# No–Poaching Clauses in Franchise Contracts
## Anticompetitive or Efficiency Enhancing?


Francine Lafontaine[1]

Saattvic[2]

and

Margaret Slade[3 4 5]


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**Abstract**:

No–poaching clauses (NPCs) have recently come under scrutiny due to their potentially anti–competitive impact on wages. However they can also enhance efficiency. We use data from the US chain restaurant industry to assess the effect that such clauses have on wages and we find robust evidence of a negative impact. Specifically, the legal cases, proposed legislation, and negative attention surrounding NPCs, which led many chains to remove such clauses from their contracts, caused wages in those chains to rise by about 5% relative to chains that did not have NPCs. We show that the impact of removal is greater for franchisors with larger shares of the job ad market, which is a measure of the job opportunities that are denied to their employees under NPCs. We also find that the effect of the clauses on the wages of managers is not statistically different from the effect on the wages of workers. We attribute these consequences to the removal of frictions and barriers to labor mobility.



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[1] Ross School of Business, University of Michigan, and CEPR

[2] Sauder School of Business, University of British Columbia

[3] Corresponding author, m.slade@mail.ubc.ca, 6000 Iona Drive, Vancouver School of Economics, The University of British Columbia, V6T 1L4, Canada



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# 1 Introduction:

A no–poaching clause (NPC) is a restraint on employers' behavior that prevents them from hiring employees of other firms.[1] NPCs can be horizontal, in which case the agreeing employers are competitors, or they can be vertical, in which case the employers are in an upstream/downstream relationship.

To illustrate, if McDonald's and Burger King were to agree not to hire each other's workers, that agreement would be horizontal. On the other hand, if an NPC prohibiting franchisees from hiring workers employed elsewhere in the McDonald's chain were embedded in McDonald's franchise contract, it would be a vertical agreement between an upstream franchisor and its downstream franchisees. In both cases, however, although the clause restricts workers' labor market mobility, those workers are not party to the agreement and, as such, need not be aware of the restriction.

We are interested in establishing the effect that vertical NPCs have on wages. We assess wages in the chain restaurant industry, which has been an important focus of antitrust action with respect to vertical NPCs. However, since NPCs are prevalent in many other industries, such as lodging, health and fitness, tax preparation, and retail, our findings should have broader implications.

A vertical NPC is a type of vertical restraint. However, unlike most vertical restraints, such as exclusive dealing, resale price maintenance, and tying, which are discussed and analyzed in every Industrial Organization textbook and survey of vertical restraints, to our knowledge, NPCs are never mentioned in those discussions. Nevertheless, like other vertical restraints, NPCs can increase market power, albeit in labor markets, in which case they would be expected to lower wages, or they can be efficiency enhancing, in which case they could lead to higher wages.

The principal anticompetitive theory that has been relied on to argue against NPCs is traditional monopsony, which is based on the idea that NPCs reduce the number of employers or buyers. However, restaurants are numerous and the market for low wage workers is thick. We therefore do not base our anticompetitive effects analysis on traditional monopsony. Instead, we rely on the idea that NPCs increase labor market frictions, such as search and

[1] NPCs should not be confused with non–compete clauses, which are agreements between employers and employees (not other employers) that prevent employees upon leaving a firm from entering into competition with their current employer. Balasubramanian, Chang, Sakakibara, Sivadasan, and Starr (2022) and Starr, Prescott, and Bishara (2021) find evidence that noncompete clauses and their enforcement lower wages.

information costs, and limit workers' job market opportunities. In the labor literature, this has been referred to as modern or dynamic monopsony (Manning, 2021).

The principal pro–competitive justification for NPCs is that they increase efficiency by protecting firm specific worker training and increasing employee retention.

Given that the predictions of the competing theories go in opposite directions, we take them to the data. We assemble a rich data set that includes restaurant chain characteristics, franchise contracts for those chains, and online job ads posted by their restaurants. The latter data, which is the most important, comes from Burning Glass Technologies (BGT), now Lightcast.

We use these data to assess how the removal or non-enforcement of NPCs from franchise contracts affected worker wages. Starting in 2016, vertical NPCs began to attract attention.[2] In particular, employees of franchised chains filed class action suits, states' attorneys general brought civil cases against franchisors, lawmakers proposed legislation that would outlaw vertical NPCs, and academic articles analyzed the effects of NPCs.[3] Consequently, hundreds of franchisors dropped NPCs from their contracts, either voluntarily or after legal settlements. Furthermore, we expect that even those franchisors that did not drop the clauses stopped enforcing them when they realized that enforcement could trigger expensive legal action.

This setting provides us with a natural experiment to asses the effect that the elimination of the clauses had on wages. In particular, in the period prior to their abandonment, not all franchise contracts contained NPCs and many chain restaurants were operated corporately, in which case there was no contract and thus no such restraint. We make use of this difference to evaluate the time pattern of wages in the two groups: those with NPCs and those without.

In our empirical work we face a number of econometric issues that could bias our estimates of the NPC effect. First, sample selection could be a problem. Specifically, although our data consist of essentially the universe of online job ads, only a small fraction of those ads have information on wages, and that subsample might not be representative.

Second and more important, we discovered that, for a large fraction of the ads that contain wage information, that information had been estimated by third party platforms. Moreover, wage estimation began in 2018, a time that overlaps with the period when NPC

[2] Horizontal (or 'naked') NPCs were prosecuted by the US Department of Justice in the early 2010s.

[3] Notably, a draft of a paper on NPCs in franchise contracts later published by Krueger and Ashenfelter (2022) focused attention on the issue.

clauses were removed. Third party wage estimation is therefore another potential source of bias in our estimates of the wage effects of NPCs.[4]

In our empirical analyses, we first establish the effect of removal or cessation of enforcement on wages in establishments of chains that had adopted NPCs relative to chains that didn't have such a clause in the initial period. We then perform a number of robustness checks. First, we assess how a chain's ad market share – a measure of a chain's wage–setting power – changes the size of the NPC effect. In addition, we examine different sorts of clauses – those that apply to all employees and others that are limited to managers. We also assess whether, within the NPC group, franchisors that retained their NPCs differ from those that did not. Finally, we estimate separate equations for workers and managers, thus allowing for differential responses.

## 2 The Legal and Legislative Background

Broadly speaking, there are two types of antitrust violations, each involving different levels of analysis to build a prosecution case. Some violations involve conduct, like horizontal agreements among competitors to fix prices, which are believed can never enhance efficiency and are thus *per se* illegal. Prosecution for such violations proceeds criminally in the U.S., and merely requires demonstration that the alleged behavior has occurred. Other violations involve conduct, like vertical restraints, that can be anticompetitive or efficiency enhancing depending on the context. In the U.S., such violations are prosecuted under the rule of reason as civil cases that require defining a market and establishing that competitive harm has occurred in that market.

Given that horizontal agreements on prices among competitors are *per se* illegal, one might expect horizontal NPCs to be treated similarly. On the other hand, given that vertical NPCs are vertical restraints, one might expect them to be considered under the rule of reason. However, ambiguity as to their legal treatment remains, as we explain below.

[4] Hirsch and Schumacher (2004) analyze the bias that failure to include the treatment variable in earnings imputation induces.

## 2.1 Vertical Cases

In October 2016, the Department of Justice (DOJ) and Federal Trade Commission (FTC) jointly published their *Antitrust Guidance for Human Resource Professionals,* which warned that, "going forward, the DOJ intends to proceed criminally against naked wage–fixing or no–poaching agreements" and "may bring criminal, felony charges against the culpable participants in the agreement, including both individuals and companies."[5] Although that document made the government's position on horizontal NPCs clear, it offered no guidance on how to treat vertical NPCs. Nevertheless, it generated interest in and questions about the legal status of vertical clauses.

The first vertical NPC case after the Guidelines were published was a nationwide class action suit launched in February 2017, which was brought by employees against Carl's Jr.[6] Similar suits were brought against McDonald's in June 2017, and several other restaurant chains thereafter. Those cases suffered a setback in August 2021 when two courts examining suits against Jimmy John's and McDonald's ruled that nationwide employees do not constitute a class, and instead that the labor markets are local. In 2022, the U.S. District court further found that the clauses were ancillary restraints and thus legal. However, in August 2023, those decisions were reversed, thereby increasing the risk associated with enforcement of the clauses.

Although the Federal Government did not get involved with vertical NPCs for some time, many state governments did. In July 2018, the Attorney General of the State of Washington announced that it had entered into its first Assurances of Discontinuance (AODs) concerning NPCs with seven franchisors, who promised not to enforce the clauses and to remove them from their franchise contracts going forward. In the same month, the Attorneys General of ten states and the District of Columbia announced that they were investigating NPCs in franchise agreements of fast–food franchisors. Over time, hundreds of franchisors across various industries signed AODs.[7]

The Federal Government entered the debate once again when, in March 2019, the DOJ filed a Statement of Interest in the pending case of Stigar v. Dough Dough, Inc.[8] In that

[5] `https://www.justice.gov/atr/file/903511/download`, Page 4.

[6] There is at least one earlier vertical NPC case. In 1992 a restaurant manager failed to win a case on this issue against Jack–in–the–Box in a US District Court in Nevada.

[7] In particular, 237 franchisors from many industries signed AODs as a result of the Washington State initiative.

[8] Corrected Statement of Interest of the United States of America, Joseph Stigar v. Dough

Statement, it took the position that most NPCs in franchise agreements are not horizontal agreements between competitors and so should be subject to rule of reason analysis.[9]

Meanwhile, the courts have not been consistent in their treatment of vertical cases. Some judges have taken the position that conspiracies between franchisors and franchisees are impossible because the franchisor's relationship with its franchisee is akin to that of a corporation and its divisions, whereas, at the opposite extreme, others have ruled that a categorical *per se* rule can apply. Somewhere in the middle, still others have applied the rule of reason.[10] Since Statements of Interest are not legally binding, this situation is apt to persist for some time.

## 2.2 Proposed Legislation

Both federal and state lawmakers have proposed bills that would clarify the legal position of vertical NPCs by writing it into law.

The "*End Employer Collusion Act*" co–sponsored by Senators Elizabeth Warren and Corey Booker, which was introduced in the US Senate in March 2019, would make NPCs in franchise agreements *per se* illegal. A companion bill was introduced in the US House of Representatives by Representative Keith Ellison in the following month. Those bills were referred to appropriate Senate and House subcommittees, and as of this writing, no further action has been taken.

Also in 2019, a bill was introduced in the New York State legislature that would ban vertical NPCs in the franchise context. That bill was sent to the Senate Rules Committee, where it remains as of this writing.

Note that *per se* illegality contradicts the position taken by the DOJ. Moreover, those bills did not rely on empirical evidence on the effects of anti–poaching clauses on wages because there was none at the time.

Finally, in July 2021, President Biden issued a wide–ranging Executive Order on "*Promoting Competition in the American Economy"*, which signaled the Federal Government's

Dough, Inc, No. 2:18-cv-00244-SAB (ED Pa Mar 8, 2019) available at https://www.justice.gov/atr/case-document/file/1141731/dl.

[9] The Statement did, however, distinguish two scenarios where franchise agreements could still merit a *per se* standard: i) where the franchisees of the same brand agreed amongst themselves not to compete for labor and ii) where the franchisee and franchisor compete for labor in the same market. The latter could happen when the franchisor has corporate and franchised restaurants in the same labor market.

