The Effects of Cultural Distance on Labour Force Participation of Immigrants in the United Kingdom

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Abstract

The present study sought to examine the relationship between cultural distance and employment rates among immigrants in the United Kingdom. The cultural distance between the host country and the home country was calculated using the Cultural Fixation Index, a novel and highly robust tool for cross-cultural group comparisons. The analysis revealed a significant negative relationship between cultural distance and group-level differences in employment rates. The relationship held true when controlled for the effects of genetic distance, size of the migrant population, education levels, population of the home country, GDP per capita of the home country, and regional identifiers. The results were robust to the inclusion and exclusion of controls, with the main model explaining 71% of variance in employment rates. Whilst the obtained findings are consistent with the broader literature on acculturation and barriers to employment, this study represents the first attempt to offer direct support for the link between cultural distance and labour force participation among immigrants. Although the generalizability of the obtained results needs to be further investigated, this research offers important considerations for future studies, theoretical advancements on acculturation, and targeted interventions.

Keywords: cultural distance, immigration, employment rates, cultural fixation index

Introduction

In 2021, the number of foreign-born residents living in the United Kingdom exceeded 9.5 million (Office for National Statistics, 2021). While the overall fiscal contribution of UK immigrants remains positive, there is substantial variability in the socio-economic situation of foreign-born workers (Dustmann & Frattini, 2014). Although migrants' heterogeneity is sometimes discussed as an extraneous variable in the economic equation, or investigated using simple proxies (e.g., language proficiency), much of this variability remains unexplained. One factor which has the potential to bring substantial explanatory power to this issue is culture. With studies supporting the relationships between cultural diversity and innovation (Schimmelpfennig et al., 2021), social connectedness and trade flows (Bailey et al., 2021), and cultural attitudes and labour market outcomes (Algan et al, 2012), cultural variables prove to be important predictors of economic outcomes. Yet, little is still known about the direct relationship between immigrants' socio-economic situation and the cultural differences between their home and host country. With the theoretical advancement on acculturation and collective brain models supporting the prospective for this link, there is a need for a direct assessment of this relationship.

While the socio-economic variables affected by culture could range from wealth to educational attainment, unemployment is arguably the most important of such measures from the psychological perspective. Besides affecting the workers' financial situation and the broader economy, unemployment causes unique psychological consequences. Across countries, unemployment and underemployment had been associated with a decline in individuals' long-term earnings (Cooper, 2013), mental health, psychological well-being, and physical health (Wanberg, 2012). Even short periods of unemployment can cause long-term consequences (Brand, 2015), which can affect people beyond the unemployed individual (e.g., children, spouses; Fryer, 2002). Crucially, many of those negative effect are not fully eliminated with subsequent reemployment (Brand, 2015). The severity of these consequences can be even more pronounced for foreign-born workers, for whom the unemployment periods bear negative effects on the adaptation to the host culture (Yijälä & Luoma, 2019). Worse adaptation can in turn lead to higher employment losses (Drydakis, 2012), creating a vicious cycle for the immigrants and the broader economy. These considerations are especially vital in the context of the United Kingdom, where both first- and second-generation immigrants are at a higher risk of unemployment compared to the native workers (Algan et al., 2010).

While immigrants' employment is often investigated in the context of social support or language proficiency, research suggests that it could be also affected by factors related to one's cultural values. For example, cultural norms relating to family obligations have been associated with lower attachment to the labour market (Naldini et al., 2016), while the variance in uncertainty avoidance has been related to differences in workplace performance (Cohen, 2007). Similarly, cultural differences have been associated with heterogeneity in the rates of self-employment (Vinogradov & Kolvereid, 2007), workplace incivility (Welbourne et al., 2015), communication with executives (Tosi & Greckhamer, 2004), approach to deadlines (Arman & Adair, 2012), perception of justice in the workplace (Shao et al., 2013), sensitivity to workplace bullying (Escartín et al., 2011), and even attitudes towards workplace gifts (Castaneda et al., 2013). With such wide-ranging findings, it is reasonable to assume that immigrants' work behaviour in the host country should be at least partially affected by the characteristics of their home culture. While this does not offer direct support for the relationship between culture and foreign-workers unemployment, it could still help explain how culture could affect workers' ability to find and keep a job.

For foreign-born workers, the potential effects of cultural differences could be further affected by their ability to adapt to the host culture. In cultural psychology, it is commonly assumed that interaction with new culture leads to acculturation – the process of changing cultural patterns in response to the prolonged contact with another culture (Schwartz et al., 2010). In the context of migration, acculturation is mostly concerned with how exposure to the host culture affects migrants' psychological and socio-economic outcomes. One recognized theory on such processes comes from Berry (2006), who argues that the acculturation approach is mostly dependent on individuals' relative preferences for maintaining the heritage culture or adopting the cultural patterns of the host country. The embraced approach is in turn directly related to psychological and socio-economic outcomes, with the acculturation strategy affecting immigrants' employment returns (Drydakis, 2012), job satisfaction, performance ratings, and workplace stress (Leong, 2001). While acculturation strategies can be influenced by personal expectations or political context (Ward & Geeraert, 2016), the adoption of a particular strategy is also directly affected by the cultural distance between the heritage and host culture (Demes & Geeraert, 2014; Galchenko & Van De Vijver, 2007). With cultural differences being linked to increases in acculturative stress and worsen socio-cultural adaptations (Taušová et al., 2019), these results offer additional support for the potential relationship between cultural distance and migrants' labour force participation.

Still, surprisingly few researchers evaluated the direct link between immigrants' economic situation and the extent of the "cultural clash" between their home and host cultures. Although economists show differences in the fiscal contribution of immigrants from various countries, they often overlook the role of culture in this phenomenon. At the same time, while cultural psychologists show the relationship between acculturation and employment, and cultural differences and acculturation, they rarely focus on the direct explanatory power of cultural distance. Even studies focused on cultural attributes are usually limited to a single immigrant population or a specific cultural dimension, making it difficult to establish the overall amount of variance in economic outcomes that can be attributed to cultural discrepancies.

One tool which allows to directly measure the effects of cross-cultural differences between societies is the cultural fixation index (CF_{ST}). Introduced by Muthukrishna et al. (2020), the CF_{ST} offers a novel method for the identification of cultural groupings and analysis of discrepancies in cultural dimensions. The proposed tool treats cultural attributes similarly to genetically transmitted traits, estimating the cultural profiles based on the distribution of cultural attributes. In its calculations, the CF_{ST} makes no assumptions about the unidimensionality or in-group homogeneity of cultural traits. Contrarily to tools that focus on point estimates (e.g., distances calculated from Hofstede's index scores), the CF_{ST} stresses the importance of frequencies and variations in cultural attributes. This allows comparing cultures beyond the mere mean differences, emphasising the multidimensionality of cultural space. At the same, by calculating the scores directly from the data on cultural values, the CF_{ST} outperforms tools that estimate cultural differences from distribution-based indirect measures (e.g., genetic distance). Consequently, the CF_{ST} offers a uniquely robust, evolutionary-sound and theoretically justifiable method for high-resolution cultural analyses (Muthukrishna et al., 2020).

