

# Who profits from occupational licensing?

Andreas Haupt, Karlsruhe Institute of Technology

[andreas.haupt@kit.edu](mailto:andreas.haupt@kit.edu)

(Accepted for: American Sociological Review)

**Abstract:** Sociologists have debated intensively how and why occupations matter for economic inequality. I argue that occupational licensing alters wage setting, depending on the characteristics of the licensing system. Licensing does not only restrict market entry as in the US. Some governments, like that of Germany, also regulate task prices and set occupation-specific wage floors for licensed occupations. I claim that the US system leads to a growing licensing wage advantage across the distribution, and that the German system leads to a falling one. Furthermore, I discuss that women may benefit especially from licensing, because for them it reduces typical disadvantage in the wage setting. I present unconditional and gender-specific quantile treatment effects based on CPS-MORG and BIBB/BAuA data from 2018. In the US, wage premiums are highest for employees in the upper middle and are small for those in the bottom and the top. For Germany, the wage premium is the largest for licensed employees at within the lower quarter and reduces significantly towards the top. In both countries, women profit significantly more from licensing. These results challenge claims about the role of licensing for inequality in the top, and suggest that licensing reduce penalties faced by disadvantaged groups.

**Keywords:** occupational licensing, wage inequality, gender inequality, quantile treatment effects

**Acknowledgements:** This study would not have been possible without the data-gathering work of Nina Müller, Yannick Harksen, Ronja Niedermayer, and Anna Becker. The study profited greatly from discussions with René Krieg, Merlin Schaeffer, Jonathan Latner, Florian Hertel, Gerd Nollmann, Nils Witte, Barbara Binder, Blaise Melly, and the participants of the GESIS workshop “Causality in the Social Sciences”. Anthony Strittmatter provided me with the syntax for the Translated Quantile Treatment Effects, for which I am very grateful. Scholars can access all syntax files and occupational data for the US used for this study following this link: <https://osf.io/q6chw/>.

**Funding:** This study was supported by the German Research Foundation (DFG) (grant no. 265326967).

## **1. Introduction**

The role of occupations in generating inequality of labor incomes is hotly debated in sociology (Haupt and Ebner 2020; Leicht 2020; Sakamoto and Wang 2020; Wilmers 2020). Within this discussion, the theory of occupational closure stands out as a prominent explanation of between occupational pay differentials (Bol and Drange 2017; Murphy 1988; van de Werfhorst 2011; Weeden 2002). Scholars who apply this theory claim that occupations create barriers to labor market entry in order to reduce competition and leverage this reduced competition to their economic advantage, typically resulting in higher wages (Murphy 1984; Stigler 1971; Weber 1922; Weeden and Grusky 2014).

Occupational licensing – the permission of the state to work within an occupation legally – is the most obvious type of occupational closure. It is also a very prevalent labor market institution in many countries, covering a share of between 18% and 25% of all employees across different countries (Kleiner and Krueger 2013; Koumenta et al. 2014). Scholars and policy makers have repeatedly argued that licensing is a state-driven monopoly with the potential to reduce competition substantially and create wage advantages for licensed employees, at the cost of social welfare (Kleiner and Krueger 2010; Weeden and Grusky 2014; White House 2015).

Indeed, various studies on the US find a robust association between licensing and average wages, with estimated premiums ranging typically between 9% and 18% (see Redbird (2017) for an overview). Evidence for other countries – such as for Canada (Zhang 2018), China (Chi, Kleiner, and Qian 2017), Germany and the UK (Bol and Weeden 2015; Witte and Haupt 2019) – show similar results. These results have been taken as evidence for the plausibility of closure theory and the speculated mechanism linking closure and wages (Drange and Helland 2018; Zhang and Gunderson 2020). Furthermore, the similarities in the size of the association across countries serve as evidence for the claim that this mechanism works in a similar way across different labor markets (Bol and Weeden 2015; Koumenta et al. 2014).

In this paper, I add to this debate in three ways. First, I draw on theories of wage setting to describe how licensing changes the conditions of wage bargaining. This allows me to theorize not only about the influence of licensing on average wages but also to hypothesize about how licensing alters the chances of receiving high and low wage offers. The theory I propose is able to incorporate the arguments of current closure theory, by showing that a reduced supply of licensed employees increases bargaining power in their favor.

Second, I challenge the assumption that licensing affects wages similarly across different labor markets. I show important differences between licensing systems across countries and connect these differences to the wage-setting process. To understand the institutional structure of occupational licensing, we cannot view it merely as a set of regulations governing labor market entry. For example, governments may be bound by legal principles that stipulate which occupations can be licensed and which cannot. In order to issue and control processes within a closed occupational market, governments can also transfer part of their executive power to occupational boards and give them more or less authority to regulate affairs within their market. Lastly, they can issue price-setting rules for licensed tasks. Such structural differences change the conditions for the wage setting of licensed employees, and this can alter the licensing wage advantage across the wage distribution between countries.

Third, I analyze how licensing systems have different consequences across genders over the wage distribution. Recent literature suggests that licensing especially improves wages for disadvantaged groups (Blair and Chung 2022; Koumenta, Pagliero, and Rostam-Afschar 2021; Witte and Haupt 2019). However, it is not clear whether this advantage stems from reduced penalties in low-wage or high-wage settings, and whether this is the same across licensing systems. I argue that licensing especially helps women to counter wage penalties in the upper half of the wage distribution, and that this is particularly the case for the US.

Thus, my aim here is to test novel theoretical predictions about the consequences of licensing for wages in two different institutional settings. A comparison of Germany and the US is informative for this purpose, because their constitutions differ strongly with respect to occupational licensing. In the US, occupational licensing is a policy choice of governments, which is not in potential conflict with constitutional law. Governments in the US have also delegated a wide range of competencies to occupational boards, and the Supreme Court has declared price-setting rules unconstitutional. In contrast, occupational licensing is in conflict with the constitutional guarantee of free occupational choice in Germany. Because of this, the benefits from licensing a particular occupation must be sufficiently clear to justify abrogating this constitutional guarantee, which sets strong limits on licensing for governments. German occupational boards have very limited authority, and there are standard price-setting rules for

licensed occupations. Thus, both countries can serve as interesting cases for studying the relevance of these institutional differences for the wage structure.

## **2. The previous discussion about licensing and wages**

Occupational closure theory, in its most commonly used form, rests at its core on the following line of reasoning: a) social closure changes the supply-and-demand relation within the occupational labor market; b) the reduction of the labor supply is sufficient to produce a significant labour supply shortage; and c) because there is a labor shortage, wages increase, because the prices of occupation-specific skills increase. Most empirical studies of the wage effects of licensing apply this line of reasoning (Bol and Drange 2017; Weeden 2002; Albert 2016; Gittleman and Kleiner 2016; Kleiner and Krueger 2013; Bol 2014; Blair and Chung 2017; Timmons et al. 2018; Zhang and Gunderson 2020; Chambers and O'Reilly 2021).<sup>1</sup> For instance, in their comparison between the UK and Germany, Bol and Weeden (2015:357) state that “[t]he standards for licensure are often set by occupational agents or an organization that directly represents the occupation (e.g., a lawyer’s bar association); as with occupational control over apprenticeships, this gives occupational representatives indirect control over the number and qualities of licensees. [Thus,] occupational licenses affect wages by restricting opportunities to apply skills.”

This line of reasoning has inspired much sociological research, but it can be challenged both theoretically and empirically. First, this theory posits that wages are the prices that are paid for skills, which are freely sold on a stock exchange-like labor market. As social closure restricts supply for employees, it increases skill prices and thus affects wages. However, sociology offers a rich understanding of the fact that wages are a result of power struggles, sometimes collectively, sometimes individually (Kalleberg, Wallace, and Althausen 1981; Sauer et al. 2021; Stainback, Tomaskovic-Devey, and Skaggs 2010; Western and Rosenfeld 2011). These theories teach us that wages are not mere prices that change due to supply-and-demand curves but are the result of complex wage-setting processes, which depend strongly on the distribution of power between the employees and employers, as well as the context in which the wage setting

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<sup>1</sup> Weeden (2002) theorized about further characteristics of closed occupations. According to her study, closed occupations are able to channel demand for tasks, signal that they are the only legitimate supplier of specific tasks, create and defend that demand, and channel the demand toward their occupation. These characteristics are certainly of importance for the *revenues* of the firms selling these tasks. However, neither Weeden (2002) nor studies using her work make clear how these increased revenues relate to wage setting. Higher revenues are not mechanically linked to higher wages: there needs to be some kind of rent sharing between employees and the employer, and this needs to be elaborated and modeled.

takes place (Morgan and Cha 2007; Sauer et al. 2021; Sørensen 1996). Current discussions about the link between occupational closure and wages could be strengthened by drawing on these theories, as I seek to do here.

Closure theory also faced empirical challenges. Law and Marks (2013), for example, compare the wages of registered and practical nurses between 1950 and 1970 in the US. During this time, these occupations changed from being subject to certification to being subject to licensing in some states but not in others. The authors estimate no changes in wages attributable to changed licensing status (see also Law and Marks 2009, 2017). Furthermore, Redbird (2017) uses the variation of licensing across US states over time to study wage effects. She, too, finds that there is no increase in the occupational mean wage after the licensing of an occupation within a state. If wages increase as a direct consequence of licensing *and* the mechanism works in the same way for all licensed occupations or across labor markets, we should be able to observe wage increases in such cases. Thus, the process connecting licensing with wages might be less mechanical than the standard line of reasoning suggests.

Some scholars have relaxed the assumption that licensing works the same for all occupations, and have speculated about whether more powerful and prestigious occupations generate even higher premiums because they hold more control over their markets (Kleiner and Vortnikov 2017; Weeden and Grusky 2014; Weeden 2002). Because these occupations are typically located in the upper quarter of the distribution, licensed employees should gain larger wage advantages in upper parts of the wage distribution as compared to the lower parts. Since newly licensed occupations are typically middle- or low-wage ones, this could also explain the null findings cited above (Deyo, Kleiner, and Timmons 2018). However, the evidence of larger wage advantages of licensed employees in upper parts of the distribution as compared to middle and lower parts is mixed: Weeden (2002) finds the highest wage premiums for licensed employees for professions. Kleiner and Vortnikov (2017) report the highest wage advantages for high-earning licensed employees. In contrast, Gittleman, Klee, and Kleiner (2015) report the highest relative wage advantages in the bottom quartile of the US wage distribution. In a follow-up study, Gittleman and Kleiner (2016) report the largest advantages in the bottom and top quartiles as compared to the middle. Studies for Canada (Zhang and Gunderson 2020) and China (Lyu, Zhang, and Ye 2022) suggest the highest advantages in the upper-middle of the wage distribution but not in the top. For European countries, Bol and Weeden (2015) estimate

higher coefficients for lower parts of the German wage structure relative to higher parts, which is opposite to the situation in the UK. Koumenta and Pagliero (2019) estimate higher wage dispersion due to licensing for *both* tails of the wage distribution across Europe.

Overall, the pattern is not clear. It ranges from null findings to inconsistent findings across the wage distribution. However, the inconsistent results suggest at least that the licensing wage advantage is not uniform across the wage distribution. Nevertheless, as of now, we lack a theoretical framework that is able to make inferences about such patterns. Furthermore, an international comparison based on the available studies suggests that the influence of occupational licensing on wages differs across countries. It is an open theoretical question as to why and how country-specific differences in licensing systems matter.

### **3. Licensing and wage setting in a comparative perspective**

The aim of this paper is to use a general understanding of wage setting with licensing as a special kind of context in which the wage setting takes place. I use this framework to make inferences about the following: a) the licensing wage premium across the wage distribution, which I understand as an additional wage component for licensed employees in comparison to unlicensed employees; b) differences in the licensing premium between countries; and c) differences in the premium across genders. To do this, I first discuss theories of wage setting. In a second step, I describe the licensing systems of the USA and Germany, and how they differ. My central claim is that cross-country differences between licensing systems strongly alter the wage-setting process for licensed employees. The German system reduces opportunities for extensive rent sharing due to price fixing for licensed tasks but also sets occupation-specific wage floors for many licensed occupations, which could lead to high premiums in the lower parts of the wage distribution. The US system could lead to larger licensing premiums in the top, because prices for licensed tasks are not fixed. In combination with strong bargaining power of licensed employees this could result in substantial rent sharing, especially for high-earners. I furthermore argue that licensing in both systems especially benefits women.

#### *3.1 Wage bargaining and wage posting*

Employees can either bargain over wages or face a take-it or leave-it situation in which the employer is unable or unwilling to bargain – a situation referred to as wage posting. Empirical studies showed that both practices coexist (Hall and Krueger 2012; Sauer et al. 2021). While it remains unclear which kind of wage setting has the larger incidence, we know that wage posting

is more likely to apply for low-wage jobs and that the opportunity to bargain increases across the wage distribution (Brenzel, Gartner, and Schnabel 2014; Lachowska et al. 2022).

Since licensed employees are located across the entire distribution, we need to include both wage posting and wage bargaining to understand the licensing wage advantage. I will therefore outline a theoretical model of the wage-setting process and then provide an argument as to how licensing can alter each part of it. As Manning (2011) shows, wage posting and wage bargaining do not rest on completely different logics. Instead, we can understand wage posting as a special kind of bargaining situation, where the power of employees is to decline unfavorable offers and the power of employers is to decline the bargaining. Thus, I will start with a model of wage bargaining and elaborate how wage posting deviates from the bargaining situation when necessary.

In most general terms, we can model the wage ( $w$ ) of an employee based on three elements: the bargaining power of the employee ( $\alpha$ ); the maximum contribution of revenue attributable to the employee within the firm ( $p$ ); and the lowest wage offer acceptable to the employee, which is referred to as the reservation wage ( $b$ ). The maximum contribution and the minimal offer define two ends of a continuum. This is the defined range in which wage setting is possible in the given bargaining situation. The distribution of bargaining power between employee and employer determines the result of the bargaining. The following equation expresses the wage in light of this relation between the two bargaining parties:

$$w = \alpha \cdot p + (1 - \alpha) \cdot b.$$

The application of this model to licensing and wages leads to three general expectations. First, if licensed employees can legitimately claim that their work contributes more to revenue compared to unlicensed employees, we can assume that licensed employees earn higher wages compared to unlicensed employees—even if licensed and unlicensed employees have equal bargaining power. Second, if licensed employees have higher bargaining power than unlicensed ones, they can force employers to share higher parts of the revenue (Sauer et al. 2021; Morgan and Cha 2007). Third, if licensed employees have a higher bar about an acceptable minimum pay, we can expect that they have a lower risk of being paid less than we would expect of an unlicensed employee with similar characteristics.

We can also draw some general expectations for the case of wage posting. If employers are free to set wages without bargaining and without constraints, like minimum wages or collective agreements, they can push wages toward minimal acceptable offers (Card 2022; Manning 2021). If licensed employees can decline such offers more often than unlicensed employees, they can reduce their risk of being paid below what we would expect for an employee with similar characteristics. A powerful position within labor markets enables employees to say no to bad offers. This power builds upon the number of better paid alternative jobs. For licensed employees, this number could be higher, because they can seek employment both in their licensed occupation and in alternative occupations, whereas a similar unlicensed employee can only seek employment in occupations without licensing. Since wage posting is very likely prevalent in the lower part of the wage distribution, we can expect that this would increase wages for licensed employees earning moderate wages.

These general expectations show how incorporating simple wage setting models can deepen our understanding of the relationship between licensing and wages. With them, we can analyze how occupations create different environments that allow employees to refuse low-wage offers, claim to contribute to larger parts of the company's revenue, or, in a bargaining situation, push wages upwards. My aim here is to connect these theoretical constructs with the characteristics of countries' licensing systems. Different rules within these systems can change the position of licensed employees within their specific labor markets. This can also help us to understand the differences in wage premiums between countries and genders that have already been reported in the literature (Bol and Weeden 2015; Blair and Chung 2017).

### **3.2 Differences in licensing systems and wage setting**

Depending on the specific implementation of a country's licensing system, the licensing wage premium can be based on a reduction in low-wage risks or an increased chance of earning high wages. We therefore have to set the specific rules of the licensing system as boundary conditions of the wage-setting situation.

#### *3.2.1 Occupational licensing and minimum wage offers*

In this step, I discuss why occupational licensing is associated with increased minimum wage offers in Germany but not in the US. The German system influences minimum wage offers by



applying occupation-specific wage floors for many licensed occupations, based on the strong connection of such occupations to basic public goods. There are no such wage floors in the US.

The German state is constitutionally obliged to ensure the supply of high-quality basic public goods (Schwark 1997). These goods are public security, education, public health, and the reason of the state (Haupt 2016). Occupations providing these goods must do so with sufficient quality. Licensing is, from this perspective, the state's solution to the problem of how to avoid the provision of low-quality public goods (Zhou 1993). However, occupational licensing is a restriction of the constitutional right of all persons falling under German law to choose an occupation freely (article 12 of the German constitution). A restriction of a constitutional right is no small affair: it must be justified by higher interests of the state, and it is limited by the range of these interests. In this case, the duty to supply basic public goods is given a higher weight than freedom of occupational choice, but this restriction only applies to those occupations which are necessary to supply these goods. Thus, a German occupation can be licensed only if it has a very close connection to a basic public good (Bundesverfassungsgericht 1958).

An important consequence of the state's obligation to ensure high-quality public goods is that there are occupation-specific wage floors for occupations associated with these goods. If the supply of these goods falls below a publicly or politically acceptable threshold, the wage floor for these occupations rises, very likely due to public pressure, increased competition between states or organizations, or court decisions. For example, there has been a broad public debate about the shortage of qualified health care personnel, as well as teachers, child care workers, and physicians, in Germany over the past two decades (Bellmann et al. 2013; Deutscher Lehrerverband 2001; Wissdorf 2014). The reactions to these shortages have differed. In the case of teachers, some German states have increased their competitiveness by paying higher base salaries (Seifert and Fertmann 2009). This has also been done for the police and for firefighters (Hausner, Heinrich, and Huelgas 2015). For health care occupations, especially for low-paid workers, such as geriatric nurses, the German government introduced occupation-specific minimum wages in 2010, and has increased them four times since then (*Pflegearbeitsbedingungenverordnung 1-5*). Furthermore, judges and state attorneys sued the German state because of their low wage floor, winning their case in 2015 (Bundesverfassungsgericht 2015). Since then, the German state has had to pay higher base

salaries for these occupations. The judges explicitly stated that low entry salaries could lead to negative selection into these occupations, which is harmful to the state's duty of providing high-quality judges and state attorneys, and would thus be harmful to the reason of the state as a basic public good. Court decisions do not only concern public servants, such as judges. According to a court decision in 2007, a fully employed private attorney must earn at least 2,300 EUR a month, which is approximately 2,560 USD (Anwaltsgerichtshof NRW 2007). The judges argued that a wage below this level is not conducive to ensuring the accuracy and diligence necessary for this kind of work, and that this has the potential to harm the quality of the public good associated with the practice of law (Gaier 2015). In addition, they stated that every employee within an occupation with a chamber has the right to be properly paid. Since every employee of a licensed occupation with a chamber in Germany must be a member, this ruling created occupation-specific wage floors for professions.

Thus, the distinctive feature of licensed occupations in Germany is that a (perceived) growing number of vacancies or a reduced quality of candidates can create jurisdictional pressure to set a higher wage floor. This is not the case in the US. The institutional architecture in the US does not create a comparable link between occupational licensing and a state duty to guarantee the provision of basic public goods. Thus, specific wage floors for licensed occupations are not part of social policies, and the government cannot be sued because of a low wage within a licensed occupation.

In sum, occupational licensing should lead to a highly reduced risk of earning low wages in Germany, resulting in a strong licensing premium for low-wage employees. For the US, we cannot expect such a protection against low wages *specifically* for licensed employees.

### *3.2.3 Occupational licensing and maximum wage offers*

The general bargaining model predicts high wage offers if employees have high bargaining power *and* are able to attribute a high amount of the firm's revenues to their work. The second point is a result of product markets, but not the labor market – it is a consequence of the value of services or products, which in turn increases the value of an employee for a firm.

In line with prior research, I assume that licensed professions have at least some influence on the product market (Kleiner and Park 2010; Timmons, Hockenberry, and Durrance 2016;

Weeden 2002). Licensed occupations represent the only legitimate source of supply for a set of services or products. They also represent relevant actors in the process of determining the prices of these products – in some cases simply because licensed persons are self-employed or are the CEOs of organizations (Dingwall and Fenn 1987; Habinek and Haveman 2019). High prices for occupational tasks and products, in combination with high bargaining power, would thus result in substantial wage advantages.

As for differences in minimum wage offers, governments can regulate licensed occupations in different ways. Licensed occupations can have legally binding price-setting schemes to various degrees, or such schemes can be defined as illegal. The first is the case in Germany, and the latter is currently the case in the USA.<sup>2</sup>

Whether or not there are price-setting regulations can make a huge difference for the wage-setting situation. On the one hand, such schemes can enable occupations to increase the minimum prices for their services, which allows licensed employees to take part in more generous rent sharing (Mocetti, Rizzica, and Roma 2021; Rostam - Afschar and Strohmaier 2019). On the other hand, such schemes can also set maximum prices for occupational tasks, creating very strong wage caps. Employers typically have no incentive to pay their employees more than the part of the firm's revenues attributable to them, as defined by price schedules. If their contribution to the organization's revenue is reduced due to price fixing, we should therefore expect a smaller licensing advantage compared to a situation without price fixing.