[10] For more on this issue, see Herrold and Martino (2021).

willingness to use antitrust laws to probe activities that can illegally restrict workers' wages.

The discussion above provides strong evidence that, starting in October 2016, the perceived risks to franchisors and franchisees that were associated with enforcing NPC clauses grew over time. Indeed, there was not just a one time event for each franchisor, but instead there was a sequence of many events and the information about those events was common to all parties. Furthermore, it became clear that legal cases can be extremely expensive and time consuming for franchisees, who perhaps cared most about these clauses, and franchisors. For these reasons, we model the treatment as a diffusion of information concerning the costs and benefits of enforcement.

# 3 Previous Literature

In this section, we briefly discuss two strands of the literature related to our research: traditional monopsony notions of labor market power and labor market frictions in non–concentrated markets. We then discuss research that looks at NPCs more specifically.

**Traditional Monopsony Power.**[11] A strand of this literature has focused on correlations between employer concentration and wages (for example, Azar, Marinescu, Steinbaum, and Taska (2020), Benmelech, Bergman, and Kim (2022), Lipsius (2018), Rinz (2022)).[12] A second approach is to estimate labor supply elasticities directly, often using data on job applications, not employment.[13] For example, Azar, Marinescu, and Steinbaum (2019) examine correlations between applications-based measures of supply elasticities, labor market concentration, and wages, whereas, Azar, Berry, and Marinescu (2022) estimate a structural model to assess those relationships.

Regardless of how monopsony power is estimated, much of that research provides evidence in support of traditional monopsony models. However, according to Azar, Marinescu, Steinbaum, and Taska (2020), the six digit Standard Occupational Classification (SOC) code industry that we focus on – Combined Food Preparation and Serving Workers, Including Fast

[11] We only discuss the literature dealing with the relationship between employer market power and wages. Starting with Dobbelaere and Mairesse (2013), there is also a large IO literature that assesses labor markdowns – the labor equivalent of product markups – using a production function approach. However, that literature is less closely related to our work.

[12] Some studies have relied on job application concentration – a measure based on job vacancy shares, not employment. One reason for this new measure is that it is amenable to use with very large data sets of individual job postings.

[13] As summarized in Manning (2021), there is a large labor economics literature devoted to the estimation of labor supply elasticities. Consistent with imperfect labor markets, this literature finds evidence of upward-sloping labor supply curves.

Food – is at the low end of moderately concentrated. In addition, workers involved in those activities can seek employment in related industries, leading us to expect that traditional monopsony is unlikely to be very important in our setting.

**Labor Market Frictions.** For many years search theorists recognized that, even with large numbers of buyers, their models were incompatible with standard notions of perfect competition (see for example, Burdett and Mortensen (1998) and Van den Berg and Ridder (1998)). As a result, applied researchers have also considered how frictions of various sorts might affect labor market outcomes. For example, Fox (2010) finds evidence of moderately high switching costs that inhibit skilled workers from changing employers in response to outside offers, and Card, Cardoso, Heining, and Kline (2018) show how idiosyncratic tastes for different workplaces provide a microeconomic foundation for imperfect competition in labor markets.

**NPCs.** More closely related to our paper, Naidu (2010) was, to our knowledge, the first to examine the effect of no–poaching restrictions, in this case in the agricultural labor market in the postbellum South. He finds that the restrictions lowered labor market mobility, wages, and the returns to experience for black workers. Similarly, Herrera-Caicedo, Jeffers, and Prager (2024) find evidence that horizontal no–poaching agreements reduced labor flows across participating firms, and slowed hiring and internal promotion rates.

Vertical NPCs and their potential efficiency or monopsony–enhancing effects have been the focus of an emerging, mostly empirical, literature, much of which focuses on NPCs in franchise contracts.[14] Krueger and Ashenfelter (2022) (to our knowledge, the first in this line) develop a game in which NPCs reduce the number of competitors for labor to the number of franchisors, rather than the number of franchisees, and calculate HHIs with and without NPCs. However, Levy and Tardiff (2018) criticize Krueger and Ashenfelter's assumption that NPCs convert the franchisees of a chain into a single decision–making entity and they calculate different HHIs that indicate that the reduction in competition is considerably smaller.

Two recent papers by Levy, Tardiff, Zhang, Sun, and Yamron (2020) and Callaci, Gibson, Pinto, Steinbaum, and Walsh (2024) are closest to our research. Both examine wage changes due to the removal of NPCs in franchise contracts and, whereas the first finds no effect, the

[14] Hoey, Peeters, and Principe (2021) and Battiston, Espinosa, and Liu (forthcoming) are exceptions. The former study NPCs in European soccer markets and find that they led to a very minor reduction in revenue inequality. The latter find that a temporary placement firm reduces its inefficient use of reassigning workers to different clients after a new policy allows it to prevent poaching directly.

second finds a substantial and significant increase in wages after removal.

Those two papers differ from our research in several ways. First, the data and markets are different; the former considers county-level wages for quick–service restaurant workers in Rhode Island and southwest Florida while the latter assesses wage effects across many US industries. In contrast, we focus on wages in food service chains – both fast food and seated – across the US. Second, we base our analysis on theoretical models that explain the countervailing effects that NPCs can induce. Third, we investigate how ad market share – a measure of wage setting power – contributes to the strength of the NPC effect. Fourth while Callaci, Gibson, Pinto, Steinbaum, and Walsh (2024) also use job ad data from BGT, they do not correct for the potential biases that we find are important.[15] Finally, both papers assess only the wage effects of NPC clause removals that were triggered by the Washington State Attorney General and model the removals as discrete timed events. We, however, assess removal that is due to a broader set of circumstances and model the effect of ceasing to enforce the NPC clause as a gradual process.

# 4 Pro and Anticompetitive Models of NPCs

As with most vertical restraints, the adoption of no–poaching clauses can be motivated by and have both pro and anticompetitive consequences. The academic, legal, and policy literature has focused on increased monopsony power as the principal anticompetitive motive for adoption whereas encouraging specific investment in worker training has been the principal efficiency justification. In this section we assess motives in more depth and develop models that highlight the theoretical predictions concerning the effects of NPCs on wages.

## 4.1 Monopsony Power

### 4.1.1 Monopsony and Concentration

Traditional monopsony power models rely on the notion of fewness. In particular, as the number of buyers is reduced, monopsony power tends to increase. In the context of franchising, Krueger and Ashenfelter (2022) develop a Cournot–style monopsony model that is

[15] The latest version of Callaci, Gibson, Pinto, Steinbaum, and Walsh (2024) assesses wage imputation indirectly by removing two wage posting platforms, LinkedIn and Indeed, from their data. Neither of those platforms is a large supplier of estimated wages in our data.

the buyer version of common monopoly models in the spirit of Cowling and Waterson (1976) and Dansby and Willig (1979). In that model, NPCs lead to greater monopsony power and lower wages because each worker faces fewer potential employers.

Although their model predicts that the adoption of NPCs leads to increased concentration and labor market power, in the context of chain restaurants, that increase is apt to be small. The problem is that, even in a mid–size city, the number of restaurants tends to be large. Indeed, in addition to numerous franchise chain restaurants, there are many corporate–chain and local restaurants that do not belong to a chain that compete for the same workers. Furthermore workers in restaurant chains can seek employment in related industries.

#### 4.1.2 A Broader Definition of Monopsony: Labor Market Frictions

The term monopsony power has also been applied to situations that do not involve fewness. In fact, any factor that causes labor supply to slope upwards yields some level of buyer power and results in wage markdowns.[16] A number of recent papers have broadened the definition of monopsony to include various forms of labor market frictions that limit workers' job opportunities even in unconcentrated labor markets.[17]

In 2016 the Council of Economic Advisors (CEA) issued a brief that summarizes these ideas.[18] In particular, it states that

> *. . . (L)abor market competition can be restricted even when the number of employers is large. Competition in the labor market requires that workers be able to switch employers easily in response to changes in wages or working conditions . . . (A)ny factor that limits worker mobility or makes workers reluctant to change employers – even if not the result of any intentional action on the part of the firm – can give firms some wage setting power.*

The CEA paper goes on to list potential frictions, which include the costs of acquiring and processing information about job alternatives and heterogenous preferences over job characteristics such as physical location, that endow employers with some degree of market power over workers.

In Appendix A, we develop a job search model in the spirit of McCall (1970) that demon-

[16] This is similar to the demand side where any factor that causes downward sloping demand for a firm's product allows it to charge a markup over marginal cost. Such factors include heterogeneous preferences over product characteristics (differentiated products) and imperfect information about the availability of competing products.

[17] See, for example, Hemphill and Rose (2018) for a discussion of the broader definition of monopsony.

[18] `https://obamawhitehouse.archives.gov/sites/default/files/page/files/20161025_monopsony_labor_mrkt_cea.pdf`

strates that an NPC can be such a practice. In the model, there are $N$ chains each with $n$ franchisees. All workers in the relevant labor market are endowed with a job and a wage at one of the franchised establishments. Each period, workers can choose between staying at their current job or searching for a new job and switching. If a worker chooses to search, she receives competing wage offers from all establishments and picks the highest one.

If there is no NPC at her firm, the worker chooses the highest of $nN - 1$ independent offers all drawn from the distribution of wages in this market. With an NPC at her firm, she chooses the highest of $n(N-1)$ independent draws from the same wage distribution. Because the distribution of the maximum of $nN - 1$ offers stochastically dominates the distribution of the maximum of $n(N - 1)$ offers, the threshold wage below which the worker chooses to search will be lower when her firm has an NPC. In other words, some workers will not search, and will remain at firms that pay wages that are below those that would have led them to search without the NPC. Thus average wages in the market will be lower.

There are several features of the above model that are consistent with how we believe job search works in this industry. First, buyers post wages. Second, instead of a single equilibrium wage, the model yields an equilibrium wage distribution. Third, the equilibrium is not based on the assumption that all chains in the industry adopt NPCs.[19] Indeed, as shown in Appendix A, if any firm adopts such a policy, average market wages fall and, as more firms adopt, the average wage continues to fall. Finally, the NPC's effect on wages works through worker decisions to search less frequently, i.e. the model emphasizes exactly ways in which NPCs can enhance labor market frictions.

In sum, if establishments possess market power over workers in this industry, we believe that job market frictions, such as information and search costs, and establishment specific amenities, such as location, are the most likely explanation. In particular, non–wage attributes of jobs are likely to be a higher fraction of total compensation for low wage workers.

#### 4.1.3 Collusion

The idea of overt collusion has also surfaced in the vertical NPC context. For example, in Stigar v Dough Dough, the plaintiffs alleged that hub and spoke horizontal conspiracies existed among the franchisees and franchisors. However, in a statement of interest, the DOJ argued that there were no horizontal agreements among the franchisees. Without collusion

[19] See Table 1 which shows that 80 of the 165 chains in our main data set have an NPC.

among the franchisees, the hub and spoke is a wheel without a rim. To date, no allegations of collusion have prevailed in court. Furthermore, it seems unlikely that collusion has been an important factor in an industry where a single franchisor can have thousands of franchisees – the potential colluders – and where franchisee entry and exit are frequent.