By utilizing the unique advantages of CF_{ST}, this study aims to add to the debate on the impact of culture on immigrants' socio-economic outcomes. Addressing the gap present in the literature, we seek to investigate if the cultural distance between the home and host culture can explain the differences in employment rates of immigrants in the United Kingdom. To disentangle the amount of variance that is attributable to cultural differences, our research controls for numerous potential covariates (e.g., education). At the same time, by utilizing a direct measure of economic activity, it seeks to identify if the proposed model could explain – and potentially predict – immigrants' contribution to the labour force. As such, this research aims to provide additional predictive power for economic analyses, a better understanding of barriers to full employment, and new arguments for the introduction of targeted psychological interventions.

Research question: Does the cultural distance between the country of birth and the country of migration predict the employment rates of immigrants in the United Kingdom?

H_1: Cultural distance between the country of birth and the country of migration predicts the employment rates of immigrants in the United Kingdom.

H_0: Cultural distance between the country of birth and the country of migration does not affect the employment rates of immigrants in the United Kingdom.

Methods

Measures

To answer the proposed research question, the study used country-level secondary data. All utilized datasets were checked for methodological adherence to the guidelines from the 2nd edition of the BPS Code of Human Research Ethics (2021). Before study commencement, the institution's ethics approval was obtained. The research has been preregistered in the Open Science Framework on the 2nd of March 2022. The analysis plan, raw datasets and associated codebooks were compiled in a preregistration compendium and submitted internally to the university on the 4th of January 2022.

Dependent Variable

The employment rates were derived from the Eurostat 2011 European Census. Eurostat collates the national censuses of over 30 European countries, offering rich, records of socio-demographic statistics on the European population. As the national censuses collect the data on all residents, they offer a uniquely representative, cross-sectional database. Results of the European Census are publicly available, and there is no restriction on the usage of the aggregated data. Although the data collection methods vary between countries, all censuses are run according to the European statistical legislation. In the United Kingdom, the 2011 Census questionnaire was delivered mainly through the post.

The variables derived from the Eurostat dataset included the residents' current activity status by the country-level place of birth for the UK subset (i.e., the overall number of UK residents born in a given country who are economically active, non-active, employed, or unemployed). The requested data was limited to the overall number of residents with the given status; no individual-level data was obtained. In the Eurostat dataset, economic activity is a self-reported measure compatible with the definition from the International Labour Organisation. As the economic activity data is collected only on residents who are above the age of 16, the derived aggregated data did not include data on younger participants. Further information on the data collection and variables' definition for the 2011 Census can be found in the Eurostat Quality Report (Office of National Statistics, n.d.). The data was downloaded from the European Commission website on the 3rd of November 2021.

Independent Variable

The cultural distance was based on the cultural fixation index (CF_{ST}) derived from the "Cultural Distance" dataset (Culturalytics, n.d.). The index is calculated as the ratio of the between-group variance to the within-groups variance on the responses to the chosen questions from the World Value Survey (WVS). The utilized questions concern culturally transmissible values, beliefs, and behaviours, with the CF_{ST} subdimensions utilizing the responses on topics ranging from financial principles to sexuality values. Importantly, contrarily to the measurement of genetic or linguistic distance, the cultural fixation index can be considered as a direct measure of culture and does not face the limitation of estimating cultural values from related proxies. The index is highly robust even to question loss and is an effective measure of cultural differences beyond WEIRD (Western, Educated, Industrialized, Rich and Democratic) societies (Muthukrishna et al., 2020). The dataset is publicly available; more information on the index methodology and the variables included can be found on the Culturalytics website (n.d.).

WVS – the source of the data for the cultural distance estimates – is the largest non-commercial social science survey. Collecting data on over 100 countries, its results can be taken as representative of over 94% of the world population. The survey waves are run every five years, across all residents aged 18 years and older, with a minimum sample size of 1200 participants per country. The survey utilizes probability sampling, ensuring nationally representative results. Where possible, the data is collected during a face-to-face interview. In some cases, responses are recorded using postal or telephone interviews (World Value Survey Association, 2020). Depending on the type of question, the WVS utilizes, among others, Likert-type, binary and categorical scales. The full questionnaires for the WVS waves underlying the derived variables can be found on the Culturalytics webpage (n.d.).

For this study, the cultural distance data was restricted to the CF_{ST} calculated from the 2005-2009 and 2010-2014 WVS waves (Inglehart et al., 2018a; Inglehart et al., 2018b). This represented the most recent grouping for which the CF_{ST} for the United Kingdom was available. The data was downloaded directly from the Culturalytics website on the 18th of November 2021.

Control Variables

Migrant Population Size. Migrant population size was included as a control variable to adjust for the size of the migrant community (i.e., the number of UK residents born in the given country). The increased migrant community size may lead to network effects, in which the utility of migrants increases with the increased size of their ethnic groups (e.g., through financial support, availability of social capital, community relationships, lowered language barriers, availability of guidance in the job search process, facilitated the flow of information, conformity with the group rules, affinity bias, etc.). The importance of this control is supported by findings that personal networks and ethnic concentrations have a significant effect on migrants' labour market integration (Maani et al., 2015) and occupational prestige (Mullan, 1989).

The migrant population size was derived from the Eurostat 2011 European Census and reflects the number of UK residents who were born in the given country. This variable is part of the same dataset that was used as a source of the labour force participation rates; thus, the details of the data representativeness, collection method and access date match the ones described in the Dependent Variable section.

Genetic Distance. The genetic distance was controlled for to ensure that the genetic differences do not shrink the true effect sizes for the cultural distance. In the dataset, genetic distance represents the differences in frequencies of alleles in the investigated populations (i.e., how frequencies differ from the ones we should observe with truly random mate selection). Thus, it can be seen as a measure of similarity in transmitted characteristics, and it is closely related to the time since the populations' last common ancestor. By including the variable in the model, we can investigate the effects of culture beyond the effects of genes. The importance of this control is related to its real-life significance in explaining genotype – and thus phenotype – differences (i.e., allowing us to focus on cultural distance, and move beyond the potential effect of physical attributes or visible cues that might lead to discrimination). Moreover, as the genetic distance itself is predictive of economic outcomes (Saha & Mishra, 2020), its inclusion in the model removes its potential for yielding the third variable problem. The importance of this control is proved by the significant correlation between the genetic distance and income differences across time and populations, which is hypothesised to be caused by its negative effect on the diffusion of innovation and spread of development (Spolaore & Wacziarg, 2009).

The utilized genetic distance measure was calculated based on the human microsatellite variation (i.e., variance in the parts of DNA that have high diversity and mutation rates, which allows for analysis of nuanced differences). The country-level distance had been obtained by matching the populations based on ethnic composition data. The details on the calculation involved can be found in Spolaore and Wacziarg (2017). This approach to genetic distance yields a measure that is highly correlated with other metrics of genetic relatedness, supporting its high reliability. The variable was downloaded on the 3rd of November 2021 from Enrico Spolaore's website (n.d.).

Note.

The remaining control variables were derived from the Varieties of Democracy dataset (V-Dem; Coppedge et al., 2021). V-Dem provides statistics on important socio-economic indicators on countries around the world, compiling publicly available data from numerous databases. All variables derived from V-Dem have been restricted to 2011 scores, to match the date of collection of the dependent variable. The whole V-Dem database, including the datasets, the methodology booklets and codebooks were downloaded on the 18th of November 2021. As these procedures remained constant across variables, the following descriptions focus solely on the motivation for this choice of controls, codebooks' identifiers for the chosen variables, variables' definitions, and their original sources.

