

Does Immigration Affect Native Wages? A Meta-Analysis

Clément Nedoncelle, Léa Marchal, Amandine Aubry & Jérôme Héricourt

Highlights

- This meta-analysis synthesises findings from 88 studies published between 1985 and 2023, providing a comprehensive assessment of reduced-form estimates of the wage effect of immigration.
- Our results show that the average wage effect is centred around zero, with substantial heterogeneity across studies.
- We highlight the critical role of contexts and methodological choices in shaping wage estimates.
- Our findings emphasise the need for replication studies and greater transparency in methodological choices.



Abstract

The impact of immigration on native workers' wages has been a long-standing debate in labour and international economics. This meta-analysis synthesises findings from 88 studies published between 1985 and 2023, providing a comprehensive assessment of reduced-form estimates of the wage effect of immigration. Our results align with the existing literature, showing that the average wage effect is centred around zero, with substantial heterogeneity across studies. We highlight the critical role of contexts and methodological choices in shaping wage estimates. In particular, we find that shift-share instrumental variables correct for an upward bias of the OLS. Our findings emphasise the need for replication studies and greater transparency in methodological choices.

Keywords

Immigration, Labour Market, Meta-Analysis, Wage.

JEL

C80, J61, J15, J31

Working Paper

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CEPII Working Paper
Contributing to research in international
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EDITORIAL DIRECTOR:
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VISUAL DESIGN AND PRODUCTION:
LAURE BOIVIN

ISSN 2970-491X

May 2025

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Does Immigration Affect Native Wages? A Meta-Analysis*

Clément Nedoncelle[†] Léa Marchal[‡] Amandine Aubry[§] Jérôme Héricourt[¶]

1 Introduction

The economic impact of immigration on natives, particularly concerning employment and wages (Goldin et al., 2011), has been a focal point of policy discussions and academic debates. The answer to this question has, for instance, influenced international migration policies in many high-income countries since the mid-1970s. Extensive research in labour economics has contributed significantly to this debate by investigating the wage effects of immigration. The empirical literature has produced mixed and, at times, contradictory results. Some studies conclude that immigration adversely affects native wages, while others report positive or neutral impacts (Dustmann et al., 2016; Edo, 2019a). A few surveys have attempted to synthesise the findings of the literature. Specifically, Blau and Kahn (2015) conclude that “most research does not find quantitatively important effects of immigration on native wage levels or the wage distribution.” Further insights into the U.S. context can be found in Blau and Mackie (2017), and into the European context in Kerr and Kerr (2011). Edo (2019a) also conclude that immigration has distributional consequences, as it alters the skill composition of the workforce, creating both winners and losers among native workers.

The first meta-analysis of the empirical literature on this question, conducted by Longhi et al. (2005) and based on 18 articles published until 2003, indicates that immigration has a statistically significant but quantitatively small negative impact on native wages. A 1% point

*The names of the authors appear in a random order (AEA randomization code: ICZoMMYmfVnC).
Acknowledgements: This work is part of the NaWaCC project financially supported by a public grant overseen by the German and the French National Research Agencies (reference: ANR-17-FRAL-0011). We thank Anne-Célia Disdier and Jérôme Valette for their constructive remarks and suggestions. We also thank Benoît Chaulvet, Abdoulmagid Moustapha, Michaela Rank and Martín A. Valdez Quintero for helping us build the dataset. We thank participants of the 2023 DIMIG and Aarhus-Kiel workshops, and the LEM and LED-Paris 8 seminars. The usual disclaimer applies. **Declarations of interest:** none. **Data availability statement:** The authors confirm that the data supporting the findings of this study is available within the article’s supplementary material.

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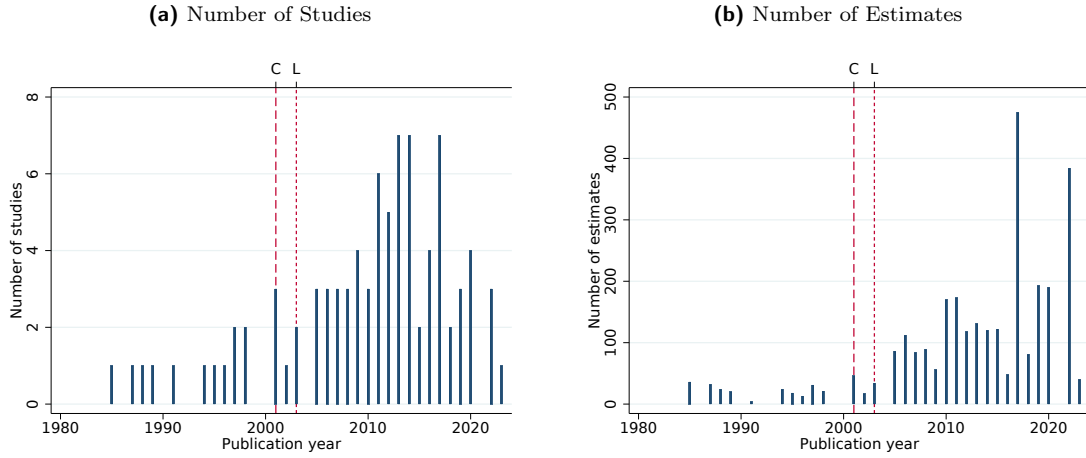
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increase in the immigrant labour share leads to a 0.6% decrease in native wages. This average effect, however, hides significant heterogeneity across individual studies. Similar results have been proposed by Longhi et al. (2010) using a set of seven articles.

We complement the literature with an updated, comprehensive meta-analysis exploring the variation in the wage effect of immigration. Since the early 2000s, there has been a significant increase in research analysing this effect, along with notable methodological advances. A key development in this field is the use of shift-share instruments (Bartik, 1991), first introduced in the field by Card (2001)'s seminal work. Our sample includes 88 studies published between 1985 and 2023, collectively reporting 2,992 reduced-form estimates of the wage effect of immigration. This extensive sample allows us to reflect on these methodological advances and provide a comprehensive overview of the evolving research in the field.

Figure 1 depicts the evolution of scholar production of reduced-form estimates of the wage effect of immigration over time. Figure 1(a) shows a surge in the number of studies after the mid-2000s, and Figure 1(b) presents a similar pattern for the number of estimates reported in these studies over time. The vertical dashed line (labelled "C") corresponds to the year of publication of David Card's seminal article in which he used a supply-push component of recent immigrant inflows to instrument immigration shares, akin to the famous shift-share instrumental variable (Card, 2001). Our research sample includes studies conducted after 2001, allowing us to assess the specific impact of these shift-share instruments on estimating the wage effect of immigration. Furthermore, the vertical dotted line (denoted "L") marks the year 2003, representing the last sample year of the sample used in the meta-analysis by Longhi et al. (2005). This demarcation underscores that most studies in the field have been produced in the past two decades and thus were not included in Longhi et al. (2005). Our research sample, therefore, enables us to re-assess the literature on the effect of immigration on native wages, including the numerous studies published after 2003.

Figure 1: Scholar Output on the Wage Effect of Immigration Over Time

Note: These figures show the production of reduced-form estimates of the wage effect of immigration over time. Our sample includes 88 studies published between 1985 and 2023, reporting 2,992 reduced-form estimates. Figure 1(a) shows the number of studies, and Figure 1(b) shows the number of estimates over time. The vertical dashed line (“C”) marks the publication year of [Card \(2001\)](#). The vertical dotted line (“L”) marks the year 2003, which is the last sample year of the meta-analysis by [Longhi et al. \(2005\)](#).

Context and method heterogeneity could be the two main factors contributing to the lack of consensus regarding the direction of the wage effect in the existing research. Context heterogeneity refers to differences in the contexts of the studies, such as countries or periods. For instance, [Longhi et al. \(2005\)](#) note the negative impact of immigration on wages is less pronounced in the U.S. than in European countries. This difference could be attributed to individual countries’ labour market structural characteristics.

Second, variations in wage effect estimates across studies could be attributed to differences in empirical methodologies employed by researchers. [Dustmann et al. \(2016\)](#) identify three types of reduced-form models. First, *the pure spatial approach* evaluates the impact of immigration on native wages across regions; second, *the national skill-cell approach* focuses on estimating the effect within specific skill, education, and occupation cells at the national level; third, *the mixed approach* takes into account both regions and skill cells. The latter two models are comparable, relying on a similar rationale concerning skill cells. However, they provide relative effects, whereas the pure spatial approach yields total effects, accounting for all channels through which a supply shock in a given region may affect workers’ wages – including complementarity and adjustment effects ([Borjas and Edo, 2025](#)). An earlier literature survey on this research question, with a methodological focus, can be found in [Okkerse \(2008\)](#).

We conduct a state-of-the-art meta-analysis following the methodology of [Havránek et al. \(2020\)](#) and [Stanley et al. \(2013\)](#). Our objective is to uncover the sources of heterogeneity in the wage effect estimates of immigration available in the existing literature. We examine a broad range of econometric estimates from diverse sources to pinpoint regularities in how the wage effect of immigration varies across studies. In economics, meta-analyses have become a valuable tool for analysing the magnitude and time trends of key economic findings¹.

Our sample includes reduced-form estimates of the wage effect of immigration. These estimates primarily consist of semi-elasticities (also referred to as *effect size* in the work of [Longhi et al., 2005](#)) and include some elasticities and other types of estimates.

Our results can be summarised as follows. First, our findings are consistent with the conclusions of the existing literature. We find that the wage effect of immigration is centred around zero, yet with substantial heterogeneity across studies.

Second, we show that estimates are influenced not only by the quality of a study but also by context and method heterogeneity. Differences in countries, sample periods, and economic structures play distinct roles in shaping the estimated wage effect of immigration. Method heterogeneity is also a significant determinant of both the magnitude and sign of the estimated wage effect of immigration. In particular, the choice of estimate type (semi-elasticities vs. elasticities) and the methodological approach adopted by the authors lead to significantly different estimates. Specifically, the mixture approach yields larger and more negative estimates, while the pure spatial approach produces smaller but more positive estimates compared to the national skill-cell approach. Other econometric choices also play a crucial role. Including covariates, using residual wages, and leveraging the data's time dimension help explain the variance in estimates. Lastly, employing an IV-2SLS estimator results in more negative estimates of greater magnitude than the OLS estimator, confirming that instrumental variables correct for the upward bias of the OLS.

Third, we find mixed evidence regarding the existence of publication bias. Specifically, we find that estimates published in leading academic journals are more frequently negative and tend to be smaller in magnitude when negative but larger when positive.

Our study contributes to the literature by employing a comprehensive, state-of-the-art meta-analysis methodology. Our sample incorporates many recent studies, allowing us to explore contemporary data characteristics and recent methodologies as determinants of the estimated wage effect. Recent contributions to the field often use disaggregated data, such as individual-

¹Notable examples include [Weichselbaumer and Winter-Ebmer \(2005\)](#), exploring the gender wage gap; [Bajzik et al. \(2020\)](#), investigating sources of variation in the Armington elasticity; [Disdier and Head \(2008\)](#), exploring the distance effect on trade; [Görg and Strobl \(2001\)](#), examining spillover effects from multinational companies; and [Jeppesen et al. \(2002\)](#), studying the relationship between manufacturing plant location decisions and environmental regulations.

level data from administrative sources, spanning long periods. Additionally, there has been a noticeable shift towards advanced econometric techniques focused on inferring causality, particularly those addressing the endogenous relationship between immigration and wages, as discussed in [Adão et al. \(2019\)](#), [Goldsmith-Pinkham et al. \(2020\)](#), and [Jaeger et al. \(2018\)](#). Since our sample includes estimates from recent studies, it enables us to assess how much methodological choices contribute to the observed variance in the wage estimates.

While systematic reviews and meta-analyses help synthesise evidence, their findings depend on the quality of the underlying studies. We extensively document our paper selection process to mitigate concerns related to sample selection bias. In addition, we control for the observed quality of the study as much as possible and investigate potential publication bias in our sample of studies. However, many studies in this literature may share similar limitations, such as insufficient controls for occupational and spatial displacement or the lack of a valid instrumentation strategy. Instead of drawing definitive conclusions on the effect of immigration on natives' wages, our meta-analysis highlights that method heterogeneity accounts for a large part of the observed variation in the estimated wage effect.

This meta-analysis has two primary implications for future research. First, we show that context heterogeneity plays a role in estimating the wage effect of immigration. This finding underscores the necessity of replication studies focusing on various case studies to ensure external validity. Second, we show that method heterogeneity also plays a crucial role. Consequently, economists should be encouraged to discuss the implications of their methodological setup. Given the influence that quantitative research can exert on the ongoing policy debate about the advantages and disadvantages of immigration (e.g., during the 2024 U.S. presidential campaign), the importance of these discussions in the field is undeniable.

In the next section, we detail the scope of our analysis. In [section 3](#), we describe the data and our empirical strategy. In [section 4](#), we analyse the sources of variation in estimates across studies. We propose a set of extensions in [section 5](#). [Section 6](#) concludes and discusses the implications of our results for future research.

2 Scope of Analysis

A substantial number of empirical studies have estimated reduced-form equations (see the reviews by [Blau and Kahn, 2015](#); [Dustmann et al., 2016](#)). These studies typically relate labour market outcomes to changes in immigration as follows:

$$\ln w_{ct} = \beta M_{ct} + \Gamma A'_{ct} + \text{FE} + \varepsilon_{ct} \quad (1)$$

In this equation, M_{ct} denotes a measure of the immigrant supply shock, that is the immigration share (or inflow rate) of type- c workers (where c also denotes the cell of the worker) at time t , A'_{ct} includes time-varying controls for type- c workers, such as the supply of native workers in a given cell at time t , and FE denotes a set of fixed effects.² These fixed effects may account for time, skill cells, and geographical location. However, additional fixed effects for the employment sector may be included in the analysis.

