.json* file for the no poach project. Any text containing an exact match with a keyword is extracted, so, for example, the keyword “employ” extracts all the following text variants: “employee”, “employer”, “employment”, “unemployment”, etc.

Listing 1. Tags and keywords in keywords.json file

```
{
  "nopoach": ["solicit", "employ", " hire", "recruit", "covenant", "staff", "personnel"],
  "nopoach_nohire": ["solicit", "employ", " hire", "recruit", "covenant", "staff", "personnel"],
  "narrow_nopoach": ["solicit", "employ", " hire", "recruit", "covenant", "staff", "personnel"],
  "noncompete": ["solicit", "employ", " hire", "recruit", "covenant", "staff", "personnel", "non
    compet", "noncompet", "not compet", "not to compet" ],
  "jurisdiction": ["solicit", "employ", " hire", "recruit", "covenant", "staff", "personnel",
    "california addend", "state of washington", "north dakota", "washington state",
    "washington law", "california law", "in california", "in the state of california", "under
    california", "california provision"],
  "limitations": ["solicit", "employ", " hire", "recruit", "covenant", "staff", "personnel"]
}
```

Step 1 yields relevant and irrelevant keyword containing text within a context window. This massively reduces the volume of data and enables users to rapidly analyze the text for the relevant content. Step 2 involves using a n-gram analysis tool in CRAML to understand the patterns of text found in the extracted chunks. The n-gram tool allows the user to quickly see the most frequently appearing chunks of n length inside the extracted text. The user proceeds to write rules that are exact matches or Regular Expressions. The rules are used to classify all or a sample of the extracted text. Rules proceed in a priority level to allow over-writing over earlier rules with subsequent rules. Rules files for the analysis here are available as replication materials.

For the franchise document data, iterative exploration of keywords and adjustments to rules led to the development of a set of over 500 rules and 6 tags to classify suspect anti-competitive

clauses in the corpus. I first focused on finding all employee no poach clauses. As one rule for the no poach tag states: *“you may not seek to employ or retain any employee or independent contractor who is at any time employed by us.”* I found that many documents also contained language that went further than prohibiting an employer from soliciting another party's employee, but also prohibited an employer from hiring or employing. I created a separate tag these no hire clauses, as in the following example from the no hire rule set, which states that: *“party shall not hire or solicit to hire any person employed then or within the preceding year by the other party.”* As noted above, covenants not to compete or noncompete agreements are another type of restraint on employee mobility that appear sometimes in franchise documents. I created a tag for noncompete clauses.

A “naked” clause applies to all employees, and a “narrow” clause applies to a particular group of workers, such as managers, executives, sales workers, those with access to trade secrets and confidential information, or workers earning above a certain level. I create a fifth tag for “narrow” language that limits the coverage of an employee noncompete or no poach agreement. One example of a narrow tag rule is *“managerial employees must sign the non competition...”* Another narrow tag rule requires *“employees receiving training from us to execute non disclosure and non solicitation...”* Because the first requires managers, and the second requires trained employees, to sign anti-competitive agreements, these clauses are narrower than the naked clauses that apply to all workers.

I considered the language of the Washington Addendum and decided it was a narrow and jurisdictional noncompete clause, and wrote rules accordingly. This is why noncompetes appear to grow in use in franchise documents after 2017. The exact language in the addendum includes the following sentence: *“Pursuant to RCW 49.62.020, a noncompetition covenant is void and unenforceable against an employee, including an employee of a franchisee, unless the employee’s earnings from the party seeking enforcement, when annualized, exceed \$100,000 per year (an amount that will be adjusted annually for inflation).”* Because the language makes noncompetes

enforceable employees earning over \$100,000, and because it is possible later to focus only on the naked noncompetes, I thought it was appropriate to flag this, and the FTC's recent blanket ban on employee noncompetes regardless of income supports the notion that these clauses are anti-competitive in nature and deserve scrutiny, even if narrow and limited to a certain jurisdiction.

I also noted that some of the language limiting restraints upon employee mobility also forbade anti-competitive clauses. Because many franchises voluntarily ended their practice of enforcing no poach or noncompete covenants, I searched for limits to anti-competitive practices found within the text and created a "limitations" tag. One rule of the limitations tag states that a "*covenant is void and unenforceable against an employee.*" One limitations tag rule states that the franchisor must "*not restrict restrain or prohibit a franchisee from soliciting or hiring any employee.*" Some clauses state that anti-competitive clauses do not apply in certain jurisdictions, such as California, Washington, or North Dakota. I created a sixth "jurisdiction" tag to capture similar language. As one rule from this tag indicates, the purpose of such clauses is that "jurisdiction" exceptions should "*not affect the enforceability of the covenants not to compete in other jurisdictions.*"

Each tag indicates whether any part of a document contains language that fits its rules. Tags are distinct and separate: the "no poach" tag is meant to capture all no poach clauses, naked and narrow, those that do and do not apply in certain jurisdictions, and those voided in other parts of the agreement for use against employees. Later, using the tags merged back with the metadata, I create variables for analysis that best correspond to the definitions in the previous section. For example, the variable that tracks naked no poach clauses is defined as *nopoach == 1, limitations == 0, jurisdiction == 0*, and *narrow == 0*.

During Step 2, independent validation in which a third researcher hand-coded 706 chunks indicates a 91% match between an independent third party and the extrapolation of rules, suggesting a high degree of inter-rater reliability in ability to detect characteristics of no poach clauses. While

the emphasis here is to ensure that there is strong inter-rater reliability between the user and an independent observer in this test example, I do not claim perfect identification of all no poach and noncompete clauses in this paper. Instead, an emphasis is placed upon a methodological advance to describe with a high degree of accuracy and recall the contents of an entire corpus with an expert-defined scheme, and tools that ease the process by which a user can accurately classify the documents according to a schema.

Step 2 was complete when the rule sets produced results that demonstrated high inter-rater validity and I was satisfied based upon an inspection of the extrapolated results that all rules were correctly classifying all chunks within a random sample of n observations per rule. Step 3 produces a dataset of classified chunks that produced results for each rule. Step 4 uses the classified chunks based upon rule extrapolation to train a machine learning model to detect anti-competitive clauses in franchise documents. The training data uses *nopoach == 1* rules file to tag each chunk as containing a likely anti-competitive clause. I also performed an exact-match based extrapolation of rules to yield a dataset at the level of each record in the metadata. Step 5 merges the tags back with the metadata, and indicates which filings have a probabilistic (machine learning model prediction based) or rule-based exact match with various clauses related to anti-competitive behavior.