GDP Per Capita. GDP per capita of the country of birth was included as a control variable to adjust for the between-countries differences in productivity, residents' approximate level of socioeconomic status from before migration, and potential financial support received from the country of birth. The GDP variable (*e_migdppcln* in the V-Dem dataset) was derived from the 2nd edition of the Maddison Project Database and represents the gross domestic product per capita transformed by the natural logarithm. This variable is based on benchmark comparisons of prices and is expressed in inflation-adjusted US dollars (Inklaar et al., 2018).

Education. Education was included as a control variable to adjust for the level of education and approach to education in migrants, and the effect of education on the attitude towards host society and ease of acculturation (De Vroome et al., 2014). As no direct data on the level of migrants' education was available, the level of education in the country of birth was included as its proxy. The education variable is available in the V-Dem dataset as *e_peaveduc* and is originally derived from the dataset offered by the Clio Infra project (2021). The variable represents the average years of education among citizens older than 15 in each country. Although this dataset derives the year-specific data based on cross-analysis of other databases, rather than the primary data collections, all data for the 2010 benchmark was derived from the Central Statistical Agencies, supporting the high reliability of the 2011 scores.

Population. The population size of the country of birth was included in the analysis to control for the effects of the increased number of potential migrants. The size of the pool of potential migrants might affect the profile of the candidates who ultimately manage to migrate, leading to potential candidate selection and unobserved clustering. This also allows us to control for migrants' familiarity with novel cultures – as bigger countries tend to represent an assembly of smaller communities, migrants from such nations may be more accustomed to cultural differences and differing populations.

The total population size (identified as *e_wb_pop* in the V-Dem codebook) was originally obtained from the World Bank Development Indicators (WBDI; World Bank, 2019). WBDI offers a representative, compiled source of global development data on national, regional, and global levels. The offered population size variable is derived from official sources, including national censuses, United Nations reports and other international databases. Although the data quality may depend on the statistical systems of participating countries, WBDI can be still regarded as an exceptionally reliable database for such a metric.

Regional Identifier. The regional identifier was included as a control variable to adjust for the influence of geographical factors on immigrants' situations and decrease the probability of occurrence of the Simpson's paradox (i.e., ensure that the potential group clustering does not lead to misleading results by concealing the true trend). The variable reflects a categorical score for the geographic region in which a country is located (e.g., West Asia, Southern Europe etc.). Identified as *e_regiongeo* in the V-Dem, it has its source in the database from the United Nations Statistics Division (2013). As this exclusive level of clustering might have potentially led to a loss of the between-country variation, the variable was transformed into continent-level categorization.

Analysis Plan

The data was prepared for analysis through variable processing, outliers' removal, missing data imputation and assumptions checks. The initial relationship between cultural distance and employment rates was checked with a simple linear model with one dependent (employment rates) and one independent (cultural distance) variable. For the confirmatory analysis, the relationship was analysed using multiple regression analysis. The confirmatory model included one dependent (employment rates), one independent (cultural distance), and six control variables (GDP per capita distance, genetic distance, migrant population size, education distance, population size distance, regional identifier). For both models, the results were investigated using the least square regression. The significance of the effects was further checked with 5000 bootstrapped resamples, as per the recommendations from Banjanovic and Osborne (2016). The procedure was performed due to its effectiveness in controlling for Type 1 error. The models were also investigated with the post-hoc power analysis. For the confirmatory model, the robustness of the results was subsequently checked by evaluating nested models with varying combinations of control variables.

Results

Preliminary Analyses

Data Preparation.

The employment rates were calculated by dividing the number of employed respondents by the number of economically active respondents for each country. GDP per capita and education variables were transformed to GDP and education distance by subtracting the country score from the UK score, to facilitate the interpretation of their effects in the context of cultural and genetic distance. The regional identifier was transformed from regional to continent level by clustering the groups.

For the migrant population size, the variable was log-transformed before the further analysis. This was done to allow for relative, rather than additive interpretation of differences in the population sizes, and to correct for the severe skew present in the dataset ($skew_{PopulationSize} = 3.53$, $z = 12.96$; $skew_{LogPopulationSize} = -0.52$, $z = -1.92$; see Appendix A for details). Following that reasoning, the total population size was log-transformed before being converted to population distance. As the remaining variables followed a relatively normal distribution, no further transformations were performed.

Data screening.

Due to the use of a dataset with varying inclusion criteria, the data was restricted to the countries for which both the dependent and independent variables were present. For the regional identifier, which was objective in nature (i.e., representing the continent in which the given country is located), the missing case was imputed by hand (n = 1). The resulting dataset contained 3.3% of missing data across other control variables. The distribution of missing data was tested using the MCAR test from Jamshidian et al. (2014). The non-parametric test of homoscedasticity suggested that the data was MCAR (p = 0.08). Consequently, the data was imputed using the Random Forests methodology, with the MissMech package (Stekhoven, 2022). This approach was selected as it can deal with categorical variables and has been shown to outperform other methods across missingness types (Kokla et al., 2019). As this method deviates from the one proposed in the preregistration (i.e., Multiple Imputation), the significance of the main results was also tested on the dataset prepared in accordance with the preregistered approach.

The outlier analysis has been performed according to the guidelines from Tabachnick and Fidell (2013), and Osborne (2013). As per their recommendations, all univariate outliers (n = 1) were removed. The dataset contained no multivariate outliers. As such, the final sample consisted of 77 countries (see Appendix B for descriptive statistics).

Following the data cleaning procedures, the investigated models were checked for the assumptions using the performance R package (Lüdecke et al., 2021). As per the guidelines from Best and Wolf (2014), both models were inspected for the assumption of linearity, homoscedasticity, normality of residuals, autocorrelation, and multicollinearity. The visual inspection of the figures allowed us to accept the initial assumptions. According to the recommendations from Fox and Monette (1992), the assumption of multicollinearity was further investigated using the Generalized Variance Inflation Factor (GVIF); for all covariates, the GVIF score was below 2. The normality of residuals was further tested with the Shapiro-Wilk's test; the results allowed to reject the hypothesis that the residuals follow a non-normal distribution (p = .18). Thus, all assumptions were accepted.

Simple Model

The simple relationship between the cultural distance and employment rates was investigated using linear regression analysis. Results indicated that cultural distance negatively predicts employment rates when the no control variables are imposed (b_1 = -0.38,

$t(76) = -7.02$, $p < .001$; Table 1.). The correlation between cultural distance and employment rate was large ($\beta = -.63$). The bootstrapped confidence intervals associated with the regression did not include zero, confirming the result's significance ($b_1 = -0.38$, 95%CI [-0.48, -0.27]). The visual representation of the relationship can be found in Appendix C.

Model analysis indicated that cultural distance explains 40% of variance in employment rates ($R^2_{adj} = .387$, $F(1, 76) = 48.998$, $p < .001$). The post-hoc power analysis indicated that the results have met the recommended 80% statistical power (Cohen, 1988), with two-sided analysis indicating power of 0.99 (n = 77, $r = -.63$).

Table 1.

Regression Results for the Simple Linear Relationship Between Cultural Distance and Employment Rates.

Predictor	Unstandardized		Standardized		*SE*	*t*	Model Fit 95% CI
	b	95% CI	β	95% CI			
(Intercept)	0.95**	[0.94, 0.97]			0.009	111.71	
Cultural Distance	-0.38**	[-0.48, -0.27]	-.63	[-.81, -.45]	0.054	-7.02	
							$R^2 = .395$** [.22,.53] $R^2_{adj} = .387$**

Note. A significant *b*-weight indicates the *β*-weight correlations are also significant.
* indicates $p < .05$. ** indicates $p < .01$.