#### 4.1.4 Franchisor Incentives

Although franchisees benefit from imposing NPCs under the monopsony model, it is not clear why franchisors would favor their adoption. Indeed, after adoption, if restaurant wages fall and if labor supply is upward sloping, employment falls, which, unless workers are unproductive, causes a reduction in output. Furthermore, unless demand is inelastic, smaller output leads to decreased establishment level revenue and thus lower franchisor revenue, given that the latter is a percentage of franchisees' revenues.

We believe that franchisors adopt NPCs to increase the value of the chain by eliminating frictions among franchisees. Franchisors can expand revenue by adding establishments, which is the typical way in which they grow. When a chain is more harmonious, it is easier to recruit franchisees and hire and retain employees in those establishments.

### 4.2 Protection of Investment in Training

Whereas critics of the use of no–poaching clauses claim that they strengthen monopsony power, defenders stress traditional vertical–restraints defenses, such as the protection of specific investments. In the context of franchising, that defense can be summarized as follows.

Typically franchisees bear the cost of training new employees in their establishment and, as long as the employee stays with the establishment that provided the training, both employer and employee benefit. However, once trained, the employee can be poached. In other words, employers in the same chain can free ride on a rival franchisee's chain specific investment. This sort of poaching lowers the value of training from the employer's perspective and leads to underinvestment. A no–poaching clause can alleviate this underinvestment.

In Appendix B, we develop a dynamic model that illustrates this common free riding problem in the context of chain restaurants. The setup is a discrete–time infinite–horizon model with a free–entry zero–profit assumption. Buyers have no monopsony power.

Workers quit at a fixed rate due to, for example, graduation from high school or college, moving out of the local labor market, retirement, and so on. This means that establishments must train new hires. There are two sorts of training: the first endows the worker with skills that are transferable within the chain – chain specific investment – whereas the second is specific to the establishment.

With an NPC, a manager or franchisee can train a new employee, pay for the training up front, and amortize the cost of the training over the employee's expected job tenure.[20] This solution is efficient. However, in the absence of an NPC, the worker can be poached by a rival franchisee who does not need to reinvest in skills transferable within the chain. This reduces expected tenure in the initial job, making it difficult to amortize the initial investment. The current employer, anticipating poaching, will be unwilling to pay for training.

One solution to this problem is to have the worker pay for the training up front, which is also efficient. However, if the employee is financially constrained, this solution is infeasible.

When financial constraints pose a problem, which is apt to be the case for low wage workers, the manager can subsidize some portion, $s$, of the training costs up front, where $s = 0$ corresponds to worker pays everything up front and $s = 1$ corresponds to manager pays everything up front. In Appendix B, we show that, as $s$ moves away from zero and towards one, thereby relaxing the financial constraint, the no–poaching constraint becomes more difficult to satisfy. Furthermore, it can be impossible to satisfy both. This means that, in many cases, there will be underinvestment in training and lower wages, a problem that an NPC can help address.[21]

So far we have considered only training costs. However, high turnover is another problem for franchisors, franchisees, and their employees. The efficiency model also shows that NPCs help alleviate the turnover problem and thus reduce labor costs. Efficiency considerations could therefore be valid reasons for adopting NPCs.

# 5 Franchising and the Food Service Industry

Much of the legal attention, press coverage, and political scrutiny concerning vertical NPCs has focused on franchise contracts. Franchising is an important organizational form in the

[20] In a zero profit equilibrium, training costs must eventually be recovered, at least in expected value.
[21] We discuss the nature of training costs in the next section.

US economy. Data from the 2017 US Census documented almost 500,000 franchised chain establishments, collectively employing nearly 10 million people. In comparison, there were 11.5 million jobs in manufacturing in the US that same year. If labor market distortions can be attributed to NPCs in franchise contracts, the aggregate effect on the labor market could be substantial.

According to the 2017 Census, accommodation and food services (2-digit NAICS 72) is the largest sector in terms of both number of establishments (230,689) and employment (5,605,232) in franchised chains. Moreover it is the industry with the highest percentage of establishments that are part of franchised chains (about 36%).[22]

Franchising is an organizational form that lies between vertical integration and arm's length transactions. A franchisee is an independent businessman who makes hiring, purchasing, and training decisions. Franchisees also bear the costs of those decisions as well as all other costs that are incurred in the operations of the establishment. In business–format franchising, the type of franchising used in the restaurant industry, the franchisor supplies a business format and receives an upfront fixed fee and an ongoing portion of revenues.

Not all restaurant chains are franchises – chains can be completely corporate, in which case the company owns and operates all of its establishments. For example, Chipotle and the Cheesecake Factory are completely corporate chains. It is also possible for franchise chains to own and operate some of their establishments themselves. In practice, the fraction of corporate establishments in franchised chains tends to be low, but it also varies widely.[23] For example, Subway has no corporate establishment and only five percent of McDonald's restaurants are corporate. In contrast, Panda Express operates about 95% of its restaurants itself.[24]

The relationship between the franchisee and franchisor is governed by a franchise contract that lays out the duties of both parties as well as restrictions on the behavior of each. Most franchise contracts contain several vertical restraints, the most important being exclusive dealing. Importantly, a franchise contract is the same for all U.S. franchisees joining a franchised chain at a given point in time. Therefore, it is not possible for a chain to drop a vertical restraint in one region. Instead, if a restraint is dropped (or added), the change

[22] For a detailed discussion of franchising in the US economy, based on data from the 2007 Economic Census, see Kosová and Lafontaine (2011).

[23] See Blair and Lafontaine (2005) for more on this.

[24] When a chain has a comprehensive NPC that applies to all employees, it applies to all of its establishments regardless of governance.

applies to all new contracts nationally.[25]

There is substantial variation in NPCs across franchisors. They can restrict poaching of the franchisor's employees only, or they can apply to all employees of restaurants in the chain. They can also specify a type of worker, such as a manager, or they can apply to all types of employees. In our baseline empirical work we classify chains as treated if they had an NPC that applies to all workers – a comprehensive NPC. However, we also assess manager only clauses.

We focus on two efficiency motives for adopting NPCs: protection of investment in training and reducing employee turnover. One might think that training of restaurant workers and managers is not a major issue. However, chain restaurant employees receive both on and off the job training. The first might consist of learning about inventory and restocking policy as well as food preparation and service.[26] In addition, many managers must undergo additional training in corporate facilities. For example, McDonald's managers must attend Hamburger University, which is located in Chicago. And whereas the franchisor invests in and maintains the training facility, the franchisee pays the expenses that are related to sending employees to that facility.

More generally, high turnover, whether of trained or untrained employees, is a fundamental problem for chain restaurants. To illustrate, in 2020 annual turnover in accommodation and food services was estimated to be 130%, greater than in any other sector.[27] Furthermore, high turnover in fast food is often seen as a crisis. For example, a CNBC August 2019 headline states that 'Panera is losing nearly 100% of its workers every year as fast–food turnover crisis worsens.'[28] An NPC could be a response to both training and turnover problems.

[25] However, some state level legal constraints can be dealt with using state-specific cover pages.

[26] Friebel, Heinz, and Zubanov (2022) estimate that direct on-boarding and training costs of new cashiers in a grocery chain, a job that could be considered similar to that of a worker in a fast-food restaurant, costs 2.25 days of wages. In addition, they estimate that the disruption for incumbent workers and the time needed for a new hire to get up to speed is equivalent to about 12.5 weeks of wages, an estimate they consider conservative. See their web appendix, Section A.11.

[27] Reported in `https://www.zippia.com/advice/employee-turnover-statistics/` based on BLS data.

[28] `https://www.cnbc.com/2019/08/29/fast-food-restaurants-in-america-are-losing-100percent-of-workers-every-year.html`

# 6 The Data

We use a number of sources to compile a novel data set on the chain restaurant industry. In this section, we briefly describe our data sources and variables of interest. Details on these and on the methodology used to construct our final data set are available in Appendix C.

Our core data are US online job postings from BGT (now Lightcast), a company that scrapes a large number of sources daily to obtain essentially the universe of online job postings in several countries. Some of those postings contain wage data. For our analyses, compared to wage data for all employees, an advantage of using data on wages from job ads for new hires is that offered wages should respond quickly to changes in the labor market. In contrast, wages of the currently employed could take some time to adjust.

We limit ourselves to data between 2014 and 2019, a period that includes the series of events described in Section 2. We start in 2014 because the BGT online job postings data are too thin prior to this, and we end in 2019 in order to avoid changes to job posting behavior caused by the Covid-19 pandemic.

We supplement the job ad information with information about restaurant chains from Nation's Restaurant News (NRN), an American trade publication that covers the food service industry and provides information about the top 200 chains by US food service revenue each year. Across the period of our data, this list consists of 229 distinct chains, 161 of which are franchised. Interestingly, a few retail chains are sufficiently large in terms of their restaurant activity to be present in the ranking of top restaurant chains.[29]

We obtained information on which of the franchised chains in the listings above had NPCs before 2016 by inspecting franchise agreements, most of which we obtained from Franchimp.[30] NPCs can differ across franchisors. The most important difference for our purposes is whether the clause applies to all employees or solely to managers. With our baseline sample, we assess the difference between no clause whatsoever and a comprehensive clause that applies to all workers. We assign the 165 chains in this set to one of two groups: those that had a comprehensive NPC prior to 2016 – the 'NPC group' – and those that did not, which includes franchised chains with no NPC as well as corporate chains – the

[29] They are Barnes and Noble, Costco, Walmart, and Target. Five convenience store chains also serve prepared foods and are included in these listings, including e.g., 7-Eleven, Circle K and Stripes.

[30] The FTC requires that franchisors provide a franchise disclosure document (FDD) to potential franchisees. Franchimp has assembled a large set of such documents from states that require that these documents be filed with some agency, and it makes them available for a fee. We are grateful to Janet Bercovitz for providing us with disclosure documents in her possession.

'non–NPC group.' In our analysis of effects for managers, we also include ads from the 23 chains in our data with manager-only NPCs.

Table 1 summarizes some chain characteristics for the NPC and non-NPC groups, averaged over the period of our data. The Table shows that the two groups contain a similar number of chains, and they have similar numbers of establishments. However, in the second panel showing information for franchised chains only, we find that the franchised chains without an NPC are much larger on average than are the other franchised chains or the corporate chains.[31]

Table 1: Chain Characteristics – 2014-19 averages

| | NonNPC | NPC | Total |
|---|---|---|---|
| Total Number of Chains | 85 | 80 | 165 |
| Establishments per Chain | 860.1 | 925.6 | 891.9 |
| % of Chains Franchised | 20.0 | 100.0 | 58.8 |
| Number of Franchised Chains | 17 | 80 | 97 |
| Establishments per Franchised Chain | 3286.2 | 925.6 | 1460.0 |
| % of Establishments Franchised | 81.8 | 67.9 | 69.0 |

The BGT data include occupation codes based on the O*NET Resource Center classification as well as occupation group and job title information.[32] After eliminating ads from restaurants located outside metropolitan or micropolitan statistical areas (MSAs), where NPCs are not expected to be relevant, as well as ads outside the food and retail occupation groups, and finally removing those with missing values on variables of interest and outliers with wages above $60/hr., our data set comprises 1,705,474 individual postings for the 165 chains. We then use job titles to identify managerial positions as well as managers that operate at the district or regional level, i.e. oversee a potentially large set of restaurants.[33]

Table 2 contains the breakdown of these job postings by year. The second row of that Table shows that a very small proportion of job postings contain wage data, and that proportion varies significantly over time.[34] Notably, there is an extremely high skew towards later

[31] This is because this small set of 17 chains includes Subway, which had over 26,000 establishments, as well as 7-Eleven, Taco Bell, and other large chains. However, this group also contains some much smaller chains.

