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The effect of labor-market differentials on interregional migration in Spain: A meta-regression analysis

Maximiliano Alvarez[1] | **Vicente Royuela**[2]

[1]School of Earth and Environmental Sciences, Queensland Centre for Population Research, The University of Queensland, Saint Lucia, Queensland, Australia

[2]Faculty of Economics and Business, AQR-IREA Research Group, Universitat de Barcelona, Barcelona, Spain

Correspondence
Maximiliano Alvarez, School of Earth and Environmental Sciences, Queensland Centre for Population Research, The University of Queensland, Brisbane 4072, Queensland, Australia.
Email: m.alvarez@uq.edu.au

Vicente Royuela, Faculty of Economics and Business, AQR-IREA Research Group, Universitat de Barcelona, Av. Diagonal 690, Barcelona 08034, Spain.
Email: vroyuela@ub.edu

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Abstract

This paper performs a meta-regression analysis to derive the role of techniques, data and variable's definition on the effect of the labor-market determinants on interregional migration. We use Spain as a case of study, a country with heterogeneous and even counterintuitive behavior of internal migration flows to its labor-market drivers. We use data from studies released over the last 40 years. The results show that migration flows respond to labor-market differentials in a theoretically consistent way. We find that the vast diversity in the studies' attributes is behind the significant heterogeneity of their estimated effects. Differences in aggregation level, variables measures, model specification, and the national economic context influence the identification of the push and pull effects.

KEYWORDS

gravitational model, internal migration, labor markets, meta-analysis, Spain, spatial equilibrium

1 | INTRODUCTION

Internal migration is a key instrument to propel spatial equilibrium in labor markets within a country. There is a vast international literature analyzing this phenomenon, both from the study of migration consequences and the analysis of its push and pull factors. Despite the importance of the topic, to our knowledge, only a few works have tried to develop a systematic review of the empirical research employing meta-analysis techniques. Ozgen et al. (2010) focuses on the consequences of internal migration on regional imbalances and only a non-published report (Bardsley & Ederveen, 2003) reviews the influence of labor market differentials on international and interregional migration altogether. This contrasts with the use of this technique to establish the determinants of other types of flows, such as international trade (Polák, 2019). Consequently, we consider it is time to perform a systematic analysis to uncover the underlying effect of spatial labor market differentials on migration flows and recognize the research characteristics that lead to the observed heterogeneity of outcomes.

Meta-analyses synthesize and assess empirical studies examining a comparable topic. They help consolidate an overall effect size of a variable of interest. They are also useful to detect whether a particular piece of literature suffers from publication bias, which could be due to an inclination of reviewers and editors to favor studies with statistically significant results or results consistent with theoretical presumptions, and the researchers' criteria for selecting specifications that lead to conventionally accepted results. Moreover, meta-regressions are useful to determine whether the variation of estimated effects in the literature is due to the heterogeneity of employed approaches, including variations in the type of data, the period covered, spatial aggregation, estimation techniques, model specifications, etc.

The international heterogeneity in labor markets prevents us from analyzing the responsiveness to spatially unequal economic shocks. Cultural differences and diverse labor market institutions (such as minimum wages, collective bargaining coverage, or unemployment and welfare benefits, to name a few) are linked to the local labor market mobility and subsequently to spatially diverse unemployment rates and labor force participation. Consequently, we focus on a single country, Spain, which arises as a particularly good case of study to perform our analysis: it is a country characterized by a prolonged high and spatially unequal unemployment rate; probably due to this fact, there is a significant number of works investigating the responsiveness of internal mobility to regional labor markets differentials (we collected 36 studies from 1980 to 2020); and, many of these works have obtained heterogeneous and disputing results, sometimes labeled as enigmatic.

We contribute to the literature in several ways. First, to our knowledge, this is the first work conducting a meta-analysis that exclusively deals with the effect of regional labor market factors on migration between regions. Second, focusing on the Spanish case, we estimate a consolidated effect of labor-market push and pull factors while examining its sources of variation. Here, we examine whether the response of migration flows to spatial wages and unemployment differentials during the 2008–2014 Spanish recession differs from the reaction in periods with different national economic conditions. Last, while most meta-analyses consider the effect size of a single factor, we employ the meta-analytic techniques to the effect of four interconnected variables: wages and unemployment at both destination and origin. Our findings reveal that wages and unemployment differentials are relevant for explaining internal migration flows, particularly for migration between provinces. However, the estimated effects exhibit significant heterogeneity due to the diversity in the original studies' design. Differences in the data's spatial aggregation, variables measure, and model specifications can explain a significant part of the outcomes' heterogeneity.

The remainder of this paper is structured as follows. Section 2 briefly reviews the literature on the determinants of migration flows, with a specific focus at the empirical literature in Spain. Section 3 describes the collection of original studies, coding, and meta-analytic procedures. Section 4 presents the consolidated push and pull labor-market effects, publication bias, and attributes of the original studies that explain part of the variation of estimated effects. Section 5 provides a discussion, and the last section offers concluding remarks.

2 | DETERMINANTS OF INTERREGIONAL MIGRATION FLOWS

Early neoclassical economists sought the migration decision as a form of human capital investment where individuals compare the net present value (NPV) associated with different locations. If an individual attains the highest NPV in a region different from the current location, she decides to migrate (Sjaastad, 1962). Later, Todaro (1969) pointed out that the migration decision needed to be adjusted by individuals' expectations; thus, the possibility of being unemployed for some periods needs to be considered, particularly in the first periods of job search in a new location. He devised that the region's unemployment rate could approximate the probability of being unemployed. Therefore, it is often formulated that an individual's probability of migrating from an origin to a potential destination crucially depends on the comparison between wages and the unemployment rate in both regions and the costs of moving. The emphasis on geographic variation of economic opportunities in the migration decision, particularly regarding wages, has given rise to what is known as the disequilibrium hypothesis, which establishes that individuals respond to these differentials by migrating from low- to high-wage regions (Greenwood, 1975).

The disequilibrium approach has been questioned by arguing that non-economic factors, such as climatic conditions, natural amenities, and built environment, are also relevant for an individual's staying or migrating decision. This literature stream is labeled as spatial equilibrium (Graves, 1980; Knapp & Gravest, 1989; Marston, 1985), where it is plausible to have people encouraged to stay in low-wage regions or even to observe enlarged migration inflows to these low-wages regions, as lower wages could be compensating for better amenities (Graves, 1976). Graves (1983) proposed to add rents as the single variable to account for amenities since they capitalize on amenity variations. The spatial equilibrium implies that we should only see variations in population growth as short-term adjustments to supply or demand shocks.

The new economic geography also has implications for interregional migration flows (Crozet, 2004; Krugman, 1991). Krugman (1991)' model assumes monopolistic competition in a manufacturing sector that exhibits increasing returns and can move across regions. The model produces spatial agglomeration. Agglomerated regions offer better access to markets which improve the provision of goods and services, lower the probability of unemployment, and have higher real wages due to reduced transportation costs and economies of scale. This, in turn, invites more firms and people—the backward and forwards linkages, respectively—until congestion fully offsets those benefits. Building on Krugman's new economic geography, Crozet (2004) modeled the migration decision as a function of wages, unemployment rate, transport costs (bilateral distance), and the region's access to markets and found that access to markets significantly influenced interregional migration in Europe, supporting Krugman's forward linkage.

Another form to achieve agglomeration is linked to human-made amenities. Although since long it has been contended that amenities become more important in driving migration compared to economic opportunities as income increases because amenities could be a superior good (Graves, 1983), Glaeser et al. (2001) argued that are human-made amenities, particularly in cities and attractive to high human capital, the ones that attract population. The authors showed that people's increasing attraction to specific human-made amenities had raised housing prices faster than wages in large cities. Agglomeration arises because the attraction of high-skilled workers to these amenities raises the endowment of both, better amenities and high-skilled people, which in turn encourages even more high-skilled workers as they see their productivity increase through knowledge spillovers, producing endogenous growth (Berry & Glaeser, 2005; Faggian et al., 2019). Also, high-skilled workers' attraction to agglomerations is strongly related to the industry mix and structural changes, including the industry's life cycle. In particular, the appeal of agglomerations to high-human capital seems to be greater at earlier stages of the industry's life cycle (Simonen et al., 2018).

The above theories have contributed to understanding the elements to include in an individual's utility function when modeling migration choice, which in turn have micro-founded the macro models of bilateral migration flows. The transition from individual to aggregate models of migration flows results from the product between the probability of migrating from an origin region to a particular destination region of a representative individual and the total population of the source region (Ramos, 2017). Therefore, the expected number of bilateral migrations is also a function of the variables discussed above, observed in both origin and destination regions. These variables include wages, unemployment rate, housing prices, market potential, human capital, migration costs, and other factors to be discussed in the following section. The empirical setting is known as gravity or spatial interaction models and has as distinctive features the distance between the locations, which is used to approximate the moving costs, and origin and destination populations, which could represent market potentials.

A list of methodological challenges arises when studying bilateral migration flows. First, the strongly endogenous nature of the spatial systems makes accounting for endogeneity troublesome. The use of simultaneous equation models using changes in these variables as endogenous is indeed very demanding in terms of data and identification, as they require many exclusion restrictions, which are not easy to develop due to the lack of sound instruments. Common approaches to address it are the use of lags in explanatory variables and fixed effects to account for unobservable permanent characteristics (Beine et al., 2016).

In the same line, an essential aspect of the analysis of migration flows is the hypothesis of independence of irrelevant alternatives, which is expected not to hold as changes in the attractiveness of third regions can affect the migration volume between a pair of regions. This issue is known as multilateral resistance to migration (Bertoli & Moraga, 2013) and biases the estimates of push and pull factors. Beine et al. (2016) propose a couple of alternatives to address this problem, such as a common-correlated effects estimator (Pesaran, 2006) to approximate unobserved common factors causing the cross-sectional dependence, or the use of complex structures of fixed effects that combine cross-sectional and time fixed effects, which can be particularly numerous for bilateral flows over time.

2.1 | The Spanish case

Spain is a country with a persistently high unemployment rate, averaging 16% between 1980 and 2018. When Spain joined the European Monetary Union in the early nineties, its unemployment rate stood at 24%. After 15 years of continued economic growth, unemployment was still around 8% in 2007. In the Great Recession, the unemployment rate soared up to 25% in 2013, and 10 years after the start of the crisis, unemployment is still high, at 15% in 2019. Jaumotte (2011) described the Spanish labor market as of high unemployment rates, high cyclicality of employment and unemployment, a large share of temporary contracts, and a high degree of wage rigidity. According to Wölfl and Mora-Sanguinetti (2011), the lack of geographical mobility of workers aggravated the regional disparities in unemployment by hampering labor market adjustments. The Spanish Great Recession broadened these already sizable disparities of labor-market conditions across regions (Poggi, 2019).

Regarding interregional mobility, Santillana (1981) is often cited as the first describing the massive movements of people between Spanish regions during the 1960s and 1970s, from the more impoverished regions to more industrial areas, such as Madrid, Catalonia, and Basque Country, that enjoy higher wages and more employment opportunities. According to Raymond and García-Greciano (1996), these moves helped to reduce Spanish regional disparities. However, the high economic instability of the 1980s and early 1990s reduced the migratory flows. Indeed, poorer regions became net immigration regions, while wealthier regions lost population. Increased social benefits and return migration of retirees were listed among potential drivers of these flows.

