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Keep It Simple: A Methodological Discussion of Wage Inequalities in the Spanish Hospitality Industry

Francisco Sánchez-Cubo [1,*], José Mondéjar-Jiménez [1], Alejandro García-Pozo [2] and Mauro Maltagliati [3]

[1] Department of Applied Economics I, University of Castilla-La Mancha, 16071 Cuenca, Spain
[2] Department of Applied Economics, University of Málaga, 29071 Malaga, Spain
[3] Department of Statistics, Informatics, Applications 'G. Parenti' (DiSIA), University of Florence, 50121 Florence, Italy
* Correspondence: francisco.scubo@uclm.es

Abstract: Human capital in hospitality has been widely addressed by applying sophisticated econometric methods. However, for the Spanish case, there was a gap in the analyses as the crucial importance of collective agreements was undervalued. This paper redesigns the conceptualisation of the variables and applies a subsequent new classification to job positions, as it deals with the outliers at different levels of rigorousness. Then, linearised and quantile regressions were run for each case, obtaining an outcome of thirty values for each variable. The analyses and comparisons show the high importance of collective agreements on salaries, the noticeable low values of human capital variables, and provides additional information for the nationality and gender gaps, the latter strikingly high in upper professional categories. Overall, this paper demonstrates the importance of a proper study design to prevent advanced econometric models from falling into bias and it minimises the differences between methods.

Keywords: linearised regressions; hospitality; human capital; quantile regressions; Spain

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1. Introduction

Sixty years have passed since the beginning of human resources studies from a perspective of human capital [1,2]. This approach provided the workers with conscious decisions in their labour careers—e.g., developing a skill or acquiring more education would eventually increase their salaries. Concurrently, this theory gave the enterprises the responsibility of polishing their recruitment methods to select better employees from an increasing heterogeneous pool of workers, choosing from a range of productivity predictors such as their years of education or previous experience, among others. Nevertheless, more theories arose and competed against the human capital theory but the latter remained the predominant one. These other theories were (1) the competence theory, in which education serves as a predictor of the required further training of the employee [3]; (2) the signalling theory, in which education is a predictor of the employee performance [4–7]; (3) the assignment theory, which introduced the education–skills mismatch and its negative effects on productivity [8]; and (4) the heterogeneous knowledge theory, which disassociated education from knowledge and skills [9]. As seen, the crucial variable around all these theories was education, apart from Mincer [10], who modelled the human capital theory by introducing the variable of experience.

Following the approach of mismatches regarding education, other authors more recently identified the existence of a mismatch resulting from the differences between the required level of education for a job position and the actual education level of the employee, resulting in the well-known "educational mismatch" [11–15]. This mismatch has several consequences that may influence aspects such as employee productivity [16]—and so the power of education as a productivity predictor—or the relation between the level of education and salaries [17].

In addition, it seems true that slight differences might exist between countries and/or regions [18–20] and between industries and sectors—e.g., the energy industry [21]. Regarding this, the scope of this work is to analyse the hospitality and tourism industries—defined as the subgroups of the accommodation and catering of the CNAE-09 [22,23]. Such a decision relies on: (1) the importance of the tourism industry in Spain—12.7% Spanish employment and 12.6% of the GDP in 2019, according to the latest pre-COVID-19 pandemic data [24]; (2) the differences in the Spanish hospitality/tourism labour market with respect to other countries because of its weak internal mobility [25,26] but high turnover rates, which is higher than other industries [12,27]; (3) the distinguishing characteristics of the hospitality industry regarding jobs, wage differences, and labour stability [28]; (4) the feminisation of the industry, which may lead to differences in human capital returns and wage differences [12,29]; and (5) the particular labour market in Spain, which is characterised by high unemployment and turnover rates [30] and regular labour reforms [31,32], the last one coming into effect on 31st December 2021 [33]. All these elements suggest that the Spanish labour market and, more specifically, its hospitality industry, despite sharing some characteristics with other countries, deserves particular differentiation.

Thus, over the decades, the methodologies used to assess the overall phenomenon have evolved from Mincer's equation [10] by adding variables to this first regression or by applying new methodologies based on it, as shown hereafter. Firstly, researchers started by adding more explanatory variables to the equation in an attempt to increase the share of variance explained by human capital variables such as tenure [17], education mismatch [34], business-related variables such as its size [35,36], or by individual-related characteristics such as age, nationality, or sex [37,38]. Plus, the latter has been widely studied from the perspective of the gender gap [34,39]. However, not only has extended Mincer regression been applied but also Oaxaca–Ransom [40] and Oaxaca–Blinder [41] equations, productivity approaches [16], or, lastly and, presumably, more accurately, quantile regressions [12,27,42].