[32] O*NET is the Occupational Information Network, developed under the sponsorship of the U.S. Department of Labor.

[33] Specifically, manager jobs are defined as those whose BGT "CleanJobTitle" contains the words "manager" or "supervisor" or "director" or "lead." Regional or district managers are those manager jobs whose same title contains the words "region" or "district."

[34] As described further in the data appendix, we found that some of the available wage data in the BGT

years – 2018 and 2019 – when much higher proportions of postings include wage information.

Table 2: Sample Information: Number of Ads by Year

| Sample | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | Total |
|---|---|---|---|---|---|---|---|
| All ads | 201,317 | 204,132 | 294,449 | 263,494 | 316,162 | 425,920 | 1,705,474 |
| Wage ads | 4,929 | 4,661 | 8,702 | 9,963 | 57,693 | 128,251 | 214,199 |
| Non est. wage ads | 4,929 | 4,661 | 8,702 | 9,963 | 23,338 | 39,222 | 90,815 |

All ads is the sample of ads from establishments in our 165 chains.
Wage ads is the sample of ads with wage information.
Non est. wage ads is the sample of ads with wages that are not estimated.

Upon further investigation, we found that a number of wages were estimated by the online platforms posting the ad rather than being provided by the potential employer. We identified such estimated wages by searching the full ad text for specific statements indicating that the wages were estimated. The third row in Table 2 shows the number of ads where we ascertained that the wage was not estimated by an online platform.

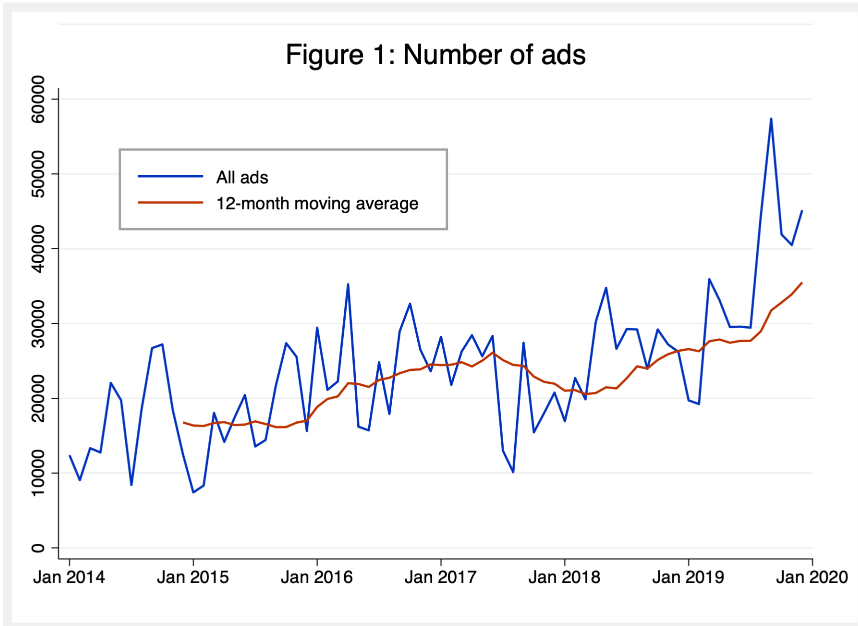
Figure 1 graphs the total number of ads, with and without wage information, posted each month in our final data set. Since employment in fast–food restaurants, and thus ads for new workers, is highly seasonal, the figure also shows a 12–month moving average of the number of postings. In contrast to the large increase in the number of ads with wage information, it is clear from the figure that no corresponding large increase or break in the total number of ads occurred between 2017 and 2018.

Figure 2 shows the fraction of ads with any wage information – the dashed line – and the fraction with non–estimated wages – the solid line. The two lines diverge dramatically in early 2018 when estimation became prevalent, which coincides with our 'removal' period.

The introduction of estimated wages by third party platforms likely accounts for the dramatic increase in ads with wage information. However, there is also an uptick in the number of ads with non-estimated wages. Sran, Vetter, and Walsh (2020) postulates that, beginning in late 2017, a spate of state bans on inquiries into job seekers' pay histories led companies to post wages in ads more often. Unfortunately, the salary history inquiry bans started at around the same time as wage estimation, making it difficult to distinguish between the two explanations. In our empirical work, we control for the state bans.[35]

CSV files were problematic. We were able to validate about 90% of the wage information using the full text of the ads. We retain the ads with non-validated wage data in our overall sample, but exclude them from the set of wages described here or used in our analyses.

[35] Data on salary history inquiry bans can be found at https://www.hrdive.com/news/salary-history-ban-states-list/516662/.



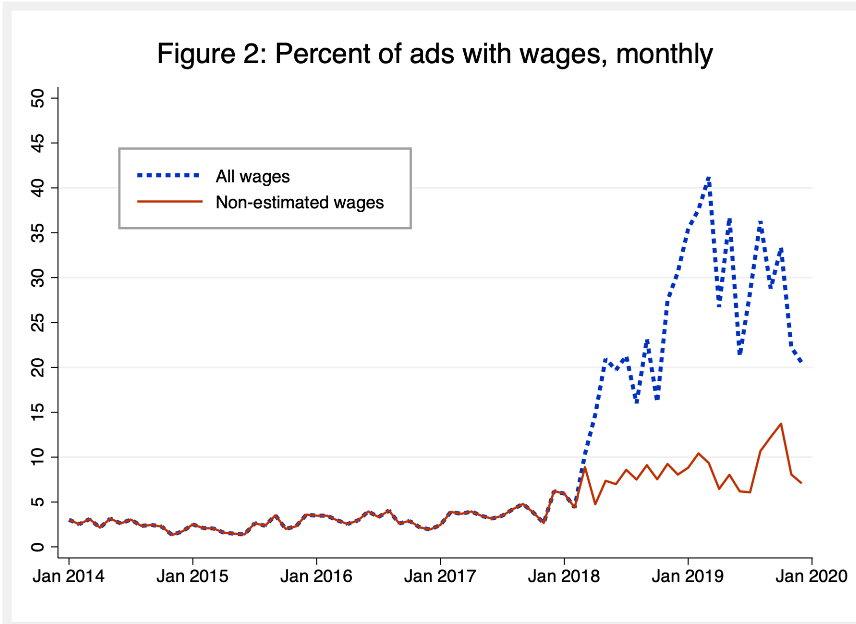

Turning to job postings characteristics, Table 3 contains the breakdown of postings between managerial, and non-managerial, or worker positions, as well as information about average wages offered for those positions. Not surprisingly, this table shows that the majority of the job ads are for workers rather than managers, and that offered wages are greater for managers. The sample of non–estimated wages has slightly lower compensation for managers, whereas for workers, the average wage is similar across the samples.

Table 3: Manager and Worker Information

| | ALL ADS | WAGE ADS | | NON EST. WAGE ADS | |
|---|---|---|---|---|---|
| Job zone | Num. Ads | Num. Ads | Mean wage | Num. Ads | Mean wage |
| 1 - Workers | 1,177,214 | 147,355 | 11.93 | 57,343 | 12.36 |
| 2 - Managers | 528,260 | 66,844 | 18.06 | 33,472 | 16.63 |

ALL ADS is the sample of ads from establishments in our 165 chains.
WAGE ADS is the sample of ads with wage information.
NON EST. WAGE ADS is the sample of ads with wages that are not estimated.
Mean wages are in current US dollars per hour.

Finally, the BGT data distinguish among various sources for the job postings. Some ads are published directly on the website of the establishment that has a vacancy. However, most are published on intermediary or third party platforms, which are websites that are used by multiple employers to advertise their job vacancies. Those sources are classified as (paid) job boards, which is the most common source, followed by free job boards. Other sources,




which are relatively small, are recruiters and intermediaries.[36]

As a prelude to more detailed analysis, we assess the evolution of average wages in the NPC group as well as the evolution of relative wage differences between the two groups. Figure 3 shows yearly average log wages for the NPC group (those chains that had a comprehensive NPC). The figure shows a smooth gradual increase in wages up to 2017. However, between 2017 and 2018, the average wage begins to increase slightly more rapidly whereas between 2018 and 2019, the increase is substantially higher.

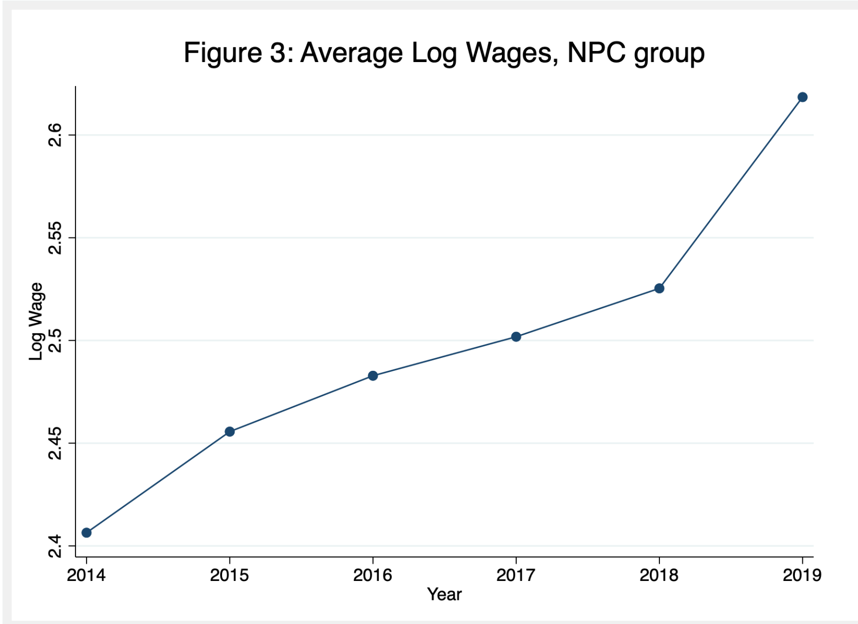
Figure 4 contains annual average differences in log wages between the two groups, non–NPC minus NPC. It is clear that the differences, despite remaining mostly positive, are reduced in the second half of the period relative to the first.

# 7 The Empirical Model

## 7.1 The Estimating Equations

Our objective is to evaluate the effect that not enforcing or removing NPCs from franchise contracts had on wages posted by restaurants in the NPC group. Our setting, however, is somewhat different from a typical event study.

[36] Recruiters work closely with employers whereas job boards simply advertise on their behalf and intermediaries are similar to recruiters but mainly work for temporary employment agencies.




First, we believe that there is no clear date when 'the event' occurred. In particular, we do not focus on the date when the clause was dropped by each chain. Instead, we believe that the ceasing to enforce NPCs, which removed a barrier to labor market mobility, is what matters and we expect that effect to be gradual. We therefore model the transition as starting in 2016 and being virtually complete by the end of 2019.

We justify our gradual approach as follows. Event studies are valid when they assess the arrival of new or unanticipated information (surprises).[37] In Section 2, we document how information flowed in this market, starting with the publication of joint DOJ/FTC Guidelines in October 2016, which was followed by the first vertical NPC no–poaching case in February 2017, and other subsequent events. We do not believe that the end result of scrutiny and legal action – the removal of a clause in a contract later on – can be seen as new or unanticipated. Indeed, after the Guidance document was published, legal professionals began to advise franchisors' HR departments on how to mitigate the risks associated with enforcing NPCs.[38]

[37] For example, with a stock market event, since the stock price takes into account all of the available information and expectations about the future, if an event is fully anticipated, the stock price should not react.

