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Occupational Regulation, Institutions, and Migrants' Labor Market Outcomes*

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Abstract

We study how licensing, certification and unionisation affect the wages of natives and migrants and their representation among licensed, certified, and unionized workers. We provide evidence of a dual role of labor market institutions, which both screen workers based on unobservable characteristics and also provide them with wage setting power. Labor market institutions confer significant wage premia to native workers (4, 1.6, and 2.7 log points for licensing, certification, and unionization respectively), due to screening and wage setting power. Wage premia are significantly larger for licensed and certified migrants (10.3 and 6.6 log points), reflecting a more intense screening of migrant than native workers. The representation of migrants among licensed (but not certified or unionized) workers is 15% lower than that of natives. This again implies a more intense screening of migrants by licensing institutions than by certification and unionization.

Keywords Occupational regulation · Licensing · Certification · Unionization · Migration · Wages

JEL Classification J61 · J31 · J44 · J71 · J16

1. Introduction

How do labor market institutions impact the labour market outcomes of migrant workers? We consider three major labor market institutions, namely occupational licensing, certification, and unionization. Occupational licensing entails that only those who meet certain prescribed standards of competence (usually in the form of educational credentials, work experience and examinations) can legally practice an occupation. Licensing affects a sizeable proportion of the workforce; about 22 percent of workers in the EU are required to hold a license to do their job (Koumenta and Pagliero 2019), while estimates for the US range between 20% (Gittleman et al. 2018) and 29% (Kleiner and Krueger 2013). In the case of certification, practitioners may voluntarily apply to have their skills certified by a state-appointed regulatory body or a professional

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association. Certification may provide access to a protected title, but it is not a legal requirement to practice the occupation. Currently about 22% of workers in the EU hold a professional certification related to their main job.[1] Finally, unionization is the most well-known labor market institution and it has been the subject of a vast literature. Membership is about 23% in the EU (Fulton 2015) and 11% in the US according to the 2020 union membership rate reported by the U.S. Bureau of Labor Statistics.

We provide a theoretical framework for comparing migrants and natives in terms of wages and representation among licensed, certified, and unionized workers. Our approach is based on two characteristics of institutions: whether they confer wage setting power to their members and whether they screen their members based on their individual characteristics (see Table 1). The systematic comparison of migrants and natives across institutions sheds light on two mechanisms by which institutions may affect the labor market outcomes of natives and migrants. The first is wage setting power. Occupational licensing confers legal monopoly power to an organized profession, which has exclusive rights over specific activities. Through their ability to control entry into the occupation, insiders can affect labor supply and thus wages. Similarly, by organising in collective bargaining, unionization also confers wage setting power to its members. However, certification does not provide exclusive rights to specific activities, nor does it engage in collective bargaining, so it does not give any wage setting power to its members.

The second and less studied mechanism is screening. Occupational licensing regulates entry into a profession by selecting its members based on individual characteristics, often through professional exams, educational and experience requirements. In the absence of licensing, these individual characteristics are typically unobservable (or very costly to verify) to employers and consumers. They are also typically unobservable to researchers. For example, workers are heterogeneous in quality, or productivity, which can be assessed by specific professional exams, but is otherwise not observable. Moreover, migrants differ from natives in terms of cultural characteristics, educational credentials, local knowledge, and language proficiency. All these variables are relevant – to some extent – for admission into licensed professions. Obtaining a license thus implies having passed a screening process and provides a signal of individual characteristics. Certification also screens workers according to their individual characteristics, although the entry standards may be different. Becoming a union member on the other hand does not involve any screening based on individual characteristics.[2]

We propose an additive decomposition of the effects of wage setting power and screening. We exploit the fact that benefits from wage setting power are shared by all licensed and unionized workers. However,

[1] For the US, figures range from 6% (Kleiner and Krueger 2013) to 8% (Gittleman et al. 2018). However, definitions differ significantly across studies. The former study only focuses on government certification and the latter only on private certification, while estimates for the EU include both government and private certification (Koumenta and Pagliero 2019).

[2] In this paper, we focus on screening based on characteristics such as education, work experience, and ability. This is different from the entry restrictions that may be associated with the union shop (also known as closed-shop).

TABLE 1
Labor market institutions

	No Screening of members	Screening of members
No wage setting power	Unregulated market	Certification
Wage setting power	Unionization	Licensing

Notes: The table compares labor market institutions according to the presence of screening mechanisms and wage setting power.

the benefits from screening are enjoyed only by workers who meet the standards for obtaining a license or certification. Overall, our results provide evidence of a dual role of institutions, which screen workers according to unobservable characteristics and provide them with wage setting power. We show that both mechanisms are important in explaining the labor market outcomes of migrants. To our knowledge, this is the first paper that decomposes the effects of institutions into these two channels. Since the academic and policy debate on occupational regulation has mainly focused on the wage setting power of institutions, this paper contributes by highlighting the role of screening, which has not received much attention in the literature.[3]

We use data from the European Union Survey of Occupational Regulation (EU-SOR), which is a representative sample of the labor force within the EU-28 member states providing detailed information on occupational regulation and migration. The survey was carried out by a market research company in 2015 by means of telephone interviews (about 26,000 individuals were interviewed). The data discern, in a way comparable across all EU states, whether an individual holds a license to legally practice an occupation, or a certification—which is not legally required—or union membership. The data further include a rich set of individual characteristics such as age, gender, education, and wage. In the EU, workers with the same individual characteristics, in the same industry and type of occupation face different types of regulations across countries (and sometimes regions). This generates significant variability in regulation that can be used in the empirical analysis.

Using OLS fixed-effects wage regressions, we find that labor market institutions confer significant wage premia to affiliated native workers. After accounting for observable characteristics, the average licensing wage premium is 4 log points, the certification premium 1.6, and the union wage premium 2.7. The first is explained by the screening effect and wage setting power of licensing institutions, the second by the screening effect of certification institutions, and the third by the wage setting power of unions. The difference between the licensing and certification wage premium for natives (2.4 log points or 60% of the licensing

[3]The notion of screening *by* institutions discussed in this paper is different from the notion of self-selection into occupations of the Roy (1951) model, which has been adapted to self-selection into migration in contributions by Borjas (1987). In this type of models migrants self-select based unobservable characteristics. In contrast, in this paper, we are concerned with institutions selecting workers by setting entry standards, which are formal requirements to obtain a license or certification.

wage premium) can be attributed to the legal requirement of holding a license, which is the defining characteristic of licensing.

The licensing and certification wage premia for migrants are much higher, 10.3 and 6.6 log points, respectively. This is because they incorporate a large screening effect (61% and 75% of the two wage premia respectively) that is specific to migrant workers. The union wage premium is not higher for migrants, reflecting the absence of screening into union membership. Migrant wage gaps (i.e. wage differences between natives and migrants) reflect differences in wage premia between natives and migrants. The migrant wage gap for workers with no institutional affiliation is 8.3 log points, and for unionized workers is about the same (8.7 log points). However, the gap is significantly lower for certified (3.3 log points) and licensed (2 log points) workers. This progressive drop in the migrant wage gap can be attributed to the increasing intensity of screening of migrant workers.

We also estimate the difference between natives and migrants in the probability to be licensed, certified, and unionized (the migrant representation gap). This is substantial for licensed workers (3.2 percentage points or 15%), which implies that there is a large difference in screening for natives and migrants. We find no significant representation gap among certified workers, which implies the absence of large differences in screening for natives and migrants in certified markets. We find no significant representation gap for unionization, which is consistent with no screening by unions.

To provide additional evidence on screening by institutions, we compare the labor market outcomes of immigrants from different countries. If migrants from countries that are culturally distant from the host country are worse in terms of unobservable variables, then the migrant wage gap for unregulated and unionized workers is expected to be larger for these workers. In contrast, since licensed and certified migrants are subject to the same screening process, independently of the country of origin, the migrant wage gap is expected to be the same for these workers, independently of the country of origin. To test this hypothesis, we measure cultural distance across countries based on language differences and differences in legal origin. Our results on wage and representation gaps support the notion that certification and licensing, but not unionization, screen migrants based on unobservable characteristics that are correlated with cultural differences.

2. Related literature

The impetus for regulating occupations derives from its capacity to address market failures arising from information asymmetries between consumers and practitioners. However, occupational licensing may also result from the efforts of organized interest groups to restrict entry and increase the wages of licensed workers (Stigler 1971; Friedman and Kuznets 1954). Since licensed professions are largely self-regulated, entry standards may be set too high, relative to the social optimum (Akerlof 1970; Shapiro 1986).[4]

In practice, the two motives for regulation are not mutually exclusive and are both consistent with a wage premium for licensed workers, which has been well documented in the literature.[5] There is a small but growing literature on the possible effects of licensing on migrants' wages and representation in regulated occupations. Using Canadian data, Gomez et al. (2015) show that the licensing wage premium is larger for migrants than for natives and that migrants are less represented in licensed professions than natives. Cassidy and Dacass (2021) document similar patterns in the US. Licensing wage premia are larger for migrants, which are underrepresented in licensed professions. Using data from Germany, Rostam-Afschar (2014) finds that delicensing (and reduced migration costs due to the 2004 enlargement to the European Union) raised entry of EU migrants into crafts occupations, and Brücker et al. (2021); Anger et al. (2022) show that recognition of migrant's foreign qualifications increased their employment rates and wages. Tani (2020) studies the skills mismatch of highly educated migrants and finds that licensing raises hourly wages and reduces over-education. The literature on occupational regulation and migration has focused entirely on licensing. Using data from the US, Federman et al. (2006) find that language proficiency requirements for manicurists in the US restrict entry by immigrant workers and affect their dispersion across the country. Johnson and Kleiner (2020), Kleiner et al. (1982), Pashigian (1979), and Holen (1965) show that licensing reduced interstate migration in the US. Absent within these empirical studies is a comparison of the possible effects of licensing and certification, despite the importance of certification as a less restrictive policy alternative to licensing. Moreover, the implications of the differences in screening and wage setting power of licensing, certification, and unionization have not been explored. In this paper, we address these gaps.