From all the above, two issues stand out. First, the education variable remains the central axis for studying human capital in the hospitality industry as it is the main factor in which individuals can invest to improve their human capital. However, nowadays it lacks power as a productivity predictor given the previously mentioned educational and competences mismatch. These phenomena coexist since the latter simply diminishes the returns on human capital from an education level, but it is still relevant for the individuals for improving their human capital and because educational level might also act as a barrier to entry in many job positions [43]. Secondly, most of the methodologies employed rely on the mean as the statistical reference, which undoubtedly biases the results in samples with noticeable outliers. That is the case with the Quatriennal Wage Structure Survey of the National Statistics Institute [44] when only selecting hospitality workers. For these cases, the quantile regression approach—usually using the median as the quantile of reference—is gaining popularity, as it solves part of the problem [27,42]. Nevertheless, much of the initial problem still remains if all the analysis is left to the econometry over the whole sample, not considering the particularities of the industry for the Spanish case.

In this line, this piece of work addresses a gap that needs to be addressed before applying more and more sophisticated econometric models, since the main problem may lie in the treatment of the original database. Therefore, the aim of the study is to redesign the analysis by taking into account—as variables in the model—the particularities of the Spanish hospitality sector, strongly influenced by the sectoral collective agreements and the differences between accommodation and catering services, as well as the diverse distribution of the job positions—as a grouping variable. Hence, the study question lies in identifying whether there are differences in the explanatory power of the proposed redesigned models when considering the full sample or professional categories, and between linearized models and quantile regressions. That redesign of the models and the comparison between estimation methods, together with the obtained results, entail the main contribution of this work. Consequently, this paper is organised as follows. After this brief introduction, the methodology section describes the procedure of redesigning the analyses and the chosen methods: the extended Mincer regression and the quantile regression using the median as the statistical reference. Then, the results are displayed and discussed in the subsequent section. All the above will eventually lead to some conclusions and future lines of research.

2. Materials and Methods

As previously introduced, apart from the many statistical outcomes, this paper addresses a methodological debate in the field of human capital returns, but, specifically, in the hospitality industry. Moreover, the study analyses the Spanish case, which uses the Quadrennial Wage Structure Survey [44], since it is the most used for these studies because of its level of detail. Delimiting by the CNAE-09 [22] categories for accommodation—I55—and catering—I56—the final sample contains the observations of 7331 individuals. The study variables were selected from the ones stated in the previous studies in the literature. Transformations were only required in categorical variables—labour category and business size, in education—which was a categorical variable and was transformed to a numerical one, and in wages, which were represented in gross euros per hour and their natural logarithm, following the treatment given in the previous literature. Table 1 summarises the basic descriptive statistics for the whole sample—FS—and the subsamples—99 and 95—at two thresholds of eliminating outliers above the 99 and 95 percentiles, respectively. These outliers were not identified as the highest values of the whole sample but as the ones of each of the labour categories. Consequently, in sum, Table 1 proves that the subsequent cuts on the sample did not affect its representativity but corrected the skewness and kurtosis of the variable wages, especially when natural logarithms were applied.

The division of the latter variable into four resulted from a revision of the former variable, which divided the labour categories into seven, following Anghel et al. [45]. This division seemed inaccurate for the Spanish hospitality case, strongly influenced by collective agreements, which are noticeably homogeneous at the national and regional levels. These collective agreements, following the national-level agreement [46], mandatorily state three professional categories: managers, specialists/professionals, and assistants. However, looking over the data and the jobs within the second professional group suggests that they should be divided into two. The resulting categories are as follows—CNO2 [47] codes, as classifiers of the job position, in brackets: first (11–15), second (21–38), third (41–84), and fourth (90–98).

The rest of the variables were defined as in the previous literature. In the first place, education, tenure, and wages are the only quantitative variables; the latter two are continuous while the first one is discrete. Thus, education is measured in terms of completed years of education, extracted from the declared 'highest education' of the respondents in the original database. Tenure is also contained in it, and no transformations were required. Conversely, gross wages were adapted to the gross hourly wage, and then natural logarithms were applied. Secondly, dummy variables are the majority in the models, and they go as follows: subindustry (being 0 in the accommodation industry (I55) and the catering industry (I56)), market (being 0 local, regional, and national markets and 1 international market), nationality (being 0 foreigners and 1 Spaniard), collective agreement (being 0 enterprise collective agreement and 1 sector national or regional level), responsibility (being 0 without responsibility and 1 to have some sort of it, in terms of subordinates), sex (being 0 women and 1 man), type of contract (being 0 temporary contracts and 1 indefinite contract), and type of working day (being 0 part time and 1 full time). Lastly, labour category and business size are the categorical variables. The first one was mostly used for classification purposes. It was also included in the general models but inverted for a better interpretation, i.e., one stands for the fourth professional category while four stand for the first professional category. Concerning business size, one stands for micro-businesses (1 to 9 employees), 2 for small businesses (10–49 employees), 3 for medium ones (50 to 199)—the official classification included up to 249 employees [48], but the database stops at 199 and 4 for large companies (200 employees or more).