[38] The situation is summarized in an ABA 2018 article as follows. "Amidst all of these lawsuits, government actions, and mounting risks surrounding anti–poaching provisions, many franchisors are trying to determine what they should do. The answer to this question should begin with a robust assessment of the importance of these provisions to the franchise system. It appears that many franchisors have either determined that these provisions are not critical to their systems or have concluded that the time, effort, and cost of fighting to preserve their provisions simply outweigh the benefits they provide. Other franchisors may just be waiting on the sidelines while the legal challenges play out in other systems." (Forgas, , Rao, and Wall, 2018)

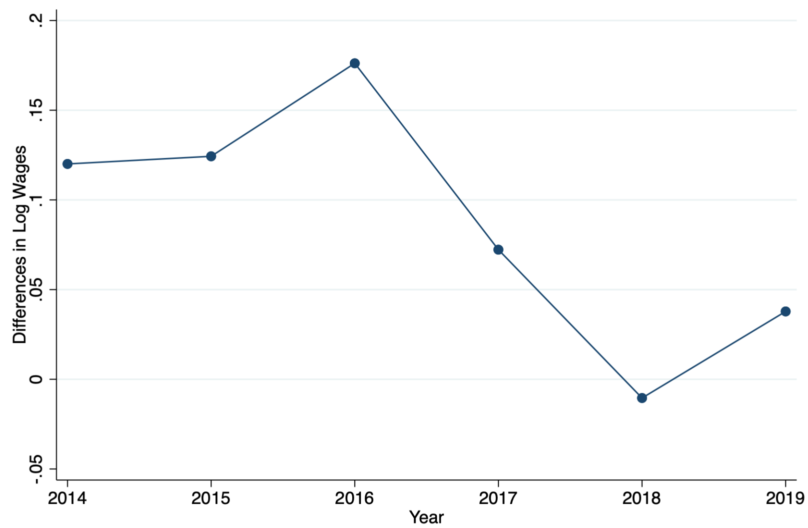


Figure 4: Differences in Log Wages, non-NPC minus NPC

A second reason why our setup is unusual is that the reason a firm ended up being treated, i.e. the adoption of an NPC, occurred before the start of our data. However, the policy that we evaluate is the removal of the treatment, which occurred during our sample period.

We have two groups of chains: those that had a comprehensive NPC for all employees – the NPC or treatment group – and those that did not have any sort of NPC clause in the initial period, which include corporate as well as non NPC franchise chains – the controls. We then compare wages in ads from chains in the two groups. Treatment is thus at the group level whereas outcomes (wages) are at the level of the individual ad.

We evaluate the difference in two ways. First, we interact the NPC dichotomous variable with year dummies for the years 2016 to 2019, which allows us to evaluate the transition period; and second, we estimate a long difference in differences (DID) model.[39]

Let $i$ denote an ad, $c$ a chain, $m$ a geographic market (MSA), $s$ a state, and $t$ a year. The transition estimating equation is

$$log(w_i) = \beta_0 + \beta_{t(i)}\mathrm{I}(t(i) \geq 2016)\mathrm{NPC}_{c(i)} + f(x_i) + \gamma_{c(i)} + \mu_{m(i)} + \delta_{t(i)\times s(i)} + u_i, \qquad (1)$$

where $w_i$ is a wage from an ad that was posted in year $t(i)$ by chain $c(i)$, $\mathrm{I}(\cdot)$ is an indicator

[39] Applications of DID usually use panel data. However, it has become common to also use the term when repeated cross section data are used, and DID commands in common software packages such as Stata are set up for both sorts of data.

function that equals one if its argument is true and zero if false, NPC is a dichotomous variable with NPC $= 1$ if the establishment that posted the wage belongs to a chain that had a comprehensive NPC and zero otherwise, $x$ is a vector of covariates such as ad characteristics, $\gamma$ is a set of chain fixed effects, $\mu$ a set of market (MSA) fixed effects, and $\delta$ a set of state/year fixed effects. We use state/year fixed effects to control for factors that vary at the state level, such as state antitrust policy and minimum wages. This formulation allows the effect of the removal of NPCs to be different in each year between 2016 and 2019.

The disturbance $u$ captures measurement error in the wage. In particular, some ads post a range of wages and, when this occurs, we set $w$ equal to the mean.[40] However, the wage that is received is likely to differ from the mean. Furthermore, posted and received wages can differ even when a single wage is posted.

The long DID estimating equation is

$$log(w_i) = \beta_0 + \beta \mathrm{I}(t(i) = 2018 \text{ or } 2019)\mathrm{NPC}_{c(i)} + f(x_i) + \gamma_{c(i)} + \mu_{m(i)} + \delta_{t(i)\times s(i)} + u_i. \quad (2)$$

This version omits ads posted in the years 2016 and 2017 and compares the 'before' period (2014, 2015) to the 'after' period (2018, 2019). The remaining variables are as in (1).

# 8 Estimation

A number of econometric issues surface when estimating the wage equations, the most important of which are potential biases from third party wage estimation and sample selection. With both potential biases, in addition to performing standard tests of significance, we compare coefficients with and without a bias correction to determine if, in addition to being statistically significant, the correction is economically important.

## 8.1 Estimated Wage Bias

When employers do not supply a wage in an ad, intermediaries can estimate wages for them. We do not know how the intermediaries estimate wages. For example, they could use

[40] Marinescu and Wolthoff (2020) show that their results are robust to alternative (to using the mean) ways of dealing with wage ranges.

machine learning,[41] a hot deck procedure,[42] or a regression. However, the exact method is unimportant for our purposes. Any method must estimate a wage for an ad with no wage as a function of the information that they can gather, which can be past data on wages and ad, employer, and market characteristics. To the extent intermediaries do not condition on whether the restaurant chain associated with the ad had an NPC, the resulting estimate would not capture the effect of ceasing to enforce or removal.

The issue of wage estimation is particularly important with our data due to its prevalence and timing. We address this problem by excluding ads with estimated wages from our sample (see Appendix C). For comparison purposes, the first specifications of our wage equations are estimated using both the set of all ads with wage information (*All wage*) and the set of ads with wages that were not estimated (*Non–est. wage*). Our robustness checks, however, are estimated using the smaller sample of non–estimated wages.

## 8.2 Sample Selection Bias

A potential for sample selection bias occurs because the ads that have wage information might be systematically different from those that do not. Furthermore, Table 2 shows that the fraction of ads that do not have wage data is large, and the fraction that do not have wages that were supplied by employers is even larger. It is therefore important to determine if our two wage samples are representative.

To control for sample selection, we estimate two–equation Heckman–style models. Our selection equations, which explain the presence or absence of wage information, are probits that are estimated on the full sample of the chains' online ads. Those equations include all of the variables that are in the wage equations, plus instruments that affect sample selection but not wages.

For this purpose we use two instruments. First, in mid February of 2018, LinkedIn was the first to announce the availability of its wage estimation algorithm.[43] Moreover, soon after, other job boards began to estimate wages. We therefore use a dichotomous variable that is zero until February 2018 and one thereafter as our first instrument.

[41] For an example of constructing estimated wages using machine learning see Kenthapadi, Ambler, Zhang, and Agarwal (2017).

[42] For an example of constructing estimated wages using the hot deck procedure, see Hirsch and Schumacher (2004).

[43] `https://blog.linkedin.com/2018/february/13/introducing-salary-insights-on-jobs.`

The second instrument is constructed as a moving average of the number of online ads posted in the state by the 165 chains over the previous six months. The moving average is normalized so that, for each state, its average equals 100 in 2014. The rationale for this instrument is that, as more competitors post online ads, employers want to distinguish their ads and one way to do this is to post more information.

The standard errors in our selection regressions are obtained by bootstrapping.[44]

## 8.3 Endogenous Treatment

While we view the removal of NPCs in franchise contracts as an exogenous event, one might wonder if treatment – the presence or absence of an NPC – is endogenous. Indeed, chains chose whether to include such a clause in their contracts. However, we do not believe that endogeneity presents a problem here.

The decision to include an NPC was made many years prior to the beginning of our sample period. However, characteristics that might have influenced that decision, such as chain wage, size, and the fraction of a chain's restaurants that are franchised, are highly persistent in our data. Therefore, the chains that chose an NPC might still be systematically different from those that did not. For example, they might be the ones that had lower wages and thus greater retention problems. However, since the treatment decision was taken at the chain level, inclusion of chain dummy variables removes the effect of persistent differences in characteristics.

## 8.4 Identification

Identification of our model relies on two assumptions: parallel trends and no spillovers. The parallel trends assumption requires that the pre–event behavior of wages be similar in the two groups. Statistical tests of this assumption exist and are routinely used. However, we have only two time periods – 2014 and 2015 – prior to 2016, and it would be very hard to reject the parallel trends assumption formally. Nevertheless as can be seen in figure 4, the behavior of wages was very similar in 2014 and 2015. Indeed, the difference in average log

[44] Stata's command to estimate the classic Heckman selection model in one step, which uses likelihood methods, did not converge, most likely because of the very large number of fixed effects we included in the model. The two-stage estimation method is known to produce incorrect standard errors. As we saw very little change in the estimates after 50 replications, we used 100 replications to generate our estimates of standard errors.

wages – control minus treatment – was 0.120 in 0 2014 and 0.124 in 2015, which implies that relative wages were very stable across those two years.

The second assumption, stable unit treatment value assumption or SUTVA, implies that treatment does not indirectly affect untreated observations. Satisfying this assumption induces a tension between choosing a control group that is sufficiently different from the treated so that there are no spillovers and choosing one that is sufficiently close so that, absent the treatment, wages in the two groups would be very similar.

In our setting, one could choose the controls to be only ads posted by franchisors with no NPC, or one could also include ads for restaurant workers in corporate chains, or those ads could also be augmented with ads for retail workers in corporate chains. At the other extreme one could choose workers in, for example, real estate or tax preparation chains. It should be clear that, as one moves from one extreme to the other, spillovers become less likely while, at the same time, similar behavior of wages absent the policy becomes less plausible.

We have chosen our controls to be ads for restaurant jobs in non–NPC and corporate chains as well as retail jobs in large corporate chains that also have restaurant employees.[45] If there were spillovers due to, for example, wages in the control group rising as those in the treatment group rose, our estimated NPC wage effects would be conservative.[46]

# 9 Results

Our two specifications of the wage equation, which we call the transition model (equation 1) and the long DID model (equation 2), are estimated on two samples, all ads with wage information (*All wage*) and only ads with wage information that was supplied by an establishment of one of the chains (*Non–est. wage*). However, the probits for the selection equations are estimated on the larger sample of all ads, i.e. those with and without wage information (*All ads*).

In addition to the NPC variables, each equation contains *Salary question ban*, which equals one if salary history inquiries were banned in the state and time period; and dummy variables for manager and district manager. Furthermore, specifications contain chain, mar-

[45] In addition to restaurant workers, corporate chains such as Walmart and Target employ retail workers. We retain all ads for these chains in our sample. As these chains are all corporate, those ads are part of our control group.