Germany sets standard price schedules for licensed occupations, because the state has not only the obligation to secure the supply of high-quality basic public goods, but also to ensure that these goods are affordable. It would be a violation of the German constitution's welfare principle if the public were not able to afford standard medical services, or if the prices of these services strongly increased the payroll taxes paid in order to obtain such services.<sup>3</sup> The government regulate prices on the grounds of fee structures and scales of charges for the occupations in question. The fee schedule for dentists, for instance, determines that the

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<sup>2</sup> Germany is not a unique case for enacting price regulations for licensed tasks. They also exist in Italy, as discussed by Mocetti, Rizzica, and Roma (2021), and in France, as shown by Choné (2017).

<sup>3</sup> For instance, §71, 3 of the Code of Social Law V defines the principle of contribution stability for public health insurance contributions ("*Grundsatz der Beitragssatzstabilität*"). The share of these contributions of all taxpayers in relation to their gross earnings should not increase over time.

“resection of a root tip of an anterior tooth” should cost at least 25.87 EUR, but not more than 90.55 EUR (German Dental Association 2011:Nr. 3110). Chimney sweeps may charge 12.28 EUR for basic services for each house and have fixed prices for every additional task associated with their duties. Architects, construction engineers, tax consultants, and most health-related professions are also subject to price regulations. Although some health-related professions, such as physiotherapists and nurses, are unregulated by fee structures, they are subject to §125 of the Code of Social Law V (*Sozialgesetzbuch V*). According to this paragraph, health insurers are required to enter into statutory contracts defining maximum prices for services provided. For example, the contract for speech therapists fixed the costs for each standard treatment lasting 30 minutes at 23.66 EUR in 2015 (Verband der Ersatzkassen 2014).

A notable exception to the price regulation of licensed occupations in Germany concerns practices that are not part of the state-defined activity of the occupation. In such a case, it is possible for practitioners of particular licensed occupations to set prices freely. For example, it is a common practice among lawyers to offer consulting services; since these services are not considered specialized to lawyers, the remuneration for them is unregulated by the government. The same is possible for health care services that are not part of the standard catalog of the occupation in question. Physicians can offer services such as aesthetic interventions or practices outside of traditional medicine to clients, and can freely bargain over the prices for these services.

Price regulations, especially for licensed services, did exist in the US until the Supreme Court ruled against them in 1975. In *Goldfarb v. Virginia State Bar*, the U.S. Supreme Court (1975) ruled that setting minimum prices for law services was not exempt from antitrust policy because law services are part of trade and commerce. Furthermore, the court made any “learned profession” subject to this rule. It also banned maximum fees in 1981 (U.S. Supreme Court 1981). Since then, all occupation-specific fee schedules in the US have been illegal. According to Noah (2009), the result for medicine was a paradigm shift: “Where once government had sought to police the health care sector mainly to protect patients, now it sought to police it mainly to protect a competitive health care marketplace. A thriving health care bazaar, it was assumed, would serve patients' interests” (see also: Relman 1991). In contrast, the prices for licensed services typically increased steeply. There is – theoretically – no upper bound for the prices of occupational tasks in the US. Typically, large US law firms, accountancy firms, and

medical organizations have high market power because they offer strongly regulated services, and prices for their services and products are not subject to regulation. They can sell specialized products or services at very high prices (Krishnan 2001; O'Neill 2015; Lancaster 2016).

I expect that statutory price schemes set upper bounds for the wages of German licensed employees in the upper half of the wage distribution, especially in the top. German licensed occupations are not the major stakeholder for the construction of these price schemes; governments, healthcare insurers, and the public are. They all have an interest in preventing sky-rocketing prices for basic public goods, and this strongly reduces the maximum prices for licensed services. Thus, even with very high bargaining power, licensed employees with high wage potential should face strong caps on their wage offers. For the US, I do not expect such a boundary effect.

### *3.2.3 Occupational licensing and differences in bargaining power*

I assume that occupational licensing typically increases the bargaining power of employees. This advantage increases with the substitutability of employees, which is based largely on the competition between employees within a labor market. The higher the entry requirements of occupations, the lower the *additional* potential labor supply within the occupational market, which could lead to reduced competition.

Entry requirements vary strongly across occupations within a country. Licensed labor markets for professionals, such as physicians or attorneys, have very high entry requirements across all states in the US (Vaney Olvey, Hogg, and Counts 2002). However, there are also many occupations, such as crane operators or horse trainer assistants in Arkansas, with much lower entry requirements (Carpenter et al. 2012). I assume that higher entry requirements reduce substitutability within the occupation-specific labor market. This could increase the number of vacancies that we would expect without licensing, or with lower licensing requirements, which then creates more exit options for licensed employees. Using these exit options to move between firms, or just using them as a credible threat targeted at the current employee, increases the bargaining power of employees and enables them to decline low wage offers. Higher entry requirements seem to be correlated with occupational status. Thus, we should expect that higher-status employees within licensed occupations have more bargaining power in relation to

those in lower-status occupations, as previous research has argued (Kleiner and Vorotnikov 2017; Weeden and Grusky 2014).

At an institutional level, occupational boards could play a crucial role in this matter. Scholars have theorized about their role in the past, but we have little empirical knowledge about their implications for wage bargaining and setting (Pagliero 2019). Here, I compare differences between the capabilities of German and US occupational boards, and I investigate how such capabilities could influence the bargaining power of licensed employees.

In Germany, occupational boards take the form of occupational chambers. As such, they are part of the executive branch of the state. Technically, an occupational chamber is an occupation-specific public corporation (*“Berufsständische Körperschaft”*) that is implemented and supervised by the state to regulate occupation-specific affairs. Every practitioner of an occupation with a chamber must be a member. Chambers have the right to advise the government on matters relating to qualification standards for the occupation. They issue licenses but do not examine qualifications required for occupational access itself. Chambers create codes of conduct and report the misbehavior of their members to the judicative body. As members of the executive branch, German chambers have a limited set of powers. They have no legal ground for setting or changing the qualification standards of an occupation. If they identify misbehavior or hold the opinion that someone should not practice within the occupation-specific labor market, they may send cease and desist letters, but a court needs to decide whether there has indeed been a violation of a norm or law, and, if so, what sanctions are appropriate. They also lack the power to set quotas for practitioners because the German Constitutional Court has limited the application of such quotas to very rare cases and has made such cases independent of occupational chambers (Bundesverfassungsgericht 1958).

In all US states, occupational boards have the authority to advise the government about the requirements for market entry, to examine and license the candidates, to define codes of conduct, and to sanction unprofessional behavior (Svorny 2000). The competence to examine candidates is a crucial difference in the power of boards between the two countries. If candidates apply for a US license, they need to pass an exam, which is – at least in the case of professions

- issued by an occupational board.<sup>4</sup> German occupational boards, in contrast, do not have the authority to create and oversee exams for occupational entrants.<sup>5</sup> The authority of US boards to examine candidates includes the definition of cut-off scores, which indicate the minimum competency needed to exercise the occupation without causing harm to the public (Mehrens 1995). Both the level of difficulty of exams and cut-off scores have increased for a number of occupations over time. Typically, officials claim that the quality of new candidates has dropped compared to that of older cohorts, and that more stringent quality standards solve the (potential) problem of low-quality service providers. However, studies for lawyers (Merritt, Hargens, and Reskin 2000) and teachers (Goldhaber 2011) find no evidence for this claim. In contrast, Merritt, Hargens, and Reskin (2000:933) argue that “states have raised bar passing scores without evidence that prevailing standards were inadequate, and despite evidence that examinees’ average performance was increasing”. Along these lines, Pagliero (2013) finds a strong correlation between an increased number of law students and the level of the cut-off score, implying that it is adjusted according to student numbers. Furthermore, US boards seem to have much more leeway in terms of non-educational requirements. Broscheid and Teske (2003) report a strong positive correlation between the share of public members on US medical boards and the choice of educational-based entry requirements. The more independent a board is in terms of the requirement for public members on the board and the strength of public budgetary control, the more likely it is that candidates need to provide letters of recommendation, undergo personal interviews, finger printing, and pay high fees for the examination.

In sum, occupational boards in Germany have much lower authority to regulate the affairs of their market as compared to those in the US. This should increase the bargaining advantage of US licensed employees as compared to German employees. Furthermore, if boards increase barriers to entry in proportion to the status of the occupation, then occupations with a higher status will increase the bargaining power of employees to a greater degree. In this case, occupational licensing creates a Matthew effect: high-status, high-paid occupations have more

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<sup>5</sup> German boards do have their own exams for Meister diplomas or specialized occupational tasks (e.g., “*Facharztprüfung*”). However, these cases do not constitute licensing. The Meister diploma is a requirement for self-employment. Candidates for the examination of a specialized occupational task first need to obtain a license; this is not issued by the chamber/board itself.

powerful boards, which enables them to control market entry, resulting in higher bargaining power and therefore higher wages for otherwise already well-paid employees.

#### *3.2.4 The licensing wage premium in its institutional context*

If the institutional differences between countries have the proposed effect within the wage bargaining situation, there should be different patterns in the licensing wage premium across the wage distribution, for both countries. *I expect that the licensing advantage will increase across the wage distribution for the US but decrease across the wage distribution for Germany.*

The US system enables licensed employees to participate in rent sharing to a much larger extent as compared to unlicensed employees. Licensed occupations can strongly profit from the deregulation of price setting for their services, to which they have exclusive access, which increases the revenue attributable to them. If licensing also leads to increased exit options within their closed labor markets, licensed employees increase their bargaining power. The combination of both should result in increased chances of receiving high wage offers. This should be especially the case for high-status licensed occupations, because these have the highest capabilities to increase prices for services and have the highest barriers to entry. Recent evidence also shows that high-wage occupations increasingly sort into high-paying firms (Wilmers and Aepli 2021), which could further strengthen the position of high-status licensed employees in the bargaining situation. On the other side of the status spectrum, the US has licensed occupations with low status, low entry requirements and much smaller capacity to increase prices than in healthcare or law professions. It may therefore be the case that licensed employees, which we would expect within the lower parts of the distribution given their other characteristics, gain only a very small licensing wage premium.

The German licensing system sets very strong limits on rent sharing in the top, because it regulates prices strongly and licensed occupations are a minor collective actor in the construction of these prices. In contrast to the US, the licensing regulations target low wages of licensed employees specifically due to the governmental obligation to supply high-quality basic public goods in sufficient quantity. We can therefore expect that the licensing wage advantage should be especially large in the lower parts of the wage distribution and should decline toward the top.



### *3.3 Gender and the licensing wage advantage*

So far, expectations about the licensing wage premium have assumed homogenous consequences of licensing for wages across genders. However, past research has shown that women seem to profit more from licensing than men (Blair and Chung 2017; Koumenta, Pagliero, and Rostam-Afschar 2021; Witte and Haupt 2019). This is also the case for immigrants in comparison to natives (Cassidy and Dacass 2021; Rohrbach-Schmidt 2020; Drange and Helland 2018) and for Black in comparison to White employees (Blair and Chung 2022).

It is theoretically and empirically unclear whether the reported reductions in wage disadvantages due to licensing are based on reduced risk of low pay or reduced penalties in the top. Here, I assess this question for gender. Specifically, I ask whether licensed men and women have a different licensing premium as compared to similar unlicensed employees of the same gender.

It is important to distinguish this within-gender question from a between-gender one, especially in the case of a wage-setting model.<sup>6</sup> Bargaining behavior, as well as the returns of it, differ *across* genders (Sauer et al. 2021). Men bargain more often (Kugler et al. 2018) and change firms more often, thereby creating even more bargaining opportunities (Hirsch and Lentge 2022). If men and women bargain for wages, the returns are much higher for men as compared to women (Card, Devicienti, and Maida 2014; Kline et al. 2019; Sauer et al. 2021). It is unclear whether licensing changes these advantages. However, if licensing systems amplify them, we should observe higher premiums for men as compared to women, which is not consistent with the current literature.

A possible solution to this conundrum could be that licensing systems create environments that enable women in particular to deal better with typical wage-setting problems. I will discuss a selection of these problems here, and how licensing systems might alter them.

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<sup>6</sup> Scholars theorized about dual-closure strategies, where a privileged group within an closed occupation (like licensed men) try to exclude “usurping” groups, like women or people of color (see for example: Parkin (1979); Witz (1990)).

A typical problem in wage-setting situations, which women especially face, are prejudices about their competences (Eagly and Mladinic 1994; Vaan and Stuart 2022). Highly standardized regulations governing entry into an occupation could counter such prejudices and thus reduce women's disadvantage in wage setting (Blair and Chung 2017; Koumenta, Pagliero, and Rostam-Afschar 2021). The higher the skill requirements for entry into the occupation are, the more women should be able to counter prejudices about their competence. The license is in this case a very strong signal about individual competence.

Furthermore, women are much less likely to work in firms or organizations that provide the opportunity for significant rent sharing (Card, Cardoso, and Kline 2016). For them, working in a licensed occupation might be one of the few opportunities to do so. In contrast, unlicensed men are more likely to work in jobs that enable them to extract economic rents, like high management positions or STEM occupations. If the German price setting for licensed tasks reduces the creation of occupation-specific rents, this should reduce the licensing wage premium in the top. However, in comparison to other women, reduced rent sharing could mean a substantial advantage, whereas for men it could mean there is no longer an advantage at all.

Lastly, women are more prone to underestimating the worth of their work, and therefore start with lower wage expectations in the bargaining situation (Säve-Söderbergh 2019; Sin, Stillman, and Fabling 2022). The specific institutional structure of licensed occupations could reduce such information asymmetries. For example, occupational boards or associations may report on salaries, which can increase the pay transparency within the occupation (Genitheim and Eggert 2021; for the case of law in both countries see: NALP 2022). In principle, any occupational association can report such data. However, the requirement of having such an association or board, as well as the requirement of being a member of them for most licensed employees, can lead to better information about the pay structure. For the German case, price regulations for licensed tasks can also serve to increase pay transparency, because they show very openly how much a firm can charge for a specific task. Occupation-specific wage floors could also reduce pay differences, especially for new entrants into the occupation.

In sum, there is a strong reason to expect that licensing systems reduce women's disadvantages in the wage-setting process. Overall, reducing these disadvantages leads to obtaining higher wages. Thus, I expect that the reported higher wage premiums of licensed women stem

primarily from higher payoffs in the upper half of the wage distribution. This should be especially the case for the US, because the German licensing system reduces the opportunities for rent sharing.

## **4. Data and methods**

### *4.1 Data*

I use data from the German BIBB/BAuA Employment Survey 2018, for the German case, and the Merged Outgoing Rotation Groups (MORG) of the Current Population Survey (CPS) of 2018 (version 2.5), provided by the Center for Economic and Policy Research (2020) (CEPR) for the US case. The BIBB/BAuA Employment Surveys are representative samples of the German working population, sampling persons above the age of 15 and who work a minimum of 10 hours each week, every six years (Hall, Hünefeld, and Rohrbach-Schmidt 2020; Hall et al. 2015). The surveys yield detailed information on working conditions, worker qualifications, and socioeconomic background. The CPS is a survey of approximately 60,000 households. I use the responses from the labor force supplement asked of households in months four and eight of their time in the CPS, which are independent samples. The sample is therefore very large, but the information is not as detailed as the German data. However, it includes demographic information on schooling and age, and information on the worker's main job held, such as industry, occupation, and the sector of employment.

The analytic sample for each country is limited to non-institutionalized civilian employees between 18 and 64 years of age, working at least 10 hours per week. I exclude persons with missing occupation information and use imputed wage data offered by the CEPR. For Germany, I work with 16,147 observations, and for the US with 142,919.

### *4.2 Variables*

The dependent variable is the natural logarithm of the gross hourly wages in 2018 dollars. For the US case, I use the hourly wage information provided by the Center for Economic and Policy Research (2020), which includes tips, commissions, and bonuses. For employees reporting only a weekly wage, the hourly wage is the weekly wage divided by the hours worked. Wage information in the CPS is top-coded. For such respondents, information about the average

weekly wage was calculated assuming that the distribution of weekly pay follows a log-normal distribution (Greene 2018).<sup>7</sup> I did this calculation for men and women separately.<sup>8</sup>

The German data offer working hours per week and monthly labor earnings but no direct information about the hourly wage. Thus, I divide the monthly earnings by the average number of working days per month and the weekly hours by five. The relation of both offers an estimate of the gross hourly wage. A substantial share of the German workforce – for example, teachers – holds service contracts without any specifications on working hours. I use self-reported typical working hours instead of working hours for these cases. Since some respondents reported illegally high typical working hours, I top-coded them to 70 hours per week. To facilitate comparisons between the two countries, I convert German wages into 2018 dollars, using the average exchange rate per year.

Gathering licensing data for the US is a notoriously difficult task. Research prior to 2015 for the US needed to combine “objective” licensing information from administrations or associations with existing large-scale surveys, because these surveys did not ask about licensing directly (Weeden 2002; Redbird 2017). This created serious concerns about over-reporting of licensing, because many occupational codes in the surveys include both licensed and unlicensed occupations and separating the two is not possible. Since 2015, the CPS has included self-reported information about occupational licensing (Cunningham 2019). However, these data also show some serious problems. Self-reported licensing data can lead to a substantial share of false positives and false negatives (Furth 2016). Thus, we cannot take self-reported licensing information as an error-free measure. To solve this issue as far as possible, I constructed a *plausible license* information for occupations, building on as much research and data as possible but correcting for possible sources of error. I explain the construction of this variable in detail in appendix A. For Germany, I rely on the licensing data of Haupt, Witte, and Nollmann (2018).

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<sup>7</sup> More detailed information on the construction of the hourly wage variable can be found at: <https://www.epi.org/data/methodology/>.

<sup>8</sup> In several robustness tests, I analyzed whether different methods of dealing with top-coded weekly earnings lead to different results (see appendix D6). This was not the case. The only exception is the estimate at the 99th percentile for US women. Different choices result either very large positive or slightly negative wage premium estimates. I have therefore chosen not to show this estimate in the main analysis of the paper, but several estimates can be found in graph D13 in appendix D6.

I use an education measure that differentiates between three levels of educational degrees (low, medium, high). For the US, the low education category refers to persons without a high school degree, the medium education category includes those having completed high school or some college education, and the high education category refers to persons with a college or graduate school degree. For Germany, employees without a vocational degree fall into the category of low education, those with a vocational degree (including *Meister/Techniker* degrees) are referred to as medium-educated employees, and highly educated employees are those holding degrees from universities.

I measure work time using three categories, based on the typical working time reported: part-time (10–35 hours), full-time (36–49 hours), and over-work (50+ hours). The data for work experience differ strongly between datasets. Since there is no direct measure in the CPS, I use the common approximation “age – years of schooling – 6” for work experience. For the German data, I calculate “2012 – year of career start – years of work interruptions”. For both countries, I group experience into seven categories (0–4; 5–9; 10–14; 15–19; 20–24; 25–29; 30+). I harmonize the information about the industry of employment using 16 categories, which are similar in both countries.

As an additional control, I include information on the gender composition in the occupation. Since many jobs in the educational and health care systems are licensed, and since these professions typically have high concentrations of women, the wage premiums of licensing could be neutralized by this (Witte and Haupt 2019). I define occupations as dominated by men or women when 70% or more are of one gender or the other, and as mixed when there is no gender domination. The variable is based on the three-digit versions of the respective occupational codes. In cases where there are small numbers of observations within occupational cells, I carefully merge them with neighboring occupations to achieve as much homogeneity as possible within the newly created occupational categories, without merging licensed and unlicensed categories. Age and gender are also included as controls.

Some variables have different categories in each country. Since Germany and the US differ strongly in their ethnic and racial composition, the questionnaires differ, too. However, it is very likely that citizens representing the ethnic majority in both countries have a higher propensity to enter licensed occupations (Rohrbach-Schmidt 2020; Blair and Chung 2017). I

thus include a measure to control for the ethnic majority and for ethnic minorities, even if the information is not the same in both countries. For the US, I include race measurements across four categories (non-Hispanic White, non-Hispanic Black, Hispanic, and other). The German data allow for a distinction only between employees with and without a migration background. Individuals have a migration background if they are German citizens and report not being a native German speaker. Last, I include information about the region of employment. I expect that the industrial, and therefore occupational, composition differs markedly within each country between regions. For the US, I distinguish four regions (East, Central, South, and Mountain/Pacific), and for Germany, three large regions (Northeast [ex GDR], Northwest, South).

### 4.3. Methods

#### 4.3.1 The effect of licensing across the wage distribution: Unconditional Quantile Treatment Effects (QTE)

In order to estimate unconditional Quantile Treatment Effects (QTE), I use the approach described by Borgen, Haupt, and Wiborg (2021a, 2021b).<sup>9</sup> At its core, it uses the basic fact that a variable of a randomized treatment identifies the QTE in a bivariate Conditional Quantile Regression (CQR) (Chernozhukov and Hansen 2005). Borgen, Haupt, and Wiborg (2021a) show that we can leverage this to produce a two-step estimator for cases of non-randomized treatments, as shown in Figure 1.