Table 1. Descriptive statistics of the studied variables.

	Min–Max			**Mean (Std. Dev.)**			**Skewness**			**Kurtosis**		
	WS	**99**	**95**	**WS**	**99**	**95**	**WS**	**99**	**95**	**WS**	**99**	**95**
Education		2–17		8.524 (3.251)	8.523 (3.247)	8.512 (3.232)	0.645	0.644	0.646	−0.045	−0.045	−0.03
Tenure		0.08–48.50		7.876 (8.493)	7.834 (8.455)	7.657 (8.311)	1.616	1.616	1.642	3.104	3.121	3.302
Subindustry		0–1			0.547 (0.498)		−0.188	−0.189	−0.187	−1.965	−1.965	−1.965
Labour category		1–4		1.851 (0.656)	1.85 (0.656)	1.85 (0.654)	0.627	0.624	0.617	1.105	1.102	1.091
Market				0.259 (0.438)	0.258 (0.438)	0.258 (0.437)	1.103	1.105	1.109	−0.783	−0.779	−0.77
Nationality		0–1		0.877 (0.328)	0.877 (0.328)	0.876 (0.329)	−2.301	−2.296	−2.288	3.297	3.274	3.236
Collective agreement				0.921 (0.269)	0.922 (0.268)	0.925 (0.263)	−3.133	−3.151	−3.228	7.819	7.928	8.419
Responsibility				0.17 (0.371)	0.16 (0.37)	0.16 (0.366)	1.805	1.813	1.862	1.258	1.288	1.467
Sex				0.381 (0.486)	0.381 (0.486)	0.379 (0.485)	0.491	0.492	0.498	−1.76	−1.76	−1.753
Business size		1–4		3.214 (0.995)	3.21 (0.997)	3.199 (1.004)	−1.001	−0.995	−0.976	−0.229	−0.244	−0.294
Type of contract		0–1		0.813 (0.390)	0.813 (0.390)	0.809 (0.393)	−1.608	−1.604	−1.575	0.586	0.573	0.481
Type of working day				0.486 (0.500)	0.487 (0.500)	0.487 (0.500)	0.056	0.053	0.052	−1.997	−1.998	−1.998
Hourly salary		3.095–119.732 | 70.413 | 45.676		10.232 (5.589)	9.952 (4.576)	9.458 (3.697)	5.008	3.312	2.866	50.869	22.03	15.764
Ln (hourly salary)		1.13–4.79 | 4.25 | 3.82		2.238 (0.384)	2.224 (0.361)	2.19 (0.323)	1.160	0.925	0.779	2.468	1.481	1.475

Source: Authors.

Regarding the methodology used, the current state of the arts in the study of human capital in hospitality has evolved from extended Mincer equations [49–51] to quantile regressions [27,42]. The aim is to avoid the likely bias of strongly skewed samples, as is the case of the one for hospitality in Spain, by substituting the mean with the median as a statistical reference. It is stated that the bias is reduced without losing information due to extreme values and without trimming the original sample by using this technique. Thus, the same model was run as linearised and quantile regression—using the whole sample—to corroborate this statement. However, these outcomes would not consider the points previously made about the singularities of the Spanish hospitality sector, and the noticeable differences between professional categories would strongly bias the results of the estimations, providing few new outcomes to the extant literature.

Consequently, to provide a more accurate insight into each professional category and to limit the influence of outliers, several additional models were run by delimiting the sample by these categories and the number of individuals—the whole sample, or up to 99 or 95 percentiles. As a result, 30 regressions were run, and their results are displayed in the upcoming section.

3. Results

This section compiles the results of running the aforementioned models, in which the dependent variable is the natural logarithm of the hourly wages—in Euros—and the independent variables are the rest included in Table 1—except for hourly wages. This model is run using linearised regressions—which are indeed semilogarithmic, thus they are linearised—and quantile regressions at the 50 percentile—which is the median. As previously explained, subsamples are extracted to consider the particularities of the Spanish hospitality sector—i.e., the division into four professional categories—and the nuances of including outliers at different levels—99 and 95 percentiles. Thirty models result from all these divisions, and their outcomes are compiled in Tables 2 and 3.

Table 2. Goodness of fit of the models.

		All	G1	G2	G3	G4
LR	WS	0.245	0.280	0.314	0.168	0.091
	99	0.268	0.284	0.325	0.192	0.092
	95	0.299	0.323	0.331	0.219	0.103
QR	WS	0.139	0.209	0.207	0.115	0.061
	99	0.144	0.220	0.210	0.120	0.062
	95	0.155	0.251	0.212	0.131	0.069

Note: LR use conventional R2 while QR use pseudo-R2. Source: Authors.

