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

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March 24, 2023

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 of such clauses on wages and we find robust evidence of a negative effect. Specifically, we find that 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 5–6% relative to chains that never imposed NPCs. We attribute this effect to the removal of frictions and barriers to mobility in labor markets.

Keywords: No–Poaching Clauses, Efficiency Enhancing, Anticompetitive Impact, Franchising, Chain Restaurants

JEL Classifications: J31, J43, J63, K21, L43, L83

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[4] We thank Thomas Lemieux, Vadim Marmer, and Joris Pinske for helpful discussions and comments, and Janet Bercovitz for giving us access to franchise disclosure documents. We also thank Robert Picard for his assistance with the data and code.

[5] Margaret Slade would like to acknowledge funding from the Centre for Innovative Data in Economics Research (CIDER), UBC.

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 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. Moreover, since we focus on low–wage jobs, we expect some of the monopsony arguments – those based on labor market concentration – to have less relevance in these markets, allowing us to highlight other factors for the use and effects of the clauses.

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 cause wages to rise.

The principal anticompetitive theory that has been used to argue against NPCs is traditional monopsony, which is based on the idea that NPCs reduce the number of potential employers or buyers. However, in many markets, restaurants are numerous and the market

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

for low wage workers is thick. We therefore do not base our analysis of anticompetitive effects on traditional monopsony. Instead, we rely on the idea that NPCs increase labor market frictions, such as search and information costs, and limit workers' job market opportunities. In the labor literature, this has been referred to as modern or dynamic monopsony.[2]

The principal pro–competitive justification for NPCs is that they increase efficiency. In this paper, we emphasize the potential effect of NPCs on worker training and retention as possible efficiency–enhancing motives for adoption.

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 source, which is the most important, comes from Burning Glass Technologies (BGT), now Lightcast.

We use these data to assess how the removal of NPCs from franchise contracts affected worker wages. Starting in 2016, vertical NPCs began to attract attention from competition authorities, the legal profession, consultants, lawmakers, and academics.[3] 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[4] . Consequently, hundreds of franchisors dropped NPCs from their contracts, some voluntarily and others 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 crippling and potentially 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, at the time of 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 lead to biases in our estimates of the NPC effect. First, sample selection could be a problem. Specifically,

[2] See Manning (2021).

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

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

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 clauses were removed. We expect wage estimation or imputation by third parties to lead to an upward bias in our estimates of the response of wages to the removal or cessation of enforcement of NPCs.[5]

To illustrate, suppose that the third party platforms included ads from non–NPC employers in the comparison group that was used to estimate wages in the NPC group, and vice versa. The result would be that, for reasons having nothing to do with the removal of NPCs, wages in the two groups would become more similar after 2018, when wage estimation began. Failure to account for this would thus cause an upward bias in the OLS estimates of the effect of removal of NPCs.

To anticipate results, we find that the process leading to non-enforcement and removal of NPCs, which occurred over several years, resulted in average wage increases of 5–6% in the chains that had adopted NPCs relative to those chains that had not. We therefore conclude that NPCs depressed wages. Moreover, we find that both of the potential biases (due to sample selection and third party wage estimation) are statistically significant. However, compared to addressing sample selection, the removal of estimated wages from the data has a much greater effect. Indeed, we find that failure to remove those wages results in an upward bias in the effect of treatment of 40–45%. To our knowledge, although many researchers have used the BGT data on wages, none of them has corrected for the bias that third-party wage estimation might induce.

2 Previous Literature

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

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

Traditional Monopsony.[6] 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)).[7] A second approach is to estimate labor supply elasticities directly, often using data on job applications, not employment.[8] 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 and industry that we focus on – Combined Food Preparation and Serving Workers, Including Fast Food – is at the low end of moderately concentrated, and workers involved in these 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. Finally, more closely related to our paper, Naidu (2010) examines the effect of restrictions on agricultural labor poaching in the postbellum South and finds that the restrictions lowered labor market mobility, wages, and the returns to experience for black workers.

[6] 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.

[7] 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.

[8] 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.

Recently, frictions and other imperfections in the labor market have also received more attention in policy and antitrust circles. For instance, a Council of Economic Advisors Issue Brief (2016)[9] describes how monopsony power can result not only from employer concentration or collusion, but also from competition–restricting practices (like non–compete clauses), search costs, and labor market frictions.

Vertical Restraints. In contrast to the literature on the potential anticompetitive effects of various vertical restraints, including labor market restrictions, economists have also developed models showing how different types of vertical restraints can potentially promote efficiency. Furthermore, empiricists have attempted to distinguish between situations where restraints have different effects.

Most of the early empirical literature on vertical restraints, summarized in Lafontaine and Slade (2008), finds that voluntarily adopted vertical restraints are usually efficiency enhancing. However, many of those studies are not causal. In addition, some more recent studies have found causal evidence of welfare lowering vertical restraints (for example, Nurski and Verboven (2016) and De los Santos and Wildenbeest (2017)).

NPCs. NPCs and their potential efficiency or monopsony–enhancing effects are the focus of an emerging, mostly empirical,[10] literature, much of which focuses on NPCs in franchise contracts.[11] Krueger and Ashenfelter (2022) (the first in this line, to our knowledge) 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 that research and calculate new HHIs that indicate that the reduction in competition is considerably smaller.

Two recent papers by Levy, Tardiff, Zhang, Sun, and Yamron (2020) and Callaci, Pinto, Steinbaum, and Walsh (2022a) are closest to our research. Both examine wage changes due to the removal of NPCs in franchise contracts. The first finds no effect, while the second finds a small but significant increase in wages. These papers differ from our research in several ways. First, the former paper considers quick–service restaurant workers in Rhode Island and southwest Florida only, while the second assesses wage effects across many industries.

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

[10] Shy and Stenbacka (2019) is an exception. They develop a model to analyze theoretically the effects of anti–poaching clauses and find that they are detrimental to workers but beneficial to employers. The welfare effects are ambiguous.

[11] Hoey, Peeters, and Principe (2021) is an exception. They study NPCs in European soccer markets and find that they led to a very minor reduction in revenue inequality.

We focus on restaurant chains across the US. Second, while Callaci, Pinto, Steinbaum, and Walsh (2022a) also use job ad data from BGT, they do not correct for the potential biases, which we find have a sizable effect on our estimates. Third, and finally, both papers regard the removal of NPCs triggered by the Washington State Attorney General as a discrete event, whereas we take a gradual approach.