Turning to the migration literature, the earnings differentials between migrants and natives have been dominant themes. Within this body of work there is consensus that wage outcomes for migrants relative to observationally equivalent natives are inferior (e.g. Chiswick and Miller 2009; Friedberg 2000; Borjas 1985). However, the literature has not investigated the potential role of licensing regulations in explaining the migrant wage gap. Since licensing requires demonstrating specific skills, the licensing status of workers may proxy for characteristics that are typically not observed by researchers (and are difficult for employers to verify) and may contribute to explaining the migrant wage gap. In fact, our results show that the migrant wage gap is significantly reduced when individual characteristics captured by licensing status are taken into account.

The idea that labor market institutions may screen workers and that occupational regulation may provide a signal of unobservable worker characteristics is related to the literature on screening and signaling

[4]Two surveys of the literature on occupational licensing are Kleiner (2000) and Pagliero (2019). Pagliero (2011) provides an empirical test of the two alternative motives for licensing regulations.

[5]See, for example, Koumenta and Pagliero (2019), Gittleman and Kleiner (2016), Kleiner and Krueger (2013), Pagliero (2010), Kleiner and Kudrle (2000).

in labor markets (Stiglitz 1975; Spence 1973). The starting point is that—in the absence of perfect information about worker productivity—characteristics such as formal education and work experience are used as signals. However, to the extent that the signaling power of qualifications is labor market specific, when such qualifications have been obtained abroad by migrants, their ability to address information asymmetries might be compromised, thus impacting their wages (Sanromá et al. 2015; Borjas 2014; Chiswick and Miller 2009). Since occupational licensing and certification involve the formal recognition of educational and work experience credentials by the state or a professional body in the host country, it may act as a better signal or screening mechanism of migrants' human capital in the local labor market. The literature on statistical discrimination offers a complementary explanation why occupational regulation might affect the wages of migrants, whereby ethnicity and migrant status are used as proxies for productivity relevant characteristics that are hard to observe (Blair and Chung 2018; Arrow 1973; Phelps 1972).

Finally, labor mobility and the integration of migrants into the labor market have been important policy concerns for many decades. More recently, the role that occupational regulation plays in facilitating or hindering these processes has received attention by policy-makers across the globe. In the EU for example, where labor mobility is one of the key pillars of the Single Market, policy has focused on harmonising entry requirements into regulated occupations across Member states. The labor shortages in health occupations associated with the Covid-19 pandemic forced many US states to establish reciprocity agreements in order to facilitate interstate migration of licensed professionals (Bayne et al. 2020). Australian and Canadian governments have been working on establishing formal channels for recognition of foreign qualifications as a means to deal with chronic labor shortages in licensed occupations (Hawthorne and Wong 2011). Our paper contributes in building the evidence base related to these important policy initiatives (von Rueden and Bambalaite 2020; Hermansen 2019).

3. Theoretical framework and identification

The objective of this section is to illustrate the different empirical implications of licensing, certification, and unionization for the migrant wage gap and the migrant representation gap among licensed, certified, and unionized workers. The model captures the main trade-offs implied by occupational regulation and focuses on the different labor supply effects of the three labor market institutions. The key point is that, unlike unions, certification and licensing institutions screen workers based on unobservable characteristics.

There is a unit mass of native workers. Workers are heterogeneous in their observable characteristics x and their productivity. The productivity of worker i is $q_i = Q(x_i) + \tilde{q}_i$, where $\tilde{q}_i$ is a continuous random variable with zero mean, distribution F_q and support $[q_{min}, q_{max}]$. This random idiosyncratic component of quality is observable to the worker but not to employers and consumers (asymmetric information). Differences in productivity can be interpreted as differences across workers in output per unit of labor or differences in efficiency units supplied. Workers are paid in proportion to their expected productivity. Hence, the wage of a worker with characteristics x is $w(x) = \omega Q(x)$, where ω is the unit wage. The unit wage is determined in a competitive market in which aggregate labor supply and demand are equated. $w(x)$ is the competitive benchmark wage of workers with no institutional affiliation and is assumed to be independent of any labor market institution.

Markets exogenously vary in type of regulation. Hence, workers with the same characteristics may be subject to different types of regulation. This captures the notion that labor market institutions vary across countries and regions even within narrowly defined groups of workers defined, for example, by occupation and education.[6] A certification or a license is available to the group of workers with characteristics x with probability $p_c(x)$ and $p_l(x)$ respectively. The possibility to join a union is available with probability $p_u(x)$. Probabilities $p_c(x)$, $p_l(x)$, and $p_u(x)$ are mutually exclusive and independent of $\tilde{q}$ and labor demand.

Certification

A certification—when available—certifies that $\tilde{q} \geq \bar{q}_c$, where $\bar{q}_c$ is the minimum quality standards. This captures the idea that certification provides a signal of workers' quality when there is asymmetric information. The probability of obtaining a certification, conditionally on it being available, is then $\pi_c(x)$. The wage of a certified worker is $w_c(x) = \omega E(q|\tilde{q} \geq \bar{q}_c) = w(x) + \omega E(\tilde{q}|\tilde{q} \geq \bar{q}_c) = w(x) + w_c$, where w_c is the wage premium due to the higher expected productivity of certified workers $(\omega E(\tilde{q}|\tilde{q} \geq \bar{q}_c))$.

Unionization

A union—when available—provides the worker with wage setting power, which implies a higher unit wage ($\omega_u \geq \omega$). However, differently from certification, unions do not screen workers. Hence, the wage of a unionized worker is $w_u(x) = \omega_u Q(x) = \omega Q(x) + (\omega_u - \omega)Q(x) = w(x) + w_u$, where w_u is the union wage premium.

Licensing

A license—when available—provides the licensed worker with wage setting power, which implies a higher unit wage ($\omega_l \geq \omega$), and also certifies that $\tilde{q} \geq \bar{q}_l$, where $\bar{q}_l$ is the minimum quality standard. Hence, the wage of a licensed worker is $w_l(x) = \omega_l E(q|\tilde{q} \geq \bar{q}_l) = \omega_l(Q(x) + E(\tilde{q}|\tilde{q} \geq \bar{q}_l)) = w(x) + w_l$. The wage of a licensed worker $w_l(x)$ is higher than the benchmark wage $w(x)$ because the unit wage is higher and also because the expected quality of a licensed worker is higher. Hence, she benefits from the licensing wage premium w_l.

[6] Workers with the same characteristics in two different countries may or may not have the possibility of obtaining a license or a certification, depending on local licensing or certification regulations (see Section 4 for more details). For example, according to the OECD's Occupational Entry Regulations Indicator 2020, aestheticians are licensed in Austria, Belgium, France, Hungary, Italy, Portugal, Slovenia, certified in Poland, but neither licensed nor certified in Finland, Germany, Spain, Sweden, or the UK. Similarly, the unionization rate may be different across countries, implying differences across workers in the potential to join a union.

3.1 Migrant workers

There is also a unit mass of migrant workers. Migrant workers are heterogeneous in terms of x and $\tilde{q}$, as natives, but also in terms of other variables $\tilde{z}$, such as knowledge of local culture and professional standards, quality of foreign credentials, language proficiency, and integration into the host country. These variables negatively affect migrants productivity—relative to natives—and are unobservable, or costly for employers and consumers to verify. This adds a second source of asymmetric information, which is relevant only for migrants.[7]

The productivity of migrant worker i is then $q_i = Q(x_i) + \tilde{q}_i + \tilde{z}_i$, where $\tilde{z}$ is a continuous random variable with $E(\tilde{z}) < 0$ and distribution F_z (independent of x and $\tilde{q}$) with support $[z_{min}, 0]$. The negative support captures the fact that unobservable variables $\tilde{z}$ tend to be worse for migrants than natives. Hence, the expected wage of a migrant worker with characteristics x is $w_m(x) = \omega Q(x) + \omega E(\tilde{z}) = w(x) - m$, where m is the migrant wage gap.

Certification

A certification certifies that a migrant worker meets the standards in terms of $\tilde{q}$ and $\tilde{z}$, that is $\tilde{q}_i \geq \bar{q}_c$ and $\tilde{z}_i \geq \bar{z}_c$. Hence, the expected wage of a certified migrant worker is $w_{mc}(x) = \omega E(q|\tilde{q} \geq \bar{q}_c \textit{ and } \tilde{z} \geq \bar{z}_c)) = \omega Q(x) + \omega E(\tilde{q}|\tilde{q} \geq \bar{q}_c) + \omega E(\tilde{z}|\tilde{z} \geq \bar{z}_c) = w(x) + w_c - m_c$.