Confirmatory Model

The confirmatory model included cultural distance, employment rates, and six control variables (genetic distance, population size, population distance, education distance, GDP per capita distance, and regional identifier). Results indicated that the negative effect of cultural distance on employment rates remained significant when the control variables were included ($b_1 = -0.19$, $t(65) = -2.918$, $p = .004$). The main correlation became moderate when controls were introduced (β = -.31). The significance of this result was confirmed with the bootstrapped confidence intervals (b_1 = -0.19, 95%*CI* [-0.32, -0.06]). The visual representation of the main relationship with the control included can be found in Appendix C.

Further examination supported that the full model was significant, explaining 71% of variance in employment rates (R^2_{adj} =.658, $F(1, 65) = 14.296$, $p < .001$; Table 3.). The post-hoc power analysis indicated that the study was sufficiently powered, with a two-sided analysis indicating a power of 0.99 (n = 77, R^2 = .708). The performance of the simple and confirmatory model was subsequently compared with ANOVA; the results revealed that the model with all controls should be preferred over the simple model with no controls ($F(10, 75) = 6.943$, $p < .001$).

The robustness of the results was tested across nested models, with different combinations of control variables. The significance of the main relationship held across all cases (Appendix D). Similarly, the significance of the main relationship held when the missing data imputation was performed according to the alternative methods proposed in the preregistration (b_1 = -0.19, $t(65) = -2.982$, $p < .001$; Appendix E). To address the critique of the unnecessary outlier removal (Bakker & Wicherts, 2014), the confirmatory analysis was also applied to the data with no outliers removed. The test revealed that the relationship became insignificant when the dataset included the previously removed single univariate outlier (b_1 = -0.09, $t(66) = -1.470$, p = 0.15; Appendix F).

Table 2.

Regression Results for the Relationship Between Cultural Distance and Employment Rates, with Control Variable Included

Predictor	Unstandardized		Standardized		*SE*	*t*	Model Fit 95% CI
	b	95% CI	β	95% CI			
(Intercept)	0.81**	[0.74, 0.88]			0.034	23.487	
Cultural Distance	-0.19**	[-0.32, -0.06]	-.31	[-.44, -.18]	0.064	-2.918	
Genetic Distance	0.89**	[0.36, 1.43]	.31	[-.23, .85]	0.269	3.320	
Log Population Size	0.01**	[0.01, 0.01]	.40	[.40, .41]	0.002	4.272	
Education Distance	-0.00*	[-0.01, -0.00]	-.26	[-.26, -.26]	0.002	-2.084	
Distance GDP	-0.00	[-0.02, 0.01]	-.11	[-.11, -.09]	0.005	-0.912	
Population Distance	0.00	[-0.00, 0.01]	.06	[.06, .07]	0.002	0.668	
Region: Asia	0.02	[-0.01, 0.04]	.20	[.17, .22]	0.011	1.559	
Region: Europe	0.04*	[0.01, 0.07]	.37	[.33, .40]	0.015	2.407	
Region: North America	0.03	[-0.00, 0.07]	.19	[.15, .22]	0.017	1.992	
Region: Oceania	0.04	[-0.01, 0.09]	.14	[.09, .19]	0.025	1.605	
Region: South America	0.04**	[0.01, 0.07]	.27	[.24, .30]	0.015	2.772	
							R^2 = .708** [.52,.75] R^2_{adj} = .658**

Note. A significant *b*-weight indicates *β*-weight correlations are also significant.
* indicates p < .05. ** indicates p < .01.

Table 3.

Analysis of Variance for the Confirmatory Model of Cultural Distance and Employment Rates.

Model	Sum of Squares	*df*	Mean Square	*F value*	*PRE*	*p*
Model	0.111	11	0.010	14.296	0.708	< 0.001
Error	0.046	65	0.001			
Total	0.156	76	0.002			

Exploratory Analysis

Methods

With the confirmatory results' supporting a negative relationship between cultural distance and employment rates, the further exploratory analysis focused on investigating the relative role of the different dimensions of CF_{st} in this relationship.

Measures

The supplementary variables for the exploratory analysis were derived from the previously described Cultural Distance database. The derived subdimensions were group membership, which includes attitudes toward trust, nationalism and discrimination; politics, which includes attitudes toward egalitarianism and democracy; beliefs, which includes attitudes toward spirituality, morality and norms; social relationships, which includes attitudes toward relationships, interdependence and child-rearing; financial, which includes attitudes toward economy and finance; sexuality, which includes attitudes toward gender and sexual relationships; law, which includes attitudes toward security and legislation; and miscellaneous, which includes attitudes toward other variables, such as innovation, leisure and consumerism (see Muthukrishna et al., 2020, for a more detailed description).

Analysis Plan

The exploratory analysis followed the steps of the confirmatory analysis, with the overall cultural distance being replaced by the individual subdimension. To consider the potential outliers associated with each subdimension, the screening procedures were repeated for the new variables. The exploratory dataset contained 1.5% of MCAR data. The missing cases were imputed using the Random Forest approach. Outlier removal ($n_{univariate} = 1$, $n_{multivariate} = 0$) yielded the final sample of 77 countries. The exploratory analysis was performed using eight independent least square regressions models; each model included one dependent (employment rates), one independent (single subdimension), and six control variables (GDP per capita distance, genetic distance, migrant population size, education distance, population size distance, regional identifier).

Results

Results indicated that six of the eight individual subdimensions had a significant negative effect on the employment rates when all controls were included (beliefs: b_1 = -0.08, $t(65)$ = -2.858, p = .01, law: b_1 = -0.08, $t(65)$ = -2.214, p = .03; political: b_1 = -0.14, $t(65)$ = -2.542, p = 0.01; sexuality: b_1 = -0.10, $t(65)$ = -4.035, p = < .001; group membership: b_1 = -0.14, $t(65)$ = -2.646, p = 0.01; social relationships: b_1 = -0.20, $t(65)$ =-2.573, p = 0.01). The significance of all relationships was confirmed with bootstrapped confidence intervals. The main effect was insignificant for the financial and miscellaneous dimension (financial: b_1 = -0.06, $t(65)$ = -0.592, p = 0.56; miscellaneous: b_1 = -0.01; $t(65)$ = -1.333; p = .19) Among the subdimensions that had a significant effect on employment rates, the two models with the best fit were sexuality (R^2_{adj} = .687, $F(1, 65)$ = 16.134, p < .001) and beliefs (R^2_{adj} = .652, $F(1,65)$ = 13.934, p < .001). Results of all exploratory analyses can be found in Appendix G.

Discussion

Our findings support that when controlling for genetic distance, population size, population distance, education distance, GDP per capita distance, and regional identifier, the cultural distance between the home and host country explains the employment rates of immigrants in the United Kingdom. While the cultural distance alone allowed us to explain 40% of the variance in employment rates, the addition of controls increased our explanatory power to 71%. The main effect was robust across varying imputation methods and inclusion or exclusion of controls. Although the investigated sample included only 77 records, the strength of the main relationship allowed the results to reach the recommended power. Exploratory analyses revealed that the relationship between cultural distance and employment remained significant for subdimensions associated with beliefs, law, politics, sexuality, group membership and social relationships, but not for the dimensions associated with finances and miscellaneous variables. At the same time, the relationship between the overall cultural distance and employment rates became insignificant when the single identified univariate outlier was not removed from the sample.

