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Amandine Aubry

Univ. Lille, CNRS, IESEG School of Management, UMR 9221 - LEM - Lille Économie Management, F-59000 Lille, France | amandine.aubry@univ-lille.fr

Jérôme Héricourt

Univ. Lille, CNRS, IESEG School of Management, UMR 9221 - LEM - Lille Économie Management, F-59000 Lille, France, and CEPII, France | jerome.hericourt@univ-lille.fr

Léa Marchal

Pantheon-Sorbonne University (Paris 1) and Centre d'Économie de la Sorbonne (UMR CNRS 8174)| lea.marchal@univ-paris1.fr

Clément Nedoncelle

Université Paris-Saclay, INRAE, AgroParisTech, Economie Publique, 78850, Thiverval-Grignon, France | clement.nedoncelle@inrae.fr

Does Immigration Affect Wages? A Meta-Analysis*

Amandine Aubry[†], Jérôme Héricourt[‡], Léa Marchal[⋆], and Clément Nedoncelle[△]

[†]Univ. Lille, CNRS, IESEG School of Management, UMR 9221 - LEM - Lille Économie Management, F-59000 Lille, France; amandine.aubry@univ-lille.fr

[‡]Univ. Lille, CNRS, IESEG School of Management, UMR 9221 - LEM - Lille Économie Management, F-59000 Lille, France, and CEPII, France; jerome.hericourt@univ-lille.fr

[⋆]Pantheon-Sorbonne University (Paris 1) and Centre d'Économie de la Sorbonne (UMR CNRS 8174); lea.marchal@univ-paris1.fr

[△]Université Paris-Saclay, INRAE, AgroParisTech, Economie Publique, 78850, Thiverval-Grignon, France.; clement.nedoncelle@inrae.fr

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Abstract

Does immigration deter native wages? No decisive answer has been provided until now. We provide an up-to-date meta-analysis of the literature investigating this topical question, based on 2,146 estimates from 64 studies published between 1972 and 2019. We confirm the *average* effect of immigration on native wages is negative and close to zero. This average effect hides a large heterogeneity across studies. Variation across estimates can be explained by the presence of structural heterogeneity such as the country of analysis, whereas little variance can be attributed to heterogeneity in research designs. Finally, on top of these structural determinants, we estimate a strong, robust, and negative effect of publishing in leading academic journals.

Keywords: Immigration, Labor Market, Meta-Analysis, Wage

JEL Codes: C80, J61, J15, J31

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1 Introduction

Should immigration be restricted and upon which conditions? This question has been hotly and extensively debated over the past decades, with a focus on the economic consequences for native workers in terms of employment and wage (Goldin et al., 2012). For instance, in 2012, Theresa May stated, "Uncontrolled, mass immigration displaces British workers, forces people onto benefits and suppresses the wages for the low paid" (December 12, 2012, *The Times*). This argument was a keystone of the *Brexit* campaign. Another example can be found in the Republican Party nomination acceptance speech of Donald J. Trump, who declared, "Decades of record immigration have produced lower wages and higher unemployment for our citizens, especially for African-American and Latino workers" (July 21, 2016).

A large literature in labor economics contributes to the policy debate by analyzing the wage effect of immigration. The standard analysis usually models the relationship between the labor market and immigration using a partial-equilibrium model consisting of a constant-returns-to-scale production function that combines a number of input factors. This canonical model predicts that a labor supply shock leads to a decrease in the marginal product of factors that are close substitutes and to an increase in the marginal product of factors that are close complements.

However, empirical results are mostly unclear. As pointed by Dustmann et al. (2016), some analyses conclude immigration reduces native wages, and others show either a positive or a null impact. In their critical survey of the literature on immigration and income, Blau and Kahn (2015) conclude that " most research does not find quantitatively important effects of immigration on native wage levels or the wage distribution." In the only meta-analysis of the empirical literature available until now, Longhi et al. (2005) use a set of 18 articles published until 2003 and find the impact of immigration on native wages is positive and statistically significant but quantitatively small: a 1 percentage point increase in the proportion of immigrants in the labor force lowers the wages of natives by only 0.1%. However, the authors note this average result hides substantial heterogeneity across studies.

Method and *structural* heterogeneity are the two usual suspects for explaining the lack of consensus on the sign of the wage elasticity across studies. First, differences in the estimation of the wage effect across studies seem to depend on the empirical method implemented by the authors. In particular, Dustmann et al. (2016) report the national skill-cell approach, the regional approach, and the mixed approach provide estimates that are poorly comparable even if these three reduced-form models are based on the same canonical model. The authors also note results differ across studies due to differences in the assumptions made (i) on the homogeneity of the elasticity of native wages to immigration along the skill/education distribution and (ii) on the fact that natives and immigrants compete within defined skill cells. Second, structural heterogeneity refers to differences in the structural features of the sample of each study such as the countries or the periods of analysis. Longhi et al. (2005) find the wage effect of immigration is larger in the U.S. than in European countries. The authors explain these results by differences in the geographical mobility of workers across these two areas. In addition, Blau and Kahn (2015) mention that most of the negative wage effects of immigration have been found using structural approaches for the U.S. labor market.

In this article, we perform a meta-analysis to further investigate the sources of variation in the estimated wage effect of immigration across studies. Meta-analyses have been increasingly used by economists to analyze the magnitude and the time trend of keystone economic results. Among others, see Weichselbaumer and Winter-Ebmer (2005) about the gender wage gap, Bajzik et al. (2020) regarding the sources of variation in the Armington elasticity, Disdier and Head (2008) concerning the distance effect on trade, Görg and Strobl (2001) on the spillover effects from multinational companies, and Jeppesen et al. (2002) regarding the relationship between manufacturing plant location decisions and environmental regulations.

Our sample includes 64 studies published between 1972 and 2019, reporting 2,146 β-estimates of the wage effect of immigration. Our analysis puts forward three main results. First, we confirm the *average* effect of immigration on native wages is close to zero. Our baseline meta-estimate of the impact of immigration on natives is equal to -0.044, whereas Longhi et al. (2005) find a meta-estimate of -0.119. Additionally, the β-estimates are concentrated around zero and mostly lie between -0.5 and 0.5. This limited – close to null – immigration effect is the main feature of this literature. One could imagine clear-cut positive and negative estimates were found in the literature such that the average effect would be zero. This is, however, not the case: most estimates are quantitatively close to zero.

Second, we investigate the sources of differences in the β-estimates. We find the structural heterogeneity is the main determinant of the immigration effect. Differences across country setup and the structure of the data explain, in part, why the estimated wage effects of immigration vary across studies. On the other hand, we find a minor impact of method heterogeneity. We estimate that differences in the empirical strategy, the estimator, the use of fixed effects, the definition of the variables of interests, or the use of strategy to account for endogeneity issues – which are advocated to be a determinant of the wage elasticity (Dustmann et al., 2016) – have only a limited impact. Our regressions display small and non-significant coefficients regarding these features of the β-estimates.

Finally, we estimate a strong, robust, and negative effect of publishing in leading academic journals. *Ceteris paribus*, leading academic journals provide more negative estimates of the impact of immigration on native wages, even after controlling for the potential publication bias. Controlling for method and structural heterogeneity, we estimate that this feature of the study appears to be the largest determinant of the magnitude of the estimate.

Our contribution to the literature is threefold. First, a large number of studies have contributed to the literature on the effect of immigration on the labor market, and could not have been investigated in the Longhi et al.'s (2005) meta-analysis. Therefore, we collected a larger sample than theirs. Ours includes 64 studies made on 17 different countries as well as studies on groups of countries such as the OECD. However, this increased sample does not change the quantitative conclusion reached in Longhi et al. (2005): immigration has a small, close to zero, deterrent effect on native wages. Second, this extended sample allows us to focus on additional determinants of the estimated immigration effect. In particular, we focus on additional and recent data characteristics and methods as determinants of the effect. Recent papers on the topic have increasingly used disaggregated data (e.g., from administrative sources) on longer time spans. Additionally, the recent literature witnessed an increased use of sophisticated econometric methods.[1] In particular regarding the endogeneity of immigration and wages (see, e.g., the discussion about endogeneity issues in Jaeger et al. 2018). Crucially, our sample includes the estimates of these recent studies and allows us to assess whether the recent methodological improvements affect the estimates. Our conclusion goes against this hypothesis. We find that none of the methodological changes can explain the variance in the estimates. Third, our results emphasize the systematic difference between estimates published in leading journals and those published in other outlets, even after controlling for publication bias as well as method and structural heterogeneity. Our results stand in sharp contrast to Brodeur et al. (2020), who document no empirical evidence of differential publication bias between papers in leading journals and others. Investigating the sources of this discrepancy is beyond the scope of this paper. Yet, we believe this result is important regarding the policy consequences of these estimates.

[1] Brodeur et al. (2020) write, for instance, "The associated change in the focus of empirical economics towards explicit causal inference is arguably the most important re-orientation in the discipline of the past two decades" (p.3657).

Although results from leading journals are likely to receive more attention, they may be differ from the average results in the literature. This feature may have non-negligible implications for the policy debate.

In the next section, we review the theoretical underpinnings common to the empirical studies included in our meta-analysis. In section 3, we describe the data collection. We then provide a set of descriptive statistics on the sample of β-estimates and motivate the need for meta-regressions. In section 4, we analyze the sources of variation in estimates across studies and provide a meta-elasticity. section 5 concludes and discusses the implications of our results for future research.

2 The Workhorse Framework

2.1 The Canonical Model

The effect of immigration on native wages has been analyzed in a canonical model developed in Borjas (2003). This model is extensively described in the surveys of Dustmann et al. (2016) and Blau and Kahn (2015). It consists of a partial-equilibrium model relying on a CES production function with constant returns to scale that combines capital (K) and labor (L). The production function takes the following form :

$$Q_t = (\lambda_{Kt} K_t^{\nu} + \lambda_{Lt} L_t^{\nu})^{\frac{1}{\nu}} \tag{1}$$

In equation (1), λ_{Kt} and λ_{Lt} denote the productivity parameters at time t and sum to unity. Any change in these parameters indicates a capital- or a labor-biased technological change. $\nu = \frac{\sigma-1}{\sigma}$ and σ denotes the elasticity of substitution between capital and labor. The labor aggregate takes the following form:

$$L_t = \left(\sum_c \theta_{ct} L_{ct}^{p} \right)^{\frac{1}{p}} \tag{2}$$

In the above equation, c refers to a *cell* that contains workers sharing the same characteristics, such as their skills, education, geographic area, sector of activity, or a combination of these characteristics. θ_{ct} is the productivity parameter of workers in cell c at time t ($\sum_c \theta_{ct} = 1$). Finally, $p = \frac{\sigma_c-1}{\sigma_c}$, where σ_c is the elasticity of substitution across workers of different cells.

The log-linearized version of the first-order condition ($\partial Q_t/\partial L_{ct}$) of the cost minimization of equation (1) provides the wage of a type-c worker at time t, and is defined by

$$\log w_{ct} = (p-1)\ln L_{ct} + (1-\nu)\ln Q_t + (\nu - p)\ln L_t + \ln \lambda_{Lt} + \ln \theta_{ct} \tag{3}$$

equation (3) shows the wage elasticity is determined by the magnitude of the immigration shock. This *direct effect* is captured by $(p-1)\ln L_{ct}$. The elasticity also depends on changes in the aggregate labor and capital supply. These *composition effects* are captured by $(1-\nu)\ln Q_t$ and $(\nu-p)\ln L_t$. Finally, the elasticity depends on changes in the *productivity parameters*, captured by $\ln \lambda_{Lt}$ and $\ln \theta_{ct}$.