Unionization

Migrants benefit from the wage setting power of unions. Hence, $w_{mu}(x) = \omega_u E(q) = \omega_u Q(X) + \omega_u E(\tilde{z}) = w(x) + w_u - m - (\omega_u - \omega)E(\tilde{z}) = w(x) + w_u - m_u$, where $m_u \geq m$ and $m_u \geq m_c$.[8]

Licensing

A license provides the migrant licensed worker with wage setting power, which implies a higher unit wage ($\omega_l \geq \omega$), and also certifies that $\tilde{q} \geq \bar{q}_l$ and $\tilde{z}_i \geq \bar{z}_l$, where $\bar{z}_l$ is the minimum quality standard in terms of $\tilde{z}$. Hence, the expected wage of a migrant licensed worker is $w_{ml}(x) = \omega_l E(q|\tilde{q} \geq \bar{q}_l \textit{ and } \tilde{z} \geq \bar{z}) = w(x) + w_l + \omega_l E(\tilde{z}|\tilde{z} \geq \bar{z}) = w(x) + w_l - m_l$.

The first row of Table 2 reports the expected wage of unregulated, unionized, certified, and licensed workers (conditional on observable characteristics). The difference between the average wage of native licensed workers and workers with no institutional affiliation identifies the licensing wage premium w_l. The

[7]Also natives may be heterogeneous in terms of these characteristics. However, if natives are sufficiently better than migrants in terms of these variables, then the minimum quality standards set by institutions are not binding for natives, and introducing additional heterogeneity does not change the main results of the model.

[8]The migrant wage gap for unionized workers m_u is larger than m, since the productivity difference between migrants and natives is valued with a higher unit wage. Similarly, m_u is larger than m_c, since the productivity difference between migrants and natives is larger for unionized than certified workers, and this difference is valued with a higher unit wage ($m_u = -\omega_u E(\tilde{z}) > -\omega E(\tilde{z}|\tilde{z} \geq \bar{z}_c) = m_c$).

TABLE 2
The migrant wage gap

	No certification, license, or union		Unionized		Certified		Licensed
Natives	w	$\leq$	$w+w_u$		$w+w_c$	$\leq$	$w+w_l$
Migrants	$w-m$	$\leq$	$w+w_u-m_u$		$w+w_c-m_c$	$\leq$	$w+w_l-m_l$
Migrant wage gap	m	$\leq$	m_u	$\geq$	m_c	$\geq$	m_l

Notes: The table reports the expected log wage for native and migrant workers conditional on observable characteristics. The migrant wage gap is higher for certified than licensed workers $(m_c \geq m_l)$ if $\bar{z}_l$ is sufficiently high relative to $\bar{z}_c$.

corresponding differences for certified and unionized workers identify w_c and w_u. The difference $w_l - w_c$ for natives can be interpreted as the wage effect of the legal requirement to hold a license.

The second row in Table 2 reports the average wage for migrant workers, conditional on characteristics x. The third row reports the average wage differences between natives and migrants. The migrant wage gap for workers without a license, certification, or union membership identifies m. The migrant wage gap for unionized, certified, and licensed workers identify m_u, m_c, and m_l.

Since licensed workers do not face competition from unlicensed workers, licensed occupations have an incentive to restrict entry beyond the efficient level and to set too high standards (Leland 1979, Shapiro 1986).[9] This is relevant for the comparison of columns 3 and 4 in Table 2. In our setting, if entry standards are higher in licensed markets—for whatever reason—then $\bar{q}_c \leq \bar{q}_l$ and $\bar{z}_c \leq \bar{z}_l$. This implies that the licensing wage premium is higher than the certification wage premium for both natives $(w_c \leq w_l)$ and migrants $(w_c - m_c \leq w_l - m_l)$. Moreover, if $\bar{z}_l$ is sufficiently high relative to $\bar{z}_c$, then the migrant wage gap is higher for certified than licensed workers $(m_c \geq m_l)$.[10] This implies that the migrant wage gaps in Table 2 decrease from left to right $(m_u \geq m_c \geq m_l)$, reflecting the increasing intensity of screening of the three labor market institutions.

3.2 Representation of migrants among unionized, certified and licensed workers

When a certification or licensing institution is available, native workers who meet the standards $\tilde{q} \geq \bar{q}_c$ or $\tilde{q} \geq \bar{q}_l$ obtain the certification or the license. Hence, the probabilities of obtaining a certification or a license for workers with characteristics x, conditionally on it being available, are $\pi_c(x)$ and $\pi_l(x)$. A certification or license—when available—certifies that a migrant worker meets the standards in terms of both $\tilde{q}$ and $\tilde{z}$,

[9]However, certification markets do not necessarily lead to efficient outcomes either (Shapiro 1986), making the comparison of standards in certified and licensed markets theoretically ambiguous.

[10]If $\bar{z}_l$ is sufficiently high, then the difference in expected productivity between licensed natives and migrants becomes small relative to the corresponding difference between certified natives and migrants, hence $m_c = -\omega E(\tilde{z}|\tilde{z} \geq \bar{z}_c) \geq -\omega_l E(\tilde{z}|\tilde{z} \geq \bar{z}_l) = m_l$.

that is $\tilde{q} \geq \bar{q}_c$ and $\tilde{z} \geq \bar{z}_c$ for certification, and $\tilde{q} \geq \bar{q}_l$ and $\tilde{z} \geq \bar{z}_l$ for licensing. Since migrants face one more constraint than natives, the probability of obtaining a certification or license is lower for migrants than for natives with the same observable characteristics, $\pi_c(x)\mu_c$ and $\pi_l(x)\mu_l$, where $\mu_c \leq 1$ and $\mu_l \leq 1$ measure the lower certification and licensing probabilities of migrants relative to natives.[11]

Table 3 reports the migrant representation gaps. A native worker obtains a certification if she is of high quality and a certification is available, that is with probability $\pi_c(x)p_c(x)$. For a migrant, the probability of obtaining a certification is $p_c(x)\pi_c(x)\mu_c$. A native obtains a license with probability $\pi_l(x)p_l(x)$ and a migrant with probability $\pi_l(x)p_l(x)\mu_l$. Hence, the migrant representation gap among certified workers in relative terms—that is as a ratio—identifies μ_c. The migrant representation gap among licensed workers—again as a ratio—identifies μ_l. Since unions do not select members based on their characteristics, we expect equal representation of migrants and natives.

If licensed occupations have an incentive to apply higher standards than certification, then $\mu_l(x) \leq \mu_c(x)$. Hence, we expect increasing ratios from left to right in Table 3. The difference $\mu_c(x) - \mu_l(x)$ identifies the effect of the legal requirement to hold a license on the representation of migrants. If positive, the difference $\mu_c(x) - \mu_l(x)$ measures the additional difficulty for migrants to enter a licensed profession, relative to a certified profession. Clearly, as argued above, a positive difference $\mu_c(x) - \mu_l(x)$ does not imply that licensing is more efficient than certification, as licensing may well set standards that are too high from a social point of view.

TABLE 3
The migrant representation gap

	Licensed		Certified		Unionized
Natives	$\pi_l p_l$		$\pi_c p_c$		$\pi_u p_u$
Migrants	$\pi_l p_l \mu_l$		$\pi_c p_c \mu_c$		$\pi_u p_u$
Migrant representation gap (ratio)	μ_l	$\leq$	μ_c	$\leq$	1

Notes: The table reports the expected probability of being licensed, certified, or union member conditional on observable characteristics.

3.3 Efficiency and screening

The empirical literature on licensing provides examples in which licensing boards set entry requirements that seem too high from a social point of view or impose unnecessary costs to potential entrants by screening workers on variables that are weakly correlated with productivity or quality of the service provided (Han and Kleiner 2021; Basso et al. 2021; Koumenta et al. 2019; Thornton and Timmons 2013; Pagliero 2011; Federman et al. 2006). However, there is also evidence to the contrary (Anderson et al. 2020; Larsen et al.

[11] $\mu_c \equiv P(q_i \geq \bar{q}_c, z_i \geq \bar{z}_c)/\pi_c(x)$ and $\mu_l \equiv P(q_i \geq \bar{q}_l, z_i \geq \bar{z}_l)/\pi_l(x)$.

2020). Our theoretical framework can allow for screening based on variables $\tilde{q}$ that are weakly correlated, or even completely uncorrelated, to workers' productivity. In this case, $\tilde{q}$ cannot be interpreted as heterogeneity in productivity. This implies that licensing is inefficient, since it restricts entry without providing a valuable signal to employers. Although the interpretation of the model is different, the comparison of natives and migrants across labor market institutions, which is the focus of this paper, is largely unaffected and the results on the migrant wage and representation gaps are unchanged. Appendix A provides more details on wage gaps in this case.

4. Institutional setting, data and summary statistics

Occupational regulations vary widely across countries, even for the same profession. In the European Union, occupations are generally regulated at the country level, but sometimes at the regional or city level. These significant differences derive from differences in legal traditions (e.g. crafts persons in Germany), differences in the organisation of labor markets (e.g. more self-regulation of professional associations versus more direct government intervention), and type of regulation.