[46] An alternative would be retail workers in corporate chains alone. However, there were too few ads for such jobs and the treatment and control groups were very unbalanced.

ket (MSA), detailed ONET occupation code, job source (e.g., job board), and interacted state/year fixed effects.

Standard errors are clustered at the MSA×year level, which allows for correlation among shocks that are associated with restaurants in the same geographic market and time period.

## 9.1 Baseline Specifications

Our baseline sample contains ads from all chains with a comprehensive NPC that applies to both workers and managers or no NPC at all.

### 9.1.1 Transition Equations

Table 4 contains the results from estimating the transition model using both samples, (*All wage*) and (*Non–est. wage*). With the transition model, the first four coefficients in each column show the effect in each year between 2016 and 2019 of the arrival of information concerning the potentially hostile treatment of NPCs in franchise contracts. One expects the coefficients to increase in magnitude and significance over time. With each sample, the first equation is estimated by OLS whereas the second includes a correction for sample selection.

First consider the *All wage* sample. The first set of results, which shows the OLS coefficients and their standard errors, indicates that, in each year the coefficients of the NPC variables are positive. However, the effect is significant at 5% only in the last year, which shows an increase of 3.6% by the end of the period. Furthermore, the OLS specifications indicate that banning salary history inquiries was associated with 7.5% higher wages, and, not surprisingly, wages for district supervisors are highest followed by managers.

Compared to OLS, the correction for sample selection reduces the magnitude of the NPC effect in 2019 from 3.6% to 1.9%. Moreover, the coefficient of the inverse Mills ratio is highly significant, indicating that sample selection bias is present.

The results for the *Non–est. wage* sample are qualitatively similar: removing NPCs and banning salary history inquiries raised wages and workers with more responsibility received higher pay. However, the magnitudes of the NPC effects are larger in this sample. Indeed, the estimate of the 2019 NPC removal effect has increased from 3.6% to 4.8% (a 33% increase). In contrast, the effect of banning salary history inquiries is reduced from 8% to 2.6%.

Table 4: Baseline Transition Equation: OLS and Selection, Two Samples

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *All Wage* | | *Non–Est Wage* | |
| | OLS | Selection | OLS | Selection |
| 2016*npc | 0.005 | 0.006 | 0.019 | 0.019 |
| | (0.020) | (0.021) | (0.019) | (0.017) |
| 2017*npc | 0.006 | -0.009 | 0.007 | 0.004 |
| | (0.018) | (0.018) | (0.016) | (0.017) |
| 2018*npc | 0.018 | 0.003 | 0.019 | 0.017 |
| | (0.016) | (0.016) | (0.015) | (0.016) |
| 2019*npc | 0.036** | 0.019 | 0.048*** | 0.048*** |
| | (0.016) | (0.016) | (0.015) | (0.015) |
| Salary question ban | 0.077*** | 0.080*** | 0.026*** | 0.029** |
| | (0.018) | (0.019) | (0.008) | (0.013) |
| Manager | 0.088*** | 0.089*** | 0.013 | 0.013 |
| | (0.017) | (0.017) | (0.011) | (0.012) |
| District Manager | 0.612*** | 0.628*** | 0.727*** | 0.733*** |
| | (0.033) | (0.035) | (0.031) | (0.032) |
| Constant | 2.520*** | 2.444*** | 2.553*** | 2.533*** |
| | (0.010) | (0.021) | (0.008) | (0.050) |
| Inv. Mills ratio | | 0.073*** | | 0.015 |
| | | (0.020) | | (0.033) |
| $R^2$ | 0.559 | 0.560 | 0.622 | 0.622 |
| Ads | 214,167 | 214,167 | 90,738 | 90,738 |

The dependent variable is ln(wage).
20xx*npc is the NPC variable interacted with a 20xx year dummy.
All equations contain chain, MSA, occupational code, ad source, and state/year fixed effects.
Standard errors in parentheses.
Robust standard errors clustered at the MSA×year level.
Standard errors for the selection equations are bootstrapped, 100 replications.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Comparing OLS and selection estimates from the *Non–est. wage* sample, we see that the magnitudes of all coefficients have hardly changed and, unlike the estimate from the *All wage* sample, the coefficient of the IMR is no longer significant. It appears that sample selection is unimportant when the sample of non–estimated wages is used.[47] However, our results highlight the importance of testing for sample selection in analyses that use uncorrected data.

### 9.1.2 Long DID Equations

With the long DID specification, the effect of banning NPCs in franchise contracts is condensed into a single parameter. The average over the 'after' period (2018 and 2019) is compared to the average over the 'before' period (2014 and 2015), and the 'middle' period (2016 and 2017) is dropped.[48] In Table 5, the NPC effect is given by the first coefficient in each equation. Other than this change, the organization of this table is the same as that of Table 4.

Comparing Tables 4 (transition) and 5 (long DID) shows that the results are similar in magnitude and significance. For example, we see that banning NPC clauses had a positive and significant effect on wages and that effect is estimated to be larger in the *Non–est. wage* sample, 4.7% compared to 3.7%. In addition, the correction for sample selection reduces the NPC effect in the *All wage* sample but not in the *Non–est. wage* sample. Furthermore, the coefficient of the IMR is significant in the former but not in the latter. Finally, the effect of banning salary history questions is reduced in magnitude (to 1.6%) and significance (to 10%) for the non–estimated wage data.

# 10 Robustness Checks

We perform a number of robustness checks. Since we believe that the larger sample is biased, all regressions in this section are based on the *Non–est. wage* sample. Since sample selection bias does not arise in this sample, we show only OLS regressions. Moreover, we focus on the long DID estimations, since those estimates are easier to interpret while being very similar to the results from the transition equations.

[47] The lack of significant coefficients of the IMR is not due to weak instruments. In fact the coefficients of both IVs are significant in the probit equations (t-stats of 6.25 and 8.11 respectively).

[48] Table 4 shows that the controversy surrounding NPC clauses had little effect in the middle period.

Table 5: Baseline Long DID: OLS and Selection, Two Samples

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *All Wage* | | *Non–Est Wage* | |
| | OLS | Selection | OLS | Selection |
| 2018-19*npc | 0.037** | 0.018 | 0.047*** | 0.045*** |
| | (0.017) | (0.018) | (0.015) | (0.015) |
| Salary question ban | 0.073*** | 0.076*** | 0.016* | 0.019 |
| | (0.019) | (0.020) | (0.009) | (0.014) |
| Manager | 0.100*** | 0.098*** | 0.022** | 0.023** |
| | (0.017) | (0.016) | (0.011) | (0.012) |
| District Manager | 0.559*** | 0.573*** | 0.707*** | 0.715*** |
| | (0.039) | (0.038) | (0.038) | (0.041) |
| Constant | 2.515*** | 2.438*** | 2.553*** | 2.526*** |
| | (0.010) | (0.025) | (0.008) | (0.049) |
| Inv. Mills ratio | | 0.079*** | | 0.020 |
| | | (0.025) | | (0.035) |
| $R^2$ | 0.553 | 0.554 | 0.616 | 0.616 |
| Ads | 195,497 | 195,497 | 72,065 | 72,065 |

The dependent variable is ln(wage).
2018-19*npc is the NPC variable interacted with 2018 and 2019 year dummies.
All equations contain chain, MSA, occupational code, ad source, and state/year fixed effects.
Standard errors in parentheses.
Robust standard errors clustered at the MSA×year level.
Standard errors for the selection equations are bootstrapped, 100 replications.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 10.1 Additional Explanatory Variables

### 10.1.1 Job Ad Market Share

We first explore interactions between the franchisor's ad market share and the NPC variable. The reason for doing this is as follows. When a clause is included in a franchise contract, if the ads that are associated with that franchisor constitute a large share of ads locally, which usually means that there are many establishments of that brand, the presence of an NPC forecloses a large share of jobs to an employee of one of those establishments. We therefore expect the clause to result in a greater wage reduction. The new variable is constructed as an interaction of the *2018-19*npc* variable with *AMS*, the franchisor's percentage share of job ads, with and without wage information, in the MSA and the before period (2014–2015).

Table 6 shows the results from adding this variable to our regressions. In that Table, as well as in those that follow, column 1 contains the baseline specification for comparison purposes. The interaction between the NPC variable and the franchisor's ad market share is added in column 2. Results show that, with a very low ad market share, the effect of an NPC is to lower wages by 3.1%. However, an increase in 1% in ad market share causes the effect to rise by 0.6%, implying that, in terms of wages, franchisees of larger chains benefit more from operating under an NPC.

### 10.1.2 Market Demographics

All regressions include fixed effects that control for invariant market characteristics. However, there can be time varying characteristics that affect wages and perhaps indirectly affect the NPC wage reduction. To test this we add two demographic variables, yearly county-level per capita income and unemployment rate, both in percent. Results, in column 3 of Table 6, show that the coefficients of both variables are positive and significant. On the other hand, the NPC coefficient is virtually unchanged. Demographics therefore affect wages but not the estimate of the wage lowering power of the NPC. Finally, column 4, which contains results when both sets of new variables are added, shows that coefficient estimates and conclusions are hardly altered compared to separate inclusion.

It might be surprising that the coefficient of unemployment is positive. However, when times are bad, it is often the low wage workers who are laid off, which has the effect of increasing the average wage.

Table 6: Ad Market Share and Demographics Added

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| 2018-19*npc | 0.047*** | 0.031** | 0.047*** | 0.031** |
| | (0.015) | (0.015) | (0.015) | (0.015) |
| 2018-19*npc*AMS | | 0.006*** | | 0.006*** |
| | | (0.001) | | (0.001) |
| Log Per Cap Income | | | 0.029** | 0.028** |
| | | | (0.012) | (0.012) |
| Unemployment Rate | | | 0.012** | 0.011** |
| | | | (0.005) | (0.004) |
| Salary question ban | 0.016* | 0.018** | 0.014 | 0.017* |
| | (0.009) | (0.009) | (0.009) | (0.009) |
| Manager | 0.022** | 0.023** | 0.022** | 0.023** |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| District Manager | 0.707*** | 0.706*** | 0.705*** | 0.704*** |
| | (0.038) | (0.038) | (0.038) | (0.038) |
| Constant | 2.553*** | 2.553*** | 2.193*** | 2.200*** |
| | (0.008) | (0.008) | (0.138) | (0.138) |
| $R^2$ | 0.616 | 0.617 | 0.616 | 0.617 |
| Ads | 72,065 | 72,065 | 72,065 | 72,065 |

The dependent variable is ln(wage).
The sample is non–estimated wage ads.
2018-19*npc is the NPC variable interacted with 2018 and 2019 year dummies.
AMS is the associated franchisor's ad market share
All equations contain chain, MSA, occupational code, ad source, and state/year fixed effects.
Standard errors in parentheses.
Robust standard errors clustered at the MSA×year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## 10.2 Different Samples

The next set of robustness checks evaluates the NPC effect on wages using different samples: First, comparing franchisors that are known to have dropped NPCs with those that have not, and second, comparing NPC effects for managers and non–managers or workers.

### 10.2.1 Franchisors that Dropped NPCs

We have assumed that, due to the negative attention and court cases, all NPC franchisors had stopped enforcing NPCs by the end of the period. While the majority dropped NPCs from their contracts, not all did so. We assess whether wages posted by franchisees of franchisors that dropped the NPC clause rose more than wages posted by those franchisees whose franchisors did not. To do this, we searched the 2019 (plus or minus a year) franchise contracts of all franchisors that once had an NPC and identified franchisors that still had a clause.