Although this study represents the first attempt at measuring the effects of country-level cultural distance on employment rates, our findings stand in line with the broader literature on fiscal outcomes. Related results have been reported by Lundborg (2013), who found significant effects of the country of origin on the employment rates of immigrants in Sweden. While this study did not measure cultural differences directly and did not control for important extraneous variables (e.g., education level, language proficiency), Lundborg did hypothesise that the better performance of immigrants from Eastern Europe and Latin America was attributable to the cultural distance. Similarly, the effects of country of birth on employment rate have been also reported for the immigrants in England (Price, 2001), Canada (Bauder, 2001), Belgium (Corluy et al., 2011) and the United States (Chiswick & Hurst, 2000). Although such research did not focus on the cultural distance, and cannot directly support our results, it still reports variability that is consistent with our findings.

One potential explanation for the pattern of obtained results comes from the research on acculturation. The greater distance between cultures "implies the need for a greater culture shedding and culture learning" (Berry, 2008), which can lead to an internal conflict, decreased participation in host country activities, and a more challenging acculturation process. This hypothesis finds support in the empirical literature, with the perceived cultural distance being directly linked to worse acculturation outcomes, lower self-esteem, and higher stress levels (Galchenko & Van De Vijver, 2007). At the same time, the successful acculturation to the host country has been associated with greater employment probabilities (Nekby & Rödin, 2010).

The effect of cultural differences can be also explained by research on discrimination. Studies suggest that cultural differences can affect attitudes towards immigrants, with cultural distance being positively related to higher levels of prejudice, and negative out-group attitudes among natives (Mahfud et al., 2015). Discrimination is in turn directly related to immigrants' attitudes towards host culture (Tan & Liu, 2014), and broader acculturation outcomes (Berry & Hou, 2017). At the same time, discrimination can also directly influence work opportunities. As suggested by Lundborg (2013), the perception of cultural differences can lead to employer uncertainty and cause employment discrimination. This is supported by findings on the negative influence of foreign-sounding names on earnings and recruitment outcomes (Bertrand & Mullainathan, 2004). Crucially, the strength of the disadvantage caused by the foreign-sounding resume has been shown to be greater for workers from more culturally distant countries (Fossati et al., 2020).

The evaluation of the potential explanations can be further influenced by the results of our exploratory analysis. Although we obtained significant effects for six subdimensions of cultural distance, the two subdimensions which allowed us to reach the highest explanatory power were sexuality and beliefs. While the results of the former could be partially explained by the clash in cross-cultural approaches to sexuality, the obtained effects require further examination. The literature on the relationship between sexuality and immigration outcomes is limited, and the true effect might have been inflated by extraneous factors (e.g., the United Kingdom could be an outlier in terms of sexuality, which would influence the distances and affect results). On the other hand, the results obtained for beliefs stand in line with the broader literature on religion and spirituality. Besides its link to religious discrimination, religious affiliation can also have an impact on labour market attachment, work behaviour or job preferences (Alidadi, 2017). The importance of such effects is supported by the findings on the relationship between religion on labour market disadvantage, which remains significant even when controlled for workers' ethnicity (Lindley, 2002).

Interestingly, our exploratory analysis has also shown no significant relationship between employment rates and cultural differences in the dimension of financial attitudes. Although this finding is counterintuitive, it may be that the effect of financial attitudes became irrelevant when decupled from the differences that are directly associated with discrimination or work behaviour (e.g., attitudes on norms, religion). However, it may also be that the cultural differences in financial attitudes are simply not pronounced enough to exhibit an effect; among all subdimensions, financial had the smallest range, and lowest standard deviation. A similar case can be made for the miscellaneous dimension, which also was not linked to the employment rates, and had the antepenultimate smallest range. However, this effect could also be explained by the sheer nature of the miscellaneous dimension; as it represents an agglomeration of various items, its explanatory power is expected to be low.

Whilst the main findings of our research are consistent with the broader literature, there are several limitations that need to be considered when evaluating our study. Firstly, it is crucial to note that our model became insignificant when the single univariate outlier was not removed. Although we followed the guidelines from Tabachnick and Fidell (2013), preregistered our approach prior to the analysis, and confirmed the extremity of our outlier with the more robust MAD method (Leys et al., 2013), the removal of influential outliers remains controversial in the field. In the case of our study, this is further affected by the relatively small sample size. Although we used high-quality datasets (i.e., nationally representative, from unbiased sources), the differences in the inclusion criteria restricted our analysis to 77 countries. Thus, the accuracy of our results should be further tested on an alternative sample, using different data sources, or utilizing records from different periods.

Secondly, the generalizability of our results is also affected by our concentration on the United Kingdom. Compared to other countries, the immigrants in the United Kingdom are outliers in terms of fiscal contribution, and skill levels (Algan et al., 2010). At the same time, the United Kingdom is not representative in terms of the number of accepted immigrants, and its migration policies. This limitation is particularly important in the context of our independent variable; as the cultural distance was calculated for a single host country, the obtained estimates might have been skewed by the unique characteristics of the chosen population. In other words, we cannot establish if the obtained effects were driven by true cultural distances or affected by the host country's national culture (Brouthers et al., 2016). Although the distribution-focused nature of CF_{st} may partially alleviate this issue, the United Kingdom still represents a unique host country, and a WEIRD culture (Muthukrishna et al., 2020). Thus, the validity of our result should be investigated in a sample of countries with different migration patterns, and diverse CF_{st} scores.

Thirdly, we cannot rule out that the observed effect was driven by factors other than cultural differences. While we tried to control for a large number of external variables, the country-level analysis forced us to use indirect proxies. For example, our control for education was based on the average level of education in the home countries. This fails to capture that the immigrant's educational attainment might increase after migration or might be fundamentally different from the average education level in their home country in the first place. Due to the focus on country-level differences, we also did not control for language proficiency, which has been shown to be an important predictor of employment rates among immigrants in the United Kingdom (Dustmann & Fabbri, 2003). Similarly, we also did not control for race, which might potentially affect employment through discrimination. While its influence might have been partially captured by controlling for the genetic distance, future studies could benefit from including it in their controls.

Our results were also limited by the utilized measure of immigrants' employment rates. Although the use of the Census records allowed us to obtain nationally representative data, it has been suggested that population censuses provide lowered estimates of true labour force participation rates (Ilostat, n.d.). While consistently low estimates should not influence the results (i.e., they should affect all records equally, and thus should not affect the differences), the use of Census data has also forced us to use the workers' country of birth as a proxy for their immigration status. The use of such measure does not allow us to extend the results to second-generation immigrants, control for the time since migration, or consider migrants who do not identify with the culture of their country of birth (e.g., come from multicultural families, lived in a different country). Accordingly, it would be beneficial to check if our results remain significant across alternative proxies for immigration status, and different economic measures (e.g., earnings, different measures of employment). The latter approach would also allow to examine the potential influence of "survival jobs", whose incidence may skew the estimates of employment among migrants (Dean & Wilson, 2009)

Lastly, it is important to consider the limitations related to the use of cultural distance. By focusing on the between-country comparisons, we assume that the cultural characteristics of the immigrant populations are equivalent to the cultural characteristic of their countries of origin. This does not account for the individual differences in cultural values, the effects of acculturation, or the inherent differences in immigrants' cultural profiles (the differences in cultural values may be the reason for migration in the first place). Although such cultural heterogeneity is partially addressed by the CF_{st}'s focus on in-group frequencies and variation, these effects might have distorted the strength or significance of our effects.