In the case of licensed occupations, migrants generally need to obtain a license in the destination country. Depending on the specific occupation, country of origin and destination, there may be several ways of doing so. Migrant workers need to satisfy the requirements in the destination country, usually a long and costly endeavour, that involves country-specific professional exams and educational requirements.[12] If specific professional qualifications have already been obtained in the country of origin, a less costly procedure may be available, but it is usually not automatic.[13]

The European Union Survey of Occupational Regulation (EU-SOR) is specifically designed to capture occupational regulation. It covers the individuals residing in the 28 EU member states, aged 15 and above. The survey was carried out by TNS (a market research company) in March and April 2015 by means of telephone interviews (Computer Assisted Telephone Interviews). A total of 26,640 individuals, about 1,000 for each country and 500 for Cyprus, Malta, and Luxembourg, were interviewed providing data on their licensing, certification and trade union membership status. A worker is defined as licensed if she obtained a license or passed an exam that is required, in addition to education, to *legally* practice a profession. A

[12]For example, hairdressers without a secondary vocational degree, perhaps because it is not required in the country of origin, as in Denmark, cannot hope for recognition in a country that requires a secondary degree for obtaining a license, like in Germany. Therefore, they would need to obtain one (involving training of more than 400 hours and fees of around 4,000 Euro in Germany) or apply for an exemption to operate a barber shop.

[13]Automatic recognition of professional qualifications is limited to a few professions based on EU law (Directive 2005/36/EC). It involves doctors, nurses, dental practitioners, veterinary surgeons, midwives, pharmacists, and architects. Given the limited scope of the automatic recognition, a European Professional Card was introduced in 2013 with the aim of facilitating the recognition for nurses, pharmacists, physiotherapists, mountain guides, and real estate agents.

TABLE 4
Summary statistics

	I Hourly wage (Euro)	II Unionized	III Certified	IV Licensed	Observations
Natives	9.267	0.324	0.187	0.214	13,792
	(0.069)	(0.004)	(0.003)	(0.003)	
Migrants	11.072	0.300	0.188	0.169	1,222
	(0.229)	(0.013)	(0.011)	(0.012)	
Migrant gap	-1.805^{***}	0.024^{*}	-0.001	0.046^{***}	
	(0.239)	(0.014)	(0.012)	(0.012)	

Notes: Definitions of licensed, certified, and unionized are described in Table B.1. Figures are weighted by survey weights provided by the EU-SOR. Standard errors are in parentheses. Significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations based on the EU-SOR 2015.

worker is defined as certified if she obtained a license or passed an exam, in addition to education, which is not required to legally practice a profession. A worker is unionized if she is a member of a trade union.[14]

Table B.1 and Appendix B define the main variables used in the paper and describe some key questions used in the survey. This approach to measure occupational licensing was pioneered by Kleiner and Krueger (2013) and it is currently used, for example, in the Survey of Income and Program Participation and the Current Population Survey (Gittleman et al. 2018; Cassidy and Dacass 2021).[15] Detailed information on a variety of individual characteristics, similar to those commonly included in labor force surveys, was also collected.[16] These include net wages, hours worked, age, educational attainment, occupation, country of residence, industry in which the firm or organization operates, and its size. We focus on workers between 25 and 65, with non-missing information on wages, and exclude those in military occupations.

Table 4 provides descriptive statistics of the differences between natives and migrants across the 28 European countries in our sample. Migrant hourly wages are on average slightly higher than those of their native counterparts. This difference is entirely due to the large difference in wages between receiving and sending countries. Unionization is 2.4% higher among natives. There are no significant differences in the probability to be certified. Licensing is more prevalent among natives. The 4.6% migrant gap in licensing is highly significant.

[14] We do not address here the many issues related to differences in union coverage across occupations and countries, discussed in the literature on unionization.

[15] The survey approach provides an individual measure of licensing attainment. The alternative is to measure licensing coverage, obtained by matching labor force survey data with information on which professions are licensed in each country. The advantages of the direct measurement of licensing attainment, relative to coverage, are discussed in Koumenta and Pagliero (2019).

[16] More details on the survey and the data are described in Koumenta and Pagliero (2019).

5. The migrant wage and representation gaps

In order to measure the migrant wage gap across labor market institutions (licensing, certification, and unionization), we estimate a classic wage regression model,

$$\begin{aligned}\log(w_{ionc}) &= \beta_0+\beta_1 X_{ionc}+\beta_2 \text{Migrant}_{ionc} \\ &+ \sum_{j=1}^{3}\gamma_j \text{Institution(j)}_{ionc}+\sum_{j=1}^{3}\delta_j \text{Migrant}_{ionc}\times \text{Institution(j)}_{ionc} \\ &+ \theta_o+\theta_n+\theta_c+\varepsilon_{ionc},\end{aligned} \tag{1}$$

where the dependent variable $\log(w_{ionc})$ denotes net hourly log-wage of individual i, in occupational group o, industry n, and country c.[17] The matrix X_{ionc} includes individual characteristics (age, age^2, indicators for public sector employment, 5 levels of education achieved, and 4 size classes of the firm or organization in which the individual is working).

The indicator variable $Migrant_{ionc}$ is equal to one if the respondent is a migrant. Three indicator variables, $Institution(j)_{ionc}$, $j=1,2,3$, describe whether the worker is licensed, certified, or unionized. The model includes direct effects and interactions between $Migrant_{ionc}$ and $Institution(j)_{ionc}$.[18] Finally, θ_o, θ_n, and θ_c are occupational group-, industry-, and country-specific fixed effects, and ε_{ionc} captures unobserved determinants of wages. Together with individual characteristics, fixed effects contribute to making individuals more comparable in terms of observables. The coefficients β_2 and δ_j capture the average migrant wage gap across labor market institutions (conditional on observed individual characteristics). Even accounting for these fixed effects, there is still significant variability in labor market regulation across specific occupations (within an occupational group and country) and also across countries for a specific occupation.[19]

[17] We consider broad occupational groups defined by one-digit ISCO codes. Each group includes a large number of specific occupations. For example, the occupational group "professionals" includes 94 occupations (four-digit level), such as secondary education teachers, nursing professionals, accountants, early childhood educators, social work and counselling professionals, lawyers, economists, and pharmacists.

[18] Licensed and certified status are mutually exclusive (see Table B.1). However, it is possible that some licensed or certified workers are also unionized. In these cases, the empirical model (1) assumes that workers benefit from both institutions in an additive manner. The results are not affected if we drop these workers from the sample.

[19] The variation in regulation across countries for specific occupations is substantial. For example, accountants are unregulated in Finland, Poland, Slovenia, Spain, and Sweden, but regulated elsewhere. Architects are regulated in Belgium but civil engineers are not, neither is regulated in Finland or Sweden, while both are regulated in most other EU countries. Similarly, hairdressers are regulated in Germany but cosmetologists are not, and neither is regulated in Spain, Sweden, or the UK, whereas both are regulated in Belgium and Italy. We can systematically assess this variability by comparing Root Mean Squared Error (RMSE) in regressions with institution indicators as dependent variables and fixed effects θ_o as independent variables. A RMSE close to zero would indicate that the fixed effects absorbed all variation. When including a constant only, the RMSE is 0.408, 0.390, 0.467 for

Table 5 reports the estimated coefficients. The negative migrant gap (higher wages for migrant workers) observed in Table 4 and in Table 5, column I disappears as soon as we control for country fixed effects. In column II, the gap is 10.7 log points. Individual controls in column III explain about 1.7 log points of the migrant gap estimated in column II. Occupational group and industry fixed effects explain additional 2.6 log points of the gap, leaving an unexplained gap of about 6.4 log points (column VI).

TABLE 5
Wage regression results

	I	II	III	IV	V	VI	VII
Dependent variable	Log wage	Log wage	Log wage	Log wage	Log wage	Log wage	Log wage
Migrant	0.235	-0.107***	-0.090***	-0.069***	-0.065***	-0.064***	-0.083***
	(0.146)	(0.022)	(0.019)	(0.019)	(0.020)	(0.019)	(0.023)
Licensed						0.045***	0.040***
						(0.013)	(0.013)
Certified						0.020	0.016
						(0.013)	(0.014)
Unionised						0.026**	0.027**
						(0.012)	(0.011)
Migrant × Licensed							0.062*
							(0.035)
Migrant × Certified							0.050*
							(0.026)
Migrant × Unionised							-0.004
							(0.029)
Country FE		✓	✓	✓	✓	✓	✓
Individual controls			✓	✓	✓	✓	✓
Occupation FE				✓	✓	✓	✓
Industry FE					✓	✓	✓
Observations	15,014	15,014	15,014	15,014	15,014	15,014	15,014
Adj. R-squared	0.006	0.704	0.758	0.772	0.775	0.776	0.776

Notes: OLS regressions using the full sample (weighted using sample weights provided by EU-SOR 2015). The dependent variable is log hourly wage. Individual controls include age, age^2, indicators for lower secondary, upper secondary, post-secondary, university, and PhD education, gender, firm size dummies, public sector dummy. Indicators for occupations are defined for 1-digit ISCO codes. Indicators for industry are defined for 1-digit NACE codes. Standard errors clustered by country are reported in parentheses, significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations based on the EU-SOR 2015.