The coefficient of interest, β , represents the semi-elasticity (or effect size) of native wages to immigration in a specific cell-year combination. In this wage equation, an increase in the availability of type- c labour – attributed to immigration – leads to a decrease in its marginal product when natives and immigrants are close substitutes within a cell c ($\beta < 0$). Conversely, the wage effect might be positive when they act as complements.

Different cell aggregation levels and combinations of fixed effects yield different wage effects (Dustmann et al., 2016). In the national skill-cell approach, a cell accounts for workers' skill levels. This approach includes cell-(time) fixed effects. Consequently, β captures the relative impact of immigration on native wages within specific skill groups at the national level. In the mixed approach, a cell combines workers' skill levels and regions, and skill-(time) and location-(time) fixed effects are included. β captures the relative impact of immigration within skill groups and regions. The pure spatial approach also considers workers' skill levels and regions to determine cells, yet it contains only skill-(time) fixed effects. This approach accounts for all channels through which immigration supply shock in a region may affect workers' wages (Borjas and Edo, 2025). Thus, β captures the total impact of immigration on native wages within specific skill groups across regions.

Several studies deviate from equation (1) because their left-hand side variable (w_{ct}) is not log-transformed. These studies, therefore, report semi-elasticities. In some other studies, both w_{ct} and M_{ct} are log-transformed, causing β to become an elasticity. Other studies do not log-transform the variables of interest. Additionally, some authors use first-differences, analysing how changes in wages are affected by changes in the immigrant supply over time.

One major threat to identification in the literature is the potential endogeneity of immigration (M_{ct}) to native wages (w_{ct}). For instance, immigrants may select their location based on local labour market conditions. Since the publication of Card (2001)'s article, the primary method to infer causality in a reduced-form specification has been to use a shift-share instrument in an Instrumental Variable(IV)-2SLS setting.

²Following standard theoretical models, in which the wage effects are proportional to the relative change in employment, the immigration share would typically consist of a ratio of the number of immigrants over the total population (or total employment). Inflow rates usually consist of a ratio of incoming migrants over the total population. See Card and Peri (2016), who highlight disagreement about the denominator choice).

Our analysis excludes studies leveraging difference-in-differences (DiD) methods capturing the immigration shock through the interaction of a treatment and a time dummy variable, like the study on the Mariel boatlift episode by [Card \(1990\)](#). In contrast, we collected reduced-form estimations that use an *explicit* measure of immigration. As a result, estimates of the wage effect of immigration obtained from a DiD design are not comparable to wage estimates collected for this meta-analysis. To include DiD estimates in our analysis, one should have determined the magnitude of the supply shock (the treatment) to convert the DiD coefficient into wage elasticity. However, the magnitude of the supply shock is often not reported in studies using DiD designs.

Finally, we omit studies calibrating structural models of the labour market, like [Ottaviano and Peri \(2012a\)](#). Structural models entail estimating the parameters of a production function and then using counterfactual analysis to calculate the wage effect of immigration. We exclude these studies because strong assumptions need to be formulated regarding the functional form of the production function and the degree of complementarity between natives and immigrants. In contrast, estimations of reduced-form models allow a more agnostic stance regarding these assumptions. In addition, the analytical statistic employed to evaluate predictions from structural models differs from those used for assessing the quality of estimates from reduced-form models, making direct comparisons difficult.

3 Data and Empirical Strategy

This section details the data collection process before developing a two-stage state-of-the-art method ([Havránek et al., 2020](#); [Stanley et al., 2013](#)). The first stage consists of analysing the distribution of collected estimates. We show that sampling errors account for only a small portion of the variation in the estimates, highlighting the need to investigate other sources of heterogeneity using meta-regressions. The second stage consists of meta-regressions aimed at pinpointing the regularities and sources of heterogeneity observed in empirical studies.

3.1 Data Collection

We collected empirical studies estimating the direct wage effect of immigration. Using the EconLit search engine, we systematically searched for English-language studies, focusing on journal articles, working papers, books, and collective volumes. Specifically, we targeted studies with titles containing combinations of two keywords, such as *immigration* and *native*.³ In total, we

³Following [Longhi et al. \(2005\)](#) and [Disdier and Head \(2008\)](#), we favoured keyword searches over JEL classification codes, as these codes have changed over time and are not always included in studies, particularly in books and collective volumes.

employed 47 keyword combinations. We included papers listed in EconLit up to May 2019. Additionally, we complemented our dataset using Litmaps, a literature search engine designed for researchers (though not specifically for economists), which allowed us to include papers published until 2023.

To ensure comprehensive coverage, we checked whether our systematic search included studies referenced in the meta-analysis by Longhi et al. (2005) and the survey by Dustmann et al. (2016). We augmented our sample with four studies from Longhi et al. (2005) and eight studies referenced in Dustmann et al. (2016). In line with systematic and automated search principles, we abstained from adding other studies to our sample (Havránek et al., 2020; Stanley et al., 2013).

Our sample includes studies that estimate a reduced-form model using an explicit measure of immigration. From each study, we identified all regressions yielding estimates of the wage effect of immigration. We collected information on the associated standard errors, t-statistics, and sample sizes whenever possible. Additionally, we gathered data on whether the estimates are the preferred ones, the identification strategy (OLS, IV-2SLS, or other models), the set of fixed effects, and the covariates included, if any. We also recorded details about the study (such as publication year and number of authors) and its context (such as the country and period of analysis). Our dataset includes 2,992 estimates from 88 studies. The list of studies is presented in Appendix A, Table A.1.

Our benchmark analysis is conducted on the entire sample of estimates (including semi-elasticities, elasticities, and other types of estimates). However, we perform several robustness checks to test the comparability of the estimates. Whenever possible, i.e. when the magnitude of the immigration shock was reported in the study, estimates initially reported as elasticities were converted into semi-elasticities. Conversely, estimates were also transformed into elasticities whenever possible. We obtained 2,750 semi-elasticities (collected from 78 studies), 2,001 elasticities (collected from 66 studies), and 1,969 estimates from 63 studies for which both semi-elasticity and elasticity forms are available.

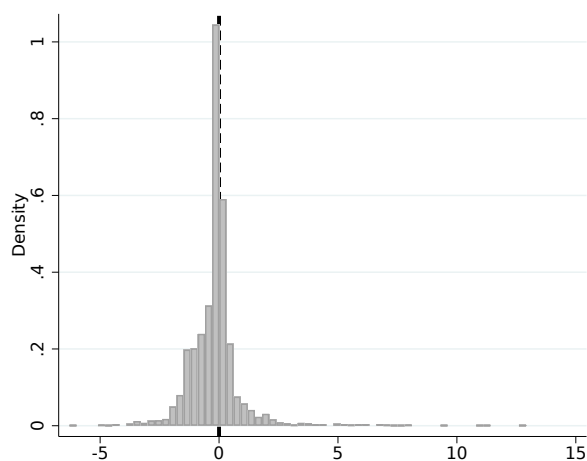
3.2 Data Analysis

Descriptive statistics are presented in Appendix A Table A.2. Our sample includes 2,992 estimates from 88 studies published from 1985 to 2023. 13.7% of the estimates are sourced from leading general journals – *the American Economic Review*, *the Journal of the European Economic Association*, *the Journal of Political Economy*, *the Quarterly Journal of Economics*, and *the Review of Economic Studies* – as well as the leading journal in labour economics, the *Journal of Labour Economics*.

The studies in the sample are based on data from 23 countries and data from groups of countries such as the OECD. The U.S. labour market is the focus of 37.4% of the estimates, and Anglo-Saxon countries (the U.S., the U.K., Canada, and Australia) account for 54.9% of the estimates. Other countries analysed include Austria, Colombia, Costa Rica, Denmark, France, Germany, Greece, Ireland, Israel, Italy, Malaysia, New Zealand, Norway, Peru, South Africa, South Korea, Spain, Thailand, and The Netherlands. Only 9% of the estimates were derived from cross-sectional data (as opposed to time-varying datasets), and 47.7% used an IV-2SLS estimator in contrast to OLS or other estimators, among which 36.5% employed a shift-share instrument à la [Card \(2001\)](#).

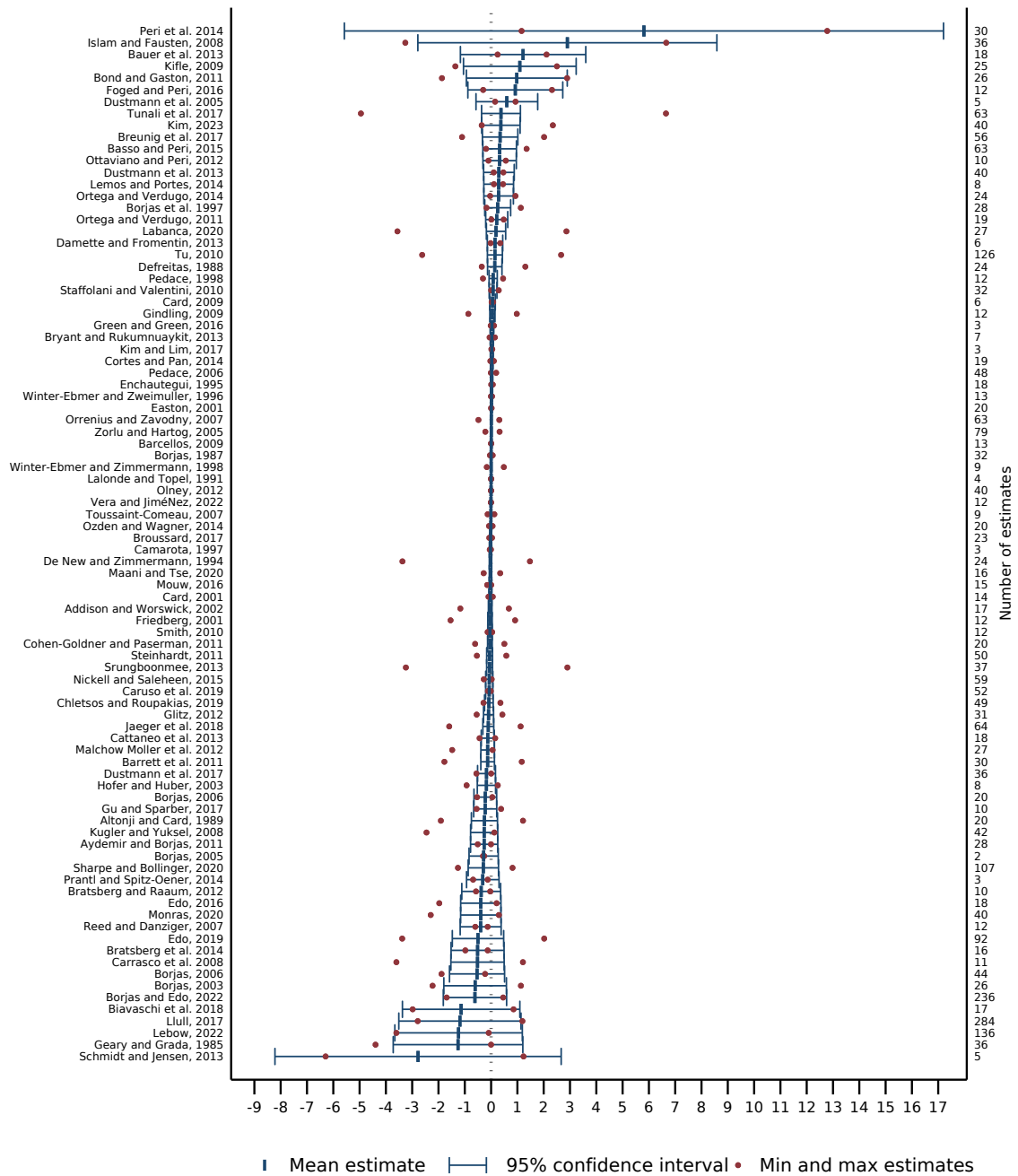
Figure 2 shows the distribution of estimates, including semi-elasticities, elasticities, and other estimates. A notable sample characteristic is the small magnitude of the estimates and a distribution biased towards negative values. The average wage effect is -0.1516 , with a standard deviation of 1.1714. In the appendix, Figure A.1(a), we report the distribution of (converted) semi-elasticities. The mean effect of immigration on native wages stands at -0.2650 , with values ranging from -3.600 to 3.125 . These statistics align with the findings presented by [Longhi et al. \(2005\)](#). Finally, Figure A.1(b) displays the sample of (converted) elasticities and suggests that a 1% surge in the immigrant labour force corresponds, on average, to a -0.0329% decline in native wages.

Figure 2: Density of the Estimates



Note: This figure shows the density of estimates of the wage effect of immigration. The sample contains 2,992 estimates from 88 studies. The vertical dashed line represents an estimate value of zero.

Figure 3: Between- and Within-Variation of the Estimates



Note: This figure shows the within- and between-study variation across 2,992 estimates collected from 88 studies. For each study, it displays the mean estimate along with its 95% confidence interval, calculated using the mean standard error. Dots show the minimum and maximum estimates within each study. The right axis indicates the number of estimates reported per study.