To address these limitations, future studies could consider focusing on the individual-level data. Such an approach would allow to directly control for important covariates (e.g., education level, language proficiency), explore the impact of the clustering effects (e.g., gender, race), measure the individual differences in cultural values, and investigate the result among second-generation immigrants. This last area is especially interesting in the context of the United Kingdom, where the differences in economic outcomes between first- and second-generation immigrants are particularly pronounced (Algan et al., 2010).

At the same time, future research could also benefit from investigating the potential mechanisms behind our results. While the link between cultural distance and employment rates might be mediated by acculturation or discrimination, it could also be related to the issues around cooperation, social identity, cultural brain, or barriers to information flow. Such analysis could be also coupled with the investigation of the temporal validity of our findings. Since the 2011 Census, immigration, employment, and even cultural patterns might have been influenced by globalization, Brexit, and the COVID-19 pandemic. While these global dynamics create new challenges for researchers interested, they also further support the importance of obtaining strong, and reliable predictors of socio-economic outcomes.

Despite its shortcomings, our research offers novel evidence for the role of culture in immigration outcomes. With the confirmed explanatory power, the cultural distance could be applied to better understand the opportunities for micro-interventions, differential allocation of social support, or changes in the immigration policies. Similarly, our results offer strong arguments for the inclusion of cultural distance in future research attempts; its strong influence over between-group variance could increase the predictive power of both economic and psychological analyses. Although more and more scholars acknowledge the importance of moving beyond WEIRD-ness, the power of cultural differences remains underestimated by practitioners. We trust that the present study displayed that the cultural variables could offer important predictors for real-world outcomes. While the link between cultural distance and employment among immigrants should be investigated across different settings, our findings add a small piece to the growing literature on the far-reaching effects of culture.

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Appendices

Appendix A

Distribution Analysis for Population Size

Note: The below figures are presented for the data prior to the outlier removal.

Figure A1.

Distribution of Population Size Before Log Transformation

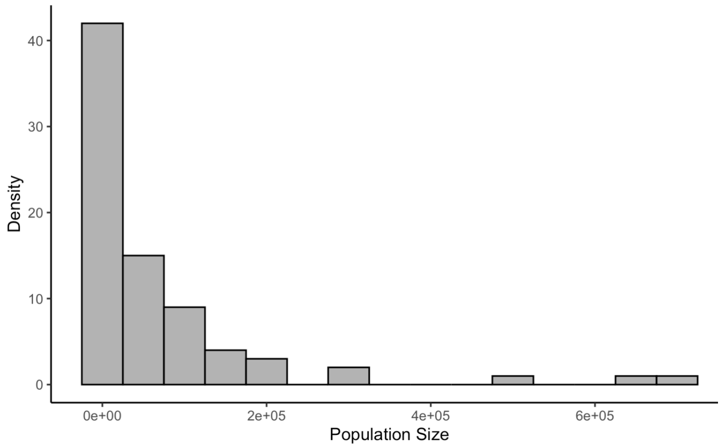


Figure A2.

Distribution of Population Size After Log Transformation

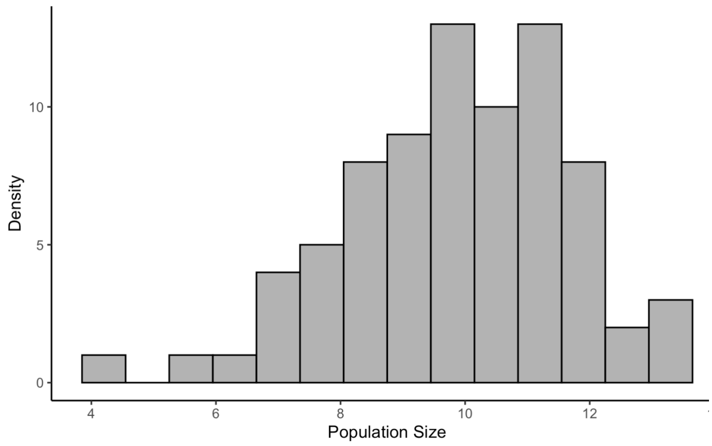


Table A1.

Descriptive Statistics for Population Size Before and After Log Transformation.

Condition	*M*	*SD*	Skewness		Kurtosis	
			estimate	*Z-score*	*estimate*	Z-score
Population Size	69,717.12	129,790.02	3.53	12.96	13.69	25.44
Log Population Size	9.87	1.84	-0.52	-1.92	0.47	0.87

Appendix B

Descriptive Statistics for the Cleaned Dataset

Table B1.

Descriptive Statistics for Employment Rates, Cultural Distance, and Control Variables.

Variable	*N*	*M*	*SD*	Skewness		Kurtosis	
				estimate	*Z-score*	*estimate*	*Z-score*
Employment Rates	77	0.90	0.05	-1.03	-3.7	0.72	1.33
Cultural Distance	77	0.14	0.08	0.54	1.97	-0.20	-0.37
Log Population Size	77	9.87	1.85	-0.50	1.86	0.42	0.78
Genetic Distance	77	0.02	0.02	- 0.67	2.45	1.04	-1.93
Education Distance	77	4.15	2.72	0.70	2.57	0.30	0.55
Distance GDP	77	0.89	1.01	0.48	1.76	0.22	0.41
Population Distance	77	1.19	1.58	-0.26	-0.94	0.05	0.10

Figure B1.

Distribution of Employment Rates of Immigrants in the UK (Country-Level).