In column VII, we interact the migrant and institutions indicator variables. The estimated conditional expectations of wages for the different groups of workers can then be compared with their theoretical counterparts in Table 2. The coefficient β_2, which corresponds to $-m$ in Table 2, is -0.083. This implies that the migrant wage gap for workers without a license, certification or union membership (m) is 8.3 log points. For natives, the licensing wage premium (w_l) is 4 log points, the certification premium (w_c) 1.6, and the union wage premium (w_u) 2.7. The coefficients of the interactions of the licensed and certified indicators

licensing, certification, and unionization, respectively. Including the fixed effects, the RMSE decreases to 0.389, 0.385, 0.390, but remains far from zero.

with the migrant indicator are large, 6.2 and 5 log points, respectively. Hence, the wage increase associated with licensing and certification is substantially larger for migrants than natives.[20] [21]

Table 6 reports the estimated moments corresponding to the model predictions in Table 2. To ease the interpretation, the estimated mean salaries are reported as differences from the mean salary of unregulated natives (w). Hence, the results in the first row correspond to the union, certification, and licensing wage premia w_u, w_c, w_l. The results in the third row, which are obtained as linear combinations of the coefficients in Table 5, correspond to the migrant wage gaps (m, m_u, m_c, m_l).

The estimates for the wage premia w_u, w_c, w_l are in line with the hypothesis that $w_u \geq 0$ and $w_l \geq w_c \geq 0$. The p-values of the tests $w_u = 0$ and $w_l \geq w_c$ are equal to 0.017 and 0.009. The union wage premium w_u results from the wage setting power of the institution. The certification wage premium w_c results from the screening of workers operated by certification institutions based on $\tilde{q}$. The licensing wage premium w_l results from the combined effect of screening and the wage setting power of licensing institutions.[22] Since the defining difference between licensing and certification is the legal requirement to hold a license, the results imply that $4 - 1.6 = 2.4$ log points (or 60%) of the licensing wage premium can be attributed to the legal requirement to hold a license.

In the second row of Table 6, the average wage of migrants grows from left to right, going from -0.083 for migrant workers with no institutional affiliation to 0.020 for licensed migrants (an increase of 10.3 log points). Although the differences between contiguous cells in the table are not statistically significant, the difference between columns I and IV is highly significant (p-value 0.005). The difference between column I and III is also highly significant (p-value 0.005).

Using the same notation as Table 2, the second row of Table 6 implies that the 10.3 log points licensing wage premium observed for migrants has two components. The first ($m - m_l$) is screening based on unobservables $\tilde{z}$, and is specific to migrants. The second is the licensing wage premium (w_l), which is common to licensed migrants and natives. Using the estimated parameters, we find that the first component contributes 6.3 log points to the licensing wage premium for migrants and the second 4 log points. Hence, the specific screening of migrants explains 61% of the large wage premium for licensed migrants, the rest being explained by the common licensing wage premium. A similar decomposition can be performed for the 6.6

[20] We also estimated column VII of Table 5 without occupation and/or industry fixed effects. The results are not significantly affected.

[21] We also estimated the main specification including country-occupation interactions on top of country and occupation fixed effects. The results remain very similar. The licensing wage premium changes from 4.0% to 4.2%, the certification premium from 1.6% to 1.7%, the union wage premium from 2.7% to 2.8%. For migrants, the licensing wage premium changes from 6.2% to 5.2%, the certification wage premium from 5.0% to 6.1%, the union wage premium remains virtually unchanged.

[22] These two cannot be disentangled because certification and licensing institutions may apply different entry standards $\bar{q}_c$ and $\bar{q}_l$, which are not identified from the data.

TABLE 6
The migrant wage gap

	I No certification, license, or union	II Unionized	III Certified	IV Licensed
Natives	0	0.027	0.016	0.040
		(0.011)	(0.014)	(0.013)
Migrants	−0.083	−0.060	−0.017	0.020
	(0.023)	(0.036)	(0.033)	(0.035)
Migrant wage gap	0.083	0.087	0.033	0.020
	(0.023)	(0.033)	(0.034)	(0.033)

Notes: Panel A reports estimated average wages for different groups of workers, corresponding to those described in Table 2. The results are computed using the estimated coefficients of equation (1), reported in Table 5. All the values are expressed as differences from the average wage of natives with no institutional affiliation (w), in the top-left corner. Panel B reports the estimated values of the parameters used in Table 2 that are not reported in Panel A. Standard errors (in parentheses) are obtained with the Delta-method.

log points certification wage premium for migrants ($-0.017+0.083=0.066$), where the two components $m-m_c$ and w_c contribute 5.0 and 1.6 log points, respectively. Hence, screening explains 75% of the wage premium, the rest being explained by the certification wage premium.

The third row of Table 6 reports the estimated migrant wage gaps, corresponding to m, m_u, m_c, and m_l in Table 2.[23] The migrant wage gap is about the same for workers with no institutional affiliation (0.083) and unionized workers (0.087). The migrant wage gap then progressively decreases for certified (3.3) and licensed workers (2.0). This drop is very large, as the migrant wage gap for licensed workers is less than 1/4 of that for workers with no institutional affiliation. The difference between licensed workers and workers with no institutional affiliation is statistically significant (p-value 0.076), and so is the difference between certified workers and workers with no institutional affiliation (p-value 0.052).[24] Using the notation from Table 2 once again, the progressive drop in the migrant wage gap reflects the increasing screening of migrants in terms of unobservables ($m_u \geq m_c \geq m_l \geq 0$). The difference $m_c - m_l$ measures the wage effect of the legal requirement to hold a license on migrants' screening based on $\tilde{z}$. The size of this effect is about 2/3 of the migrant wage gap for licensed workers ($m_c - m_l/m_l$).

Although this is the first paper focusing on screening and wage setting power across institutions, some of our results can be compared with previous estimates. Our results on the licensing wage premium in the EU are broadly consistent with the literature on the US (Kleiner 2000; Kleiner and Krueger 2013;

[23]Note that the theoretical model implies that the migrant wage gap is higher for certified than licensed workers ($m_c \geq m_l$) if $\bar{z}_l$ is sufficiently high relative to $\bar{z}_c$.

[24]However, the differences in migrant wage gap between contiguous cells are not statistically significant (p-values 0.89, 0.20, and 0.78 respectively).

Gittleman and Kleiner 2016), which also finds a positive and significant premium. Our estimates of the licensing wage premium for migrants in the EU are in line with those obtained in the literature for Canada and the US (Gomez et al. 2015; Cassidy and Dacass 2021). Our results on the importance of screening on unobservables are also consistent with the smaller licensing wage premia obtained by Cassidy and Dacass (2021) when including language proficiency among the independent variables in wage regressions. Using the notation of this paper, language proficiency is one of the many variables correlated with unobservable cultural differences $\tilde{z}$ between migrants and natives. Finally, the union wage premium is consistent with the literature on unionization (Blanchflower and Bryson 2004).

5.1 The migrant representation gap

In order to measure the representation of migrant workers in licensed occupations, we estimate the linear probability model

$$\text{Licensed}_{ionc} \quad = \quad \beta_0 + \beta_1 X_{ionc} + \beta_2 \text{Migrant}_{ionc} + \theta_o + \theta_n + \theta_c + \varepsilon_{ionc}. \tag{2}$$

We also estimate the corresponding models in which the dependent variable is an indicator for certified and unionized workers. Table 7 reports the estimated coefficients.[25] Table 8, Panel A summarizes the results by reporting the predicted values for the probabilities to be licensed, certified, and unionized (for mean values of the covariates) corresponding to the model predictions in Table 3.

Migrants are about 3.2 percentage points less likely to be licensed than natives, after controlling for differences in individual characteristics, country, occupational group, and industry. This corresponds to a 15% difference. Migrants are 0.9 percentage points more likely to be certified than natives, but this difference is not significantly different from zero. Finally, migrants are 1.4 percentage points less likely to be unionized, but again this difference is not significantly different from zero.

Using the same notation as Table 3, our results imply that $\mu_l = 0.85$ and $\mu_c = 1.05$. Hence, $\mu_l - \mu_c = -0.2$, with a standard error of 0.107 (p-value 0.051), which is consistent with our hypothesis that licensing screens migrants more intensely than certification (Table 2). This implies that licensing poses a significantly higher barrier to entry for migrants than natives (about 20%), while obtaining a certification or joining a union are not more difficult for migrants than natives.

The representation of migrants among unionized workers is only slightly smaller than that of natives, implying a ratio 0.957, which is not significantly different from 1. The representation of migrants among certified workers is not significantly different for migrants and natives. This implies that μ_c is not significantly different from 1.

[25] Results are robust using a probit model instead of a linear probability model.