A stream of literature has signaled the Spanish unresponsive and sometimes counter-intuitive migration across labor market differentials. According to Bentolila (1997), internal migration flows did not respond to high unemployment levels in the regions of residence; De la Fuente (1999) found a weak role of income and unemployment rate differentials on migration; Bentolila et al. (1991) obtained low elasticities of population flows with respect to lagged real wages and unemployment; Antolin and Bover (1997) found emigration from regions with higher wages than the average and a tiny effect of the unemployment rate. Mulhern and Watson (2009) and Mulhern and Watson (2010) termed the unresponsive Spanish interregional migration as an "enigma." However, the authors claimed to have resolved such enigma using data from the 1990s and finding significant responsiveness to relevant labor-market variables in a way more consistent with a disequilibrium perspective.

However, several other authors have found that wage and unemployment differentials do matter, including García-Ferrer (1980), Ródenas (1994), and Juarez (2000). Maza and Villaverde (2004b) and Maza (2006) acknowledged the influence of regional income disparities in the decision to move. In this line, Clemente et al. (2016) confirmed these findings regarding the relevance of labor market factors on internal migration, especially when the economic situation in the origin region is relatively unfavorable.

The discrepancy of results seems to hold regardless of the research's design. Antolin and Bover (1997) considered a micro data set, which allowed them to take into account a list of personal features. Despite this alternative approach, they found inconclusive results on the effect of wage differentials. It is not surprising that different types of individuals might have distinct motivations for moving. The increased prevalence of international immigrants in Spain has motivated researchers to take a more in-depth look at the singularities of this group and discern whether foreigners behave differently from the native Spanish population. Several authors have analyzed the internal flows of foreign-born residents in Spain (Clemente et al., 2016; Conde-Ruiz et al., 2008; Gutiérrez-Portilla et al., 2018; Liu, 2018; Maza et al., 2013; Reher & Silvestre, 2009; Viñuela et al., 2019). They all found different mobility patterns, suggesting that international immigrants are more mobile than Spanish natives, and they are more responsive to job opportunities and job promotion possibilities. It has also been argued that the immigrants' inclination for settling in large cities and more affluent areas have reinforced Spanish territorial imbalances.

Despite the more sophisticated analyses and more extensive and granulated data sets, the "enigmatic" results (but coherent under spatial equilibrium) are still present in recently applied empirical research. Liu (2018) found a negative parameter of the response of migration flows to real wage per worker in destination regions, and Hierro et al. (2019) observed a positive and significant effect of the unemployment at the provinces of destination.

Overall, the internal migration literature in Spain exhibits a vast diversity in the approaches to empirically model migration. To name a few, works using microdata consider whether an individual migrates to a specific destination via multinominal models. Among the studies drawing on regionally aggregated data, some examine net migrations, although the majority consider gross flows. As for the explanatory variables, we also find significant diversity in how they are introduced in the empirical models. Some authors contrast destination and origin features by considering their ratios or differences in the two regions. Others, on the contrary, prefer to include both origin and destination characteristics separately. More recently, there is a tendency for employing the ratio of expected wages (wages times one minus unemployment rate) between destination and origin (Gutiérrez-Portilla et al., 2018; Maza et al., 2019), following Todaro (1969)'s hypothesis.

3 | RESEARCH DESIGN

A meta-analysis applies statistical methods to systematically review and assess empirical studies investigating a comparable topic, offering several advantages over narrative literature reviews. For example, it uses a comprehensive search method to collect as many studies that empirically estimate an effect of interest, uses statistical techniques that ease an objective synthesis of findings and possesses tools for clarifying the reasons for inconclusive outcomes. Meta-analyses have been extensively employed in a variety of topics in social sciences. For instance, in economics, they have been used to consolidate the determinants of international trade (Polák, 2019) or the effect of information and communication technologies (ICT) on economic growth (Stanley et al., 2018). Regarding migration issues, meta-analyses have almost exclusively addressed the consequences of migration. For example, Longhi et al. (2010) analyzed the impact of immigration on the labor markets of the host countries, Larkin et al. (2019) explored the effect of immigrants on house prices, and Nijkamp et al. (2011) examined the influence of international migration on international economic linkages. In terms of internal migration, Ozgen et al. (2010) assessed the consequences of net internal migration on the spatial asymmetries in economic growth within a country. Regarding the drivers of migration, to our knowledge, only Bardsley and Ederveen (2003) examine the effect of wages and unemployment differentials on labor mobility, but they combine both internal and international migration.

The apparent inconsistency across applied research regarding the economic determinants of interregional migration flows in Spain inspired us to conduct the first study that employs meta-analytic techniques to examine the push and pull labor-market factors of internal migration. We aim to consolidate the estimated effects of the empirical literature in Spain and, through meta-regressions, to identify their sources of heterogeneity.

3.1 | Data

In this paper, we follow the reporting guidelines for meta-regression analysis in economics presented in Havránek et al. (2020). We searched for all econometric studies published during the last four decades that empirically estimated the effects of wages or unemployment of either region of origin (push factors) or region of destination (pull factors) on the internal migration flows in Spain. The combination of words used in the search was: province OR region AND migration AND Spain in Google Scholar. All the referenced and citing related articles with relevant estimates were included in the data set, with November 2020 as the cut-off date of the search. As a result, we obtained 209 observations from 36 econometric studies dated from 1980 to 2020. The sample includes both journal articles and working papers to minimize potential publication bias and include pieces written both in English and in Spanish. Appendix A provides the references for the 36 primary studies included in the meta-analysis.

3.2 | Effect size and coding

The comprehensive search mentioned above yielded 36 studies that estimated the effect on internal migration flows of at least one push or pull labor-market factor. These 36 studies yield 209 regressions, which in turn give 126 estimates of the effect of the unemployment rate at the destination, 172 of wages at the destination, 94 of the unemployment rate at the origin, and 127 of wages at the origin.[1] A few studies estimated the effect of employment instead of unemployment. Devillanova and García Fontes (2004) reported the effect of employment at origin (two estimates) whereas Lago and Aguayo (2004) (one estimate), Viñuela et al. (2019) (one estimate) and Melguizo and Royuela (2020) (24 estimates) of the employment rate at the destination. In those cases, to homogenize all papers in the data set, we recover the effect of unemployment by multiplying the coefficient by minus one.[2]

To make all the effect sizes comparable, we converted all the estimated coefficients (e.g., marginal propensities or elasticities) of the relevant regional economic factors found in the primary studies to a common effect size, a partial correlation, r, defined as $r = \frac{t}{\sqrt{t^2 + df}}$, where t is the t-statistic of the pertinent regression coefficient, and df

[1]Gutiérrez-Portilla et al. (2018) and Maza et al. (2019) estimated the effect of geographical differences in expected wages (wages times one minus unemployment rate). Those estimates are not included in the meta-analysis as it is not possible to isolate the effect of wages from unemployment.

[2]By doing so we are assuming that the labor force is a constant fraction of the working age population, such that changes in the unemployment rate can be approximated by the additive inverse of the changes in the employment rate. In the case of Lago and Aguayo (2004), they calculated employment rate as one minus the unemployment rate, hence the coefficient of unemployment rate in this study is correctly recovered by multiplying the coefficient of the employment rate by minus one.

the degrees of freedom. The degrees of freedom are approximated by the number of observations minus the number of explanatory variables, including any fixed effect in the regression. The standard error of each partial correlation is calculated as $SE = \sqrt{\frac{1-r^2}{df}}$ (Stanley & Doucouliagos, 2012). Some studies reported the estimated coefficient, b, together with its standard error, SE_b. In such cases, we computed the related t-statistic required to calculate the partial correlation as $t = \frac{b}{SE_b}$.[3,4]

In addition to the correlation coefficients and respective standard errors, we coded several characteristics of the original regressions that might be relevant to finding a specific outcome. Table 1 lists all the attributes coded from the regressions, and the rationale of their inclusion is detailed in the meta-regression subsection. The data set with all coded observations is available in the Supporting Information.

3.3 | Meta-analysis: Descriptive statistics

A meta-analysis starts by providing an overall effect size of the variable of interest and a statistic of its variability. The natural candidates for these summary statistics are the (unweighted) average of all point estimates found in the original studies and its standard deviation. However, the main purpose is to predict the true population effect size, and given that estimates differ in precision (standard error), it becomes convenient to provide additional weight to those estimates that have higher precision and less weight to those with lower precision. Thus, a commonly reported summary effect is the fixed effects (FE) estimator, which consists of the weighted average of all effect sizes (in our case, the partial correlations), where the weights are given by the reciprocal of the squared standard error (variance) of the estimate.

However, the *FE* estimator assumes that all the reported effect sizes are drawn from the same population with a fixed mean, implying that their observed variation is only due to sampling error, known as within-study variance. Further heterogeneity is considered by assuming that the true effect size that each regression attempts to predict comes from a distribution of population effects. This additional source of variation can be due to that studies differ in many methodological aspects and population targeted. Then, the observed effect sizes may deviate from the population mean effect size due to two sources of variation, the within-study and a between-study variance. The estimator that considers both sources of heterogeneity is the random effects (RE) estimator. It is calculated similarly as the FE estimator, but with the reciprocals of the sum of both the within- and the between-study variance as weights. Several approaches proposed to estimate the between-study variance have been proposed (see Schwarzer et al. (2015) and Viechtbauer et al. (2015) for a summary). We use the restricted maximum-likelihood estimator since it corrects some downward bias of the maximum likelihood estimator.

Most meta-analyses on economic issues identify an excess of heterogeneity (Stanley & Doucouliagos, 2012). The Cochran's Q-test has been devised to examine if there is significant heterogeneity in the estimated effect sizes. It has homogeneity as the null (Cochran, 1954) and a Q-statistic exceeding the upper-tail critical value of χ^2 with $n-1$ degrees of freedom is significant evidence of heterogeneity (Cooper et al., 2009).

[3]Gutierrez Portilla (2014) reported a standard error of one of the estimated effects of the unemployment rate at destination as 0.000. A standard error cannot be zero, and, in this case, it should belong to the interval (0.000, 0.0005), as any value in the interval [0.0005, 0.0015) would have been rounded to 0.001. For all analyses presented in this paper, we used as standard error a value of 0.0002, as it is very close to the midpoint of (0.000, 0.0005). We also estimated using alternative values within such interval, such as0.0001 and 0.0004, and the results remained almost unaltered.

[4]In other cases, the information provided to compute the t-statistic was less straightforward. Lindley et al. (2002) (one estimate of unemployment at origin) presented the coefficient with its associated p value. We transformed it to the corresponding t-statistic using the number of observations minus the number of regressors and fixed effects employed in the regression as the df. Viñuela et al. (2019) (one estimate of the effect of unemployment at destination) only provided the level of statistical significance by using * for significance at the 10% level, ** for significance at the 5% level, and *** for significance at the 1% level. Greenberg, Michalopoulos, & Robins (2003) suggested to use the midpoints, that is, 0.075 (midpoint between 0.05 and 0.1), 0.03 (midpoint between 0.01 and 0.05), and 0.005 (midpoint between zero and 0.01), respectively. Viñuela et al. (2019) found that employment at the destination is statistically significant at the 1% level. We essentially follow Greenberg et al. (2003)'s recommendation but taking into account that most statistical software typically rounds the values. Thus, we assumed that the p value was 0.002.