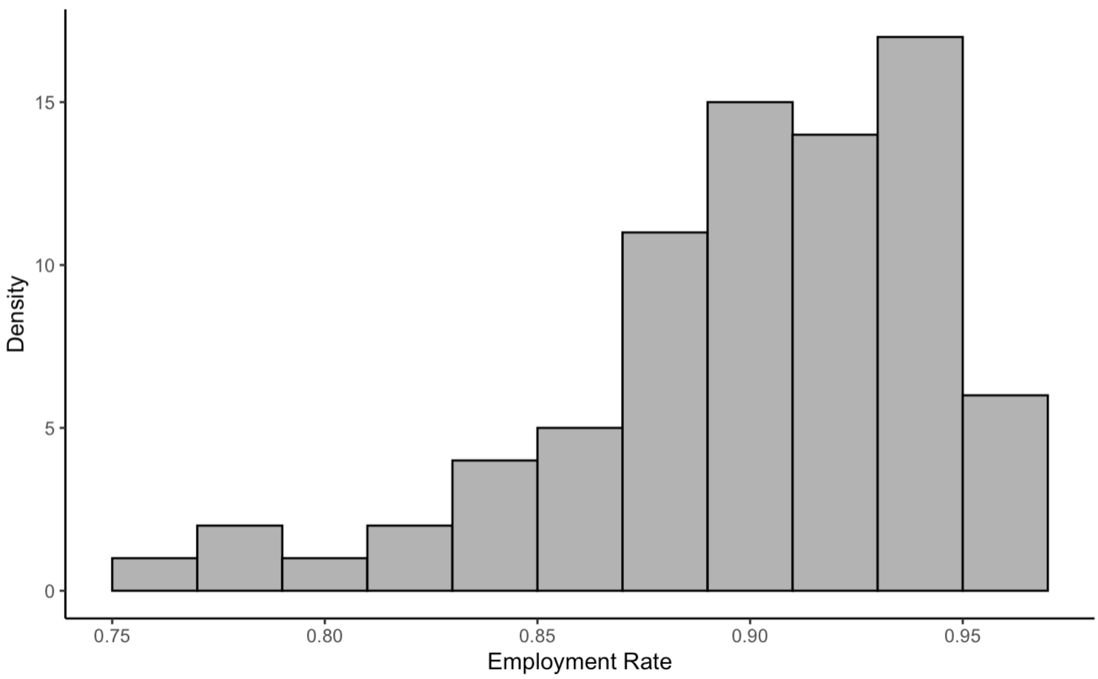
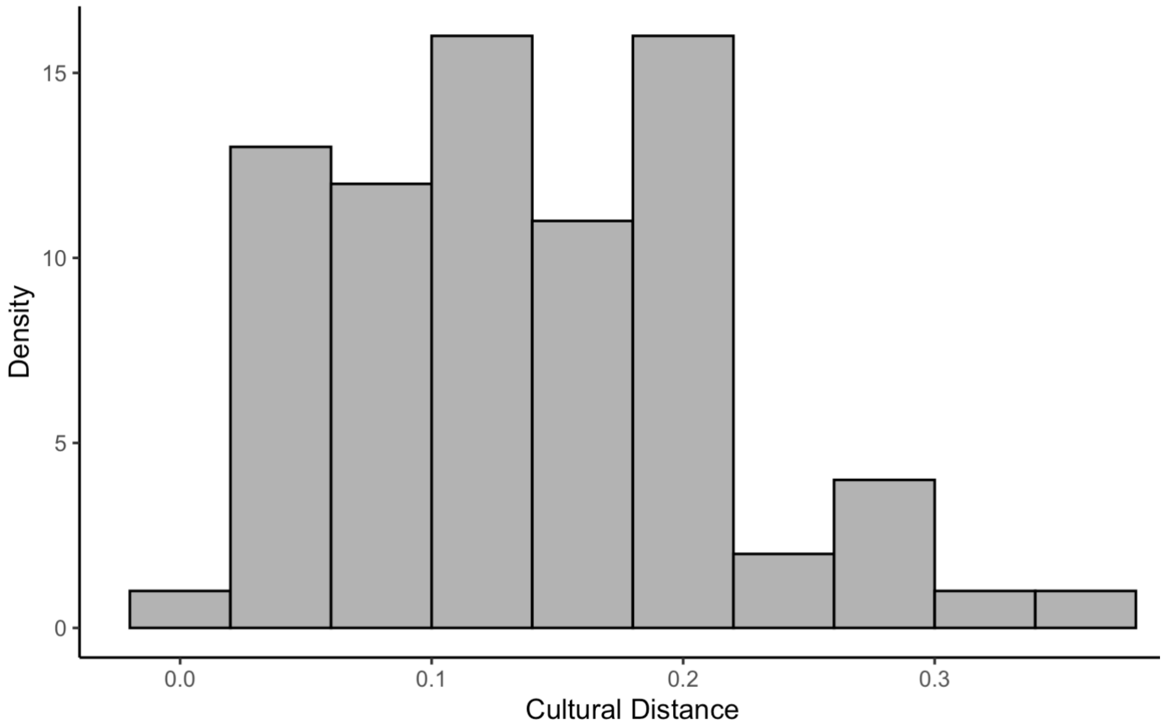


Figure B2.

Distribution of Cultural Distance from Immigrants' Home Countries to the UK (Country-Level).



Appendix C

Visual Representation of The Simple Model

Figure C1.

The Simple Relationship Between Cultural Distance and Employment Rates of Immigrants in The UK (Country-Level).

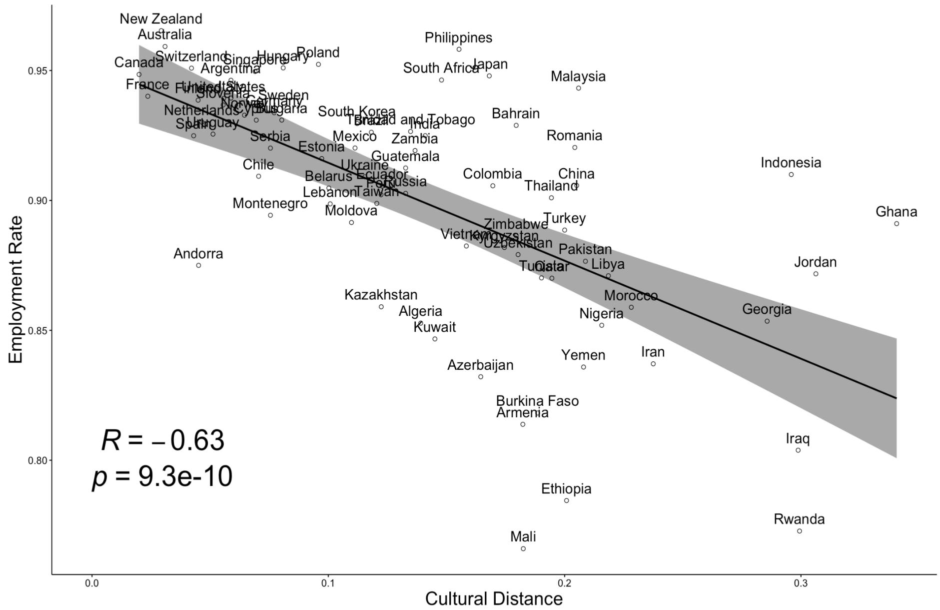
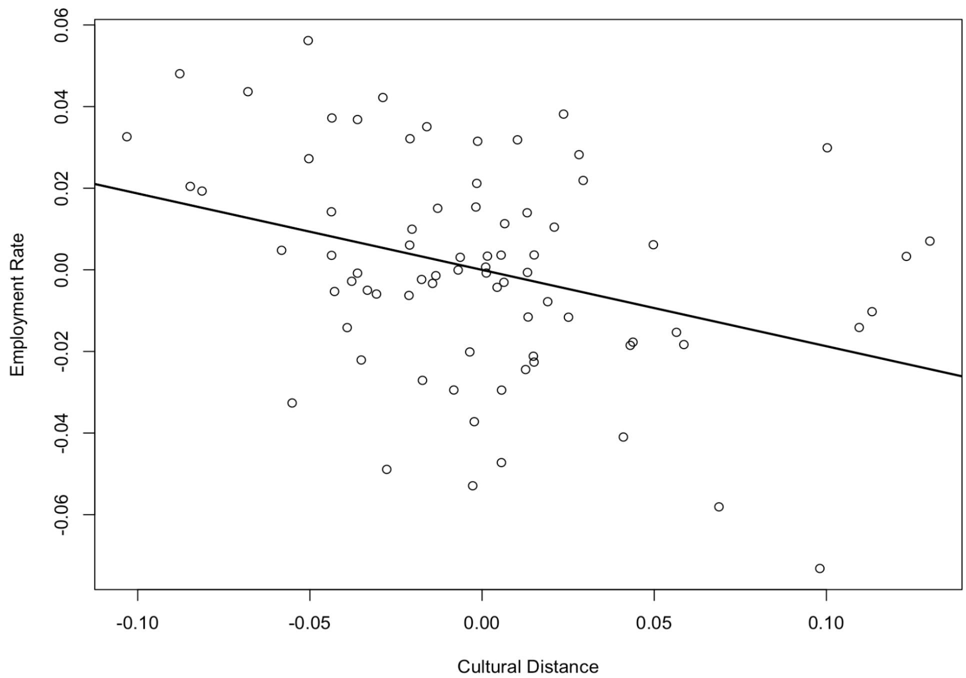


Figure C2.