We justify our gradual approach as follows. Event studies typically assess the arrival of new or unanticipated information. In Section 3.1, we document how information flowed in this market, starting with the publication of joint DOJ/FTC Guidelines in October 2016 and followed by the first vertical NPC no–poaching case in February 2017. We do not believe that the end result of scrutiny and legal action – the removal of a clause in a contract several years later – can be seen as new or unanticipated. Furthermore, we believe that our different assumptions about the timing of events account for the fact that we find more economically sizable wage effects compared to the other studies.

3 The Legal 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 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 the legal treatment of these restraints remains, as we explain below.

3.1 Vertical Cases

In October 2016, the Department of Justice (DOJ) and Federal Trade Commission (FTC) jointly published their *Antitrust Guidance for Human Resource Professionals,*[12] 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."[13] That document, which made the government's position on horizontal NPCs clear, offered no guidance on how to treat vertical NPCs.

The first vertical NPC case after the above Guidelines was a nationwide class action suit brought by employees against Carl's Jr in February 2017.[14] Similar suits were brought against McDonald's in June 2017, and several other restaurant chains thereafter. These 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 were local. Those rulings could be fatal to class action suits because it would be very costly to bring one for each local labor market.

Although the Federal Government did not get involved with vertical NPCs for some time, many state governments did. In July 2018, 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. Many other states later joined those efforts and over time, hundreds of other franchisors across various industries signed AODs.

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. In that Statement, it took the position that most NPCs in franchise agreements are not horizontal NPCs between competitors and should be subject to the rule of reason analysis.[15]

[12] `https://www.justice.gov/atr/file/903511/download`

[13] Page 4.

[14] There is at least one earlier NPC case. In 1992 a Jack–in–the–Box franchisee failed to win a case on this issue against its franchisor in a US District Court in Nevada.

[15] 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.

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.[16] Since Statements of Interest are not legally binding, this situation is apt to persist for some time.

3.2 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*". Among other things, that Order signaled a willingness of the Federal Government to use antitrust laws to probe activities that can illegally restrict workers' wages.

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

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 discuss motives in more depth. In each case, we also assess the effect of NPCs on wages, which forms the basis of our empirical strategy.

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 monopsony model in a Cournot–like framework that is the buyer version of common monopoly models in the spirit of Cowling and Waterson (1976) and Dansby and Willig (1979). In that model, increases in monopsony power in the labor market lead to reductions or markdowns on the wage that would be set equal to the value of the worker's marginal product in competitive markets.

A symmetric version of their first order condition, with N chains each with n establishments, relates the markdown, μ, to the structure of the labor market and the industry labor supply elasticity, ϵ,[17]

$$\mu = \frac{VMP - w}{w} = \frac{s}{\epsilon} = \frac{1}{nN\epsilon}, \tag{1}$$

where VMP is the value of the marginal product of a worker in each establishment, w is the wage that the worker receives, and s is an establishment's share of employment in the local labor market.

It is clear from (1) that, holding the elasticity of labor supply constant, a reduction in either the number of chains or in the number of establishments per chain increases the markdown. Moreover, when chains adopt no–poaching constraints, the effective number of establishments competing for the worker in the labor market is reduced. In other words, prior to the imposition of the constraint, a worker can accept a job offer from any other

[17] Krueger and Ashenfelter (2022) also include a conduct parameter in their model.

establishment. However, after the imposition, jobs in restaurants in the worker's own chain are no longer an option.

Although this model predicts that the adoption of NPCs leads to increased labor market power, and therefore greater markdowns, in the context of chain restaurants, that increase is apt to be small. The problem is that, even in a mid–size city, both N and n tend to be large.[18] Furthermore, in addition to franchise chain restaurants, there are many corporate–chain and local restaurants that do not belong to a chain but compete for the same workers. Finally, workers in restaurant chains can seek employment in related industries.

In their model, Krueger and Ashenfelter (2022) focus on the inward shift in demand for labor that is associated with the imposition of an NPC. However, there is also an inward shift in the supply of labor when this restraint is imposed. Indeed, just as each worker can seek employment from fewer establishments when NPCs are present, each establishment has access to fewer potential workers. As Manning (2021) notes in his discussion of monopsony (p. 12), '*A fall in the supply of labor would lead to lower employment and, to the extent that there is diminishing marginal product of labor, a higher wage.*' In other words, wage predictions from demand and supply shifts are of opposite signs and so the actual change, which will vary depending on specific circumstances, becomes an empirical issue.

4.1.2 A Broader Definition of Monopsony

The term monopsony power has 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 markdowns relative to the value of the worker's marginal product.[19] 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.[20]

In 2016 the Council of Economic Advisors (CEA) issued a brief that summarizes these ideas.[21] In particular, it states that

[18] In rural areas, it is likely that each chain has only one restaurant, in which case an NPC has no effect.

[19] 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.

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

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

... (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.

Whereas it is unlikely that competition authorities should try to address the original friction giving rise to buyer power, especially if it is related to differences across employers or amenities provided to employees, they can prohibit practices that enhance labor market frictions if those practices are expected to lead to worse conditions for workers or lower wages.

In Appendix A, we develop a job search model in the spirit of McCall (1970) that demonstrates 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.[22] 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 posted jobs are likely to be a higher fraction of total compensation for low wage workers.

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 problem.

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.

[22] See Table 1 which shows that only 80 of the 134 chains in our data have an NPC.

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.[23] 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 re-invest 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.

As we discuss in the next section, there are training costs both up and downstream in this industry. Moreover, so far we have considered only training costs. But as we note below, 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. Considerations of efficiency could therefore be valid reasons for adopting NPCs.

5 The Institutional Setting

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 US economy. Data from the 2017 US Census indicate that there were almost 500,000 establishments of franchised chains in the US at that time, and that those establishments employed nearly 10 million people. In comparison, there were 11.5 million jobs in manufacturing in

[23] In a zero profit equilibrium, training costs must eventually be recovered, at least in expected value.

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, at about 36%.[24]

Franchising is an organizational form that lies between vertical integration and arm's length transactions. A franchisee is an independent business that 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 a fixed fee and a portion of revenues.[25]

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's is a completely corporate chain. It is also possible for franchise chains to own and operate some of their establishments themselves. In practice, the fraction of corporate establishments tends to be low, but it also varies widely.[26] For example, Subway has no corporate establishment and only ten percent of McDonald's restaurants are corporate. In contrast, Panda Express operates about 95% of its restaurants itself.[27]

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.[28] Importantly, a franchise contract is the same for all franchisees associated with a franchisor 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 applies to

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

[25] The other type of franchising, typically called traditional franchising, is where the upstream firm supplies a product that the franchisee sells. Retail gasoline stations are often, and new car dealerships are all – because of state regulations – operated as traditional franchises. Business–format franchising, however, is the type of franchising that employs the vast majority of employees (about 85% of franchised chain employees by our calculation based on the 2017 Census data).