Table 3. Results of the estimations of the models.

			All	G1	G2	G3	G4
Education	LR	WS	0.009 *** (0.001)	0.052 *** (0.013)	0.014 *** (0.004)	0.006 *** (0.002)	−0.002 (0.003)
		99	0.008 *** (0.001)	0.038 *** (0.013)	0.014 *** (0.004)	0.006 *** (0.001)	0.0005 (0.003)
		95	0.007 *** (0.001)	0.029 ** (0.012)	0.012 *** (0.003)	0.005 *** (0.001)	−0.001 (0.002)
	QR	WS	0.007 *** (0.0012)	0.023 (0.0153)	0.014 *** (0.0042)	0.007 *** (0.0015)	−0.002 (0.0025)
		99	0.007 *** (0.0012)	0.02 (0.015)	0.014 *** (0.0042)	0.007 *** (0.0015)	−0.001 (0.0024)
		95	0.006 *** (0.0011)	0.021 (0.0145)	0.012 *** (0.0041)	0.006 *** (0.0014)	−0.002 (0.0024)
Tenure	LR	WS	0.008 *** (0.001)	0.014 *** (0.004)	0.01 *** (0.002)	0.008 *** (0.001)	0.006 *** (0.001)
		99	0.007 *** (0)	0.013 *** (0.004)	0.009 *** (0.002)	0.007 *** (0.001)	0.005 *** (0.001)
		95	0.006 *** (0)	0.012 *** (0.003)	0.008 *** (0.001)	0.006 *** (0.001)	0.004 *** (0.001)
	QR	WS	0.007 *** (0.0005)	0.011 ** (0.0047)	0.011 *** (0.0018)	0.007 *** (0.0006)	0.004 *** (0.0009)
		99	0.007 *** (0.0005)	0.011 ** (0.0045)	0.011 *** (0.0019)	0.007 *** (0.0006)	0.004 *** (0.0009)
		95	0.006 *** (0.0005)	0.011 ** (0.0044)	0.01 *** (0.0018)	0.006 *** (0.0006)	0.003 *** (0.0009)
Labour category	LR	WS	−0.16 *** (0.011)	−0.22 * (0.12)	−0.193 *** (0.036)	−0.147 *** (0.014)	−0.129 *** (0.018)
		99	−0.16 *** (0.01)	−0.185 (0.112)	−0.192 *** (0.034)	−0.15 *** (0.012)	−0.129 *** (0.017)
		95	−0.165 *** (0.009)	−0.313 *** (0.106)	−0.184 *** (0.031)	−0.151 *** (0.011)	−0.134 *** (0.016)
	QR	WS	−0.136 *** (0.0098)	−0.226 (0.1393)	−0.178 *** (0.0409)	−0.139 *** (0.0124)	−0.109 *** (0.017)
		99	−0.136 *** (0.0097)	−0.204 (0.1335)	−0.181 *** (0.0409)	−0.135 *** (0.0122)	−0.11 *** (0.0165)
		95	−0.141 *** (0.0092)	−0.33 ** (0.1331)	−0.158 *** (0.0391)	−0.138 *** (0.0117)	−0.111 *** (0.016)
Market	LR	WS	0.036 *** (0.011)	−0.148 (0.09)	0.016 (0.036)	0.046 *** (0.014)	0.043 ** (0.019)
		99	0.038 *** (0.01)	−0.081 (0.085)	0.023 (0.034)	0.047 *** (0.013)	0.035 * (0.018)
		95	0.039 *** (0.009)	−0.098 (0.077)	0.042 (0.031)	0.053 *** (0.012)	0.031 * (0.016)
	QR	WS	0.055 *** (0.0103)	−0.129 (0.1051)	0.038 (0.0406)	0.056 *** (0.0131)	0.069 *** (0.0178)
		99	0.054 *** (0.0103)	−0.131 (0.1015)	0.035 (0.0407)	0.06 *** (0.0129)	0.064 *** (0.0173)
		95	0.05 *** (0.0098)	−0.111 (0.097)	0.06 (0.0389)	0.058 *** (0.0125)	0.065 *** (0.0169)
Nationality	LR	WS	−0.034 *** (0.012)	0.113 (0.128)	−0.083 * (0.048)	−0.05 *** (0.016)	0.012 (0.019)
		99	−0.033 *** (0.011)	0.095 (0.12)	−0.092 ** (0.045)	−0.046 *** (0.015)	0.013 (0.018)
		95	−0.029 *** (0.01)	0.044 (0.107)	−0.07 * (0.042)	−0.035 *** (0.013)	0.008 (0.016)
	QR	WS	−0.031 *** (0.0113)	0.063 (0.1493)	−0.037 (0.0545)	−0.04 *** (0.0147)	−0.014 (0.0177)
		99	−0.034 *** (0.0113)	0.08 (0.1425)	−0.032 (0.0544)	−0.041 *** (0.0144)	−0.01 (0.0173)
		95	−0.031 *** (0.0107)	0.056 (0.1344)	0.002 (0.052)	−0.031 ** (0.0139)	−0.01 (0.0167)