The Added Variable Plot for Relationship Between Cultural Distance and Employment Rates of Immigrants in The UK (Country-Level; Control Variables Included).



Appendix D

Multivariate Analysis of the Control Models

Figure D1.

Analysis of the Nested Models for the Relationship Between Cultural Distance and Employment Rates in Immigrants in the UK (Country-Level).

Covariates	Dependent Variable				
	Employment Rates				
	(1)	(2)	(3)	(4)	(5)
Cultural Distance	-0.38** (0.05)	-0.23** (0.06)	-0.24** (0.06)	-0.17* (0.08)	-0.19** (0.06)
Education Distance		-0.01* (0.00)	-0.01* (0.00)	-0.01* (0.00)	-0.00* (0.00)
Population Distance		-0.01** (0.00)	-0.00 (0.00)	-0.01** (0.00)	0.00 (0.00)
Distance GDP		-0.01 (0.01)	-0.00 (0.00)	-0.01 (0.01)	-0.01 (0.01)
Log Population Size			0.01** (0.00)		0.01* (0.00)
Region: Asia				0.00 (0.01)	0.02 (0.01)
Region: Europe				0.01 (0.02)	0.04* (0.02)
Region: North America				0.02 (0.02)	0.03 (0.02)
Region: Oceania				0.03 (0.03)	0.04 (0.03)
Region: South America				0.02 (0.02)	0.04** (0.02)
Genetic Distance					0.90** (0.27)
Constant	0.95** (0.01)	0.97** (0.01)	0.87** (0.03)	0.95** (0.02)	0.81** (0.03)
Observations	77	77	77	77	77
R^2	.395	.562	.629	.577	.708
R^2_{adj}	.387	.537	.603	.521	.658
Residual Std. Error	0.036 (df = 75)	0.031 (df = 72)	0.029 (df = 71)	0.031 (df = 67)	0.027 (df = 65)
F	48.998** (df = 1; 75)	23.056** (df = 4; 72)	24.119** (df = 5; 71)	10.172** (df = 9; 67)	14.296** (df = 11; 65

Note. Standards errors are presented in the brackets.
* indicates p < .05. ** indicates p < .01.

Appendix E

Robustness Test with the Alternate Data Screening Approaches

Table E1.

Model for the Relationship Between Cultural Distance and Employment Rates in Immigrants in the UK (Country-Level; Missing Data Imputed with Multiple Imputation).

Predictor	*b*	*SE*	*t*	*p*	Model Fit
(Intercept)	0.81**	0.03	23.511	< .001	
Cultural Distance	-0.19**	0.06	-2.908	.005	
Genetic Distance	0.88**	0.27	3.248	.002	
Log Population Size	0.01**	0.00	4.223	< .001	
Education Distance	-0.00*	0.00	-2.093	.040	
Distance GDP	-0.01	0.01	-0.894	.375	
Population Distance	0.00	0.00	0.639	.525	
Region: Asia	0.02	0.01	1.524	.132	
Region: Europe	0.04*	0.02	2.383	.020	
Region: North America	0.03	0.02	1.981	.052	
Region: Oceania	0.04	0.03	1.594	.116	
Region: South America	0.04**	0.02	2.751	.008	
					R^2 = .706**

Note. * indicates p < .05. ** indicates p < .01.

Appendix F

Robustness Test with the Alternate Outlier Treatment

Table F1.

Model for the Relationship Between Cultural Distance and Employment Rates in Immigrants in the UK (Country-Level; No Outliers Removed).

Predictor	Unstandardized		Standardized		*SE*	*t*	Model Fit 95% CI
	b	95% CI	β	95% CI			
(Intercept)	0.82**	[0.75, 0.89]			0.04	22.644	
Cultural Distance	-0.09	[-0.20, 0.03]	-.16	[-.27, -.04]	0.06	-1.470	
Genetic Distance	0.75*	[0.18, 1.31]	.25	[-.31, .82]	0.28	2.591	
Log Population Size	0.01**	[0.00, 0.01]	.37	[.36, .37]	0.00	3.699	
Education Distance	-0.01*	[-0.01, -0.00]	-.33	[-.33, -.32]	0.00	-2.489	
Distance GDP	-0.01	[-0.02, 0.00]	-.16	[-.17, -.14]	0.01	-1.301	
Population Distance	0.00	[-0.01, 0.01]	.02	[.01, .02]	0.00	0.166	
Region: Asia	0.01	[-0.02, 0.03]	.06	[.03, .09]	0.01	0.495	
Region: Europe	0.03	[-0.00, 0.06]	.30	[.27, .34]	0.02	1.874	
Region: North America	0.03	[-0.01, 0.07]	.16	[.12, .20]	0.02	1.611	
Region: Oceania	0.04	[-0.02, 0.09]	.13	[.08, .18]	0.03	1.396	
Region: South America	0.04*	[0.01, 0.07]	.24	[.21, .27]	0.02	2.346	
							R^2 = .665** [.46, .71] R^2_{adj} = .610**

Note. A significant *b*-weight indicates *β*-weight correlations are also significant.
* indicates p < .05. ** indicates p < .01.

Appendix G

Exploratory Analysis

Table G1.

Analysis of Independent Relationships between the Subdimensions of Cultural Distance and Employment Rates in Immigrants in the UK (Country-Level).

Covariates	Dependent Variable							
	Employment Rates							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beliefs	-0.09** (0.03)							
Law		-0.09* (0.04)						
Political			-0.14* (0.06)					
Sexuality				-0.10** (0.03)				
Group Membership					-0.14* (0.05)			
Social Relationships						-0.20* (0.08)		
Financial							-0.06 (0.10)	
Misc								-0.10 (0.07)
Genetic Distance	0.78** (0.27)	0.84** (0.28)	0.86** (0.28)	0.54 (0.27)	0.68* (0.28)	0.95** (0.28)	0.91** (0.30)	0.91** (0.29)
Log Population Size	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01'** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)	0.01** (0.00)
Education Distance	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00	-0.00 (0.00)	-0.01* (0.00)	-0.01* (0.00)	-0.01* (0.00)
Distance GDP	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.010 (0.005)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Population Distance	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.003 (0.00)	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)
Regional Identifier	Included	Included	Included	Included	Included	Included	Included	Included
Constant	0.79** (0.03)	0.79** (0.03)	0.80** (0.03)	0.81** (0.03)	0.79** (0.03)	0.81** (0.04)	0.79** (0.04)	0.80** (0.04)
Observations	77	77	77	77	77	77	77	77
R^2	.702	.688	.695	.732	.697	.696	.667	.674
R^2_{adj}	.652	.636	.643	.687	.646	.644	.610	.618
Residual Std. Error (df = 65)	0.027	0.027	0.027	0.025	0.027	0.027	0.028	0.028
F Statistic (df 1; 65)	13.934**	13.047**	13.470**	16.134**	13.617**	13.514**	11.813**	12.201**

Note. The effects for the discrete levels of regional identifier were excluded from the table to increase readability.
For the covariates, unstandardized coefficients are presented.
* indicates p < .05. ** indicates p < .01.