TABLE 1 Definition of the explanatory variables to use in the meta-regression analysis

Variable	Definition	u_d, mean (SD)	w_d, mean (SD)	u_o, mean (SD)	w_o, mean (SD)
se	Standard error of the partial correlation	0.03 (0.04)	0.04 (0.04)	0.03 (0.04)	0.04 (0.04)
article	1 if the estimation comes from a study published in a refereed journal; 0 otherwise	0.72 (0.45)	0.79 (0.41)	0.63 (0.49)	0.74 (0.44)
maza	1 if the estimation comes from a study with Adolfo Maza as coauthor; 0 otherwise	0.24 (0.43)	0.17 (0.38)	0.28 (0.45)	0.2 (0.41)
dmyear	Average year of the data used with respect to the mean average year	−0.17 (13.06)	−0.3 (20.45)	0.48 (13.18)	−0.17 (17.6)
dmtimespan	Number of years covered with respect to the mean number of years	−0.09 (6.41)	−0.45 (6.48)	0.27 (6.38)	0.06 (7.23)
*rece*08 − 14	1 if the 2008-2014 Spanish recession covers most of the examined period; 0 otherwise	0.37 (0.49)	0.27 (0.45)	0.24 (0.43)	0.18 (0.39)
individual	1 if the regression employs individual data; 0 if it utilizes aggregated data	0.06 (0.24)	0.04 (0.20)	0.13 (0.34)	0.07 (0.26)
panel	1 if the analysis employs panel data; 0 otherwise	0.75 (0.43)	0.55 (0.50)	0.65 (0.48)	0.49 (0.5)
province	1 if the observations correspond to provincial or municipal divisions; 0 for regional	0.57 (0.50)	0.68 (0.47)	0.51 (0.50)	0.61 (0.49)
net	1 if the migration variable is net migration; 0 otherwise	0.21 (0.41)	0.16 (0.36)	0.12 (0.32)	0.09 (0.29)
relative	1 if the relevant factor is included in relative terms; 0 otherwise	0.37 (0.49)	0.32 (0.47)	0.5 (0.50)	0.43 (0.50)
y	1 if the analysis uses GDP per capita or other than wages; 0 if it uses wages	0.37 (0.48)	0.52 (0.50)	0.45 (0.50)	0.65 (0.48)
lagged	1 if the relevant explanatory factor is lagged; 0 otherwise	0.71 (0.46)	0.64 (0.48)	0.57 (0.50)	0.53 (0.50)
fixed	1 if the number of fixed effects included in the regression is greater or equal than the number of spatial units; 0 if lower	0.63 (0.48)	0.48 (0.50)	0.57 (0.50)	0.43 (0.50)
house	1 if the regression controls for housing prices; 0 otherwise	0.58 (0.5)	0.42 (0.5)	0.59 (0.5)	0.42 (0.5)
distance	1 if the regression controls for the distance; 0 otherwise	0.64 (0.48)	0.7 (0.46)	0.56 (0.5)	0.71 (0.46)
educ	1 if the regression controls for education; 0 otherwise	0.18 (0.39)	0.13 (0.33)	0.34 (0.48)	0.24 (0.43)
factors	1 if the regression includes both wages and unemployment; 0 otherwise	0.56 (0.50)	0.41 (0.49)	0.76 (0.43)	0.56 (0.50)
foreigners	1 if the analysis employs data on foreigners only; 0 otherwise	0.18 (0.39)	0.13 (0.33)	0.15 (0.36)	0.13 (0.33)

Note: Standard deviations (SD) are in parentheses. The mean of the binary variables can be described as their proportion of realization. For instance, the mean of *article* in the unemployment at destination data set equals 0.72, which means that 72% of the estimates of the effect of unemployment in the region of destination on the internal migration between regions were published in refereed journals. The remaining 28% correspond to estimates not published in refereed journals, such as estimates that appeared in either working or conference papers. The mean values of *dmyear* and *dmtimespan* are not zero because the mean year were rounded before demeaning.

Abbreviations: u_d, unemployment at destination; w_d, wages at destination; u_o, unemployment at origin; w_o, wages at origin.

On the other hand, the combination of findings assumed that the sample of estimated effects was representative of the population of all possible effect sizes of interest. Card and Krueger (1995) noticed there are three reasons to suspect that the sample of reported effect sizes might not be representative, an issue known as publication bias. First, the tendency of reviewers and editors to favor studies with statistically significant results. Second, the reviewers and editors' predisposition toward accepting works with results consistent with theoretical presumptions. Third, the researchers' criterion for conventionally accepted results influencing the model specification.

A visual inspection of publication bias is done with a funnel plot, which is a scatter diagram of the effect sizes measured along the horizontal axis against their standard error measured in decreasing order along the vertical axis. Usually, dotted lines denoting a pseudo 95% confidence interval (CI) around zero for a given standard error are also drawn ($\pm 1.96SE$). A funnel shape is generally expected. Estimates concentrate in the top and dissipate in the bottom because more precise (lower standard error) estimates do not require to be large to become statistically significant, so they are less likely to be affected by the first reason of publication bias. In contrast, less precise estimates (larger standard errors) need to be large to become statistically significant. If a significant number of observations fall outside the 95% CI, especially around the bottom, there is an indication of bias for publishing statistically significant results. Large dispersion of estimates around the top of the funnel plot might be attributable to an excess of heterogeneity. Asymmetric funnel graphs might manifest the second and third reasons for publication bias.

3.4 | Meta-regression

The push and pull labor-market effects estimated across the literature might be subject to substantial heterogeneity because regressions vary in the type of data used, the period covered, spatial aggregation, estimation techniques, model specifications, etc. Therefore, the next step is to systematically establish how regression's characteristics can be behind the diversity of effect sizes found in the empiric research in Spain.

We estimate the incidence that several regression features have on their calculated partial correlation coefficients through multivariate meta-regressions. Since we have four effect sizes of interest, we need to estimate four meta-regressions. The dependent variable in each meta-regression is the partial correlation of the estimated labor-market effect found in the empiric literature in Spain, that is, the unemployment rate and wages in the destination regions and the unemployment rate and wages in the origin regions. The explanatory variables correspond to the characteristics of the regressions from where the effect sizes were drawn on. Then, the meta-regression model associated with each of the relevant labor-market factors is given by

$$r_{ij} = \beta_{0j} + \sum_{k=1}^{K} \beta_{kij} x_{kij} + \epsilon_{ij} \quad \text{for} \quad j = 1, 2, 3, 4, \tag{1}$$

where i is for the i-th estimated partial correlation of the labor-market factor j, r_{ij} ($j = 1, \ldots, 4$ are for the unemployment rate and wages at the destination and unemployment rate and wages at the origin). x_{kij} is the moderator variable k, which correspond to each of the coded regression characteristics, ϵ_{ij} are random errors, and the β_{kij} is a parameter that denotes the effect of the study characteristic k over the partial correlation of each of the labor-market factors.

Finally, regarding the estimation procedure, the meta-regression model (1) is estimated by weighted least squares (WLS), using the inverse of each estimated correlation coefficient's variance ($1/SE_i^2$) as weights. In this way, more precise estimates have greater weight. WLS regression is preferred because it accommodates heteroskedasticity, which is usually an issue in meta-analyses in social science due to publication bias and excess of heterogeneity. Compared to the traditional meta-regression approaches, Stanley and Doucouliagos (2017) showed that WLS generally outperforms both the FE and RE. On the other hand, the assumption of independence among observations might not hold here because most of the studies provide more than one observation. To make consistent inferences regarding the significance of the moderators under within-study dependence, we estimate consistent standard errors by calculating a cluster-robust co-variance matrix, where each study is a cluster.

Table 1 summarizes the moderator variables included in the meta-regression Equation (1), including their means and standard deviations. The first three concern publication bias. The standard error (*se*) of the partial correlation of the pertinent effect size is included to account for publication bias caused by systematic selection of statistically significant effects. The variable *article* accounts for publication bias that can result from the predisposition that some journal editors and reviewers to publish conventionally accepted results. We also added the variable *maza* to account for the multiple studies where Adolfo Maza, most of the time with José Villaverde, is a coauthor (seven articles). We include this dummy variable because researchers tend to build on their previous works and may have an inclination to validate their previous findings. In the second group of moderators, the variables *dmyear* and *dmtimespan* are included to identify trends in the effect sizes while controlling for differences in time coverage. The variable *rece*08 − 14 is added to ascertain whether the Spanish 2008–2014 crisis exerted some influence on people's migratory response to regional differences in the labor market.

The third group of variables (*individual*, *panel*, and *province*) concern to the data types. We include *individual* to distinguish estimates that originate from individual-level data from those that come from aggregate data. The former not only benefit from having a larger number of observations but also because individual data exhibit more variation (Orcutt et al., 1968). This facilitates the statistical significance of the regression coefficients of studies employing individual data. Then, we expect studies based on individual data might be less likely to be subject to publication bias. The variable *panel*, on the other hand, is added to control for differences in data structures, panel data versus (pooled) cross-sections.

The variable *province* is included to assess variations in effect sizes that can emerge due to differences in the spatial aggregations (e.g., regional, provincial, or municipal) since more spatial disaggregation allows the observation of some short-distance moves that studies drawing on higher-level regions cannot. Table 1 shows that between half and two-thirds of the estimations, depending on the labor-market factor, are about migration between provinces,[5] which overall contain shorter distance migrations than migrations between regions (autonomous communities), which make the remaining fraction of estimates. Regarding how exploring distinct territorial divisions can influence the estimated effect sizes, we expect larger effects of labor-market variables for shorter migration distances, for example, between provinces instead of autonomous communities, as some migration flows involve lower transportation, psychological, and information costs. Nevertheless, Biagi et al. (2011) and Niedomysl (2011) indicate that longer-distance migrations are more labor-driven while shorter-distance migrations are more amenities-driven, implying that migration flows might be more responsive to variations in more distant labor markets. Therefore, the territorial definition of the unit of analysis is associated with the role of distance in migration decisions.

The fourth set contains three moderator variables that pertain to the diversity of measures of relevant variables. The first is the binary variable *net*, which is added to assess whether employing net instead of gross flows matters for the estimation of the effect of labor-market factors. To illustrate the consequences of using net over gross flows when interpreting the effects, let consider two regions, 1 and 2, with m_{12} the migration flow from region 1 to region 2, and m_{21} the migration flow from region 2 to region 1. A linear regression that relates the two with a feature x observed in the two regions would be $m_{12} = \beta_{12} + \beta_o x_1 + \beta_d x_2 + \epsilon_{12}$, and $m_{21} = \beta_{21} + \beta_o x_2 + \beta_d x_1 + \epsilon_{21}$. β_{12} and β_{21} are the intercepts, and ϵ_{12} and ϵ_{21} the error terms. β_o and β_d are the coefficients of interest, which give the

[5]There are 19 regions (autonomous communities), but most studies examine migration between 17; and 59 provinces (including islands), but most studies include either 47 or 50. We included in the province category three studies that examine migrations between territiories smaller than provinces. Arauzo-Carod and Liviano-Solís (2013) provided three estimates of the effect of wages at the destination on migration between 946 municipalities; Viñuela et al. (2019) provided one estimation of the effect of unemployment at the destination on migration between 843 local labor markets (LLM); and Melguizo & Royuela (2002) provided eight estimations of the effect of unemployment and wages at the destination on migrations between 483 LLM and eight estimations on migrations across functional urban areas (FUA).

effect of a unit change in x at the origin and destination, respectively. The net migration flow of region 2 with respect to region 1, nm_{21}, is

$$nm_{21} = m_{12} - m_{21} = \beta^*_{21} + (\beta_d - \beta_o)(x_2 - x_1) + \epsilon^*_{ij},$$

where β^*_{21} and ϵ^*_{21} are the new intercept and error in the net flows regression. Note the effect of a unit increase in x_2 in a net migration regression is $\beta_d - \beta_o$, and in x_1 is $\beta_o - \beta_d$, respectively. Given that β_o and β_d should have opposite signs, then $|\beta_d - \beta_o| = |\beta_o - \beta_d|$ is greater than $|\beta_d|$ and $|\beta_o|$, with the latter being the coefficients in a gross migration regression. Therefore, we should observe the coefficients associated with the labor-market variables to be larger in magnitude in regressions employing net migration than when examining gross migration flows.