Table 3. *Cont.*

			All	G1	G2	G3	G4
Collective agreement	LR	WS	−0.043 *** (0.015)	0.019 (0.168)	−0.122 ** (0.059)	−0.004 (0.02)	−0.069 *** (0.025)
		99	−0.035 ** (0.014)	0.188 (0.162)	−0.115 ** (0.056)	−0.01 (0.018)	−0.046 * (0.024)
		95	−0.008 (0.013)	0.131 (0.149)	−0.051 (0.054)	0.029 * (0.017)	−0.034 (0.021)
	QR	WS	−0.005 (0.0143)	0.29 (0.1946)	−0.065 (0.0674)	0.019 (0.0183)	−0.021 (0.0231)
		99	0.002 (0.0143)	0.35 * (0.1921)	−0.067 (0.0679)	0.033 * (0.018)	−0.008 (0.0226)
		95	0.025 * (0.0138)	0.169 (0.1868)	−0.04 (0.067)	0.057 *** (0.0178)	0.003 (0.0222)
Responsibility	LR	WS	0.186 *** (0.012)	0.278 (0.293)	0.159 *** (0.032)	0.147 *** (0.014)	0.13 * (0.07)
		99	0.18 *** (0.011)	0.228 (0.274)	0.158 *** (0.031)	0.14 *** (0.013)	0.146 ** (0.066)
		95	0.162 *** (0.01)	0.145 (0.244)	0.13 *** (0.028)	0.12 *** (0.011)	0.156 *** (0.06)
	QR	WS	0.182 *** (0.0114)	0.247 (0.3409)	0.144 *** (0.037)	0.153 *** (0.0127)	0.167 ** (0.0652)
		99	0.182 *** (0.0114)	0.273 (0.3251)	0.137 *** (0.0372)	0.147 *** (0.0125)	0.181 *** (0.0631)
		95	0.17 *** (0.0109)	0.121 (0.306)	0.133 *** (0.0355)	0.125 *** (0.0123)	0.149 ** (0.0618)
Sex	LR	WS	0.02 ** (0.008)	0.226 *** (0.084)	0.135 *** (0.032)	0.014 (0.01)	−0.024 (0.016)
		99	0.019 ** (0.008)	0.223 *** (0.08)	0.129 *** (0.031)	0.01 (0.009)	−0.013 (0.015)
		95	0.016 ** (0.007)	0.241 *** (0.073)	0.132 *** (0.028)	0.002 (0.008)	−0.009 (0.014)
	QR	WS	0.023 *** (0.0078)	0.35 *** (0.0981)	0.154 *** (0.0368)	0.011 (0.0094)	−0.005 (0.0149)
		99	0.024 *** (0.0078)	0.316 *** (0.0948)	0.148 *** (0.0369)	0.008 (0.0092)	−0.001 (0.0145)
		95	0.019 *** (0.0074)	0.309 *** (0.0913)	0.15 *** (0.0353)	0.004 (0.0089)	0 (0.0141)
Business size	LR	WS	0.02 *** (0.004)	0.109 ** (0.044)	0.054 *** (0.019)	0.018 *** (0.005)	0.015 * (0.008)
		99	0.017 *** (0.004)	0.116 *** (0.042)	0.048 *** (0.018)	0.014 *** (0.005)	0.015 ** (0.007)
		95	0.014 *** (0.003)	0.099 *** (0.038)	0.042 ** (0.016)	0.011 *** (0.004)	0.014 ** (0.006)
	QR	WS	0.01 ** (0.0039)	0.075 (0.0515)	0.057 *** (0.0217)	0.009 ** (0.0046)	0.006 (0.0071)
		99	0.01 *** (0.0039)	0.083 * (0.0496)	0.054 ** (0.0216)	0.008 * (0.0045)	0.006 (0.0069)
		95	0.009 ** (0.0037)	0.076 (0.0472)	0.041 ** (0.0206)	0.007 (0.0044)	0.005 (0.0067)
Type of contract	LR	WS	0.049 *** (0.011)	0.204 (0.209)	0.107 ** (0.043)	0.048 *** (0.013)	0.029 (0.019)
		99	0.053 *** (0.01)	0.178 (0.195)	0.102 ** (0.04)	0.055 *** (0.012)	0.03 * (0.018)
		95	0.054 *** (0.009)	0.14 (0.174)	0.086 ** (0.037)	0.056 *** (0.011)	0.036 ** (0.016)
	QR	WS	0.022 ** (0.0099)	0.127 (0.2429)	0.062 (0.049)	0.025 ** (0.012)	−0.004 (0.0174)
		99	0.022 ** (0.0099)	0.105 (0.2316)	0.061 (0.0489)	0.027 ** (0.0118)	0 (0.0169)
		95	0.024 ** (0.0093)	0.079 (0.2177)	0.061 (0.0458)	0.028 ** (0.0113)	0.004 (0.0164)
Type of working day	LR	WS	−0.01 (0.009)	0.247 ** (0.111)	0.037 (0.033)	−0.017 (0.011)	−0.02 (0.015)
		99	−0.003 (0.008)	0.226 ** (0.104)	0.027 (0.031)	−0.008 (0.01)	−0.013 (0.014)
		95	0.002 (0.007)	0.172 * (0.093)	0.032 (0.029)	0.004 (0.009)	−0.011 (0.013)
	QR	WS	−0.006 (0.008)	0.184 (0.1293)	0.044 (0.0376)	−0.013 (0.0099)	−0.031 ** (0.0137)
		99	−0.005 (0.0079)	0.19 (0.1235)	0.042 (0.0376)	−0.012 (0.0097)	−0.027 ** (0.0133)
		95	−0.006 (0.0075)	0.151 (0.1166)	0.044 (0.036)	−0.007 (0.0094)	−0.021 (0.013)
Intercept	LR	WS	1.947 *** (0.029)	0.924 * (0.475)	2.01 *** (0.112)	2.11 *** (0.038)	2.177 *** (0.046)
		99	1.936 *** (0.027)	1.005 ** (0.444)	2.038 *** (0.106)	2.111 *** (0.035)	2.133 *** (0.043)
		95	1.906 *** (0.024)	1.43 *** (0.408)	2 *** (0.098)	2.058 *** (0.031)	2.115 *** (0.039)
	QR	WS	2.301 *** (0.0371)	1.26 ** (0.552)	1.875 *** (0.1276)	2.062 *** (0.0345)	2.147 *** (0.0422)
		99	1.934 *** (0.0269)	1.209 ** (0.5273)	1.896 *** (0.128)	2.048 *** (0.0339)	2.127 *** (0.0411)
		95	1.914 *** (0.0256)	1.609 *** (0.5113)	1.882 *** (0.1225)	2.023 *** (0.0329)	2.11 *** (0.0403)
Subindustry as variable	LR	WS	0.09 *** (0.007)				
		99	0.088 *** (0.007)				
		95	0.091 *** (0.006)				
	QR	WS	0.072 *** (0.0065)				
		99	0.072 *** (0.0065)				
		95	0.075 *** (0.0062)				