Several refinements of this general model have been proposed over time. For instance, Card and Lemieux (2001) assume imperfect substitution across experienced and inexperienced workers by further nesting CES functions into the aggregate labor supply, whereas Borjas (2003) assumes imperfect substitution across age groups. Lewis (2011) makes alternative assumptions on the degree of substitution between factors of production.

The canonical model consists of a partial-equilibrium model that mirrors a closed competitive labor market. Therefore, it provides predictions on the wage effect of immigration in the short term, but it excludes adjustments of the native labor supply that may occur in the medium term and affect natives' employment. It also excludes adjustments that may take place through trade dynamics or institutional changes (Blau and Kahn, 2015).

2.2 The Wage Effect of Immigration

A large number of empirical studies have estimated reduced-form equations derived from the canonical model described in the previous section. This approach generally relates labor market outcomes to changes in immigration as follows :

$$\log w_{ct} = \beta \ln \mathrm{M}_{ct} + \Gamma C'_{ct} + \mathrm{FE} + \varepsilon_{ct} \tag{4}$$

M_{ct} is the immigration stock (or flow) of type-c workers at time t, C'_{ct} is a vector of time-varying controls for type-c workers such as the supply of native workers and productivity parameters, and FE denotes a set of fixed effects. Based on the canonical model, FE should include, at least, time fixed effects. Additional ones may be included, such as the fixed effects capturing the level of skill, the education, the age, the area, or the sector of the worker. Equation (4) shows an estimation of the *direct wage effect* is possible if the composition and productivity effects highlighted in equation (3) are adequately controlled for by covariates, as well as cell and time fixed effects.

The parameter of interest (β) captures the elasticity of native wages to immigration in a given cell-year combination. This wage equation predicts that an increase in the availability of type-c labor leads to a decrease in its marginal product ($\beta < 0$) if natives and immigrants are close substitutes within a cell c. If they are complements, however, the wage effect may be positive. β may also be null if some forces of adjustment are at work. In a number of studies, equation (4) is transformed into a first-difference equation (Dustmann et al., 2016). Other papers depart from the canonical model because their variables of interest (w_{ct} and M_{ct}) are not log-transformed, so β is, sometimes, interpreted as a semi-elasticity or a level effect.

Note the assumption of competition between native and immigrant workers depends on the definition of the cell c. Different levels of cell aggregation enable one to estimate different wage elasticities. For instance, in the national skill-cell approach, c refers to the skill (or education) level of the individual. Therefore, β captures the impact of immigration on native wages within skill groups at the national level. By contrast, in the area approach, c refers to the geographic location of the worker. β thus captures how native wages react to an area-specific immigration shock. Finally, the mixed approach exploits variations across skills *and* geographic areas.

The immigration stock or flows (M_{ct}) may be endogenous to native wages (w_{ct}) in equation (4). One of the main concerns in the literature is that immigrants may select their location based on the conditions of the local labor market. The instrumental variable strategy has been the dominant technique to tackle these endogeneity issues.

2.3 Other Approaches in the Literature

The wage elasticity of immigration may be obtained from other approaches that we do not include in this meta-analysis. Nonetheless, these approaches make a significant contribution to the literature. In particular, we exclude studies that estimate structural models of the labor market (among others, see Borjas, 2003 and Ottaviano and Peri, 2012). These structural approaches consist of estimating the parameters of a fundamental production function (such as equation 1) and using a counterfactual analysis to compute the wage effect of immigration. We exclude these studies because strong assumptions regarding the functional form of the production function as well as the degree of complementarity between natives and immigrants need to be formulated, whereas standard estimations allow one to remain agnostic regarding these two features. In addition, the analytical statistics to assess the quality of structural-model predictions and standard estimations are different and cannot be compared.

We also exclude natural experiment designs that rest upon exogenous sources of immigration, such as the Mariel boatlift experiment (see the seminal study of Card, 1990). Natural experiments mostly rely on difference-in-differences in which the immigration shock is captured by the interaction of a treatment and a time dummy variable, whereas standard estimations (e.g., the estimation of equation 4) use a direct measure of the immigration shock. Therefore, estimates of the wage effect of immigration obtained from a discontinuity design are not directly comparable to wage elasticities.

3 The Data

In this paper, we estimate *meta-regressions*, a particular type of meta-analysis. A meta-regression analysis is a systematic review of econometric estimates such as regression coefficients or transformations of regression coefficients. It consists of a two-step approach. In the first step, described in this section, the coefficients of interest and associated information are collected. A data analysis is then performed to study the distribution of the estimates and investigate the presence of sampling error and publication bias. In a second step, described in section 4, meta-regressions are performed to summarize and explain the variation routinely found among reported econometric results (Stanley et al., 2013).

3.1 Data Collection

We collect a set of empirical studies that estimate reduced-form equations derived from the canonical model presented previously. The methodology used to select the studies follows the guidelines provided by Stanley et al. (2013) and is detailed in Appendix A. To build a sample as representative of the literature, we first searched English-language studies in a systematic way using the search engine EconLit. We restricted our search to journal articles, working papers, books, and collective volumes. We searched for studies whose title included a combination of two keywords, such as *immigration* and *native*.[2] In total, we used 47 combinations of keywords. Second, we assessed whether the sample obtained was representative of the literature. We checked whether our systematic search captured the studies included in Longhi et al. (2005) and in the most recent survey in the field (Dustmann et al., 2016). We added four studies included in Longhi et al. (2005) and eight studies cited in Dustmann et al. (2016) to our sample of articles.

For each study in the sample, we identified all regressions that provide estimates of the wage effect of immigration as well as the corresponding standard errors and their types, such as robust or clustered. When available, we also collected the p-value, the t-test, the R^2 (or adjusted R^2), and the level of significance associated with these coefficients. To analyze the variance in β-estimates across studies, we collected information related to the study itself (such as the publication year or the number of authors),

[2] Like Longhi et al. (2005) and Disdier and Head (2008), we favored the search through keywords over JEL classification codes because the latter have drastically changed over time. Moreover, JEL codes are not reported by all studies, especially by books and collective volumes.

the sample of interest (e.g., the studied country or the time dimension of the data), the definitions and measures of the variables of interest (wages and immigration), and the estimation methods (e.g., the estimator or the use of fixed effects).

Our complete dataset includes 3,465 β-estimates collected across 104 studies. We used a Grubbs correction to exclude outlier estimates. We also restricted our sample to observations for which a standard error was reported, because this statistic is required to control for publication bias. Consequently, our benchmark sample includes 2,146 β-estimates collected across 64 studies. In a sensitivity analysis, we report estimates on the whole sample to show that the results are comparable to our benchmark analysis.

Descriptive statistics for the β-estimate and a number of variables related to the characteristics of the study are reported in Appendix B, Table A.1. Our sample comprises studies published between 1972 and 2019. Only 3% of the observations have been collected from leading general journals (*American Economic Review*, *Econometrica*, *Journal of the European Economic Association*, *Journal of Political Economy*, *Review of Economic Studies* and *Quarterly Journal of Economics*) as well as the top-field journal in labor economics (*Journal of Labor Economics*). On average, studies are written by two authors. The sample includes studies conducted in 17 countries as well as studies in several countries such as the OCDE countries. Thirty percent of the estimates in the sample are computed with samples analyzing the U.S. Other large countries analyzed are Australia, Austria, France, Germany, Israel, Norway, and the United Kingdom. Finally, many β-estimates have been obtained from large samples of observations, which is in line with the recent surge of micro-level administrative data.

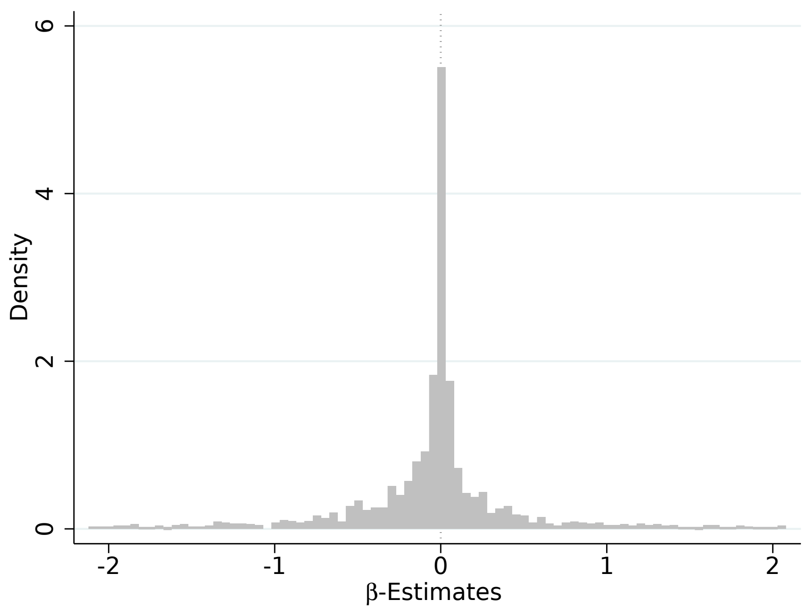
3.2 Data Analysis

Figure 1 displays the distribution of β-estimates. A striking feature of the data is that estimates are small, ranging from -2 to +2, and concentrated around zero. The average effect of immigration on native wages is equal to -0.04 (Appendix B, Table A.1). However, the magnitude of this figure is hard to interpret because the sample includes elasticities, semi-elasticities, and point estimates. When we only consider log-log estimations, which make up 26% of the sample (19 studies), we find an average wage elasticity of 0.05 (ranging from -2.03 to 2.04). This feature of the data corroborates the results in Longhi et al. (2005) and Blau and Kahn (2015).

To analyze further the variance between the estimates, we provide a forest plot showing the results of the 64 studies in Figure 2. We depict the average wage effect of immigration as well as the 95% confidence intervals for each study. Confidence intervals are computed using the standard error reported for each β-estimate. Figure 2 also describes the number of estimations found in each study. At the bottom of the figure, we plot the estimated average effect and the associated 95% confidence interval obtained with a random-effects model and a fixed-effects model in all studies. The overall picture suggests the average effect of immigration on native wages is not significantly different from zero.