TABLE 7
Probability to be licensed, certified, or unionized

Dependent variable	I Licensed	II Licensed	III Licensed	IV Licensed	V Licensed	VI Certified	VII Unionized
Migrant	-0.046***	-0.047**	-0.034**	-0.036**	-0.032**	0.009	-0.014
	(0.015)	(0.017)	(0.015)	(0.015)	(0.015)	(0.012)	(0.018)
Country FE		✓	✓	✓	✓	✓	✓
Individual controls			✓	✓	✓	✓	✓
Occupation FE				✓	✓	✓	✓
Industry FE					✓	✓	✓
Observations	15,014	15,014	15,014	15,014	15,014	15,014	15,014
Adj. R-squared	0.001	0.014	0.042	0.069	0.091	0.026	0.303

Notes: OLS estimates of the linear probability model (2) using the full sample (weighted using sample weights provided by EU-SOR 2015). The dependent variables are binary indicators for being licensed, certified, and unionized. Individual controls include age, age^2, indicators for lower secondary, upper secondary, post-secondary, university, and PhD education, gender, firm size dummies, public sector dummy. Indicators for occupations are defined for 1-digit ISCO codes. Indicators for industry are defined for 1-digit NACE codes. Standard errors clustered by country are reported in parentheses, significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations based on the EU-SOR 2015.

TABLE 8
The migrant representation gap

	I Licensed	II Certified	III Unionized
Natives	0.213	0.186	0.323
	(0.002)	(0.002)	(0.002)
Migrants	0.181	0.195	0.309
	(0.013)	(0.010)	(0.014)
Migrant representation gap (ratio)	0.849	1.048	0.957
	(0.065)	(0.061)	(0.049)

Notes: Panel A reports the expected probabilities to be licensed, certified, and unionized, corresponding to those described in Table 3. The results are computed using the estimated parameters of equation (2) reported in Table 7. Panel B reports the estimates of the parameters used in Table 3. Standard errors (in parentheses) are obtained with the Delta-method.

Given the existence of a certification wage premium for migrants, we expected a lower proportion of migrants among certified workers. This result could be driven by a combination of different factors. First, the precision of our estimates is limited. The 95% confidence interval is fairly large [0.927,1.263], hence we cannot exclude values slightly below 1, which would be consistent with more intense screening of migrants than natives. Second, our simple theoretical framework may not capture some other mechanisms that affect the representation gaps. Third, control variables and fixed effects may not fully capture the heterogeneity between natives and migrants.

Our results on the representation gaps resonate with previous results in the literature, highlighting the difficulties faced by migrants in meeting the entry standards or having their educational credentials and professional experience recognized in a foreign country (Johnson and Kleiner (2020), Federman et al. (2006)). They are also consistent with Rostam-Afschar (2014) in that the share of immigrants is decreasing with the strictness of licensing regulations.

5.2 The migrant gaps and differences between country of origin and destination

In Section 3, we interpreted $\tilde{z}$ as characteristics of migrants that cannot be observed by the econometrician and are costly for market participants to measure precisely. These include, for example, language proficiency, quality of foreign credentials, knowledge of local professional standards and culture. The model also shows how these variables impact the migrant wage gap and how institutions, by screening migrant workers, influence the migrant wage gap. The results in Section 5 are consistent with the model, but can we provide more direct evidence of these mechanisms? We can make some progress on this question by comparing labor market outcomes of immigrants coming from different countries. If migrants coming from countries that are culturally distant from the host country are worse in terms of unobservable variables $\tilde{z}$, then the wage penalty m is expected to be larger for these workers. Hence, the migrant wage gap for workers with no institutional affiliation and unionized workers is expected to be larger. In contrast, since licensed and certified migrants are subject to the same screening, independently of the country of origin, m_l and m_c are expected to be the same. Hence, also the migrant wage gap is expected to be the same for licensed and certified workers, independently of the country of origin.

To test these hypotheses, we classify migrant workers based on whether their country of origin is outside (external migrants) or inside the EU (internal migrants). For internal migrants, we also have information about the country of origin, hence we can investigate how the similarity of the country of origin and destination affects the migrant gaps.[26] We evaluate the similarity between countries based on two characteristics: type of legal system and language.[27] Each captures some determinants of the cost of integrating into the host country, although they are likely to be far from capturing the full unobserved heterogeneity in $\tilde{z}$.

We classify internal migrants based on whether the country of origin and destination share the same legal origin (English common law, French civil law, German civil code, Socialist law, Scandinavian legal

[26] We do not observe the country of origin for external migrants and therefore cannot use this group in the analysis of differences between origin and destination country. The distinction between internal and external migrants is not a good proxy for cultural similarity in the EU, since external migrants are a very heterogeneous group, which includes migrants from countries that are culturally and linguistically quite similar to the destination country.

[27] This type of data has been used in the literature before, for instance, by Ortega and Peri (2013).

tradition).[28] We further classify internal migrants based on whether the country of origin and destination share the same primary language.[29] We then expand the specification of model (1) by including indicator variables for each group of migrants and interactions with the indicators for unionization, certification, and licensing. The estimation sample remains unchanged.[30]

Table 9, Panel A reports the estimated migrant wage gaps for migrants coming from countries with common and different legal origins. Starting with workers with no institutional affiliation, we find that the migrant wage gaps (corresponding to m) for migrants from countries with different legal origins is large (0.099) and significantly different from zero. However, the gap for migrants from countries with common legal origins is small (0.018) and not statistically significant.

TABLE 9
The migrant wage gap and cultural similarity

	I No certification, license, or union	II Unionized	III Certified	IV Licensed
Panel A. Migrant wage gap and similarity in legal origins				
Migrants from countries with common legal origin	0.018	−0.023	−0.049	0.067
	(0.047)	(0.053)	(0.054)	(0.085)
Migrants from countries with different legal origin	0.099	0.157	0.071	−0.044
	(0.044)	(0.047)	(0.082)	(0.051)
Panel B. Migrant wage gap and similarity in languages				
Migrants from countries with common primary language	0.058	−0.009	0.003	0.059
	(0.048)	(0.074)	(0.072)	(0.099)
Migrants from countries with different primary language	0.063	0.134	0.028	−0.030
	(0.037)	(0.044)	(0.065)	(0.054)

Notes: The table reports estimated migrant wage gaps for internal migrants (relative to natives). In Panel A, migrants are grouped based on the similarity of the legal origins of the country of origin and destination. In Panel B, migrants are grouped based on the primary language spoken in the country of origin and destination. The results are computed using the estimated regression coefficients reported in Table C.1 columns II and III respectively (results in Panel A and B come from two separate regressions). Standard errors (in parentheses) are obtained with the Delta-method.

The migrant wage gaps for unionized workers (corresponding to m_u) is also large and significantly

[28] Data on the legal origin comes from Botero et al. (2004) and captures similarities in institutional configuration and type of regulation.

[29] For example, Austria and Germany, or Ireland and the UK, share the same primary language. German is the official language at the national level in Austria, Belgium, Germany, and Luxembourg; French in Belgium, France, and Luxembourg; English in Ireland, Malta, and the UK; Dutch in Belgium and the Netherlands, Greek in Cyprus and Greece, Swedish in Finland and Sweden. The language classifications are taken from the CEPII gravity database described in Head et al. (2010).

[30] Table C.1 in the appendix reports the regression results, which are rearranged and presented in table C.2 and C.3 using the same format used for our main results in Table 6.

different from zero for the first group (0.157), but not for the second (-0.023). As expected, migrant wage gaps (m_c and m_l) drop for certified and licensed workers (because of screening) and differences across groups become much smaller and not significantly different from zero.

These results provide more direct evidence that migrants from more culturally distant countries are worse in terms of unobservables $\tilde{z}$. They also support the notion that certification and licensing, but not unionization, screen migrants, hence reducing the migrant wage gap. We find similar results by classifying countries based on the primary language spoken. Table 9, Panel B reports the results. Starting with workers with no institutional affiliation or unionized, we find that wage gaps are marginally larger for migrants from countries with different languages, relative to migrants from countries with the same language, but this difference is not statistically significant. For unionized workers the difference is much larger and statistically significant (p-value 0.072). Migrant wage gaps for migrants with different primary language drop for certified and licensed workers from 0.134 to 0.028 in column III and -0.03 in column IV and are not significantly different from zero. The differences between groups also become small and not significantly different from zero.[31] The point estimate of the wage gap for licensed workers with common primary language is large (0.059). Although not statistically significant (s.e. 0.099), this result is somewhat difficult to interpret. In spite of this limitation and the large standard errors, the results in Table 9 seem to be in line the view that cultural similarity is correlated with unobserved heterogeneity.

We also explore the role of differences in legal origin and language on the migrant representation among licensed, certified, and unionized workers. If migrants coming from countries that are culturally distant from the host country are worse in terms of unobservable variables $\tilde{z}$, then their representation among licensed and certified workers is expected to be lower. In contrast, their representation among unionized workers, which are not selected according to their individual characteristics, is expected to be the same.

We include in model (2) indicator variables for each group of migrant.[32] Table 10, Panel A reports the estimated migrant representation gaps (ratios). The representation gap among licensed workers (μ_l) is larger for migrants from countries with different legal origins. In column I, the probability to be licensed for migrants from countries with the same legal origin is 90% of that of natives. This estimate (0.900) is not significantly different from 1 (p-value 0.443). The same probability for migrants from countries with different legal origins is only 74% of that of natives. This value (0.736) is significantly different from 1 (p-value 0.001). The difference between the estimates for the two groups is large (16 percentage points). In

[31]These results are robust using alternative classifications. For example, we also classify countries as similar if they share the same primary language or if the primary language of the country of origin is spoken by at least 9% of the population in the destination country. This is a classification used in the literature by Beine et al. (2013) and Docquier et al. (2012).