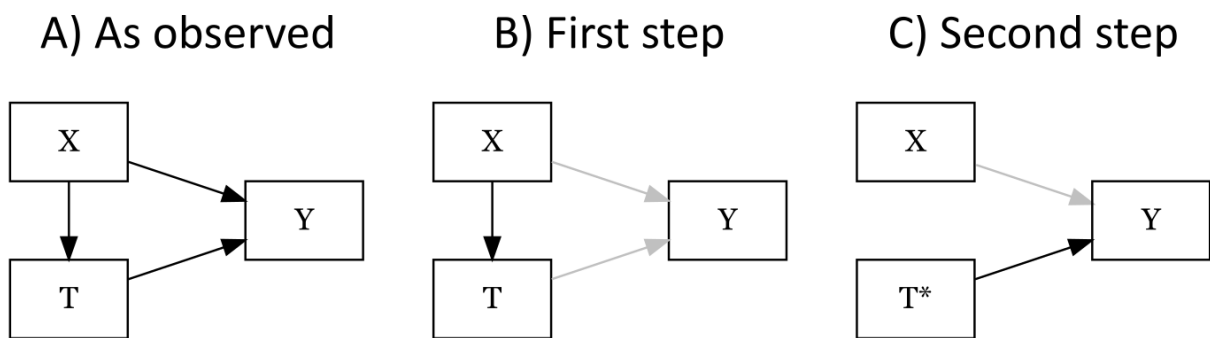


Figure 1: The two-step estimation of the Residualized Quantile Regression (RQR). Black arrows indicate which path is the sole focus of each step

<sup>9</sup> The generalized quantile regression offered by Powell (2020) also estimates QTEs but uses different statistical techniques in comparison to the RQR. Both approaches offer very similar estimates and the use of either one does not change any conclusion drawn in this paper (see Appendix D4).

In the first step, scholars need to model the selection into treatment. To do so, they can regress the treatment variable  $T$  on observables  $X$ : for example, by estimating a multivariate linear model (Figure 1B). The residuals of this regression can serve as new treatment variable  $T^*$ . Given that the selection model identifies all paths into the treatment, the residuals refer to the part of the treatment which is randomly assigned. This is, of course, a very strong assumption and scholars have to deal with unobserved paths into the treatment in many cases. However, we can at least state in such cases that the residualized treatment is independent of the observables  $X$  and can serve as an approximately randomized treatment. Thus, the first step decomposes the treatment variable into a part that is explained by observables and a residual part that is orthogonal to any function of  $X_i \cdot T_i^*$  (i.e., the so-called Conditional Expectation Function Decomposition property; Cunningham (2021:56)). In a second step, scholars can then use the randomly assigned part of the treatment in the form of the residualized treatment variable  $T^*$  in a bivariate CQR to estimate the QTE (Figure 1C).

Some past studies have used Unconditional Quantile Regressions (UQR) to estimate QTEs. However, UQR models estimate how the overall distribution would change if all units were treated (Firpo, Fortin, and Lemieux 2009). Thus, in this case, UQR estimates how the overall wage distribution would change if all employees received the licensing wage premium (Rios-Avila and Maroto 2022). This influence is not only a function of the licensing premium but also of the share of unlicensed employees at different parts of the distribution and the shape of the unconditional wage distribution (Borgen, Haupt, and Wiborg 2022). The estimand for this paper is the outcome difference between employees, which we expect to observe at the same point of the wage distribution in absence of a licensing premium. This is a different estimand compared to the influence on the overall distribution.

#### *4.3.2 The gender-specific effect of licensing across the wage distribution: Translated Quantile Treatment Effects (TQTE).*

The gender-specific wage premiums of licensing are technically an interaction term within the unconditional QTE framework described above. Interacting the treatment with gender leads to four distributions: wages of untreated men, untreated women, treated men, and treated women. For this paper, I want to compare employees of the same gender with different licensing status *at the same point* on the overall wage distribution. However, neither the median wages

of unlicensed women nor the median wages of licensed ones can be equivalent to the overall median wage. The same is the case for men. Thus, in order to evaluate differences in wages due to licensing at the median of the unconditional wage distribution across genders, we need a cross-walk between quantiles of the four treatment groups toward the overall distribution.

The *translated quantile approach* proposed by Strittmatter (2019) offers a framework for constructing such cross-walks (see Figure 2). In a first step, scholars need to select a reference distribution for anchor points between the unconditional and the conditional distribution. It is common to use the distribution of all untreated. Given that the treatment is randomized, the distribution of all untreated is equal to the unconditional distribution in the absence of any treatment. Scholars can estimate the quantile values of this distribution and use these as the reference points in the next step. In the second step, we can then use the reference points and locate them within the distributions of untreated women and men. We thus ask: if the median wage of the untreated is 25 USD, what is the corresponding quantile for untreated men and women? This quantile is the *relative rank* of persons within each sub-group toward the reference distribution. If untreated men earn higher wages than women, their relative rank toward the median will be *lower* than the median within the reference distribution and the relative rank of women will be *higher*. Figure 2 shows this logic using the 95<sup>th</sup> percentile. In a last step, scholars can use the different relative ranks across genders to estimate differences between the treated and untreated within each gender at the same point of the reference distribution. In the case of the 95<sup>th</sup> percentile, we therefore estimate separate quantile regressions for each gender using their respective relative rank for the unconditional 95<sup>th</sup> percentile.



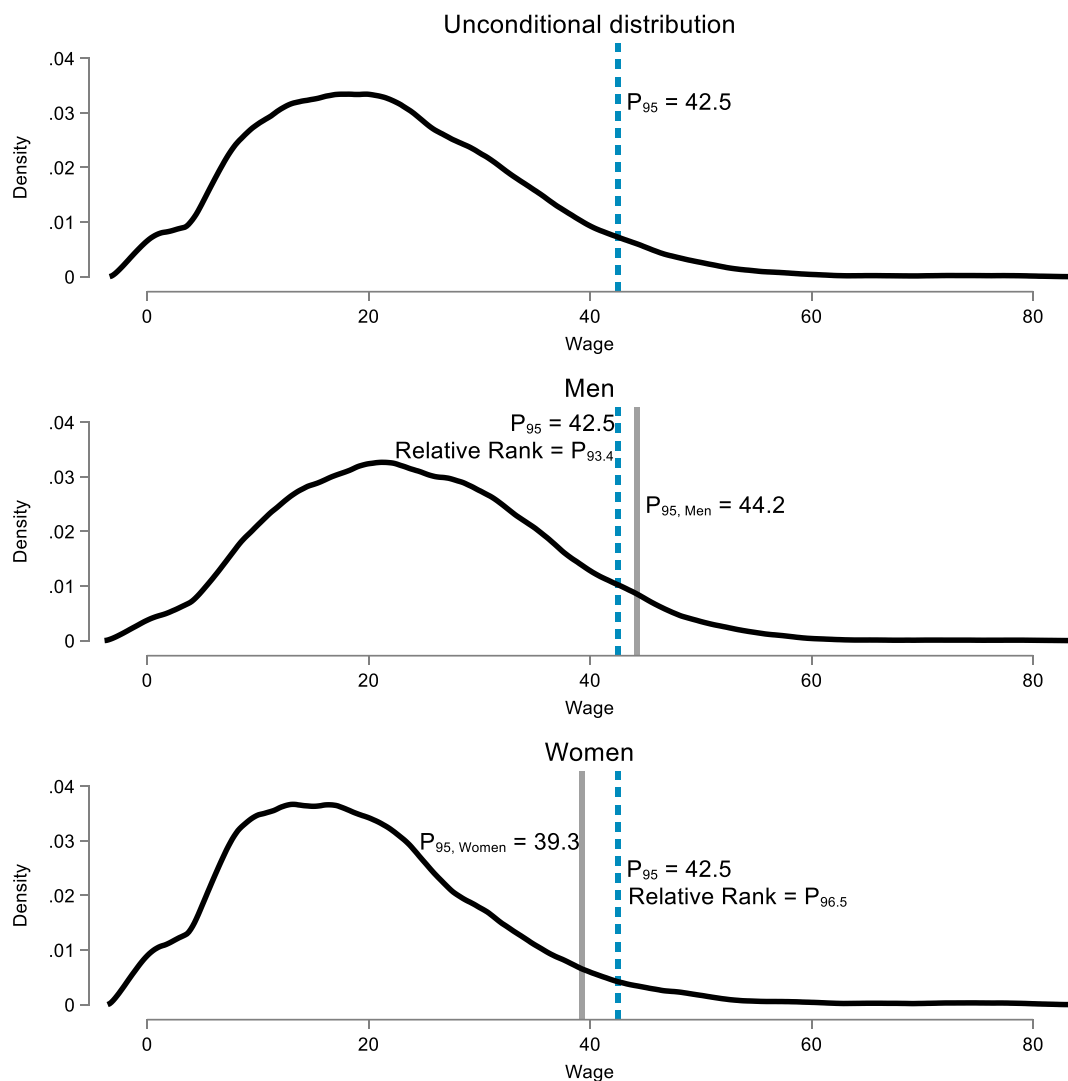


Figure 2: The location of the unconditional 95<sup>th</sup> percentile value within the distribution of men and women, with their corresponding relative ranks

The few previous applications of the translated quantile approach analyzed gender-specific effects of a randomized treatment (Bitler, Hoynes, and Domina 2014; Strittmatter 2019; Doss et al. 2022). Occupational licensing is not a randomized treatment, which leads to several challenges for the estimation of TQTE.

First, a randomized treatment allows for an easy identification of the QTE for each group by estimating bivariate conditional quantile regressions. The bivariate relation of licensing with wages within each gender would still be confounded with many other characteristics. Estimating multivariate quantile regression for each group is not a solution here, because the beta-coefficients of these regressions are no longer localized at the required relative rank (Wenz

2018). Instead, I estimate the QTE for each group using the RQR framework described above. The residualized licensing status is independent of the influence of covariates. Thus, I can use this variable in a bivariate quantile regression to localize the QTE at the relative ranks for each gender.

Second, a randomized treatment offers a clear-cut control group, which can serve as an easily justifiable reference distribution, because the compositions of the treatment and control group do not differ. Furthermore, the shape of the distribution without treatment can serve as a blueprint for the counterfactual unconditional distribution without treatment. In order to construct a similar reference distribution for licensing, I need predicted quantile values of unlicensed employees which differ only by chance from those of similar licensed employees. Unfortunately, neither the RQR framework nor other QTE models, like the generalized quantile regression (Powell 2020), can predict such quantile values. I thus need to approximate them by using the unconditional quantile value of all untreated (unlicensed) observations. In a series of simulations, I show that this approximation is very satisfactory (see Appendix E). However, the interpretation of the *exact* location of the gender-specific QTE needs to be approached with some caution.

Third, as outlined by Strittmatter (2019), the translated quantile approach introduces additional sources of uncertainty due to the estimation of the relative ranks and separate QTEs within groups and he proposes to bootstrap the whole process. In contrast to a randomized treatment, the residualized treatment of the RQR introduces additional modeling uncertainty. Therefore, I include this additional source of error by including the estimation of the residualized licensing information in the bootstrap. For each country, I use 200 replications. The bounds of the reported confidence intervals refer to the fifth and 95<sup>th</sup> percentiles of the result distribution.

## **5. Results**

### *5.1 Descriptive results*

In 2018, approximately 24% of all US employees and 19% of all German employees needed a license to work. In the US, average wages differ by 5.5 USD between licensed and unlicensed employees, which represents a raw relative wage difference of 23%. This difference is much smaller in Germany, at 0.75 USD in absolute terms and 6% in relative terms.

Going beyond averages reveals striking distributional differences between the two countries (Figure 3). For the US, the distribution of licensed occupations shifts strongly toward higher wages. It has smaller differences in lower *and* higher parts, compared to the middle. In contrast, distributional differences are much larger in lower parts of the German wage distribution compared to the middle; the differences even turn negative at the top.

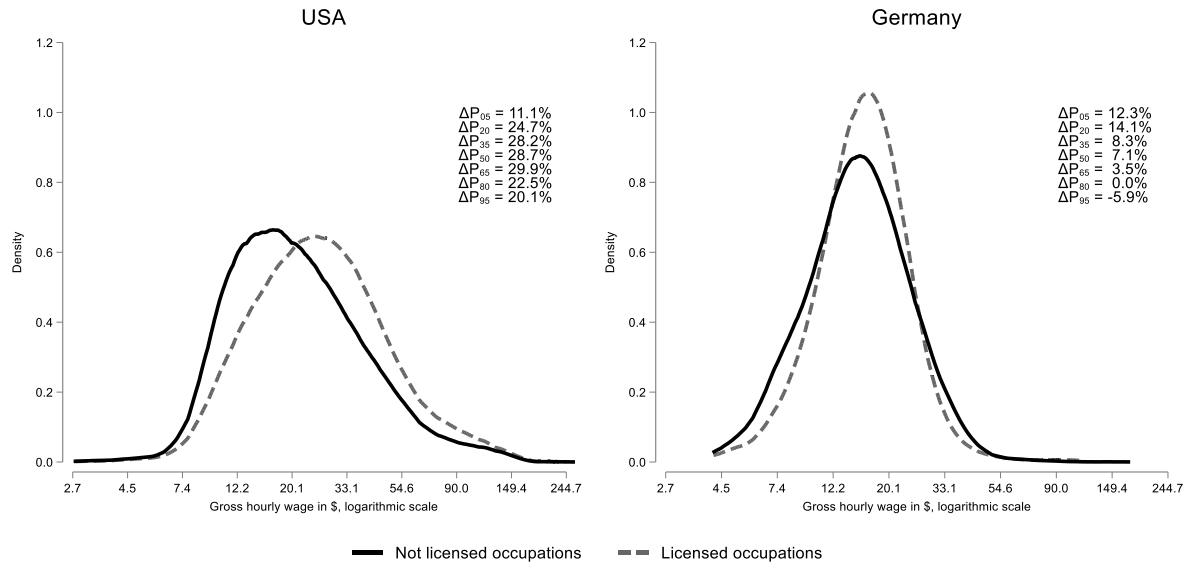


Figure 3: Wage distributions of licensed and unlicensed occupations in the US and Germany, 2018. Sources: CPS-MORG and BIBB/BAuA Employment Survey

In the US, wage differentials between licensed and unlicensed employees *within* genders are large and positive, with the highest differences in the middle for both genders. In Germany, the differences are higher for employees of both genders in the lower parts of the distribution. As expected, women experience larger differences in the top compared to men in both countries, but especially so for the US. However, upper percentile values for women are far lower than for men. This shows that even if women profit more in *relative* terms from licensing, high-earning licensed men still outnumber their female counterparts in the upper parts of the distribution

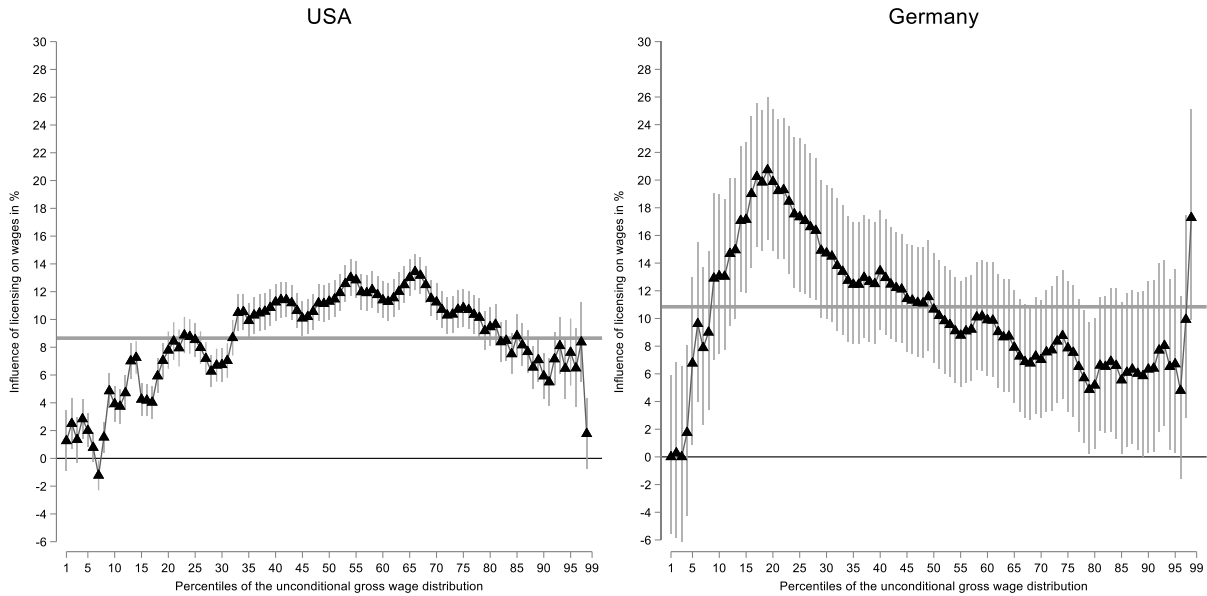
*Table 1: Wages and wage differences between licensed and not-licensed employees across genders and countries at different percentiles. Sources: CPS-MORG and BIBB-BAuA Employment Survey 2018*

		USA			Germany		
		Not licensed	Licensed	$\Delta$ in %	Not licensed	Licensed	$\Delta$ in %
Men	P05	8.7	9.7	10.5	6.0	7.3	19.0
	P20	12.2	15.3	23.1	9.3	10.8	15.6
	P35	16.1	20.2	23.8	11.3	13.5	18.3
	P50	20.5	25.9	25.1	13.5	15.5	13.3
	P65	27.0	33.3	22.4	16.1	18.4	13.3
	P80	37.8	44.8	18.2	20.1	20.8	3.5
	P95	72.4	83.1	14.6	29.2	29.3	0.2
Women	P05	7.8	8.8	11.4	5.0	6.0	16.9
	P20	10.4	13.2	24.7	7.3	9.1	21.5
	P35	13.3	17.3	28.6	9.4	11.1	17.0
	P50	16.1	22.5	37.0	11.4	12.9	12.1
	P65	20.5	28.5	37.1	13.5	15.0	10.0
	P80	28.4	38.2	33.3	16.4	17.6	6.9
	P95	50.4	64.3	27.0	23.2	23.8	2.5

## 5.2. Multivariate results

The average wage premiums across both countries are very similar: 8.6% for the US and 10.8% for Germany. The results show clearly that both averages rest upon very different patterns across the distribution.

The licensing wage premium for the US ranges between 2.5% and about 12.5%. The results show a bell-shaped pattern across the wage distribution. Coefficients increase from the lowest percentiles toward the 70<sup>th</sup> percentile and decrease slightly afterwards. In contrast to expectations, the results do not show a monotonically increasing premium across the distribution. Licensed employees with the characteristics of middle earners profit most in relative terms. This suggests that within high-wage earners licensed employees do not have higher bargaining power or seem to claim higher parts of the revenue compared to unlicensed employees. High-wage earners still profit considerably from licensing, but – in relative terms – not as much as earners with medium-wage characteristics.

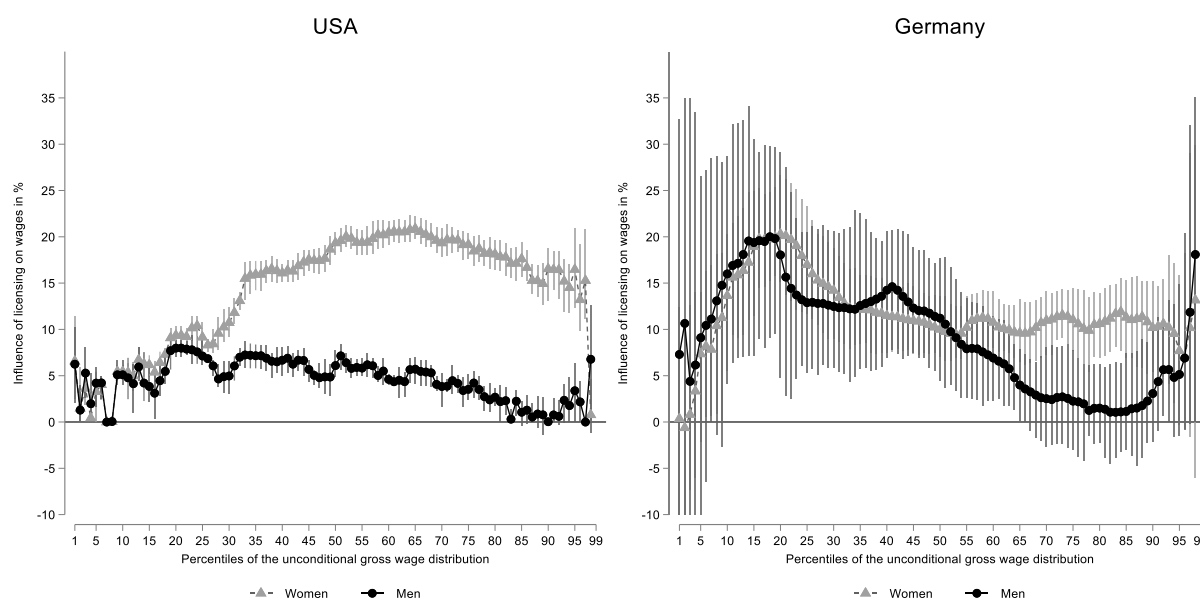


*Figure 4: The licensing wage premium across the gross wage distribution in 2018. Results of QTE models for the US ( $N = 142,919$ ) and Germany ( $N = 16,147$ ). The horizontal gray lines refer to the multivariate OLS licensing estimate for each country.*

The results for Germany are very much in line with my expectations. Estimates range from a wage premium of about 20% in the bottom to about 3.5% at the top of the distribution. I estimate the largest premiums of approximately 18%–20% for licensed employees, which we would expect between the fifth and 20<sup>th</sup> percentiles. Occupation-specific wage-floors seem to push these employees upwards within the wage distribution. The premium declines consistently from the 20<sup>th</sup> percentile toward the top. For the last two percentiles, I estimate a substantially increasing wage advantage. The estimates for the top quantiles are, however, very imprecise. The results at the very top could refer to members of professions which can leverage mandatory pay schemes to their advantage, or whose firms have high product market power, such as specialized law firms or private hospitals.