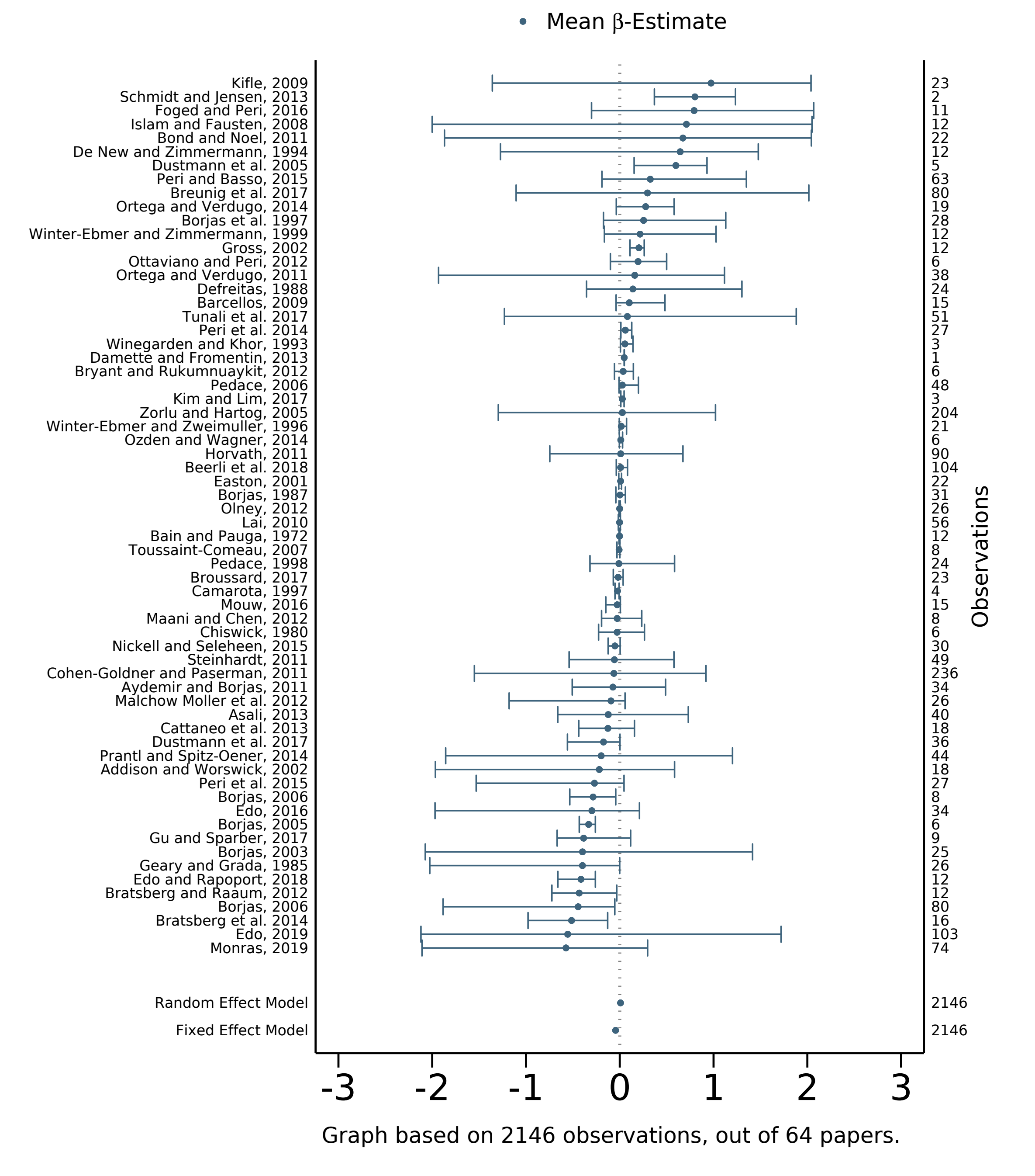
We replicate this exercise with the observations obtained with the full set of observations (3,485 β-estimates from 104 studies). Doing so, we can assess whether restricting the sample to estimates for which a standard error is provided changes the key features of the distribution of β-estimates. Results reported in Appendix B, Figures A.2 and A.4, show the results obtained from the full sample are similar to those presented herein. Therefore, working with our restricted sample is not expected to dramatically change the results. On the other hand, it enables us to control for the presence of a publication bias that can affect the results, as discussed in section 3.4.

Figure 1 – Estimated Density of the β-Estimates



Graph based on 2146 observations, out of 64 papers.

Figure 2 – Within- and Between-Variation of the β-Estimates



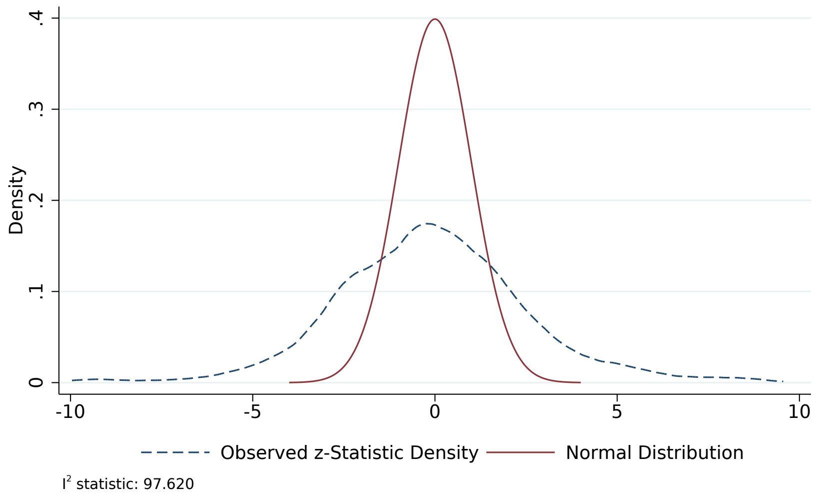
3.3 Sampling Error

The variance in the wage effect of immigration described previously could be the result of coefficients estimated using data on different countries and years. If all subsamples were drawn from a population facing the same wage effect of immigration, β-estimates would only differ from the true population mean by a deviation called sampling error.

We follow the approach proposed by Disdier and Head (2008) to investigate how much of the variance observed in the sample of estimates can be explained by this sampling error. In particular, the z-statistic evaluates by how many standard deviations (below or above the observed population mean) a β-estimate is located. Let $\hat{\beta}_i$ denote an individual estimate of the wage effect of immigration and $\tilde{\beta}$ an estimate of the population mean. Under the null hypothesis of a unique population mean, the z-statistics, denoted $z_i = (\hat{\beta}_i - \tilde{\beta})/se(\hat{\beta}_i)$, should follow a Student's t-distribution. Because many degrees of freedom exist in our case (2,082), the t-distribution should approximate a Normal distribution under the null hypothesis of sampling error. Figure 3 shows the observed distribution of the z-statistics (z_i) together with the Normal distribution as a reference point for the case of a common population parameter. We find that the observed z-statistics is over-dispersed with respect to the Normal distribution. Therefore, sampling error explains only a small part of the observed variance in the estimates of the wage effect of immigration ($\hat{\beta}_i$).

We then compute the I^2 statistic (Higgins et al., 2003), which indicates the proportion of observed variance that is not arising from sampling errors. This statistic is close to 97.6%. Together, Figure 3 and the I^2 statistics call for an investigation of other sources of heterogeneity than sampling error.

Figure 3 – Distribution of the z-Statistics



3.4 Publication Bias

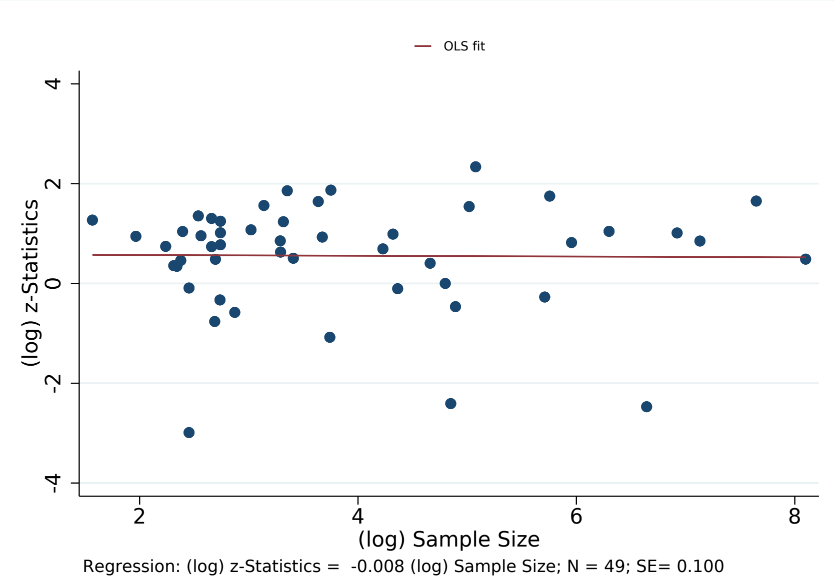
A general concern in meta-analyses is the selective reporting and publication of significant coefficients. Publication bias – whereby the statistical significance of a result determines its probability of being published – might be at play in our sample. As a result, the published results would differ systematically from the full set of estimates (including estimates from working papers, books, and collective volumes). We therefore investigate the presence of such a bias in our sample.

First, sampling theory states that the absolute value of the t-statistic should be proportional to the square root of the degrees of freedom. The degree of freedom of an analysis can be approximated using the sample size. We thus analyze the relationship between the significance of the β-estimates and the sample size. The absence of a positive correlation would indicate the presence of a publication bias. For this exercise, we restrict our sample to β-estimates for which we know the associated sample size and standard error, and we follow Card and Krueger (1995) by keeping one estimate per paper. In particular, we keep the median estimate of each paper, which reduces our sample to 49 estimates (for 49 studies).

We compute a z-statistic dividing the β-coefficient by its standard error. We then regress this statistic on the sample size.

Figure 4 presents the relation of z-statistics to sample size. We find no strong correlation between the significance of the estimates and the sample size.[3] We find that increasing sample size does have a positive effect on the significance of the β-estimates that sampling theory predicts. In sharp contrast, Card and Krueger (1995) find a negative relationship in their meta-analysis, and Görg and Strobl (2001) find a slightly negative correlation in their study of productivity spillovers from multinational corporations.

Figure 4 – Relation of z-Statistics to Sample Size



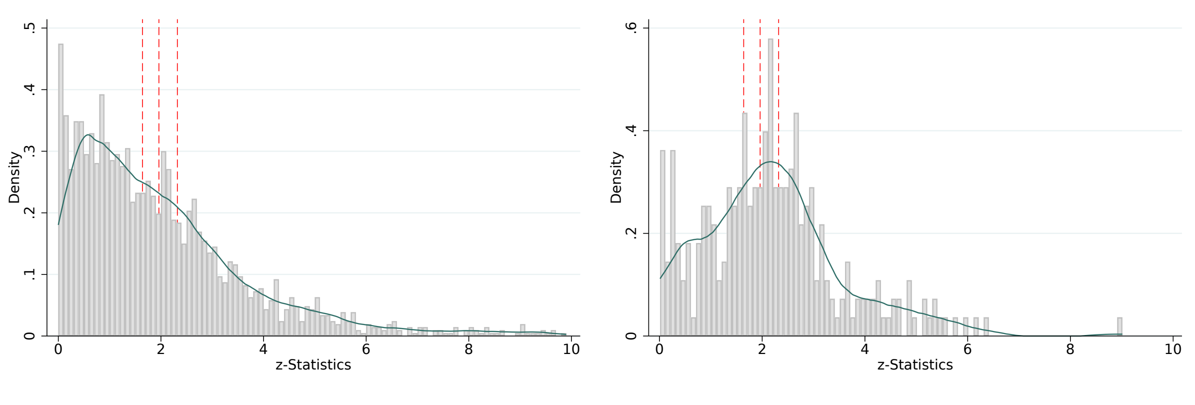
Second, we follow a recent contribution by Brodeur et al. (2020) and check for the concentration of reported z-statistics associated with our sample of estimates just above or below the standard significance levels used in the literature (1.64 for a 10%, 1.96 for a 5%, and 2.32 for a 1% significance level). Any observed surplus of observations just above a threshold can be taken as evidence of publication bias (or "p-hacking") if the underlying distribution of test statistics is continuous.

Results are presented in Figure 5. Using the benchmark sample, we find the test statistic is distributed equally around significance thresholds, which suggests a limited publication bias (Figure 5-a). We then replicate this exercise for articles published in leading journals (Figure 5-b). Although a spike occurs in the number of observations at the 1% significance level, spikes of similar magnitude can be observed elsewhere in the distribution. However, we cannot fully exclude that a publication bias is at play in the data. In the following section, we control for possible publication bias by including the standard error of the estimate in the meta-regressions.

[3] In Appendix B, we provide the results using two different estimates: Figure A.5 shows the results using the first estimate reported in the study, and Figure A.6 shows the results obtained using the estimate displaying the highest R-squared. Both figures show no evidence of a relationship between the z-statistics and the sample size pointing toward a potential publication bias in the data.

Figure 5 – Distribution of z-Statistics

(a) Baseline sample (b) Leading journals only



Note: z-statistics are in absolute value.