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

[27] When a chain has an NPC, it applies to all of its establishments regardless of governance.

[28] For a discussion of various restraints in franchise contracts see Callaci, Pinto, Steinbaum, and Walsh (2022b). For an analysis of the economics of vertical restraints and their antitrust treatment, see Blair and Lafontaine (2005).

all new contracts nationally. NPCs are one possible restraint, although until recently, they had received little attention.

There is substantial variation in NPCs across franchisors. They can restrict poaching from establishments in a specific geographic area, such as a state, or they can apply to all restaurants in a chain. They can also specify a type of worker, such as a manager, or they can apply to all employees. Finally, they can specify a time period, say five years, or time can be unlimited. In our empirical work we classify chains as treated if they ever had an NPC, regardless of scope.

We focus on two efficiency motives for NPCs in franchise contracts: 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.[29] 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. Furthermore, 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.[30] 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.'[31] An NPC could be a response to both training and turnover problems.

[29] 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.

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

[31] `https://www.cnbc.com/2019/08/29/fast-food-restaurants-in-america-are-losing-100percent-of-workers-e` `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 dataset are available in Appendix C.

Our core data are US online job postings from BGT, 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 covers the series of events described in Section 3.1, beginning with the DOJ/FTC Guidelines in October 2016. 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 potentially 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 revenue each year. In addition to revenues, NRN provides information on the number of franchised and corporate restaurants in each chain and year.

We focus on chains that had at least 50 establishments nationally in all years between 2014 and 2019 to ensure establishments are likely to be competing for workers. We obtained information on which of the franchised chains had NPCs before 2016 using data in Krueger and Ashenfelter (2022) when available, and then by inspecting franchise agreements, most of which we obtained from the California or Minnesota state government websites.[32]

Since unskilled workers have been the focus of much of the debate on NPCs in the franchise context, we similarly focus on the vast majority (93%) of job postings in our data that are for occupations that require no or very little skills according to the O*NET Resource

[32] Several states require chains to submit financial disclosure documents (including franchise agreements) every year in order to operate in that state. Four states publish these documents online, out of which California and Minnesota publish some historical documents. We are also grateful to Janet Bercovitz for providing us with some disclosure documents.

Center.[33] To guard against outliers, we exclude a few postings with wages above $60/hr. Finally, we exclude chains whose establishments had fewer than 5 job postings for unskilled workers in the BGT data in the pre-period, i.e., 2014 or 2015.

After eliminating observations with missing values on variables of interest, our dataset comprises 2,369,632 individual postings for 134 chains. Those chains had 206,835 establishments and sales of $275 billion in 2019. In comparison, the top 200 chains in the NRN data in 2019 had 226,000 establishments and sales of $302 billion, so the excluded chains are relatively small and their exclusion does not materially affect coverage.

We assign each of the 134 chains to one of two groups: those that had an NPC prior to 2016 – the 'NPC group' – and those that never had one, which includes franchise chains with no NPC as well as corporate chains – the 'non–NPC group.'

Table 1 summarizes some chain characteristics for the two groups. Sales and units are 2014–15 averages, corresponding to our 'before' period. The table shows that, on average, the NPC group contains more chains, more establishments, and higher chain revenue. However, sales revenue per establishment is higher for the non-NPC group. Furthermore, the NPC group has more establishments of every food type except for casual dining and in–store restaurants, where the non–NPC group dominates.

Table 2 contains the breakdown of 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. Notably, there is an extremely high skew towards later years – 2018 and 2019 – when much higher proportions of postings include wage information.

Upon further investigation, we found that some of the available wage data were estimated by the online platforms posting the ad rather than being provided by the potential employer.[34] We identified such estimated wages by searching the postings' text for common phrases that indicated the wages were estimated. The third row in Table 2 shows the number of ads where we ascertained that the wage was not estimated in this way.

Figure 1 graphs the total number of ads posted each month. 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

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

[34] Notably, LinkedIn started using its LinkedIn Salary product to add estimated wages to online job postings in early 2018. See `https://blog.linkedin.com/2018/february/13/introducing-salary-insights-on-jobs`.

Table 1: Chain Characteristics – 2014-15 averages

	NonNPC	NPC	Total
Number of Chains	54	80	134
Restaurants per chain	1,338	1,500	1,435
% Franchised	30	68	52
Chain sales ($M)	1,338	1,947	1,702
Sales per unit ($K)	2,492	1,488	1,892
Restaurant Type:			
C-store	8	1	9
Beverage/Snack	2	12	14
Burger	6	14	20
Casual dining	23	14	37
Chicken	2	7	9
Family	5	7	12
Mexican	3	3	6
Misc QSR	1	7	8
Pizza	2	8	10
Sandwich	2	7	9

Table 2: Sample Information: Number of Ads by Year

Sample	2014	2015	2016	2017	2018	2019	Total
All ads	321,153	288,529	402,954	372,452	420,749	563,795	2,369,632
Wage ads	8,212	7,245	10,359	12,211	75,895	195,336	309,258
Non est. wage ads	8,168	7,225	10,338	12,186	31,704	54,780	124,401

All ads is the sample of ads from establishments in our 134 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.

the number of ads with wage information, it is clear from the first row in Table 2 as well as Figure 1, that no corresponding large increase or break in the total number of ads occurred between 2017 and 2018.

Figure 1: Number of ads

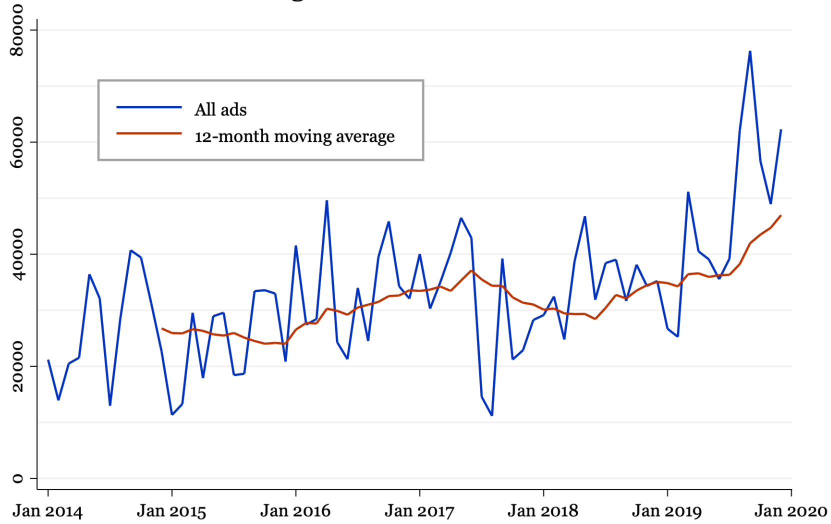


Figure 2 shows the fraction of ads with any wage information – the solid line – and the fraction with non–estimated wages – the dashed line. It is obvious that there were very few estimates in the early years. However, the two lines diverge dramatically in early 2018 when estimation became prevalent.