In a last step, I test whether licensing leads to different wage premiums for both genders. This is indeed the case (Figure 5). For the US, I estimate similar payoffs for both genders within the lowest quarter of the wage distribution. Above this point, licensing wage premiums decline toward zero for men but increase for women. However, the coefficients for women do not increase monotonically across the distribution but reach a maximum of about 20% around the 70<sup>th</sup> percentile and decline marginally toward the top.

The results do not speak in favor of the general assumption that licensed occupations with the highest status have the largest wage premiums. Instead, the results are very much in line with the expectation that working in a licensed occupation leads to wage premiums for women. The results for Germany strengthen this assumption, too. The estimates are very similar for the lower half of the wage distribution but women show higher relative wages in comparison to unlicensed women in the upper part of the distribution. In contrast to the US, licensed men increase their wage premiums in the very top – but the estimates are very noisy and should be interpreted with caution.



*Figure 5: The gender-specific licensing wage advantage across the distribution in 2018. Results of Translated QTE-models for the US and Germany. Note: The estimates for the 99<sup>th</sup> percentile are not reported, see appendix D6 for a discussion.*

The results do *not* show that women out-earn men in the upper parts of the distribution. They show that comparing two women with similarly high earning potential, the licensed one receives higher wages. In both countries, women are underrepresented in the upper parts of the wage distribution (see also Table 1). We would expect an even lower share of licensed women at the top in the absence of a larger licensing premium for them. I interpret this effect primarily as a compensation mechanism: women can counter typical challenges in the wage-setting processes due to licensing premiums. Licensing is a strong signal of competence and may therefore help women to claim the worth of their work to a larger extent than unlicensed women. They may also use their labor market power to decline unfavorable wage offers or

counter bad wage offers within a bargaining situation to a much larger extend than unlicensed women.

### **5.3 Additional analyses**

For the analysis above, I used control variable sets, which aimed to be as comparable as possible. Both surveys contain unique information about employees, which could confound the licensing wage premium. Previous studies have shown a connection between unionization and licensing (Gittleman and Kleiner 2016; Zhang 2018). Indeed, the CPS data show such a connection. Unionized employees are more likely to be licensed compared to non-unionized ones (39% vs 22.5%). Including this characteristic does not matter much for the estimated magnitude of the licensing wage premium (Appendix D, Figure D1). Without the union control, I overestimate the licensing wage premium by about 0.5 to 1 percentage point between the 25<sup>th</sup> and the 70<sup>th</sup> percentile, and underestimate it by about 1 to 2 percentage points for the top 10%.

Using the German data, I can test whether licensed workers are more likely to fill managerial positions. The data offer information on whether an employee holds no management position, or a lower, middle, or upper management position. Licensed employees are marginally more likely to hold a middle management position as compared to unlicensed employees (about 3 percentage points, see Figure D2 in the appendix D). There are no such differences for low and high management positions. Controlling for management positions leads to slightly smaller estimates of the licensing premium by between 0.5 and 1.5 percentage points in the lower half of the distribution and the very top.

Furthermore, I analyzed whether mandatory minimum wages influence the licensing wage premium in the lower part of the distribution. Germany introduced a mandatory minimum wage in 2015. For this, I estimated models for the 2012 waves of the CPS-MORG and BIBB/BAuA employment survey as the most comparable data source to the ones used here (appendix D3). Comparing the results between 2018 and 2012 is informative whether the high premiums in the bottom of the distribution in Germany are sensitive to the minimum wage. Indeed, for 2012, I estimate higher licensing premiums for the lowest 15 percentiles for the German wage distribution. The results for the US are very similar between 2012 and 2018 across the distribution. Thus, the very small estimates for Germany and the US in the very bottom of the

distribution indicate that the licensing premium for low-wage earners vanish once a mandatory minimum wage is in place. This could indicate that licensed employees had more power to decline very low wages in the absence of a mandatory minimum wage, due to lower substitutability.

I also compared the results for the US using the uncorrected, self-reported licensing data and the variable used throughout the analyses here. Using the self-reported indicator, I estimate a share in licensed employees of 19% instead of 24%. The positive difference is very likely a result of under-reporting in the CPS-MORG (see the discussion in Appendix A). The corrected version used in this paper leads to lower estimates of the licensing premium especially in the lower half of the distribution (see Figure D7 in the appendix D5). The difference between estimates declines across the distribution. However, the major point remains even with under-reported licensing data: the premium has a bell-curve distribution across quantiles. I conclude that the version used in this paper is very likely a conservative estimate of the licensing premium, especially for low-wage earners.

## **6. Discussion**

This study has shown that licensing influences wages differently across the wage distribution, countries, and genders. US employees in the upper-middle of the distribution and German employees in the lower quarter profit most from licensing. Both effects are primarily driven by women, indicating that they gain the most in relative terms. My main conclusion is that for men, working in a licensed occupation is one of many means to hold pace with unlicensed occupations in terms of pay but they do not earn large wage premiums because of licensing. For women, employment in licensed occupations reduce existing disadvantages in the labor market, leading to large relative wage premiums in relation to unlicensed women.

I have argued that price- and wage-setting rules, which exist for German but not for American licensed occupations, narrow the wage-setting range substantially. On the one hand, they create occupation-specific wage floors, which limit firms' ability to set low wages. On the other hand, strong price regulations set upper limits for wage bargaining because firms cannot sell the respective services at higher prices, which limits the contribution of the licensed employee to the revenue. In the absence of price regulations and a strong role of occupational boards for maintaining and strengthening barriers to entry, firms selling the services of licensed employees



can set very high prices and licensed employees can earn very high wages – a point that has stimulated much discussion in the US especially for health care and legal services.

I also discussed that licensing can be especially rewarding for women, because it reduces penalties in the wage-setting process, which women are more prone to face. Licensing can reduce wage discrimination due to perceived lower competence, because high barriers to entry signal high levels of skill. Licensed occupations may also have higher levels of pay transparency, especially in the German case, where there is strong price regulation. For women, licensed occupations may also be one of the best options for obtaining rents, because women typically work in jobs and firms with lower chances of rent sharing.

I expected an increasing wage premium for the US. I assumed that both bargaining power and prices for licensed tasks increase across the wage distribution. A combination of both enables employees to bargain for substantial wage premiums. However, the empirical pattern proved to be more complex, with the largest premiums for the middle, not the top, which is in contrast to claims that occupational licensing especially increases inequality in the top (Weeden and Grusky 2014). I still find substantial wage advantages for licensed employees at the top, but the *relative* benefits are largest in the upper-middle. A possible explanation for this deviation from the expectations is that I compare licensed professionals with employees who typically work for firms with very strong product market power, such as tech firms, or who have very strong individual bargaining power, such as IT specialists or managers.

My application of the wage bargaining model was also based on the assumption that the wage setting between licensed and unlicensed employees would be similar without occupational licensing. However, it might also be that wage premiums enable licensed professionals to catch up with high-wage unlicensed employees in a constant race between highly productive industry jobs and service occupations, which are typically not able to hold pace with productivity increases of the industry (Baumol 2012). It is also noteworthy that the dependent variable in this study is the gross hourly wage. Employees with excessive work hours, such as those in law firms, or health professionals, might earn large annual labor incomes but less impressive hourly wages. They also might be able to bargain for advantages apart from wages, such as health care plans, subsidies for daycare, or asset shares (Morgan and Cha 2007). It can also be the case that

employees with very high bargaining power more often select into self-employment, which can reduce wage effects at the top.

In line with theoretical considerations, I showed empirically that the German system leads to strong wage premiums for low-wage employees, which decrease across the distribution. The decrease is especially strong for men, while there is only a small decrease for women. I interpret this as a combination of a gradual increase in the importance of price setting for wages, which limits bargaining for very high wages and a decrease in the relevance of wage floors, which are relevant for the lower quarter but loose importance across the rest of the distribution.

German men in the very top of the distribution seem to be an exception to diminishing wage premiums, albeit the estimate show substantial uncertainty. However, we can use it as a hint that licensed men with a very high wage potential face very favorable opportunities in the labor market, which are different to at least unlicensed men. This could be due to the lower relevance of price regulation for some occupations but this claim needs to be tested with more elaborate data on the occupational level.

The results offered here can help to shed new light on some empirical contradictions (Redbird 2017; Law and Marks 2013). Studies showing null effects of licensing analyzed the variation in wages of newly licensed occupations. Using the framework offered in this paper, such null effects can be expected. Newly licensed occupations in the US are typically low-wage ones, which show small wage advantages – especially for men. Furthermore, we do not need to expect an immediate effect of licensing on wages if we drop the assumption stock-exchange-like wage mechanism connecting licensing and wages. Increases in bargaining power and influences on prices can be a result of long-lasting struggles between occupations spanning decades (Habinek and Haveman 2019).

In sum, the results warn against simplified stories of the relationship between occupational licensing and wages. The results shown here are not in line with claims that licensing especially helps the already powerful (Weeden and Grusky 2014; Kleiner and Vortnikov 2017) nor are they in line with claims that licensing does not influence wages at all (Redbird 2017). They are much more compatible with the assumption that the licensing premium reduces existing penalties for women both in Germany and the US.

Licensing has come under a lot of pressure in the US, where de-licensing movements are strong. De-licensing an occupation might increase competition but it could also reduce wages for disadvantaged employees within licensed occupations, amplifying existing inequalities. The results of this study strongly indicate that occupational licensing is no longer used as a tool for high-status, privileged groups to gain economic advantage. On the contrary: the results suggest that licensing helps compensating disadvantages in the labor market. Against this background, the influence of licensing on wages shows similar patterns to the influence of unions on the distribution of wages. Sociology can benefit the public and policymakers by informing them about this type of influence and correcting the seemingly outdated story that licenses serve the privileged first.

## References

- Albert, Kyle. 2016. "Who benefits most from occupational certification? An examination of young workers". *Social science research* online first:in press. doi: 10.1016/j.ssresearch.2016.09.022.
- Anwaltsgerichtshof NRW. 2007. Ein Grundgehalt von 1.000 € brutto als Einstiegsgehalt für einen anwaltlichen Berufsanfänger ist unangemessen i.S.v. § 26 Abs. 1 BORA und sittenwidrig i.S.v. § 138 Abs. 1 BGB. (<http://openjur.de/u/126303.html>).
- Baumol, William J. 2012. *The cost disease. Why computers get cheaper and health care doesn't*. New Haven: Yale University Press.
- Bellmann, Lutz, Philipp Grunau, Friederike Maier, and Günter Thiele. 2013. "Struktur der Beschäftigung und Entgeltentwicklung in den Gesundheits-und Pflegeeinrichtungen-2004 bis 2008". *Sozialer Fortschritt* 62 (3):77–87.
- Bitler, Marianne, Hilary Hoynes, and Thurston Domina. 2014. "Experimental Evidence on Distributional Effects of Head Start". NBER Working Paper 20434. Cambridge, MA. Retrieved The.
- Blair, Peter, and Bobby Chung. 2017. "Occupational Licensing Reduces Racial and Gender Wage Gaps: Evidence from the Survey of Income and Program Participation". *HCEO Working Paper Series* (050):1–66.
- Blair, Peter Q., and Bobby W. Chung. 2022. "Job Market Signaling through Occupational Licensing". *Review of Economics and Statistics*:1–45. doi: 10.1162/rest\_a\_01265.
- Bol, Thijs. 2014. "Economic returns to occupational closure in the German skilled trades". *Social science research* 46:9–22.
- Bol, Thijs, and Ida Drange. 2017. "Occupational closure and wages in Norway". *Acta Sociologica* 60 (2):134–57. doi: 10.1177/0001699316659768.
- Bol, Thijs, and Kim A. Weeden. 2015. "Occupational Closure and Wage Inequality in Germany and the United Kingdom". *European Sociological Review* 31 (3):354–69. doi: 10.1093/esr/jcu095.
- Borgen, Nicolai T., Andreas Haupt, and Øyvind N. Wiborg. 2021a. *A New Framework for Estimation of Unconditional Quantile Treatment Effects: The Residualized Quantile Regression (RQR) Model*.
- Borgen, Nicolai T., Andreas Haupt, and Øyvind N. Wiborg. 2021b. "Flexible and fast estimation of quantile treatment effects: The rqr and rqrplot commands". SocArxiv.
- Borgen, Nicolai T., Andreas Haupt, and Øyvind Nicolay Wiborg. 2022. "Quantile regression estimands and models: revisiting the motherhood wage penalty debate". *European Sociological Review*. doi: 10.1093/esr/jcac052.
- Brenzel, Hanna, Hermann Gartner, and Claus Schnabel. 2014. "Wage bargaining or wage posting? Evidence from the employers' side". *Labour Economics* 29:41–48.
- Broscheid, Andreas, and Paul E. Teske. 2003. "Public Members on Medical Licensing Boards and the Choice of Entry Barriers". *Public Choice* 114 (3/4):445–59. doi: 10.1023/A:1022651002775.
- Bundesverfassungsgericht. 1958. Apotheken-Urteil, vol. 7. *BVerfGE* 7.
- Bundesverfassungsgericht. 2015. R 1-Besoldung der Jahre 2008 bis 2010 in Sachsen-Anhalt verfassungswidrig.
- Card, David. 2022. "Who Set Your Wage?". *American Economic Review* 112 (4):1075–90. doi: 10.1257/aer.112.4.1075.
- Card, David, Ana Rute Cardoso, and Patrick Kline. 2016. "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women". *The Quarterly Journal of Economics* 131 (2):633–86. doi: 10.1093/qje/qjv038.

- Card, David, Francesco Devicienti, and Agata Maida. 2014. "Rent-sharing, holdup, and wages: Evidence from matched panel data". *The Review of Economic Studies* 81 (1):84–111.
- Carpenter, Dick M., Lisa Knepper, Angela C. Erickson, and John K. Ross. 2012. "License to work: A national study of burdens from occupational licensing". *Institute for Social Justice*.
- Cassidy, Hugh, and Tennenia Dacass. 2021. "Occupational Licensing and Immigrants". *Journal of Law and Economics* 64 (1):1–28. doi: 10.1086/709834.
- Center for Economic and Policy Research. 2020. "CPS ORG Uniform Extracts, Version 2.5". Washington, DC.
- Chambers, Dustin, and Colin O'Reilly. 2021. "The economic theory of regulation and inequality". *Public Choice*:1–16.
- Chernozhukov, Victor, and Christian Hansen. 2005. "An IV model of quantile treatment effects". *Econometrica* 73 (1):245–61.
- Chi, Wei, Morris M. Kleiner, and Xiaoye Qian. 2017. "Do Occupational Regulations Increase Earnings?: Evidence from China". *Industrial Relations: A Journal of Economy and Society* 56 (2):351–81. doi: 10.1111/irel.12176.
- Choné, Philippe. 2017. "Competition policy for health care provision in France". *Health policy* 121 (2):111–18. doi: 10.1016/j.healthpol.2016.11.015.
- Cunningham, Evan. 2019. "Professional certifications and occupational licenses". *Monthly Labor Review*:1–38.
- Cunningham, Scott. 2021. *Causal Inference*. Yale University Press.
- Deutscher Lehrerverband. 2001. "Lehrermangel gefährdet den Bildungsstandort Deutschland". Memorandum (<http://www.lehrerverband.de/memlehr.htm>).
- Deyo, Darwynn, Morris M. Kleiner, and Edward J. Timmons. 2018. "A Response to "New Closed Shop: The Economic and Structural Effects of Occupational Licensure". Policy Brief. Fairfax: Massachusetts Institut of Technology.
- Dingwall, Robert, and Paul Fenn. 1987. "'A respectable profession'? Sociological and economic perspectives on the regulation of professional services". *International Review of Law and Economics* 7 (1):51–64. doi: 10.1016/0144-8188(87)90006-8.
- Doss, Christopher, Hans Fricke, Susanna Loeb, and Justin B. Doromal. 2022. "Engaging girls in math: The unequal effects of text messaging to help parents support early math development". *Economics of Education Review* 88:102262. doi: 10.1016/j.econedurev.2022.102262.
- Drange, Ida, and Håvard Helland. 2018. "The Sheltering Effect of Occupational Closure? Consequences for Ethnic Minorities' Earnings". *Work and Occupations* 46 (1):45–89. doi: 10.1177/0730888418780970.
- Eagly, Alice H., and Antonio Mladinic. 1994. "Are People Prejudiced Against Women? Some Answers From Research on Attitudes, Gender Stereotypes, and Judgments of Competence". *European Review of Social Psychology* 5 (1):1–35. doi: 10.1080/14792779543000002.
- Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux. 2009. "Unconditional Quantile Regressions". *Econometrica* 77 (3):953–73.
- Furth, Salim. 2016. "Understanding the Data on Occupational Licensing". *The Heritage Foundation*.
- Gaier, Reinhard. 2015. "Die Angemessenheit anwaltlicher Vergütung als Grundrechtsproblem" Pp. 11–26 in *Anwaltliches Berufsrecht, Berufsethik und Berufspraxis: Ausgewählte Beiträge der Jahrestagungen des Instituts für Anwaltsrecht der Humboldt-Universität zu Berlin (2007 - 2013)*, edited by Reinhard Singer. Baden-Baden: Nomos Verlagsgesellschaft mbH & Co. KG.

- Genitheim, Nicole and Kerstin Eggert. 2021. "Star 2020: Statistisches Berichtssystem für Rechtsanwälte". Nürnberg: Institut für freie Berufe.
- German Dental Association. 2011. "Dental fee schedule" ([https://www.bzaek.de/fileadmin/PDFs/goz/nov/gebuehrenordnung\\_fuer\\_zahnaerzte\\_2012\\_EN.pdf](https://www.bzaek.de/fileadmin/PDFs/goz/nov/gebuehrenordnung_fuer_zahnaerzte_2012_EN.pdf)).
- Gittleman, Maury, Mark A. Klee, and Morris M. Kleiner. 2015. "Analyzing the labor market outcomes of occupational licensing". National Bureau of Economic Research.
- Gittleman, Maury, and Morris M. Kleiner. 2016. "Wage Effects of Unionization and Occupational Licensing Coverage in the United States". *ILR Review* 69 (1):142–72. doi: 10.1177/0019793915601632.
- Goldhaber, Dan. 2011. "Chapter 6 - Licensure: Exploring the Value of this Gateway to the Teacher Workforce" Pp. 315–39 in *Handbook of the Economics of Education*, Volume 3, edited by Stephen Machin and Ludger Woessmann Eric A. Hanushek. Elsevier.
- Greene, William. 2018. *Econometric analysis*. New York, NY: Pearson.
- Habinek, Jacob, and Heather A. Haveman. 2019. "Professionals and populists: The making of a free market for medicine in the United States, 1787–1860". *Socio-Economic Review* 23:245. doi: 10.1093/ser/mwy052.
- Hall, Anja, Lena Hünefeld, and Daniela Rohrbach-Schmidt. 2020. "BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2018 . suf\_1 .0". Bonn: Federal Institute for Vocational Education and Training.
- Hall, Anja, Anke Siefer, Michael Tiemann, and Federal Institute for Vocational Education and Training. 2015. "BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2012 (SUF)".
- Hall, Robert E., and Alan B. Krueger. 2012. "Evidence on the Incidence of Wage Posting, Wage Bargaining, and On-the-Job Search". *American Economic Journal: Macroeconomics* 4 (4):56–67. doi: 10.1257/mac.4.4.56.
- Haupt, Andreas. 2016. "Erhöhen berufliche Lizenzen Verdienste und die Verdienstungleichheit?". *Zeitschrift für Soziologie* 45 (1):39–56.
- Haupt, Andreas, and Christian Ebner. 2020. "Occupations and Inequality: Theoretical Perspectives and Mechanisms". *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie*. doi: 10.1007/s11577-020-00685-0.
- Haupt, Andreas, Nils Witte, and Gerd Nollmann. 2018. *Index für das Ausmaß beruflicher Geschlossenheit und berufliche Lizenzierung*. GESIS Data Archive.
- Hausner, Karl Heinz, Michael Heinrich, and Carl Huelgas. 2015. "Diskrepanzen in Finanzkraft und Besoldung nach der Föderalismusreform". *Wirtschaftsdienst* 95 (10):671–77. doi: 10.1007/s10273-015-1885-9.
- Hirsch, Boris, and Philipp Lentge. 2022. "Non-base compensation and the gender pay gap". *LABOUR*. doi: 10.1111/labr.12229.
- Kalleberg, Arne L., Michael Wallace, and Robert P. Althausen. 1981. "Economic segmentation, worker power, and income inequality". *American Journal of Sociology* 87 (3):651–83.
- Kleiner, Morris M., and Alan B. Krueger. 2010. "The prevalence and effects of occupational licensing". *British Journal of Industrial Relations* 48 (4):676–87.
- Kleiner, Morris M., and Alan B. Krueger. 2013. "Analyzing the Extent and Influence of Occupational Licensing on the Labor Market". *Journal of Labor Economics* 31 (2):173–202.