Note: Beta coefficients (Dev. Err. in parentheses for LR. Std. Err. In parentheses for QR). *p*_values: *** < 0.01; ** < 0.05; * < 0.1. Source: Authors.

First, Table 2 summarises the goodness of fit of the models. When it comes to linearised regressions, since they were run using ordinary least squares (OLS), it was measured through adjusted R2s. Conversely, since OLS do not apply to quantile regressions, the goodness of fit of those models was calculated through pseudo-R2s, which result from the differences in the mean absolute error (MAE) of the null model and the corresponding full model. Although it might be considered a truism, the steady increase in both goodness of fit as the sample shrinks—even if the loss of individuals is scarce—is highly relevant, since it may support some statements addressed in the discussion section. Another interesting point in this table is that the model fits better in the highest groups (G1 and G2) even though they contain significantly fewer individuals. The assumptions made from this were discussed in the following section.

Straightaway, the results of the estimations are displayed in Table 3. Together with the results of Table 2, this table constitutes one of the main contributions of this piece of work since it summarises the results of thirty models, allowing a compact, direct, and easy comparison of the values. Overall, it stands out that most variables barely contribute to the dependent variable, despite being statistically significant. However, the division into professional groups seems to shed some light on these figures. Specifically, the effect of the variables seems to decrease with the professional category, i.e., the independent variables contribute more to explaining wages in upper professional groups than in the lower ones. Next, apart from some exceptions, the differences between subsamples are imperceptible. The same phenomenon applies to the form of estimation, as the differences in the values between linearised regressions and quantile regressions are clearer but mostly indiscernible. The variables identifiable under the first phenomenon are education and tenure, which stay almost constant and whose effect, in terms of increases proportional to an additional year of education or tenure, is almost 0. Nationality and sex for the whole sample also applies to this. In addition, most of the variables present similar values between subsamples but slightly differ between the method of estimation, always being the values for the lower quantile regression. The variables under this description are subindustry, market, sex—for the first and second professional categories—and labour category when used as a variable. In addition, there is a group of variables that follow a pattern, whose values are similar within the calculation method used, which decrease as the sample decreases: years of education—for the first group results in linearised regressions; market—for the fourth groups; nationality—for the second and third groups; responsibility—for all except the first and fourth groups; size—except for the first group; type of working day—but only the linearised regression results for the first group and the quantile regression ones for the fourth are statistically significant; and the intercept—for all except the first and second group—but it has no economic meaning [52]. Nevertheless, some variables present exceptions from the previous generalisation. Mainly, these exceptions are just slight variations without a pattern, which apply to the rest of the variables and cases not mentioned previously.