The regressions that estimate the effect of labor-market determinants on net migration include the labor-market variable measured at the same region for which the net migration is assessed. In the above example, region 2′s net migration is modeled as $nm_{21} = \beta^*_{21} + (\beta_d - \beta_o)x_2 + \epsilon^*_{ij}$. Given that net migration is migration inflows minus outflows, we coded these estimates as the effect of destination factors, unless they are expressed in relative terms, in which cases we coded these estimates as the effect of both destination and origin factors, with the coefficient of the factor at origin having the opposite sign of the coefficient of the factor at the destination. We do this because when the relevant variable enters the linear model in relative terms, the effects of a change in the variables at destination and origin are restricted to have the same magnitude but opposite sign. To see this, consider the model: $log\,(m_{ij}) = \beta_0 + \beta_1 log\,(\frac{x_j}{x_i}) + \epsilon_{ij}$, which is equivalent to $log\,(m_{ij}) = \beta_0 + \beta_1 log\,(x_j) - \beta_1 log\,(x_i) + \epsilon_{ij}$. This bring us to our next moderator, *relative*, to account for the estimates resulting from regressions where the relevant labor-market factors are in relative terms.

Besides using net or gross flows, or measuring the explanatory variables in absolute or relative terms, further heterogeneity can result from the measure used to denote wages. A significant number of studies use GDP per capita as a proxy of wages, mainly due to the unavailability of a time-consistent and regionally-disaggregated measure of wages. We added the dummy variable *y* to determine whether using GDP per capita rather than wages plays a role in the diversity of outcomes. Regressions employing regional GDP per capita could find larger effects than those using wages as GDP per capita is a broader measure that may also capture some regional differences in amenities as it also proxy standards of living. However, if the share of nonworkers (e.g., retirees) is large in some regions, variations in GDP may deviate from changes in wages, making its effect on migration more a reflection of preferences for amenities rather than an arbitrage of labor markets.

The fifth group of two moderator variables is included to signal econometric specifications aimed at limiting the endogeneity of the labor-market determinants. Recall that failing to address endogeneity biases the results. The two binary variables are *lagged* and *fixed*. The first indicates whether the labor-market factors are lagged one period to narrow the well-established simultaneity between regional indicators of economic performance and internal migration[6]. That is because economically motivated migration flows can help to correct spatial labor-market dis-equilibria by reducing the excess of labor supply in regions with relatively high unemployment and low wages and increasing it in regions with relatively low unemployment and high wages. Then, regressions not accounting for this simultaneity, that is, employing observations of labor-market indicators contemporaneous to the migration flows, will likely find unresponsiveness or even counterintuitive responses.

fixed is added to control the omission of time-invariant relevant factors in the relationship. The regional fixed effects can be monadic of either the regions of origin or destination and dyadic of the origin-destination migration flow. In addition to regional fixed effects, some studies also attempt to account for further endogeneity caused by multilateral resistance to migration by combining them with time fixed effects (Beine et al., 2016)[7]. For simplicity, the binary variable *fixed* takes the value of 1 if the number of fixed effects is greater or equal than the number of spatial units (regions, provinces or municipalities) and 0 otherwise.

[6]See Ozgen et al. (2010) for a meta-analysis about the reverse relationship, that is, the effect of interregional migration on regional convergence.
[7]See Ramos (2017) for a summary of the distinct specifications of fixed effects and endogeneity issues in origin-destination migration flows models.

The last category of moderator variables refers to other factors included in the original regressions of internal migration and specifically targeted populations. The first of them is housing prices (*house*), which is often added into the migration models to account for spatial differences other than labor-markets-related, that can be relevant for a location choice, such as natural and built environment amenities, as housing should be more expensive in places with better amenities. Consistent with the equilibrium perspective, spatial differences in amenities can limit the arbitraging of labor market differentials since high real wages or low unemployment could compensate for low amenities. Hence, the inclusion of housing prices controls for amenity migration and therefore, we expect estimates of the effect of the labor-market factors on migration to be more coherent with a spatial arbitrage when housing prices are in the regression than when they are not.

The second variable belonging to moderators included in the migration regressions is *distance*, which is introduced to signal the regressions that add bilateral distance to consider the migration costs between a pair of regions. As with geographic aggregation noted above, the direction in which distance can influence the estimates of labor market pull and push factors is not straightforward. Given that migration costs reduce the possibilities of arbitrage between labor markets, regressions omitting them would find lesser migration responses to regional labor market disparities if the differences are larger for regions further apart, which should be the case as spatial dependence is often encountered in the Spanish economy (Arauzo-Carod & Liviano-Solís, 2013; Maza et al., 2013; Viñuela et al., 2019). However, as noticed earlier, this could be lessened if shorter-distance migration is more amenity-motivated than longer-distance so that the sensitivity of migration to labor market differentials could not decay but increase with distance. Nonetheless, all examined works use migration across administrative boundaries (or functional urban areas and local labor markets as in Melguizo & Royuela, 2020), and then they do not generally include short-distance moves driven by amenities or housing adjustments. Therefore, there might be a distance-decaying effect of spatial labor-market differentials, making the inclusion of distance essential to identify the responsiveness of migration to spatial differentials in wages and unemployment.

The variable *educ* is included to capture the variation in the estimates that might result from whether to control for differences in the educational level (or qualifications, or human capital) or not. Education is connected to migration since more qualified individuals tend to be more mobile between regions (Bernard & Bell, 2018; Faggian et al., 2007) as they benefit more from migrating (Korpi & Clark, 2015). Thus, regions with higher levels of education should exhibit larger migration outflows. However, it has been shown that higher human capital can also prevent people from leaving the region (Piras, 2017). Moreover, it has also been suggested that education (or human capital) is positively connected with real wages (Shapiro, 2006) and negatively connected with the region's unemployment rate (Elhorst, 2003). Therefore, omitting education may lead to endogeneity, which biases the estimation of the effects of the labor-market factors: as a destination, not accounting for levels and quality of education would overestimate the pulling effect of wages and unemployment because regions with relatively large dotation of high-skilled workers attract more individuals whereas omitting this variable at the origin would underestimate the pushing effect of wages and unemployment, as places with more educated people are likely to display higher wages and employment opportunities.

The fourth variable in this category, *factors*, is added to inspect whether the estimated effect size of a labor-market determinant in regressions including both regional wages and unemployment together differ from those omitting one of them. This is important not only because the two can drive interregional migration flows but also because they determine each other. Like in any market, supply-demand analysis implies that the higher the wages, the more supplied and less demanded labor, leading to more unemployment (Blanchard et al., 1992). However, a negative association seems to be the empirical regularity (Blanchflower & Oswald, 1995). Therefore, omitting one of the factors may bias the estimated effect size of the other. The direction of the bias depends on the sign of their relationship.

The last moderator in this category is *foreigners*, which is introduced in the meta-regression to control for differences in the effect sizes that might arise as a consequence of targeting a specific population. Empiric evidence suggests greater mobility of foreigners compared to natives (Newbold, 1996; Recaño & Roig, 2006)

TABLE 2 Average effects and heterogeneity test of the partial correlation of the labor-market factors

Factor	Unweighted	FE	RE	Q
u_d	−0.082***	−0.007***	−0.078***	6468.815***
w_d	0.155***	0.053***	0.145***	48,095.063***
u_o	0.098***	0.003***	0.085***	5087.58***
w_o	−0.122***	−0.029***	−0.113***	14,074.035***

Note: ***, ** and * indicates significance at the 1%, 5% and 10% level.

Abbreviations: u_d, unemployment at destination; w_d, wages at destination; u_o, unemployment at origin; w_o, wages at origin.

and that their responses to labor-market differentials also differ (Gutiérrez-Portilla et al., 2018; Maza et al., 2019)[8].

4 | RESULTS

Table 2 reports the unweighted average, the FE, the RE, and the Q-statistic for detecting heterogeneity for each of the partial correlations of each of the push and pull labor-market determinants of internal migration in Spain. The results show that the consolidated effect of each labor-market factor is consistent across the three estimators, suggesting that people in Spain have behaved expectedly regarding variations in the labor markets across regions. In the case of migration inflows, the link is negative with a regions' unemployment rate and positive with wages (or income per capita). Moreover, migration outflows are positively correlated with a source region's unemployment rate while negatively related with wages. All the results are statistically significant at the 1% level. Additionally, migration flows seem to be more responsive to variations in wages than to the unemployment rate. Also, migration flows exhibit a greater response to wages at the destination than at the origin, while for the unemployment rate, the response seems slightly larger at origin than at the destination. The Q statistic rejects homogeneity at the 1% level for the four labor-market factors, thus evidencing excess of heterogeneity in the estimates, implying that we should rely more on the RE estimations.

Figure 1 exhibits the funnel plots of each labor-market determinant to establish if publication bias is present in the estimated effect sizes. Overall, the plots show that although several estimates spread out, an important portion of them cluster at the top of the graph, close to zero but inclined to the theoretically expected side. These asymmetries in the funnel plots can eventually result from publication bias due to the preference for publishing outcomes consistent with standards views. The significant dispersion exhibited by some of the more precise estimates suggests that heterogeneity should not only be ascribed to sampling error, which is consistent with the findings of the Q test for heterogeneity reported in Table 2. Moreover, although fewer estimates are at the bottom of the plots, these estimates are the most dissipated, evidencing bias for publishing significant results.

The excess of heterogeneity put in evidence by Cochran's Q-test and the funnel plots, together with the visual indication of publication bias, prompt us to examine the extent to which the studies' attributes might be behind the heterogeneous outcomes. We do this by estimating one meta-regression for each of the labor-market effects on internal migration, as given in Equation (1), using the moderator variables defined in Table 1 and explained in the previous section. The WLS estimates with clustered errors are shown in Table 3. It can be appreciated that the

[8]An additional well-established factor behind variations in the propensity to migrate is age (Bernard, Bell, & Charles-Edwards, 2014; Karahan & Rhee, 2014). Unfortunately, very few estimates of the determinant of interregional migration in Spain either controlled for or targeted a specific age group, preventing us from including it as a moderator variable in this meta-regression (exceptions include Antolin & Bover (1997) and some recent estimates in Melguizo and Royuela (2020) and Maza (2020)).