- Kleiner, Morris M. and Kyoung Won Park. 2010. "Battles among licensed occupations: Analyzing government regulations on labor market outcomes for dentists and hygienists". National Bureau of Economic Research Papers w16560. National Bureau of Economic Research.
- Kleiner, Morris M., and Evgeny Vorotnikov. 2017. "Analyzing occupational licensing among the states". *Journal of Regulatory Economics* 52 (2):132–58. doi: 10.1007/s11149-017-9333-y.
- Kline, Patrick, Neviana Petkova, Heidi Williams, and Owen Zidar. 2019. "WHO PROFITS FROM PATENTS? RENT-SHARING AT INNOVATIVE FIRMS". *The Quarterly Journal of Economics* 134 (3):1343–404. doi: 10.1093/qje/qjz011.
- Koumenta, Maria, Amy Humphris, Morris M. Kleiner, and Mario Pagliero. 2014. "Occupational regulation in the EU and UK: prevalence and labour market impacts". Queen Mary University of London.
- Koumenta, Maria, and Mario Pagliero. 2019. "Occupational Regulation in the European Union: Coverage and Wage Effects". *British Journal of Industrial Relations* 57 (4):818–49. doi: 10.1111/bjir.12441.
- Koumenta, Maria, Mario Pagliero, and Davud Rostam-Afschar. 2021. "Occupational licensing and the gender wage gap". Hohenheim Discussion Papers in Business, Economics and Social Sciences.
- Krishnan, Ranjani. 2001. "Market restructuring and pricing in the hospital industry". *Journal of Health Economics* 20 (2):213–37.
- Kugler, Katharina G., Julia A. M. Reif, Tamara Kaschner, and Felix C. Brodbeck. 2018. "Gender differences in the initiation of negotiations: A meta-analysis". *Psychological bulletin* 144 (2):198–222. doi: 10.1037/bul0000135.
- Lachowska, Marta, Alexandre Mas, Raffaele Saggio, and Stephen A. Woodbury. 2022. "Wage Posting or Wage Bargaining? A Test Using Dual Jobholders". *Journal of Labor Economics* 40 (S1):S469–S493. doi: 10.1086/718321.
- Lancaster, David. 2016. "The billable hour-its history and future: Management". *Without Prejudice* 16 (8):6–9.
- Law, Marc T., and Mindy S. Marks. 2009. "Effects of Occupational Licensing Laws on Minorities: Evidence from the Progressive Era". *Journal of Law and Economics* 52 (2):351–66. doi: 10.1086/596714.
- Law, Marc T., and Mindy S. Marks. 2013. "From certification to licensure: evidence from registered and practical nurses in the United States, 1950-1970". *The European Journal of Comparative Economics* 10 (2):177.
- Law, Marc T., and Mindy S. Marks. 2017. "The Labor-Market Effects of Occupational Licensing Laws in Nursing". *Industrial Relations: A Journal of Economy and Society* 56 (4):640–61. doi: 10.1111/irel.12190.
- Leicht, Kevin T. 2020. "Occupations and Inequalities in the 21st Century: What's in your Wallet?". *Research in Social Stratification and Mobility* 70:100550. doi: 10.1016/j.rssm.2020.100550.
- Lyu, Mengjie, Tingting Zhang, and Hua Ye. 2022. "Labor Market Impacts of Occupational Licensing and Delicensing: New Evidence from China". SSRN 4106684.
- Manning, Alan. 2011. "Imperfect Competition in the Labor Market" Pp. 973–1041 in *Handbook of Labor Economics*, Volume 4, Part B, edited by David Card and Orley Ashenfelter. Elsevier.
- Manning, Alan. 2021. "Monopsony in Labor Markets: A Review". *ILR Review* 74 (1):3–26. doi: 10.1177/0019793920922499.

- Mehrens, William A. 1995. "Licensure Testing: Purposes, Procedures, and Practices" Pp. 33–58 in *Licensure testing: Purposes, procedures, and practices*, edited by James C. Impara. Lincoln, Neb.: University of Nebraska-Lincoln.
- Merritt, Deborah J., Lowell L. Hargens, and Barbara F. Reskin. 2000. "Raising the bar: A social science critique of recent increases to passing scores on the bar exam". *University of Cincinnati Law Review* 69:929–66.
- Mocetti, Sauro, Lucia Rizzica, and Giacomo Roma. 2021. "Regulated occupations in Italy: Extent and labour market effects". *International Review of Law and Economics* 66:105987. doi: 10.1016/j.irl.2021.105987.
- Morgan, Stephen L., and Youngjoo Cha. 2007. "Rent and the Evolution of Inequality in Late Industrial United States". *American Behavioral Scientist* 50 (5):677–701. doi: 10.1177/0002764206295018.
- Murphy, Raymond. 1984. "The Structure of Closure: A Critique and Development of the Theories of Weber, Collins, and Parkin". *The British Journal of Sociology* 35 (4):547–67. doi: 10.2307/590434.
- Murphy, Raymond. 1988. *Social closure. The theory of monopolization and exclusion*. Oxford University Press.
- NALP. 2022. "2022 Public Service Attorney Salary Report". National Association for Law Placement.
- Noah, Timothy. 2009. "Did Warren Burger Create the Health Care Mess?: The 1975 antitrust decision that gave you physician-owned hospitals.". *Slate*. 2009 ([http://www.slate.com/articles/news\\_and\\_politics/prescriptions/2009/07/did\\_warren\\_burger\\_create\\_the\\_health\\_care\\_mess.html](http://www.slate.com/articles/news_and_politics/prescriptions/2009/07/did_warren_burger_create_the_health_care_mess.html)).
- O'Neill, Liam. 2015. "If more competition is the answer, why hasn't it worked?". *Anesthesia and analgesia* 120 (1):3–4. doi: 10.1213/ANE.0000000000000476.
- Pagliari, Mario. 2013. "The impact of potential labor supply on licensing exam difficulty". *European Association of Labour Economists 21st annual conference, Tallinn, Estonia, 10-12 September 2009* 25:141–52.
- Pagliari, Mario. 2019. "Occupational Licensing in the EU: Protecting Consumers or Limiting Competition?". *Review of Industrial Organization*. doi: 10.1007/s11151-019-09711-8.
- Parkin, Frank. 1979. "The marxist theory of class: A bourgeois critique". *London: Tavistock*.
- Powell, David. 2020. "Quantile treatment effects in the presence of covariates". *Review of Economics and Statistics* 102 (5):994–1005.
- Redbird, Beth. 2017. "The New Closed Shop? The Economic and Structural Effects of Occupational Licensure". *American Sociological Review*:0003122417706463. doi: 10.1177/0003122417706463.
- Relman, Arnold S. 1991. "The health care industry: Where is it taking us?". *New England journal of medicine* 325 (12):854–59.
- Rios-Avila, Fernando, and Michelle Lee Maroto. 2022. "Moving Beyond Linear Regression: Implementing and Interpreting Quantile Regression Models With Fixed Effects". *Sociological Methods & Research*:004912412110361. doi: 10.1177/00491241211036165.
- Rohrbach-Schmidt, Daniela. 2020. "Licensing, Educational Credentialing, and Wages Among Foreign Skilled Workers in Germany". *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie* 72 (S1):375–400. doi: 10.1007/s11577-020-00681-4.
- Rostam-Afschar, Davud, and Kristina Strohmaier. 2019. "Does Regulation Trade Off Quality against Inequality? The Case of German Architects and Construction Engineers". *British Journal of Industrial Relations* 57 (4):870–93. doi: 10.1111/bjir.12445.



- Sakamoto, Arthur, and Sharron Xuanren Wang. 2020. "The declining significance of occupation in research on intergenerational mobility". *Research in Social Stratification and Mobility* 70:100521. doi: 10.1016/j.rssm.2020.100521.
- Sauer, Carsten, Peter Valet, Safi Shams, and Donald Tomaskovic-Devey. 2021. "Categorical Distinctions and Claims-Making: Opportunity, Agency, and Returns from Wage Negotiations". *American Sociological Review*:000312242110385. doi: 10.1177/00031224211038507.
- Säve-Söderbergh, Jenny. 2019. "Gender gaps in salary negotiations: Salary requests and starting salaries in the field". *Journal of Economic Behavior & Organization* 161:35–51. doi: 10.1016/j.jebo.2019.01.019.
- Schwark, Eberhard. 1997. "Wirtschaftsordnung und Sozialstaatsprinzip". *Deutsche Zeitschrift für Wirtschafts-und Insolvenzrecht* 7 (3):89–100.
- Seifert, Vanessa, and Ludger Fertmann. 2009. "Länder streiten sich um die besten Lehrer: Abwerbungen: Einige Bundesländer locken Junglehrer mit finanziellen Anreizen". *Hamburger Abendblatt*. 2009.
- Sin, Isabelle, Steven Stillman, and Richard Fabling. 2022. "What Drives the Gender Wage Gap? Examining the Roles of Sorting, Productivity Differences, Bargaining, and Discrimination". *Review of Economics and Statistics* 104 (4):636–51. doi: 10.1162/rest\_a\_01000.
- Sørensen, Aage B. 1996. "The structural basis of social inequality". *American Journal of Sociology* 101 (5):1333–65.
- Stainback, Kevin, Donald Tomaskovic-Devey, and Sheryl Skaggs. 2010. "Organizational Approaches to Inequality: Inertia, Relative Power, and Environments". *Annual Review of Sociology* 36 (1):225–47. doi: 10.1146/annurev-soc-070308-120014.
- Stigler, George J. 1971. "The theory of economic regulation". *The Bell journal of economics and management science* 2 (1):3–21.
- Strittmatter, Anthony. 2019. "Heterogeneous earnings effects of the job corps by gender: A translated quantile approach". *Journal of Labor Economics* 61:101760. doi: 10.1016/j.labeco.2019.101760.
- Svorny, Shirley. 2000. "Licensing. Market Entry Regulation." Pp. 296–328 in *The regulation of contracts*, edited by Boudewijn Bouckaert and Gerrit de Geest. Cheltenham: Edward Elgar.
- Timmons, Edward J., Jason M. Hockenberry, and Christine Piette Durrance. 2016. *More Battles Among Licensed Occupations: Estimating the Effects of Scope of Practice and Direct Access on the Chiropractic, Physical Therapist, and Physician Labor Market*. George Mason University.
- Timmons, Edward J., Brian Meehan, Andrew Meehan, and John Hazenstab. 2018. "Assessing growth in occupational licensing of low-income occupations: 1993-2012". *Journal of Entrepreneurship and Public Policy* 7 (2):178–218. doi: 10.1108/JEPP-D-18-00006.
- U.S. Supreme Court. 1975. *GOLDFARB ET UX. v. VIRGINIA STATE BAR ET AL.*
- U.S. Supreme Court. 1981. *Arizona v. Maricopa County Medical Society*.
- Vaan, Mathijs de, and Toby Stuart. 2022. "Gender in the Markets for Expertise". *American Sociological Review* 87 (3):443–77. doi: 10.1177/00031224221087374.
- van de Werfhorst, Herman G. 2011. "Skills, positional good or social closure? The role of education across structural–institutional labour market settings". *Journal of Education and Work* 24 (5):521–48.
- Vaney Olvey, Cindy de, Andy Hogg, and Wil Counts. 2002. "Licensure requirements: Have we raised the bar too far?". *Professional Psychology: Research and Practice* 33 (3):323–29.

- Verband der Ersatzkassen. 2014. "Vergütungsliste gemäß § 125 SGB V für die Abrechnung stimm-, sprech-, sprachtherapeutischer Leistungen" (<https://www.vdek.com/vertragspartner/heilmittel/rahmenvertrag.html>).
- Weber, M. 1922. *Wirtschaft und Gesellschaft*. English translation: *Economy and society*. An outline of interpretive sociology. Berkley: University of California Press.
- Weeden, Kim A. 2002. "Why do some occupations pay more than others? Social closure and earnings inequality in the United States". *American Journal of Sociology* 108 (1):55–101.
- Weeden, Kim A., and David B. Grusky. 2014. "Inequality and Market Failure". *American Behavioral Scientist* 58 (3):473–91.
- Wenz, Sebastian E. 2018. "What Quantile Regression Does and Doesn't Do: A Commentary on Petscher and Logan (2014)". *Child development*.
- Western, Bruce, and Jake Rosenfeld. 2011. "Unions, Norms, and the Rise in U.S. Wage Inequality". *American Sociological Review* 76 (4):513–37.
- White House. 2015. "Occupational Licensing: A Framework for Policymakers". Washington, DC: Report prepared by the Department of the Treasury Office of Economic Policy, the Council of Economic Advisers and the Department of Labor.
- Wilmers, Nathan. 2020. "Job Turf or Variety: Task Structure as a Source of Organizational Inequality". *Administrative Science Quarterly* 65 (4):1018–57. doi: 10.1177/0001839220909101.
- Wilmers, Nathan, and Clem Aeppli. 2021. "Consolidated Advantage: New Organizational Dynamics of Wage Inequality". *American Sociological Review* 86 (6):1100–30. doi: 10.1177/00031224211049205.
- Wissdorf, Flora. 2014. "Mangel an Pflegepersonal erreicht gravierende Maße". *Die Welt* (12.03.).
- Witte, Nils, and Andreas Haupt. 2019. "Is Occupational Licensing More Beneficial for Women than for Men? The Case of Germany, 1993/2015". *European Sociological Review* 24:633. doi: 10.1093/esr/jcz060.
- Witz, Anne. 1990. "Patriarchy and Professions: The Gendered Politics of Occupational Closure". *Sociology* 24 (4):675–90. doi: 10.1177/0038038590024004007.
- Zhang, Tingting. 2018. "Effects of Occupational Licensing and Unions on Labour Market Earnings in Canada". *British Journal of Industrial Relations* 69 (2):290. doi: 10.1111/bjir.12442.
- Zhang, Tingting, and Morley Gunderson. 2020. "Impact of Occupational Licensing on Wages and Wage Inequality: Canadian Evidence 1998–2018". *Journal of Labor Research* 41 (4):338–51.
- Zhou, Xueguang. 1993. "Occupational Power, State Capacities, and the Diffusion of Licensing in the American States: 1890 to 1950". *American Sociological Review* 58 (4):536–52.

## Appendix A: Construction of a plausible licensing information

Since 2015, the CPS has included self-reported information about occupational licensing (Cunningham 2019). In research prior to 2015, data for the US needed to combine “objective” licensing information from administrations or associations with surveys (Weeden 2002; Redbird 2017).

I claim that we cannot take self-reported and objective licensing information as error-free measures. Instead, I argue that we need to construct *plausible license* information for occupations, building on as much research and data as possible but correcting for possible sources of error. The inclusion of objective licensing information in surveys entails two severe challenges. First, it is difficult to collect data about licensing in the US because the licensing regulations for occupations differ across states, over time, and sometimes across districts within states. This makes a single collection of licensing information prone to under-reporting. Second, the occupational categories within the surveys are in many cases not identical to the occupations falling under licensing rules. The problem is twofold. A) In many cases, even detailed occupational codes include licensed as well as not-licensed occupations. For example, the category “accountants and auditors” includes *certified public accountants*, who are licensed in many US states, while all other kinds of accountants or auditors are unlicensed. B) Most occupational classification systems include residual categories, which are used for the coding of very small occupations as well as unclear or insufficient occupational information of some respondents. The SOC2010 lists “Other healthcare practitioners and technical occupations” as category 29-9000, which could include a wide range of licensed and unlicensed health care occupations. The licensing information used in this study is a dummy variable, distinguishing two possible *legal states of an occupation* – either an occupation is licensed within a state or not. However, the relation of occupations to heterogeneous occupational categories blurs this distinction and leads to a number of false positives and false negatives. If I assign all employees in the category “13-2011 Accountants and auditors” licensing status, I create a large number of false positive licensed employees because certified public accountants are a small group within the larger category of accountants and auditors. If I assign all employees in the category “Other healthcare practitioners and technical occupations” the status of unlicensed, I very likely create false negatives because at least some employees in this category are licensed.

My aim was to construct a plausible licensing value for each occupational category for the US for the years 2012 and 2018 to deal with both challenges.

### A1. Construction of plausible licensing data for the CPS 2012

I constructed plausible licensing information for the 2012 data following four steps.

The first step was to compare previous licensing data offered by Summers (2007), Gittleman and Kleiner (2016), Redbird (2017), and the *licensing finder* of the platform *careeronestop*, which uses information from the US Department of Labor.<sup>10</sup> I created a list of each occupation mentioned at least once in each source for every US state. If all sources were in line with the occupation’s licensing, I assigned this occupation to the list of licensed occupations.

However, the sources offered conflicting information about a substantial number of occupations. In this case, the second step was to search for licensing laws regarding the occupation in a state. If I found a licensing law, I counted the occupation within the state as licensed. This step aimed to reduce the number of missing occupations per state in the licensing list. This list, together with all syntax files for the analysis offered here, is openly accessible on: <https://osf.io/q6chw/>.

The third step was to connect the data about single occupations to the Standard Classification of Occupations of 2010 (SOC2010). The CPS-MORG 2012 offers 2010 Census codes (OCC2010) for occupational classification, but many licensing sources offered only information about the SOC2010. Thus, I used a crosswalk from OCC2010 to SOC2010 offered by the Bureau of Labor Statistics.<sup>11</sup> In cases where official sources offered information about the SOC2010 code of licensed occupations, I used these codes. If I did not have such information, I searched for the occupational title in O\*NET. If O\*NET offered more than one plausible SOC2010 code, I decided which was the most plausible.

Licensing regulations can change over time. Thus, as a fourth step, I needed to backcode the licensing information to 2012 if the licensing status of an occupation within a US state changed between 2012 and the data

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<sup>10</sup> <https://www.careeronestop.org/Toolkit/Training/find-licenses.aspx>

<sup>11</sup> <https://www.bls.gov/cps/cenocc2010.htm>

collection phase. I used the information from the literature about changes in licensing (Timmons and Thornton 2018; Thornton and Timmons 2015), as well as the LegiScan database, which offers information about legislative changes in every US state.<sup>12</sup> I searched every occupational title for every state to track changes in licensing legislation. Most of the changes did not concern the regulation of entry but rather administrative rules. If I found legislation changing an occupation from licensed to unlicensed, or vice versa, in a state, I changed the information in the database. In sum, these changes were minor (relating, for example, to the licensure of genetic counselors in Idaho in 2015 or of lactation consultants in Georgia in 2016).

I combined the licensing list with the survey data using SOC2010-state cells as the fifth step, leading to “raw licensing” information. I assume that this version includes a share of false positives and false negatives that is too large to ignore, especially in terms of comparability over time. Thus, a last step was to reduce the number of false positives and negatives as much as possible. I used the self-reported licensing data of a pooled CPS-MORG of 2017 and 2018 as an additional data source to estimate the possibility of false positive and false negative licensing information.<sup>13</sup> Thus, to describe the construction of the plausible licensing information, we need to understand the nature of the self-reported licensing data.

Since 2015, the CPS has included questions about the licenses and certifications of respondents using a filter made up of three questions (Allard 2016). The first question is, “Do (you/name) have a currently active professional certification or a state or industry license? Do not include business licenses, such as a liquor license or vending license.” If respondents said yes, they were asked the second question: “Were any of (your/his/her) certifications or licenses issued by the federal, state, or local government?” The third question is: “Was your certification or license required for the job?”<sup>14</sup> If the answer to all three questions was yes, I assume the employee was working in a licensed occupation.

My strategy here is to combine both types of licensing data, thereby using the strengths of each type to reduce errors. The objective licensing data likely create more false positives than false negatives because the licensing list operates on the occupational category level. For example, I list certified public accountant under the SOC2010 code 13-2011. Merging the licensing list with the CPS data assigns the same code licensing status to all accountants and auditors, but certified public accountants are a minority among all accountants and auditors. This leads to a large over-reporting, which I aim to avoid. The CPS data of 2017/2018 allow me to assess the severity of the problem because I can calculate the shares of licensed employees within each category. By using these shares, I can reduce the number of false positives in the 2012 data. If more than 75% of employees within a state-occupation cell claim to have no license but should have one according to my list, I count this case as a false positive. If more than 75% claim to have one but should not, I count this category as a false negative.

According to the 2012 data, 9.1% of cases were false positives and 0.27% false negatives. There are two major reasons for false positives. First, some retail salespersons are licensed (those selling pharmaceuticals or cars), but the large majority are not. Instead of assigning no retail salespersons licensing status, I assigned the status only to those who work as salespersons in the automobile industry or in pharmacies. Second, some occupational categories are very heterogeneous, but it was not clear beforehand whether the licensed groups outweighed the unlicensed groups. For example, I counted “Truck drivers/Taxi drivers” as licensed in many states, but this produced a large number of false positives. Thus, I overwrote the original “objective” licensing information in cases with more than 75% false positives. The few false negative cases were due to residual categories, such as “Therapists, all others”, which I did not list as licensed because it is unclear which occupations are included in these categories. I also overwrote the original value if the share of employees within such state-occupation cells exceeded 75%.

## **A2. Construction of plausible licensing data for the CPS 2018**

It is not plausible that self-reported licensing information for the 2018 data is an error-free measure. For example, 18% of all employed lawyers, 12% of all dentists, and 13% of all physicians and surgeons claimed to work as such but to hold no active license, but all US states license these occupations. The reasons for this under-reporting are manifold, as discussed by Furth (2016) and Cunningham (2019). One of the largest obstacles seems to be that many responses refer to the occupation of the spouse and other relatives of the anchor person during the

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<sup>12</sup> <https://legiscan.com/>

<sup>13</sup> The licensing information of 2015 and 2016 is as yet not comparable with later CPS information. Thus, I pooled only the information for 2017 and 2018.