Apart from the patterns and the statistically significant low values, the most interest relies on those variables with the lowest and highest impacts. Regarding the largest effects, three variables significantly affect the final salaries: the subindustry—which shows how working in the catering subindustry penalises from 14% to 16%; the responsibility—which increases wages by 17% to 18%; and the labour category—which affects from 7% to 9%. Plus, the type of working day returns high values for the first professional category when estimated through linearised regressions, but it is mostly not statistically significant for the rest of the cases due to its extremely low impact. Conversely, but in line with these low impacts, the rest of the independent variables also have these small values. The most striking cases are the variables years of education and tenure, whose figures are statistically significant but extremely close to 0, steadily lowering as the professional group decreases in importance.

Lastly, the values of nationality and sex should be carefully assessed since they have been the subject of debate in many studies using previous databases. The first variable seems to penalise Spanish workers for the whole sample and groups 2 and 3, being especially noticeable in the values of group 2, since they vary from a 7% to 9% gap while about 3% is observed in the rest of the statistically significant ones. Similarly, but with larger gaps, the variable sex is statistically significant for the whole sample and groups 1 and 2. In fact, group 1 presents one varying from 22.3% to 35%, depending on the subsample selected. Then, group 2 significantly diminishes such figures, but a gap between 12.9% to 15.4% remains. Since the results of the estimations for groups 3 and 4 are not statistically significant and constitute a great share of the sample, the overall gap dramatically reduced to a gap of 1.6% to 2.4%. The subsequent discussion of all results is performed in the following section.

4. Discussion

Once the results are displayed, some comments can be carried out on them. Firstly, the ones resulting from Table 2 are made. It was shown that, as the sample was shrunk to more homogeneous values, the goodness of fit increased, which seems to be a truism but unveils differences between professional categories. Indeed, the higher the group, the explanatory power of the model increased for both linearised and quantile regressions. Apart from the acceptable fit of the models—compared to the extant literature—the most noticeable information extracted from this table is that the salaries of the employees in the lower groups are poorly explained by the independent variables, no matter the estimation method. That could be interpreted as a flawed model formulation, but it would imply that higher groups are also wrong. However, conversely, these groups present much better fits. That evidence cannot be interpreted alone, but a glance is needed at Table 3. Running the models at a disaggregated level evinces how the highest groups are more influenced by the explanatory variables, contrary to the lowest groups. This phenomenon might be the consequence of stiffer regulations in the collective agreements that penalise those workers in lower categories, as their years of education, tenure, or any other variable barely increases their salaries, apart from responsibility—which is only applicable for 20 employees out of 2048 in the fourth group. Unfortunately, this point has not been quantitatively addressed previously in the hospitality-related literature, thus comparisons cannot be made. However, indirect correlations could be made since the variable regulation always have a negative sign in the literature, which suggests that collective agreements slightly diminish the wages of employees [42], at least for the Spanish case—e.g., Liu and Zhang [53] found that collective agreements benefited hospitality employees in China.

Nevertheless, more direct effects can be found in the extant literature, which provides directly comparable results for both linearised and quantile regressions. As stated in the results section, it is a matter of the whole picture that these figures draw, not of an abundance of small or high values. Thus, Table 3 compiles and compares up to 30 data points to measure each variable with different criteria, which provides an accurate view of the likely estimator of the variable at different stages. In fact, variables such as education and tenure already had low values since the eldest studies [17,54], or experienced studies which inferred it [40]. Likewise, the high values of responsibility [37] are also documented in the literature, but it is not a recurring variable. Similarly, the other two variables with the highest impact—professional category and subindustry—are barely documented and were not found to be included as part of the regression. Conversely, the rest of the variables in the models are widely documented despite their medium-to-low impact: type of contract and type of working day [34,40], business size [39,50], or type of market [42].