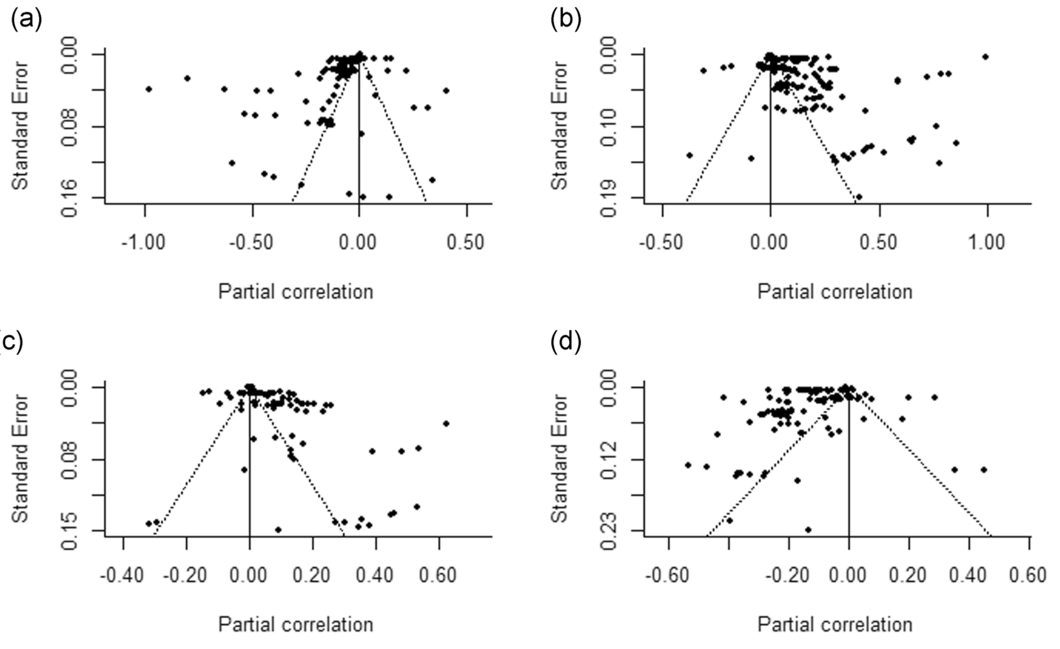

FIGURE 1 Funnel plots of the partial correlations of the labor-market factors. (a) Unemployment at destination, (b) wages at destination, (c) unemployment at origin, and (d) wages at origin

estimated effect sizes are not moderated by the same attributes, neither is the proportion of their variability explained by the covariates, which ranges from 45% for unemployment at destination up to 85% for wages at destination. We proceed now to describe how the research features moderate the estimated effect sizes.

The first regressor is the standard error of the partial correlation, and it is found that significantly affects the estimates of the labor-market factors at the origin. Specifically, less precise estimates are significantly associated with more negative effects of wages at origin and more positive effects of the unemployment rate at the origin. Then, there is significant evidence that the estimated effects of these factors suffer from publication bias that arises from specifying models that lead to more significant outcomes and are consistent with theoretical presumptions. These modeling features are distinct to those already considered as moderators in our meta-regressions. On top of that, the variable *article* affects the estimated effects of wages at the origins, implying that regressions in articles published in peer-reviewed journals tend to find a more prominent pushing role of wages in the theoretically expected direction.

In addition, the dummy variable *maza* indicates that regressions in studies co-authored by Adolfo Maza find a weaker push effect of unemployment and wages at the origins but a stronger pull effect of wages at the destinations. Concerning the push effects, the two factors entered into the regressions as separate origin variables in only two of the 26 estimates (Maza & Villaverde, 2008). Maza and Villaverde (2008) found a positive effect of income at the origin on outflows in the two regressions, although the coefficient of the second, a spatial regression, is not statistically significant. To examine if this study is behind the less negative estimated effects of wages at the origin in Maza's regressions, we reestimated the meta-regression for wages at the origins, dropping the two observations of Maza and Villaverde (2008). We find that the coefficient of the variable *maza* as well as the other variables remain almost unaltered. It could be that other research features distinctive of Maza's works not controlled in our meta-regressions are causing the lesser strength of the push factors and the stronger pull effect of wages at the destination of his estimations. These can be, for example, the use of semiparametric regressions (Maza & Villaverde, 2004a, 2004b), spatial filtering techniques (Maza & Villaverde, 2008; Maza et al., 2013), or the inclusion of the share of economic sectors as moderators, to mention some.

The findings also reveal that all the estimated parameters have been stable over time, and they do not change with the length of the period covered. However, regressions focusing on the 2008–2014 Spanish recession find a

TABLE 3 WLS with clustered standard errors meta-regressions for each of the labor-market factors

Variable	u_d	w_d	u_o	w_o
se	−2.046	−0.674	2.700***	−3.750**
article	0.032	−0.072	0.030	−0.189**
maza	−0.036	0.308***	−0.115**	0.555***
dmyear	0.001	−0.005	−0.002	−0.005
dmtimespan	−0.006	0.003	−0.002	0.004
*rece*08 − 14	0.035	−0.235*	−0.003	−0.390***
individual	−0.087	0.039	0.290***	0.021
panel	0.022	0.088	0.093	0.002
province	−0.109**	0.324***	0.059**	−0.214***
net	−0.175	0.243*	0.400***	−0.353***
relative	0.065**	−0.225**	−0.071***	0.092
y	0.025	−0.058	0.000	−0.014
lagged	−0.026*	−0.064*	0.021	0.073
fixed	0.019	−0.022	0.093***	−0.120
house	−0.022	0.144	−0.035*	−0.054
distance	−0.026	−0.249*	0.116***	0.184
educ	0.005	−0.031	−0.082***	−0.011
factors	−0.024	0.008	0.080***	−0.050
foreigners	−0.026	0.021	0.049***	−0.037
intercept	0.039	0.196	−0.265***	0.156
R^2	0.45	0.85	0.59	0.68
Observations	126	172	94	127

Note: The dependent variable in every regression is the estimated partial correlation of the labor market factors.
Abbreviations: u_d, unemployment at destination; w_d, wages at destination; u_o, unemployment at origin; w_o, wages at origin; WLS, weighted least squares.
***, **, and * Significance at the 1%, 5%, and 10% level.

larger pushing effect of wages at the origin. These results may suggest that the number of people who fled some of the economically depressed areas of the country was particularly large during the recession.

Data characteristics such as employing individual or panel data do not seem to significantly moderate the effect of the labor market factors, except that the triggering effect on outmigration of a larger unemployment rate at the origin appears to be stronger when drawing on individual data. In contrast, the estimated labor-markets push and pull effect are found to be enlarged in regressions examining migration flows between smaller spatial units. As noted in the previous section, this could be because of the inclusion of shorter-distance moves, for example, between provinces within the same autonomous community, involve lower costs that make the arbitrage of labor-market disparities easier.

Concerning the measures used for the relevant variables in the original studies, we find that assessing the impact on the net instead of gross flows exacerbates the effects for all labor-market determinants but unemployment at the destinations. We anticipated this result since the push effect is subtracted from the pull when assessing net flows, and since they should have opposite signs, the magnitude of this subtraction is larger than the magnitude of the individual coefficients. Regarding measuring the labor-market factors in relative terms, it moderates the estimated effect sizes of all factors except wages at the origin. This result implies that rising wages or reducing unemployment at the destination relative to the origin imply lower migration inflows than considering the wages and unemployment at the two ends separately. Similarly, the effect of unemployment at origin is also diminished when using variables in relative terms. As noted in the previous section, using relative measures assumes that an individual is indifferent to whether an increase in a relative variable comes from an increase at the destination or a reduction at the origin. This could be a problem if an individual's responses to changes in labor-market factors at the destinations and origins are asymmetric, which can be the case as the pull effect of wages seems to be stronger than the push, and the push effect of the unemployment rate slightly stronger than its pull counterpart (Table 2).

On the other hand, employing GDP per capita instead of wages in the estimations does not seem to influence the estimated effects of the labor-market factors on interregional migration. The result implies that despite that differences in regional GDP per capita could capture variations in living standards, it does not fail to depict differences in economic opportunities, and therefore, GDP per capita can be used to proxy wages when the latter is not available for some periods or geographies.

Regarding econometric specifications, including a vast number of fixed effects, at least equal to the number of spatial units, significantly accentuates the unemployment rate pushing effect at the origin. Likewise, lagging the variables—mainly to reduce reversal causality—appears to find a stronger pulling effect of the unemployment rate but a weaker pulling effect of wages. That is, using the previous year rather than a contemporary observation finds an effect of unemployment more consistent with a spatial arbitraging, while the opposite seems to happen with wages.

Finally, unemployment at the origin seems to be the factor more severely affected by the addition of other determinants of interregional migration flows such as other labor-market factors (either wages at origin or destination or unemployment at destination), housing prices, distance, and education. This suggests that the unemployment rate at origin can be the most endogenous variable in the system, leading to biased estimates of its effect on interregional migration flows when some of these factors are omitted. Specifically, ignoring either wages at origin or unemployment and wages at the destination and distance between the regions biases downward the effect of the unemployment rate at origin on outmigration, whereas neglecting housing prices and education biases the effect upward. Furthermore, the estimates of wages at destination seem to be biased when ignoring distance, as regressions omitting distance seems to overestimate its impact on migration inflows. Last, foreigners are significantly more responsive to the unemployment rate in their current regions than natives.

5 | DISCUSSION

Our main findings support the role of labor market variables in shaping migration flows in Spain. Average effects are larger for wages than for unemployment and display the expected disequilibrium sign: higher income and lower unemployment in destination areas attract people, and lower wages and higher unemployment in origin areas are push factors for movers. Therefore, we find that the Spanish literature provides support to the disequilibrium hypothesis. That is, the economy is often in a spatial disequilibrium, and interregional migrants tend to exploit the opportunity of economic disparities across regions.

However, the estimated effects might not be the result of an absolutely representative sample of the true underlying effects, in particular for the factors at the origin, since we detect significant evidence of publication bias as the size of the estimated effects of the labor-market factors at the origin is correlated with their standard errors in the direction implied by the disequilibrium hypothesis. Therefore, we cannot discard that the specification and model selection of some studies were driven by obtaining more intuitive and significant results.

We also found that the estimated push and pull factors are significantly heterogeneous. The meta-regression results imply that the estimated effects are severely affected by specific research characteristics. Although the influence that these research features exert on the estimated effect sizes varies from one factor to another, some

TABLE 4 Predicted partial correlation coefficients of the four labor-market factors

Factor	Interregional	Interprovincial
u_d	0.024	−0.085**
w_d	−0.115	0.208**
u_o	0.031	0.090***
w_o	−0.097	−0.310**

Abbreviations: u_d, unemployment at destination; w_d, wages at destination; u_o, unemployment at origin; w_o, wages at origin.
***, **, and * Significance at the 1%, 5%, and 10% level.

appear common. These include the authors, the spatial division for which internal migration is recorded, whether using net or gross flows, and whether measuring the factors in one end relative to the other or having them separated. On the other hand, other features seem to have negligible impacts on the estimations, such as the examined period, its duration, data structure (either panel or cross-section), and whether using GDP per capita or wages.

The literature review and subsequent discussion for the selection of research attributes as explanatory variables in the meta-regression helped us identify some practices that might be better than others to estimate the effects of the determinants of interregional migration flows. For instance, lagging the explanatory variables and accounting for unobservable fixed features could limit endogeneity. In the same line, the inclusion of other variables relevant for interregional migration flows in the regressions, which can be correlated with some of the labor-market factors, is also beneficial for obtaining unbiased estimations of the relevant parameters. These variables include housing prices, bilateral distance and the level of education. On the other hand, some specifications are not recommended because they involve information loss and impose questionable coefficients constraints. These practices include using net rather than gross flows or entering the labor-market factors in relative terms.