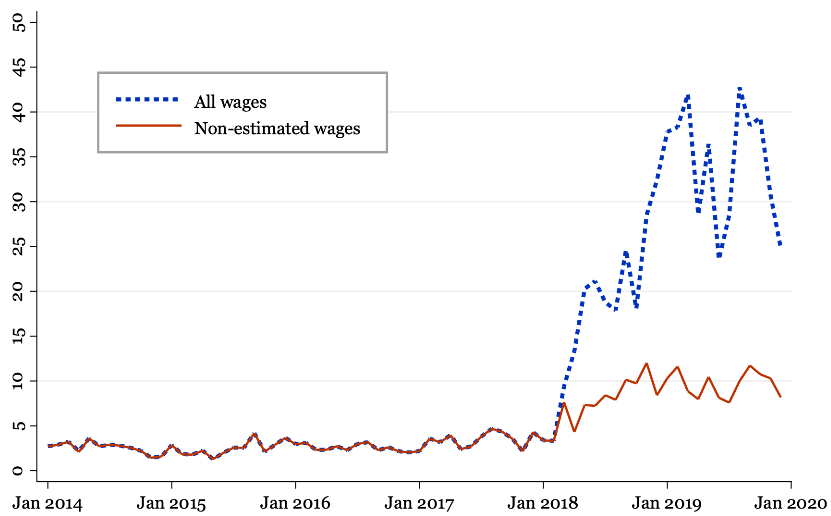
Although we expect that the introduction of new estimation algorithms by third party platforms likely account for the dramatic increase in ads with wage information, other explanations have been proposed. For example, Sran, Vetter, and Walsh (2020) postulates that, beginning in late 2017, a spate of 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 simply control for the state bans.[35]

We think that it will be important in our analyses to exclude ads with wages that were estimated by third parties. Indeed, failure to do so will cause a bias in our estimates of the effect of banning NPCs[36] : if in forming their estimates the platforms do not distinguish

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

[36] See Hirsch and Schumacher (2004) for an analysis of this type of bias.

Figure 2: Percent of ads with wages, monthly



between ads from NPC and non–NPC chains, compared to actual wages, the resulting estimated wages in the two groups will look more similar. In other words, if non–NPC wages are included in the comparison group that is used to estimate missing NPC wages and vice versa, the difference between wages in the two groups will tend to disappear, and there will be an upward bias in the OLS estimates of the effect of removing NPCs.

We believe it is highly unlikely that information about the presence or absence of an NPC is used by third party platforms when they generate wage estimates. After all, information about this contract clause, of which employees often are unaware, is not in the ad, nor is it part of the information collected by job boards, or in LinkedIn data or other common sources of wage data. Of course, platform analysts could obtain franchise contracts and extract and use the information on NPCs. However, there is nothing to suggest that they do or even why they would given, for example, that franchise chain ads are only a small subset of the ads that they track.

Finally, since the problem with estimated wages surfaces in the later years of our data, which coincides with our 'after' period, we expect the potential bias to be sizable.

Turning to characteristics of the job postings, as mentioned previously, our data include occupations classified as requiring little or no, or only some, prior work experience and skill, namely job zones 1 or 2 in the O*NET classification.[37] For reference, restaurant and shift

[37] See Appendix C for details.

manager jobs fall into job zone 2, while restaurant worker jobs fall into job zone 1, in this classification. Table 3, which contains the breakdown of postings between the two skill levels, shows that the majority of online ads in the restaurants chains are for job zone 2, the higher skill level. This also holds true for the two sub-samples with wage data.

Table 3: Job Skill Information

	ALL ADS	WAGE ADS		NON EST. WAGE ADS	
Job zone	Num. Ads	Num. Ads	Mean wage	Num. Ads	Mean wage
1 - Little skill	682,541	93,893	11.51	35,013	11.38
2 - Some skill	1,687,091	215,365	15.57	89,388	15.01

ALL ADS is the sample of ads from establishments in our 134 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 US dollars per hour.

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 to job seekers.

Table 4, which contains information about the sources of the ads, shows that a (paid) job board is the most common source, followed by a free job board.[38] Other sources of job ads in the data, which are relatively small, are recruiters – who work closely with employers whereas job boards simply advertise on their behalf – and intermediaries – which are similar to recruiters but mainly work for temporary employment agencies. It is clear that wages are estimated almost exclusively by job boards, both free and paid.

Tables 3 and 4 also show average wages of each category for the two restricted samples, revealing that there is little difference in average wages across samples. However, there are, not surprisingly, notable differences across skill levels (or equivalently job zones). Furthermore, it appears that low wage jobs tend to be advertised by the company or sent to free job boards, whereas ads for higher paying jobs tend to go to the other platforms.

[38] BGT classifies job boards that charge fees as 'job boards' whereas those that do not are 'free job boards.'

Table 4: Ad Source Information

	ALL ADS	WAGE ADS		NON EST. WAGE ADS	
Ad Source	Num. Ads	Num. Ads	Mean wage	Num. Ads	Mean wage
Employer	340,283	4,494	12.94	4,490	12.94
Free Job Board	468,766	71,247	12.88	15,652	12.24
Job Board	1,307,028	226,684	14.84	97,457	14.31
Job intermediary	20,970	2,487	13.19	2,472	13.17
Recruiter	232,585	4,346	14.55	4,330	14.54

ALL ADS is the sample of ads from establishments in our 134 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.

7 The Empirical Model

7.1 The Estimating Equations

Our objective is to evaluate the effect that the non-enforcement or removal of no–poaching clauses from franchise contracts had on the wages posted by restaurants in those chains. Our setting, however, is somewhat different from a typical event study.

First, there is no clear date when the event occurred. In particular, we do not believe that the removal of an NPC from a franchise contract made a discrete difference to the wages that were posted by restaurants in that chain. Instead, we believe that the cessation of enforcement of NPCs, which removed a barrier to labor market mobility, is what matters and we expect that effect to be gradual.