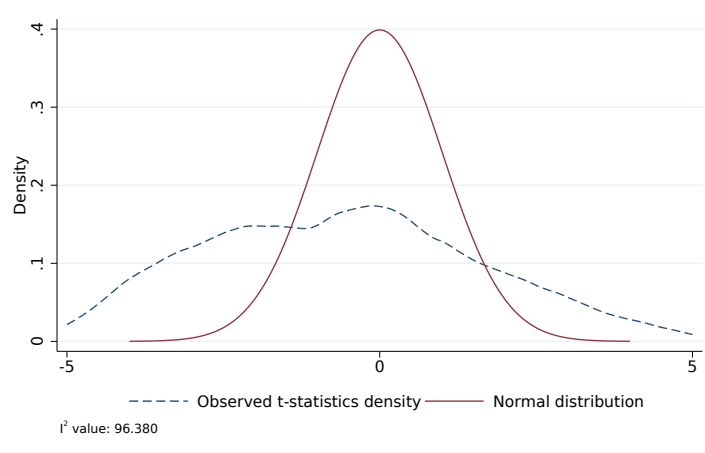
Figure 3 presents a forest plot showing the variation in wage effect estimates both within and between studies. For each study, the figure displays the mean estimate along with its 95% confidence interval. Dots represent the minimum and maximum estimates reported within each study, capturing the range of variation. The distribution of estimates is centred around zero, with substantial heterogeneity across studies. Mean estimates closer to zero display higher precision. The right axis indicates the number of estimates reported per study, providing insight into the density of estimates within individual studies.

3.3 Sampling Errors

The observed variance in the wage effect of immigration might result from coefficients estimated using data from different countries, periods, or methodologies. If all subsamples were drawn from a population with a unique wage effect of immigration, the deviation of the estimates from the population mean would be attributed solely to a deviation known as *sampling error*.

Following Disdier and Head (2008), we explore how much of the observed variance in the sample of estimates can be attributed to sampling errors. Specifically, the z-score evaluates by how many standard deviations an estimate deviates from the observed population mean, whether below or above. Let $\hat{\beta}_i$ denote an individual estimate of the wage effect of immigration, $\tilde{\beta}$ be the population mean, and σ be the population standard deviation. Under the null hypothesis of a unique population mean, the z-score, defined as $z_i = (\hat{\beta}_i - \tilde{\beta})/\sigma$, should follow a Student's t-distribution. Given our sample size, the t-distribution should approximate a Normal distribution if the variance arises exclusively from sampling errors. We approximate the unobserved z-score using the t-statistic, $\hat{\beta}_i/se(\hat{\beta}_i)$.

Figure 4 shows the distribution of observed t-statistics alongside the Normal distribution, which serves as a benchmark under the assumption of a unique population mean. The figure suggests that the observed t-statistics exhibit greater dispersion than expected under normality. This implies that sampling errors account for only a small portion of the variance in wage effect estimates of immigration.

Figure 4: Distribution of the t-Statistics

Note: This figure shows the observed distribution of t-statistics (dashed line) alongside the Normal distribution (solid line) for the sample of estimates reporting a t-statistic. The value of the I^2 statistic is reported at the bottom of the graph.

Note that the validity of this exercise depends on the accuracy of standard error estimates, which may be underestimated in many studies. For instance, early studies often fail to account for spatial clustering, and few studies using shift-share instrumental variables adjust for clustering at the shift-share level (Adão et al., 2019). If standard errors are systematically too small, t-statistics may be inflated, potentially biasing our conclusions.

Lastly, following Higgins et al. (2003), we compute the I^2 statistic, quantifying the fraction of observed variance that cannot be attributed to sampling errors. The calculated I^2 is 96.38%. This, along with Figure 4, highlights the need to explore additional sources of heterogeneity beyond sampling errors alone.

3.4 Empirical Strategy

We use a fixed-effects meta-regression model as our benchmark, which assumes that different studies may exhibit distinct wage effects of immigration and that the studies included in the meta-analysis represent the entire population of interest. Unlike a random-effects model, this approach does not require the sample of estimates to be a random sample of the *true* population.⁴ We, nonetheless, use a random-effects model in a robustness check.

Beyond the inherent quality of a study, we examine two primary sources of heterogeneity. Context heterogeneity relates to the structural characteristics of the data. However, even when context attributes are held constant, method heterogeneity can significantly affect the results.

⁴See *Stata 18 Meta-Analysis Reference Manual* (2023).

Econometric choices can influence the estimates' direction, magnitude, and statistical significance.

We use the following benchmark model:

$$\hat{\beta}_{i,s} = \Theta_1 \text{Quality}'_{i,s} + \Theta_2 \text{Context}'_{i,s} + \Theta_3 \text{Method}'_{i,s} + \lambda_{t(s)} + \varepsilon_{i,s} \quad (2)$$

where $\hat{\beta}_{i,s}$ denotes the i^{th} estimate of the wage effect of immigration reported in study s .

The first set of variables controls for the quality of the study and the estimates. It includes a binary variable equal to one if the study is published in a leading academic journal (AER, JEEA, JLE, JPE, Restud, and QJE) and another binary variable equal to one if it incorporates a theoretical model. The latter variable reflects whether the empirical analysis is grounded in theoretical foundations. Additionally, following Longhi et al. (2005), we control for the standard error of the estimate to account for its precision and, consequently, for potential publication bias.

We analyse context heterogeneity using a set of covariates that account for the structural characteristics of the samples used to derive the estimates. It includes a binary variable equal to one for Anglo-Saxon countries, capturing the literature's bias toward these regions, particularly the United States. Another binary variable is equal to one for developing countries. These variables may reflect country-specific structural features, such as persistent features of labour markets and labour legislations. Additionally, we include a categorical variable indicating whether the mid-year of the sample period falls before 1973 (the year of the first oil crisis), between 1973 and 2007 (preceding the subprime crisis), or after 2007.

We examine method heterogeneity using a set of categorical variables that account for econometric choices. First, we include the estimate type (semi-elasticities, elasticities, or other specifications). We also incorporate a categorical variable capturing the methodological approach adopted (national skill-cell, mixture, pure spatial, or other methods). These two variables control for the underlying functional form chosen by the authors.

Additionally, we include a binary variable equal to one if the estimation contains covariates and a binary variable equal to one for cross-sectional data estimations (as opposed to panel or pooled data). Another binary variable equals one when the authors use residual wages computed from individual data. This method may produce more accurate estimates and facilitate causal inference.

Finally, we include a binary variable indicating the estimator used (OLS, IV-2SLS, and other estimators), as studies addressing endogeneity tend to produce more causal estimates. We also include a set of publication year dummies, $\lambda_{t(s)}$, to capture methodological trends over time, such as the increasing use of causal inference methods.

Table A.3 in Appendix A presents an overview of the binary and categorical variables used in the analysis and the number of observations in each category.

4 Results

4.1 Main Results

Estimates of the wage effect of immigration. We present the results of the benchmark meta-regressions in Table 1. Columns (1) to (3) sequentially examine the determinants of the wage effect of immigration: quality, context heterogeneity, and method heterogeneity. In column (4), we incorporate the standard error of the estimates into the regression model. Column (5) further accounts for time trends by incorporating publication year dummies. This final model is our preferred specification.

The main findings from Table 1 are as follows. The quality of a study, measured by its publication in a leading academic journal and the inclusion of a supporting theoretical model, significantly influences the estimated wage effect of immigration.

Context heterogeneity helps rationalise the variance in the estimates. The impact of immigration on natives' wages in Anglo-Saxon and developing countries is significantly different from that of other countries. Differences across study periods also account for some variance.

Method heterogeneity also helps to explain the variance in the estimated wage effects. All variables capturing the authors' econometric choices have a significant impact. In particular, the instrumental variable approach (IV-2SLS), commonly used in the literature to address causality, corrects an upward bias of the OLS estimator. This finding aligns with the meta-analysis by Longhi et al. (2005), which shows that the absence of instrumentation tends to yield larger effect sizes.

Magnitude, sign, and significance of the estimates. Our sample of estimates includes both negative and positive values. Therefore, each estimate can be decomposed into magnitude and sign.

Results are presented in Table 2, columns (1) to (4). In column (1), we use the absolute value of the estimate. In column (2), we include a binary variable equal to one if the estimated wage effect is positive and zero otherwise. Columns (3) and (4) show the results for estimates with negative values (reported in absolute terms) and those with positive values. The sizes of these two subsamples are relatively similar, with 1,623 negative estimates from 76 studies and 1,089 positive estimates from 74 studies.

Estimates published in leading academic journals are more frequently negative and tend to be smaller when negative but larger when positive. Similarly, the backing of a supporting theoretical model is associated with more negative wage effects. Yet, using a theoretical model increases the magnitude of negative estimates and decreases the magnitude of the positive ones. Finally, the coefficient associated with the estimates' standard errors is significant and positive, suggesting the potential presence of publication bias in the existing literature.

Regarding context heterogeneity, studies focusing on Anglo-Saxon countries tend to report smaller wage effects, which are more likely to be positive. This finding aligns with [Longhi et al. \(2005\)](#), which shows that studies on European countries yield significantly smaller effect sizes than those on the United States. Studies examining developing countries produce more positive estimates, with smaller magnitudes when negative and larger magnitudes when positive. Additionally, different sample periods appear to play distinct roles in shaping the estimated wage effect of immigration.

Even after accounting for quality and context heterogeneity, method heterogeneity appears to be a significant determinant of both the magnitude and sign of the estimated wage effect of immigration. First, the type of estimate plays a role, as elasticities yield significantly smaller estimates than semi-elasticities. Elasticities – obtained when both variables of interest are log-transformed – are more likely to produce positive estimates.

Next, the mixture and pure spatial approaches produce estimates that differ significantly from those of the national skill-cell approach. Specifically, the mixture approach yields larger and more negative estimates, while the pure spatial approach generates smaller but more positive estimates.

Other econometric choices also play a significant role. Including covariates and using residual wages reduce the magnitude of the estimates and lead to more negative values. Additionally, using cross-sectional data, as opposed to panel or pooled data, produces larger and more positive estimates. Lastly, employing an IV-2SLS estimator results in more negative estimates of greater magnitude compared to the OLS estimator, confirming that instrumental variables correct for the upward bias of OLS.

Finally, our sample includes wage effects with substantial heterogeneity in their standard errors. To focus on more accurate estimates, we restrict our analysis to those with a minimum significance level of 10%, reducing our sample to 1,582 estimates. This subsample reveals that only some of the benchmark results hold.

In particular, the quality of the study and the estimates continue to have a significant impact. However, the sign associated with the leading academic journal dummy is now negative, suggesting a downward publication bias in these outlets. The Anglo-Saxon country dummy primarily

drives context heterogeneity. In contrast, method heterogeneity is influenced mainly by the use of residual wages (although the sign of this variable is now negative) and the choice of estimator.

Skills of immigrants and native workers. We now examine the heterogeneity of the wage effect of immigration across native workers, incorporating the skills of immigrants and native workers as additional determinants. Scholars have extensively studied the impact of immigration on wages for both groups, yet the debate primarily focuses on the effects of unskilled immigration on the labour market. As emphasised by George Borjas, in the U.S. context, immigrants often share characteristics similar to those of unskilled U.S. workers, who are the most likely to be affected by an immigration shock in the short term (see, e.g. [Borjas, 2003a](#)).

While some studies classify individuals as high-, medium-, or low-skilled based on their educational attainment, others rely on occupational classifications. For our meta-analysis, *high-skilled individuals* are defined as those who have attained higher education or hold a high-skilled position. In contrast, *low-skilled individuals* are those with only primary education or employed in blue-collar positions. It is important to note that some studies do not account for skill levels, which reduces our sample size.

In Table 3, columns (1) and (2) focus on estimates associated with low-skilled natives, while columns (3) and (4) examine estimates related to high-skilled natives. In each case, we introduce a categorical variable to account for the skill level of the immigrant population. Odd-numbered columns report results for the magnitude of the estimates, whereas even-numbered columns present results for their sign.

We find that wage estimates published in leading academic journals are larger for low-skilled natives (column 1) but smaller and more negative for high-skilled natives (columns 3 and 4). Studies incorporating a theoretical model yield smaller and more negative estimates for both groups. Additionally, theoretically founded studies produce consistently smaller estimates for both low- and high-skilled natives.

Context heterogeneity appears to play a significant role in determining the magnitude of estimates, yet only for low-skilled natives. Regarding the sign of the estimates, studies focused on Anglo-Saxon and developing countries tend to report more positive estimates for both groups.

Compared to high-skilled immigration, low-skilled immigration reduces the magnitude of the estimated wage effect for low-skilled natives and leads to more negative wage effects for both low- and high-skilled natives. Additionally, we find larger coefficients for low-skilled workers. The finding that low-skilled immigration creates substitution effects with native workers of the same skill level, while high-skilled immigration generates complementarities (or weaker substitution effects), aligns with the existing literature ([Blau and Kahn, 2015](#)).

The methodological choices made by authors sometimes have opposite effects on low- and high-skilled natives. In particular, the type of the estimate, the approach, and the use of residual wages tend to influence these two groups differently. These findings align with [Dustmann et al. \(2016\)](#), who show that the estimated wage effect of immigration varies significantly across skill groups, depending on the methodological approach used by the authors.