Table 7 shows regression results where the treated are franchisors who had dropped their NPC clauses by 2019 and the controls are chains that did not have such a clause in the pre-period. The ads of franchisors that had not dropped their NPCs by 2019 are excluded from these analyses.[49] The table shows that, with this sample, the NPC effect is reduced from 4.7% to 3.0%. Moreover, although the effect of a 1% increase in ad market share is still associated with a 0.6% increase in the size of the NPC effect, the intercept – the value at zero share – is reduced from 3.1% to a statistically insignificant 1.5%.

It is surprising that the estimated NPC effects are smaller in this sample compared to our baseline. Furthermore, although the estimate of each NPC coefficient is contained in the 95% confidence interval of the corresponding coefficient from the other sample, the differences in estimates are sizable and we cannot explain the reductions in magnitudes. Nevertheless, our results are consistent with franchisees of all NPC chains ceasing enforcement when it became controversial and potentially costly, regardless of whether the chain dropped the clause.

### 10.2.2 Managers and Workers

We now turn to analyses that separate managers and lower-level workers, identified using job titles. Furthermore, since we want to evaluate the relative effectiveness of different clauses,

[49] The dropped ads – those that were posted by franchisors that had not dropped the NPC from their franchise contracts by 2019 – were only 10.8% of the total.

Table 7: Only Franchisors That are Known to Have Dropped NPCs

| | (1) | (2) |
|---|---|---|
| 2018-19*npc | 0.030** | 0.015 |
| | (0.015) | (0.015) |
| 2018-19*npc*AMS | | 0.006*** |
| | | (0.001) |
| Salary question ban | 0.021* | 0.023** |
| | (0.011) | (0.010) |
| Manager | 0.025** | 0.026** |
| | (0.011) | (0.011) |
| District Manager | 0.699*** | 0.700*** |
| | (0.041) | (0.041) |
| Constant | 2.556*** | 2.554*** |
| | (0.008) | (0.008 |
| $R^2$ | 0.634 | 0.634 |
| Ads | 64,287 | 64,287 |

The dependent variable is ln(wage).
The sample is non–estimated wages excluding NPC chains that have not dropped the clause
2018-19*npc is the NPC variable interacted with 2018 and 2019 year dummies.
AMS is the associated franchisor's ad market share
All equations contain chain, MSA, occupational code, ad source, and state/year fixed effects.
Standard errors in parentheses.
Robust standard errors clustered at the MSA×year level.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

we augment the managerial sample with ads from those chains that have a narrower, i.e., manager-only NPC, which we add to the treatment, or NPC, group. We also created a new indicator variable, $npc_m$, which equals one if the clause applies only to managers, and we interacted that indicator with the NPC and ad share (AMS) variables.

Table 8: Managers and Workers

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | *Managers* | | *Workers* | |
| | *Comprehensive NPC* | | *Manager only NPC added* | | | |
| 2018-19*npc | 0.060*** | 0.043*** | 0.052** | 0.035 | 0.066*** | 0.053*** |
| | (0.025) | (0.025) | (0.024) | (0.024) | (0.018) | (0.019) |
| 2018-19*$npc_m$ | | | -0.014 | -0.008 | | |
| | | | (0.028) | (0.030) | | |
| 2018-19*npc*AMS | | 0.008*** | | 0.009*** | | 0.005*** |
| | | (0.002) | | (0.002) | | (0.001) |
| 2018-19*$npc_m$*AMS | | | | -0.004 | | |
| | | | | (0.004) | | |
| Salary question ban | 0.014 | 0.018 | 0.031* | 0.032* | 0.020** | 0.022** |
| | (0.014) | (0.016) | (0.016) | (0.017) | (0.010) | (0.010) |
| District Manager | 0.663*** | 0.661*** | 0.640*** | 0.639*** | | |
| | (0.039) | (0.040) | (0.036) | (0.036) | | |
| Constant | 2.741*** | 2.740*** | 2.760*** | 2.760*** | 2.450*** | 2.450*** |
| | (0.011) | (0.011) | (0.012) | (0.012) | (0.009) | (0.009) |
| $R^2$ | 0.590 | 0.591 | 0.591 | 0.592 | 0.593 | 0.593 |
| Ads | 25,013 | 25,013 | 28,547 | 28,547 | 46,910 | 46,910 |

The dependent variable is ln(wage).
2018-19*npc and 2018-19*$npc_m$ are the NPC and $NPC_m$ variables interacted with 2018 and 2019 year dummies.
AMS is the associated franchisor's ad market share
All equations contain chain, MSA, occupational code, ad source, and state/year fixed effects.
Standard errors in parentheses.
Robust standard errors clustered at the MSA×year level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First consider the managerial samples in Table 8. The first two columns contain estimates obtained from a sample of ads for managers whose contracts contain a comprehensive NPC. This sample produces estimates of the NPC effects that are slightly higher than those for the full sample in Table 6. Indeed, NPCs lower managerial wages by 6% rather than by 5%.

With the second pair of columns in Table 8, the sample has been augmented by adding ads posted for positions with a manager only NPC. With this sample, coefficients of variables that contain interactions with $npc_m$, which are contained in rows 2 and 4, are never significant.

Moreover, compared to Table 6, the coefficients of the direct NPC variables in row 1 are now more similar in magnitude if not always significance. As before, the magnitudes are consistent with a 5% average rise in wages after removal. Finally, the evidence suggests that, in terms of lowering managerial wages, manager only NPCs are marginally less effective (the direct effect falls from 6% to 5% when ads with manager only contracts are added).

Next, consider the estimates from the non–manager or worker sample. A priori, we do not know whether, compared to managers, the NPC effect for workers should be larger or smaller. The fact that some franchisors chose to have a manager only NPC suggests that the wage lowering benefits of such clauses might be larger for that group. On the other hand, due to their training, wage increasing efficiency augmentation could also be more important for managers. The net effect is therefore ambiguous.

Comparing the worker coefficients of the NPC variables in the first row of Table 8, we see that estimates of the worker direct effects are slightly larger than those from the two managerial samples. In particular, NPC removal for workers is associated with a 6.6% wage increase. However, the effect of the interaction with ad share is smaller for workers, 0.5% compared to 0.8% or 0.9%. Since the effect on workers is not consistently greater or smaller than the effect on managers,[50] we do not have robust evidence that one group is more disadvantaged by NPCs compared to the other.

# 11 Conclusions

A no–poaching clause is but one of many possible vertical restraints that can appear in a franchise contract. Until quite recently, however, NPCs received little attention from academics, lawyers, and policy makers. Nevertheless, we believe that they are important constraints with potentially broad consequences for labor markets.

As with most vertical restraints, theoretical predictions concerning the effects of NPCs are ambiguous. In particular, those restrictions can increase monopsony power of employers or they can enhance efficiency in training and retention of employees. However, our research finds that, in our chain restaurant setting, the former effect dominates. Specifically, we find strong support for the hypothesis that NPCs increased buyer power, limited workers' labor market opportunities, and suppressed wages.

[50] The two lines, 4.3 + .8 AMS and 5.3 + .5 AMS, from columns 2 and 6 in Table 8 cross at AMS = 3.333, which is somewhat higher than the AMD mean of 2.5.

In our data, there are two potential sources of bias in the estimates of the NPC effect; the facts that only a small fraction of online job ads contain wage information and that much of that information was estimated by third party platforms. When we perform corrections for those biases, we find evidence of both. However, the two are not equally important. In particular, the removal of estimated wages leads to larger estimates of the NPC effect that are both statistically significant and economically important (in the 27% to 33% range). In contrast, selection bias is only present in the larger sample of all wage ads, not in the smaller sample of wages that were supplied by the employers.

Using the smaller sample of ads with non–estimated wages leads to additional conclusions: First, franchisors that had larger shares of the job ad market in the pre period, when the no–poaching clauses were in effect, were more adversely affected by removal, which implies that the clauses endowed them with greater wage setting power. Second, limiting attention to the NPC or treated group, the NPC effect is not greater for those franchisors that dropped the clauses compared to those that did not. This supports the notion that ceasing to enforce was as important as removing the clauses. Finally, comparing managers and workers, we cannot conclude that the NPC effect was larger for one group compared to the other, which means that labor market restrictions that limit worker mobility have negative consequences for even the lowest paid and least trained employees.

NPCs have appeared in franchise contracts in many other industries and removal and non enforcement arising from the controversy are likely to have affected those industries as well. Moreover, since in the U.S., employment in franchise chains is not much lower than employment in manufacturing, the labor market ramifications could be very large. We conclude that there are compelling reasons for antitrust authorities to pay attention to NPCs in the vertical context. Nevertheless, if we are to fully understand the consequences of NPCs, there is a need for more empirical work in other settings.[51]

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[51] For example, see Battiston, Espinosa, and Liu (forthcoming) for a case where introducing a no–poaching policy led firms in the temporary employment sector to reduce their inefficient use of job rotation of employees across clients, which they relied on to prevent poaching prior to the policy.

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# APPENDICES

# A Job Search Model

Consider the following simplification of a partial equilibrium job search model adapted from McCall (1970). Assume that there are $N$ symmetric chains, each with $n$ symmetric franchisees, and, for simplicity, that these are the only potential employers in the market. Each worker works for a franchisee and is endowed with a wage $w$.[52] Each period, workers choose between staying at their current jobs or searching for a new job and switching. If workers choose to search, they receive wage offers from all the competing firms, with each wage drawn independently from a distribution $F(w)$ on a compact domain $[0, B]$.[53] The worker then picks the highest of the competing offers.

Without NPCs, a worker who chooses to search gets $nN-1$ offers. Denote the distribution of the highest of $nN-1$ offers as $G(w)$. Since each offer is independent

$$G(w) = [F(w)]^{nN-1}. \tag{3}$$

Let $\beta$ be the discount factor. The Bellman Equation for a worker whose wage is $w$ is

$$v(w) = \max\left\{w + \beta v(w), \int_0^B (w' + \beta v(w'))dG(w')\right\} \tag{4}$$

where $v(w)$ is the value of the current wage. The first term on the right hand side is the value of choosing to stay put, whereas the second is the value of choosing to search.

The value of choosing to search is independent of the current wage, $w$, so if the worker's wage is such that she chooses to stay put this period, she will make that choice every period and earn $\frac{w}{1-\beta}$. Hence, if the worker chooses to stay put, it must be that

$$\frac{w}{1-\beta} > \int_0^B (w' + \beta v(w'))dG(w'). \tag{5}$$

This implies that there exists a threshold or reservation wage $R$ beyond which the worker

[52] The wage in this simple model can be interpreted as representing the many features of a job that are valued by the worker, including compensation, benefits, characteristics of the employer, and so on.
[53] The lower bound on this interval is simply a normalization.

will not search, which is defined by

$$\frac{R}{1-\beta} = \int_0^B (w' + \beta v(w'))dG(w') = \mathbf{E}_G w + \beta \int_0^B v(w')dG(w'). \tag{6}$$

This allows us to rewrite the value function as

$$v(w) = \begin{cases} \frac{w}{1-\beta} & \text{if } w \geq R \\ \frac{R}{1-\beta} & \text{if } w \leq R \end{cases} \tag{7}$$

Substituting 7 into 6, after some algebra, the threshold wage $R$ satisfies

$$R = \mathbf{E}_G w + \frac{\beta}{1-\beta} \int_R^B (w' - R)dG(w'). \tag{8}$$

Now consider the imposition of an NPC. The worker can no longer get offers from competing establishments in the same chain, which reduces the number of potential offers to $n(N-1)$. The maximum of $n(N-1)$ independent offers is distributed

$$\tilde{G}(w) = [F(w)]^{n(N-1)} \tag{9}$$

where

$$G(w) = [F(w)]^{nN-1} < [F(w)]^{n(N-1)} = \tilde{G}(w), \qquad \forall w \in (0, B). \tag{10}$$

In other words, $G(w)$ first order stochastically dominates $\tilde{G}(w)$.