As we documented above, starting in mid 2016, there were a number of events, such as the release of position and academic papers as well as the instigation of class action law suits that targeted certain franchisors, that alerted all franchisors to the perils of enforcing NPCs. It is likely that franchisors started by wondering if only horizontal NPCs were at risk but as time went on, ended up convinced that enforcement of vertical clauses could trigger costly legal action. We therefore believe that the transition started in 2016 and was virtually complete by the end of 2019, and we specify a model in which the wage effect evolves over time.

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 once had an NPC – the NPC or treatment group – and those that never had such a clause, which include corporate as well as non NPC franchise chains – the controls. We then compare wages in ads from restaurants 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] Specifically, we drop ads from 2016 and 2017, assume that 2014 and 2015 is the 'before' period, and that 2018 and 2019 is the 'after' period.

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

$$log(w_i) = \beta_0 + \beta_{t(i)}\mathrm{I}(t(i) \geq 2016)\mathrm{NPC}_{c(i)} + f(x_i) + \gamma_{c(i)} + \mu_{m(i)} + \delta_{t(i)\times s(i)} + u_i, \qquad (2)$$

where w_i is a wage from an ad that was posted in year $t(i)$, I(.) is an indicator 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 ever had an NPC and zero otherwise, x is a vector of covariates such as ad characteristics, γ is a set of chain fixed effects, μ a set of market (MSA) fixed effects, and δ 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.

Finally, we cluster standard errors at the MSA×year level, which allows for correlation

[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.

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

among shocks that are associated with restaurants in the same geographic market and time period.

The long DID estimating equation is

$$log(w_i) = \beta_0 + \beta \mathrm{I}(t(i) = 2018 \text{ or } 2019)\mathrm{NPC}_{c(i)} + f(x_i) + \gamma_{c(i)} + \mu_{m(i)} + \delta_{t(i)\times s(i)} + u_i. \quad (3)$$

With this version, the years 2016, 2017 are omitted and the 'before' period (2014, 2015) is compared to the 'after' period (2018, 2019). The remaining variables are defined as in (2).

7.2 Estimation

There are a number of econometric issues that surface when estimating the wage equations. The most important are the biases that are associated with the presence in the data of wages that were estimated by intermediaries and with 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.

7.3 Estimated Wage Bias

When an employer does not supply a wage in an ad, intermediaries can supply one for them. We do not know how the intermediaries estimate wages. For example, they could use machine learning,[41] a hot deck procedure,[42] or they could run a wage regression. However, the method that they use is not important from our point of view. Indeed, any method must estimate a wage for an ad with no wage by looking at wage ads in a 'comparable' group. The question is: what makes two ads comparable? and the answer is that the two ads must have similar non wage characteristics.

We have noted several reasons why the issue of wage estimation is particularly important with our data, including the timing of the increase in number of estimated wages in the data which roughly coincides with the removal of NPC clauses. We deal with this estimation problem by removing the ads with estimated wages from our sample (see Appendix C).

[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).

Specifically, all specifications of our wage equations are estimated using both the set of all ads with wage information and the set of ads with wages that were not estimated.

7.4 Sample Selection

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 restricted samples are representative.

To control for sample selection, we estimate two–equation models, *a la* Heckman. 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. Since LinkedIn announced the availability of its wage estimation algorithm in mid February of 2018, the first instrument is a dichotomous variable that is zero until February 2018 and one thereafter. To our knowledge, this was the first algorithm to become available and it was followed by many others.

The second instrument is constructed as a moving average of the number of online ads posted by the chains in the same state 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.

We show bootstrapped standard errors in the tables below.[43]

7.5 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

[43] 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 60 or more replications, we used 100 replications to generate our estimates of standard errors.

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 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. In particular, they might be the ones that would have the greatest benefit from inclusion and, if that were true, it would bias the OLS estimates of the NPC effect downwards. However, since the treatment decision was taken at the chain level, inclusion of chain dummy variables removes the effect of persistent differences in characteristics. Furthermore, if, after conditioning on the chain dummies, some endogeneity remained, our estimates of the effects of removal would be conservative.

8 Results

Our two specifications of the wage equation, which we call the transition model (equation 2) and the long DID model (equation 3), 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). In addition, the selection equations are estimated on the sample of all ads (ALL ADS).

In addition to the NPC variables, each equation contains JobZone2, which indicates that the ad was for the more skilled classification; Salary Inq. Ban, which indicates that salary history inquiries were banned in the region and time period; and four of the five ad source variables (JobBoard is the base case). Finally, all specifications contain market (MSA), chain, and state/year fixed effects.

8.1 Transition Models

Table 5 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 over time, at least initially.

Table 5: OLS and Selection Corrected Wage Equations: Transition Model

	(1)	(2)	(3)	(4)
	ALL WAGE		NON EST. WAGE	
	OLS	Selection	OLS	Selection
NPC2016	0.026	0.025	0.033	0.033
	(0.028)	(0.030)	(0.027)	(0.025)
NPC2017	0.082***	0.063***	0.067***	0.052**
	(0.024)	(0.024)	(0.025)	(0.026)
NPC2018	0.115***	0.100***	0.063***	0.058**
	(0.019)	(0.018)	(0.023)	(0.022)
NPC2019	0.097***	0.082***	0.065***	0.067***
	(0.019)	(0.017)	(0.022)	(0.021)
JobZone2	0.258***	0.259***	0.221***	0.228***
	(0.005)	(0.005)	(0.005)	(0.005)
Salary Inq. Ban	0.089***	0.100***	0.042***	0.054***
	(0.016)	(0.018)	(0.012)	(0.015)
Employer	0.007	-0.059***	-0.016	-0.058**
	(0.010)	(0.015)	(0.010)	(0.023)
Free Job Board	-0.095***	-0.069***	-0.093***	-0.120***
	(0.008)	(0.008)	(0.008)	(0.014)
Intermediary	-0.001	-0.026***	-0.033***	-0.016
	(0.007)	(0.008)	(0.007)	(0.011)
Recruiter	-0.005	-0.073***	-0.003	-0.040
	(0.023)	(0.027)	(0.024)	(0.033)
Constant	2.347***	2.256***	2.378***	2.237***
	(0.012)	(0.026)	(0.013)	(0.065)
IMR		0.088***		0.092*
		(0.016)		(0.043)
R^2	0.301	0.301	0.316	0.316
Obs. Wage Equation	309,237	309,234	124,340	124,340
Obs. Selection Eqn.		2,368,745		2,357,195

The dependent variable is ln(wage).
NPC20xx is the NPC variable interacted with a 20xx year dummy.
All equations contain chain, MSA, 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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. Moreover, with the exception of 2016, they are significant with magnitudes that range between 8% and 12%.