Finally, the nationality and gender gaps could be addressed since the results shown in this paper contain both variables. Starting with the first, it might be surprising to see that it penalises Spanish workers, but the differences are mostly about 3%, which could be easily explained by characteristics of the job position, which may attract foreigners to better-paid jobs within a category. Thus, the figures for the Spanish worsen, but it would not be necessarily fully caused by discrimination. Similarly, the variable sex presents noticeable values since the general gap is especially small—1.6% to 2.4%—and could be caused by the same reasons as the previous variable. However, in this case, the division into professional categories sheds light on the issue. Thus, the low values in categories 3 and 4 are not statistically significant, while the gap in categories 1 and 2 varies from 22.3% to 35%. Therefore, since categories 3 and 4 constitute a great share of the sample, they balance the general gap, but it is clearly identified in the highest categories. In this case, it seems less probable that the gap is fully caused by job characteristics, and thus the extant studies need to be continued [34].

Nevertheless, it was not in the scope of this study to dismantle the gender gap, but, rather, to identify where it took place. Since previous studies already analysed it for the general sample [27,42], further studies from the present one might delve into the dismantling of the gap with the acquired additional information. In this line, the gender wage gap is shown, nuanced by the compensating forces of both extremes and, thanks to the redesign of the job position variable into the professional category one, clearly identified in the highest positions, which account for a reduced part of the workforce but should be addressed by the pertaining stakeholders to guarantee the equality of opportunity. Concerning this last assertion, the lack of statistical significance of the lowest categories, as well as their values close to 0, collective agreements could have had a likely influence on those job positions, which are especially stiff, and their salaries mostly fixed with a greater level of equality. In fact, the problem identified in the previous literature due to this issue belongs to the field of educational mismatch [34,40], which produces losses in human capital returns.

5. Conclusions

This piece of work aimed to address a specific gap never addressed before in the academic literature regarding human capital in the hospitality industry, particularly in a Spanish case. This gap mainly refers to the treatment of the original database rather than applying more sophisticated econometric methods, since it seems an essential issue to address before executing them. Consequently, the objective was to redesign the analysis by taking into account the particularities of the Spanish hospitality sector, strongly influenced by the sectoral collective agreements, considering the differences between subindustries and job positions. Then, classic and novel econometric methods were applied.

Redesigning these key aspects of the original and most-used database, specifically when it comes to the new distribution of the job positions following the mandatory professional categories of the sectoral collective agreements. Thus, applying these professional categories to subdividing the sample, at the same time that the outliers were trimmed at different levels of rigorousness, resulted in a new point of view for an already widely used database. Moreover, both new scopes allowed running linearised and quantile regressions, as an example of the most used methodologies in this field, to easily compare their results and their fit to the sample.

The results of these regressions provided very useful insights into what happens in the different professional categories in the Spanish hospitality industry, allowing a more accurate decision-making process. In addition, the goodness of fit of almost all the models was recorded to be incremented compared to the extant literature, especially in the upper professional categories. That leads to the overall conclusion that the lower professional groups are far stiffer when it comes to the collective agreements and, thus, the particular variables of a worker barely influence their final salary, depriving the individuals benefiting from additional education or tenure, among others, and, subsequently, making the human capital theory inapplicable at these categories. Conversely, the contrary effect was demonstrated in the higher professional categories, since more variables have statistically significant effects on the workers' final salary. However, the greatest effects were recorded for those categories unrelated to the human capital theory but the job position, subindustry, and the employee's level of responsibility. Besides, in line with the subindustry variable, catering employees were shown to be penalised compared to their accommodation counterparts, which may arise from the differences in the regulation of their contracts, which is generally less stiff than the collective agreements in hospitality—despite the inclusion of references to catering services, these can be under a wider range of different regulations.

Lastly, the outcome of the regressions also provided information regarding the variables nationality and sex, which were commonly used in the literature to assess discrimination. Thus, the overall gap was noticeably small concerning both variables—about 3% and from 1.6% to 2.4%, respectively—but their distribution among professional categories differed. While the first had relatively low values in all statistically significant estimators along the groups, sex was not statistically significant in the lower ones—with values very close to 0—but had a large gap in the upper ones. This phenomenon showed that the gender gap is an issue of these higher professional categories, which may help policymakers and stakeholders as it is clearly identified where it happens. Nevertheless, further studies should be carried out to decompile this gap in this particular professional group. Furthermore, it should be required to determine how much of these gaps—and the narrower ones—are caused by characteristics of the job positions or the staff distribution, and how much is caused by discrimination.

Therefore, the aforementioned might be a further line of research to keep delving into the analysis of the particular industry of hospitality in Spain, providing nuances in the human capital theory to the contemporary characteristics of the job market. Plus, further studies on identifying additional key variables that may affect the returns on the human capital of the employees of this industry would be a promising future line of research for the authors. Finally, the main limitation of the study is that the database is from 2018, quadrennial, and, despite being the most up-to-date one and still barely used in the human capital literature, it was released in the second half of 2020, and, thus, COVID-19 data would not available until 2024, referring to 2022 values.

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