4 Meta-Regressions

4.1 Empirical Strategy

Preliminary analysis has shown 97.60% of the observed variance in the β-estimates cannot be attributed to sampling error. Two other sources of heterogeneity can be explored thanks to a meta-analysis : structural and methodological heterogeneity. On the one hand, variations in the wage effect of immigration could be explained by the presence of structural heterogeneity. Structural features of the data include, among others, the geographical area, industry, and time period of interest. These features may affect the wage effect of immigration. On the other hand, variations could be explained by method heterogeneity. Holding structural characteristics constant (or even using the same data), the selection of specific econometric models, the set of control variables, and fixed effects may affect the sign, the magnitude and the significance of the wage effect.

We analyze these two sources of heterogeneity with the following meta-model :

$$\hat{\beta}_{i,s} = \Theta_1 \text{Study}'_s + \Theta_2 \text{Sample}'_{i,s} + \Theta_3 \text{Variables}'_{i,s} + \Theta_4 \text{Method}'_{i,s} + \varepsilon_{i,s} \quad (5)$$

$\hat{\beta}_{i,s}$ denotes the ith estimate of the wage effect of immigration presented in study s. The first vector of variables, denoted Study'_s, controls for the characteristics of the study. It includes a binary variable equal to 1 if the study is published in a leading journal, categorical variables for the type of publication (journal article, working paper, book or collective volume), and a binary variable equal to 1 if the β-estimate is an elasticity. The latter variable allows us to make the results comparable across studies. In addition, similarly to Longhi et al. (2005), we include the standard error of the β-estimate to control for the possible presence of a publication bias.

We then explore the structural heterogeneity across studies by including two additional vectors of covariates. The first vector, $\text{Sample}'_{i,s}$, controls for the characteristics of the sample of observations the authors used to obtain the β-estimate. It includes categorical variables for the country studied, categorical variables for the structure of the data (cross section, panel, pooled cross section, time series), and a binary variable equals to 1 if the dataset used disaggregated data at the individual level. The second one, $\text{Variables}'_{i,s}$, controls for the definition and measurement of the two key variables of interest, native wages, and immigration. It includes categorical variables for the type of wage variable used in the analysis (hourly, weekly, monthly, yearly, or other). It also contains categorical variables for the skill (or education) level of individuals whose wage is analyzed (high skilled, low-medium skilled, or all skill groups). Then, it includes a categorical variable used to define immigrants (birthplace, citizenship, or other definitions). We also control for the level of skills (or education) of immigrants (high skilled, low-medium skilled, or all skill groups).

Finally, the vector of variables, $\text{Method}'_{i,s}$, aims at controlling for the method heterogeneity. It includes a categorical variable for the labor market (metropolitan, regional, or national scale). A second categorical variable defines the estimator used to obtain the β-estimate (OLS, IV, difference-in-differences, or other estimators). We also control for estimations that include some set of fixed effects, as well as for the fact that immigrants may speak the official language of the destination country.

4.2 Baseline Results

We report the results of the baseline meta-regression in Table 1. We identify the determinants of the wage effect of immigration using an unweighted OLS estimator. We start by exploring the impact of the study characteristics in column (1). The sources of structural heterogeneity across studies are analyzed from column (2) onward, where we report the results of a regression that includes additional variables related to the sample of interest used to obtained β-estimates. In columns (3) and (4), we investigate both sources of heterogeneity: structural and method heteroskedasticity, respectively. In column (3), we include variables to control for the definition and measurement of the variables of interest (i.e., native wages and immigration). In column (4), we report the results of an estimation controlling for the method used by the authors of the studies included in the sample. Finally, column (5) restricts the sample to papers exclusively based on wage elasticities. In all columns, standard errors are clustered at the study level to control for within-study correlation and dependence across errors.

Close-to-Zero Wage Effect. First, the results of the baseline meta-regressions in Table 1 (columns 1 to 4) show that the average meta-effect of immigration on the wage of natives is negative but small in the surveyed literature (-0.044). Nonetheless, when we restrict our sample to elasticities (column 5), we find that, on average, a 1% increase in immigration increases native wages by 0.053%, which is again close to zero. For comparison, Longhi et al. (2005) found an elasticity of -0.119. Our result confirms the conclusion of this paper, that is, that the impact of immigration on native wages is small. Moreover, our results do not seem to be driven by a publication bias: the coefficient of the standard errors is not significant in all estimations.

Lower Coefficients in Leading Journals. Then, analyses published in leading academic journals exhibit significantly lower coefficients than estimates unpublished or in other journals (see descriptive statistics provided in Appendix B, Figure A.3). Table 1 confirms this result (column 1). Introducing additional control variables sequentially in columns (2) to (4) does not affect this result. We estimate that the negative impact of leading journals is not affected when controlling for either the methodology variables or the structural heterogeneity sources. All other things equal, leading academic journals provide more negative estimates of the impact of immigration on native wages. We estimate that this feature of the study characteristics is the largest determinant of the size of the estimate (this variable exhibits the largest point estimate, around -0.4) and the coefficient is fairly stable across specifications.

In addition, we do not estimate any significant impact of studies published in an academic journal (compared with unpublished working papers, books, and collective volumes). We also find that studies reporting elasticities do not find different estimates than other studies (columns 1 to 4).

Structural Characteristics Matter. Third, we find the heterogeneity across estimates found in the literature is driven, in part, by the structural characteristics of the studies (columns 3 and 4). In particular, the country under study has some influence on the outcome of the analysis. The impact of immigration on wages in Anglo-Saxon countries is not significantly different from that in the U.S. (which is the reference category). The effect is, however, significantly less negative (closer to zero) in other countries (excluding France). The type of data used also explains part of the heterogeneity. Analyses run on time series tend to report higher wage effects than analyses made on cross-section data (the reference category). In column (3), we do not find a significant impact of the different types of measures and definitions of the variables of interest – immigration and wages – on the magnitude of the effect. We do not observe any differing effect related to the definition of wages nor to the skill group of workers affected by the immigration. We do not find any effect related to the definition of immigrants (birthplace as the reference definition) nor to their skill level.

A Limited Impact of Method Heterogeneity. Fourth, we find little impact of the methods on the sign and magnitude of the β-estimates. Based on existing literature surveys, the definition of the labor market is expected to affect the wage estimates of immigration (Dustmann et al., 2016, Longhi et al., 2005). For example, immigration generates an adjustment process within the labor market such as the departure of native workers from specific local areas to escape the fiercer competition induced by an increase in the number of workers. For this reason, an analysis at the local level may overestimate the wage effect of immigration. However, we find no significant difference across studies focusing on a regional or a national labor market compared with studies focusing on smaller areas such as cities (the reference category).

We then study the effect of estimators used by researchers. An important concern in the analysis of the wage effect of immigration is the potential presence of an omitted variable bias. For instance, the correlation between the wage of natives and immigration may be driven by unobserved characteristics such as demand effects. Another endogeneity issue is related to reverse causality. Researchers have dealt with these concerns using various techniques. The difference-in-differences method is broadly used in this literature to infer causality and makes up 20% of the sample. This estimator is expected to eliminate unobserved characteristics that may bias the analysis. We find this method provides significantly lower estimates (i.e., more negative) than the ones computed with OLS. About 18% of the β-estimates are obtained using instrumental variables in a two-stage least-squares setting (IV-2SLS), an alternative method used to deal with endogeneity issues. The shift-share instrumental variable proposed by Card (2001) is one well-known instrument in this literature. Other types of instruments include (highly debatable) lagged values of immigration as well as some additional, external variables. Yet, we find no evidence that estimates computed with IV-2SLS estimators significantly differ from estimates computed using OLS (the reference method). This result could either reflect the absence of endogeneity, the violation of the exclusion restriction by the instrumental variables, or additional noise coming from the 2SLS methodology.

In addition, we do not find evidence in favour of a bias introduced by fixed effects. The literature raises the concern that fixed effects, by absorbing unobserved heterogeneity, determine the type of variance used to identify the main effects. The estimated parameters for the comparison of studies with and without fixed effects do not display any significant difference, suggesting no detectable impact of the use of fixed effects on the wage effect of immigration. Similarly, we find no effect of the ability of immigrants to speak the language of the destination country on the wage effect of immigration.

Subsamples. Finally, column (5) of Table 1 reports results computed from a subsample including only elasticities (19 studies, 555 β-estimates). This meta-regression enables us to assess whether including all coefficients regardless of their interpretation could affect the results. Contrary to the baseline results, studies published in leading academic journals does not differ from other studies. The lack of significance comes from the fact that the dataset contains little variation in that dimension, because only one study (and six β-estimates) has been published in a leading academic journal. In addition, the coefficient associated with journal articles is now positive and significant, though at the 10% level. In line with the baseline results, we find the structural heterogeneity explains part of the variation across studies. In particular, the wage effect of immigration in Anglo-Saxon countries as well as in other countries (including France) is significantly larger than in the U.S.. Moreover, we find some evidence that the definitions used to determine the variables of interest (wages and immigration) could slightly affect the wage effect of immigration. Lastly, the method heterogeneity seems to matter as well. We find that the scope and the definition of the labor market affect the magnitude of the β-estimates. Studies using a regional or national definition of the labor market tend to estimate a more negative effect of immigration than studies focusing on metropolitan areas.

Conclusions. Overall, we find the wage effect is negative but close to zero. The structural heterogeneity observed across studies helps rationalize the variance of the effect. Differences across studied countries, the structure of the data (cross-section, panel, and time series) and, to a lesser extent, the definition of the variables of interest partly explain why the estimated wage effects of immigration vary across studies. On the other hand, we find little effect of heterogeneity in the methods to explain the variation observed across studies. Yet, point estimates suggest estimates in leading journal are lower than other journals (even after controlling for methods and structural heterogeneities) and that they may be the largest determinant of the wage effect of immigration.

Table 1 – Meta-Regressions - Benchmark Results

	(1)	(2)	(3)	(4)	(5)
Study characteristics					
Leading academic journal	-0.425***	-0.387***	-0.433***	-0.351***	0.881
	(0.095)	(0.097)	(0.124)	(0.118)	(1.010)
Journal article	0.010	0.053	-0.027	-0.056	0.215*
	(0.065)	(0.081)	(0.088)	(0.096)	(0.112)
Elasticity	0.063	0.123	0.032	-0.008	
	(0.065)	(0.083)	(0.101)	(0.107)	
Standard error of the estimate	-0.062	-0.091	-0.086	-0.075	-0.042
	(0.098)	(0.109)	(0.109)	(0.109)	(0.124)
Sample of interest					
Studied country: Anglo-Saxon countries (ref.: the U.S.)		0.093	0.065	0.147	0.747*
		(0.114)	(0.114)	(0.111)	(0.401)
Studied country: France (ref.: the U.S.)		0.003	-0.008	0.109	1.877**
		(0.119)	(0.112)	(0.113)	(0.888)
Studied country: Other countries (ref.: the U.S.)		0.122	0.153	0.220**	0.807**
		(0.104)	(0.106)	(0.103)	(0.341)
Individual data		-0.045	-0.024	0.052	0.320
		(0.091)	(0.096)	(0.119)	(0.190)
Data structure: Panel data (ref.: cross-section data)		0.083	0.099	0.040	-0.344
		(0.089)	(0.080)	(0.083)	(0.303)
Data structure: Time series (ref.: cross-section data)		0.310	0.333*	0.313*	-1.581***
		(0.272)	(0.190)	(0.169)	(0.402)
Definition and measurement of the variables of interest					
Definition of wages: Weekly (ref.: hourly)			0.202*	0.156	0.015
			(0.104)	(0.101)	(0.043)
Definition of wages: Monthly/Yearly (ref.: hourly)			0.066	0.044	-0.047
			(0.090)	(0.095)	(0.294)
Definition of wages: Other definition (ref.: hourly)			0.174**	0.140	1.003***
			(0.082)	(0.086)	(0.207)
Affected skill group: Low-medium (ref.: high)			-0.020	-0.044	-0.080
			(0.111)	(0.111)	(0.153)
Affected skill group: All or undefined (ref.: high)			-0.052	-0.081	0.001
			(0.105)	(0.110)	(0.134)
Definition of immigrants: Citizenship (ref.: birthplace)			0.013	0.079	0.413
			(0.106)	(0.102)	(0.655)
Definition of immigrants: Others (ref.: birthplace)			-0.210*	-0.136	0.987*
			(0.116)	(0.125)	(0.494)
Immigration skill group: Low-medium (ref.: high)			0.005	0.025	-0.458
			(0.096)	(0.091)	(0.403)
Immigration skill group: All or undefined (ref.: high)			0.097	0.074	-0.301
			(0.099)	(0.095)	(0.201)
Method variables					
Geographical scope: Region (ref.: city)				-0.003	-1.188*
				(0.100)	(0.604)
Geographical scope: Country (ref.: city)				-0.153	-1.442*
				(0.101)	(0.755)
Empirical strategy: IV-2SLS (ref.: OLS)				0.082	-0.029
				(0.068)	(0.051)
Empirical strategy: Difference-in-differences (ref.: OLS)				-0.190**	
				(0.093)	
Empirical strategy: Others (ref.: OLS)				0.008	1.171
				(0.092)	(0.706)
Fixed effects				0.055	0.306
				(0.066)	(0.441)
Language				0.012	
				(0.088)	
Observations	2,146	2,146	2,146	2,146	555
Studies	64	64	64	64	19
R^2	0.089	0.111	0.141	0.154	0.365
Estimator	OLS	OLS	OLS	OLS	OLS
Meta-estimate	-0.044	-0.044	-0.044	-0.044	0.053
Meta-estimate S.D.	0.155	0.173	0.196	0.204	0.259