The OLS specifications also indicate that salaries for the more skilled jobs are on average 26% higher than those for the less skilled, and that banning salary history inquiries was associated with 9% higher wages. Finally, only wages in ads posted by free job boards are significantly lower than those posted by job boards and none are significantly higher.

Compared to OLS, the correction for sample selection reduces the magnitudes of the NPC estimates. In particular, as before, the effect in 2016 is not significant but, with the other three years, the magnitudes now range between 6% and 10% compared to 8% and 12%.

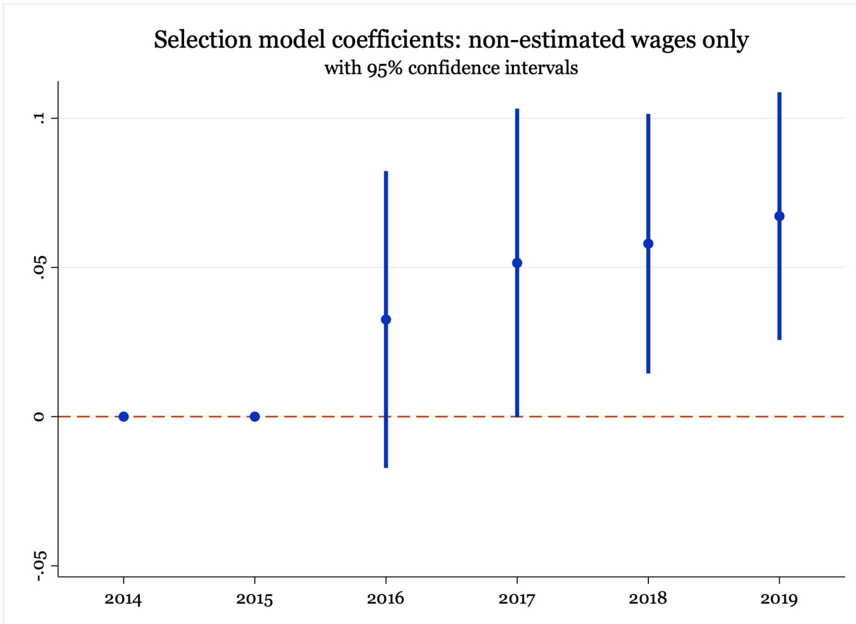
With the selection correction, the coefficients of JobZone2 and Salary Inq. Ban are very similar to their OLS values. However, wages from all ad sources are now significantly lower than those from job boards and the differences tend to be larger in magnitude. Finally, the coefficient of the inverse Mills ratio (IMR) is positive and highly significant, indicating that sample selection bias is present.

The results for the NON EST. WAGE sample are qualitatively similar: removal of NPCs and banning salary history inquiries raised wages and higher skilled workers are paid more. However, the magnitudes are almost universally smaller, as predicted. For example, the OLS estimates of the NPC effects for 2017–2019 now range between 6% and 7% compared to 8% and 12% with the larger sample, and the estimates from the selection model range between 5% and 7%, compared to 6% and 10%.

With both NON EST. WAGE equations, the more skilled jobs command 22–23% higher wages, compared to 26% with the ALL WAGE sample. Furthermore, the effect of banning salary history inquiries has been reduced from 9–10% to 4–5%.

Comparing OLS and selection estimates from the NON EST. WAGE sample, we see that the magnitudes are now much closer. This can be explained by the fact that, unlike the estimate from the ALL WAGE sample, the coefficient of the IMR is now only marginally significant. It appears that sample selection is less important when the smaller sample is used. Since researchers to date have not excluded estimated wages from the BGT data, these results highlight the importance of correcting for sample selection in any analysis that uses the uncorrected data.

Figure 3, which pertains to the NON EST. WAGE sample with correction for sample selection, illustrates the dynamic consequences of non enforcement and removal of NPCs. The figure shows that the yearly NPC effects increase over time, as expected.



8.2 Long DID Models

With the long DID specification, the effect of banning NPCs in franchise contracts is condensed into a single parameter, which is the average over 2018 and 2019 (the 'after' period). That effect is given by the first coefficient in each equation in Table 6. Other than this change in specification, this table is organized in the same way as 5.

Consider first the estimates of the NPC effect. With the ALL WAGE sample, the move from OLS to selection causes the estimate to fall from 11% to 9%, and with the NON EST. WAGE sample, the reduction is from 5.9% to 5.5%. With both samples, therefore selection reduces the magnitudes of the effects. However, as with the transition equations, the correction is more important for the ALL WAGE than for the NON EST. WAGE sample.

Comparing the NPC effect in the two samples, the OLS estimates fall from 11% to 5.9%, and the selection estimates are reduced from 9% to 5.5%. The removal of estimated wages therefore reduces the magnitude of the estimated effects, which confirms the existence of a positive bias in the OLS estimates.

The DID coefficients of the other explanatory variables in the two samples are almost

Table 6: OLS and Selection Corrected Wage Equations: Long DID Model

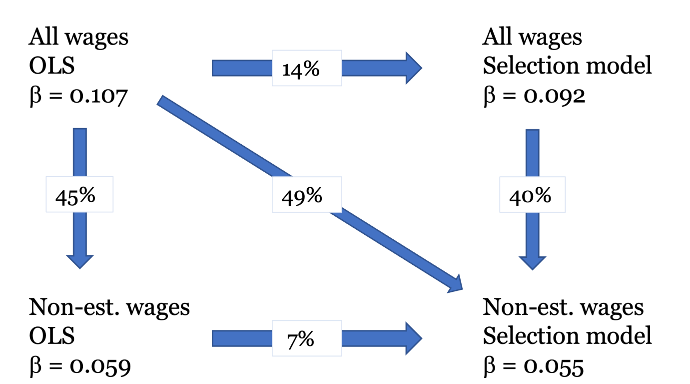
	(1)	(2)	(3)	(4)
	ALL WAGE		NON EST. WAGE	
	OLS	Selection	OLS	Selection
NPC1819	0.107***	0.092***	0.059**	0.055**
	0.019	0.019	0.023	0.023
JobZone2	0.262***	0.261***	0.224***	0.228***
	0.006	0.006	0.006	0.005
Salary Inq. Ban	0.086***	0.097***	0.042***	0.059***
	0.016	0.019	0.010	0.014
Employer	0.014	-0.046***	-0.011	-0.067**
	0.010	0.017	0.011	0.026
Free Job Board	-0.095***	-0.068***	-0.106***	-0.149***
	0.008	0.011	0.010	0.019
Intermediary	-0.004	-0.025***	-0.031***	-0.009
	0.007	0.008	0.007	0.011
Recruiter	0.113**	0.023	0.090*	0.032
	0.044	0.050	0.047	0.054
Constant	2.343***	2.272***	2.385***	2.211***
	0.012	0.023	0.013	0.065
IMR		0.074***		0.120**
		0.016		0.046
R^2	0.308	0.308	0.321	0.322
Obs. Wage equation	286,668	286,665	101,790	101,790
Obs. Selection equation		1,593,541		1,581,806

The dependent variable is ln(wage).
NPC1819 is the NPC variable interacted with 2018 and 2019 year dummy variables.
All equations contain chain, MSA, 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

identical to those obtained from the transition specification. In particular, for JobZone2, the ALL WAGE estimates are 26%, and the NON EST. WAGE estimates are 22–23% and, for Salary Inq. Ban, the comparable estimates are 9–10% and 4–6%.