Table 4 presents the predicted partial correlation coefficients of hypothetical regressions of migration for the two types of spatial units, regions (autonomous communities) and provinces. They draw on the estimates of the meta-regressions presented in Table 3, together with what can be considered better practices for estimating the determinants of interregional migration flows in Spain. The results, however, should be taken with caution because "defining 'best practices' is subjective since different studies may have different ideas about what best practices should be" (Polák, 2019, p. 117). Here, the best practices include regressions that draw on aggregate panel data structure to better deal with unobservables[9], consider gross migration flows, all labor-market factors added separately, and use measures of wages rather than overall income or GDP. With respect to econometric specifications, they consider fixed effects and lags of the explanatory factors. The hypothetical regressions also control for other potential determinants of migrations that can be correlated with the labor-market factors of interest, such as distance, housing prices, and education. Finally, they examine the 2010-2019 period to observe at least a decade and make them current.[10]

[9]Although this does not mean that examining migration flows is preferred over those examining individuals' migration propensities. We opted for the former as annual data over more extended periods is usually available at the aggregate level. The same is true for data on several potential explanatory factors.

[10]Given the selected period, and following our codification of Table 1, the hypothetical regressions do not focus on the 2008–2014 Spanish recession, so the related dummy is set to zero accordingly. Although statistically speaking, longer periods should be preferred, the estimates of the meta-regressions suggest that changing the examined period has very little influence on the predicted effects. The dummy variable *maza* is also set to zero. Given the effects estimated in the meta-regressions, a Maza and co-authors' regression will predict weaker push and stronger pull effects, particularly of migration across provinces, as most of their estimates correspond to Interprovincial migration. In addition, we also consider those estimates that are more representative of the whole population by setting the foreigners dummy to zero. Finally, we chose the percentile 25th as the standard error of the partial correlation in each factor to avoid having a predicted effect susceptible to bias for publishing significant results, but at the same time, with relatively low standard errors. The reader can infer how the predictions are affected by changing some of these features by looking at the meta-regressions estimates.

The predicted partial correlations given by our hypothetical "better-practices" regressions show that economic opportunities significantly drive interprovincial but not interregional migration flows. Specifically, higher wages boost interprovincial inflows while larger unemployment rates discourage them, and an increased unemployment rate enlarges interprovincial outflows while higher wages prevent them. Moreover, at least for interprovincial migration, wages tend to matter more than unemployment differentials, and they tend to matter more at the origin than at the destination. Therefore, we can conclude that the interprovincial migration flows have shown responses that fully accord with a spatial arbitrage of labor markets. In contrast, labor-market differentials across regions have not been as successful in motivating interregional migration, perhaps due to either a small number of regions (17 Spanish autonomous communities), heterogeneous delineation of such regions (substantial size differences), or due to other factors (e.g., amenity differentials) having a more prominent role.

Nevertheless, our estimations are based only on models selection and specifications that have been adopted in the Spanish literature thus far, and we cannot infer what would have been estimated otherwise. We have already noticed, for example, that one important determinant of migration often omitted in the Spanish literature is the age composition of a region's population (some exceptions include Antolin and Bover (1997) and some estimates in Melguizo and Royuela (2020) and Maza (2020)). Specifically, young adults, aged between 20 and 40, have a significantly higher migration propensity, linked to transitions in the life course such as education and labor-force entry (Bernard et al., 2014; Rogers & Castro, 1981). Alvarez et al. (2021) shows that the proportion of young adults has been the most significant transformation shaping interregional migration trends in OECD countries. Moreover, the triggers of migration can differ across age groups. Maza (2020) found that wages, unemployment and amenities drive interprovincial migration of older adults in Spain while only unemployment drives it for the youth. Controlling for age is important in the Spanish case since there are important variations in the age composition of the population across provinces. For instance, the proportion of the population aged 65+ generally exceed 30% in the north-western provinces, while the proportion of people aged 20–40 in these provinces is below 22%. In contrast, the proportion of people aged over 65 is below 20% in provinces in the south, islands, and North Africa, while the share of young adults above 26% (INE, 2021). Then, we should observe disproportionately high migration flows from young-population provinces, responsive to economic conditions, and disproportionately low migration flows from North-western provinces, driven by non-economic factors.

Regarding modeling issues, we early noticed that the volume of bilateral migration not only depend on the attributes of the two regions involved but also on the attractiveness of a set of potential destinations, which include other regions in the country and possibly international destinations as well. This is known as multilateral resistance to migration, and Bertoli and Moraga (2013) and Beine et al. (2016) advocate the use of a combination of origin, destination, and time effects as well as estimating with common correlated effects (Pesaran, 2006) to deal with it. Although the combination of fixed effects is becoming more common (Maza et al., 2019; Melguizo & Royuela, 2020), no study has estimated the impact of the determinants of internal migration flows in Spain with common correlated effects. This contrast with related empiric works in other countries like Italy (Piras, 2017). The meta-analysis results endorse accounting for common factors or recognizing the hierarchical structure of the data by adopting a multilevel approach as the 2008–2014 Spanish recession seems to have affected individuals' response to wages differentials. Although Maza and Villaverde (2008), Arauzo-Carod and Liviano-Solís (2013), Maza et al. (2013) and Viñuela et al. (2019) employ spatial methods that also lessen the cross-sectional dependence.

In addition to cross-sectional dependence, serial dependence can also be an important issue as past migration flows could influence later flows. The empiric works on the determinants of internal migration in Spain have not modeled the dynamic relationships of internal migration flows with their determinants. Furthermore, the likely nonstationarity of the relevant variables has not been investigated, which is relevant to shed light on the persistence of the fluctuations and because regressions between nonstationary and non-cointegrated variables can be spurious (Granger & Newbold, 1974). Among further benefits from estimating dynamic panels are distinguishing between short- and long-run relationships as well as direct and indirect effects. For example, Alvarez et al. (2021) find that the short-term effect of regional disparities (measured by regional GDP per capita) on overall internal migration intensities is stronger in the short run than in the long run. Their result could be interpreted in terms of adjustments toward spatial equilibrium. Alecke et al. (2010) found that the negative effect of unemployment tends to disappear over time, but the positive effect of wages persists. Alecke et al. (2010) also found that human capital had a negative direct impact on net internal migration, but when considering the indirect effect through the influence of human capital over the other factors, the effect turns positive. Further applied research could explore these issues in Spain while taking advantage of recent econometric developments that estimate dynamic models handling cross-sectional dependence through common correlated effects (Chudik & Pesaran, 2015).

6 | CONCLUSIONS

Despite the considerable number of empiric works analyzing the drivers of interregional migration flows, no work has attempted to perform a meta-analysis of the topic to date. This paper fills this gap by conducting a meta-analysis on the effect of wages and unemployment rates, at origin and destination, on bilateral migration flows within Spain. We focus on Spain because of the abundance of empiric works there and the large disagreement of findings. Moreover, Spain has been characterized by a long-lasting high unemployment rate with significant economic fluctuations, which means that interregional migration flows in Spain have taken place under unique conditions. We collected 36 econometric studies dating from 1980 to 2020 to provide consolidated estimates of the push and pull labor-market factors on internal migration flows, investigate the existence of publication bias, and identify research features that might be behind the diversity of estimates.

The overall effects suggest that internal migration flows in Spain have responded in the conventionally expected way, that is, people tend to locate into regions with higher wages and lower unemployment rates. Also, migration flows are more responsive to monetary factors than to unemployment differentials, and both have a stronger effect at origin than at the destination. However, these results should be taken with caution since the results also show evidence of publication bias. Moreover, the diversity of features in the original studies appears to be behind the wide variety of estimated effect sizes.

Predictions from the estimation of the meta-regressions provide us with more profound conclusions. That is, the selection and specification of more robust models that limit the inherent endogeneity of the labor-market factors by including fixed effects, using lags of the explanatory factors, and controlling for other internal migration determinants, imply that four labor-market factors indeed drive interprovincial migration flows (or between smaller spatial units) in the direction implied by a spatial disequilibrium in labor markets. On the other hand, migratory flows between more extensive geographies, such as interregional flows (between autonomous communities), might not be the best spatial unit for the analysis for labor mobility in Spain as labor does not show responsiveness to regional variations in the labor markets.

Finally, although there is a considerable number of studies examining the drivers of bilateral migration flows in Spain, there are still opportunities to continue exploring the topic. Such work should rely on gross instead of net flows and include the variables from which individuals derive utility for the regions of origin and destination separately. Also, future research should consider the inclusion of all potential explanatory factors in conjunction with the traditional economic determinants, even if the interest is only on the latter. Their addition in the regressions not only allow to explore their influence on internal migration flows but also to reduce biases from omitting relevant regressors. These potential factors can be the regional endowment of human capital, international migration flows, the share of young adults, housing prices, bilateral distance, to mention some. Last, such future research can exploit dynamic panel models that accommodate common shocks or make use of multilevel information as we noticed that the national economic context could influence the identification of the regional determinants of bilateral flows.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Maximiliano Alvarez https://orcid.org/0000-0002-7647-0063

Vicente Royuela http://orcid.org/0000-0002-7647-0063

REFERENCES

Alecke, B., Mitze, T., & Untiedt, G. (2010). Internal migration, regional labour market dynamics and implications for german east-west disparities: Results from a panel var. *Jahrbuch Für Regionalwissenschaft*, *30*(2), 159–189. https://doi.org/10.1007/s10037-010-0045-3

Alvarez, M., Bernard, A., & Lieske, S. N. (2021). Understanding internal migration trends in OECD countries. *Population, Space and Place*, *107*, e2451–1449. https://doi.org/10.1002/psp.2451

Antolin, P., & Bover, O. (1997). Regional migration in Spain: The effect of personal characteristics and of unemployment, wage and house price differentials using pooled cross-sections. *Oxford Bulletin of Economics and Statistics*, *59*(2), 215–235. https://doi.org/10.1111/1468-0084.00061

Arauzo-Carod, J. M., & Liviano-Solís, D. (2013). *Migration determinants at a local level*. Universitat Rovira i Virgili.

Bardsley, N., & Ederveen, S. (2003). *The influence of wage and unemployment differentials on labour mobility in the EU: A meta-analysis* (Project Report). Centraal PlanBureau.

Beine, M., Bertoli, S., & Fernández-Huertas Moraga, J. (2016). A practitioners' guide to gravity models of international migration. *The World Economy*, *39*(4), 496–512. https://doi.org/10.1111/twec.12265

Bentolila, S. (1997). Sticky labor in Spanish regions. *European Economic Review*, *41*(3-5), 591–598. https://doi.org/10.1016/S0014-2921(97)00002-0

Bentolila, S., Dolado, J. J., & the Libra Universita. (1991). Mismatch and internal migration in Spain, 1962–86. In F. P. Schioppa, & La Sapienza and the Libra Universita (Eds.), *Mismatch and labour mobility* (pp. 182–234). Cambridge University Press.