The threshold wage $\tilde{R}$ under this new scenario satisfies

$$\tilde{R} = \mathbf{E}_{\tilde{G}} w + \frac{\beta}{1-\beta} \int_{\tilde{R}}^B (w' - \tilde{R})d\tilde{G}(w'). \tag{11}$$

If the new threshold wage is lower than the initial one, then workers search less frequently and observed wages will be lower. To see whether this is true, first recognize that $R$ satisfies

$f(R) = h_G(R)$ and $\tilde{R}$ satisfies $f(\tilde{R}) = h_{\tilde{G}}(\tilde{R})$, where

$$f(x) = x, \tag{12}$$

$$h_G(x) = \mathbf{E}_G w + \frac{\beta}{1-\beta}\int_x^B (w' - x)dG(w'), \text{ and} \tag{13}$$

$$h_{\tilde{G}}(x) = \mathbf{E}_{\tilde{G}} w + \frac{\beta}{1-\beta}\int_x^B (w' - x)d\tilde{G}(w'). \tag{14}$$

By first order stochasic dominance, $h_{\tilde{G}}(x) < h_G(x)\ \forall x$, or $h_{\tilde{G}}(x)$ lies below $h_G(x)$ everywhere. Since $f(x)$ slopes upward, the value of $x$ which satisfies $f(x) = h_{\tilde{G}}(x)$ (i.e. $\tilde{R}$) is strictly lower than the value of $x$ that satisfies $f(x) = h_G(x)$ (i.e. $R$).

We conclude that the new threshold wage is lower than the initial threshold wage. This implies that the worker is less likely to search.

We now consider the effect on the industry average wage as more firms adopt NPCs. In this model, workers are in one of two equilibria – a high threshold wage equilibrium if the chain associated with the employer does not have an NPC, or a low threshold wage equilibrium if the associated chain has an NPC. When a chain adopts an NPC, it pushes all the workers of its franchisees from the high to the low threshold wage equilibrium, while having no effect on workers affiliated with other chains. This causes some mass in the distribution of industry wages to move left and reduces the industry average. Furthermore, as more firms adopt NPCs, it pushes the average wage further down, and, in the limit, all workers search less frequently.

# B Efficiency Model

The dynamic efficiency model, which illustrates a common free–riding problem, is a discrete–time infinite–horizon problem with a free–entry zero–profit assumption.

Assume that there are $N$ chains each with $n$ franchisee employers that have no monopsony power. Assume also that workers quit at a rate $q$ and establishments must train new hires. There are two sorts of training and the establishment pays for both. The first, which endows workers with skills that are transferable within the chain, costs $c_c$. The second, which is specific to the establishment, costs $c_r$. The per period value of a trained (untrained) worker is $\bar{v}$ ($\underline{v}$), with $\bar{v} - c_c - c_r > \underline{v}$.

Consider an equilibrium with an NPC. Hiring will occur until the long run cost of a trained worker equals the long run benefit to the establishment,

$$w(1+(1-q)+(1-q)^2+\ldots)=\bar{v}(1+(1-q)+(1-q)^2+\ldots)-c_c-c_r, \tag{15}$$

where $w$ is the wage. The equilibrium steady state wage is $w^*=\bar{v}-q(c_c+c_r)$, and the full cost of training is amortized over the worker's expected job tenure.

Now suppose that NPCs are banned. The value of a trained worker to another establishment in the same chain is $\bar{v}-qc_r>w^*$. Rival establishments therefore have incentives to poach. Knowing this, establishments will be unwilling to amortize the cost of training.

One solution is to offer a wage of $\bar{v}-c_c-c_r$ in the first period and pay $\bar{v}$ thereafter, i.e., the untrained worker must pay the full cost of training up front. With this payment, poaching will not occur. However, it will be infeasible if the worker is financially constrained.

If the worker is financially constrained, an establishment can subsidize the worker's training at a rate $s$, i.e., the subsidy, is $s(c_c+c_r)$. With this payment, poaching will not occur if the value to the current establishment is greater than the value to the rival,

$$\bar{v}-qs(c_c+c_r)>\bar{v}-qc_r \quad \Rightarrow \quad s<\frac{c_r}{c_c+c_r}. \tag{16}$$

If $c_r$ ($c_c$) is zero, the no–poaching constraint can never (always) be satisfied. For intermediate values, to avoid poaching, the subsidy must be small and there is therefore a tension between the financial constraint and the no–poaching constraint.

When poaching cannot be eliminated, training will not occur and productivity and thus wages will be lower because workers will receive $\underline{v}$. As long as poaching can occur, wages will be higher when NPCs are in place.

# C Data Sources and Construction

## C.1 NRN Data

Our first data source is the National Restaurant News (NRN), an American trade publication that covers the food service industry. That source publishes data on the 200 largest food service chains in the U.S. each year, assessed on the basis of actual, estimated or projected

U.S. systemwide food service sales or corporate revenue for the organizations latest completed fiscal year. A total of 229 distinct chains appeared in one or more of the 2014–2019 Top 200 chain lists. [54] The lists include information about the number of each chain's establishments that are franchised and the number that are corporate. We classify all chains with a positive number of franchises in the pre-period as franchised chains, therefore susceptible to having an NPC in that time frame; there are 161 such chains in the listings. The remaining 68 chains are classified as corporate.[55]

## C.2 NPC Information

We looked for Franchise Disclosure documents (FDDs) for 2014, plus or minus a year, for the 161 franchised chains in the listings to determine whether the chain had a no–poaching clause in its contract at that time. We used Franchimp.com as our main source of FDDs, though we obtained the FDD for a few chains through other means (internet, Frandata, and a colleague, Janet Bercovitz). Despite our efforts, we were unable to find FDDs for 26 of the 161 franchised chains. This reduced the sample of chains with NPC information to 203 (68 corporate and 135 franchised).

Our reading of the franchise contracts in the FDDs led us to identify three mutually exclusive types of no–poaching clauses (NPCs): 81 cases of comprehensive NPCs, i.e. clauses that apply to all employees and reference all franchisees and typically the franchisor and its subsidiaries. However, one of those chains (Chuck E. Cheese) had no ads in the BGT data in 2014–2019, so we have 80 comprehensive NPC chains in our final set.. Another group of 23 franchised chains had manager-only NPCs, which only constrain the franchisee from not hiring managerial staff from other franchisees or the franchisor. Yet another 13 franchised chains had purely vertical NPCs, which state that the franchisee is not allowed to hire current employees of the franchisor. Finally, one chain (Famous Dave's) required that franchisees who hired staff from other franchisees in the chain compensate the franchisee whose staff they hired. We exclude this chain, and the chains with purely vertical NPCs from our analyses to ensure a clear distinction for the treatment. In most of our analyses, we also exclude ads from the 23 chains with manager only NPCs, for the same reason. However, we include them

[54] The surveys are identified by the publication based on when they are published, but the data are for the latest completed fiscal year that ended the year before. We follow their convention.

[55] Four of the chains we classify as corporate have franchised outlets in later years in the data: one starts doing so in 2017, one is 2018, and two in 2019. None of these could have NPCs in the pre-period, so we include them in our control group.

as part of the treated group when we examine effects for managers only. The remaining 17 franchised chains had no NPC clause.

## C.3 BGT Data

Our job ads data come from BGT, now Lightcast. The full data set consists of essentially the universe of US online job postings between 2011 and 2020 according to the company's web site[56] .

BGT provides the data in two forms. First, it provides the full ad text in XML format. But second, it processes each posting to extract several standardized fields from the posting's text, which it makes available in CSV format. The latter included much of the information of interest for our project, including job title, occupation, employer, the geographic location of the job, and information on offered wages, if any. Not all ads, however, contain information in every field. In particular, the wage information is often missing.

From the BGT data, we extracted all jobs posted between 2014 and 2019 by one of the above chains. To do this, we first created a list of all distinct employer names in the data. We then used regular expressions to extract lists of employer names that were likely to be related to each of the chains in our data. The use of regular expressions turned out to be particularly important to identify the ads related to franchised chains where each franchisee is the owner of an independent business, so even the standardized employer names can be quite different from the chain brand name. We then manually checked – in some cases via internet searches – each list to identify a final list of relevant employer names for all the chains.

While all the extracted ads were associated with employer names that were consistent with the chains in our data, important information was missing in some, and for others, there was information that contradicted the notion that these were restaurant or retail job ads. We therefore excluded postings that BGT for example identified as coming from the government or education sectors, as well as postings where BGT could not identify a source. We further restricted the sample of ads to those that BGT classified as belonging to the food or retail occupation groups. To guard against outliers (for example, the possibility that BGT's algorithm mistakenly interpreted a bonus as an hourly wage), for those ads that included wage information, we only kept those with wages below $60/hr.

[56] `https://lightcast.io/about/data`

For each job ad, BGT provides information on the county, and on the Metropolitan and Micropolitan Area (MSAs). These are, on average, smaller than Commuting Zones and Labor Market Areas but larger than counties. There are 929 MSAs in the U.S. according to the Office of Management and Budget, and our data include ads from more than 900 of them. We do not include ads posted for jobs in areas that do not belong to an MSA because they are unapt to have several establishments of the same chain competing with one another for workers. We use the county information to obtain data on per capita income and unemployment rates in the local area.

With the above restrictions, and after also removing ads with missing data on key variables, we were left with 2,258,291 ads for 201 chains, of which 1,705,474 are for the 165 chains in our main data set. We calculate the 2014-15 ad market share for each chain in each MSA using the larger sample of 2,258,291 ads as this gives us shares for the 23 chains with manager-only NPCs used in Table 8, and shares that are more representative of the overall set of jobs in the chain restaurant sector as a whole.

We relied on the ad text (XML) files to obtain additional information of interest. This included information such as the source of the ad but also information that allowed us to examine the data on wages in more detail. We identified two main issues in the set of ads with wages: first, for about 10 percent of the ads, we were unable to validate the wage information using the text of the ad. In some cases, this was because the ad turned out to be about several jobs, and the wage was unrelated to the job information. In other cases, the amount mentioned was a bonus, or a description of the firm's revenues, and so on, i.e. other amounts in dollars. We address this issue by keeping these 10% of ads as part of our overall sample, but treat them as not having wage data in our analyses.

Second, we used the ad text to identify the job domain where it was posted and statements suggesting that the wage data were estimated by the web site where it was posted rather than provided by the employers. Estimated wages are those for which the text surrounding the wages includes one of several standard expressions such as 'estimated' and 'similar jobs pay.' We found that four platforms: in order of importance, SimplyHired, Snagajob, Glassdoor and CareerBuilder account for almost all of the wages that were estimated. We keep these ads in the overall sample and the sample of all wages, but exclude them from the non–estimated wage data set.