[32]Table C.4 in the appendix reports the estimated regression coefficients, which are rearranged and presented in Tables C.5 and C.6 using the same format used for our main results on the representation gap in Table 8.

columns II and III, the estimates for the representation gaps for certified and unionized workers are closer to 1, which indicates that there are no large differences in representation relative to natives.

TABLE 10
The migrant representation gap and cultural similarity

	I Licensed	II Certified	III Unionized
Panel A. The migrant representation gap (ratio) and similarity in legal origins			
Migrants from countries with common legal origin	0.900	0.955	0.930
	(0.130)	(0.124)	(0.075)
Migrants from countries with different legal origin	0.736	1.203	0.873
	(0.068)	(0.112)	(0.098)
Panel B. Migrant representation gap (ratio) and similarity in languages			
Migrants from countries with common primary language	0.927	1.015	0.716
	(0.183)	(0.149)	(0.118)
Migrants from countries with different primary language	0.764	1.122	0.969
	(0.070)	(0.103)	(0.064)

Notes: The table reports estimated migrant representation gaps (ratios) for internal migrants (relative to natives). In Panel A, migrants are grouped based on the similarity of the legal origins of the country of origin and destination. In Panel B, migrants are grouped based on the primary languages spoken in the country of origin and destination. The results are computed using the estimated regression coefficients reported in Table C.4 columns II and III, V and VI, VIII and IX, respectively (results in Panel A and B come from separate regressions). Standard errors (in parentheses) are obtained with the Delta-method.

We find similar results in Table 10, Panel B. The probability of being licensed for migrants from countries with the same primary language is 93% of that of natives (not significantly different from 1). The corresponding probability for migrants from countries with a different primary language is 76% of that of natives. This estimate is again significantly different from 1.[33]

These results are consistent with licensing creating a significant barrier to entry for migrants from more distant cultural backgrounds. For certification, we know from Table 7 that there is no significant difference in the representation between migrants and natives. Hence, when we compare migrants from countries with different legal tradition or language, it is not surprising to find again no significant representation gap. For unionization, our results are consistent with the absence of screening of members.

[33]The estimated value 0.716 for unionized workers suggests a weak representation of migrants from countries with common primary language among unionized workers. However, the corresponding value for migrants from countries with common legal origin does not confirm this results (0.930 not significantly different from 1). This result is largely due to a few countries (Belgium, Luxembourg, Austria and Germany) that have more than one common primary language according to the CEPII definition of common primary language. After dropping these countries, the effect changes from 0.716 to 0.918 and is not statistically different from one, without significant changes in the main results.

6. Conclusion

This paper systematically compares migrant wage and representation gaps for three important labor market institutions: occupational licensing, certification, and unionization. Institutions provide significant wage premia, which can be explained by the wage setting power of licensing and unionization (but not certification), and the screening of workers by licensing and certification (but not by unionization). We also find that licensing (but not certification and unionization) constitute a significant barrier to entry for migrants, who are different from natives in terms of unobservable variables.

The paper focuses on differences across the EU 28 countries and between migrant and native workers in each country. The empirical approach is based on a decomposition of the screening and wage setting power of labor market institutions. The paper contributes to the literature by providing the first evidence of the importance of both mechanisms for migrants' labor market outcomes. In spite of its empirical relevance, the screening mechanism has received less attention in the literature than the wage setting mechanism. Our results on the importance of screening do not necessarily imply that occupational licensing institutions maximize social welfare. It is possible that existing entry standards are set too high (or too low) from a social welfare point of view. Moreover, entry standards may screen workers on variables that are imperfectly correlated with productivity or quality of the service provided.

We contribute to the policy debate by providing new evidence on the importance of occupational regulation for the integration of migrant workers. Our results suggest that policy interventions may try to promote the signaling effect of licensing and certification (for instance by fostering accessibility of information), while limiting the entry restrictions of licensing (for example easing the recognition of foreign credentials). Programs aimed at bridging the gap between natives and migrants in terms of variables such as quality of educational credentials, local knowledge, and language proficiency, which are typically unobservable, have the potential to greatly improve access to licensed occupations and reduce the migrant wage gap. A review of licensing exams may reveal which of these variables are critical for guaranteeing the safety of the public. Reducing unnecessary requirements related to cultural differences may equally benefit migrant workers, with no risk of harming consumers. Our results on certification show that it preserves some of the signaling value of licensing, while being less detrimental to the integration of foreign workers.

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Appendix

A Screening on variables unrelated to productivity

In our model, a higher expected value of $\tilde{q}$ leads to a proportionally higher expected wage, since the productivity of worker i is $q_i = Q(x_i) + \tilde{q}_i$ and workers are paid in proportion to their productivity. Hence, we interpret $\tilde{q}$ as a productivity shock. However, it is possible to allow for a weaker correlation of $\tilde{q}$ with productivity by assuming that $q_i = Q(x_i) + \theta \tilde{q}_i$ where $0 \le \theta \le 1$. If $\theta = 0$ the variable $\tilde{q}$ captures heterogeneity across workers that is not related to productivity. Hence, screening is not providing any signal of workers' productivity and licensing is inefficient.

In this case, the effects of institutions on the representation of migrants (the migrant representation gaps) are clearly unchanged, so Table 3 is unchanged. Consider now the results on expected wages in Table 2. The expected benchmark wage and the expected wage for unionized workers (in columns 1 and 2) are unchanged, since screening does not play any role. However, the expected wage of a native certified worker must now be equal to the generic benchmark wage w. The expected wage of a native licensed worker is $w_l(x) = \omega_l Q(x) = w(x) + w_l'$. Note that there is still a licensing wage premium w_l' because of the wage setting power of licensing institutions ($\omega_l > \omega$).

Let's now focus on migrants. The expected salary of a migrant certified worker is $w_{mc}(x) = \omega Q(x) + \omega E[\tilde{z}|\tilde{z} \ge \bar{z}_c] = w(x) - m_c$ and that of a migrant licensed worker is $w_{ml}(x) = \omega_l Q(x) + \omega_l E[\tilde{z}|\tilde{z} \ge \bar{z}_l] = w(x) + w_l' - m_l$. Migrant wages are still lower than those of natives because of the lower productivity captured by $\tilde{z}$. Table A.1 reports the expected wages and migrant wage gaps. The migrant wage gaps are unchanged. The only new insight is that the wage of certified natives is equal to the benchmark wage, hence there is no certification wage premium for natives.

TABLE A.1
The migrant wage gap under imperfect screening

	No certification, license, or union		Unionized		Certified		Licensed
Natives	w	$\le$	$w + w_u$		w	$\le$	$w + w_l'$
Migrants	$w - m$	$\le$	$w + w_u - m_u$		$w - m_c$	$\le$	$w + w_l' - m_l$
Migrant wage gap	m	$\le$	m_u	$\ge$	m_c	$\ge$	m_l

Notes: The table reports the expected log wage for native and migrant workers conditional on observable characteristics under the assumption that $\theta = 0$.

In Table 6, we find a positive certification wage premium for natives (1.6 log points), which is consistent with other papers that have also documented a positive certification premium. However, the standard error is large, hence we cannot reject the null of zero certification wage premium, nor can we exclude fairly large certification premia. In conclusion, this empirical test does not have the power to provide conclusive evidence on whether variables $\tilde{q}$ are related to productivity or not.

Finally, it is possible to model the migrant wage gaps when also the variable $\tilde{z}$ is unrelated to productivity. If this is the case, then there are no differences in expected productivity between migrants and natives and the model cannot explain the observed differences in wages between migrants and natives.

B Details on Key Variables in the EU-SOR

TABLE B.1
Definition of key variables

Variable	Definition
Migrant	Indicator variable equal to one if the respondent reported being born in a country different from the country of residence in 2015.
Licensed	Indicator variable based on the question (asked after a question on highest educational attainment): ‘In addition to this education, do you have a professional certification, license or did you have to take an exam which is required to practice your occupation?’ and ‘Without this professional certification, license or exam would you be legally allowed to practice your occupation?’. An individual is classified as ‘licensed’ if she answers ‘Yes’ to the first question and ‘No’ to the second. We exclude a small number of licensed workers who are in the process of obtaining their qualification.
Certified	A worker is classified as ‘certified’ if she answers ‘Yes’ to the first question and ‘Yes’ or ‘Don’t know/No answer’ to the second question. We exclude a small number of certified workers who are in the process of obtaining their qualification.
Unionised	Indicator variable equal to one if respondent reports to be member of a trade union.

Notes: A more detailed description of the questionnaire is available in Koumenta and Pagliero (2017). Interviewer instructions for question on legal requirement: “Refer to the respondent’s specific occupation and personal circumstances. Refer to the current laws and regulations affecting the respondent’s occupation (current main paid job)”.