Note: This table reports meta-regression results. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses. The regressions presented in columns (1) to (4) use the baseline sample, and the regression presented in column (5) uses only wage elasticities.

4.3 Robustness Tests

We report a set of robustness tests in Appendix C. In Table A.2, we use alternative error clustering. In Table A.3, we test alternative estimation strategies. We discuss publication bias and alternative samples in Table A.4. Finally, we propose alternative specifications in Table A.5.

Alternative Standard Error Clustering. No consensus exists in the meta-analysis literature concerning the cluster within which observations should be correlated. Our sample covers about four decades, over which paradigms of research and data availability have greatly changed. We, therefore, take into account that β-estimates may not be independently distributed across these dimensions. Table A.2 reports results obtained by clustering standard errors at different levels. We cluster the standard errors by publication year in column (1), by publication decade in column (2), and by method of estimation and publication decade in column (3). We compare these results with those obtained with robust standard errors in column (4) and with robust and bootstrapped standard errors in column (5), because the dependent variable is itself obtained from estimations. The results show the significance of the baseline results is not related to any specific level of error clustering. In addition, the significance of the results increases with robust and bootstrapped standard errors. Overall, this set of results corroborates the conclusions drawn in section 4.2.

Alternative Estimation Strategies. We run four alternative models of estimations that are common in the literature of meta-analyses. Results are reported in Table A.3. We start by reporting the results using a random-effects model in column (1). This specification follows the methodology proposed by Borenstein et al. (2010) and Disdier and Head (2008). This model assumes the true β-estimate may vary across studies and that the sample of observations is a *random* sample of β-estimates that could have been observed. The advantage of a random-effects model is its ability to estimate the mean of a distribution of effects, in which each study matters because it provides information about a wage effect of immigration that no other study has estimated. Although weaker than our baseline findings, the results corroborate heterogeneity arising from leading academic journals and from the use of various definitions of immigrants. Using this specification, we find that studies controlling for the fact that immigrants may speak the language of the destination country exhibit significantly more negative estimates.

From column (2) to column (4), we show the results obtained using weighted least squares (WLS). We do not use WLS in our baseline analysis, because we cannot exclude that the weights are uncorrelated with the disturbances, which would render the estimator inefficient. However, common practice in meta-regression analyses is to explain the heterogeneity in results across studies by means of a linear-regression model estimated with WLS to account for the precision and quality of the β-estimates (e.g., see Longhi et al., 2005). We report the results using this alternative estimator for comparison purposes. Column (2) reports the results when WLS are based on weights defined as the inverse of the standard errors of the estimate. By doing so, we increase the weight of accurate estimations. In column (3), we describe results from WLS estimation with a composite quality index as the weighting scheme. We follow Longhi et al. (2005) to define the weight for each β-estimate as the sum of three quality indices. The first one gives a higher weight (equal to 2) to studies published in leading journals and a lower weight (equal to 1) to the other studies. The second index gives a higher value (equal to 2) to estimates for which robust standard errors are reported, and 1 otherwise. The third index gives a higher value (equal to 2) to estimates that have been computed by means of more sophisticated econometric techniques such as 2SLS, and 1 otherwise. As we sum these three indices, the quality weight ranges from 3 to 6. In column (4), we use the product of both types of weights (the inverse of the standard errors times the quality index). Columns (2) to (4) confirm most of our baseline OLS results. However, we find weak evidence that the structure of the data (cross section, panel, and time series) and the definition of the variables of interest have an impact on the wage effect of immigration. Therefore, structural heterogeneity is exclusively driven by differences across studied countries.

Publication Bias and Alternative Samples. We now further discuss the possible presence of a publication bias and investigate the robustness of the main results to the use of alternative subsamples. Results are presented in Table A.4. In particular, we assess whether restricting the sample to observations for which a standard error is reported does not bias the estimation of equation (5). We start by excluding the standard error of the β-estimate from the list of covariates (column 1). In this meta-regression, we keep the benchmark sample of 2,146 observations. In column (2), we repeat this exercise using the full sample of observations. The sample increases by 40 studies that do not report standard errors. The results of these estimations are in line with our baseline estimates. The meta-effect is negative but small in both regressions (-0.044 and -0.023). We find structural heterogeneity is mostly driven by differences across studied countries and that method heterogeneity is driven by the scope of the labor market as well as the empirical strategy implemented by the authors. In column (3), we modify the baseline model by adding the size of the sample used to obtain the β-estimate as an additional covariate. This modification allows us to assess whether including an additional control for publication bias has an effect on the results. Because the authors do not always report the size of the sample, the sample reduces to 53 studies (1,740 observations). Although the significance of the coefficients of interest is smaller, we find similar results to the baseline findings, which again points toward the absence of a publication bias.

Additionally, we estimate the baseline model on a subsample of studies published after 2000 (column 4). By doing so, we homogenize the sample of observations with respect to unobserved trends in research designs that have been changing gradually in recent decades. This strategy reduces the sample to 52 studies and 1,943 observations. We find a meta-effect equal to -0.054. We also find differences in β-estimates across studies published in leading academic journals and others, as well as differences across the structure of the data used by the authors (cross section, panel, and time series) are the only two remaining sources of variation.

Finally, in column (5), we report the results, once we restrict our analysis to the articles studied by Longhi et al. (2005) that are included in our sample. The subsample includes only seven studies (143 β-estimates). Our aim is to assess whether the results would be significantly affected by restricting our analysis to the papers that were investigated in this former meta-analysis. We do not attempt to compare these results with those presented in Longhi et al. (2005), because the explanatory variables used in our benchmark analysis differ from the ones defined by the authors and because our sample does not include all papers analyzed in that study. The results reported in column (5) confirm that estimates published in leading journals are, on average, smaller than those published in other types of studies, and that the scope and the definition of the labor market influence the results. However, we find the meta-estimate in the subsample is closer to zero than the one computed in our baseline estimation (-0.02 vs. -0.04). We also find that some publication bias may be at play, because the coefficient associated with the standard error is now positive and significant. In these seven studies, panel data lead to estimates of larger magnitude (negative but closer to zero) than do cross-sectional data. The definitions used to determine wages have an impact on the wage effect of immigration. However, these results need to be interpreted with caution because the subsample only includes seven studies.

Alternative Specifications. One of the main difficulties in determining the variables of interest to be included in the meta-regressions comes from the large number of covariates we collected and the potentially high correlation between them. To explore additional variables, we use three alternative specifications that we report in Table A.5. We start by exploring the lack of significance associated with the use of individual data in the baseline model (column 1). To do so, we replace the dummy variable *individual data* with categorical variables for the type of data used by the authors (census, administrative data, and survey data, which is the reference category). We find the use of census and administrative data increases the estimated effect of immigration on wages. Therefore, the current trend toward exhaustive data has an impact on the estimates. Yet, this variable captures every method heterogeneity that we could observe in the baseline model.

Then, we investigate the fact that different empirical interpretations of the canonical model could provide different estimates of the wage effect of immigration (Dustmann et al., 2016). In particular, researchers have been identifying variations in native wages from variations in immigration across national skill cells, across geographic areas (the so-called regional approach), or using a mixed approach. Yet, depending on the scale of analysis, labor market adjustments and the potential absorption of immigration may vary widely (e.g., see Card, 2001). In column (2), we test whether these alternative approaches lead to different results. Because the categorical variables controlling for the approach of the study are highly correlated with the variation in the geographical scope of the labor market, we drop that latter. In column (3), we adopt a similar strategy by substituting the geographical scope of the labor market with the size of the market studied by the authors. In both cases, we find that neither the approach used by the study nor the size of the labor market has any significant impact on the β-estimates. In addition, these alternative variables absorb variation in the β-estimates arising from the studied country.

Conclusions. All in all, this set of robustness tests strengthens the main findings in the benchmark analysis: the variance in the wage effect of immigration observed across studies is explained by the leading academic journals and by structural heterogeneity. All results nevertheless point toward a close-to-zero effect of immigration on wages and no effect of methodological heterogeneity.

5 Conclusions

In this paper, we provide a meta-analysis of the literature investigating the wage effect of immigration, based on 2,146 estimates collected from 64 studies published between 1972 and 2019. Compared with Longhi et al. (2005), our study takes advantage of the substantial expansion of the literature, based on new micro-level administrative data, a finer characterization of local labor markets and the implementation of more sophisticated econometric methods. In addition, the structural characteristics of these studies have changed significantly over time as more countries have been analyzed as well as over longer time spans.

More specifically, we identify the sources of variation in the estimated wage effects across studies by investigating study characteristics as well as the presence of structural and methodological heterogeneity. We estimate a strong, robust, and negative effect of publishing in leading academic journals. *Ceteris paribus*, leading academic journals provide more negative estimates of the impact of immigration on native wages, even after controlling for the potential publication bias. Then, our analysis shows a negative, close-to-zero wage effect of immigration. Depending on the estimation, this effect ranges from -0.09 to 0.02, the baseline estimate being equal to -0.04. The variation in the wage effect of immigration observed across studies is mainly explained by structural heterogeneity. Differences across studied countries, the structure of the data (cross section, panel, and time series) and, to a lesser extent, the definition of the variables of interest point toward the presence of structural heterogeneity. Differences in the scope of the labor market and the empirical strategy used by the authors point toward the presence of method heterogeneity, yet only for specific subsamples and specifications. Interestingly, the econometric method implemented to tackle endogeneity issues plaguing the relationship between immigration and wage does not provide significantly different estimates.

These results are important from a policy perspective. They provide a quantitative research synthesis to the ongoing policy debate on the costs and benefits of immigration (Goldin et al., 2012). Moreover, these results show promising research paths are ahead. The structural heterogeneity should be further investigated. Understanding what the exact drivers of this heterogeneity are would be interesting. For instance, can the differences in national institutions explain these variations in the estimated coefficients?