We have uncovered significant biases in the OLS estimate of the NPC effect. However, some are more important than others. Figure 4 illustrates the magnitudes of the changes in the estimates – the bias reduction – as one moves from one specification to another.[44]

Figure 4: Reduction in NPC effect due to bias correction
Long dif-in-dif results



The diagonal line in Figure 4 shows that, when both biases – those due to sample selection and to third party provision of wages – are removed, the estimated NPC effect is halved (reduced by 49%). However, the downward arrow on the left hand side indicates that almost all of the reduction (45%) is due to the removal of estimated wages. Once that is done, the reduction due to correcting for selection is small (7%).

The top horizontal arrow shows that, with the sample of all wages, the bias reduction due to correcting for selection is larger (14%). Nevertheless, the arrow on the right hand side shows that the reduction due to the removal of estimated wages still dominates (40%).

9 Conclusions

A no–poaching clause (NPC) is but one of many possible vertical restraints that can appear in a franchise contract. Moreover, until quite recently, NPCs received little attention from

[44] Figure 4 is based on the Long DID estimates in Table 6.

academics, lawyers, and policy makers. Nevertheless, we believe that NPCs 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 labor market 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 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 in the chain restaurant industry.

Since NPCs appeared in franchise contracts in many other industries, removal is likely to have affected those industries as well. Moreover, since employment in franchise chains is only slightly lower than employment in manufacturing as a whole, the labor market ramifications could be very large. We conclude that there are compelling reasons for the 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.

We estimate different specifications of our wage equation and, with each specification, we correct our initial estimates of the NPC effect for two sorts of biases. The first is due to the fact that only a small fraction of online job ads in the BGT data contain wage information, which raises the possibility that the wage sample is not representative. The second results from the fact that much of the wage information in the BGT data was estimated by third party platforms.

When we perform these corrections, we find evidence of substantial biases of both sorts. Indeed, the fully corrected estimates of the NPC effect are about half as large as the uncorrected. However, most of that reduction is due to the removal of wages estimated by intermediaries. Since many researchers have used the BGT wage data without removing wages that were estimated, our results suggest that their conclusions and recommendations could be affected. Furthermore, when the data are not purged of wage estimates, we find that the bias that is due to sample selection is substantially larger and should not be ignored.

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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.[45] Each period, workers choose between staying at their current job or searching for a new job and switching. If the worker chooses to search, she receives competing wage offers from all the competing firms, with each wage offer drawn independently from a wage distribution $F(w)$ on a compact domain $[0, B]$.[46] The worker then picks the highest one from among these competing offers.

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

$$G(w) = [F(w)]^{nN-1} . \tag{4}$$

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

$$v(w) = \max \left\{ w + \beta v(w), \int_0^B (w' + \beta v(w'))dG(w') \right\} \tag{5}$$

where, $v(w)$ is the value of the current wage w. The first term in this equation is the value

[45] The wage w in this simple model can be interpreted as a shorthand representing the many features of a job that are valued by the worker, including compensation, benefits, characteristics of the employer, and so on.

[46] The lower bound on this interval is simply a normalization.

of choosing to stay put, and the second is the value of choosing to search.

The value of choosing to search is independent of the current wage, w, in equation (5), so if the worker's wage w is such that she chooses to stay put this period, she will choose to stay put every period and earn $\frac{w}{1-\beta}$. Hence, if the worker chooses to stay put, it must be that

$$\frac{w}{1-\beta} > \int_0^B (w' + \beta v(w'))dG(w'). \tag{6}$$

This implies that there exists a threshold wage $\bar{w}$ beyond which the worker will choose to stay put, which is defined by

$$\frac{\bar{w}}{1-\beta} = \int_0^B (w' + \beta v(w'))dG(w') = \mathbf{E}_G w + \beta \int_0^B v(w')dG(w'). \tag{7}$$

This allows us to rewrite the value function as

$$v(w) = \begin{cases} \frac{w}{1-\beta} & \text{if } w \geq \bar{w} \\ \frac{\bar{w}}{1-\beta} & \text{if } w \leq \bar{w} \end{cases} \tag{8}$$

Substituting 8 into 7, after some algebra, we can express the threshold wage as

$$\bar{w} = \mathbf{E}_G w + \frac{\beta}{1-\beta} \int_{\bar{w}}^B (w' - \bar{w})dG(w'). \tag{9}$$

Now consider the imposition of NPCs. 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

$$\tilde{G}(w) = [F(w)]^{n(N-1)} \tag{10}$$

where

$$G(w) = [F(w)]^{nN-1} < [F(w)]^{n(N-1)} = \tilde{G}(w), \qquad w \in (0, B). \tag{11}$$

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

The threshold wage $\bar{\bar{w}}$ under this new scenario is

$$\bar{\bar{w}} = \mathbf{E}_{\tilde{G}} w + \frac{\beta}{1-\beta} \int_{\bar{\bar{w}}}^B (w' - \bar{\bar{w}})d\tilde{G}(w'). \tag{12}$$

If the new threshold wage is lower than the initial one, then workers search less frequently and observed wages will be lower. The difference between the threshold wages is

$$\bar{w} - \bar{\bar{w}} = \underbrace{\mathbf{E}_G w - \mathbf{E}_{\tilde{G}} w}_{A} + \frac{\beta}{1-\beta} \underbrace{\left[\int_w^B (w' - w) dG(w') - \int_w^B (w' - w) d\tilde{G}(w') \right]}_{B(w)}. \tag{13}$$

Now consider A in equation 13. Since $G(w)$ first order stochastically dominates $\tilde{G}(w)$, A, which is the difference in expected values, will be negative.