C Additional Results

TABLE C.1
The migrant wage gap and the similarity between country of origin and destination

	I	II	III	IV
Sample	Full	Full	Full	Full
Dependent variable	Log wage	Log wage	Log wage	Log wage
Subgroup	None	Legal origin	Primary language	Primary language or language spoken by $\geq$ 9%
External migrant	-0.103***	-0.104***	-0.103***	-0.103***
	(0.027)	(0.028)	(0.027)	(0.027)
Internal migrant	-0.062*			
	(0.035)			
Common subgroup		-0.018	-0.058	-0.075
		(0.047)	(0.048)	(0.045)
Different subgroup		-0.099**	-0.063	-0.056
		(0.044)	(0.037)	(0.039)
Licensed	0.041***	0.041***	0.040***	0.040***
	(0.013)	(0.013)	(0.013)	(0.013)
Certified	0.015	0.015	0.016	0.016
	(0.014)	(0.014)	(0.014)	(0.014)
Unionised	0.027**	0.027**	0.027**	0.027**
	(0.011)	(0.011)	(0.011)	(0.011)
External migrant × Licensed	0.055	0.056	0.056	0.056
	(0.034)	(0.034)	(0.034)	(0.034)
External migrant × Certified	0.063	0.063	0.063	0.063
	(0.042)	(0.042)	(0.042)	(0.042)
External migrant × Unionised	0.026	0.026	0.027	0.026
	(0.034)	(0.034)	(0.034)	(0.034)
Internal migrant × Licensed	0.068			
	(0.053)			
Internal migrant × Certified	0.039			
	(0.037)			
Internal migrant × Unionised	-0.033			
	(0.039)			
Common subgroup × Licensed		-0.049	-0.001	0.006
		(0.063)	(0.076)	(0.077)
Common subgroup × Certified		0.067	0.055	0.065
		(0.049)	(0.047)	(0.047)
Common subgroup × Unionised		0.041	0.067	0.090
		(0.077)	(0.090)	(0.092)
Different subgroup × Licensed		0.143**	0.094	0.090
		(0.069)	(0.072)	(0.073)
Different subgroup × Certified		0.028	0.036	0.032
		(0.058)	(0.048)	(0.048)
Different subgroup × Unionized		-0.058	-0.070	-0.082*
		(0.040)	(0.044)	(0.044)
Country FE	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	15,022	15,022	15,014	15,014
Adj. R-squared	0.777	0.777	0.777	0.777

Notes: OLS regressions using the full sample (weighted using sample weights provided by EU-SOR 2015). The dependent variable is log hourly wage. Subgroup indicates the variable used to group internal migrants (i.e. migrants from EU countries). Migrants are classified based on whether the legal origin or the language (primary language only or including language spoken by more than 9%) of the country of origin and destination are the same. Data on languages is taken from the Gravity database of Centre d'études prospectives et d'informations internationales (CEPII), see Head et al. (2010). Legal origin indicates either French, German, Common Law, Scandinavian or Socialist legal origin. Data is taken from Botero et al. (2004). Individual controls include age, age^2, indicators for lower secondary, upper secondary, post-secondary, university, and PhD education, gender, firm size dummies, public sector dummy. Indicators for occupations are defined for 1-digit ISCO codes. Indicators for industry are defined for 1-digit NACE codes. Standard errors clustered by country are reported in parentheses, significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations based on the EU-SOR 2015.

TABLE C.2

The migrant wage gap and similarity in legal origins

Panel A. Average wages	I No certification, license, or union	II Unionized	III Certified	IV Licensed
Natives	0	0.027	0.015	0.041
		(0.011)	(0.014)	(0.013)
Migrants from countries with common legal origins	−0.018	0.050	0.064	−0.027
	(0.047)	(0.058)	(0.056)	(0.083)
Migrants from countries with different legal origins	−0.099	−0.130	−0.055	0.085
	(0.044)	(0.048)	(0.080)	(0.054)
Panel B. Migrant wage gaps				
Migrants from countries with common legal origins	0.018	−0.023	−0.049	0.067
	(0.047)	(0.053)	(0.054)	(0.085)
Migrants from countries with different legal origins	0.099	0.157	0.071	−0.044
	(0.044)	(0.047)	(0.082)	(0.051)

Notes: Panel A reports estimated average wages for different groups of workers, corresponding to those described in Table 2. The results are computed using the estimated coefficients of equation (1), reported in Table C.1. All the values are expressed as differences from the average wage of unregulated natives (w), in the top-left corner. Panel B reports migrant wage gaps. Standard errors (in parentheses) are obtained with the Delta-method.

TABLE C.3

The migrant wage gap and similarity in language

Panel A. Average wages	I No certification, license, or union	II Unionized	III Certified	IV Licensed
Natives	0	0.027	0.016	0.040
		(0.011)	(0.014)	(0.013)
Migrants from countries with common primary language	−0.058	0.036	0.013	−0.019
	(0.048)	(0.078)	(0.072)	(0.096)
Migrants from countries with different primary language	−0.063	−0.107	−0.012	0.071
	(0.037)	(0.045)	(0.064)	(0.057)
Panel B. Migrant wage gaps				
Migrants from countries with common primary language	0.058	−0.009	0.003	0.059
	(0.048)	(0.074)	(0.072)	(0.099)
Migrants from countries with different primary language	0.063	0.134	0.028	−0.030
	(0.037)	(0.044)	(0.065)	(0.054)

Notes: Panel A reports estimated average wages for different groups of workers, corresponding to those described in Table 2. The results are computed using the estimated coefficients of equation (1), reported in Table C.1. All the values are expressed as differences from the average wage of unregulated natives (w), in the top-left corner. Panel B reports migrant wage gaps. Standard errors (in parentheses) are obtained with the Delta-method.

TABLE C.4
Probability of being licensed, certified, or unionized

Dependent variable	I Licensed	II Licensed	III Licensed	IV Certified	V Certified	VI Certified	VII Unionized	VIII Unionized	IX Unionized
External migrant	-0.024	-0.024	-0.025	0.001	0.001	0.001	0.004	0.004	0.004
	(0.016)	(0.016)	(0.016)	(0.019)	(0.019)	(0.019)	(0.026)	(0.026)	(0.026)
Internal migrant	-0.041**			0.017			-0.033		
	(0.020)			(0.018)			(0.024)		
Common language		-0.016			0.003			-0.092***	
		(0.041)			(0.018)			(0.028)	
Different language		-0.050***			0.023			-0.010	
		(0.017)			(0.022)			(0.024)	
Common legal origin			-0.021			-0.008			-0.023
			(0.031)			(0.022)			(0.023)
Different legal origin			-0.056***			0.038			-0.041
			(0.017)			(0.024)			(0.035)
Sample average	0.213	0.213	0.213	0.183	0.183	0.183	0.337	0.337	0.337
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occupation FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	15,022	15,022	15,022	15,022	15,022	15,022	15,022	15,022	15,022
R-squared	0.091	0.091	0.091	0.026	0.026	0.026	0.303	0.303	0.303

Notes: OLS estimates of linear probability models using the full sample (weighted using sample weights provided by EU-SOR 2015). The dependent variables are binary indicators for being licensed, certified, and unionized. Individual controls include age, age^2, indicators for lower secondary, upper secondary, post-secondary, university, and PhD education, gender, firm size dummies, public sector dummy. Indicators for occupations are defined for 1-digit ISCO codes. Indicators for industry are defined for 1-digit NACE codes. Standard errors clustered by country are in parentheses, significance levels are * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: Own calculations based on the EU-SOR 2015.

TABLE C.5
The migrant representation gap and similarity in legal origins

Panel A.	I Licensed	II Certified	III Unionized
Natives	0.213	0.186	0.323
	(0.002)	(0.002)	(0.002)
Migrants from countries with common legal origins	0.192	0.178	0.301
	(0.027)	(0.022)	(0.024)
Migrants from countries with different legal origins	0.157	0.224	0.282
	(0.015)	(0.021)	(0.031)
Panel B. Representation gaps (ratio)			
Migrants from countries with common legal origins	0.900	0.955	0.930
	(0.130)	(0.124)	(0.075)
Migrants from countries with different legal origins	0.736	1.203	0.873
	(0.068)	(0.112)	(0.098)

Notes: Panel A reports the expected probabilities to be licensed, certified, and unionized, corresponding to those described in Table 3. The results are computed using the estimated parameters of equation (2) reported in Table C.4. Panel B reports the estimated representation gaps. Standard errors (in parentheses) are obtained with the Delta-method.

TABLE C.6
The migrant representation gap and similarity in languages

Panel A.	I Licensed	II Certified	III Unionized
Natives	0.213	0.187	0.323
	(0.002)	(0.002)	(0.002)
Migrants from countries with common primary language	0.198	0.189	0.231
	(0.038)	(0.027)	(0.038)
Migrants from countries with different primary languages	0.163	0.209	0.313
	(0.015)	(0.019)	(0.020)
Panel B. Representation gaps (ratio)			
Migrants from countries with common primary language	0.927	1.015	0.716
	(0.183)	(0.149)	(0.118)
Migrants from countries with different primary languages	0.764	1.122	0.969
	(0.070)	(0.103)	(0.064)

Notes: Panel A reports the expected probabilities to be licensed, certified, and unionized, corresponding to those described in Table 3. The results are computed using the estimated parameters of equation (2) reported in Table C.4. Panel B reports the estimated representation gaps. Standard errors (in parentheses) are obtained with the Delta-method.