Table 1: Estimates of the Wage Effect of Immigration

	(1)	(2)	(3)	(4)	(5)
<i>Quality of the study and estimate</i>					
Leading academic journal	-0.022*** (0.001)	-0.023*** (0.001)	-0.005*** (0.002)	0.003* (0.002)	0.039*** (0.002)
Theoretical model	0.013*** (0.000)	0.013*** (0.000)	0.000 (0.001)	-0.002*** (0.001)	-0.064*** (0.002)
Estimate S.E.				-0.719*** (0.021)	-0.503*** (0.024)
<i>Context heterogeneity</i>					
Anglo-Saxon country		-0.004*** (0.000)	0.006*** (0.000)	0.005*** (0.000)	0.012*** (0.002)
Developing country		0.012*** (0.001)	0.030*** (0.001)	0.025*** (0.001)	0.137*** (0.004)
Sample mid-year: 1973-2007 (ref. before 1973)		-0.006*** (0.001)	-0.005 (0.006)	-0.002 (0.006)	-0.185*** (0.009)
Sample mid-year: After 2007 (ref. before 1973)		-0.039*** (0.001)	-0.064*** (0.006)	-0.059*** (0.006)	-0.253*** (0.009)
<i>Method heterogeneity</i>					
Estimate: Elasticity (ref. semi-elasticity)			0.013*** (0.001)	0.012*** (0.001)	0.012*** (0.002)
Estimate: Other (ref. semi-elasticity)			-0.005 (0.006)	-0.008 (0.006)	0.526*** (0.040)
Approach: Mixture (ref. national skill-cell)			-0.048*** (0.001)	-0.048*** (0.001)	-0.047*** (0.003)
Approach: Pure spatial (ref. national skill-cell)			-0.044*** (0.003)	-0.042*** (0.003)	-0.015* (0.008)
Approach: Other (ref. national skill-cell)			-0.030*** (0.001)	-0.027*** (0.001)	-0.020*** (0.003)
Covariates			0.017*** (0.001)	0.013*** (0.001)	0.005*** (0.001)
Cross-sectional data			-0.009*** (0.001)	-0.012*** (0.001)	-0.043*** (0.003)
Residual wage			-0.011*** (0.001)	-0.007*** (0.001)	-0.124*** (0.003)
Estimator: IV-2SLS (ref. OLS)			-0.000** (0.000)	-0.000** (0.000)	-0.007*** (0.000)
Estimator: Other (ref. OLS)			0.006*** (0.001)	0.006*** (0.001)	-0.254*** (0.007)
Estimates	2,936	2,712	2,712	2,712	2,712
Studies	87	86	86	86	86
Model	FE	FE	FE	FE	FE
Publication year dummies	no	no	no	no	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. The dependent variable is the estimated wage effect of immigration. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

Table 2: Magnitude, Sign, and Significance of the Estimates

	Magnitude (1)	Sign (1 if >0) (2)	Negative (3)	Positive (4)	Signif. (5)
<i>Quality of the study and estimate</i>					
Leading academic journal	-0.009*** (0.002)	-0.259*** (0.002)	-0.079*** (0.006)	0.053*** (0.006)	-0.016*** (0.004)
Theoretical model	0.006*** (0.002)	-0.162*** (0.002)	0.077*** (0.005)	-0.081*** (0.004)	-0.014*** (0.003)
Estimate S.E.	2.191*** (0.024)	1.250*** (0.024)	2.041*** (0.034)	2.026*** (0.040)	-0.211*** (0.032)
<i>Context heterogeneity</i>					
Anglo-Saxon country	-0.030*** (0.002)	0.280*** (0.002)	-0.026*** (0.003)	-0.054*** (0.004)	0.021*** (0.004)
Developing country	-0.100*** (0.004)	0.460*** (0.004)	-0.184*** (0.006)	0.059*** (0.008)	0.001 (0.008)
Sample mid-year: 1973-2007 (ref. before 1973)	-0.022** (0.009)	-0.170*** (0.009)	-0.008 (0.014)	-0.012 (0.018)	-0.033*** (0.011)
Sample mid-year: After 2007 (ref. before 1973)	0.035*** (0.009)	-0.533*** (0.009)	0.051*** (0.014)	-0.002 (0.021)	-0.026* (0.014)
<i>Method heterogeneity</i>					
Estimate: Elasticity (ref. semi-elasticity)	-0.053*** (0.002)	0.569*** (0.002)	0.054*** (0.015)	-0.034*** (0.003)	0.005* (0.003)
Estimate: Other (ref. semi-elasticity)	-0.085** (0.040)	-0.164*** (0.040)	-0.194*** (0.067)	0.045 (0.050)	0.251*** (0.043)
Approach: Mixture (ref. national skill-cell)	0.060*** (0.003)	-0.292*** (0.003)	0.047*** (0.004)	0.032*** (0.006)	-0.009** (0.004)
Approach: Pure spatial (ref. national skill-cell)	-0.036*** (0.008)	0.611*** (0.008)	-0.107*** (0.012)	0.033 (0.030)	-0.005 (0.011)
Approach: Other (ref. national skill-cell)	0.042*** (0.003)	0.144*** (0.003)	0.041*** (0.004)	0.047*** (0.006)	-0.014*** (0.004)
Covariates	-0.008*** (0.001)	-0.179*** (0.001)	-0.013*** (0.002)	0.003 (0.002)	0.003* (0.002)
Cross-sectional data	0.039*** (0.003)	0.030*** (0.003)	0.020*** (0.004)	0.018*** (0.006)	-0.008** (0.003)
Residual wage	-0.027*** (0.003)	-0.041*** (0.003)	-0.010 (0.006)	-0.170*** (0.005)	0.016*** (0.005)
Estimator: IV-2SLS (ref. OLS)	0.007*** (0.000)	-0.262*** (0.000)	0.008*** (0.000)	0.004*** (0.000)	-0.002*** (0.000)
Estimator: Other (ref. OLS)	-0.180*** (0.007)	0.486*** (0.007)	-0.371*** (0.082)	-0.220*** (0.009)	0.011 (0.018)
Estimates	2,712	2,709	1,623	1,089	1,582
Studies	86	86	76	74	84
Model	FE	FE	FE	FE	FE
Publication year dummies	yes	yes	yes	yes	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. In column (1), the dependent variable is the absolute value of the estimate. In column (2), the dependent variable is a dummy equal to one if the estimate is positive and zero otherwise. In column (3), results are obtained with a set of negative estimates (in absolute terms), and in column (4), results are obtained with a set of positive estimates. In column (5), results are obtained using a subsample of significant estimates (at a minimum level of 10%). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

Table 3: Skills of Immigrants and Native Workers

	Magnitude	Sign (1 if >0)	Magnitude	Sign (1 if >0)
	Low-skilled natives		High-skilled natives	
	(1)	(2)	(3)	(4)
<i>Quality of the study and estimate</i>				
Leading academic journal	0.513*** (0.069)	-0.017 (0.069)	-0.353*** (0.071)	-0.458*** (0.071)
Theoretical model	-0.289*** (0.039)	-0.017 (0.039)	-0.123*** (0.034)	-0.099*** (0.034)
Estimate S.E.	1.314*** (0.093)	1.481*** (0.093)	1.439*** (0.092)	-0.398*** (0.092)
<i>Context heterogeneity</i>				
Anglo-Saxon country	-0.033** (0.013)	0.225*** (0.013)	0.049* (0.025)	0.511*** (0.025)
Developing country	-0.207*** (0.059)	0.267*** (0.060)	-0.002 (0.080)	0.696*** (0.080)
Sample mid-year: 1973-2007 (ref. before 1973)	-0.171 (0.113)	0.272** (0.113)	-0.455 (0.507)	-1.088** (0.507)
Sample mid-year: After 2007 (ref. before 1973)	-0.106 (0.113)	-0.277** (0.113)	-0.409 (0.507)	-1.643*** (0.507)
Immigrants' skills: low (ref. high)	-0.003*** (0.001)	-0.743*** (0.001)	-0.001 (0.002)	-0.151*** (0.002)
Immigrants' skills: medium (ref. high)	-0.036 (0.033)	-0.732*** (0.033)	-0.011 (0.060)	-0.445*** (0.060)
Immigrants' skills: all (ref. high)	0.040 (0.040)	-0.891*** (0.040)	-0.221*** (0.071)	0.028 (0.071)
<i>Method heterogeneity</i>				
Estimate: Elasticity (ref. semi-elasticity)	0.278*** (0.089)	1.009*** (0.089)	0.133 (0.184)	-1.716*** (0.184)
Estimate: Other (ref. semi-elasticity)	0.299*** (0.076)	-0.416*** (0.076)	-0.114 (0.137)	0.462*** (0.137)
Approach: Mixture (ref. national skill-cell)	-0.182*** (0.069)	-0.215*** (0.069)	0.095** (0.046)	-0.278*** (0.046)
Approach: Pure spatial (ref. national skill-cell)	-0.452** (0.224)	0.472** (0.224)	0.738*** (0.098)	2.247*** (0.098)
Approach: Other (ref. national skill-cell)	0.018 (0.056)	0.240*** (0.056)	0.106** (0.046)	-0.233*** (0.046)
Covariates	0.233*** (0.038)	-0.408*** (0.038)	-0.176*** (0.036)	-0.687*** (0.036)
Cross-sectional data	0.008 (0.080)	0.045 (0.080)	0.017 (0.143)	-0.652*** (0.143)
Residual wage	-0.061 (0.074)	0.371*** (0.074)	-0.024 (0.039)	-0.006 (0.039)
Estimator: IV-2SLS (ref. OLS)	0.001 (0.001)	-0.226*** (0.001)	-0.001 (0.001)	-0.825*** (0.001)
Estimator: Other (ref. OLS)	0.059 (0.149)	1.086*** (0.149)	-0.955*** (0.183)	-1.778*** (0.183)
Estimates	371	370	359	359
Studies	52	52	45	45
Model	FE	FE	FE	FE
Publication year dummies	yes	yes	yes	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. In columns (1) and (3), the dependent variable is the absolute value of the estimate. In columns (2) and (4), the dependent variable is a dummy equal to one if the estimate is positive and zero otherwise. In columns (1) and (2), results are obtained using a subsample of estimates for low-skilled native workers. In columns (3) and (4), results are obtained using a subsample of estimates for high-skilled native workers. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

4.2 Robustness Tests

We present a series of robustness tests in Appendix B. Table B.4 reports results for subsamples restricted to semi-elasticities and elasticities and for a random-effects model. Table B.5 presents results for different methodological approaches and relative effects (Dustmann et al., 2016). Table B.6 controls for the formatting of wage and immigration variables and reports results by gender. Table B.7 examines displacement and heterogeneity across countries. Finally, Table B.8 helps compare our findings with the meta-analysis conducted by Longhi et al. (2005).

Type of the estimate and alternative estimation strategy. Our benchmark analysis relies primarily on semi-elasticity estimates. However, our sample also includes elasticities and other types of estimates that are not directly comparable to semi-elasticities. Since semi-elasticities are commonly used in the literature, we converted all estimates into this form whenever possible, based on the reported magnitude of the immigration shock in each study. However, using elasticities allows for the normalisation of the immigration shock (i.e., the intensity of the treatment) and facilitates more direct comparisons across studies. Consequently, estimates were also converted into elasticities whenever possible.

It is important to note that while converting estimates is feasible in principle, many studies do not provide sufficient information on the magnitude of the immigration shock to enable this transformation. As a result, we obtained a subsample of 1,732 estimates from 63 studies for which both semi-elasticity and elasticity forms were available.

Table B.4, column (1), presents results based on the set of semi-elasticities, while column (2) reports results for elasticities. The results obtained from the subsample of semi-elasticities are consistent with the benchmark findings presented in Table 1, column (5). This indicates that semi-elasticities primarily drive our main conclusions. Comparing these two subsamples, we find that most variables have opposite signs, indicating opposite contextual and methodological biases. Nonetheless, for both types of estimates, we still find that employing an IV-2SLS estimator corrects for an upward bias of OLS estimates. Finally, when examining the set of elasticities, we find that the mixture approach tends to produce more positive wage effects in response to immigration than the national skill-cell approach, consistent with Dustmann et al. (2016).

We then use a random-effects model as an alternative to the benchmark fixed-effects model. The random-effects model is widely used in meta-analysis literature and follows the methodology proposed by Borenstein et al. (2010) and Disdier and Head (2008). Unlike a fixed-effects model, it assumes that the collected studies represent a random sample from a larger population of studies. A key advantage of this approach is that it allows for the decomposition of wage effect variation into between-study and within-study components. The results, reported in column (3),

broadly confirm our main findings, except for the country binary variables and the estimate type, which exhibit opposite signs. Additionally, we find a between-study variance of 0.108, indicating substantial heterogeneity in estimates across studies.

Approaches and relative effects. Next, instead of pooling estimates from various approaches and using the approach as a control variable, as in our benchmark analysis, we perform separate meta-regressions for each subsample of estimates obtained from a pure spatial, a national skill-cell, or a mixed approach. Following [Dustmann et al. \(2016\)](#), estimates obtained from different approaches are not easily comparable and may yield very different wage effects of immigration.

Results for the pure spatial approach are presented in Table B.5, column (1). Estimates derived from this approach leverage variation over time and across space to address the question: What is the overall effect of immigration on the wages of native workers within a particular skill group? ([Dustmann et al., 2016](#)) Although the sample size is reduced to 189 observations and seven studies, we find the following results: the variance in the wage effect of immigration is affected by the quality of the study and estimate, as well as by context heterogeneity, but it does not appear to be affected by method heterogeneity. This approach, therefore, seems robust to the economic choices of the authors.

Results for the national skill-cell and mixture approaches are presented in columns (2) and (3). These approaches are more easily comparable, relying on a similar rationale based on skill cells. Specifically, they provide relative wage effects by skill group and address the question: How does immigration affect the wages of low-skilled workers relative to high-skilled workers at the national or regional level? ([Dustmann et al., 2016](#)) Our findings indicate that, beyond study quality, both context and methodological heterogeneities play a significant role in determining the variance in the relative wage effect. In column (4), we combine these two approaches, which produce relative effects, further corroborating this result.