Now consider $B(w)$ in that same equation. Using integration by parts, it can be rewritten as:

$$B(w) = \int_w^B [G(w') - \tilde{G}(w')] dw'. \tag{14}$$

which is also negative for $w \in (0, B)$.

We conclude that the new threshold wage is lower than the initial threshold wage. This implies that the worker is less likely to search, leading to more mass to the left of the observed wage distribution, and a lower average observed wage under this scenario.

We now briefly consider the effect on average observed 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 her employer does not have an NPC, or a low threshold wage equilibrium if the associated chain has an NPC. Note that the contours of either equilibria are independent of whether other chains not associated with the worker's employer have NPCs. Thus, any time 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 observed wages to move left, reducing the average observed wage. As more firms adopt NPCs, this process pushes the average observed wage further down each time.

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,

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

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,

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

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, which contains information about restaurant chains, is from National Restaurant News (NRN), an American trade publication that covers the food service industry, including restaurants and restaurant chains. That source publishes data on the 200 largest US restaurant chains measured by systemwide US sales revenue each year.[47]

We focused on chains that are large enough that they appear in the "Top 200" list every year, and that have at least 50 establishments nationally every year. There were 164 such chains in the data. In addition to sales revenue and the number of establishments, for each year the NRN publishes 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 any year as franchise chains; there are 129 such chains in the data. The remaining 35 chains are classified as corporate.

C.2 NPC Data

For the 129 franchise chains in our data, we attempted to establish whether their franchise agreements contained NPCs prior to 2016. For some chains, this information was available from Krueger and Ashenfelter (2022). For the remainder, we searched various sources to find franchise disclosure documents from years prior to 2016. Some states require that chains file disclosure documents (which include franchise agreements) with a government agency before being allowed to offer franchises in that state. Four states publish such documents online, of which California[48] and Minnesota[49] publish documents from before 2016, from where we obtained some agreements. We also purchased some disclosure documents from FranData, a franchise market research and consulting firm. We were unable to locate franchise agreements for 14 small franchised chains, and therefore eliminated them from our dataset, leaving us with 115 franchised and 150 total chains in our panel. We then manually examined available franchise agreements to establish the presence or absence of an NPC prior to 2016.

As described below, 16 chains are either not represented in the BGT data; or had very

[47] The surveys are identified by the publication based on when they are published, but the data are for the year before – i.e. the last completed fiscal year for the companies. We follow their convention.

[48] `https://docqnet.dfpi.ca.gov/search/`

[49] `https://www.cards.commerce.state.mn.us`

few postings, especially in the 'before' period in our data. We restrict our sample to chains that had more than 5 ads in the BGT data in 2014 or 2015. This leaves us with a sample of 134 chains, 31 of which are corporate.

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[50] .

BGT processes each posting to extract several standardized fields from the posting's text. Those include fields relating to the job title, occupation, employer, the employer's industry, the geographic location of the job, required credentials (in terms of experience or education), and information on offered wages, if any. Not all ads, however, contain information in every field. In particular, the wage and industry fields are often missing.

From the BGT data, we extracted all jobs posted between 2014 and 2019 by one of the 150 chains identified using the "Top 200" lists. To do this, we first extracted a list of unique employer names in the BGT data. We then used a fuzzy matching algorithm to extract close matches to the names of our chains. An exact matching strategy was not possible, given the natural variation in how employer names appear in online job postings and how accurately those are captured from the ad text by BGT's algorithm. We then manually examined each of the close matches and excluded those that were obvious errors.

Next, using this list of chain names, we extracted various fields from all job postings corresponding to each chain. Given that we used a fuzzy matching algorithm to match names, we expected to capture some postings from outside the restaurant industry. To minimize this, we excluded postings that BGT identified as coming from the government and education sectors as well as postings where BGT could not identify a sector.

BGT extracts a job title from each ad. However, we are more interested in job skills. The Occupation Information Network (O*NET) developed by the US Department of Labor's Employment and Training Administration classifies occupations into standard occupational codes (SOCs). It also classifies occupations into five 'job zones' with increasing levels of skill.[51] BGT assigns O*NET SOC codes to job postings and we used the O*NET 25.0 Data

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

[51] The levels are principally based on increasing educational and certification requirements.

Dictionary[52] to match each job posting in our data with the corresponding skill level.

93% of ads in our data are for skill levels 1 or 2. Moreover, from the O*NET dictionary, we determined that chain restaurant and shift manager jobs fall into zone 2, while restaurant worker jobs fall into job zone 1. Therefore, not only are ads for these skill levels much more numerous in our data, but also those categories include the workers and jobs that have been the focus of class action and other law suits in the chain restaurant industry. We therefore eliminated the 7% of ads for other skill levels from our data.

To guard against outliers (for example, the possibility that BGT's algorithm mistakenly interpreted a daily wage as an hourly wage), for those ads that included wage information, we only kept those with wages below $60/hr.

Finally, BGT provides information on several standard geographical areas for each ad. In our empirical work, we use the Metropolitan and Micropolitan Areas (MSAs), which 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 928 of them. We do not include ads posted for jobs in rural 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.

After also eliminating some ads with missing data on other variables of interest, we were left with a dataset of 2,369,632 individual postings for 134 chains that comprised our final sample of chains.

C.4 Estimated Wages

As the first two rows of Table 2 show, we found an explosion of postings with wage data in 2018 and 2019, without a similar explosion in the total number of postings. We manually inspected a random sample of ad texts from our dataset and found that some of the wages in later years originating from third party platforms were estimates. Those platforms sometimes provided an expected pay range, suffixed by 'estimate', or prefixed by 'similar jobs pay', which the BGT algorithm captured as a wage.

Starting from our sample of all ads with wages, using the information about words or expressions found in the ads, such as wages suffixed by 'estimate' or prefixed by 'similar jobs pay,' we identified what we classify as ads with estimated wages. The third row of Table 2

[52] `https://www.onetcenter.org/dictionary/25.0/excel/`

shows that there are very few wage estimates in the early years. However, the number of estimated wages, and thus the fraction of ads with estimated wages, grew sharply in 2018 and 2019. In particular, between 2107 and 2018 the percentage with wage estimates increased from 0.2% to 58% and that number rose again to 72% in 2019.

We sought to determine whether wages that were flagged by our methodology as being estimated in the early years of our data were in fact estimated, and found that they were not. Instead, the key phrases that we searched for were used in a different context and our procedure misclassified only a very small number of postings. Given the small misclassification percentages prior to 2018, we believe that the rate of misclassification in the later years is also very small and that our methodology to identify ads with estimated wages is therefore sound.