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Appendix

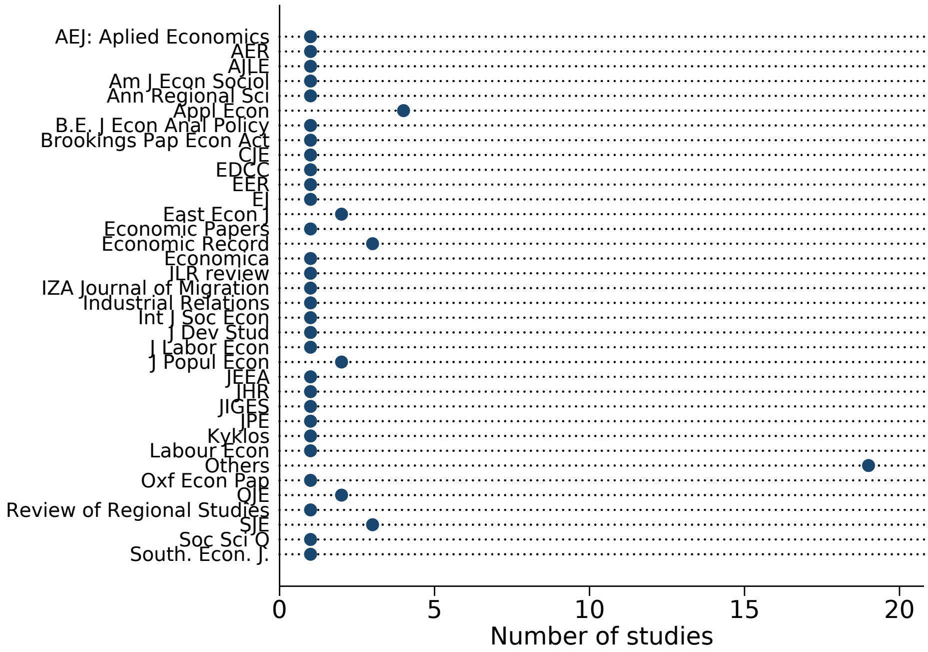
A Data Collection

The sample was built as follows. First, we searched the English-language literature in a systematic way using the search engine EconLit. We restricted our search to journal articles, working papers, books, and collective volumes. We use 47 combinations of keywords to select studies. On September 24, 2018, we searched for studies whose title include a combination of the following two keywords: *foreign, immigrant, immigration, migrant*, or *migration* and *competition, complementarity, earnings, labor/labor market, native, substitutability, substitution*, or *wage*. On May 14 and 15, 2019, we searched for studies that included either *Mariel* or *boat* in their title. This systematic search led to a selection of 4,420 studies. After removing duplicates and studies that we could not find either in libraries or online, we obtained a set of 1,302 studies. Each of these studies were screened by two readers who checked whether the study empirically analyzes the impact of immigration on native wages and whether estimates of this effect were provided. Among the studies that we dropped, 31% were excluded because they do not include estimates, 20% of those were off topic, 17% were focus only on the wages of immigrants, and 5% were either duplicates or not found. The rest of the excluded papers either analyze labor market outcomes other than wages or analyze relative wages between natives and immigrants. After removing irrelevant studies, we obtained a set of 150 studies.

Second, to assess whether the sample obtained is representative of the literature, we checked whether our systematic search captured the studies included in the meta-analysis of Longhi et al. (2005) and the survey by Dustmann et al. (2016). Among the studies we did not include in our dataset, seven do not include our keywords or were not referenced in EconLit, seven were not well referenced in EconLit, and seven were too recent to be referenced in EconLit. The algorithm of selection in EconLit captures only 500 studies by search, and these studies are selected based on the number of citations. Such a process may prevent one from finding the most recent studies. Out of these studies, 12 empirical studies provide estimates on the impact of immigration on native wages. We thus added them to our dataset. Doing so, we obtained a sample of 162 studies, including 13 out of the 18 studies analyzed by Longhi et al. (2005), and 16 out of the 26 studies referenced by Dustmann et al. (2016).

A final assessment enabled us to drop some remaining duplicates (e.g., working papers that have been published). In addition, we only kept empirical studies estimating a reduced-form model based on the canonical labor market model, and excluded structural approaches as well as natural-experiment designs. After excluding outlier estimates using a Grubbs correction, we obtained a sample of 3,485 β-estimates collected across 104 studies. We list these studies below. After keeping observations for which a standard error was reported (as this statistic is required to control for publication bias), we obtained a benchmark sample of 2,146 β-estimates collected across 64 studies.

Figure A.1 – List of Journals (Benchmark Sample)



Studies Included in the Meta-Analysis

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T. SrungBoonmee. Immigration and us native workers' wages: differential responses by education. *International Journal of Manpower*, 2013.

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B Additional Descriptive Statistics (Benchmark Sample)

Table A.1 – Summary Statistics

	Mean	**Standard Errors**	**Min**	**Max**	**N**
Study characteristics					
Journal article	0.656	0.479	0	1	64
Leading journal	0.031	0.175	0	1	64
Publication year	2008	10	1972	2019	64
No. of authors	1.813	0.794	1	4	64
Estimation characteristics					
β-estimate	-0.044	0.520	-2.120	2.068	2,146
Elasticity	0.259	0.438	0	1	2,146
Standard error	0.236	0.490	0.000	8.475	2,146
Sample size	235,306	1,189,133	8	1.14e+07	1,740
First sample year	1985	19.570	1831	2011	2,146
Last sample year	1998	11.775	1914	2014	2,146

Figure A.2 – Estimated Density of the β-Estimates (Full Sample)

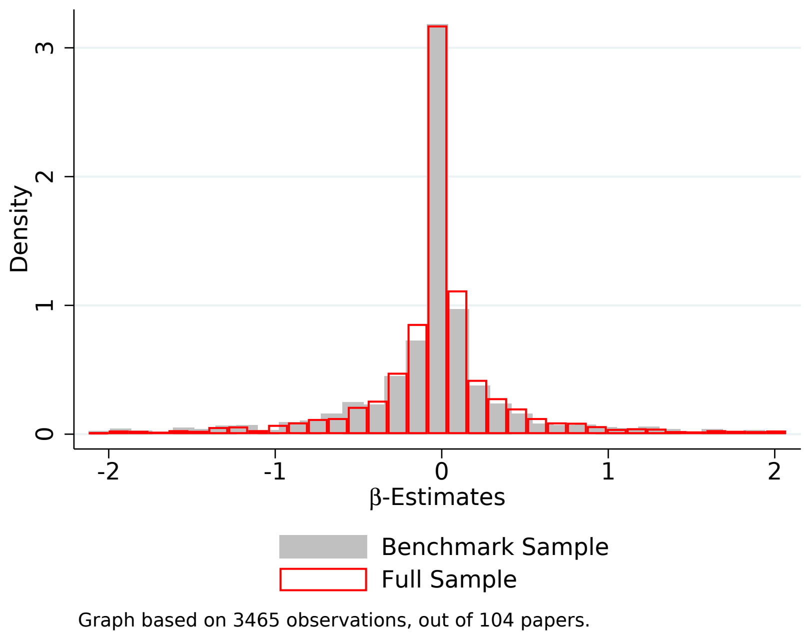
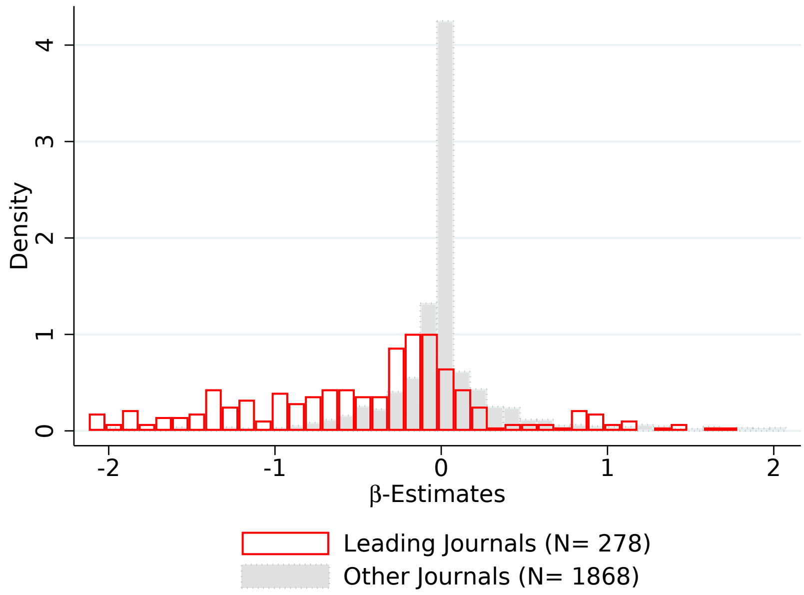


Figure A.3 – Estimated Density the β-Estimate, Leading Journals vs. Other Journals



Graph based on 2146 observations, out of 64 papers.

Figure A.4 – Within- and Between-Variation of the β-Estimates (Full Sample)

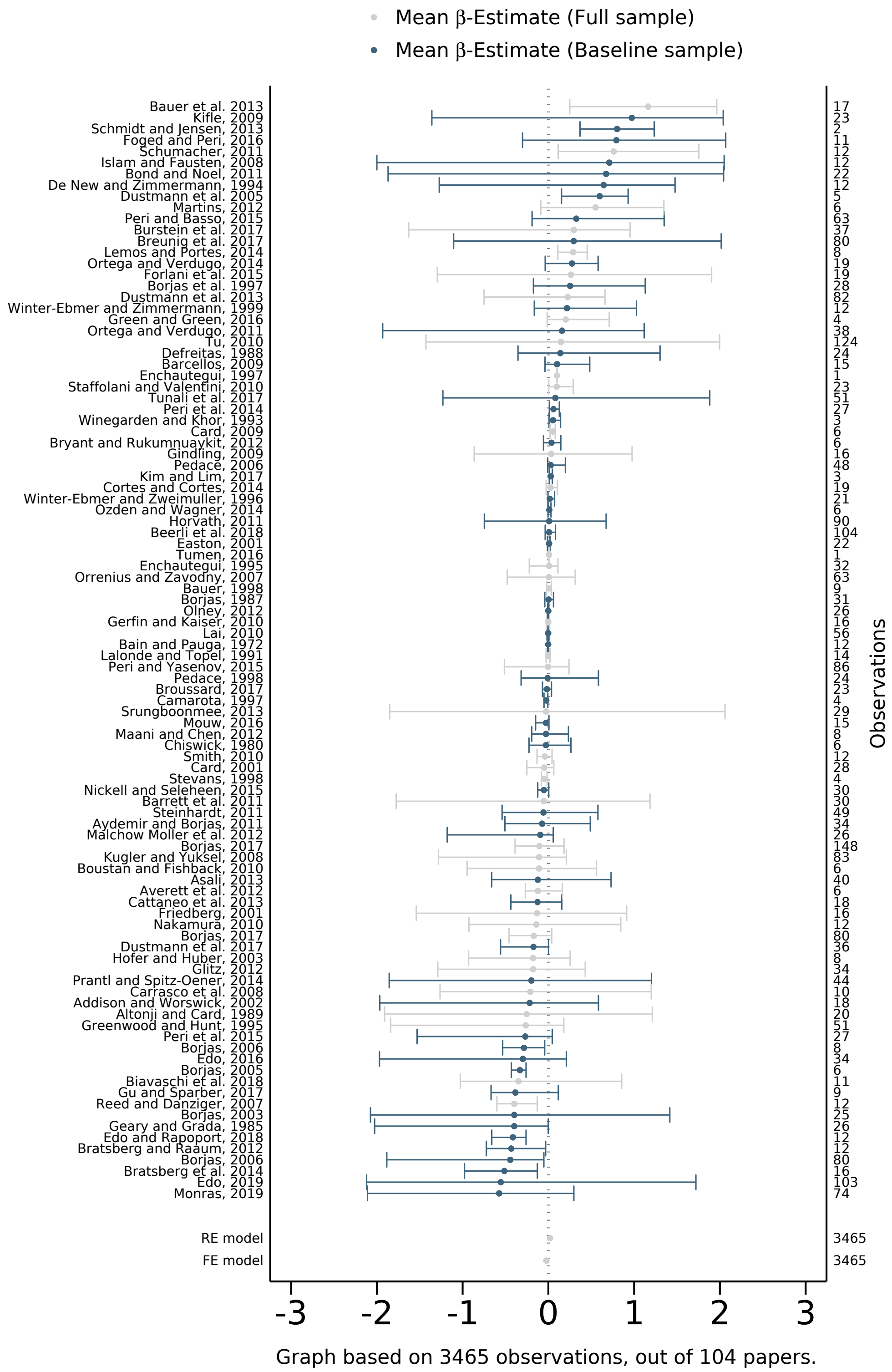


Figure A.5 – Relation of z-Statistics to Sample Size (First β-Estimate)