<sup>14</sup> The third question is not part of the CPS MORG v2.5 but is available in the Basic Monthly CPS. I merged both data sets using the variables *hrhhid*, *hrhhid2*, and *lineno*.

interview. In many cases, individuals know the relative's occupation but have a tendency to underreport the licensing requirements.

To solve the problem of under-reporting regarding the self-reported licensing data, I used a complementary strategy, but with a higher bar for overwriting information, because I attribute the individual-level data a higher plausibility as compared to the occupation-level lists. If more than 90% of cases within a state-occupation cell either counted as false negative or false positive, I overwrote the original licensing information. A total of 5.8% of all cases were false negative, and 0.4% were false positive.

I refer to the resulting version of the licensing variable as the *plausible licensing value* of an occupational category in a state and year. I assume that this version still includes some false negatives and positives. However, I claim that it is the version with the lowest error yet produced for the US.

For Germany, I rely on the licensing information provided by Haupt (2016a), who performed an exhaustive analysis of German licensing laws from 1949 to 2015. According to the US case, an occupation is defined as licensed only if the law protects the right to undertake occupation-specific actions. The protection of occupational titles (credentials) or the right to be self-employed in the German crafts (Meister diploma) is not sufficient to qualify as a licensing law because any German citizen can legally work in these occupations. I used the occupational classification of the Federal Labor Agency of 2010 (KldB 2010). Regarding data complexity, the German case is much more straightforward than the US case because the vast majority of licensing rules are federal. Only for some minor cases do states differ in their licensing laws. In some cases, they also differ in how they apply federal licensing rules, such as the licensing of private school teachers. However, these differences are minor, and I did not include between-state variations in the German data (see Haupt 2016b for a discussion).

## B. Descriptive statistics for the US and German samples

Table B1: Descriptive statistics for the US 2012/2018

	All	Not licensed	2012 Licensed	Difference	S.E.	All	Not licensed	2018 Licensed	Difference	S.E.
Wage	25.15	24.02	29.44	5.42	0.12	26.91	25.57	31.11	5.54	0.13
Plausibly licensed	20.80					24.11				
Education										
Low-skilled	6.98	8.00	3.07	-4.94	0.16	6.34	7.44	2.85	-4.59	0.15
Medium-skilled	57.54	61.33	43.08	-18.25	0.31	54.66	57.97	44.23	-13.74	0.31
High-skilled	35.49	30.66	53.85	23.18	0.30	39.01	34.59	52.92	18.33	0.30
Experience in years										
0–4	13.36	14.28	9.85	-4.43	0.22	14.02	15.26	10.10	-5.16	0.21
5–9	12.51	12.35	13.12	0.77	0.21	13.59	13.66	13.35	-0.30	0.21
10–14	11.72	11.50	12.53	1.03	0.20	12.59	12.38	13.26	0.88	0.21
15–19	11.21	10.99	12.06	1.07	0.20	11.24	10.94	12.18	1.24	0.20
20–24	11.49	11.39	11.88	0.49	0.20	10.78	10.32	12.24	1.92	0.19
25–29	11.81	11.60	12.59	0.99	0.21	10.58	10.22	11.72	1.50	0.19
30+	27.91	27.89	27.97	0.07	0.29	27.20	27.22	27.15	-0.08	0.28
Work hours										
Part-time (<35h)	21.60	22.35	18.73	-3.62	0.26	18.92	19.82	16.10	-3.72	0.24
Full-time (35-50h)	66.98	66.99	66.94	-0.04	0.30	69.96	70.12	69.47	-0.65	0.28
Over-workers (>50h)	11.43	10.66	14.33	3.66	0.20	11.12	10.06	14.43	4.36	0.19
Industry										
Ag./forestry/fisheries	1.74	2.06	0.50	-1.56	0.08	1.87	2.14	1.04	-1.10	0.08
Mining	0.73	0.81	0.42	-0.39	0.05	0.51	0.53	0.43	-0.11	0.04
Construction	5.34	5.53	4.62	-0.91	0.14	6.27	6.49	5.59	-0.90	0.15
Manu. durables	6.48	7.73	1.74	-5.99	0.16	6.22	7.00	3.77	-3.23	0.15
Manu. non-durables	3.94	4.73	0.92	-3.81	0.12	3.87	4.56	1.71	-2.85	0.12
Transportation	4.07	3.71	5.44	1.73	0.13	4.25	4.14	4.60	0.46	0.12
Communications	1.67	2.05	0.21	-1.84	0.08	1.51	1.86	0.40	-1.46	0.08
Util./sanitary	1.26	1.29	1.15	-0.14	0.07	1.23	1.27	1.11	-0.16	0.07
Wholesale trade	2.44	2.80	1.06	-1.74	0.10	2.26	2.47	1.60	-0.87	0.09
Retail	17.82	21.41	4.18	-17.22	0.24	17.33	19.13	11.65	-7.48	0.23
FIRE	6.52	6.81	5.40	-1.41	0.16	6.50	6.47	6.61	0.14	0.15
Bus./repair services	9.82	11.07	5.05	-6.02	0.19	10.44	11.75	6.35	-5.40	0.19
Entertainment/rec. services	1.92	2.30	0.48	-1.83	0.09	1.98	2.25	1.12	-1.13	0.09
Prof./other services	30.36	21.59	63.74	42.16	0.27	29.88	24.16	47.90	23.73	0.28
Government	5.46	5.58	4.98	-0.60	0.14	5.39	5.21	5.94	0.73	0.14
Occupational composition										
Male-dominated (>70%)	25.72	27.17	20.20	-6.97	0.28	29.56	30.85	25.52	-5.33	0.28
Mixed occupation	43.16	46.16	31.74	-14.42	0.31	40.00	41.35	35.76	-5.58	0.30
Female-dominated (>70%)	31.12	26.67	48.06	21.39	0.29	30.44	27.80	38.72	10.92	0.28
Female	49.11	46.71	58.25	11.54	0.32	48.77	47.22	53.65	6.43	0.31
Was or is married	55.07	53.24	62.03	8.80	0.32	52.53	50.23	59.79	9.56	0.31
Age										
16–23	10.81	12.27	5.27	-7.00	0.20	10.87	12.44	5.90	-6.54	0.19
24–31	19.48	19.56	19.20	-0.35	0.25	20.76	21.26	19.18	-2.09	0.25
32–39	18.12	17.77	19.43	1.66	0.24	19.15	18.68	20.64	1.96	0.24
40–47	18.94	18.58	20.35	1.77	0.25	17.44	16.71	19.74	3.03	0.23
48–55	19.16	18.91	20.10	1.19	0.25	17.44	17.08	18.56	1.47	0.23
56+	13.48	12.91	15.65	2.74	0.22	14.34	13.82	15.98	2.17	0.22
Region										
East	18.44	18.14	19.57	1.44	0.25	17.93	18.08	17.45	-0.63	0.24
Central	22.22	22.11	22.65	0.54	0.26	21.47	20.84	23.45	2.61	0.25
South	36.89	36.47	38.45	1.98	0.31	37.05	37.44	35.81	-1.63	0.30
Mountain and Pacific	22.46	23.28	19.33	-3.95	0.27	23.55	23.64	23.29	-0.35	0.26
Race										
White	65.87	64.61	70.66	6.05	0.30	61.19	59.18	67.54	8.36	0.30
White – Hispanic	15.39	16.63	10.65	-5.98	0.23	17.65	19.02	13.32	-5.70	0.24
Black	11.51	11.30	12.33	1.03	0.20	12.76	13.16	11.47	-1.69	0.21
Other	7.23	7.45	6.36	-1.09	0.16	8.40	8.63	7.67	-0.97	0.17

Table B2: Descriptive statistics for Germany 2012/2018

	2012					2018				
	All	Not licensed	Licensed	Difference	S.E.	All	Not licensed	Licensed	Difference	S.E.
Wage	15.35	15.15	16.32	1.17	0.16	16.19	16.03	16.74	0.72	0.15
Licensed occupation	17.47					22.81				
Education										
Low-skilled	7.97	8.92	3.48	-5.44	0.57	5.78	6.63	2.89	-3.75	0.44
Medium-skilled	69.77	73.20	53.57	-19.64	0.96	58.62	61.60	48.53	-13.07	0.92
High-skilled	22.25	17.87	42.95	25.08	0.85	35.60	31.76	48.58	16.82	0.89
Experience in years										
0-4	8.82	8.42	10.69	2.27	0.60	9.26	9.58	8.18	-1.40	0.54
5-9	12.28	11.98	13.72	1.74	0.69	12.53	12.44	12.84	0.40	0.62
10-14	12.28	11.91	14.06	2.15	0.69	12.26	12.08	12.85	0.76	0.62
15-19	12.07	11.97	12.53	0.56	0.69	11.83	11.50	12.94	1.44	0.61
20-24	13.84	13.93	13.43	-0.50	0.73	11.56	11.27	12.55	1.28	0.60
25-29	14.57	14.83	13.36	-1.46	0.74	12.85	12.75	13.18	0.44	0.63
30+	26.13	26.96	22.21	-4.76	0.93	29.71	30.38	27.47	-2.91	0.86
Work hours										
Part-time (<35h)	26.92	24.50	38.36	13.87	0.93	31.04	28.60	39.28	10.69	0.86
Full-time (35-50h)	60.35	62.86	48.49	-14.37	1.02	56.76	59.02	49.12	-9.90	0.93
Over-workers (>50h)	12.73	12.64	13.14	0.50	0.70	12.20	12.38	11.59	-0.79	0.61
Industry										
Ag./forestry/fisheries	0.69	0.81	0.12	-0.69	0.17	0.69	0.89	0.02	-0.87	0.16
Mining	0.24	0.27	0.07	-0.20	0.10	0.14	0.17	0.05	-0.12	0.07
Construction	5.53	6.22	2.24	-3.98	0.48	4.32	5.38	0.72	-4.66	0.38
Manu. durables	21.16	25.26	1.80	-23.46	0.84	16.60	20.91	2.01	-18.90	0.68
Manu. non-durables	9.23	11.03	0.71	-10.32	0.60	6.13	7.68	0.90	-6.78	0.45
Transportation	4.58	5.44	0.54	-4.90	0.44	4.61	5.83	0.46	-5.37	0.39
Communications	3.29	3.97	0.11	-3.85	0.37	4.41	5.67	0.15	-5.52	0.38
Util./sanitary	2.40	2.87	0.15	-2.72	0.32	1.86	2.37	0.16	-2.21	0.25
Wholesale trade	2.16	2.61	-0.00	-2.61	0.31	1.63	2.11	0.01	-2.09	0.24
Retail	7.37	8.46	2.22	-6.23	0.55	6.08	7.39	1.62	-5.77	0.45
FIRE	4.11	4.87	0.54	-4.32	0.42	4.40	5.57	0.42	-5.15	0.38
Bus./repair services	0.26	0.31	-0.00	-0.31	0.11	0.41	0.51	0.08	-0.43	0.12
Entertainment/rec. services	3.45	4.13	0.23	-3.90	0.38	3.73	4.75	0.25	-4.50	0.35
Prof./other services	15.81	11.21	37.58	26.37	0.74	19.21	14.70	34.46	19.76	0.72
Government	18.66	11.26	53.64	42.38	0.75	25.03	15.10	58.63	43.53	0.74
Occupational composition										
Male-dominated	37.05	42.67	10.52	-32.15	0.99	31.29	37.93	8.81	-29.12	0.84
Mixed occupation	32.39	36.25	14.18	-22.07	0.97	37.29	43.98	14.64	-29.35	0.88
Female-dominated	30.55	21.08	75.31	54.23	0.87	31.42	18.08	76.55	58.47	0.74
Women	45.72	40.42	70.73	30.30	1.02	48.92	42.73	69.85	27.12	0.91
Was or is married	66.85	66.54	68.35	1.81	0.99	65.87	63.91	72.50	8.58	0.89
Age										
16-23	4.33	4.64	2.86	-1.78	0.43	3.53	3.82	2.52	-1.30	0.35
24-31	16.67	16.32	18.34	2.02	0.79	13.81	14.51	11.45	-3.06	0.65
32-39	17.69	17.66	17.83	0.17	0.80	18.47	18.60	18.03	-0.58	0.73
40-47	24.80	25.20	22.87	-2.33	0.91	17.08	16.79	18.08	1.29	0.71
48-55	23.80	24.04	22.69	-1.36	0.90	26.09	26.33	25.24	-1.09	0.82
56+	12.71	12.14	15.41	3.27	0.70	21.03	19.95	24.69	4.74	0.76
Region										
South	31.28	31.71	29.28	-2.43	0.98	6.09	5.96	6.53	0.57	0.45
Northwest	49.51	49.38	50.12	0.74	1.05	61.77	61.53	62.60	1.08	0.91
Northeast (ex GDR)	19.21	18.91	20.60	1.69	0.83	32.14	32.51	30.87	-1.65	0.88
Migration background	15.66	16.50	11.71	-4.78	0.77	11.54	12.10	9.66	-2.44	0.60
Fixed-term contract	10.79	10.59	11.75	1.17	0.65	10.34	10.73	9.01	-1.72	0.57
Civil servant	6.33	3.43	20.01	16.63	0.49	5.44	2.98	15.82	12.83	0.44

## C. Evaluation of possible bias for QTTE estimates

I evaluated a possible bias of the QTTE estimate in the case of selection into treatment using three different data structures. Across all settings, there is a gender-specific quantile treatment effect: the effect increases positively by 0.02 for each percentile for men and increases negatively by -0.02 for each percentile for women. Each scenario has

1. 50,000 observations
2. two normally distributed, correlated covariates  $x_1 \sim N(1,1)$  and  $x_2 \sim N(2,2)$ ;  $r = 0.5$
3. a normally distributed error  $\sim N(0,14)$

The settings differ in the complexity of the associations between the treatment, gender, and the covariates. The first setting is the base scenario. The treatment is randomized and gender has no influence on the outcome. In the second setting, there is selection into the treatment conditional on both covariates and gender. In the third setting, I add that gender has itself an influence on the outcome in the form of a conditional QTTE.

I draw 100 samples for each setting and estimate the gender-specific QTTE for each sample using the QTTE method as described in the paper. Furthermore, I calculate the difference between the true QTTE and the estimated one. Below, I report the average result for the QTTE and the difference between the true and estimated QTTE across draws with an interval referring to the fifth and 95<sup>th</sup> percentiles of the result distribution.

The results indicate that the QTTE estimates are unbiased even given complex data structures. There are minor differences for men in the lowest and top quantiles but they are neither positively nor negatively biased across the settings.

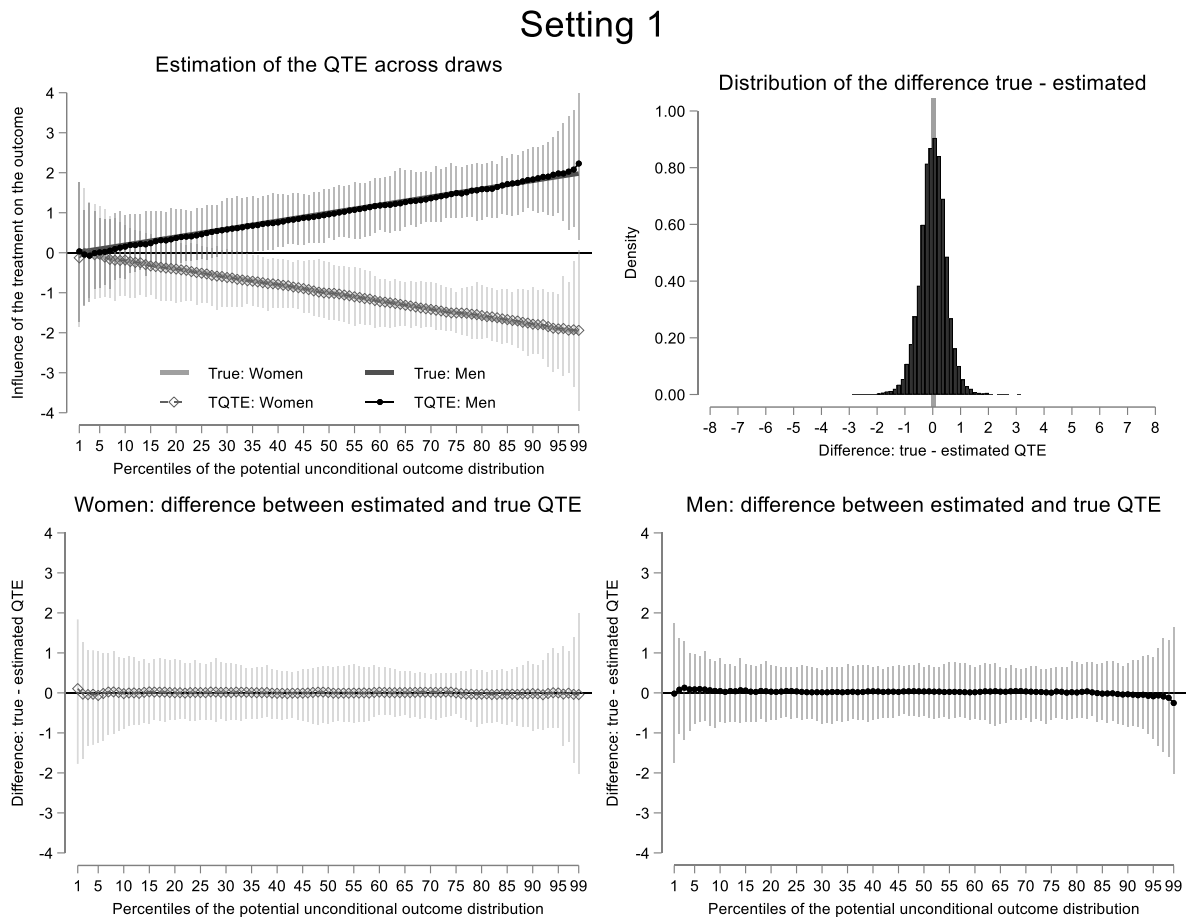


Figure C1: Simulation results for setting 1: Gender-specific QTTE, randomized treatment assignment; gender does not influence the outcome, gender is not correlated with covariates. 100 runs with 50,000 observations



## Setting 2

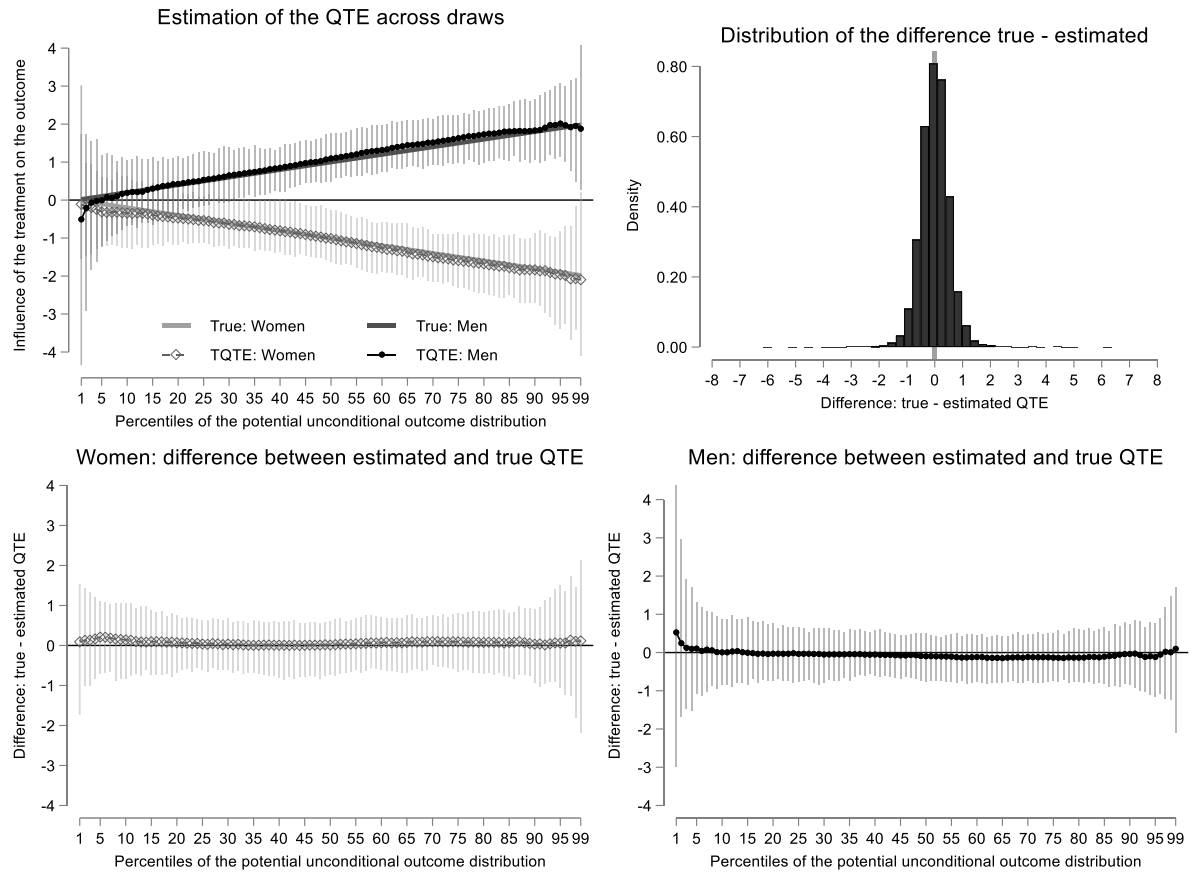


Figure C2: Simulation results for setting 2: Gender-specific QTE, selection into treatment; gender does not influence the outcome, gender is correlated with covariates. 100 runs with 50,000 observations