Bernard, A., & Bell, M. (2018). Educational selectivity of internal migrants: A global assessment. *Demographic Research*, *39*, 835–854. https://doi.org/10.4054/DemRes.2018.39.29

Bernard, A., Bell, M., & Charles-Edwards, E. (2014). Life-course transitions and the age profile of internal migration. *Population and Development Review*, *40*(2), 213–239. https://doi.org/10.1111/j.1728-4457.2014.00671.x

Berry, C. R., & Glaeser, E. L. (2005). The divergence of human capital levels across cities*. *Papers in Regional Science*, *84*(3), 407–444. https://doi.org/10.1111/j.1435-5957.2005.00047.x

Bertoli, S., & Moraga, J. F. -H. (2013). Multilateral resistance to migration. *Journal of Development Economics*, *102*, 79–100. https://doi.org/10.1016/j.jdeveco.2012.12.001

Biagi, B., Faggian, A., & McCann, P. (2011). Long and short distance migration in Italy: The role of economic, social and environmental characteristics. *Spatial Economic Analysis*, *6*(1), 111–131. https://doi.org/10.1080/17421772.2010.540035

Blanchard, O. J., Katz, L. F., Hall, R. E., & Eichengreen, B. (1992). Regional evolutions. *Brookings Papers on Economic Activity*, *1992*(1), 1–75. https://doi.org/10.2307/2534556

Blanchflower, D. G., & Oswald, A. J. (1995). An introduction to the wage curve. *Journal of Economic Perspectives*, *9*(3), 153–167. https://doi.org/10.1257/jep.9.3.153

Card, D., & Krueger, A. B. (1995). Time-series minimum-wage studies: A meta-analysis. *The American Economic Review*, *85*(2), 238–243.

Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, *188*(2), 393–420. https://doi.org/10.1016/j.jeconom.2015.03.007

Clemente, J., Larramona, G., & Olmos, L. (2016). Interregional migration and thresholds: Evidence from Spain. *Spatial Economic Analysis*, *11*(3), 276–293. https://doi.org/10.1080/17421772.2016.1153706

Cochran, W. G. (1954). The combination of estimates from different experiments. *Biometrics*, *10*(1), 101–129.

Conde-Ruiz, J. I., García, J. R., & Navarro, M. (2008). *Inmigración y crecimiento regional en españa* (Colección estudios económicos No. 09–08). FEDEA.

Cooper, H. E., Hedges, L. V., & Valentine, J. C. (2009). *The handbook of research synthesis and meta-analysis*. Russell Sage Foundation.

Crozet, M. (2004). Do migrants follow market potentials? An estimation of a new economic geography model. *Journal of Economic Geography*, *4*(4), 439–458. https://doi.org/10.1093/jnlecg/lbh029

De la Fuente, Á (1999). La dinámica territorial de la población española: Un panorama y algunos resultados provisionales. *Revista de Economía Aplicada*, *7*(20), 53–108.

Devillanova, C., & García Fontes, W. (2004). Migration across spanish provinces: Evidence from the social security records (1978–1992). *Investigationes Económicas*, *23*, 461–487.

Elhorst, J. P. (2003). The mystery of regional unemployment differentials: Theoretical and empirical explanations. *Journal of Economic Surveys*, *17*(5), 709–748. https://doi.org/10.1093/oxfordjournals.oep.a041980

Faggian, A., McCann, P., & Sheppard, S. (2007). Some evidence that women are more mobile than men: Gender differences in U.K. graduate migration behavior. *Journal of Regional Science*, *47*(3), 517–539. https://doi.org/10.1111/j.1467-9787.2007.00518.x

Faggian, A., Modrego, F., & McCann, P. (2019). Human capital and regional development. In *Handbook of regional growth and development theories*. Edward Elgar Publishing. https://doi.org/10.4337/9781788970020.00015

García-Ferrer, A. (1980). Interactions between internal migration, employment growth, and regional income differences in Spain. *Journal of Development Economics*, *7*(2), 211–229. https://doi.org/10.1016/0304-3878(80)90005-X

Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. *Journal of Economic Geography*, *1*(1), 27–50. https://doi.org/10.1093/jeg/1.1.27

Granger, C., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, *2*(2), 111–120. https://doi.org/10.1016/0304-4076(74)90034-7

Graves, P. E. (1976). A reexamination of migration, economic opportunity, and the quality of life. *Journal of Regional Science*, *16*(1), 107–112. https://doi.org/10.1111/j.1467-9787.1976.tb00954.x

Graves, P. E. (1980). Migration and climate. *Journal of Regional Science*, *20*(2), 227–237. https://doi.org/10.1111/j.1467-9787.1980.tb00641.x

Graves, P. E. (1983). Migration with a composite amenity: The role of rents. *Journal of Regional Science*, *23*(4), 541–546. https://doi.org/10.1111/j.1467-9787.1983.tb01009.x

Greenberg, D., Michalopoulos, C., & Robins, P. (2003). A meta-analysis of government-sponsored training programs. *ILR Review*, *57*(1), 31–53. https://doi.org/10.1177/001979390305700102

Greenwood, M. J. (1975). Research on internal migration in the united states: A survey. *Journal of Economic Literature*, *13*, 397–433.

Gutierrez Portilla, M. (2014). *Determinants of interregional migration in Spain: Are there differences between foreigners and natives?* Reunion de Estudios Regionales.

Gutiérrez-Portilla, M., Maza, A., & Hierro, M. (2018). Foreigners versus natives in Spain: Different migration patterns? Any changes in the aftermath of the crisis? *Annals of Regional Science*, *61*(1), 139–159. https://doi.org/10.1007/s00168-018-0862-9

Havránek, T., Stanley, T. D., Doucouliagos, H., Bom, P., Geyer-Klingeberg, J., Iwasaki, I., Reed, W. R., Rost, K., & Aert, R. C. M. (2020). Reporting guidelines for meta-analysis in economics. *Journal of Economic Surveys*, *34*(3), 469–475. https://doi.org/10.1111/joes.12363

Hierro, M., Maza, A., & Villaverde, J. (2019). Internal migration dynamics in Spain: Winners and losers from the recent economic recession. *Population, Space and Place*, *25*(2), e2176–68. https://doi.org/10.1002/psp.2176

INE. (2021). *Cifras de población y censos demográficos*. Instituto Nacional de Estadísticas.

Jaumotte, M. F. (2011). *The Spanish labor market in a cross-country perspective* (Working paper No. 11/11). International Monetary Fund.

Juarez, J. P. (2000). Analysis of interregional labor migration in Spain using gross flows. *Journal of Regional Science*, *40*(2), 377–399. https://doi.org/10.1111/0022-4146.00179

Karahan, F., & Rhee, S. (2014). *Population aging, migration spillovers, and the decline in interstate migration* (Staff report No. 699). Federal Reserve Bank of New York.

Knapp, T. A., & Gravest, P. E. (1989). On the role of amenities in models of migration and regional development. *Journal of Regional Science*, *29*(1), 71–87. https://doi.org/10.1111/j.1467-9787.1989.tb01223.x

Korpi, M., & Clark, W. A. (2015). Internal migration and human capital theory: To what extent is it selective? *Economics Letters*, *136*, 31–34. https://doi.org/10.1016/j.econlet.2015.08.016

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, *99*(3), 483–499. https://doi.org/10.1086/261763

Lago, C., & Aguayo, E. (2004). Migraciones interiores en españa: Un modelo econométrico regional 1980–2000. *Regional and Sectoral Economic Studies*, *4*(1), 121–138.

Larkin, M. P., Askarov, Z., Doucouliagos, H., Dubelaar, C., Klona, M., Newton, J., Stanley, T. D., & Vocino, A. (2019). Do house prices ride the wave of immigration? *Journal of Housing Economics*, *46*, 101630. https://doi.org/10.1016/j.jhe.2019.04.002

Lindley, J., Upward, R., & Wright, P. (2002). *Regional mobility and unemployment transitions in the UK and Spain*. Leverhulme Centre for Research on Globalisation; Economic Policy, University of Nottingham.

Liu, L. Q. (2018). *Regional labor mobility in Spain* (Working paper No. 18/282). International Monetary Fund.

Longhi, S., Nijkamp, P., & Poot, J. (2010). Meta-analyses of labour-market impacts of immigration: Key conclusions and policy implications. *Environment and Planning C: Government and Policy*, *28*(5), 819–833. https://doi.org/10.1068/c09151r

Marston, S. T. (1985). Two views of the geographic distribution of unemployment. *The Quarterly Journal of Economics*, *100*(1), 57–79. https://doi.org/10.2307/1885735

Maza, A. (2006). Migrations and regional convergence: The case of Spain. *Jahrbuch Fur Regionalwissenschaft*, *26*(2), 191–202. https://doi.org/10.1007/s10037-006-0009-9

Maza, A. (2020). Internal migration in Spain: A complementary approach. *Economies*, *8*(3), 59. https://doi.org/10.3390/economies8030059

Maza, A., Gutiérrez-Portilla, M., Hierro, M., & Villaverde, J. (2019). Internal migration in Spain: Dealing with multilateral resistance and nonlinearites. *International Migration*, *57*(1), 75–93. https://doi.org/10.1111/imig.12472

Maza, A., & Villaverde, J. (2004a). Determinantes de la migración interregional en españa: Nuevas técnicas de análisis. *Investigaciones Regionales-Journal of Regional Research*, *4*, 133–142.

Maza, A., & Villaverde, J. (2004b). Interregional migration in Spain: A semiparametric analysis. *Review of Regional Studies*, *34*(2), 156–171.

Maza, A., & Villaverde, J. (2008). A note on the need to account for spatial dependence: A case of migratory flows in Spain. *Review of Regional Studies*, *38*(1), 105–111. https://doi.org/10.52324/001c.8256

Maza, A., Villaverde, J., & Hierro, M. (2013). Explaining the settlement patterns of foreigners in Spain. *Applied Geography*, *40*, 11–20. https://doi.org/10.1016/j.apgeog.2013.01.004

Melguizo, C., & Royuela, V. (2020). What drives migration moves to urban areas in Spain? Evidence from the great recession. *Regional Studies*, *54*(12), 1680–1693. https://doi.org/10.1080/00343404.2020.1747606

Mulhern, A., & Watson, J. (2009). Spanish internal migration: Is there anything new to say? *Spatial Economic Analysis*, *4*(1), 103–120. https://doi.org/10.1080/17421770802625841

Mulhern, A., & Watson, J. (2010). Spanish inter-regional migration: An enigma resolved. *Applied economics letters*, *17*(14), 1355–1359. https://doi.org/10.1080/13504850902967464

Newbold, K. B. (1996). Internal migration of the foreign-born in Canada. *International Migration Review*, *30*(3), 728–747. https://doi.org/10.1177/019791839603000304

Niedomysl, T. (2011). How migration motives change over migration distance: Evidence on variation across socio-economic and demographic groups. *Regional Studies*, *45*(6), 843–855. https://doi.org/10.1080/00343401003614266

Nijkamp, P., Gheasi, M., & Rietveld, P. (2011). Migrants and international economic linkages: A meta-overview. *Spatial Economic Analysis*, *6*(4), 359–376. https://doi.org/10.1080/17421772.2011.610814

Orcutt, G. H., Watts, H. W., & Edwards, J. B. (1968). Data aggregation and information loss. *The American Economic Review*, *58*(4), 773–787.