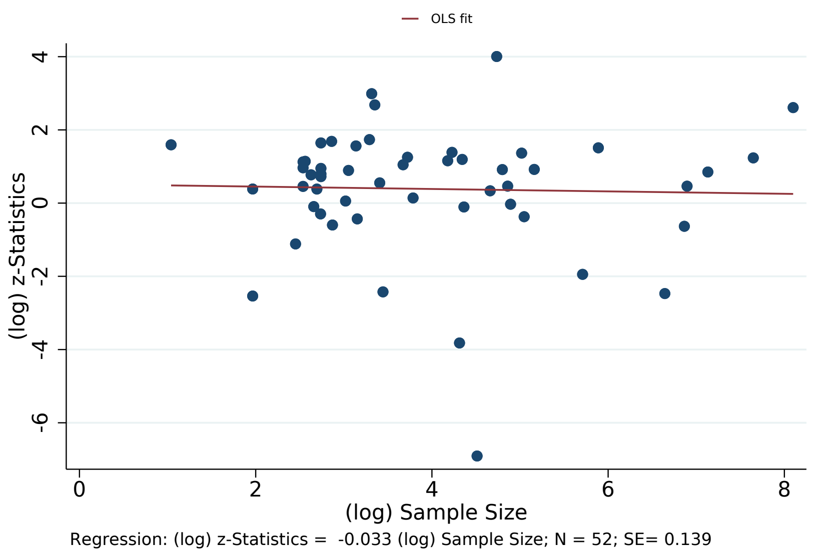
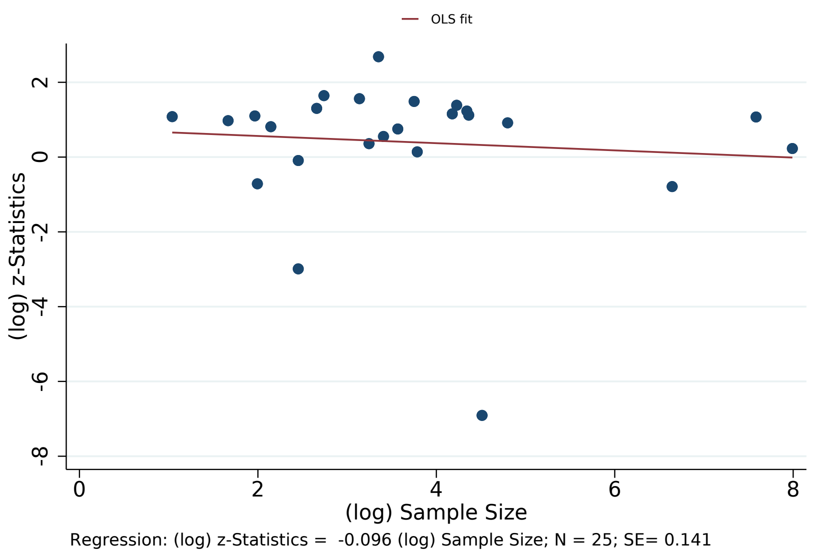


Figure A.6 – Relation of z-Statistics to Sample Size (β-Estimate with the Highest R^2)



C Additional Results

Table A.2 – Meta-Regressions - Alternative Standard Errors

	(1)	(2)	(3)	(4)	(5)
Study characteristics					
Leading academic journal	-0.351	-0.351***	-0.351***	-0.351***	-0.351***
	(0.077)	(0.080)	(0.103)	(0.060)	(0.062)
Journal article	-0.056*	-0.056	-0.056	-0.056	-0.056
	(0.007)	(0.059)	(0.108)	(0.036)	(0.037)
Elasticity	-0.008	-0.008	-0.008	-0.008	-0.008
	(0.010)	(0.100)	(0.093)	(0.038)	(0.039)
Standard error of the estimate	-0.075	-0.075	-0.075	-0.075	-0.075
	(0.022)	(0.132)	(0.119)	(0.060)	(0.062)
Sample of interest					
Studied country: Anglo-Saxon countries (ref.: the U.S.)	0.147	0.147	0.147	0.147***	0.147***
	(0.056)	(0.117)	(0.104)	(0.055)	(0.053)
Studied country: France (ref.: the U.S.)	0.109*	0.109*	0.109	0.109*	0.109
	(0.010)	(0.046)	(0.071)	(0.066)	(0.068)
Studied country: Other countries (ref.: the U.S.)	0.220	0.220*	0.220*	0.220***	0.220***
	(0.099)	(0.099)	(0.105)	(0.043)	(0.042)
Individual data	0.052	0.052	0.052	0.052	0.052
	(0.122)	(0.141)	(0.096)	(0.049)	(0.048)
Data structure: Panel data (ref.: cross-section data)	0.040	0.040	0.040	0.040	0.040
	(0.066)	(0.051)	(0.057)	(0.035)	(0.036)
Data structure: Time series (ref.: cross-section data)	0.313	0.313	0.313	0.313***	0.313***
	(0.138)	(0.228)	(0.188)	(0.119)	(0.121)
Definition and measurement of the variables of interest					
Definition of wages: Weekly (ref.: hourly)	0.156	0.156	0.156	0.156***	0.156***
	(0.223)	(0.146)	(0.139)	(0.040)	(0.040)
Definition of wages: Monthly/Yearly (ref.: hourly)	0.044	0.044	0.044	0.044	0.044
	(0.167)	(0.113)	(0.102)	(0.039)	(0.040)
Definition of wages: Other definition (ref.: hourly)	0.140**	0.140*	0.140**	0.140***	0.140***
	(0.007)	(0.068)	(0.061)	(0.035)	(0.036)
Affected skill group: Low-medium (ref.: high)	-0.044	-0.044	-0.044	-0.044	-0.044
	(0.015)	(0.116)	(0.079)	(0.053)	(0.053)
Affected skill group: All or undefined (ref.: high)	-0.081	-0.081	-0.081	-0.081	-0.081
	(0.048)	(0.085)	(0.064)	(0.057)	(0.056)
Definition of immigrants: Citizenship (ref.: birthplace)	0.079***	0.079*	0.079	0.079	0.079
	(0.001)	(0.035)	(0.054)	(0.050)	(0.050)
Definition of immigrants: Others (ref.: birthplace)	-0.136	-0.136	-0.136	-0.136**	-0.136**
	(0.090)	(0.104)	(0.155)	(0.057)	(0.057)
Immigration skill group: Low-medium (ref.: high)	0.025	0.025	0.025	0.025	0.025
	(0.075)	(0.059)	(0.046)	(0.055)	(0.052)
Immigration skill group: All or undefined (ref.: high)	0.074	0.074	0.074	0.074	0.074
	(0.127)	(0.086)	(0.059)	(0.060)	(0.059)
Method variables					
Geographical scope: Region (ref.: city)	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.056)	(0.062)	(0.047)	(0.038)	(0.037)
Geographical scope: Country (ref.: city)	-0.153	-0.153**	-0.153***	-0.153***	-0.153***
	(0.028)	(0.043)	(0.038)	(0.042)	(0.042)
Empirical strategy: IV-2SLS (ref.: OLS)	0.082	0.082	0.082	0.082**	0.082***
	(0.043)	(0.064)	(0.064)	(0.032)	(0.031)
Empirical strategy: Difference-in-differences (ref.: OLS)	-0.190	-0.190**	-0.190*	-0.190***	-0.190***
	(0.131)	(0.068)	(0.092)	(0.059)	(0.059)
Empirical strategy: Others (ref.: OLS)	0.008	0.008	0.008	0.008	0.008
	(0.115)	(0.070)	(0.084)	(0.051)	(0.052)
Fixed effects	0.055	0.055	0.055	0.055	0.055
	(0.120)	(0.071)	(0.052)	(0.038)	(0.036)
Language	0.012	0.012	0.012	0.012	0.012
	(0.010)	(0.027)	(0.083)	(0.057)	(0.055)
Observations	2,146	2,146	2,146	2,146	2,146
Studies	64	64	64	64	64
R^2	0.154	0.154	0.154	0.154	0.154
Error cluster	yes	yes	yes	none	none
Cluster level	year	decade	method-decade	none	bootstrapped
Estimator	OLS	OLS	OLS	OLS	OLS
Meta-estimate	-0.044	-0.044	-0.044	-0.044	-0.044
Meta-estimate S.D.	0.204	0.204	0.204	0.204	0.204

Note: This table reports meta-regression results obtained with the baseline sample. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are clustered within publication year in column (1), within publication decade in column (2), and within empirical method and publication decade in column (3). We reported the results using robust standard errors in column (4) and bootstrapping the errors in column (5) (1,000 replications).

Table A.3 – Meta-Regressions - Alternative Estimation Strategies

	(1)	(2)	(3)	(4)
Study characteristics				
Leading academic journal	-0.289**	-0.172***	-0.342***	-0.166***
	(0.137)	(0.040)	(0.117)	(0.039)
Journal article	0.004	-0.019	-0.035	-0.022
	(0.105)	(0.023)	(0.100)	(0.024)
Elasticity	-0.046	-0.009	0.010	-0.012
	(0.161)	(0.037)	(0.109)	(0.037)
Standard error of the estimate	-0.182	-0.119	-0.100	-0.175
	(0.118)	(0.162)	(0.114)	(0.177)
Sample of interest				
Studied country: Anglo-Saxon countries (ref.: the U.S.)	0.236**	0.021	0.161	0.024
	(0.102)	(0.026)	(0.114)	(0.025)
Studied country: France (ref.: the U.S.)	0.045	0.142***	0.082	0.146***
	(0.154)	(0.043)	(0.114)	(0.039)
Studied country: Other countries (ref.: the U.S.)	0.154	0.049**	0.232**	0.052**
	(0.106)	(0.024)	(0.104)	(0.024)
Individual data	0.033	0.020	0.037	0.021
	(0.119)	(0.061)	(0.120)	(0.059)
Data structure: Panel data (ref.: cross-section data)	0.042	0.006	0.057	0.006
	(0.113)	(0.011)	(0.088)	(0.013)
Data structure: Time series (ref.: cross-section data)	0.385	0.041	0.354**	0.043
	(0.238)	(0.029)	(0.173)	(0.030)
Definition and measurement of the variables of interest				
Definition of wages: Weekly (ref.: hourly)	-0.006	0.043	0.162	0.045
	(0.071)	(0.040)	(0.103)	(0.041)
Definition of wages: Monthly/Yearly (ref.: hourly)	-0.093	0.002	0.055	-0.001
	(0.071)	(0.015)	(0.105)	(0.015)
Definition of wages: Other definition (ref.: hourly)	-0.121	0.015	0.125	0.014
	(0.086)	(0.023)	(0.090)	(0.024)
Affected skill group: Low-medium (ref.: high)	-0.099	-0.014	-0.065	-0.017
	(0.109)	(0.016)	(0.124)	(0.017)
Affected skill group: All or undefined (ref.: high)	0.008	-0.013	-0.085	-0.015
	(0.094)	(0.017)	(0.118)	(0.017)
Definition of immigrants: Citizenship (ref.: birthplace)	0.115	0.038	0.057	0.032
	(0.108)	(0.034)	(0.099)	(0.035)
Definition of immigrants: Others (ref.: birthplace)	-0.287*	-0.031	-0.133	-0.033
	(0.150)	(0.050)	(0.126)	(0.052)
Immigration skill group: Low-medium (ref.: high)	-0.069	-0.002	0.025	-0.003
	(0.143)	(0.020)	(0.087)	(0.018)
Immigration skill group: All or undefined (ref.: high)	0.003	-0.002	0.072	-0.003
	(0.109)	(0.020)	(0.096)	(0.018)
Method variables				
Geographical scope: Region (ref.: city)	0.133	-0.015	0.011	-0.015
	(0.095)	(0.024)	(0.109)	(0.025)
Geographical scope: Country (ref.: city)	0.063	-0.071	-0.134	-0.073
	(0.103)	(0.051)	(0.105)	(0.049)
Empirical strategy: IV-2SLS (ref.: OLS)	0.059	-0.008	0.093	-0.008
	(0.049)	(0.008)	(0.071)	(0.009)
Empirical strategy: Difference-in-differences (ref.: OLS)	-0.105	-0.094***	-0.144	-0.094***
	(0.132)	(0.035)	(0.095)	(0.034)
Empirical strategy: Others (ref.: OLS)	0.032	0.012	0.031	0.012
	(0.081)	(0.014)	(0.098)	(0.015)
Fixed effects	-0.050	-0.000	0.069	-0.001
	(0.079)	(0.011)	(0.071)	(0.012)
Language	-0.125***	-0.047*	-0.000	-0.039
	(0.047)	(0.027)	(0.088)	(0.028)
Observations	2,146	2,146	2,146	2,146
Studies	64	64	64	64
R^2		0.076	0.167	0.089
Estimator	RE	WLS	WLS	WLS
Weight	none	ise	quality	quality-add
Meta-estimate	-0.010	-0.044	-0.045	-0.054
Meta-estimate S.D.	0.229	0.094	0.207	0.113