### Setting 3

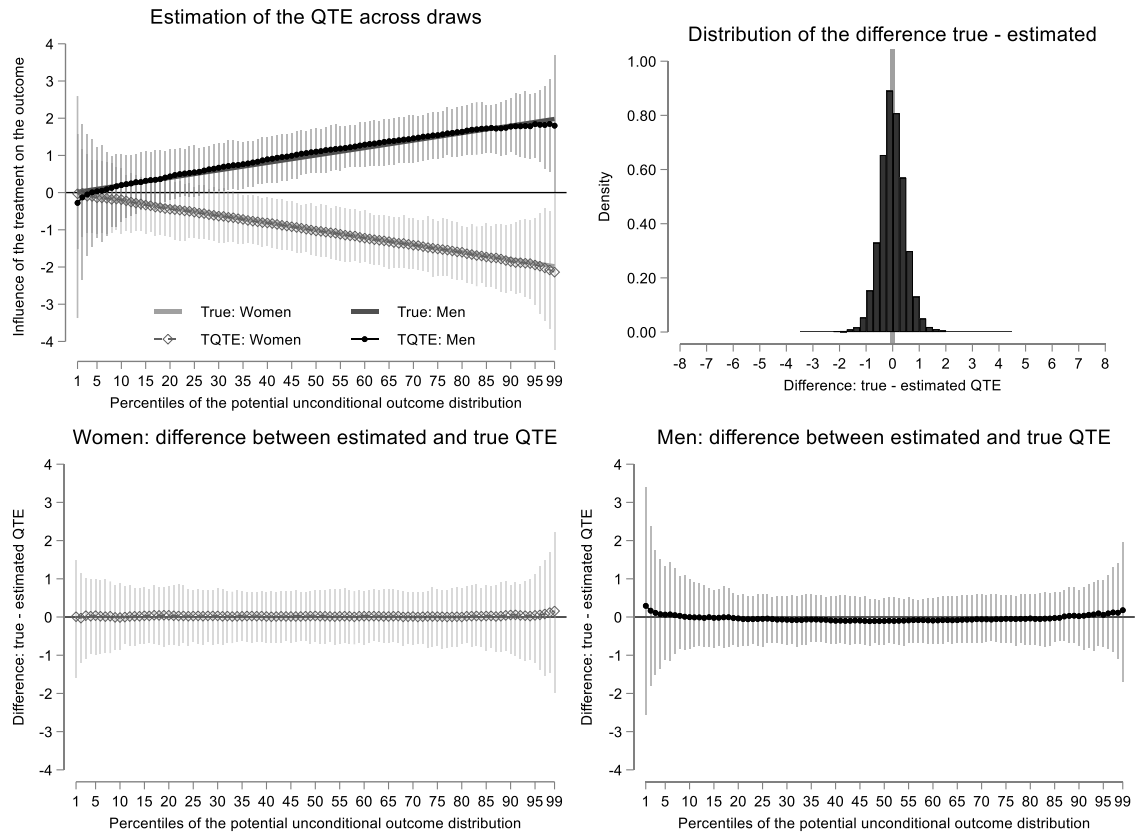


Figure C3: Simulation results for setting 3: Gender-specific QTE, selection into treatment; gender influences the outcome with a conditional QTE, gender and the treatment are correlated with covariates. 100 runs with 50,000 observations

## D. Robustness checks

### D1. Unionization and licensing in the US

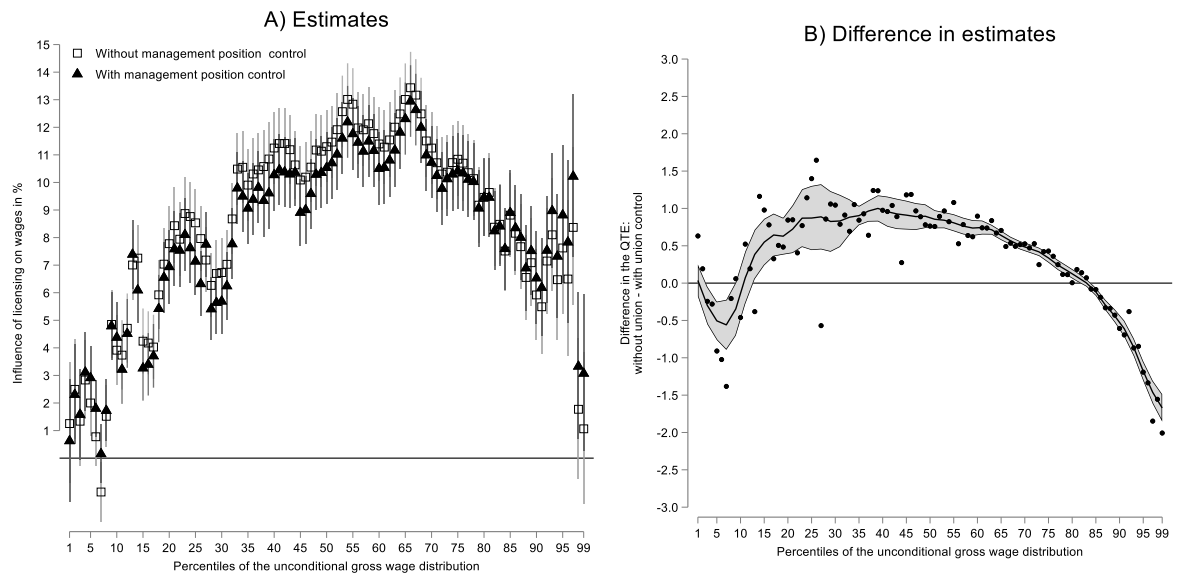


Figure D1: Difference in estimates for the licensing wage premium across the distribution for models without and with control for union membership

### D2. Management positions and licensing in Germany

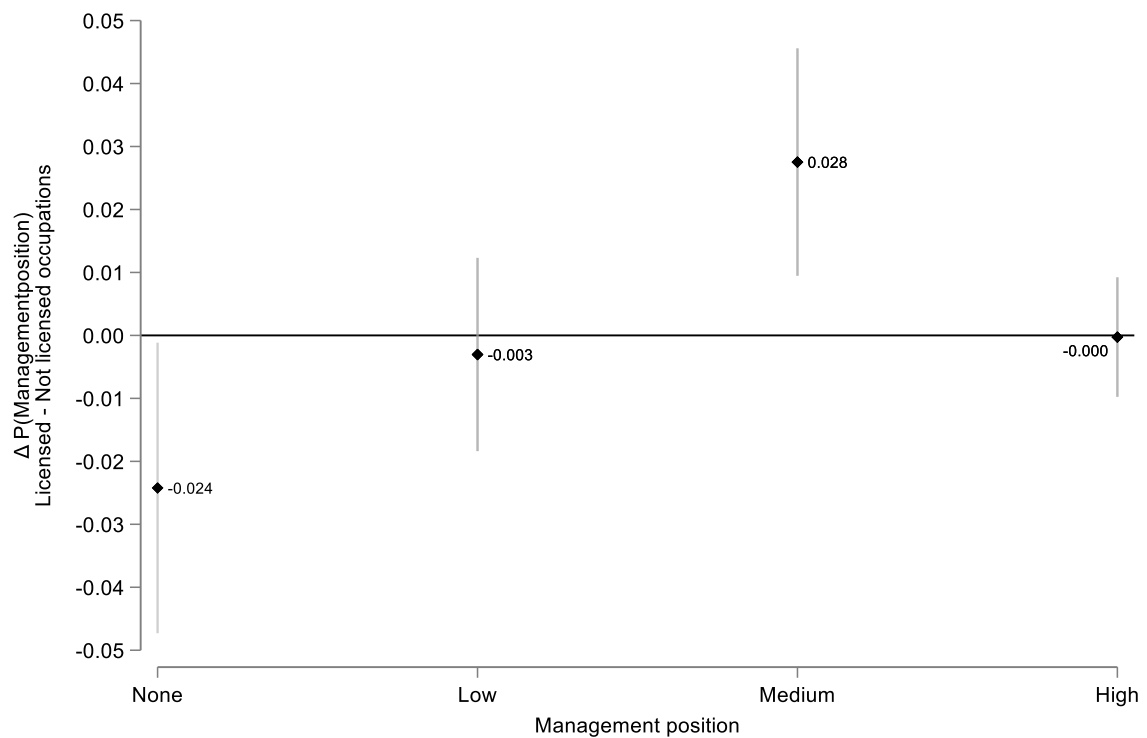


Figure D2: Differences in the probability of a management position between licensed and not-licensed occupations in Germany, 2018

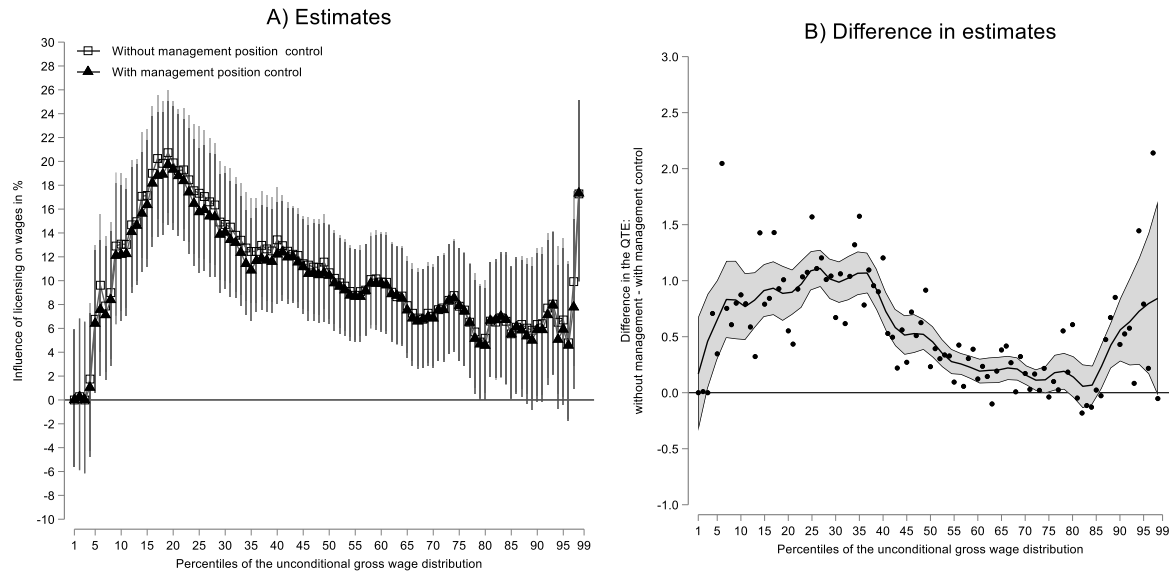


Figure D3: Difference in estimates for the licensing wage premium across the distribution in Germany for models without and with control for management positions

### D3. The licensing wage advantage in the US and Germany in 2012

For this robustness check, I used the CPS-MORG and BIBB-BAuA data from 2012. The German data are only available every six years, thus 2012 is the next available comparable year for both countries. I used the same set of covariates as for 2018 (see also Tables B1 and B2 in this appendix).

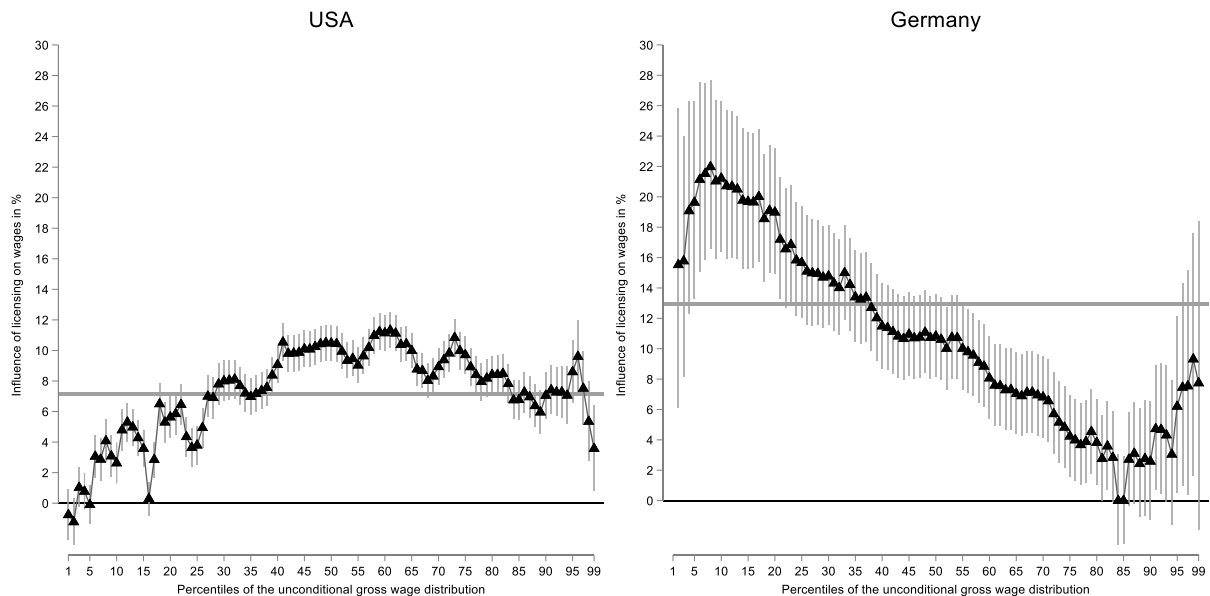


Figure D4: The licensing wage advantage across the distribution in 2012. Results of QTE models for the US and Germany. The horizontal gray lines refer to the multivariate OLS licensing estimate for each country

### D4. Alternative estimation of the QTE

As a robustness check, I compare the estimated results of this approach with results based on Generalized Quantile Regressions (Powell 2020). This method takes a very different estimation approach. It constructs a counterfactual unconditional distribution net of the QTE using proneness variables. These proneness variables predict the rank of a unit within the counterfactual distribution net of the treatment effect. This counterfactual distribution can serve as a control group and shows how the unconditional distribution would look in the absence of the treatment effect.

After the construction of the counterfactual distribution, we can compare it with the observed distribution to obtain estimates of the QTE. The results shown in the appendix align strongly with the ones reported here (Borgen, Haupt, and Wiborg 2021 show that the results of both estimation techniques align using simulations and further real data examples).

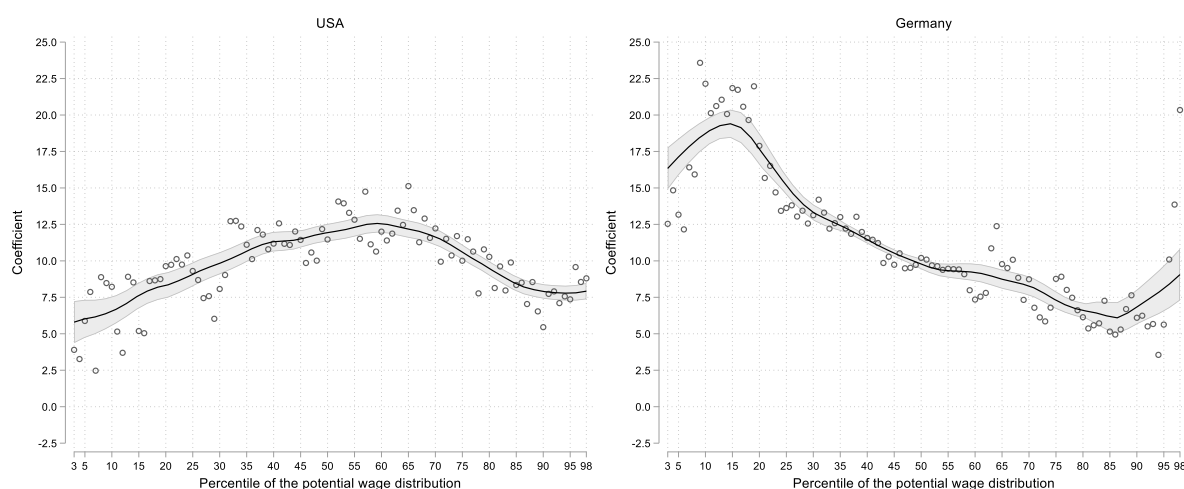


Figure D5: Estimated QTEs for 2018 using generalized quantile regression as proposed by Powell (2020). The dots refer to the average coefficient of 300 MCMC draws (after a burn-in of 200 draws). The line refers to a polynomial smoother of the coefficients across quantiles with a 95% confidence interval as the shaded area around it

## D5. Comparison of the self-reported with the plausible license information for the US

### 2018 data

In line with the assumption that the self-reporting of the licensing status leads to under-reporting, I estimate positive differences in the shares of licensed employees conditional on the variable used. The corrected licensing information leads to lower estimates of the QTE, especially in the bottom half of the wage distribution.

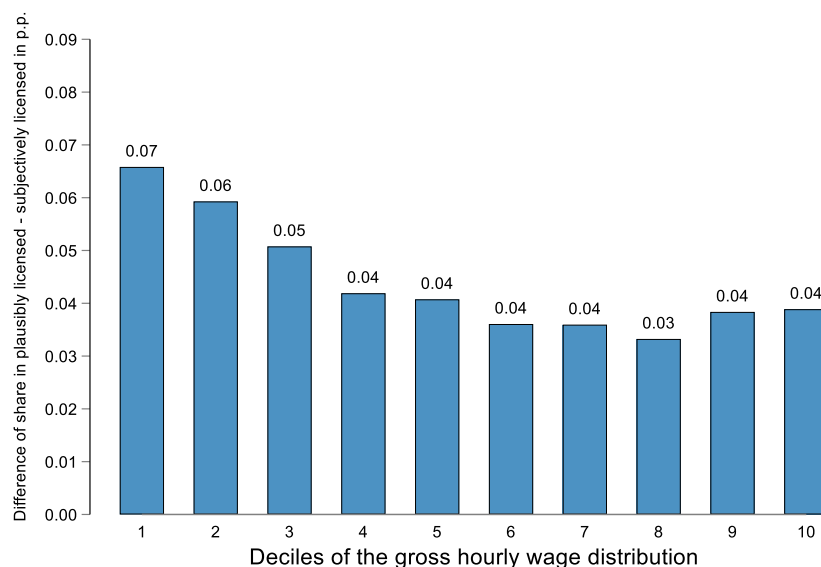


Figure D6: Differences in the share of plausibly licensed vs. self-reported licensed employees in the US in 2018 across deciles of the wage distribution

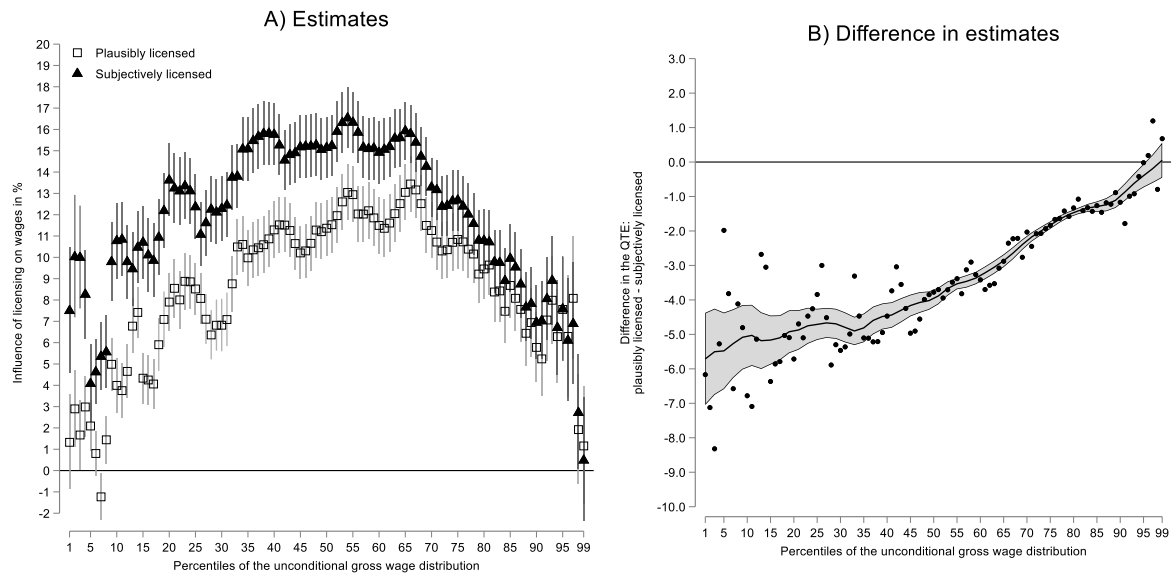


Figure D7: QTEs conditional on the licensing information used, and their difference for each quantile for the US, 2018

### 2012 data

As expected, the approach of merging occupational lists to occupational codes in the CPS-MORG leads to significant numbers of false positives. The correction leads to a reduction of the share in licensed employees and an increase of the QTE across the entire wage distribution.