Formatting of the variables of interest and gender. Following [Longhi et al. \(2005\)](#), we further investigate how authors' choices regarding the formatting of key variables influence the estimated wage effect of immigration. To this end, we introduce three additional categorical variables. First, we control for the frequency of the wage variable – specifically, whether wages are reported hourly (the reference and most common frequency in the literature), weekly, monthly, or yearly. Second, we distinguish between studies that express immigration as a share (the standard in the literature), a rate, or a level. Third, we examine how immigrants are defined, using studies that classify immigrants based on country of birth compared to those defining immigrants based on citizenship.

Results are presented in Table B.6, column (1). The main findings from Table 1, column (5), remain mostly consistent with this extended set of control variables, except for the coefficient associated with the Anglo-Saxon country dummy.

Next, we focus on the studied population. While most studies estimate the wage effect of immigration on native workers, some examine its impact on the entire workforce, including both natives and immigrants. To ensure comparability in the estimates, we restrict our analysis to studies that specifically identify wage effects on the native population. The results presented in column (2) remain consistent with those obtained for the entire sample in column (1).

Finally, we restrict our sample to studies that estimate the wage effect separately for males and females, excluding studies that combine both genders. Notably, most studies provide estimates for males (48 studies) compared to females (25 studies). The results are presented in columns (3) and (4). We find that estimates for both genders are influenced by quality, as well as context and method heterogeneity. The coefficients occasionally exhibit opposite signs, indicating that neither male nor female estimates drive the benchmark results exclusively.

Displacement and heterogeneity across countries. Many studies estimating the wage effect of immigration also examine displacement effects, which refer to the potential movement of native workers across occupations, sectors, regions, or even out of the labour force due to immigration. Occupational or sectoral displacement may occur in labour markets in countries where retraining programs facilitate worker transitions, such as Northern European countries. Regional displacement is particularly relevant in countries with a highly mobile workforce, such as the U.S. Finally, crowding-out effects are a key concern in many developed countries, such as Europe, where minimum wage regulations may constrain wage adjustments in response to supply shocks.

While our meta-analysis focuses exclusively on studies estimating the wage effect of immigration, we account for whether a study also considers displacement effects. The results are presented in Table B.7. In column (1), we include a binary variable set to one if the study addresses displacement effects. This variable also serves as an additional proxy for study quality. Introducing this control does not alter the benchmark findings. In addition, we find that studies considering displacement effects yield significantly different estimates, exhibiting a downward bias compared to those focusing solely on the wage effect of immigration. Six of the seven studies in our sample that adopt a pure spatial approach discuss displacement effects. This is why we find that estimates produced using the pure spatial approach are no longer significantly different from those using the national skill-cell approach after controlling for the displacement binary variable.

We then examine heterogeneity across countries. Labour regulations, particularly those related to minimum wages, vary widely and can significantly influence wage adjustments following supply shocks. To explore this, we analyse a subsample of estimates derived from data on Anglo-Saxon countries and the United States, characterised by low minimum wages and less stringent labour regulations, allowing for greater wage flexibility. Additionally, we analyse a set of 279 estimates from 8 studies on developing countries. In these countries, labour regulations may be absent, weakly enforced, or supplemented by informal norms, making labour market rigidities an open question.

Results for these three subsamples are presented in columns (2), (3), and (4). For Anglo-Saxon countries and the U.S., the type of estimate, the approach, and the use of cross-sectional data do not introduce the same biases in the estimates as in the benchmark analysis. However, using covariates, residual wages, and an IV-2SLS estimator yield coefficients with the same signs as in the benchmark analysis. The results indicate that both study quality and method heterogeneity play a role in the case of developing countries, though the coefficients are not always aligned with the benchmark results.

Finally, in column-(5), we examine the sectoral composition of the countries analysed in our sample of studies, as structural differences across economies may influence the wage effects of immigration. We collected data on the agricultural and manufacturing sectors as a percentage of GDP from the World Development Indicators of the World Bank. Specifically, we assign to each estimate, the share of these sectors in the first year of the sample period. In doing so, we obtain a subsample of 1,357 estimates from 43 studies.

Examining context heterogeneity, we observe that a larger agricultural sector in the studied economy is associated with an upward bias in the estimated wage effect. In contrast, a larger manufacturing sector is associated with a downward bias. We also find that study quality and method heterogeneity explain part of the variance in the estimated wage effect. However, after incorporating these additional context variables, the direction of the biases does not always align with the baseline findings.

Studies included in Longhi et al. (2005) and until/after 2003. In a last robustness test, we explore the differences between our sample and that used in the meta-analysis by Longhi et al. (2005). Our sample includes 11 of the 18 studies analysed by Longhi et al. (2005). In Table B.8, column (1), we restrict our analysis to these 11 studies, which consist of 178 estimates. This approach assesses whether narrowing the analysis to studies from the earlier meta-analysis significantly affects our results. However, the small subsample size restricts the variables that can be analysed.

In particular, the Anglo-Saxon country dummy exhibits a positive sign, a result in line with our benchmark findings. It is also in line with the conclusions of Longhi et al. (2005), who found that the wage effect of immigration tends to be smaller for European countries than for the United States. In this subsample, using an IV-2SLS estimator compared to an OLS estimator does not significantly impact the wage effect. This may reflect the substantial evolution of the literature since the meta-analysis published by Longhi et al. (2005).

In their meta-analysis, Longhi et al. (2005) analysed studies published up to 2003. In column (2), we restrict our analysis to 313 estimates from 18 studies published until 2003. While this subsample includes some studies from Longhi et al. (2005), it is not limited to them. The results occasionally differ from those in column (1), highlighting the sensitivity of the findings to the inclusion of specific studies. Notably, the Anglo-Saxon country dummy changes sign, while the IV-2SLS estimator remains insignificant.

Finally, we restrict our sample to studies published after 2003. This subsample includes 2,399 estimates from 68 studies, highlighting that the vast majority of the literature emerged after the publication of the meta-analysis by Longhi et al. (2005). The results, presented in column (3), are consistent with our benchmark findings, except for the coefficient associated with the pure spatial approach.

5 Extensions

We now present two extensions to our analysis. First, we further investigate the presence of publication bias in the data used for our meta-analysis. Second, we assess whether the recent shift of economists toward causal inference – through shift-share instrumental variables or (quasi-)natural experiments – affects the estimated wage effect of immigration. The results are reported in Appendix C and discussed below.

5.1 Publication Bias

A concern in meta-analyses is the potential for selective reporting and the publication of significant coefficients, known as publication bias. This bias implies that the likelihood of a study being published depends on the statistical significance of its estimates. Consequently, published findings may not fully represent the entire spectrum of research. To address this, we examine the presence of publication bias in our sample. First, we follow the sampling theory and analyse the correlation between the significance of the estimates and the sample size. Second, we investigate evidence of p-hacking. Third, we incorporate additional controls for study quality in our meta-regressions.

Sampling theory. Sampling theory posits that the absolute value of the t-statistic should be proportional to the square root of the degrees of freedom, which, in a regression analysis, can generally be approximated by the sample size. Therefore, we analyse the correlation between the significance of the estimates and the sample size, expecting that a positive correlation would indicate the absence of publication bias.

For this exercise, we restrict our sample to estimates for which both the associated sample size and standard error are available. Following the approach of [Card and Krueger \(1995\)](#), we retain only one estimate per study. We then compute the t-statistic by dividing the estimate by its standard error and regress it on the sample size.

Figure [C.2\(a\)](#) illustrates the relationship between the t-statistic and sample size, using the first estimate reported in each study. Consistent with sampling theory, we observe a positive correlation between the significance of the first estimates and sample size, suggesting no evidence of publication bias in our sample. However, Figure [C.2\(b\)](#), which presents results based on the median estimate from each study, shows a weaker positive correlation, indicating that some degree of bias cannot be entirely ruled out.

However, this exercise depends on obtaining an accurate measure of standard errors. If estimated standard errors are systematically biased downward, this could inflate the t-statistics, potentially leading to the incorrect conclusion that publication bias is present in our sample of studies.

P-hacking. Then, we use a method proposed by [Brodeur et al. \(2020\)](#) to assess the presence of publication bias by looking at the clustering of reported t-statistics around conventional significance thresholds (1.64 for 10%, 1.96 for 5%, and 2.32 for 1%). An excess of estimates just above these thresholds may indicate publication bias or “p-hacking”, assuming an underlying continuous distribution of t-statistics.

The results are presented in Figure [C.3](#). A noticeable concentration of t-statistics just below the 5% significance threshold appears in Figure [C.3\(a\)](#) for the entire sample. A similar pattern emerges near the 1% threshold in Figure [C.3\(b\)](#) for estimates published in leading academic journals. However, since comparable peaks occur elsewhere in the distribution, the evidence for publication bias remains inconclusive, reinforcing the findings from Figure [C.2\(a\)](#).

Quality of the study. The selective publication of estimates may be influenced by study quality. Therefore, assessing publication bias requires controlling for this factor. To do so, in our meta-regression, we test whether the coefficient associated with the estimates’ standard

errors remains significant after incorporating a comprehensive set of controls for both study and estimate quality.

The results are presented in Table C.9. In column (1), we control for the (log) number of estimates reported in each study, as some studies provide more estimates than others, potentially reflecting the extent to which the authors test the robustness of their results. In column (2), we introduce a binary variable indicating whether the estimate is derived from a large dataset (with at least 10,000 observations). We also include binary variables for estimates based on individual-level data and cell-based studies. Finally, in column (3), we control for the number of authors, which may indicate how widely the study was disseminated and commented on by peers. Throughout these specifications, the coefficient associated with the estimates' standard errors remains significant, reinforcing our premise that publication bias may exist in this literature.

Next, we replicate our analysis using a sample restricted to 199 baseline estimates from 83 studies, noting that some of them report multiple baseline estimates for different subpopulations. Authors either explicitly label these estimates as baseline, benchmark, or preferred, and when such information is unavailable, we identify the baseline estimates ourselves. These wage effects represent the study's main findings and are assumed to be of higher quality. For instance, baseline estimates are often derived from IV-2SLS regressions, including a large set of covariates and fixed effects. The results in column (4) confirm that even within this subsample – intended to be more homogeneous in quality – the coefficient associated with the standard error of the estimate remains significant. Moreover, the direction of biases introduced by methodological choices does not always align with the baseline findings.

Finally, in Table C.10, we replicate our analysis using three subsamples of estimates that are presumably homogenous in terms of quality. Column (1) focuses on studies published in leading academic journals. Since estimates from high-impact journals with stricter quality standards may be more reliable, one might expect quality, context, and method heterogeneity to have no impact on variations in the wage effect of immigration. However, differences among estimates still stem from methodological choices or other observable factors related to study quality, such as the use of a theoretical model. Additionally, the coefficient associated with the estimates' standard errors remains negative and significant.

In column (2), we exclude studies published in leading academic journals. The results from this subsample support our benchmark findings on publication bias and confirm that leading academic journals do not drive our results. In column (3), we restrict the sample to working papers, which are assumed to be of lower quality as they have not undergone peer validation offered by the publication process. Once again, the results from this subsample broadly align with our benchmark findings regarding quality and context heterogeneity.

5.2 Causal Inference

Next, we examine whether studies aiming for causal inference – reflecting the growing trend in economics over the past decade – yield significantly different estimates compared to those providing purely descriptive evidence. First, we focus on shift-share instrumental variables, introduced to the field by the seminal work of [Card \(2001\)](#) and widely used in the literature.

In [Table C.11](#), column (1), we include a binary variable for IV-2SLS estimates produced using a shift-share instrument. This additional control exhibits a negative sign and does not alter the benchmark findings. In particular, it does not affect the conclusion that IV-2SLS estimators correct for the upward bias of OLS estimates.

In column (2), we further control whether the exogeneity of the shift-share instrument was explicitly discussed by the authors of the study. Several studies emphasise the importance of demonstrating the validity of shift-share instrumental variables ([Adão et al., 2019](#); [Goldsmith-Pinkham et al., 2020](#); [Jaeger et al., 2018](#)). For instance, [Jaeger et al. \(2018\)](#) show that these instruments may fail to identify a causal effect when there is limited change in the composition of immigrant inflows by countries of origin. We find that while this control exhibits a negative sign, the coefficient associated with the use of a shift-share instrument is no longer significant. This suggests that shift-share instruments yield significantly different estimates than other instruments, such as lagged variables, but only when they are valid – presumably when the exclusion restriction holds.

Finally, in column (3), we account for studies that leverage (quasi-)natural experiments. The exogeneity of the events examined in these studies presumably enhances their potential for causal inference compared to other identification strategies. Our findings indicate that studies using (quasi-)natural experiments yield significantly different results and tend to correct a downward bias present in other estimates.

6 Conclusions

In this paper, we conduct a meta-analysis of the literature on the wage effect of immigration, covering 88 studies published between 1985 and 2023. Our study builds upon the work of [Longhi et al. \(2005\)](#) by incorporating a larger body of literature, including studies that use more advanced econometric methods. Additionally, the scope of these studies has expanded over time, analysing a broader range of countries and covering longer periods.

Specifically, our meta-analysis seeks to identify the sources of variation in the estimated wage effects of immigration across studies. We find that the wage effect of immigration is centred around zero, with substantial heterogeneity across studies. Our benchmark meta-regressions

reveal that context and method heterogeneity significantly impact the estimates in addition to study quality.

Regarding study quality, we find that estimates published in leading academic journals are more frequently negative and tend to be smaller in magnitude when negative but larger when positive. Similarly, the inclusion of a supporting theoretical model is associated with more negative wage effects. In terms of context, we show that differences in countries, sample periods, and economic structures play distinct roles in shaping the estimated wage effect of immigration.

Finally, even after accounting for quality and context heterogeneity, method heterogeneity remains a significant determinant of both the magnitude and sign of the estimated wage effect of immigration. In particular, the choice of estimate type (semi-elasticities vs. elasticities) and the methodological approach used by the authors lead to significantly different estimates. Specifically, the mixture approach yields larger and more negative estimates, while the pure spatial approach produces smaller but more positive estimates compared to the national skill-cell approach. Other econometric choices also play a crucial role. Including covariates, using residual wages, and leveraging the data's time dimension help explain the variance in estimates. Lastly, employing an IV-2SLS estimator results in more negative estimates of greater magnitude than the OLS estimator, confirming that instrumental variables correct for the upward bias of the OLS.

We acknowledge the potential for systematic bias in the literature, as highlighted by [Aydemir and Borjas \(2011\)](#) and [Peri and Sparber \(2011\)](#), particularly the possibility that many studies suffer from similar methodological issues, such as the lack of a credible identification strategy allowing for causal inference. Although pooling estimates helps mitigate the impact of sampling error and idiosyncratic methodological issues in individual studies, it does not necessarily reveal the *true* wage effect of immigration. At best, our results indicate a negligible overall impact of immigration on native wages, centred around zero, with substantial heterogeneity across studies.

Our meta-analysis suggests two main directions for future research. First, the findings highlight the importance of context heterogeneity in estimating the wage effect of immigration, emphasising the need for replication studies across various contexts to ensure external validity. Second, our results point to the importance of method heterogeneity. In this regard, economists should be encouraged to discuss how their methodological choices influence their findings. Finally, our findings underscore that the ongoing methodological debate in the field is crucial ([Adão et al., 2019](#); [Jaeger et al., 2018](#)), considering the impact of quantitative research on policy discussions about the costs and benefits of immigration.

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Appendix

A Supplementary Data Details

Table A.1: List of Studies and Classification by Approaches

	Approach				Total effects (vs relative effects)
	National skill-cell	Pure spatial	Mixture	Other	
Addison & Worswick (2002)	no	yes	no	no	yes
Altonji & Card (1989)	no	no	no	yes	
Aydemir & Borjas (2011)	yes	no	yes	no	no
Barcellos (2009)	no	no	no	yes	
Barrett et al. (2011)	yes	no	no	no	no
Basso & Peri (2015)	no	no	yes	yes	no
Bauer et al. (2013)	no	no	no	yes	
Biavaschi et al. (2018)	yes	yes	yes	no	yes
Bond & Gaston (2011)	yes	no	no	yes	no
Borjas (1987)	no	no	no	yes	
Borjas et al. (1997)	no	no	yes	no	no
Borjas (2003)	yes	no	yes	no	no
Borjas (2005)	yes	no	no	no	no
Borjas (2006a)	yes	no	yes	yes	no
Borjas (2006b)	yes	no	yes	no	no
Borjas & Edo (2022) (i)	no	no	yes	yes	no
Bratsberg et al. (2014)	yes	no	no	yes	no
Bratsberg & Raaum (2012)	no	no	no	yes	
Breunig et al. (2017)	yes	no	no	yes	no
Broussard (2017)	no	no	yes	yes	no
Bryant & Rukumnuaykit (2013)	no	no	no	yes	
Camarota (1997)	no	no	no	yes	
Card (2001)	no	no	yes	no	no
Card (2009)	no	no	no	yes	
Carrasco et al. (2008)	yes	no	yes	yes	no
Caruso et al. (2019)	no	no	no	yes	
Cattaneo et al. (2013)	no	no	yes	yes	no
Chletsos & Roupakias (2019)	yes	no	no	no	no
Cohen-Goldner & Paserman (2011)	no	no	no	yes	
Cortes & Pan (2014)	no	no	yes	yes	no
Damette & Fromentin (2013)	no	no	no	yes	
De New & Zimmermann (1994)	no	no	no	yes	
Defreitas (1988)	no	no	no	yes	
Dustmann et al. (2005)	no	no	no	yes	
Dustmann et al. (2013)	no	no	no	yes	
Dustmann et al. (2017)	no	yes	no	no	yes
Easton (2001)	no	no	no	yes	
Edo (2016)	yes	no	no	no	no

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	Approach				Total effects (vs relative effects)
	National skill-cell	Pure spatial	Mixture	Other	
Edo (2019)	no	yes	no	yes	yes
Enchautegui (1995)	no	no	no	yes	
Foged & Peri (2016)	no	no	no	yes	
Friedberg (2001)	yes	no	no	yes	no
Geary & Grada (1985)	no	no	no	yes	
Gindling (2009)	yes	no	no	no	no
Glitz (2012)	no	no	yes	no	no
Green & Green (2016)	yes	no	no	no	no
Gu & Sparber (2017)	yes	no	no	no	no
Hofer & Huber (2003)	no	no	no	yes	
Islam & Fausten (2008)	no	no	no	yes	
Jaeger et al. (2018)	no	no	no	yes	
Kifle (2009)	no	no	no	yes	
Kim (2023)	yes	no	no	no	no
Kim & Lim (2017)	no	no	no	yes	
Kugler & Yuksel (2008)	no	no	no	yes	
Labanca (2020)	no	no	no	yes	
Lalonde & Topel (1991)	no	yes	no	no	yes
Lebow (2022)	no	no	no	yes	
Lemos & Portes (2014)	no	no	no	yes	
Llull (2017)	yes	yes	no	no	yes
Maani & Tse (2020)	yes	no	yes	no	no
Malchow Moller et al. (2012)	no	no	no	yes	
Monras (2020)	no	no	no	yes	
Mouw (2016)	no	no	yes	no	no
Nickell & Saleheen (2015)	no	no	yes	yes	no
Olney (2012)	no	no	no	yes	
Orrenius & Zavodny (2007)	no	no	yes	no	no
Ortega & Verdugo (2011)	yes	no	no	no	no
Ortega & Verdugo (2014)	yes	no	yes	no	no
Ottaviano & Peri (2012)	no	no	no	yes	
Ozden & Wagner (2014)	no	no	no	yes	
Pedace (1998)	no	no	no	yes	
Pedace (2006)	no	no	no	yes	
Peri et al. (2014) (ii)	no	no	no	yes	
Prantl & Spitz-Oener (2014)	no	no	no	yes	
Reed & Danziger (2007)	no	no	no	yes	
Schmidt & Jensen (2013)	no	no	no	yes	
Sharpe & Bollinger (2020)	yes	no	no	yes	no
Smith (2010)	no	no	yes	no	no
Srungboonmee (2013)	no	no	no	yes	
Staffolani & Valentini (2010)	no	no	no	yes	
Steinhardt (2011)	yes	no	no	no	no
Toussaint-Comeau (2007)	yes	no	no	no	no
Tu (2010)	yes	yes	yes	yes	yes

Continued on next page...

	Approach				Total effects (vs relative effects)
	National skill-cell	Pure spatial	Mixture	Other	
Tunali et al. (2017)	no	no	no	yes	
Vera & Jiménez (2022)	yes	no	no	no	no
Winter-Ebmer & Zimmermann (1998) (iii)	no	no	no	yes	
Winter-Ebmer & Zweimuller (1996)	no	no	no	yes	
Zorlu & Hartog (2005)	no	no	no	yes	

Note: This table presents the list of 88 studies included in this meta-analysis and the approach each study used in estimating the wage effect of immigration (Dustmann et al., 2016). We cite the published version of each study whenever available; however, in some cases, we use the corresponding working paper to collect data for our meta-analysis. These cases are the following: (i) published in 2025, (ii) published in 2015, and (iii) published in 1999.

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Table A.2: Summary Statistics

	Mean	S.D.	Min.	Max.	N
Study characteristics					
Number of authors	1.830	0.776	1	4	88
Publication year	2009	8.590	1985	2023	88
Leading academic journal	0.205	0.406	0	1	88
Journal article	0.739	0.442	0	1	88
Book chapter	0.034	0.183	0	1	88
Working paper	0.227	0.421	0	1	88
Number of estimates	36.500	46.092	2	285	88
Theoretical model	0.330	0.473	0	1	88
Displacement effects	0.750	0.435	0	1	88
(Quasi-)natural experiment	0.182	0.388	0	1	88
Estimate characteristics					
Estimate	-0.152	1.171	-6.291	12.780	2,992
Estimate S.E.	0.644	4.618	0	145.276	2,936
Baseline estimate	0.072	0.259	0	1	2,992
Large dataset (at least 10,000 obs.)	0.904	0.295	0	1	2,992
Individual-level data	0.181	0.385	0	1	2,992
Cell-level analysis	0.949	0.220	0	1	2,992
Cross-sectional data	0.090	0.286	0	1	2,992
Anglo-Saxon country	0.549	0.498	0	1	2,762
The U.S.	0.346	0.476	0	1	2,992
Developing country	0.101	0.301	0	1	2,762
Sample mid-year: Before 2007	0.049	0.216	0	1	2,992
Sample mid-year: 1973-2007	0.810	0.393	0	1	2,992
Sample mid-year: After 2007	0.141	0.348	0	1	2,992
Semi-elasticity	0.066	0.247	0	1	2,992
Elasticity	0.053	0.224	0	1	2,992
National skill-cell approach	0.238	0.426	0	1	2,992
Mixture approach	0.127	0.333	0	1	2,992
Pure spatial approach	0.075	0.263	0	1	2,992
Covariates	0.478	0.500	0	1	2,992
Residual wage	0.282	0.450	0	1	2,992
IV-2SLS	0.477	0.500	0	1	2,992
OLS	0.504	0.500	0	1	2,992
Shift-share IV (for IV-2SLS)	0.365	0.482	0	1	1,428
Shift-share IV discussed (for IV-2SLS)	0.800	0.400	0	1	521

Note: This table presents summary statistics for the 2,992 estimates collected from 88 studies. The standard error is sometimes unavailable, and country dummies are missing for some estimates as they were derived from groups of countries.

Table A.3: Categorical Variables of Interest

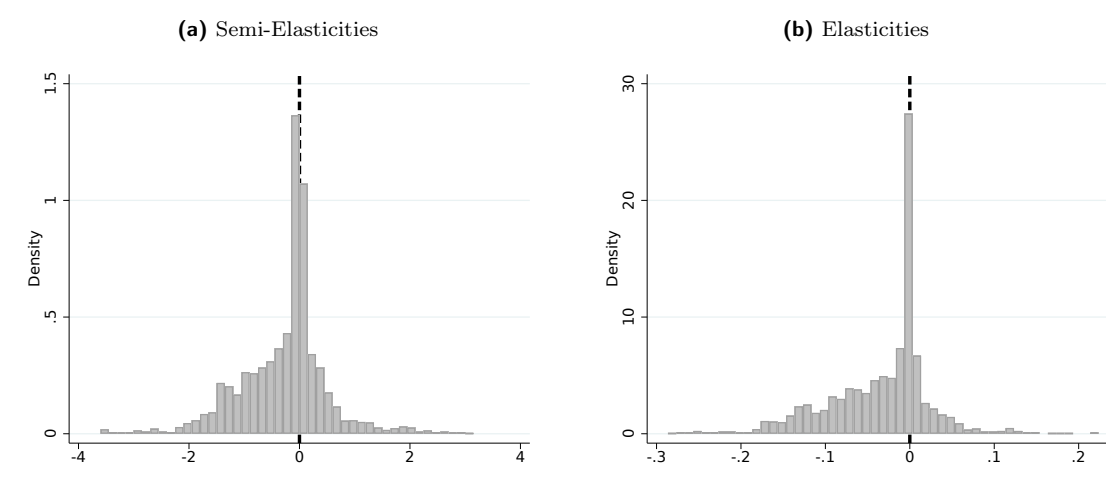
Variables of interest	Categories	N
Approach	National skill-cell	713
	Mixture	380
	Pure spatial	223
	Other	1,676
Data structure	Cross-section	269
	Pooled	1,817
	Panel	834
	Time series	72
Estimate	Semi-elasticities	2,638
	Elasticities	158
	Other types of estimate	196
Estimator	OLS	1,509
	IV-2SLS	1,428
	Other	55
Gender of the studied workers	Both genders	1,448
	Females	328
	Males	1,216
Immigration variable definition	Birth	2,107
	Citizenship	715
	Previous residence	103
	Ethnicity	3
	Unknown	64
Immigration variable format	Share	2,241
	Rate	610
	Level	141
Population of studied workers	Natives only	2,874
	Natives and immigrants	118
Publication type	Journal article	2,065
	Working paper	895
	Book chapter	32
Sample mid-year	Before 1973	147
	1973–2007	2,423
	After 2007	422
Skill-level of immigrants	Low	171
	Medium	57
	High	205
	All	2,559
Skill-level of the studied workers	Low	379
	Medium	190
	High	371
	All	2,052

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Variables of interest	Categories	N
Wage variable frequency	Hourly	761
	Weekly	871
	Monthly	688
	Yearly	516
	Other	156

Note: This table presents all categorical variables used in the meta-analysis, along with the number of observations in each category.

Figure A.1: Densities of Converted Estimates



Note: Densities of (converted) semi-elasticities and (converted) elasticities are presented in Figures A.1(a) and A.1(b) respectively. The vertical dashed line represents an estimate value of zero.

B Robustness Tests: Supplementary Details

Table B.4: Type of Estimate and Alternative Estimation Strategy

	Semi-elasticities (1)	Elasticities (2)	Random-effects (3)
<i>Quality of the study and estimate</i>			
Leading academic journal	0.021*** (0.005)	-0.060*** (0.005)	-0.029 (0.032)
Theoretical model	-0.056*** (0.005)	-0.023*** (0.005)	-0.180*** (0.027)
Estimate S.E.	-3.866*** (0.035)	-0.315*** (0.035)	-0.232*** (0.049)
<i>Context heterogeneity</i>			
Anglo-Saxon country	0.293*** (0.005)	0.001 (0.005)	-0.041 (0.029)
Developing country	0.306*** (0.006)	-0.043*** (0.006)	-0.230*** (0.043)
Sample mid-year: 1973-2007 (ref. before 1973)	-0.193*** (0.020)	0.019 (0.020)	-0.293*** (0.072)
Sample mid-year: After 2007 (ref. before 1973)	-0.254*** (0.020)	0.008 (0.020)	-0.347*** (0.077)
<i>Method heterogeneity</i>			
Estimate: Elasticity (ref. semi-elasticity)			-0.169*** (0.045)
Estimate: Other (ref. semi-elasticity)			1.098*** (0.089)
Approach: Mixture (ref. national skill-cell)	-0.201*** (0.006)	0.020*** (0.006)	0.057* (0.035)
Approach: Pure spatial (ref. national skill-cell)	0.012 (0.015)	0.065*** (0.015)	-0.140*** (0.054)
Approach: Other (ref. national skill-cell)	-0.205*** (0.005)	0.031*** (0.005)	0.140*** (0.030)
Covariates	0.014*** (0.002)	-0.005*** (0.002)	0.137*** (0.023)
Cross-sectional data	-0.190*** (0.006)	0.004 (0.006)	-0.018 (0.051)
Residual wage	-0.022*** (0.008)	0.017** (0.008)	-0.066** (0.029)
Estimator: IV-2SLS (ref. OLS)	-0.005*** (0.000)	-0.001*** (0.000)	-0.032* (0.018)
Estimator: Other (ref. OLS)	-0.360*** (0.011)	-0.025** (0.011)	-0.670*** (0.122)
Estimates	1,732	1,732	2,712
Studies	63	63	86
Model	FE	FE	RE
Publication year dummies	yes	yes	yes
Between-study variance			0.108

Note: This table presents the results of meta-regressions. Results are obtained with a fixed-effects model in columns (1) and (2) and with a random-effects model in column (3). The dependent variable is the (converted) wage semi-elasticity in column (1), the (converted) wage elasticity in column (2), and the estimated wage effect of immigration in column (3). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

Table B.5: Approaches and Relative Effects

	Pure spatial (1)	National skill-cell (2)	Mixture (3)	Relative effects (4)
<i>Quality of the study and estimate</i>				
Leading academic journal	-0.197*** (0.073)	-0.031 (0.058)	-0.367*** (0.056)	0.024* (0.013)
Theoretical model	-1.077*** (0.079)	-0.500*** (0.038)	-0.150*** (0.008)	-0.125*** (0.008)
Estimate S.E.	-0.520*** (0.108)	0.614*** (0.072)	-0.829*** (0.088)	-0.435*** (0.045)
<i>Context heterogeneity</i>				
Anglo-Saxon country	-0.975*** (0.079)	-0.412*** (0.023)	0.214*** (0.041)	-0.062*** (0.010)
Developing country	-1.401*** (0.324)	-0.381** (0.149)	0.408*** (0.120)	0.229*** (0.017)
Sample mid-year: 1973-2007 (ref. before 1973)	-0.149* (0.078)	-0.454*** (0.058)	-0.787*** (0.061)	-0.020 (0.018)
Sample mid-year: After 2007 (ref. before 1973)		0.065 (0.079)		0.290*** (0.038)
<i>Method heterogeneity</i>				
Cross-sectional data	-0.009 (0.006)	0.007 (0.005)	-0.055 (0.067)	-0.004** (0.002)
Residual wage	-0.070 (0.078)	0.100*** (0.008)	-0.174*** (0.028)	0.068*** (0.007)
Estimator: IV-2SLS (ref. OLS)	-0.010 (0.011)	-0.000 (0.002)	-0.009*** (0.000)	-0.009*** (0.000)
Estimates	189	540	371	911
Studies	7	27	20	38
Model	FE	FE	FE	FE
Publication year dummies	yes	yes	yes	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. The dependent variable is the estimated wage effect of immigration. We use estimates obtained from pure spatial approaches in column (1), national skill-cell approaches in column (2), and mixture approaches in column (3). We use a subsample of relative effects in column (4), i.e. estimates obtained from national skill-cell and mixture approaches. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

Table B.6: Formatting of the Variables of Interest and Gender

	Entire sample	Natives only	Males	Females
	(1)	(2)	(3)	(4)
<i>Quality of the study and estimate</i>				
Leading academic journal	0.083*** (0.003)	0.068*** (0.004)	0.084*** (0.030)	-7.619*** (1.508)
Theoretical model	-0.086*** (0.003)	-0.072*** (0.003)	-0.087*** (0.029)	7.619*** (1.509)
Estimate S.E.	-0.625*** (0.026)	-0.710*** (0.027)	-0.145*** (0.053)	-0.964*** (0.113)
<i>Context heterogeneity</i>				
Anglo-Saxon country	-0.015*** (0.005)	-0.012*** (0.005)	-0.492*** (0.041)	4.707*** (0.639)
Developing country	0.124*** (0.006)	0.113*** (0.006)	0.248*** (0.050)	4.019*** (0.550)
Sample mid-year: 1973-2007 (ref. before 1973)	-0.176*** (0.011)	-0.175*** (0.011)	-0.647*** (0.033)	-0.752*** (0.122)
Sample mid-year: After 2007 (ref. before 1973)	-0.251*** (0.011)	-0.253*** (0.011)	-0.042 (0.062)	-0.847* (0.481)
<i>Method heterogeneity</i>				
Estimate: Elasticity (ref. semi-elasticity)	-0.019*** (0.003)	-0.027*** (0.003)	0.092*** (0.022)	19.134*** (3.589)
Estimate: Other (ref. semi-elasticity)	0.589*** (0.040)	0.520*** (0.041)	0.688*** (0.221)	
Approach: Mixture (ref. national skill-cell)	-0.016*** (0.004)	-0.019*** (0.004)	0.153*** (0.015)	0.247 (0.464)
Approach: Pure spatial (ref. national skill-cell)	-0.042*** (0.009)	-0.052*** (0.010)	0.153*** (0.033)	5.515*** (0.904)
Approach: Other (ref. national skill-cell)	0.024*** (0.004)	0.022*** (0.004)	0.186*** (0.015)	0.307 (0.464)
Covariates	0.007*** (0.001)	0.007*** (0.001)	0.003 (0.003)	-0.034*** (0.007)
Cross-sectional data	-0.029*** (0.003)	-0.028*** (0.003)	1.300*** (0.150)	-0.033*** (0.011)
Residual wage	-0.142*** (0.003)	-0.143*** (0.003)	-0.104*** (0.020)	-0.030 (0.239)
Estimator: IV-2SLS (ref. OLS)	-0.007*** (0.000)	-0.007*** (0.000)	-0.000 (0.001)	-0.003 (0.004)
Estimator: Other (ref. OLS)	-0.157*** (0.013)	-0.151*** (0.013)		
<i>Formatting of the variables</i>				
Wage var. freq.: Weekly (ref. hourly)	0.110*** (0.005)	0.112*** (0.005)	0.430*** (0.040)	-3.457*** (1.002)
Wage var. freq.: Monthly (ref. hourly)	0.179*** (0.007)	0.175*** (0.007)	0.238*** (0.024)	3.815*** (0.356)
Wage var. freq.: Yearly (ref. hourly)	0.067*** (0.004)	0.066*** (0.004)	0.156*** (0.047)	-3.409*** (1.001)
Wage var. freq.: Other (ref. hourly)	0.116*** (0.004)	0.102*** (0.004)	0.110*** (0.019)	0.136 (0.465)
Immig. var. format: Rate (ref. share)	-0.043*** (0.005)	-0.068*** (0.006)	0.091*** (0.013)	-6.990*** (1.503)
Immig. var. format: Level (ref. share)	0.009*** (0.002)	0.007*** (0.002)	-0.002 (0.002)	-0.022 (0.547)
Immig. var. def: Citizenship (ref. birth)	0.008*** (0.002)	0.003 (0.002)	0.015*** (0.004)	0.037*** (0.008)
Immig. var. def: Other (ref. birth)	-0.011*** (0.004)	-0.010** (0.004)	-0.204*** (0.060)	-0.604* (0.350)
Estimates	2,712	2,601	1,002	326
Studies	86	83	48	25
Model	FE	FE	FE	FE
Publication year dummies	yes	yes	yes	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. The dependent variable is the estimated wage effect of immigration. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

Table B.7: Displacement and Heterogeneity Across Countries

	Displacement	Anglo-Saxon countries	The U.S.	Developing countries	Sectoral composition
	(1)	(2)	(3)	(4)	(5)
<i>Quality of the study and estimate</i>					
Leading academic journal	0.039*** (0.002)	0.180*** (0.007)	-0.229*** (0.021)	-0.491*** (0.134)	0.415*** (0.010)
Theoretical model	-0.063*** (0.002)	-0.180*** (0.007)	0.277*** (0.020)	0.728*** (0.040)	-0.089*** (0.009)
Estimate S.E.	-0.509*** (0.024)	-0.068* (0.038)	-0.569*** (0.048)	-0.908*** (0.110)	-0.743*** (0.040)
Displacement effects	-0.007** (0.003)				
<i>Context heterogeneity</i>					
Anglo-Saxon country	0.015*** (0.003)				0.138*** (0.005)
Developing country	0.140*** (0.004)				0.014 (0.009)
Sample mid-year: 1973-2007 (ref. before 1973)	-0.175*** (0.010)	0.084*** (0.015)	-0.634*** (0.049)	0.834*** (0.039)	0.251** (0.122)
Sample mid-year: After 2007 (ref. before 1973)	-0.244*** (0.010)	0.011 (0.015)			0.142 (0.122)
Agricultural sector (%of GDP)					0.050*** (0.002)
Manufacturing sector (%of GDP)					-0.018*** (0.001)
<i>Method heterogeneity</i>					
Estimate: Elasticity (ref. semi-elasticity)	0.011*** (0.003)	-0.216*** (0.010)	0.436*** (0.017)	0.002 (0.004)	-0.050*** (0.004)
Estimate: Other (ref. semi-elasticity)	0.527*** (0.040)	0.339*** (0.042)	0.288*** (0.043)		1.563*** (0.124)
Approach: Mixture (ref. national skill-cell)	-0.051*** (0.003)	0.028*** (0.004)	0.009** (0.005)	-0.748*** (0.040)	-0.037*** (0.010)
Approach: Pure spatial (ref. national skill-cell)	-0.013 (0.008)	-0.373*** (0.025)	-0.635*** (0.042)	-0.916*** (0.329)	0.047 (0.122)
Approach: Other (ref. national skill-cell)	-0.023*** (0.003)	0.081*** (0.005)	0.106*** (0.007)	-0.711*** (0.040)	-0.011 (0.010)
Covariates	0.004*** (0.001)	0.004* (0.002)	0.004 (0.002)	-0.010*** (0.002)	-0.000 (0.002)
Cross-sectional data	-0.042*** (0.003)	0.017*** (0.004)	0.005 (0.004)	-0.015 (0.009)	0.029*** (0.009)
Residual wage	-0.120*** (0.003)	-0.237*** (0.008)	0.115*** (0.012)	-0.111*** (0.008)	-0.227*** (0.006)
Estimator: IV-2SLS (ref. OLS)	-0.007*** (0.000)	-0.008*** (0.000)	-0.008*** (0.000)	-0.007*** (0.001)	-0.009*** (0.000)
Estimator: Other (ref. OLS)	-0.258*** (0.007)	-0.387*** (0.014)	0.211*** (0.024)		
Estimates	2,712	1,494	1,012	279	1,357
Studies	86	49	37	8	43
Model	FE	FE	FE	FE	FE
Publication year dummies	yes	yes	yes	yes	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. The dependent variable is the estimated wage effect of immigration. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

Table B.8: Studies Included in Longhi et al. (2005) and Until/After 2003

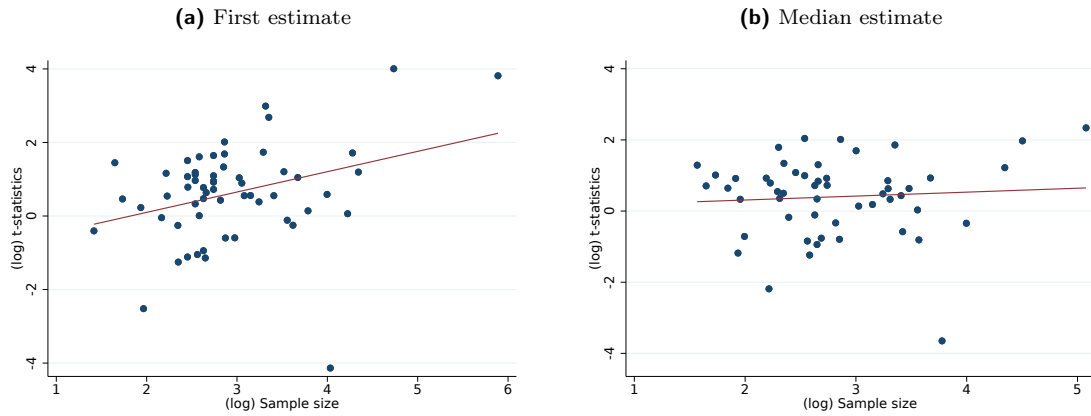
	Longhi et al. (2005)	Until 2003	After 2003
	(1)	(2)	(3)
<i>Quality of the study and estimate</i>			
Leading academic journal	-0.554 (0.345)	1.710** (0.797)	0.029*** (0.004)
Theoretical model	0.240 (0.225)	-2.148*** (0.820)	-0.077*** (0.003)
Estimate S.E.	0.425*** (0.128)	0.295*** (0.094)	-0.607*** (0.026)
<i>Context heterogeneity</i>			
Anglo-Saxon country	0.961*** (0.227)	-0.911** (0.412)	0.004* (0.002)
Developing country			0.135*** (0.004)
Sample mid-year: 1973-2007 (ref. before 1973)		-0.616*** (0.054)	-0.180*** (0.009)
Sample mid-year: After 2007 (ref. before 1973)			-0.253*** (0.009)
<i>Method heterogeneity</i>			
Estimate: Elasticity (ref. semi-elasticity)	0.485** (0.224)	-0.971** (0.412)	0.009*** (0.003)
Estimate: Other (ref. semi-elasticity)		1.173** (0.536)	0.553*** (0.040)
Approach: Mixture (ref. national skill-cell)	0.564*** (0.070)	0.540*** (0.068)	-0.045*** (0.003)
Approach: Pure spatial (ref. national skill-cell)	1.204* (0.730)	-0.498 (0.421)	0.016* (0.009)
Approach: Other (ref. national skill-cell)	0.171 (0.143)	0.152 (0.142)	-0.012*** (0.003)
Covariates	0.782* (0.443)	1.187*** (0.407)	0.004** (0.001)
Cross-sectional data	-0.427** (0.177)	-0.007 (0.006)	-0.046*** (0.003)
Residual wage	-0.646** (0.297)	0.796** (0.396)	-0.132*** (0.003)
Estimator: IV-2SLS (ref. OLS)	-0.000 (0.001)	-0.000 (0.001)	-0.008*** (0.000)
Estimator: Other (ref. OLS)		-1.625*** (0.536)	-0.256*** (0.007)
Estimates	178	313	2,399
Studies	11	18	68
Model	FE	FE	FE
Publication year dummies	yes	yes	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. The dependent variable is the estimated wage effect of immigration. The sample is limited to the studies used in the meta-analysis of Longhi et al. (2005) in column (1), and it is limited to studies published until/after 2003 in columns (2) and (3), respectively. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

C Extensions: Supplementary Details

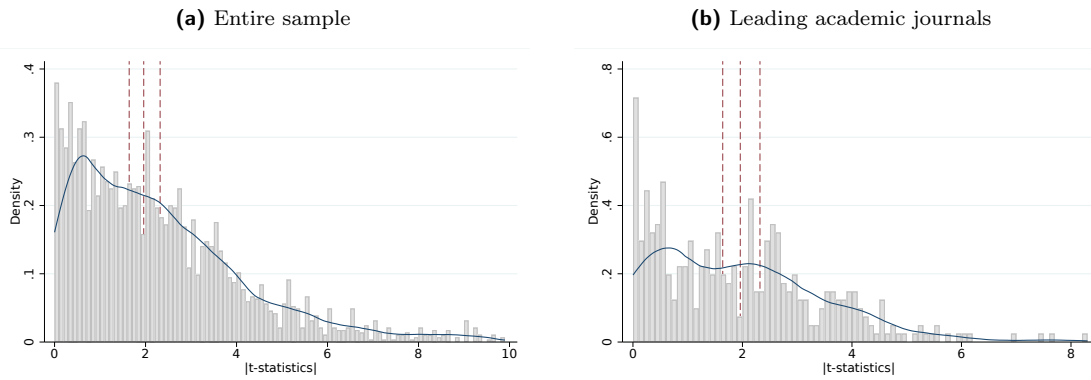
C.1 Supplementary Details on Publication Bias

Figure C.2: Relation of t-Statistics to Sample Size



Note: These figures show the relationship between the significance of the estimates, captured by the associated t-statistics, and the sample size. Figure C.2(a) has been produced using the first estimate reported in each study. Figure C.2(b) has been produced using the median estimate of each study.

Figure C.3: Distribution of t-Statistics



Note: These figures show the distribution of t-statistics in absolute values. Figure C.3(a) shows the distribution for the entire sample of estimates, and Figure C.3(b) shows the distribution for the subsample of estimates reported in leading academic journals.

Table C.9: Publication Bias - Additional Controls

	Entire sample		Baseline estimates	
	(1)	(2)	(3)	(4)
<i>Quality of the study and estimate</i>				
Leading academic journal	0.046*** (0.003)	0.046*** (0.003)	0.046*** (0.003)	-0.078*** (0.018)
Theoretical model	-0.066*** (0.002)	-0.073*** (0.002)	-0.075*** (0.002)	-0.105*** (0.014)
Estimate S.E.	-0.541*** (0.025)	-0.547*** (0.025)	-0.539*** (0.025)	-0.721*** (0.119)
(log) Nr of estimates	0.015*** (0.002)	0.020*** (0.002)	0.019*** (0.002)	
Large dataset (at least 10,000 obs.)		0.007*** (0.000)	0.007*** (0.000)	
Individual-level data		0.059*** (0.004)	0.064*** (0.005)	
Cell-level analysis		0.072*** (0.005)	0.078*** (0.005)	
Nr of authors			-0.006*** (0.002)	
<i>Context heterogeneity</i>				
Anglo-Saxon country	0.018*** (0.002)	0.062*** (0.004)	0.059*** (0.004)	0.017 (0.011)
Developing country	0.142*** (0.004)	0.180*** (0.005)	0.178*** (0.005)	0.107*** (0.025)
Sample mid-year: 1973-2007 (ref. before 1973)	-0.202*** (0.009)	-0.195*** (0.009)	-0.191*** (0.009)	-0.104*** (0.028)
Sample mid-year: After 2007 (ref. before 1973)	-0.268*** (0.009)	-0.314*** (0.010)	-0.314*** (0.010)	-0.188*** (0.054)
<i>Method heterogeneity</i>				
Estimate: Elasticity (ref. semi-elasticity)	0.024*** (0.003)	0.037*** (0.003)	0.038*** (0.003)	-0.294*** (0.015)
Estimate: Other (ref. semi-elasticity)	0.552*** (0.040)	0.570*** (0.040)	0.574*** (0.040)	0.779*** (0.143)
Approach: Mixture (ref. national skill-cell)	-0.061*** (0.003)	-0.086*** (0.004)	-0.084*** (0.004)	-0.009 (0.012)
Approach: Pure spatial (ref. national skill-cell)	-0.042*** (0.009)	-0.024*** (0.009)	-0.023** (0.009)	-0.187*** (0.058)
Approach: Other (ref. national skill-cell)	-0.035*** (0.003)	-0.066*** (0.004)	-0.066*** (0.004)	0.057*** (0.013)
Covariates	0.005*** (0.001)	0.007*** (0.001)	0.008*** (0.001)	-0.040*** (0.006)
Cross-sectional data	-0.032*** (0.003)	-0.036*** (0.003)	-0.039*** (0.003)	-0.244*** (0.021)
Residual wage	-0.138*** (0.003)	-0.132*** (0.003)	-0.136*** (0.003)	-0.392*** (0.021)
Estimator: IV-2SLS (ref. OLS)	-0.007*** (0.000)	-0.008*** (0.000)	-0.008*** (0.000)	0.053*** (0.010)
Estimator: Other (ref. OLS)	-0.252*** (0.007)	-0.230*** (0.007)	-0.233*** (0.007)	-1.056*** (0.045)
Estimates	2,712	2,712	2,712	199
Studies	86	86	86	83
Model	FE	FE	FE	FE
Publication year dummies	yes	yes	yes	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. The dependent variable is the estimated wage effect of immigration. The sample is limited to baseline estimates in column (4). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

Table C.10: Publication Bias - Subsamples

	Leading journals (1)	Leading journals excl. (2)	Working papers (3)
<i>Quality of the study and estimate</i>			
Theoretical model	0.143** (0.072)	-0.088*** (0.004)	-0.239*** (0.007)
Estimate S.E.	-0.619*** (0.079)	-0.370*** (0.028)	-0.738*** (0.058)
<i>Context heterogeneity</i>			
Anglo-Saxon country	0.125** (0.061)	0.010*** (0.003)	5.866*** (0.692)
Developing country	0.334** (0.164)	0.165*** (0.005)	0.243*** (0.036)
Sample mid-year: 1973-2007 (ref. before 1973)	0.090 (0.072)	-0.733*** (0.048)	-0.286*** (0.088)
Sample mid-year: After 2007 (ref. before 1973)		-0.810*** (0.048)	-0.355*** (0.088)
<i>Method heterogeneity</i>			
Estimate: Elasticity (ref. semi-elasticity)	-0.702*** (0.161)	0.001 (0.003)	-0.002 (0.004)
Estimate: Other (ref. semi-elasticity)		0.493*** (0.040)	-0.124 (0.528)
Approach: Mixture (ref. national skill-cell)	0.283*** (0.043)	-0.059*** (0.003)	-0.032 (0.026)
Approach: Pure spatial (ref. national skill-cell)	0.607*** (0.146)	-0.308*** (0.024)	0.102*** (0.039)
Approach: Other (ref. national skill-cell)	0.279*** (0.044)	-0.018*** (0.004)	0.005 (0.026)
Covariates	-0.018 (0.033)	0.005*** (0.001)	0.000 (0.002)
Cross-sectional data	-0.009 (0.006)	-0.053*** (0.003)	0.003 (0.005)
Residual wage	0.020 (0.030)	-0.158*** (0.003)	0.015 (0.017)
Estimator: IV-2SLS (ref. OLS)	0.015*** (0.005)	-0.007*** (0.000)	-0.009*** (0.000)
Estimator: Other (ref. OLS)		-0.279*** (0.008)	-5.861*** (0.438)
Estimates	411	2301	894
Studies	18	68	20
Model	FE	FE	FE
Publication year dummies	yes	yes	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. The dependent variable is the estimated wage effect of immigration. The sample is limited to leading academic journals in column (1), while it excludes them in column (2). The sample includes only working papers in column (3). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.

C.2 Supplementary Details on Causal Inference

Table C.11: Shift-Share Instrumental Variables and (Quasi-)Natural Experiments

	Shift-share IVs		(Quasi-) natural experiments
	(1)	(2)	(3)
<i>Quality of the study and estimate</i>			
Leading academic journal	0.038*** (0.002)	0.037*** (0.002)	0.020*** (0.003)
Theoretical model	-0.063*** (0.002)	-0.063*** (0.002)	-0.053*** (0.002)
Estimate S.E.	-0.517*** (0.024)	-0.521*** (0.024)	-0.527*** (0.024)
(Quasi) natural experiment			0.067*** (0.004)
<i>Context heterogeneity</i>			
Anglo-Saxon country	0.012*** (0.002)	0.012*** (0.002)	0.016*** (0.002)
Developing country	0.135*** (0.004)	0.134*** (0.004)	0.123*** (0.004)
Sample mid-year: 1973-2007 (ref. before 1973)	-0.189*** (0.009)	-0.189*** (0.009)	-0.246*** (0.010)
Sample mid-year: After 2007 (ref. before 1973)	-0.255*** (0.009)	-0.255*** (0.009)	-0.311*** (0.010)
<i>Method heterogeneity</i>			
Estimate: Elasticity (ref. semi-elasticity)	0.010*** (0.002)	0.010*** (0.002)	0.003 (0.003)
Estimate: Other (ref. semi-elasticity)	0.530*** (0.040)	0.522*** (0.040)	0.537*** (0.040)
Approach: Mixture (ref. national skill-cell)	-0.046*** (0.003)	-0.046*** (0.003)	-0.063*** (0.003)
Approach: Pure spatial (ref. national skill-cell)	-0.019** (0.008)	-0.019** (0.008)	-0.098*** (0.010)
Approach: Other (ref. national skill-cell)	-0.020*** (0.003)	-0.020*** (0.003)	-0.041*** (0.003)
Covariates	0.005*** (0.001)	0.005*** (0.001)	0.010*** (0.001)
Cross-sectional data	-0.042*** (0.003)	-0.041*** (0.003)	-0.050*** (0.003)
Residual wage	-0.123*** (0.003)	-0.123*** (0.003)	-0.119*** (0.003)
Estimator: IV-2SLS (ref. OLS)	-0.001** (0.000)	-0.001** (0.000)	-0.007*** (0.000)
Estimator: Other (ref. OLS)	-0.252*** (0.007)	-0.252*** (0.007)	-0.275*** (0.007)
Shift-share IV (for IV-2SLS)	-0.007*** (0.001)	0.003 (0.005)	
Shift-share IV discussed (for IV-2SLS)		-0.010** (0.005)	
Estimates	2,712	2,712	2,712
Studies	86	86	86
Model	FE	FE	FE
Publication year dummies	yes	yes	yes

Note: This table presents the results of meta-regressions obtained with a fixed-effects model. The dependent variable is the estimated wage effect of immigration. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors are reported in parentheses.