Note: This table reports meta-regression results obtained with the baseline sample. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses. The acronym *ise* refers to the inverse of the standard errors of the β-estimates. The acronym *ihs* refers to the *inverse hyperbolic sine* transformation of the β-estimates. The regression results reported in column (1) are obtained with a random-effects model. The results reported in columns (2) to (4) are obtained using weighted least squares (WLS).

Table A.4 – Meta-Regressions - Publication Bias and Alternative Samples

	(1)	(2)	(3)	(4)	(5)
Study characteristics					
Leading academic journal	-0.348***	-0.203***	-0.325***	-0.368***	-1.211***
	(0.115)	(0.073)	(0.119)	(0.124)	(0.208)
Journal article	-0.059	-0.064	-0.111	-0.035	-0.254
	(0.095)	(0.051)	(0.087)	(0.112)	(0.347)
Elasticity	-0.008	-0.002	-0.032	0.125	0.102
	(0.110)	(0.068)	(0.078)	(0.136)	(0.160)
Standard error of the estimate			0.009	-0.186	0.143**
			(0.137)	(0.130)	(0.054)
Sample size			-0.007		
			(0.011)		
Sample of interest					
Studied country: Anglo-Saxon countries (ref.: the U.S.)	0.129	0.240**	0.142	0.092	
	(0.103)	(0.112)	(0.101)	(0.128)	
Studied country: France (ref.: the U.S.)	0.113	-0.034	0.116	0.064	
	(0.113)	(0.112)	(0.106)	(0.111)	
Studied country: Other countries (ref.: the U.S.)	0.210**	0.098*	0.177*	0.173	
	(0.101)	(0.050)	(0.102)	(0.105)	
Individual data	0.057	-0.012	0.161	0.041	0.085
	(0.116)	(0.052)	(0.102)	(0.129)	(0.166)
Data structure: Panel data (ref.: cross-section data)	0.028	0.052	0.070	0.123	0.695**
	(0.082)	(0.058)	(0.077)	(0.084)	(0.249)
Data structure: Time series (ref.: cross-section data)	0.273*	0.150	0.162	0.903***	
	(0.151)	(0.130)	(0.112)	(0.211)	
Definition and measurement of the variables of interest					
Definition of wages: Weekly (ref.: hourly)	0.152	0.002	0.156*	0.173	0.405**
	(0.097)	(0.049)	(0.092)	(0.110)	(0.112)
Definition of wages: Monthly/Yearly (ref.: hourly)	0.037	-0.040	0.035	0.104	0.517***
	(0.088)	(0.064)	(0.076)	(0.101)	(0.097)
Definition of wages: Other definition (ref.: hourly)	0.142*	0.046	0.046	0.153	
	(0.081)	(0.083)	(0.095)	(0.093)	
Affected skill group: Low-medium (ref.: high)	-0.035	-0.040	-0.094	-0.067	-0.463
	(0.114)	(0.069)	(0.104)	(0.118)	(0.596)
Affected skill group: All or undefined (ref.: high)	-0.066	-0.044	-0.134	-0.010	-0.693
	(0.110)	(0.074)	(0.100)	(0.105)	(0.613)
Definition of immigrants: Citizenship (ref.: birthplace)	0.087	0.027	0.118	0.059	
	(0.100)	(0.062)	(0.095)	(0.109)	
Definition of immigrants: Others (ref.: birthplace)	-0.139	-0.001	-0.001	-0.136	
	(0.123)	(0.084)	(0.123)	(0.133)	
Immigration skill group: Low-medium (ref.: high)	0.031	0.095	0.080	-0.002	
	(0.095)	(0.083)	(0.070)	(0.085)	
Immigration skill group: All or undefined (ref.: high)	0.070	0.137	0.112	0.005	
	(0.095)	(0.084)	(0.092)	(0.083)	
Method variables					
Geographical scope: Region (ref.: city)	-0.026	-0.040	-0.084	-0.013	0.663***
	(0.100)	(0.072)	(0.142)	(0.119)	(0.101)
Geographical scope: Country (ref.: city)	-0.175*	-0.080	-0.238**	-0.139	
	(0.100)	(0.050)	(0.118)	(0.110)	
Empirical strategy: IV-2SLS (ref.: OLS)	0.077	0.065	0.103	-0.028	-0.100
	(0.069)	(0.059)	(0.067)	(0.073)	(0.076)
Empirical strategy: Difference-in-differences (ref.: OLS)	-0.205**	-0.234***	-0.279***	-0.065	
	(0.093)	(0.072)	(0.098)	(0.124)	
Empirical strategy: Others (ref.: OLS)	0.015	-0.169**	0.013	0.104	-0.074
	(0.088)	(0.080)	(0.093)	(0.108)	-0.074
Fixed effects	0.083	0.057	0.042	0.086	0.043
	(0.067)	(0.050)	(0.072)	(0.078)	(0.032)
Language	0.010	0.039	0.083	0.026	
	(0.087)	(0.075)	(0.079)	(0.099)	
Observations	2,146	3,465	1,740	1,943	143
Studies	64	104	53	52	7
R^2	0.150	0.102	0.180	0.190	0.315
Estimator	OLS	OLS	OLS	OLS	OLS
Meta-estimate	-0.044	-0.023	-0.090	-0.054	-0.023
Meta-estimate S.D.	0.202	0.157	0.198	0.229	0.319

Note: This table reports meta-regression results. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses. The regression presented in column (1) uses the baseline sample, the regression presented in column (2) uses the full sample, the regression presented in column (3) uses a sample of estimates for which the sample size is available, the regression presented in column (4) uses a sample of studies published after 2000, and the regression presented in column (5) uses a sample of the studies that are included in our benchmark sample *and* in the study of Longhi et al. (2005).

Table A.5 – Meta-Regressions - Alternative Specifications

	(1)	(2)	(3)
Study characteristics			
Leading academic journal	-0.350***	-0.303**	-0.376***
	(0.122)	(0.131)	(0.123)
Journal article	-0.016	-0.077	-0.051
	(0.093)	(0.109)	(0.111)
Elasticity	0.039	0.015	0.005
	(0.095)	(0.116)	(0.102)
Standard error of the estimate	-0.088	-0.077	-0.080
	(0.103)	(0.107)	(0.107)
Sample of interest			
Studied country: Anglo-Saxon countries (ref.: the U.S.)	0.224**	0.091	0.109
	(0.106)	(0.124)	(0.121)
Studied country: France (ref.: the U.S.)	0.061	0.056	0.040
	(0.103)	(0.117)	(0.123)
Studied country: Other countries (ref.: the U.S.)	0.277***	0.166	0.158
	(0.091)	(0.103)	(0.100)
Individual data		0.039	-0.038
		(0.102)	(0.137)
Data structure: Panel data (ref.: cross-section data)	0.081	0.039	0.064
	(0.086)	(0.094)	(0.092)
Data structure: Time series (ref.: cross-section data)	0.413**	0.267	0.331
	(0.160)	(0.172)	(0.201)
Data type: Census (ref.: survey)	0.247*		
	(0.141)		
Data type: Administrative (ref.: survey)	0.215**		
	(0.089)		
Definition and measurement of the variables of interest			
Definition of wages: Weekly (ref.: hourly)	0.169*	0.209*	0.181
	(0.095)	(0.106)	(0.111)
Definition of wages: Monthly/Yearly (ref.: hourly)	0.026	0.028	0.051
	(0.101)	(0.098)	(0.097)
Definition of wages: Other definition (ref.: hourly)	0.067	0.168**	0.160*
	(0.097)	(0.079)	(0.085)
Affected skill group: Low-medium (ref.: high)	-0.029	-0.027	-0.028
	(0.110)	(0.116)	(0.114)
Affected skill group: All or undefined (ref.: high)	-0.043	-0.053	-0.061
	(0.107)	(0.111)	(0.113)
Definition of immigrants: Citizenship (ref.: birthplace)	-0.044	0.026	0.038
	(0.085)	(0.108)	(0.108)
Definition of immigrants: Others (ref.: birthplace)	-0.290**	-0.215*	-0.209*
	(0.118)	(0.121)	(0.122)
Immigration skill group: Low-medium (ref.: high)	0.105	-0.004	0.030
	(0.104)	(0.106)	(0.091)
Immigration skill group: All or undefined (ref.: high)	0.170	0.074	0.112
	(0.108)	(0.101)	(0.099)
Method variables			
Geographical scope: Region (ref.: city)	0.013		
	(0.082)		
Geographical scope: Country (ref.: city)	-0.077		
	(0.083)		
Empirical strategy: IV-2SLS (ref.: OLS)	0.070	0.087	0.085
	(0.056)	(0.069)	(0.073)
Empirical strategy: Difference-in-differences (ref.: OLS)	0.018	-0.052	-0.040
	(0.113)	(0.118)	(0.127)
Empirical strategy: Others (ref.: OLS)	0.039	0.065	0.005
	(0.093)	(0.107)	(0.104)
Fixed effects	0.010	0.063	0.034
	(0.072)	(0.069)	(0.064)
Language	-0.005	-0.105	-0.017
	(0.081)	(0.106)	(0.113)
Approach: Area (ref.: national skill-cell)		-0.037	
		(0.098)	
Approach: Mixed (ref.: national skill-cell)		-0.118	
		(0.077)	
Market size			0.060
			(0.102)
Observations	2,146	2,146	2,146
Studies	64	64	64
R^2	0.173	0.151	0.148
Estimator	OLS	OLS	OLS
Meta-estimate	-0.044	-0.044	-0.044
Meta-estimate S.D.	0.216	0.202	0.200

Note: This table reports meta-regression results obtained with the baseline sample. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses.