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Does Immigration Affect Wages? A Meta-Analysis

Amandine Aubry
Jérôme Héricourt
Léa Marchal
Clément Nedoncelle

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L'immigration a-t-elle un impact sur les salaires ? Une méta-analyse.[1]

Amandine Aubry [2], Jérôme Héricourt [3], Léa Marchal [4], Clément Nedoncelle [5]

Résumé : L'immigration a-t-elle un impact sur les salaires ? Aucune réponse tranchée n'a été jusqu'à présent apportée à cette interrogation. Nous proposons une méta-analyse actualisée de la littérature consacrée à cette dernière, consistant en 2146 estimations issues de 64 articles publiés entre 1972 et 2019. Il apparaît qu'en moyenne, la littérature estime un effet négatif, quoique quantitativement proche de zéro, de l'immigration sur les salaires des travailleurs nationaux. Ce résultat prévaut tant pour les individus faiblement ou moyennement qualifiés que pour ceux hautement qualifiés. Cet effet moyen dissimule cependant une hétérogénéité substantielle entre les différentes études. Cette dernière apparaît de nature structurelle, et renvoie tant au pays analysé qu'à l'utilisation de données microéconomiques ou à la méthodologie empirique mise en place, telle que le recours aux différences en différences. Nous concluons enfin à un effet négatif significatif de la publication dans les revues académiques de référence, et proposons une discussion du biais potentiel de publication dans la littérature.

Mots-clés : Immigration, Marché du travail, Méta-analyse, salaire

Does Immigration Affect Wages? A Meta-Analysis

Abstract : Does immigration affect wages? No decisive answer has been provided until now. We propose an up-to-date meta-analysis of the literature investigating this question, based on 2,146 estimates from 64 studies published between 1972 and 2019. We find that, on average, the literature reports a negative and close to zero effect of immigration on native wages. This result holds for both low/medium-skilled and high-skilled native individuals. This average effect, however, hides a large heterogeneity across studies. Variation across estimates can be explained by the presence of structural heterogeneity such as the country of analysis or the use of micro-level data, as well as to heterogeneity in research designs such as the use of difference-in-differences. Finally, we estimate a significant and negative effect of publishing in leading academic journals and propose a discussion on the potential publication bias in the literature.

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

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[2]Université de Normandie—CREM (UMR-CNRS 6211), UNICAEN, Caen, France; amandine.aubry@unicaen.fr

[3]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

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

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

1 Introduction

Should immigration be restricted and upon which conditions? This question has been extensively debated over the past decades, with a focus on the economic consequences for native individuals in terms of employment and wage (Goldin et al., 2012). For instance, in 2012, Theresa May stated that "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 models the relationship between labor market outcomes 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 such as an increase in the number of immigrant workers 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 to immigrants.

However, empirical results stay unclear. As pointed by Dustmann et al. (2016), some studies conclude immigration reduces native wages, and others show either a positive or a null impact. The question is rather topical among U.S. economists who try to pin down the wage effect of immigration (*The Immigration Equation*, NYTM, July 9, 2006). On the one hand, George J. Borjas concludes to a negative effect of immigration on U.S. workers. He refers to other influential studies such as Peri and Yasenov (2015) as "simply wrong" and fraught with "questionable assumptions" and "dubious data manipulations" (Borjas, 2016). On the other hand, economists such as David Card or Giovanni Peri find a positive immigration effect, and refers to George J. Borjas research as "revisionist" and "overly pessimistic" (Card, 2005) (see also Card, 2012, Card and Peri, 2016).

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." See also Blau and Mackie (2017) for a survey on the U.S. specifically. 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. For instance, 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.

We perform a meta-analysis to further investigate the sources of variation in the estimated wage effect of immigration across studies in the existing literature. 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. The present meta-analysis contributes to pinning down certain regularities in how the wage effect of immigration varies across studies, depending on their method and structural features.

Our sample includes 64 studies published between 1972 and 2019, reporting 2,146 β-estimates of the wage effect of immigration. Our analysis concludes to three main results. First, we confirm that, on average, the effect of immigration on native wages is close to zero in the literature. Our benchmark meta-estimate of the impact of immigration on natives is significant and equals to -0.044. This negative effect of immigration holds for both low/medium-skilled and high-skilled native individuals. Moreover, 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.

Second, we investigate the sources of variation in the β-estimates. We find that both the structural and method heterogeneity determine the immigration effect. Differences across country setups and the structure of the data explain, in part, why the estimated wage effects of immigration vary across studies. As for the method heterogeneity, we estimate a significant impact of differences in the empirical strategy such as the use of strategy to account for endogeneity issues, or the use of fixed effects. In particular, we find a negative and highly significant effect of using difference-in-differences as well as shift-share instruments à la Card (2001). We also find that smaller geographical scopes of the labor market tend to provide smaller estimates of the wage effect of immigration,in line with the survey of Dustmann et al. (2016). In that survey, the authors advocate methods determine the sign and magnitude of the wage elasticity.

Finally, we estimate a strong and negative effect of publishing in leading academic journals. Controlling for structural and method heterogeneity, leading academic journals provide more negative estimates of the impact of immigration on native wages, even after controlling for a potential publication bias.

Our contribution to the literature is threefold. First, a large number of studies on the effect of immigration on the labor market have been published in the past decades, and have not been investigated in the Longhi et al.'s (2005) meta-analysis. Our sample includes more studies as well as more countries of analysis. While this increased sample does not change the main conclusions reached in Longhi et al. (2005), we find a smaller effect (closer to zero) of immigration on native wages. Our benchmark meta-estimate is equal to -0.044, whereas Longhi et al. (2005) find a meta-estimate of -0.119. Our study was performed using a large-scale and state-of-the-art meta-analysis (Stanley et al., 2013). Finally, we perform a number of robustness tests to ensure that the differences in the result of our study and the meta-analysis of Longhi et al. (2005) cannot be attributed to methodological differences.

Second, this extended and representative sample of the literature allows us to explore additional determinants of the estimated wage effect of immigration. In particular, we focus on recent data characteristics and methods as determinants of the estimated meta-effect. Recent papers in the field have increasingly used disaggregated data (e.g., from administrative sources) on rather long time spans. Additionally, the recent literature witnessed an increased use of sophisticated econometric methods aimed at inferring causality (Brodeur et al., 2020) , in particular methods tackling the endogenous relationship between immigration and wages (see the discussion 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 in favor of this hypothesis. We find that the methodological changes can explain part of 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 structural and method heterogeneity. We believe this result is important from a policy perspective. Although results from leading journals are likely to receive more attention, they may differ from the average result 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 β-estimates across studies and provide a meta-estimate of the wage effect of immigration. Section 6 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 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. 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.

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 relative 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, all things being equal. Finally, the mixed approach exploits variations across skills *and* geographic areas.

Then, 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. Difference-in-differences (DiD) exploiting natural experiments such as the Mariel boatlift episode (see the seminal study of Card, 1990), as well as the instrumental variable strategy based on the shift-share approach à la Card (2001), have been the two dominant techniques to tackle endogeneity and infer causal results.

Finally, although they make a significant contribution to the literature, 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.

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. We follow the state-of-the-art methodology that consists in two steps (Stanley et al., 2013). 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 in the existing literature 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.

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*.[1] In total, we used 47 combinations of keywords. The sample includes paper found in EconLit as of May 15, 2019. 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 survey by 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. To comply with the rule of systematic and automated search, we did not add any other article to the sample (Stanley et al., 2013).[2]

[1] 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.

[2] This implies that we did not add studies referenced by EconLit after May 15, 2019, nor update working papers that have been published at a later date in our sample.

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. 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), 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 restricted our sample to observations for which a standard error or a t-statistics were reported because these variables are 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.

3.2 Data Analysis

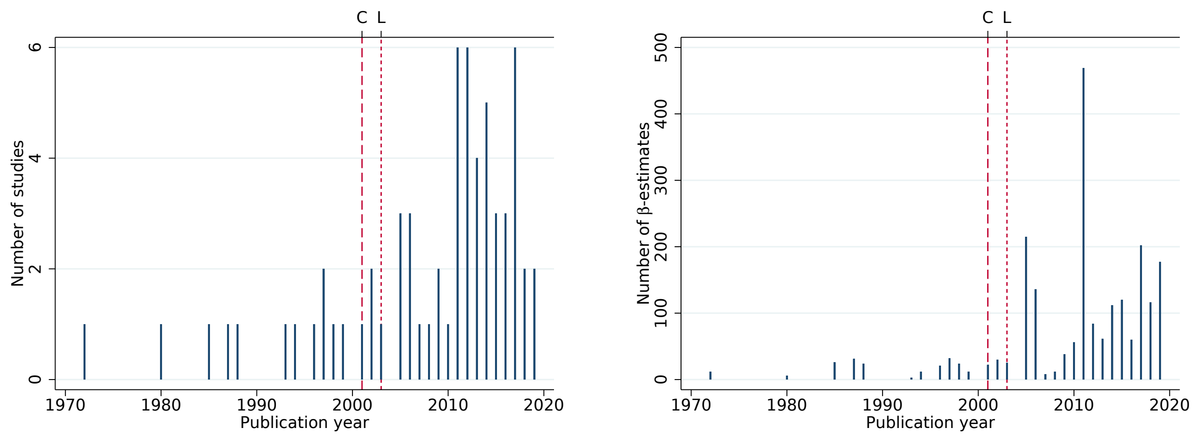
Overview. Descriptive statistics for the β-estimates included in our benchmark sample, as well as a number of variables related to the characteristics of the studies are reported in Appendix B, Table B.1. Our sample includes studies published between 1972 and 2019. Only 3% of the observations have been 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*) and 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 or conducted in groups of countries such as the OECD countries. Thirty percent of the estimates in the sample are computed with samples analyzing the U.S labor market. 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 administrative data.

The Wage Effect of Immigration Over Time. Figure 1 depicts the scientific production on the wage effect of immigration over time. Figure 1(a) shows that the number of studies surged after the mid 2000s, and Figure 1(b) shows a similar pattern for the number of β-estimates. On both figures, a vertical dash line (denoted "C") indicates the publication year of the seminal paper by David Card on the use of the shift-share instrument for immigration shocks (Card, 2001). Our sample includes studies after 2001 and therefore allows us to investigate the effect of this method on the estimation of the wage effect of immigration. In addition, a vertical dotted line (denoted "L") marks the year 2003 which is the last sample year of the meta-analysis proposed by Longhi et al. (2005). It shows that most studies in the field were produced in the past two decades and could not have been part of the latter meta-analysis.

Figure 1 – Scientific Production on the Wage Effect of Immigration Over Time

(a) Number of Studies

(b) Number of β-Estimates



Note: This figure has been produced using the benchmark sample. It depicts the scientific production on the wage effect of immigration over time. Figure 1(a) shows the number of studies and Figure 1(b) shows the number of β-estimates over time. The vertical dash line marks the publication year of Card (2001). The vertical dotted line marks the year 2003 which is the last sample year of the meta-analysis proposed by Longhi et al. (2005).

Figure 2 depicts the distribution of β-estimates of the wage effect of immigration over time, for the benchmark sample (Figure 2a), as well as for low/medium-skilled (Figure 2b) and high-skilled native individuals (Figure 2c). This figure highlights a large heterogeneity in the estimates wage effect of immigration over time and across skills. This heterogeneity can be partly disentangled by analyzing subsamples of affected population and will be studied in section 4.

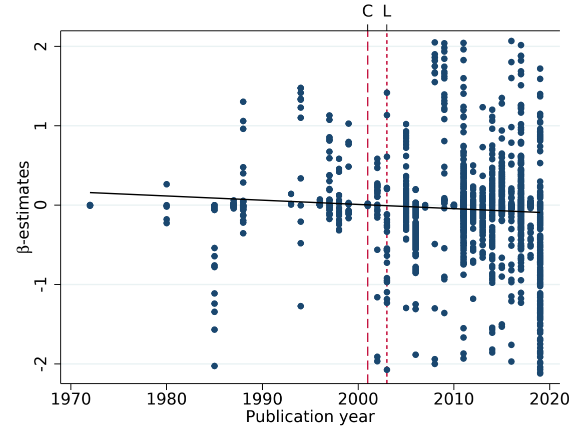
Variance Analysis. Figure 3 displays the density of β-estimates. Figure 3(a) displays the density for the benchmark sample. A striking feature of the data is that estimates are small and concentrated around zero. The average effect of immigration on native wages is equal to -0.044 (Appendix B, Table B.1). The magnitude of this figure is difficult to interpret because the sample includes elasticities, semi-elasticities and point estimates. When we only consider log-log estimations, which make up 9.6% of the sample (206 observations, 14 studies), we find an average wage elasticity of 0.025 (ranging from -0.53 to 1.03). This feature of the data corroborates the results in Longhi et al. (2005) and Blau and Kahn (2015).

The debate on the wage effect of immigration is mostly focused on low-skilled individuals. We therefore reproduce this exercise for low/medium-skilled and high-skilled native individuals in Figure 3(b). We find the density of β-estimates for low/medium-skilled natives is to the left of the distribution for high-skilled natives. Yet, there is no clearcut difference in the mean wage effect of the two groups of affected individuals. We find an average wage effect of -0.087 (ranging from -2.11 to 2.04) for low/medium-skilled natives (402 observations, 28 studies) and -0.082 (ranging from -2 to 2.07) for high-skilled natives (291 observations, 24 studies).

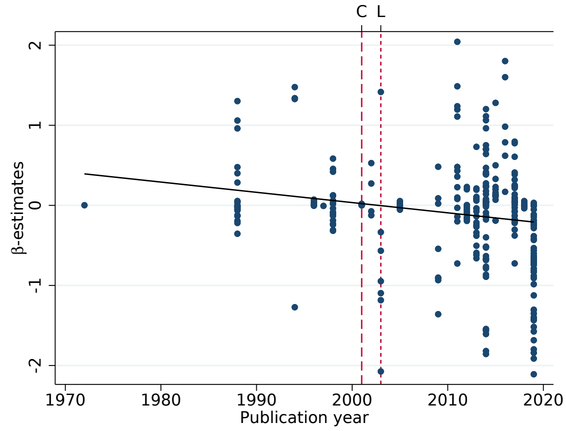
We analyze further the variance between the β-estimates across studies using a forest plot presented in Figure 4. We depict the average wage effect of immigration as well as the 95% confidence intervals for each study. Confidence intervals are computed using the standard error (or the β-estimate divided by its t-statistic) of each β-estimate. Figure 4 also describes the number of estimations found in each study. At the bottom of the figure, we plot the predicted wage effect obtained from a random-effect model and a

Figure 2 – Distribution of β-Estimates Over Time

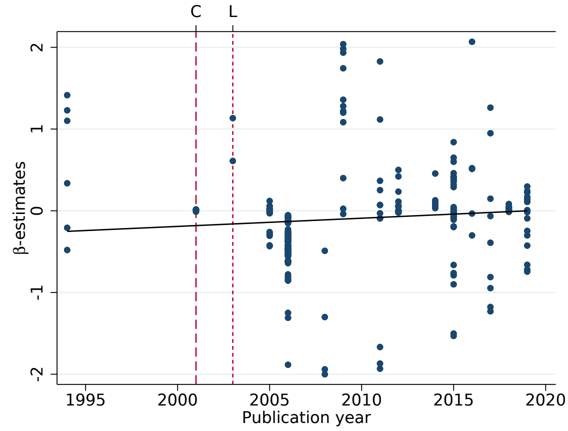
(a) Benchmark Sample



(b) Low/Medium-Skilled Natives



(c) High-Skilled Natives



Note: This figure has been produced using the benchmark sample. It depicts the distribution of β-estimates over time. Figure 2(a) shows the distribution of β-estimates for the benchmark sample which includes all native individuals irrespective of their occupation or education level. Figure 2(b) and 2(c) show the distribution of β-estimates for low/medium-skilled and high-skilled native individuals respectively. The vertical dash line marks the publication year of Card (2001). The vertical dotted line marks the year 2003 which is the last sample year of the meta-analysis proposed by Longhi et al. (2005).

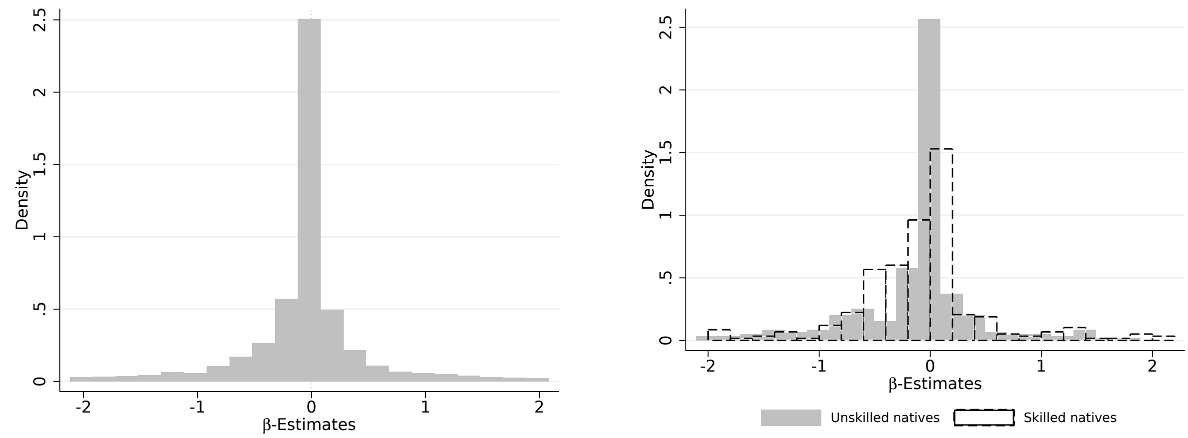
fixed-effect model using all studies of the benchmark sample[3]. These two estimations suggest the average effect of immigration on native wages is not significantly different from zero. Note that the forest plots for the subsamples of low/medium-skilled and high-skilled native individuals are similar to Figure 4.

Then, we investigate the differences between the benchmark sample and the full set of observations. We replicate the above figures with the observations obtained with the full sample (3,485 β-estimates from 104 studies). Doing so, we can assess whether restricting the sample to estimates for which a standard error is available changes the key features of the distribution of β-estimates. Results are reported in Appendix B, Figures B.1 and B.2. 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 3 – Density of the β-Estimates

(a) Benchmark Sample

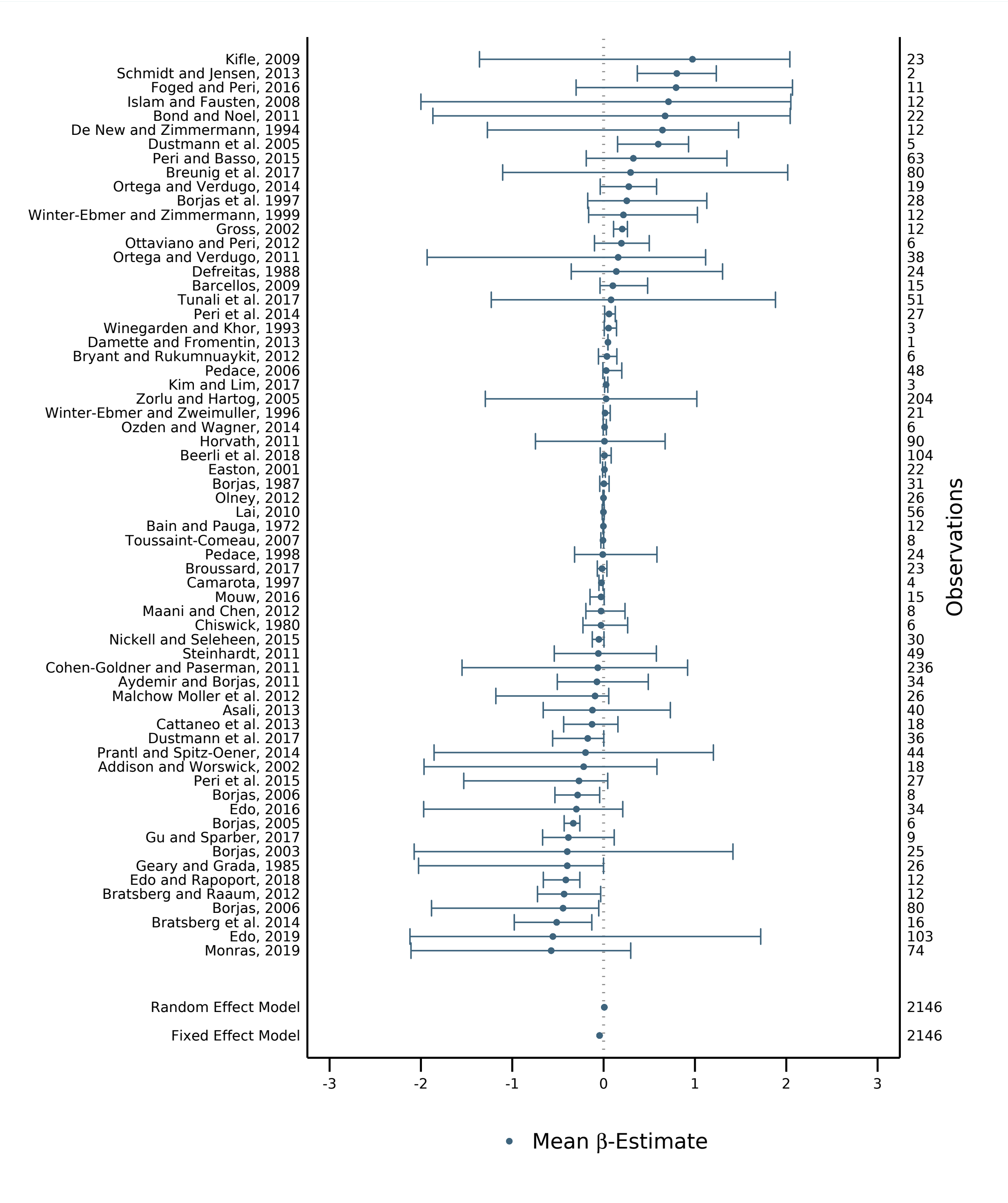
(b) Low/Medium- and High-Skilled Natives



Note: This figure displays the density of β-estimates. Figure 3(a) shows the density for the benchmark sample. Figure 3(b) shows the density for low/medium-skilled and high-skilled native individuals.

[3] In our context, a fixed-effect model assumes all studies are estimating the same (common) β-estimate, whereas a random-effect model assumes that β-estimates can vary across studies because of real differences in the effect in each study as well as sampling variability.

Figure 4 – Within- and Between-Variation of the β-Estimates



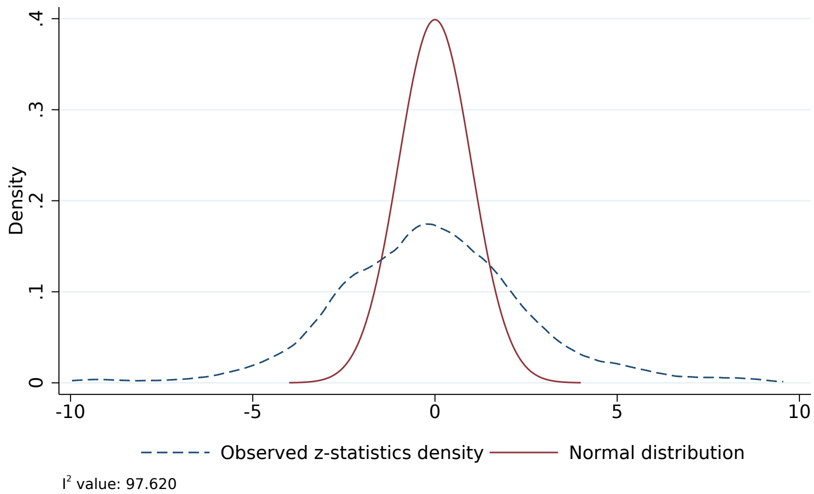
Note: This figure is a forest plot of the β-estimates included in the benchmark sample. For each study, it shows of the average β-estimate and the within-study 95% confidence interval computed using the standard errors (or the β-estimates divided by their t-statistics). The right-axis reports the number of β-estimates for each study. The predicted wage effect obtained from a random-effect and a fixed-effect model using the entire benchmark sample have been reported at the bottom of the plot.

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, years or affected populations. 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 β-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, $z_i = (\hat{\beta}_i - \tilde{\beta})/se(\hat{\beta}_i)$, should follow a Student's t-distribution. Because many degrees of freedom exist in our case, the t-distribution should approximate a Normal distribution under the null hypothesis of sampling error. Figure 5 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 ($\hat{\beta}_i$).

Figure 5 – Distribution of the z-Statistics



Note: This figure has been produced using the benchmark sample. It depicts the observed distribution of the z-statistics and the Normal distribution. z-statistics are computed using the β-estimates and the associated standard errors as follows: $z_i = (\hat{\beta}_i - \tilde{\beta})/se(\hat{\beta}_i)$.

Finally, we 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 5 and the I^2 statistics call for an investigation of other sources of heterogeneity than sampling errors.

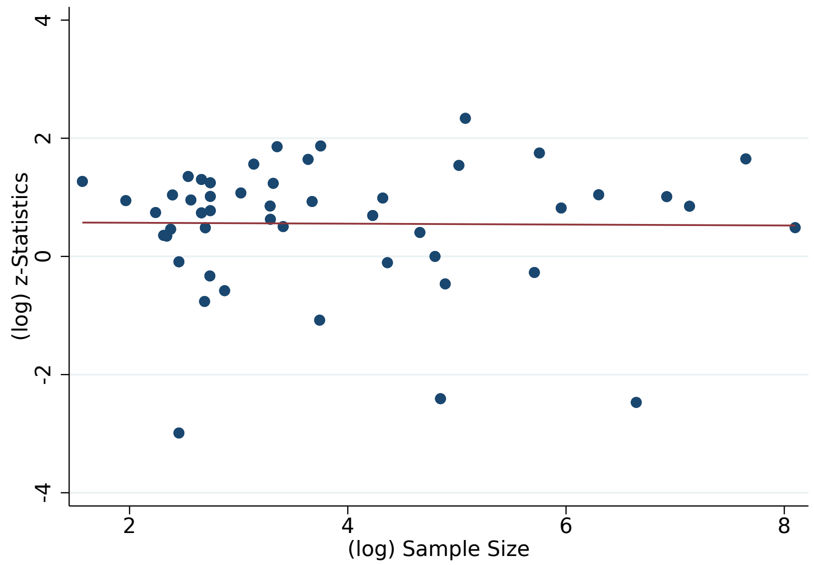
3.4 Publication Bias

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.

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 a regression 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 6 presents the relation of z-statistics to sample size. We find no strong correlation between the significance of the median β-estimates and the sample size. In Appendix B, we provide the results using two different estimates: Figure B.3(a) shows the results using the first estimate reported in the study, and Figure B.3(b) 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. Overall, 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.

Figure 6 – Relation of z-Statistics to Sample Size



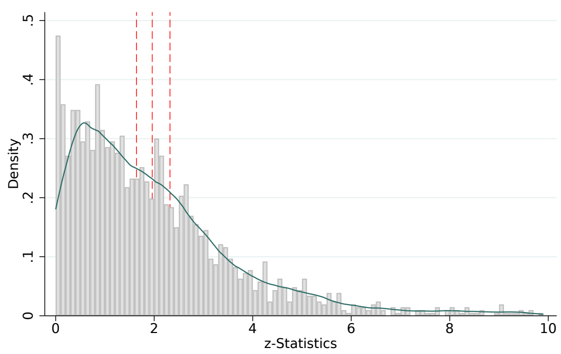
Note: This figure has been produced using the median β-estimate of each study included in the benchmark sample. It depicts the relationship between the significance of the β-estimates (captures by the associated z-statistics) and the sample size. z-statistics are computed using the β-estimates and the associated standard errors as follows: $z_i = (\hat{\beta}_i - \tilde{\beta})/se(\hat{\beta}_i)$.

Then, 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.

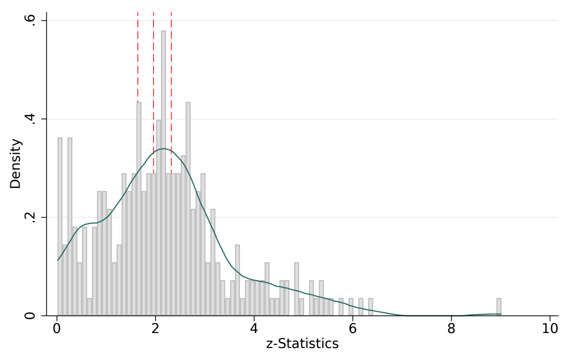
Results are presented in Figure 7. Using the benchmark sample, we find the test statistic is distributed equally around significance thresholds, which suggests a limited publication bias (Figure 7a). We then replicate this exercise for articles published in leading journals (Figure 7b). Although a spike 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 β-estimate in the meta-regressions (following Card and Krueger's (1995) and Longhi et al.'s (2005) strategy on this topic).[4]

Figure 7 – Distribution of z-Statistics

(a) Benchmark sample



(b) subsample of leading journals



Note: This figure reports the distribution of z-statistics. Figure 7(a) shows the distribution for the benchmark sample, and Figure 7(b) shows the distribution for the subsample of leading academic journals. z-statistics are computed using the β-estimates and the associated standard errors as follows: $z_i = (\hat{\beta}_i - \tilde{\beta})/se(\hat{\beta}_i)$. In these graphics, the 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 are studied in our meta-analysis: *structural* and *method* 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 time dimension, the level of disaggregation and the geographical area. 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

[4]The test implemented by Card and Krueger (1995) and Longhi et al. (2005) goes through the relationship between the β-estimates and their standard errors. In case of a publication bias, we should expect an abundance of published t-statistics around some specific thresholds, i.e. proportionality between the β-estimates and the standard errors.

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:

$$\hat{\beta}_{i,s} = \Theta_1 \text{Quality}'_s + \Theta_2 \text{Structure}'_{i,s} + \Theta_3 \text{Method}'_{i,s} + \Theta_4 \text{Definitions}'_{i,s} + \varepsilon_{i,s} \tag{5}$$

$\hat{\beta}_{i,s}$ denotes the ith estimate of the wage effect of immigration presented in study s. The first vector of variables controls for the quality of the study and β-estimate. It includes a binary variable equal to 1 if the study is published in a leading journal (AER, JPE, Restud, QJE, Ecma, JEEA, and JLE) and a categorical variable for the type of publication (journal article, working paper, book or collective volume). 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. When this variable is missing, we compute an implicit error by dividing the β-estimate by its t-statistic.

We explore the *structural heterogeneity* across studies by including a vector of covariates which controls for the characteristics of the sample of observations the authors used to obtain the β-estimate. It includes a binary variable equal to 1 if the authors used disaggregated data at the individual level, and a binary variable equal to 1 for panel data. These two variables control for the fact that individual and panel data are of higher quality and may allow for better causal inference. The use of these type of data has appeared only in the last decades of the literature, which may explain the slight change in the β-estimates over time (see Figure 2). We also include a binary equal to 1 for the U.S. as the literature is highly biased toward this country. In our benchmark sample, the U.S. account for 30% of the observations, and for 26 out of 64 studies. This variable may catch some country-specific features such as, among others, the high level of flexibility of the U.S. labor market and the poor level of worker protection in the U.S. legislation.

The third vector of variables aims at controlling for the *method heterogeneity*. It includes a categorical variable for the geographical scope of the study (national, regional, or metropolitan scale). This variable is key to the literature. For instance, a study with a national scope may poorly capture the fact that natives and immigrants compete within local labor markets. Then, we include a binary variable for the use of instrumental variables to obtain the β-estimate, and a binary variable for the use of a difference-in-differences strategy which is specific to natural experiment setups. These two binaries controlling for the widespread estimation strategies used in the literature are mutually exclusive. It allows us to control for the fact that studies tackling endogeneity issues obtain eventually more *causal* results. We also control for estimations that include some set of fixed effects to take into account the level of complexity and reliability of the implemented model.

The last vector of control variables controls for the definition and measurement of the two key variables of interest: the wage of natives and the immigration shock. It includes categorical variables for the type of wage variables used in the analysis (hourly, weekly, monthly, yearly, or other). It contains categorical variables for the skill (or education) level of natives whose wage is analyzed (low-medium skilled, high skilled, or all/undefined skill groups). Then, it includes a categorical variable that defines immigrant individuals (based on their birthplace, citizenship, or other definitions). We also control for the level of skill (or education) of immigrants (low/medium, high, or all/undefined skill groups).

In Appendix A, Table C.4 shows the categories used in the analysis and the corresponding number of observations that fall into each category. Table C.5 provides detailed information regarding the definition of the variables used in the analysis.

Finally, standard errors are clustered at the study level to control for within-study correlation and dependence across errors. Our benchmark specification consists in an unweighted OLS estimator. In an alternative specification, we include a set of study fixed effects in order to control for omitted variables related to the characteristics of the study, its author(s) in particular. This is rather important given the hot debate taking place between the leading authors of the field. Adding study fixed effects also allows us to analyze the variation in the wage effect of immigration *within* study, in particular in the method heterogeneity.

4.2 Benchmark Results

We report the results of the benchmark meta-regression in Table 1. We start by exploring the determinants of the wage effect of immigration using an unweighted OLS estimator in column (1). We then analyze the within study variation using a set of study fixed effects in column (2). We reproduce this exercise for low/medium-skilled native individuals (columns 3-4), as well as for high-skilled native individuals (columns 5-6). For each meta-regression, we report the estimated average effect of immigration on native wages, together with the bootstrapped standard errors.

Close-to-Zero Wage Effect. First, the results of the benchmark meta-regressions in Table 1 (columns 1 and 2) show that the average meta-effect of immigration on the wage of natives is negative and significant, but small in the surveyed literature (-0.044). For comparison, Longhi et al. (2005) found an elasticity of -0.119. Our result confirms the conclusion of this previous meta-analysis: the impact of immigration on native wages is small.

While scholars have been studying the effect of immigration on the wages of both low/medium-skilled and high-skilled native individuals, the debate focuses mostly on the effect of low-skilled immigration on the labor market. As stressed by George J. Borjas in the context of the U.S., immigrants are likely to have similar characteristics to low-skilled U.S. individuals. These individuals are therefore likely to be hurt the most in the short run. We therefore distinguish β-estimates obtained for low/medium-skilled and high-skilled native individuals in columns (3) to (6). We find a similar significant and average negative effects of -0.087 for low/medium-skilled native individuals, and -0.082 for high-skilled native individuals.

Quality of the Study and Publication Bias. Second, analyses published in leading academic journals exhibit significantly lower coefficients than other estimates (column 1). This feature of the study characteristics is one of the largest determinants of the size of the estimate (this variable exhibits a large point estimate, around -0.389). While the fact that leading journals publish lower β-estimates may indicate that high-quality journals publish less biased results thanks to their high scientific standards, it could also point to a potential editorial bias of these journals. Nonetheless, our results do not seem to be driven by a publication bias as the coefficient of the standard error of the β-estimate is not or barely significant. Finally, we do not estimate any significant impact of studies published in an academic journal (compared with unpublished working papers, books, and collective volumes).

When we distinguish β-estimates obtained for low/medium-skilled and high-skilled native individuals (columns 3 and 5), we find that the results associated to leading journals only holds for low/medium-skilled individuals. Similarly, we find that the coefficient of the standard error of the β-estimate is positive and significant only for low/medium-skilled individuals, which suggests the presence of a publication bias in studies focusing on these affected individuals. This result is not surprising given that the debate is primarily focused on these individuals. Even when we include study fixed effects (column 4), we still find the presence of a publication bias which indicates that the quarrel possibly goes beyond a single author or journal.

A Limited Impact of Structural Heterogeneity. Third, we find a limited impact of the structure of the data on the sign and magnitude of the β-estimates (columns 1 to 6). The country under study has some influence on the outcome of the analysis. The impact of immigration on wages in the U.S. is significantly different from that in other countries. In column (1), we find that β-estimates found for the U.S. are significantly closer to zero (or more negative) than for other countries. This result corroborates the idea that the features of the U.S. labor market and worker protection allow for absorbing immigrants quite rapidly. In the short run, immigration may lower native wages due to the increased competition on the labor market. We then explore the within study variation in column (2), as our sample includes 7 out of 64 studies that analyze more than one single country. In that case, we find that the coefficients found for the U.S. are significantly larger (or less negative and closer to zero) than for other countries. It is, however, unclear whether this result is driven by a particular type of individuals as there is not enough variation in the data to explore this feature for low/medium-skilled and high-skilled native individuals separately (columns 4 and 6).

The type of data used also explains part of the heterogeneity, yet only for the subsample of low/medium-skilled native individuals (column 3). In particular, estimations run on individual and panel data exhibit larger coefficients (or less negative and closer to zero) than other studies that use more aggregated data or data that do not observe individuals over time.

Method Heterogeneity Matters. Fourth, the heterogeneity across β-estimates found in the literature is driven, in part, by the methods implemented by the authors. 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). Labor market adjustments and the potential absorption of immigration may vary widely depending on the scale of analysis (e.g., see Card, 2001). For example, immigration may generate an adjustment process within the national 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 underestimate the absolute wage effect of immigration. We find no significant difference across studies focusing on a regional or a metropolitan labor market compared with studies with a national scope (columns 1, 3 and 5). However, the within study meta-regressions show an overall negative and significant effect of using a smaller scope (regional and metropolitan areas) as compared to a national scope (columns 2, 4 and 6), which is in line with the surveyed literature.

We then study the effect of two identification strategies largely used by scholars in the field to infer causality: instrumental variable and difference-in-differences strategies. 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. Both the instrumental variable and difference-in-differences strategies are expected to solve these endogeneity issues and to produce unbiased estimates. β-estimates in a two-stage least-squares setting make up 16% of our benchmark sample, while the difference-in-differences approach accounts for 23% of it. We find no significant impact of the instrumental variable strategy on the benchmark sample. Within study, we do find a limited negative effect of this strategy for low/medium-skilled workers (column 4), and a positive and highly significant effect for high-skilled workers (column 6). Using a difference-in-differences approach has a negative and high significant impact on the wage effect of immigration. This method is one of the largest determinants of the size of the estimate (this variable exhibits a large point estimate, around -0.224, in column 1). This result holds within study (column 2), and for the subsample of low/medium-skilled workers (columns 3 and 4).

In addition, we find some evidence that introducing some set of fixed effects affects the β-estimates. On the one hand, the literature raises the concern that fixed effects, by absorbing unobserved heterogeneity, determine the type of variance used to identify the main effects. Yet, the inclusion of fixed effects may provide better quality estimates for this same reason. They can be considered as a way to identify reliable empirical studies that aim at providing less biased coefficients. We find that the inclusion of fixed effects matters, especially for the subsample of low/medium-skilled native workers (columns 3 and 4).

Definition and Measurement of the Variables. Finally, we control for the definition and measurement of the variables of interest. Overall, we find that the definitions of the wage of natives and the explanatory variable capturing the immigration shock have a significant impact on the sign and magnitude of the estimated effect. This result highlights the importance of performing robustness tests with alternative variables for future research on the topic.

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 and the structure of the data (individual and panel data) partly explain why the estimated wage effects of immigration vary across studies and within study. On the other hand, we find a strong effect of heterogeneity in the methods to explain the variation observed across studies. The geographical scope of the study as well as the econometric model implemented by the authors (instrumental variables, difference-in-differences, fixed effects) explain a large part of the estimated wage effects of immigration. Finally, point estimates suggest estimates in leading journal are smaller than other journals (even after controlling for structural and method heterogeneity).

Table 1 – Meta-Regressions - Baseline Results

	(1)	(2)	(3)	(4)	(5)	(6)
Sample of natives	all		low/med-skilled		high-skilled	
Quality of the study and estimate						
Leading academic journal	-0.389***		-0.874***		0.285	
	(0.101)		(0.127)		(0.404)	
Journal article	-0.052		0.044		-0.262	
	(0.084)		(0.107)		(0.184)	
Standard error of the estimate	-0.054	-0.212*	0.212***	0.152**	-0.211	-0.182
	(0.098)	(0.119)	(0.049)	(0.063)	(0.154)	(0.201)
Structural heterogeneity						
Individual data	0.088	0.059	0.280**		-0.341	
	(0.109)	(0.047)	(0.119)		(0.470)	
Panel data	0.030	0.147	0.312**		0.149	
	(0.086)	(0.122)	(0.140)		(0.276)	
The U.S.	-0.182**	0.091***	0.130		-0.289	
	(0.078)	(0.015)	(0.091)		(0.226)	
Method heterogeneity						
Geographical scope: Region (ref.: country)	0.131	0.006	0.211	-0.233***	-0.116	-0.243***
	(0.082)	(0.103)	(0.132)	(0.015)	(0.247)	(0.011)
Geographical scope: City (ref.: country)	0.157	-0.233*	0.273	-0.550***	-0.375	-0.531***
	(0.097)	(0.121)	(0.167)	(0.016)	(0.262)	(0.018)
Instrumental variable	0.089	0.034	0.122	-0.126*	0.030	0.303***
	(0.068)	(0.051)	(0.094)	(0.064)	(0.184)	(0.071)
Difference-in-differences	-0.224**	-0.402***	-0.351**	-0.773***	0.488	0.075
	(0.100)	(0.052)	(0.154)	(0.040)	(0.317)	(0.044)
Fixed effects	0.032	-0.109*	0.188**	0.078**	0.138	
	(0.063)	(0.059)	(0.075)	(0.033)	(0.289)	
Definition and measurement of the variables						
Definition of wages: Weekly (ref.: hourly/daily)	0.161	-0.119**	0.165	-0.029***	-0.138	0.124***
	(0.098)	(0.052)	(0.102)	(0.001)	(0.308)	(0.008)
Definition of wages: Monthly/Yearly (ref.: hourly/daily)	0.042	-0.171***	0.212	0.953***	-0.674**	0.648***
	(0.108)	(0.064)	(0.150)	(0.009)	(0.290)	(0.007)
Definition of wages: Other definitions (ref.: hourly/daily)	0.139	-0.362***	-0.135	-0.209***	0.264	0.267***
	(0.087)	(0.068)	(0.108)	(0.004)	(0.407)	(0.051)
Affected skill group: Low-medium (ref.: all/undefined)	0.059	0.089				
	(0.107)	(0.104)				
Affected skill group: High (ref.: all/undefined)	-0.025	0.129*				
	(0.055)	(0.070)				
Definition of immigrants: Citizenship (ref.: birthplace)	0.154*		0.498***		-0.853**	
	(0.085)		(0.165)		(0.362)	
Definition of immigrants: Other definitions (ref.: birthplace)	-0.033		0.177			
	(0.092)		(0.198)			
Immigration skill group: Low-medium (ref.: all/undefined)	-0.027	0.073	-0.257**	-0.020**	-0.276	0.058***
	(0.096)	(0.158)	(0.125)	(0.009)	(0.443)	(0.014)
Immigration skill group: High (ref.: all/undefined)	0.038	0.107	-0.084		-0.180	
	(0.050)	(0.096)	(0.063)		(0.550)	
Observations	2,146	2,145	402	400	291	290
Studies	64	63	28	26	24	23
R^2	0.144	0.334	0.374	0.464	0.375	0.600
Estimator	OLS	OLS, FE	OLS	OLS, FE	OLS	OLS, FE
Meta-estimate	-0.044***	-0.044***	-0.087***	-0.087***	-0.082***	-0.082***
	(0.012)	(0.012)	(0.030)	(0.030)	(0.036)	(0.037)

Note: This table reports meta-regression results. All regressions use the benchmark sample. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses. The standard error of the meta-estimate has been bootstrapped.

4.3 Complementary Results

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. We therefore explore additional variables and alternative specifications that we report in Tables 2, 3 and 4.

Publication Bias. First, we further discuss the possible presence of a publication bias. Results are presented in Table 2. 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). In column (1) We start by excluding the standard error of the β-estimate from the list of covariates. 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 benchmark 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 empirical strategy implemented by the authors, especially the difference-in-differences strategy and the use of fixed effects. In column (3), we modify the benchmark model by adding the (log) 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). We find similar results to the benchmark findings, which again point toward a limited publication bias.

The Scope of the Labor Market. Second, we explore alternative specifications to control for the scope of the studied labor market in Table 3. In the benchmark specification, we use the geographical scope of the study (national, metropolitan and regional scope). We found a striking difference in the results when we analyze low/medium-skilled and high-skilled native workers separately. We therefore adopt this approach in Table 3.

In particular, we use a categorical variable to distinguish between the skill-cell approach (the reference category), the area approach and the mixed approach. 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 the latter variable. This alternative specification allows us to 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). While the skill-cell approach might better capture the degree of substitution between native and immigrant workers depending on their skill/education level, the omission of the geographical scope may also underestimate the impact of immigration on native wages by ignoring adjustment effects taking place at the national level for the reasons mentioned above. Results are reported in columns (1) and (3) for low/medium skilled and high-skilled native individuals respectively. We find no evidence that the approach matters for the group of low/medium-skilled natives. Yet, in line with the survey of Dustmann et al. (2016), we find that omitting the geographical dimension in the analysis of the wage effect of immigration biases the results downward for the group of high-skilled natives. Given the magnitude of the coefficients, the difference in the approach leads to substantial differences in the sign and magnitude of the coefficients. This result can be explained by the fact that labor mobility applies mostly to high-skilled individuals, while low/medium-skilled individuals may not be able to afford to cost of mobility, even if there are better job opportunities in other geographic areas.

Then, we modify the benchmark specification by adding a binary variable equal to 1 if the regression includes a set of spatial fixed effects. The inclusion of these fixed effects produces estimates of the immigration effect *within* local labor markets, and may therefore bias downward the estimate. Results are reported in columns (2) and (4) for low/medium skilled and high-skilled native individuals respectively. As expected, we find a negative and slightly significant effect of this binary variable for the group of high-skilled native individuals. We also find that adding this variable to the model captures the variation initially found for the geographical scope of the analysis.

This set of results, together with the benchmark results presented in Table 1 show that the variance between β-estimates is partly explained by the choice of the authors regarding the scope of the studied labor market, and this choice seems to matter for both low/medium-skilled individuals (Table 1) as well as high-skilled individuals (Table 1 and Table 3).

Recent Progress in Methods and Data Availability. Third, we investigate two features of the literature that have changed substantially in the recent decades in Table 4. We start by studying whether β-estimates significantly changed after the publication of the seminal paper by Card (2001) on the shift-share instrument for immigration. The shift-share instrumental variable is in fact the most well-known instrument in this literature. Other types of instruments include lagged values of immigration as well as some additional, external variables. In column (1), we include a binary variable equal to 1 for shift-share instruments *à la* Card (2001). We find a negative and highly significant effect of using this particular type of instrumental variable as compared to other types of instruments, on the estimated wage effect of immigration. Alternatively, in column (2), we add a binary variable equal to 1 if the study was published after 2001, year of publication of the paper by David Card. In this case as well, we find a negative and highly significant effect for coefficients published after 2001. This result corroborates that of column (1).

Then, we explore the lack of significance associated with the use of individual data in the benchmark model for the full sample of native individuals (Table 1, column 1). To do so, we replace the dummy variable *individual data* with a binary variable equal to 1 if the author(s) used micro-level data such as administrative and census data, which are known to be more exhaustive than survey data, and to produce estimates of higher quality. Results are reported in column (3). 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 β-estimates. Yet, this variable captures every method heterogeneity that we could be observed in the benchmark econometric model.

Comparison with the meta-analysis of Longhi et al. (2005). Finally, we attempt to compare our results with those presented in the meta-analysis of Longhi et al. (2005). Although we include a more extensive set of explanatory variables (such as covariates controlling for the quality of the study and β-estimate, as well as an extensive set of covariates describing the structural and method heterogeneity), we can compare a number of variables that our studies have in common. First, we find that the wage effect of immigration tends to be smaller (or more negative) in the U.S. than in other countries. In contrast, Longhi et al. (2005) find that the wage effect of immigration tends to be smaller for the European countries, as compared to the U.S. While the authors note that the geographical mobility is relatively lower in the EU, they do not relate this fact to their result on the wage effect of immigration in European countries. Second, our results regarding the geographical scope of the labor market are in line with those of Longhi et al. (2005). We find that the larger the scope, the larger (the closer to zero) the wage effect of immigration. Third, we find no clearcut result associated to the use of an instrumental variable strategy, unless we introduce a variable for the use of a shift-share instrument.

In that respect, our results are in line with Longhi et al. (2005) who find that β-estimates obtained from linear regressions using no instrument are significantly larger. Note that our sample covers a larger period which allows us to include a large number of studies using a shift-share instrument, while Longhi et al.'s (2005) sample stops in 2003. Fourth, in line with Longhi et al. (2005), we find that the definition and measurement of the variables of interest play an important role in the sign and magnitude of the wage effect of immigration. Lastly, Longhi et al. (2005) convert β-estimates into *effect size* in order to obtain comparable wage effects across studies. Instead, we provide a meta-regression using study fixed effects that should control for the fact that we include elasticities together with semi-elasticities and unit value coefficients in the meta-regression. If not similar, the results found within study are larger than those obtained across studies, with a small exception for the coefficient associated with the U.S. which switches sign when study fixed effects are introduced into the model.

Table 2 – Meta-Regressions - Publication Bias

	(1)	(2)	(3)
Sample of natives		all	
Quality of the study and estimate			
Leading academic journal	-0.389***	-0.173*	-0.334***
	(0.100)	(0.096)	(0.099)
Journal article	-0.051	-0.054	-0.117*
	(0.083)	(0.052)	(0.070)
Standard error of the estimate			0.011
			(0.141)
(log) Sample size			-0.011
			(0.010)
Structural heterogeneity			
Individual data	0.090	-0.026	0.170*
	(0.108)	(0.056)	(0.089)
Panel data	0.028	-0.014	0.062
	(0.085)	(0.046)	(0.078)
The U.S.	-0.174**	-0.109**	-0.170**
	(0.077)	(0.051)	(0.077)
Method heterogeneity			
Geographical scope: Region (ref.: country)	0.130	0.036	0.177*
	(0.081)	(0.078)	(0.096)
Geographical scope: City (ref.: country)	0.171*	0.081	0.258**
	(0.093)	(0.058)	(0.111)
Instrumental variable	0.085	0.081	0.086
	(0.068)	(0.061)	(0.067)
Difference-in-differences	-0.230**	-0.219***	-0.285***
	(0.099)	(0.073)	(0.096)
Fixed effects	0.054	0.112**	0.045
	(0.056)	(0.056)	(0.071)
Definition and measurement of the variables			
Definition of wages: Weekly (ref.: hourly/daily)	0.159*	0.010	0.129
	(0.095)	(0.045)	(0.077)
Definition of wages: Monthly/Yearly (ref.: hourly/daily)	0.038	-0.046	0.026
	(0.104)	(0.065)	(0.096)
Definition of wages: Other definitions (ref.: hourly/daily)	0.142	0.002	0.022
	(0.085)	(0.074)	(0.084)
Affected skill group: Low-medium (ref.: all/undefined)	0.052	0.034	0.100
	(0.108)	(0.067)	(0.106)
Affected skill group: High (ref.: all/undefined)	-0.021	-0.021	-0.030
	(0.054)	(0.042)	(0.057)
Definition of immigrants: Citizenship (ref.: birthplace)	0.155*	0.028	0.149**
	(0.083)	(0.060)	(0.068)
Definition of immigrants: Other definitions (ref.: birthplace)	-0.038	0.002	0.029
	(0.091)	(0.074)	(0.093)
Immigration skill group: Low-medium (ref.: all/undefined)	-0.030	-0.104	-0.112
	(0.098)	(0.093)	(0.071)
Immigration skill group: High (ref.: all/undefined)	0.032	0.045	-0.003
	(0.049)	(0.041)	(0.046)
Observations	2,146	3,465	1,740
Studies	64	104	53
R^2	0.142	0.086	0.178
Estimator	OLS	OLS	OLS
Meta-estimate	-0.044***	-0.023**	-0.090***
	(0.012)	(0.009)	(0.012)

Note: This table reports meta-regression results. Regressions (1) and (3) use the benchmark sample, while regression (2) uses the full sample. Standard errors of the meta-estimate have been bootstrapped. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses. The standard error of the meta-estimate has been bootstrapped.

Table 3 – Meta-Regressions - The Scope of the Labor Market

	(1)	(2)	(3)	(4)
Sample of natives	low/med-skilled		high-skilled	
Quality of the study and estimate				
Leading academic journal	-1.099***	-0.829***	-0.009	0.289
	(0.262)	(0.126)	(0.401)	(0.285)
Journal article	0.011	0.013	0.447**	-0.172
	(0.151)	(0.113)	(0.209)	(0.178)
Standard error of the estimate	0.190***	0.206***	-0.169	-0.179
	(0.048)	(0.049)	(0.135)	(0.151)
Structural heterogeneity				
Individual data	0.162	0.258*	-1.319**	-0.255
	(0.145)	(0.133)	(0.629)	(0.402)
Panel data	0.329**	0.296*	0.386	0.184
	(0.146)	(0.148)	(0.255)	(0.237)
The U.S.	0.231*	0.173	-0.843**	-0.226
	(0.126)	(0.128)	(0.302)	(0.196)
Method heterogeneity				
Geographical scope: Region (ref.: country)		0.150		0.011
		(0.145)		(0.209)
Geographical scope: City (ref.: country)		0.210		-0.168
		(0.213)		(0.251)
Instrumental variable	0.113	0.146	0.155	-0.023
	(0.092)	(0.096)	(0.131)	(0.164)
Difference-in-differences	-0.220	-0.391**	0.234	0.432
	(0.238)	(0.184)	(0.258)	(0.271)
Fixed effects	0.152**	0.083	0.802**	0.471
	(0.071)	(0.141)	(0.323)	(0.355)
Definition of the labor market: Area (ref.: skill-cell)	0.126		1.357***	
	(0.166)		(0.308)	
Definition of the labor market: Mixed (ref.: skill-cell)	-0.029		0.685**	
	(0.139)		(0.252)	
Spatial fixed effects		0.134		-0.408*
		(0.150)		(0.198)
Definition and measurement of the variables				
Affected skill group: Low-medium (ref.: all/undefined)	0.273	0.214	-0.238	-0.769**
	(0.212)	(0.146)	(0.227)	(0.294)
Affected skill group: High (ref.: all/undefined)	-0.060	-0.140	0.295	0.076
	(0.095)	(0.107)	(0.335)	(0.379)
Definition of immigrants: Citizenship (ref.: birthplace)	0.505**	0.505**	-0.734**	-0.850**
	(0.198)	(0.184)	(0.292)	(0.308)
Definition of immigrants: Other definitions (ref.: birthplace)	0.131	0.161		
	(0.254)	(0.190)		
Immigration skill group: Low-medium (ref.: all/undefined)	-0.187	-0.302**	-0.330	-0.194
	(0.152)	(0.130)	(0.429)	(0.349)
Immigration skill group: High (ref.: all/undefined)	-0.018	-0.070	0.138	-0.079
	(0.088)	(0.070)	(0.533)	(0.453)
Observations	402	402	291	291
Studies	28	28	24	24
R^2	0.367	0.376	0.432	0.421
Estimator	OLS	OLS	OLS	OLS
Meta-estimate	-0.087***	-0.087***	-0.082**	-0.082**
	(0.030)	(0.030)	(0.036)	(0.036)

Note: This table reports meta-regression results. All regressions use the benchmark sample. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses. The standard error of the meta-estimate has been bootstrapped.

Table 4 – Meta-Regressions - Recent Progress in Methods and Data Availability

	(1)	(2)	(3)
Sample of natives		all	
Quality of the study and estimate			
Leading academic journal	-0.381***	-0.364***	-0.376***
	(0.100)	(0.102)	(0.106)
Journal article	-0.051	-0.077	-0.026
	(0.084)	(0.084)	(0.067)
Standard error of the estimate	-0.059	-0.061	-0.056
	(0.098)	(0.094)	(0.090)
Structural heterogeneity			
Individual data	0.089	0.072	
	(0.106)	(0.110)	
Panel data	0.016	0.055	0.001
	(0.084)	(0.089)	(0.082)
The U.S.	-0.188**	-0.228***	-0.247***
	(0.076)	(0.083)	(0.071)
Administrative data			0.167**
			(0.073)
Method heterogeneity			
Geographical scope: Region (ref.: country)	0.148*	0.126	0.086
	(0.081)	(0.080)	(0.079)
Geographical scope: City (ref.: country)	0.159	0.130	0.100
	(0.097)	(0.097)	(0.082)
Instrumental variable	0.134*	0.084	0.066
	(0.072)	(0.066)	(0.066)
Difference-in-differences	-0.234**	-0.172	-0.121
	(0.099)	(0.105)	(0.113)
Fixed effects	0.042	0.059	-0.004
	(0.063)	(0.068)	(0.068)
Shift-share IV	-0.236***		
	(0.083)		
After 2001		-0.166*	
		(0.085)	
Definition and measurement of the variables			
Definition of wages: Weekly (ref.: hourly/daily)	0.146	0.194**	0.160*
	(0.094)	(0.095)	(0.092)
Definition of wages: Monthly/Yearly (ref.: hourly/daily)	0.048	0.044	-0.005
	(0.107)	(0.105)	(0.094)
Definition of wages: Other definitions (ref.: hourly/daily)	0.130	0.129	0.054
	(0.085)	(0.087)	(0.083)
Affected skill group: Low-medium (ref.: all/undefined)	0.062	0.076	0.045
	(0.108)	(0.106)	(0.111)
Affected skill group: High (ref.: all/undefined)	-0.022	0.001	-0.018
	(0.053)	(0.052)	(0.049)
Definition of immigrants: Citizenship (ref.: birthplace)	0.152*	0.139	0.056
	(0.083)	(0.085)	(0.068)
Definition of immigrants: Other definitions (ref.: birthplace)	-0.024	-0.078	-0.122
	(0.091)	(0.093)	(0.084)
Immigration skill group: Low-medium (ref.: all/undefined)	-0.050	-0.001	-0.095
	(0.100)	(0.091)	(0.106)
Immigration skill group: High (ref.: all/undefined)	0.027	0.020	0.049
	(0.048)	(0.050)	(0.055)
Observations	2,146	2,146	2,146
Studies	64	64	64
R^2	0.148	0.149	0.154
Estimator	OLS	OLS	OLS
Meta-estimate	-0.044***	-0.044***	-0.044***
	(0.012)	(0.012)	(0.012)

Note: This table reports meta-regression results. All regressions use the benchmark sample. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses. The standard error of the meta-estimate has been bootstrapped.

4.4 Robustness Tests

We report a set of robustness tests in Appendix C. In Table C.1, we use alternative error clustering. In Table C.2, we propose alternative specifications. Finally, we further compare our results to the sample used in the meta-analysis of Longhi et al. (2005) in Table C.3.

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 C.1 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 benchmark 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 econometric models that are common in the literature of meta-analyses. Results are reported in Table C.2. We start by reporting the results using a random-effect 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 varies 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-effect 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 benchmark findings, the results corroborate heterogeneity arising from leading academic journals and from the analysis of the U.S.

From column (2) to column (4), we show the results obtained using weighted least squares (WLS). We do not use WLS in our benchmark 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 present 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 error times the quality index). Columns (2) to (4) confirm most of our benchmark OLS results. However, we find weak evidence that the type of data (individual and panel data) and the definition of the variables of interest have an impact on the wage effect of immigration. We find that structural heterogeneity is exclusively driven by differences across studied countries, and method heterogeneity is driven by the use of difference-in-differences models.

Comparison with the Sample of Longhi et al. (2005). In Table C.4, we further explore the differences between our results and those proposed in the meta-analysis of Longhi et al. (2005). In this first meta-analysis of the wage effect of immigration, the authors use a sample of 18 studies published until 2003. In column (1), we restrict our sample to the studies published until 2003. This sample includes some studies used by Longhi et al. (2005), but not only. We see that the sample of observations reduces to 280 β-estimates and 16 studies. We find no significant effect of the quality of the study, nor of the structural heterogeneity. While we find some results regrading the method heterogeneity, the sign of the coefficients is not in line with our benchmark results. For instance, regressions using a regional scope produce larger results (or closer to zero) than regressions using a national scope analysis. Note that this subsample includes no study using difference-in-differences. In this sample, the use of fixed effects has a negative and significant effect on the estimated wage effect of immigration. Finally, the definition and measurement of the variables of interest prove to the very important, much more than what we found in the benchmark analysis.

With our method to automatically screen the literature, we have been able to recover 12 of the 18 studies used by Longhi et al. (2005). Yet, only 7 of these 12 studies report the standard errors of the β-estimates in a consistent way. In column (2), we restrict our analysis to these 7 studies (143 β-estimates) we have in common with the meta-analysis of Longhi et al. (2005). 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. In other words, we attempt to compare these results with those of column (1). Using this very restrictive sample, we find that β-estimates published in leading journals are one average larger, which contrasts with our benchmark findings. Journal articles exhibit smaller coefficients (as compared to working papers, books, and collective volumes). We also find a potential publication bias as the coefficient associated to the standard error of the β-estimate is positive and significant. Regarding the structural heterogeneity, we find that estimations performed with panel data produce smaller β-estimates, which is also at odds with our benchmark findings. The fact that studies focused on the U.S. produce smaller (or more negative) results is nonetheless in line with our benchmark results. The latter result is also in line with Longhi et al. (2005). Regarding the method heterogeneity, the results are rather in line with the subsample used in column (1). Then, while the small size of the sample does not allow us to conclude on the definition and measurement of the immigration shock, we can confirm that the definition and measurement of native wages importantly determine the estimation of the wage effect. This result is also in line with Longhi et al. (2005).

In column (3), we restrict our meta-regression to the studies published after 2003. Thus, this sample includes studies that could not have been included in the meta-analysis proposed by Longhi et al. (2005). Doing so shows that our benchmark results are driven by the 48 studies (1,866 β-estimates) that were produced after 2003. In addition, we find a significant meta-estimate of -0.050 which is in line with our benchmark meta-estimate of -0.044. In contrast, in both columns (1) and (2), we find the meta-estimates are not significant and closer to zero than the one computed in our benchmark estimation (-0.002 and -0.023 vs. -0.044).

5 Discussion

Systematic Bias. We now discuss some of the implications and interpretations of our results. Although systematic reviews and meta-analyses are important for synthesizing available evidence, they are susceptible to multiple forms of bias, including reporting bias, publication bias, evidence selection bias or bias in the primary studies. Our paper provides some results on the *average* effect in the literature controlling for most of these biases. We explicitly controlled for publication bias, and we carefully document how we collected papers in order to reduce selection bias – see Appendix A. Averaging over many β-estimates reduces the influence of sampling error and methodological issues that are idiosyncratic to one or few studies. However, we acknowledge that we cannot draw implications on the *true* causal effect of immigration on native wages partly because of the potential systematic bias in the literature. This is a concern that is already expressed in Aydemir and Borjas (2011) and Peri and Sparber (2011) (among others). Existing β-estimates are subject to systematic issues that bias results across many or all studies in a particular direction. In this case, averaging does not lead to *better* β-estimates and does not reveal the *true* effect.

Toward the *True* Causal Effect? Another obvious limit to the conclusions of our analysis is that we do not estimate the *true* and *causal* effect of immigration as we aggregate β-estimates of heterogeneous quality. Although some estimates could be precisely estimated and very relevant, we average them with potentially low-quality estimates. In principle, one could say something about the true causal effect of immigration on wages insofar as one had an objective measure of the quality of the β-estimates.

Our paper provides some grounds on this by considering results which account for a proxy of the estimation quality. Table C.2 provides results when weighting β-estimates depending on their precision and their quality. In that case, to the extent that the quality of a β-estimate can be inferred from published information[5], the meta-estimate we provide tends to be a better estimate of the true causal effect (compared to the estimate using unweighted estimations). Nevertheless, without further evidence on this issue, identifying the *true causal* effect is beyond the scope of our analysis and of any meta-analysis in economics in general.

Different Leading Journals β-Estimates. Leading academic journals provide more negative (or closer to zero) β-estimates of the impact of immigration on native wages. There are many interpretations to this result. On the one hand, this might be a signal that the true effect of immigration is more negative (or closer to zero) than the average meta-estimate. Indeed, these β-estimates could be more reliable as they are published in large audience journals, with high quality standards: β-estimates in those outlets are less likely to be biased than β-estimates in other journals. Therefore, these β-estimates would, on average, be closer to the less biased β-estimates the literature provides. On the other hand, our specifications control, among other determinants, for method heterogeneity. It implies that the difference between estimates of leading journals and other journals should not be driven by differential quality standards, methodological issues, nor by other observable determinants we have considered. Once again, our meta-analysis does not provide a decisive insight on this issue.

[5] To the best of our knowledge, in social sciences, there is no clearcut way to identify – without bias– the quality of a β-estimate. In other sciences, pre-registration of individual studies have been documented to be important in that direction.

6 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 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 method heterogeneity. We estimate a significant, 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 an average negative, close-to-zero wage effect of immigration in the literature. Depending on the estimation, this effect ranges from -0.090 to 0.009, the benchmark estimate being equal to -0.044. The variation in the wage effect of immigration observed across studies is explained by both structural and method heterogeneity. Differences across studied countries, the structure of the data (individual and panel data) 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 author(s) point toward the presence of method heterogeneity, yet the results are more stringent for specific subsamples of affected population.

This meta-analysis has two main implications for future research. First, the results show promising research paths are ahead on structural heterogeneity. We show that structural heterogeneity matters in the estimation of the wage effect of immigration. Therefore, replication studies on various study-cases should be welcome to pin-down the exact drivers of this heterogeneity. For instance, can the differences in national institutions explain these variations in the estimated wage effect? Second, we show that method heterogeneity matters as well. Economists could be encouraged to discuss the implications of their methodological choices for their estimations of the wage effect of immigration. In addition, more contributions are also in order on the methodological ground, especially to tackle the endogeneity issues, crucial in that context, in the line of work of Jaeger et al. (2018) and Adão et al. (2019). The results of this meta-analysis also highlight that the ongoing methodological debate taking place in the field concerning methodological issues should not be disregarded. The methodological issues *need* to be discussed given the implications of quantitative research to the ongoing policy debate on the costs and benefits of immigration (Goldin et al., 2012).

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Appendix

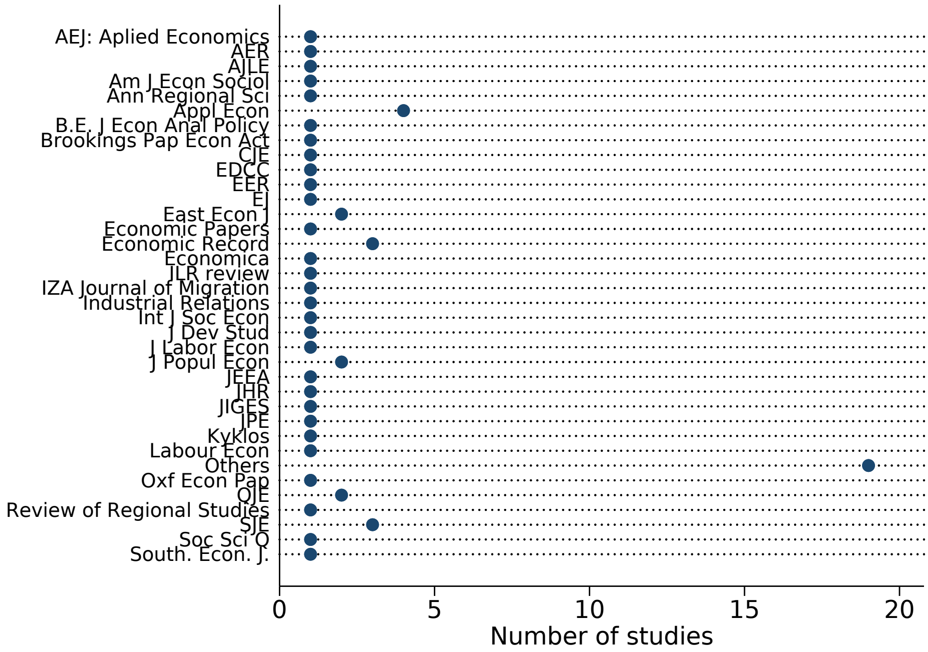
A Data Collection

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 includes 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 was 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 outliers, 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. We report the distribution of these studies by journals in Figure A.1.

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



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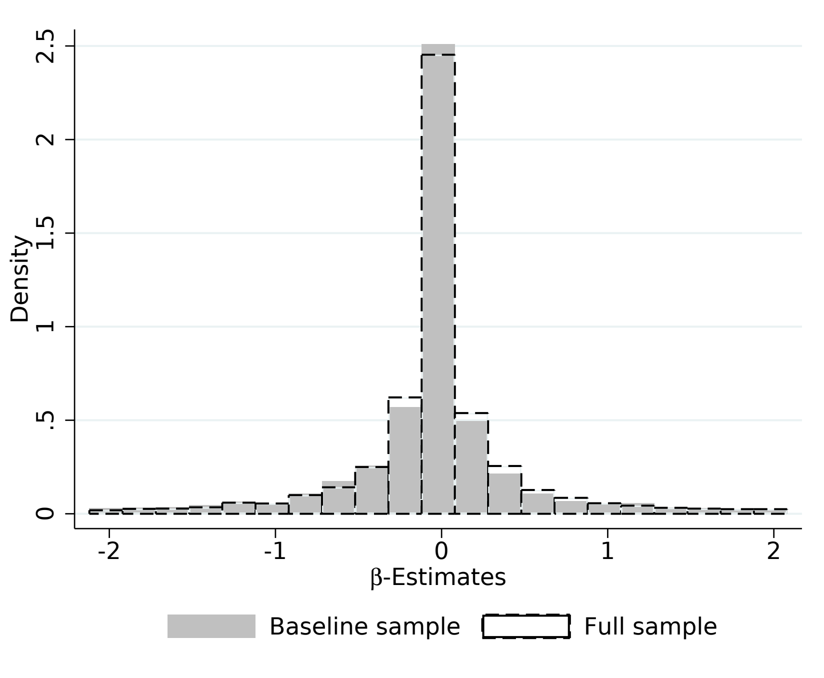
B Additional Descriptive Statistics

Table B.1 – Summary Statistics

	Mean	Standard Errors	Min	Max	N
Study characteristics					
Journal article	0.703	0.460	0	1	64
Leading journal	0.094	0.294	0	1	64
Publication year	2008	10.019	1972	2019	64
No. of authors	1.812	0.794	1	4	64
Estimation characteristics					
β-estimate	-0.044	0.520	-2.120	2.068	2,146
Standard error of the estimate	0.236	0.490	3.00e-06	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

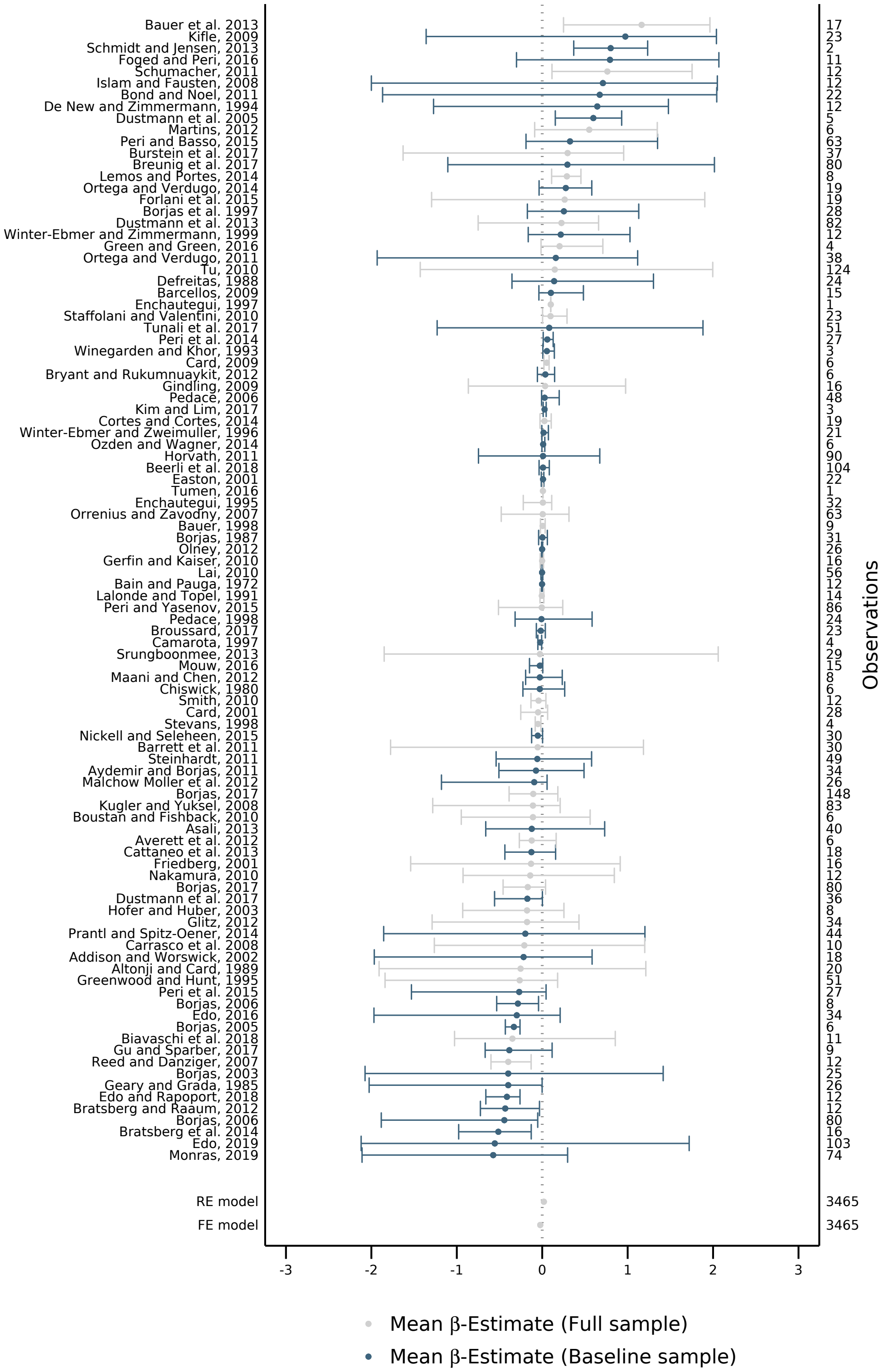
Note: This table reports summary statistics for the benchmark sample of observations.

Figure B.1 – Density of the β-Estimates (Benchmark and Full Sample)



Note: This figure displays the density of β-estimates for the benchmark and the full sample of observations.

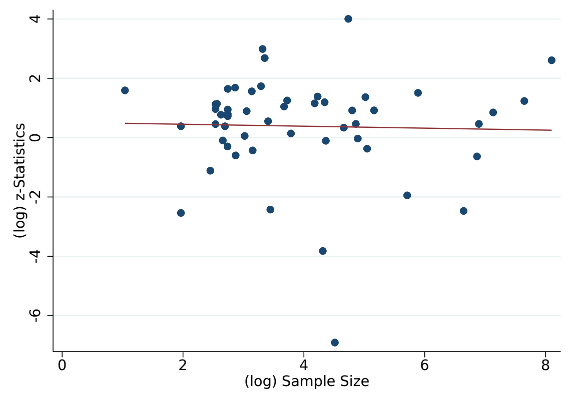
Figure B.2 – Within- and Between-Variation of the β-Estimates (Benchmark and Full Sample)



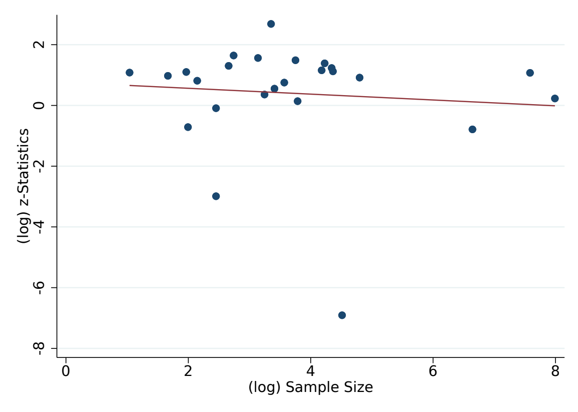
Note: This figure is a forest plot of the β-estimates included in the benchmark and the full sample. For each study, it shows of the average β-estimate and the within-study 95% confidence interval computed using the standard errors (or the β-estimates divided by their t-statistics). The right-axis reports the number of β-estimates for each study. The predicted wage effect obtained from a random-effect model and a fixed-effect model using the entire benchmark sample have been reported at the bottom of the plot.

Figure B.3 – Relation of z-Statistics to Sample Size

(a) First β-Estimates



(b) β-Estimates with the Highest R^2



Note: These figures have been produced using the benchmark sample. Figure B.3(a) has been produced using the first β-estimate of each study. Figure B.3(b) has been produced using the β-estimate with the highest R^2 of each study. These figures depict the relationship between the significance of the β-estimates (captures by the associated z-statistics) and the sample size. z-statistics are computed using the β-estimates and the associated standard errors as follows: $z_i = (\hat{\beta}_i - \tilde{\beta})/se(\hat{\beta}_i)$.

C Additional Results

Table C.1 – Meta-Regressions - Alternative Standard Error Clustering

	(1)	(2)	(3)	(4)	(5)
Sample of natives			all		
Quality of the study and estimate					
Leading academic journal	-0.389	-0.389***	-0.389***	-0.389***	-0.389***
	(0.108)	(0.064)	(0.118)	(0.062)	(0.063)
Journal article	-0.052	-0.052	-0.052	-0.052*	-0.052*
	(0.049)	(0.079)	(0.097)	(0.029)	(0.029)
Standard error of the estimate	-0.054	-0.054	-0.054	-0.054	-0.054
	(0.021)	(0.117)	(0.107)	(0.056)	(0.058)
Structural heterogeneity					
Individual data	0.088	0.088	0.088	0.088**	0.088**
	(0.145)	(0.136)	(0.087)	(0.045)	(0.044)
Panel data	0.030	0.030	0.030	0.030	0.030
	(0.106)	(0.058)	(0.094)	(0.038)	(0.038)
The U.S.	-0.182	-0.182*	-0.182**	-0.182***	-0.182***
	(0.081)	(0.090)	(0.077)	(0.035)	(0.035)
Method heterogeneity					
Geographical scope: Region (ref.: country)	0.131*	0.131***	0.131***	0.131***	0.131***
	(0.011)	(0.014)	(0.042)	(0.036)	(0.036)
Geographical scope: City (ref.: country)	0.157*	0.157***	0.157***	0.157***	0.157***
	(0.023)	(0.031)	(0.043)	(0.038)	(0.037)
Instrumental variable	0.089	0.089*	0.089**	0.089***	0.089***
	(0.039)	(0.045)	(0.040)	(0.033)	(0.032)
Difference-in-differences	-0.224	-0.224*	-0.224*	-0.224***	-0.224***
	(0.179)	(0.098)	(0.114)	(0.056)	(0.058)
Fixed effects	0.032	0.032	0.032	0.032	0.032
	(0.093)	(0.073)	(0.052)	(0.032)	(0.031)
Definition and measurement of the variables					
Definition of wages: Weekly (ref.: hourly/daily)	0.161	0.161	0.161	0.161***	0.161***
	(0.284)	(0.158)	(0.133)	(0.044)	(0.044)
Definition of wages: Monthly/Yearly (ref.: hourly/daily)	0.042	0.042	0.042	0.042	0.042
	(0.232)	(0.143)	(0.126)	(0.047)	(0.047)
Definition of wages: Other definitions (ref.: hourly/daily)	0.139	0.139	0.139**	0.139***	0.139***
	(0.063)	(0.073)	(0.053)	(0.039)	(0.041)
Affected skill group: Low-medium (ref.: all/undefined)	0.059	0.059	0.059	0.059	0.059
	(0.011)	(0.113)	(0.076)	(0.052)	(0.053)
Affected skill group: High (ref.: all/undefined)	-0.025	-0.025	-0.025	-0.025	-0.025
	(0.024)	(0.052)	(0.044)	(0.032)	(0.032)
Definition of immigrants: Citizenship (ref.: birthplace)	0.154**	0.154***	0.154**	0.154***	0.154***
	(0.003)	(0.013)	(0.056)	(0.046)	(0.046)
Definition of immigrants: Other definitions (ref.: birthplace)	-0.033	-0.033	-0.033	-0.033	-0.033
	(0.041)	(0.103)	(0.113)	(0.040)	(0.040)
Immigration skill group: Low-medium (ref.: all/undefined)	-0.027	-0.027	-0.027	-0.027	-0.027
	(0.042)	(0.052)	(0.047)	(0.057)	(0.055)
Immigration skill group: High (ref.: all/undefined)	0.038	0.038	0.038	0.038	0.038
	(0.051)	(0.031)	(0.035)	(0.035)	(0.036)
Observations	2,146	2,146	2,146	2,146	2,146
Studies	64	64	64	64	64
R^2	0.144	0.144	0.144	0.144	0.144
Estimator	OLS	OLS	OLS	OLS	OLS
Error cluster	yes	yes	yes	none	none
Cluster level	year	decade	method-decade	none	bootstrapped
Meta-estimate	-0.044***	-0.044***	-0.044***	-0.044***	-0.044***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.001)

Note: This table reports meta-regression results. All regressions use the benchmark sample. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The standard error of the meta-estimate has been bootstrapped.

Table C.2 – Meta-Regressions - Alternative Estimation Strategies

	(1)	(2)	(3)	(4)
Sample of natives		all		
Quality of the study and estimate				
Leading academic journal	-0.322**	-0.146***	-0.404***	-0.140***
	(0.129)	(0.034)	(0.098)	(0.034)
Journal article	0.009	-0.009	-0.041	-0.011
	(0.087)	(0.013)	(0.084)	(0.013)
Standard error of the estimate	-0.174	-0.110	-0.074	-0.168
	(0.113)	(0.160)	(0.100)	(0.175)
Structural heterogeneity				
Individual data	0.066	-0.003	0.085	-0.004
	(0.121)	(0.050)	(0.112)	(0.050)
Panel data	0.027	-0.007	0.059	-0.004
	(0.103)	(0.015)	(0.086)	(0.015)
The U.S.	-0.157*	-0.058***	-0.188**	-0.062***
	(0.086)	(0.022)	(0.078)	(0.022)
Method heterogeneity				
Geographical scope: Region (ref.: country)	0.055	0.051	0.123	0.054
	(0.077)	(0.043)	(0.083)	(0.044)
Geographical scope: City (ref.: country)	-0.071	0.053	0.144	0.052
	(0.102)	(0.041)	(0.103)	(0.040)
Instrumental variable	0.059	-0.008	0.097	-0.009
	(0.047)	(0.008)	(0.071)	(0.009)
Difference-in-differences	-0.152	-0.080**	-0.191*	-0.077**
	(0.109)	(0.032)	(0.100)	(0.031)
Fixed effects	-0.091	-0.009	0.037	-0.012
	(0.070)	(0.008)	(0.068)	(0.009)
Definition and measurement of the variables				
Definition of wages: Weekly (ref.: hourly/daily)	0.026	0.021	0.191*	0.022
	(0.078)	(0.017)	(0.101)	(0.018)
Definition of wages: Monthly/Yearly (ref.: hourly/daily)	-0.068	-0.000	0.065	-0.002
	(0.080)	(0.015)	(0.113)	(0.016)
Definition of wages: Other definitions (ref.: hourly/daily)	-0.082	-0.002	0.141	-0.004
	(0.092)	(0.026)	(0.093)	(0.028)
Affected skill group: Low-medium (ref.: all/undefined)	0.099	0.013	0.080	0.016
	(0.108)	(0.016)	(0.121)	(0.016)
Affected skill group: High (ref.: all/undefined)	0.088	0.001	-0.018	0.002
	(0.057)	(0.007)	(0.061)	(0.007)
Definition of immigrants: Citizenship (ref.: birthplace)	0.169*	0.024	0.154*	0.017
	(0.097)	(0.032)	(0.083)	(0.032)
Definition of immigrants: Other definitions (ref.: birthplace)	-0.145	-0.006	-0.014	-0.010
	(0.115)	(0.046)	(0.098)	(0.046)
Immigration skill group: Low-medium (ref.: all/undefined)	0.072	0.012	-0.030	0.011
	(0.142)	(0.013)	(0.091)	(0.013)
Immigration skill group: High (ref.: all/undefined)	0.084	-0.000	0.035	-0.000
	(0.079)	(0.001)	(0.049)	(0.001)
Observations	2,146	2,146	2,146	2,146
Studies	64	64	64	64
R^2		0.063	0.156	0.075
Estimator	RE	WLS	WLS	WLS
Weight	none	ise	quality	quality-add
Meta-estimate	0.009	-0.044***	-0.045***	-0.055***
	(0.017)	(0.012)	(0.013)	(0.013)

Note: This table reports meta-regression results. All regressions use the benchmark sample. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses. The standard error of the meta-estimate has been bootstrapped. The acronym *ise* refers to the inverse of the standard errors 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 C.3 – Meta-Regressions - Comparison With the Sample of Longhi et al. (2005)

	(1)	(2)	(3)
Sample of natives		all skills	
Sub-sample	pre-2003	Longui et al. (2005)	post-2003
Quality of the study and estimate			
Leading academic journal	0.114	1.738***	-0.453***
	(0.459)	(0.233)	(0.122)
Journal article	-0.073	-0.790**	-0.104
	(0.228)	(0.239)	(0.095)
Standard error of the estimate	-0.082	0.168**	-0.113
	(0.168)	(0.054)	(0.109)
Structural heterogeneity			
Individual data	-0.213	-0.009	0.103
	(0.142)	(0.141)	(0.132)
Panel data	-0.304	-1.001***	0.078
	(0.336)	(0.218)	(0.102)
The U.S.	-0.286	-1.310***	-0.255**
	(0.176)	(0.207)	(0.109)
Method heterogeneity			
Geographical scope: Region (ref.: country)	0.380**	0.766***	0.133
	(0.149)	(0.028)	(0.096)
Geographical scope: City (ref.: country)	0.067	1.359***	0.139
	(0.181)	(0.159)	(0.123)
Instrumental variable	-0.083	-0.104	0.082
	(0.060)	(0.081)	(0.087)
Difference-in-differences			-0.130
			(0.115)
Fixed effects	-0.215***	0.090	0.025
	(0.067)	(0.061)	(0.112)
Definition and measurement of the variables of interest			
Definition of wages: Weekly (ref.: hourly/daily)	-0.711***	-0.953***	0.284**
	(0.159)	(0.166)	(0.113)
Definition of wages: Monthly/Yearly (ref.: hourly/daily)	-0.660***	-0.841***	0.114
	(0.116)	(0.154)	(0.115)
Definition of wages: Other definitions (ref.: hourly/daily)	-0.582**		0.196**
	(0.211)		(0.092)
Affected skill group: Low-medium (ref.: all/undefined)	0.457	0.626	0.065
	(0.565)	(0.549)	(0.118)
Affected skill group: High (ref.: all/undefined)	-0.195	-0.374**	0.059
	(0.118)	(0.147)	(0.066)
Definition of immigrants: Citizenship (ref.: birthplace)	0.350**		0.191
	(0.138)		(0.119)
Definition of immigrants: Other definitions (ref.: birthplace)	-0.211***		-0.069
	(0.048)		(0.115)
Immigration skill group: Low-medium (ref.: all/undefined)	-0.429		0.028
	(0.555)		(0.076)
Immigration skill group: High (ref.: all/undefined)	-0.027		-0.032
	(0.093)		(0.054)
Observations	280	143	1,866
Studies	16	7	48
R^2	0.297	0.341	0.160
Estimator	OLS	OLS	OLS
Meta-estimate	-0.002	-0.023	-0.050***
	(0.030)	(0.051)	(0.013)

Note: This table reports meta-regression results. All regressions use the benchmark sample or sub-samples of it. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered at the study-level are reported in parentheses. The standard error of the meta-estimate has been bootstrapped.

Table C.4 – Categories of Variables Used in the Analysis

Categories	Obs
Not Leading Academic Journal (Ref.)	1868
Leading Academic Journal	278
Not a Journal Article (Ref.)	592
Journal Article	1554
Not Individual data (Ref.)	1273
Individual data	873
Data Structure: Cross-Section (Ref.)	660
Data Structure: Time Series	50
Data Structure: Panel	1436
Other than US (Ref.)	1520
Country: US	626
Data type: Survey (Ref.)	1310
Data type: Administrative data	836
Geographical Scope: Country (Ref.)	1338
Geographical Scope: City	355
Geographical Scope: Region	453
Estimation: OLS (Ref.)	1540
Estimation: IV	383
Estimation: Other	223
no Difference-in-difference (Ref.)	1713
Difference-in-difference	433
No FE included (Ref.)	466
Some FE included	1680
Definition of the labor market: (Skill)-cell (Ref.)	1262
Definition of the labor market: Area only	335
Definition of the labor market: Mixed	549
Definition of wages: Hourly/Daily (Ref.)	567
Definition of wages: Monthly/Yearly	427
Definition of wages: Other	574
Definition of wages: Weekly	578
Affected skill group: All groups or undefined	1453
Affected skill group: High	291
Affected skill group: Low-Medium skills	402
Definition of Immigrants: Birth place (Ref.)	1507
Definition of Immigrants: Other Definition	238
Definition of Immigrants: Citizenship	401
Immigration skill group: All groups or undefined	1646
Immigration skill group: High Skilled	233
Immigration skill group: Low-Medium skills	267

Table C.5 – Description of the Variables Used in the Analysis

Categories	Description
Not Leading Academic Journal (Ref.)	Other journals/outlets
Leading Academic Journal	Ex: AER, JPE, Restud, QJE, Ecma, JEEA, JLE
Not a Journal Article (Ref.)	Ex: Working Paper, Collective Volume, Book Chapter, Unpublished.
Journal Article	Published in an academic journal.
Not Individual data (Ref.)	The unit of observation is not at the individual level and/or the analysis is made at the aggregate (firm/industry/skill/labor market/education group/occupation) level.
Individual data	The unit of observation/analysis is at the individual level. Ex: wages are identified at the individual level and the analysis is run at the individual level.
Data Structure: Cross-Section (Ref.)	The analysis is explicitly made using the cross-sectional variation.
Data Structure: Time Series	The analysis is run using time variation only.
Data Structure: Panel	The data tracks individuals across time. Ex: Panel data, pseudo-panel data, longitudinal data, pooled cross-sections or pooled time series
Other than US (Ref.)	Sample contains other than US observations. Ex: UK, Australia, Netherlands, Germany, Switz., Israel, Norway + other groups of countries that may include the US
Country: US	Sample contains only US observations.
Data type: Survey (Ref.)	Raw data comes from survey sources.
Data type: Administrative data	Raw data comes from administrative or census data. Ex matched employer-employee data, census, ...
Geographical Scope: Country (Ref.)	Analysis at the country level or group of countries. Ex: the Netherlands, the Uk, France, group of OECD countries
Geographical Scope: Region	Analysis is at the regional level. Ex: single census division, regional labor market, regions, states, commuting zones, districts, ...
Geographical Scope: City	Analysis at the city level only. Includes: individual cities (Atlanta, Boston, San Francisco), individual metropolitan areas
Estimation: OLS (Ref.)	OLS estimation, without any correction for endogeneity bias, excluding IV and diff-in-diff estimates. Ex: OLS, least squares dummy estimations, ...
Estimation: IV	Instrumental variables estimates, in 2SLS estimations. Ex: First-diff IV, 2-step procedure IV, 2SLS, 2SLS random effect, ...
Estimation: Other	Ex: quantile regressions, (V)ECM, VAR, SURE models, ...
Difference-in-difference	Explicit mention of diff-in-diff setup. Ex: (quasi-)natural experiment methods, control group, diff-in-diff ols, diff-in-diff 2SLS, synthetic control group, ...
No FE included (Ref.)	There is no fixed effect (in any dimension) in the analysis.
Some FE included	Some fixed effect is included in the analysis. Ex: occupation, industry, sector, time, geographic fixed effects.
Definition of wages: Hourly/Daily (Ref.)	Time horizon of the wage measure. Ex: daily mean wage, log daily pay, log hourly wage, real gross hourly wages
Definition of wages: Other	Other time horizons. Ex: total labor payments over the period, inter-census change in total earnings, ...
Definition of wages: Weekly	Ex: individual average weekly wage, log weekly earning, first- difference average weekly wage
Definition of wages: Monthly/Yearly	Ex: yearly income, total annual earnings, growth rate in annual wage, monthly nominal wage, ...
Affected skill group: Low-Medium skills	Includes: unskilled, dropout, low education, manual, some college, at least high school, incomplete secondary education,...
Affected skill group: All groups or undefined	Includes either the whole set of workers, or is not explictly defined: skills are not mentionned.
Affected skill group: High	Affected group of workers: high skill only. Ex: white collars, university graduates, doctors, educated, high-skilled, ...
Definition of Immigrants: Birth place (Ref.)	Immigration is defined by birth place only. Ex: Asian-born, foreign-born, foreign-born residents, individuals born outside Denmark with non-danish parents.
Definition of Immigrants: Other Definition	Immigration is defined by the previous residence. Ex: foreign resident with work permit, marielitos, arrived after 1989, newly arrived, new legal permanent residents, ...
Definition of Immigrants: Citizenship	Immigration is defined by citizenship dimension: foreign nationality, foreign citizens, refugees, foreign passport holders, ...
Immigration skill group: Low-Medium skills	Immigrants are low- or medium-skilled. Ex: high school education, secondary, some colleges, skilled blue, dropouts, low skilled, unqualified, ...
Immigration skill group: All groups or undefined	No reference to skills (explicitly)