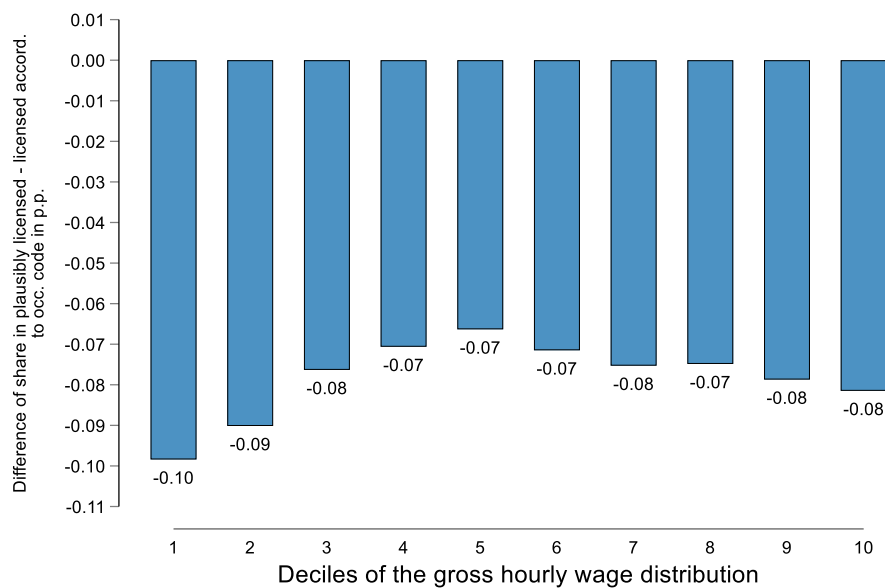


Figure D8: Differences in the share of plausibly licensed vs. licensed employees according to their matched occupational cell in the US in 2012 across deciles of the wage distribution

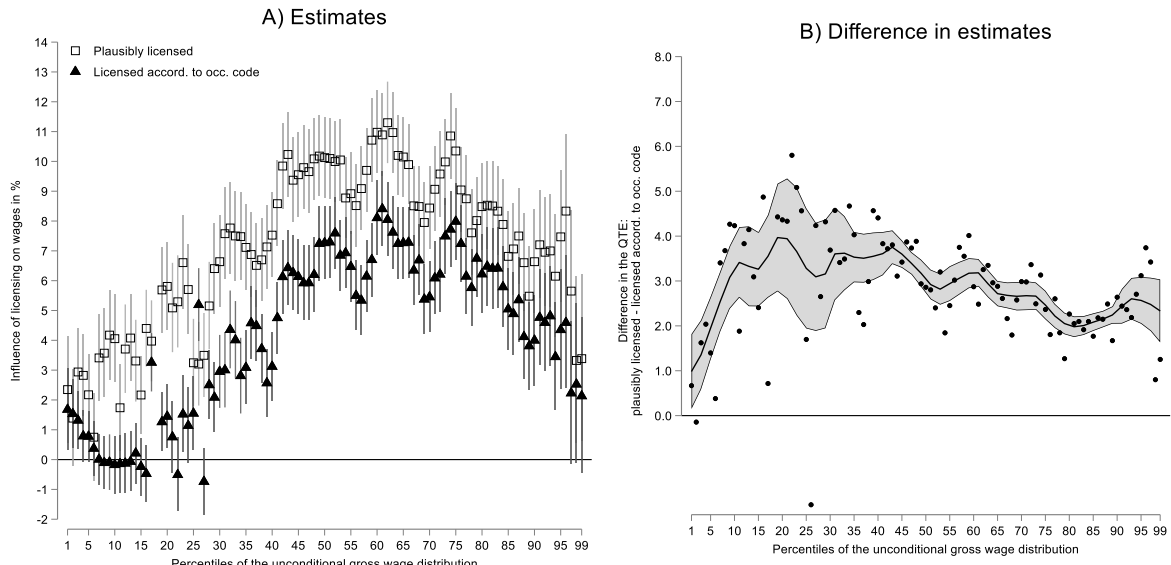


Figure D9: QTEs conditional on the licensing information used, and their difference for each quantile for the US, 2012

## D6. The influence of handling top-coded weekly earnings on QTE and TQTE estimates for 2018

Respondents with very high earnings can be subject to top-coding in the CPS. About 4% of all employees in the analytical sample are subject of such a top-coding, which splits up to 2.9% top-coded men and 1.1% top-coded women. Because licensed employees are more likely to be in the upper parts of the pay distribution, licensed respondents are a bit more likely to be subject of top-coding (5.4% off all licensed employees) compared to unlicensed ones (3.5%).

The CPS offers information about the weekly pay, which is top-coded to 2884\$ per week since 1998. Respondents with weekly pay set to 2884\$ can vary in their work hours and can therefore be located at different points of the wage distribution. However, top-coding of weekly pay results in a bunching of wages in the upper parts of the distribution, which is undesirable for quantile regressions. We also know that the true average value of these respondents is higher than the 2884\$ cutoff, leading to biased estimates, especially for top-quantiles.

The solution for dealing with these problems in this paper follows an approach of Greene (2018) to estimate gender-specific means of the weekly-pay assuming that the distribution of weekly pay follows a log-normal distribution for each gender and then construct the hourly wage (see also: Center for Economic and Policy Research 2020). The assumption here is that the distribution of weekly pay has a different shape with different average weekly pay for both genders above the cutoff.

While this is a reasonable assumption, it is not the only solution. A part of the literature multiplies top-coded weekly earnings by 1.5 to shift top-coded weekly pay information above the cutoff for both genders (see for example: Autor, Katz, and Kearney 2008). The estimation of gender-specific means maybe a concern for the analysis here, because licensing and gender are correlated. However, this multiplier may also be too conservative as a shift of top-coded wages and seems to underestimate the extent of wage dispersion in the top (Nicolau, Raposo, and Rodrigues 2023). As an alternative, I estimated a single mean of weekly pay across both genders using the approach of Greene (2018).<sup>15</sup>

<sup>15</sup> Multiple imputation of the weekly pay information is not an acceptable solution for this case because it needs covariates, which I use as adjustment factors in the quantile regression models. Including multiple imputed data into models with the same covariates biases estimates towards zero Nicolau, Raposo, and Rodrigues (2023).

Employees with top-coded weekly earnings crowd within the top five percentiles of the wage distribution independent how top-coded weekly pay is handled (Figure D10). They make up to 95% of all respondents in the top three percent.

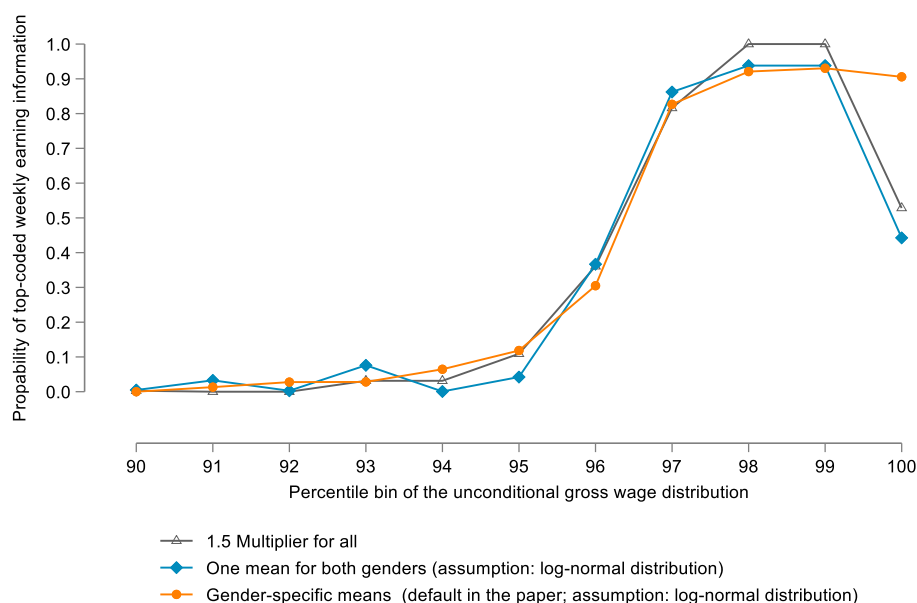


Figure D10: The distribution of top-coded wage information across the top 10% of the wage distribution conditional on the treatment of top-coded weekly pay information.

Shifting weekly wages up using a multiplier of 1.5 or estimating one mean for both genders using a log-normal distribution results in in a bunching of wages around 100\$ to 110\$ per hour (4.6 to 4.7 on a logarithmic scale, see Figure D11). Wages above this point are very likely based on reports of hourly wages. Using gender-specific means disperses wages to a larger extend and prevents bunching and it also leads to a much larger share of wages with top-coded weekly pay in the top-percentile.



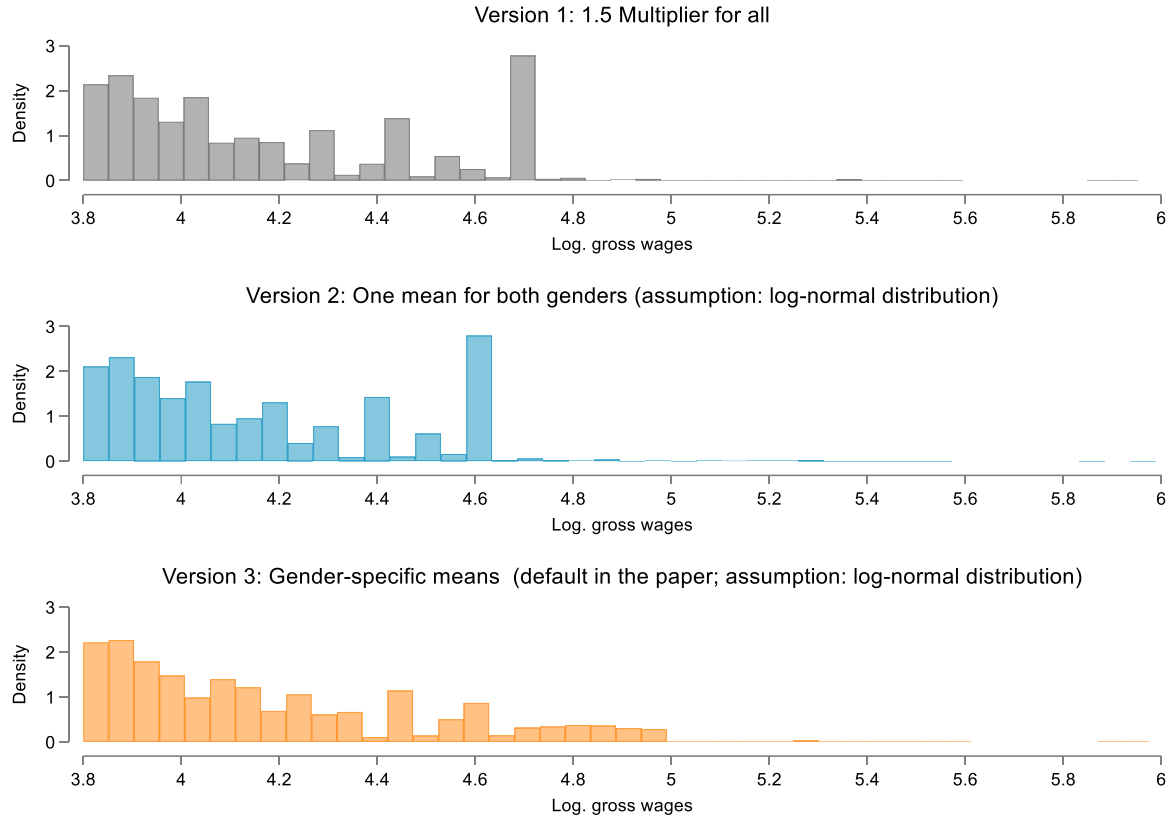


Figure D11: The distribution wages across the top 10% of the wage distribution conditional on the treatment of top-coded weekly pay information.

Results for the unconditional quantile treatment effects are largely unaffected by the choice of how to handle top-coded values. All three versions indicate a marginally decreasing licensing wage premium for the US across the top 20% of the wage distribution, which trends towards zero for the top two percentiles. Using the 1.5 multiplier even results in a negative estimate for the 98<sup>th</sup> percentile.

Alternative wage distributions matter to a small extent for the estimation of gender-specific wage premiums – but only for the estimates for women in the very top. Using the 1.5 multiplier for both genders results in the estimation of larger wage premiums for women for the 94<sup>th</sup> to 98<sup>th</sup> percentile but a precise null estimate for the 99<sup>th</sup> percentile. The other two versions produce very similar results, including a very large estimate for the 99<sup>th</sup> percentile, which deviates strongly from estimates for lower percentiles. For men, the choice of a different version does not matter. However, the results for the top two quantiles differ strongly and it is unclear, whether this is an artifact based on top-coding data or reflects an empirical social process.

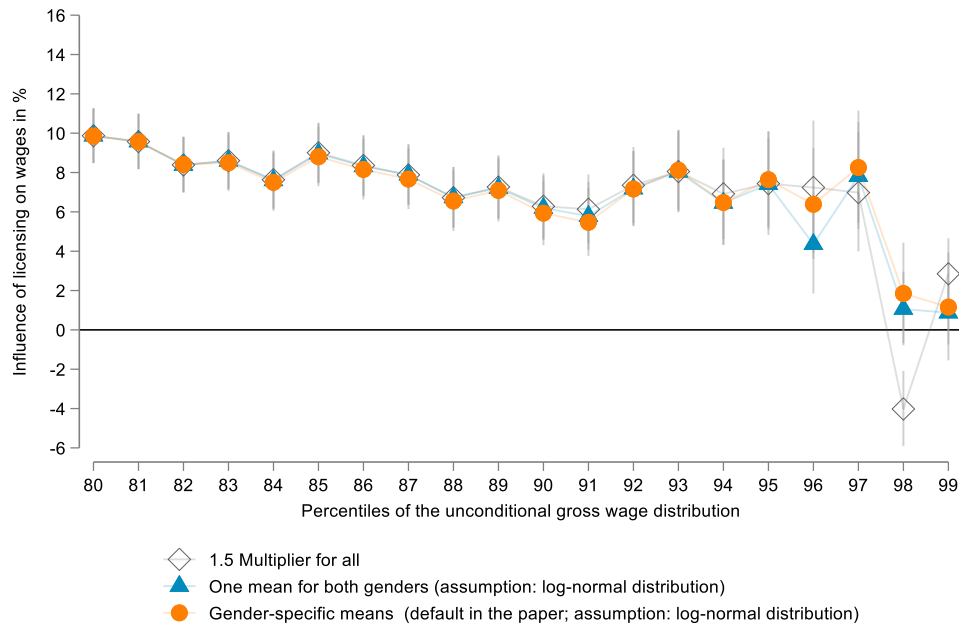


Figure D12: QTEs of licensing on wages for the upper 20 percentiles of the potential gross wage distribution using different approaches how to deal with top-coded weekly earnings.

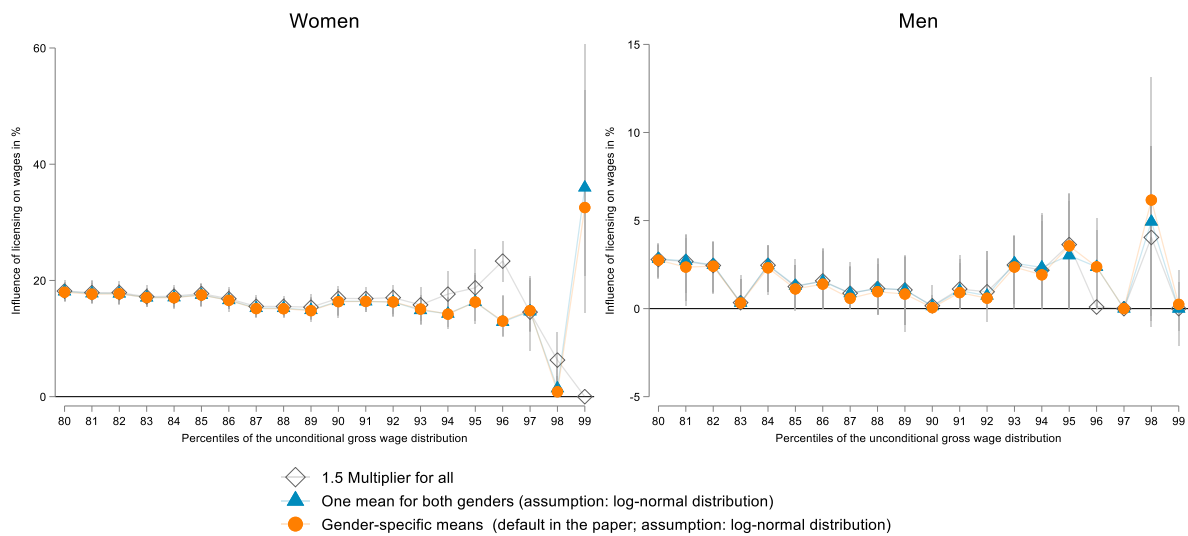


Figure D13: Gender-specific QTEs of licensing on wages for the upper 20 percentiles of the potential gross wage distribution using different approaches how to deal with top-coded weekly earnings.

Top-coded weekly earnings were cut off at 2884\$ and the methods discussed so far used this point to construct an upper-tail for the wage distribution. However, even if this is the empirical cutoff, one could argue that this does not properly reflect the start of the top-coded upper tail. Thus, I used five alternative cutoff values for weekly earnings in order to calculate gender-specific means for top-coded weekly earnings. I started with the cutoff 2885\$ and added 200\$ for five iterations.

The change of cutoff values did not matter for the results in any practical sense (figure D14). Higher cutoffs typically lead to larger QTE estimates but only in the second and in rare cases in the first digit of the model results.

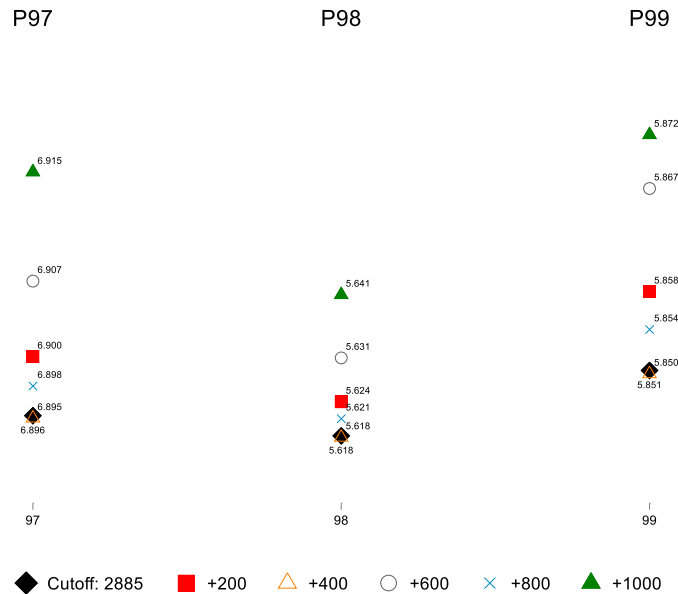


Figure D13: Estimates of the QTE of licensing on wages for different versions of the wage distribution using different cutoffs for top-coded weekly earnings.

## References

- Allard, Dorinda. 2016. “Adding questions on certifications and licenses to the Current Population Survey”. *Monthly Labor Review*. doi: 10.21916/mlr.2016.52.
- Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. “Trends in US wage inequality: Revising the Revisionists”. *Review of Economics and Statistics* 90 (2):300–23.
- Borgen, Nicolai T., Andreas Haupt, and Øyvind N. Wiborg. 2021. *A New Framework for Estimation of Unconditional Quantile Treatment Effects: The Residualized Quantile Regression (RQR) Model*.
- Center for Economic and Policy Research. 2020. “CPS ORG Uniform Extracts, Version 2.5”. Washington, DC.
- Cunningham, Evan. 2019. “Professional certifications and occupational licenses”. *Monthly Labor Review*:1–38.
- Furth, Salim. 2016. “Understanding the Data on Occupational Licensing”. *The Heritage Foundation*.
- Gittleman, Maury, and Morris M. Kleiner. 2016. “Wage Effects of Unionization and Occupational Licensing Coverage in the United States”. *ILR Review* 69 (1):142–72. doi: 10.1177/0019793915601632.
- Greene, William. 2018. *Econometric analysis*. New York, NY: Pearson.
- Haupt, Andreas. 2016a. “Erhöhen berufliche Lizenzen Verdienste und die Verdienstungleichheit?”. *Zeitschrift für Soziologie* 45 (1):39–56.
- Haupt, Andreas. 2016b. *Zugang zu Berufen und Lohnungleichheit in Deutschland*. Wiesbaden: Springer VS.
- Nicolau, João, Pedro Raposo, and Paulo M. M. Rodrigues. 2023. “Measuring wage inequality under right censoring”. *Economic Inquiry* 61 (2):377–401. doi: 10.1111/ecin.13119.
- Powell, David. 2020. “Quantile treatment effects in the presence of covariates”. *Review of Economics and Statistics* 102 (5):994–1005.
- Redbird, Beth. 2017. “The New Closed Shop? The Economic and Structural Effects of Occupational Licensure”. *American Sociological Review*:0003122417706463. doi: 10.1177/0003122417706463.
- Summers, Adam B. 2007. *Occupational licensing. Ranking the states and exploring alternatives*. Reason Foundation Los Angeles, CA.
- Thornton, Robert J., and Edward J. Timmons. 2015. “The de-licensing of occupations in the United States”. *Monthly Lab. Rev.* 138:1.
- Timmons, Edward J., and Robert J. Thornton. 2018. “There and Back Again: The De - Licensing and Re - Licensing of Barbers in Alabama” . *British Journal of Industrial Relations* 57 (4):764–90.
- Weeden, Kim A. 2002. “Why do some occupations pay more than others? Social closure and earnings inequality in the United States”. *American Journal of Sociology* 108 (1):55–101.