Ozgen, C., Nijkamp, P., & Poot, J. (2010). The effect of migration on income growth and convergence: Meta-analytic evidence. *Papers in Regional Science*, *89*(3), 537–561. https://doi.org/10.1111/j.1435-5957.2010.00313.x

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, *74*(4), 967–1012. https://doi.org/10.1111/j.1468-0262.2006.00692.x

Piras, R. (2017). A long-run analysis of push and pull factors of internal migration in Italy. Estimation of a gravity model with human capital using homogeneous and heterogeneous approaches. *Papers in Regional Science*, *96*(3), 571–602. https://doi.org/10.1111/pirs.12211

Poggi, A. (2019). Regional labour markets in Spain: Can flexibility and local democracy reduce inefficiencies? *Papers in Regional Science*, *98*(3), 1499–1516. https://doi.org/10.1111/pirs.12422

Polák, P. (2019). The euro's trade effect: A meta-analysis. *Journal of Economic Surveys*, *33*(1), 101–124. https://doi.org/10.1111/joes.12264

Ramos, R. (2017). Modelling migration. In L. Matyas (Ed.), *The econometrics of multi-dimensional panels* (pp. 377–395). Springer.

Raymond, J. L., & García-Greciano, B. (1996). Distribución regional de la renta y movimientos migratorios. *Papeles de Economía Española*, *67*, 185–201.

Recaño, J., & Roig, M. (2006). *The internal migration of foreigners in Spain*. 2006 European Population Conference—Liverpool.

Reher, D. S., & Silvestre, J. (2009). Internal migration patterns of foreign-born immigrants in a country of recent mass immigration: Evidence from new micro data for Spain. *International Migration Review*, *43*(4), 815–849. https://doi.org/10.1111/j.1747-7379.2009.00785.x

Rogers, A., & Castro, L. J. (1981). *Model migration schedules* (IIASA research report). International Institute for Applied Systems Analysis (IIASA); RR-81-030.

Ródenas, C. (1994). Migraciones interregionales en españa 1960-1989. *Revista de Economía Aplicada*, *4*, 5–36.

Santillana, I. (1981). Los determinantes económicos de las migraciones internas en españa, 1960-1973. *Cuadernos de Economia*, *9*(25), 381–407.

Simonen, J., Svento, R., Karhinen, S., & McCann, P. (2018). Inter-regional and inter-sectoral labour mobility and the industry life cycle: A panel data analysis of Finnish high technology sector. In B. Biagi, A. Faggian, I. Rajbhandari, & V. A. Venhorst (Eds.), *New frontiers in interregional migration research* (pp. 151–179). https://doi.org/10.1007/978-3-319-75886-2_8

Schwarzer, G., Carpenter, J. R., & Rücker, G. (2015). *Meta-analysis with r*. Springer. https://doi.org/10.1007/978-3-319-21416-0

Shapiro, J. M. (2006). Smart cities: Quality of life, productivity, and the growth effects of human capital. *The Review of Economics and Statistics*, *88*(2), 324–335. https://doi.org/10.1162/rest.88.2.324

Sjaastad, L. A. (1962). The costs and returns of human migration. *Journal of Political Economy*, *70*(*5*, *Part*), *2*, 80–93. https://doi.org/10.1086/258726

Stanley, T., & Doucouliagos, H. (2012). *Meta-regression analysis in economics and business*. Routledge.

Stanley, T., & Doucouliagos, H. (2017). Neither fixed nor random: Weighted least squares meta-regression. *Research Synthesis Methods*, *8*(1), 19–42. https://doi.org/10.1002/jrsm.1211

Stanley, T., Doucouliagos, H., & Steel, P. (2018). Does ICT generate economic growth? A meta-regression analysis. *Journal of Economic Surveys*, *32*(3), 705–726. https://doi.org/10.1111/joes.12211

Todaro, M. P. (1969). A model of labor migration and urban unemployment in less developed countries. *The American Economic Review*, *59*(1), 138–148.

Viechtbauer, W., López-López, J. A., Sánchez-Meca, J., & Marín-Martínez, F. (2015). A comparison of procedures to test for moderators in mixed-effects meta-regression models. *Psychological Methods*, *20*(3), 360–74. https://doi.org/10.1037/met0000023

Viñuela, A., Gutiérrez Posada, D., & Rubiera Morollón, F. (2019). Determinants of immigrants' concentration at local level in Spain: Why size and position still matter. *Population, Space and Place*, *25*(7), e2247. https://doi.org/10.1002/psp.2247

Wölfl, A., & Mora-Sanguinetti, J. S. (2011). *Reforming the labour market in Spain* (Economics Department Working Papers No. 845). OECD.

SUPPORTING INFORMATION

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APPENDIX A: LIST OF THE STUDIES INCLUDED IN THE META-ANALYSIS

1. Ahn, N., Jimeno, J. F., & García, E. (2002). *Migration willingness in Spain: analysis of temporal and regional differences*.
2. Alemán, A. H., & León, C. J. (2012). Determinants of internal and external immigration to the canary islands. *Regional Studies*, *46*(3), 391–403. https://doi.org/10.1080/00343404.2010.505912
3. Antolin, P., & Bover, O. (1997). Regional migration in Spain: The effect of personal characteristics and of unemployment, wage and house price differentials using pooled cross-sections. *Oxford Bulletin of Economics and Statistics*, *59*(2), 215–235. https://doi.org/10.1111/1468-0084.00061
4. Arauzo-Carod, J., & Liviano-Solís, D. (2013). *Migration determinants at a local level* (pp. 1–43). Universitat Rovira i Virgili.

5. Bentolila, S., & Dolado, J. J. (1991). Mismatch and internal migration in Spain, 1962-86. In F. P. Schioppa & La Sapienza and the Libra Universita (Eds.), *Mismatch and labour mobility* (pp. 182–234). Cambridge University Press.
6. Bernabé, J. M., & Albertos, J. M. (1986). Migraciones interiores en España. *Cuadernos de Geografía*, *39–40*, 175–202.
7. Clemente, J., Larramona, G., & Olmos, L. (2016). Interregional migration and thresholds: Evidence from Spain. *Spatial Economic Analysis*, *11*(3), 276–293. https://doi.org/10.1080/17421772.2016.1153706
8. Devillanova, C., & García Fontes, W. (2004). Migration across spanish provinces: Evidence from the social security records (1978-1992). *Investigationes Económicas*, *23*, 461–487.
9. García-Ferrer, A. (1980). Interactions between internal migration, employment growth, and regional income differences in Spain. *Journal of Development Economics*, *7*(2), 211–229. https://doi.org/10.1016/0304-3878(80)90005-X
10. García-Greciano, B., & Raymond, J. L. (2000). *Migratory movements and regional convergence in Spain*. European Regional Science Association (ERSA).
11. Gómez, C., & García-Perez, J. I. (2003). Flujos migratorios de trabajadores andaluces (1979-1997): un análisis económico con datos individuales. *Investigaciones Regionales*, *2*, 59–83.
12. Gutierrez Portilla, M. (2014). *Determinants of interregional migration in Spain: Are there differences between foreigners and natives?* Reunion de Estudios Regionales.
13. Juarez, J. P. (2000). Analysis of interregional labor migration in Spain using gross flows. *Journal of Regional Science*, *40*(2), 377–399. https://doi.org/10.1111/0022-4146.00179
14. Lago, C., & Aguayo, E. (2004). Migraciones interiores en españa: Un modelo econométrico regional 1980–2000. *Regional and Sectoral Economic Studies*, *4*(1), 121–138.
15. Lindley, J., Upward, R., & Wright, P. (2002). *Regional mobility and unemployment transitions in the UK and Spain*. Leverhulme Centre for Research on Globalisation; Economic Policy, University of Nottingham.
16. Liu, L. Q. (2018). *Regional labor mobility in Spain* (Working paper No. 18/282). International Monetary Fund.
17. Martínez, M. (2009). Migraciones interregionales en españa y su relación con algunas políticas públicas autonómicas. *Urban Public Economics Review*, *11*, 40–79.
18. Martínez-Torres, M. (2007). Migraciones interregionales en España, 1996-2004. *Presupuesto Y Gasto Público*, *48*, 85–106.
19. Maza, A. (2006). Migrations and regional convergence: The case of Spain. *Jahrbuch Fur Regionalwissenschaft*, *26*(2), 191–202. https://doi.org/10.1007/s10037-006-0009-9
20. Maza, A. (2020). Internal migration in Spain: A complementary approach. *Economies*, *8*(3), 59. https://doi.org/10.3390/economies8030059
21. Maza, A., & Villaverde, J. (2004a). Determinantes de la migración interregional en españa: Nuevas técnicas de análisis. *Investigaciones Regionales-Journal of Regional Research*, *4*, 133–142.
22. Maza, A., & Villaverde, J. (2004b). Interregional migration in Spain: A semiparametric analysis. *Review of Regional Studies*, *34*(2), 156–171.
23. Maza, A., & Villaverde, J. (2008). A note on the need to account for spatial dependence: A case of migratory flows in Spain. *Review of Regional Studies*, *38*(1), 105–111. https://doi.org/10.52324/001c.8256
24. Maza, A., Gutiérrez-Portilla, M., Hierro, M., & Villaverde, J. (2019). Internal migration in Spain: Dealing with multilateral resistance and nonlinearites. *International Migration*, *57*(1), 75–93. https://doi.org/10.1111/imig.12472
25. Maza, A., Villaverde, J., & Hierro, M. (2013). Explaining the settlement patterns of foreigners in Spain. *Applied Geography*, *40*, 11–20. https://doi.org/10.1016/j.apgeog.2013.01.004
26. Melguizo, C., & Royuela, V. (2020). What drives migration moves to urban areas in Spain? Evidence from the great recession. *Regional Studies*, *54*(12), 1680–1693. https://doi.org/10.1080/00343404.2020.1747606

27. Mulhern, A., & Watson, J. G. (2009). Spanish internal migration: Is there anything new to say? *Spatial Economic Analysis*, *4*(1), 103–120. https://doi.org/10.1080/17421770802625841
28. Mulhern, A., & Watson, J. (2010). Spanish interregional migration: An enigma resolved. *Applied Economics Letters*, *17*(14), 1355–1359. https://doi.org/10.1080/13504850902967464
29. Palomares-Linares, I., & van Ham, M. (2020). Understanding the effects of homeownership and regional unemployment levels on internal migration during the economic crisis in Spain. *Regional Studies*, *54*(4), 515–526. https://doi.org/10.1080/00343404.2018.1502420
30. Pons, J., Paluzie, E., Silvestre, J., & Tirado, D. A. (2007). Testing the new economic geography: Migrations and industrial agglomerations in Spain. *Journal of Regional Science*, *47*(2), 289–313. https://doi.org/10.1111/j.1467-9787.2007.00510.x
31. Raymond, J. L., & García-Greciano, B. (1996). Distribución regional de la renta y movimientos migratorios. *Papeles de Economía Española*, *67*, 185–201.
32. Recaño, J., & Roig, M. (2006). The internal migration of foreigners in Spain. 2006 European Population Conference—Liverpool.
33. Ródenas, C. (1994). Migraciones interregionales en españa, 1960-1989. *Revista de Economía Aplicada*, *4*, 5–36.
34. Santillana, I. (1981). Los determinantes económicos de las migraciones internas en españa, 1960-1973. *Cuadernos de Economía*, *9*(25), 381–407.
35. Trueba, C., Jordá, V., & Sarabia, J. M. (2012). *Determinantes de la movilidad geográfica en España: un análisis con datos de panel*.
36. Viñuela, A., Gutiérrez Posada, D., & Rubiera Morollon, F. (2019). Determinants of immigrants' concentration at local level in Spain: Why size and position still matter. *Population, Space and Place*, *25*(7), e2247. https://doi.org/10.1002/psp.2247