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Abstract: The impact of immigration on native workers' wages has been a topic of long-standing debate. This meta-analysis reviews 42 studies published between 1987 to 2019, offering a comprehensive assessment of reduced-form estimates of the wage effect of immigration. The results confirm that immigration has a negligible effect on native wages. However, a more pronounced wage impact is observable for the U.S. and in recent years. Our analysis underscores the influence of methodological advances and increased data availability in shaping wage effect estimates. Results also highlight the role of the estimator (OLS vs. IV-2SLS, as well as the use of shift-share instruments) in determining the sign and magnitude of the estimated wage effect.

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

JEL Classification: C80, J61, J15, J31

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1 Introduction

The question of whether immigration should be restricted and the implementation of such restrictions has been a focal point of debate among policymakers in high-income countries since the mid-1970s. Central to this debate is the economic impact of immigration on natives, particularly concerning employment and wages (Goldin et al., 2011). Extensive research in the field of labour economics has contributed significantly to this debate by investigating the wage effects of immigration. The empirical literature has yielded mixed and, at times, contradictory results. Some studies conclude that immigration adversely affects native wages, while others report either positive or neutral impacts (Dustmann et al., 2016).

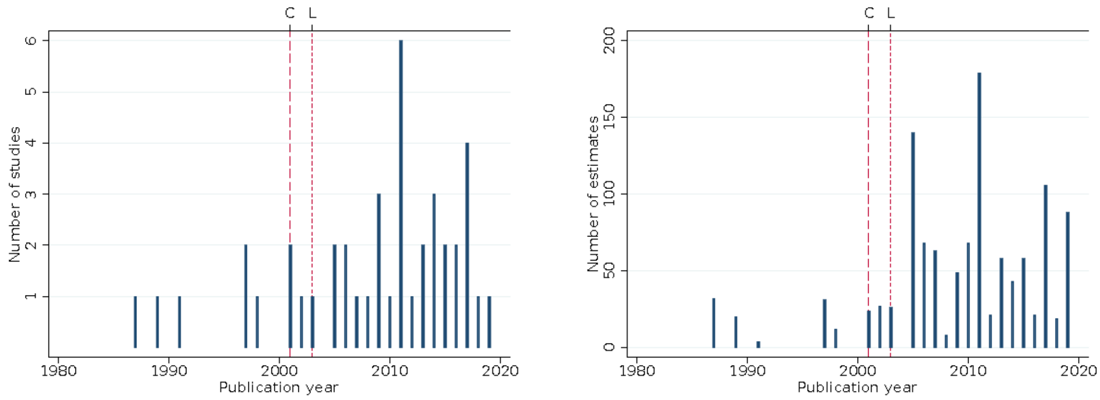
Current consensus generally agrees on a small effect of immigration on native wages. Blau and Kahn (2015), in their survey on immigration and income, conclude that "most research does not find quantitatively important effects of immigration on native wage levels or the wage distribution." Further insights into the U.S. context can be found in Blau and Mackie (2017), and into the European context in Kerr and Kerr (2011). 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% increase in the immigrant labour force leads to a 0.006% decrease in native wages. However, this average statistic hides significant heterogeneity across individual studies. Similar results have been proposed by Longhi et al. (2010) using a set of seven studies.

We complement the literature with a comprehensive meta-analysis that encompasses recent studies, providing an updated understanding of 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 shift-share instrument, first introduced in the seminal work by Card (2001). Our sample includes 42 studies published between 1987 and 2019, collectively reporting 1,165 reduced-form estimates of the wage effect of immigration. This extensive sample enables not only to reflect on these methodological advances but also to 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. A vertical dashed line (labelled "C") corresponds to the year of publication of David Card's article in which he used a shift-share instrument for the immigration shock (Card, 2001a). 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, a vertical dotted line (denoted "L") marks the year 2003, representing the last sample year of the meta-analysis by Longhi et al. (2005). This demarcation underscores that the majority of studies in this field has been produced in the past two decades and thus were not included in Longhi et al. (2005). Our research sample encompasses studies conducted after 2003, enabling us to re-assess the average wage effect of immigration.

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

(a) Number of Studies (b) Number of Estimates



Note: This figure shows the scholar production of reduced-form estimates of the wage effect of immigration over time. Our sample includes 42 studies published between 1987 and 2019, collectively reporting 1,165 reduced- form estimates of the wage effect of immigration. Figure 1a shows the number of studies and Figure 1b shows the number of estimates (semi-elasticities and elasticities) over time. The vertical dashed line (“C”) marks the publication year of Card (2001). The vertical dotted line (“D”) marks the year 2003 which is the last sample year of the meta-analysis by Longhi et al. (2005).

Context and methodological heterogeneity are 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 samples used to generate estimates, such as the countries or time 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 the structural characteristics of individual countries’ labour markets (e.g., see Ortega and Verdugo, 2014, for a discussion of the French context).

Second, variations in wage effect estimates among studies could be attributed to differences in empirical methodologies employed by researchers. Dustmann et al. (2016) identify three distinct types of reduced-form models. These models include *the pure spatial approach*, which evaluates the impact of immigration on native wages across various regions, *the national skill-cell approach*, which focuses on estimating the impact within specific skill, education, and occupation cells at the national level, and *the mixed approach*, which takes into account both regions and skill cells. The latter two models are more easily comparable as they hinge on a similar rationale concerning skill cells. Nonetheless, Dustmann et al. (2016) observe the outcomes of these two approaches may differ widely due to differences in the assumptions made about (i) the homogeneity of the native wage elasticity with respect to immigration across the skill distribution, and (ii) the degree of competition between natives and immigrants within defined skill cells. An earlier survey of the literature on this research question with a methodological focus can be found in Okkerse (2008).

In our study, we conduct a state-of-the-art meta-analysis following the methodology of Stanley et al. (2013). Our objective is to uncover the sources of heterogeneity in wage effect estimates of immigration within the existing literature. We examine a broad range of econometric estimates from diverse sources to pinpoint specific 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 findings[1].

Our sample includes 1,165 estimates of the wage effect of immigration. These estimates are either elasticities or semi-elasticities (also referred to as *effect size* since the work of Longhi et al., 2005). First, our findings obtained with the sample of elasticities are consistent with the conclusions of the existing literature. The impact of immigration on native wages, if it exists, is relatively small and negative. Our benchmark meta-regression yields an insignificant elasticity of –0.005, with a standard deviation equal to 0.022. Using our sample of semi-elasticities, we find an insignificant semi-elasticity of –0.025, with a standard deviation equal to 0.330. For comparison, Longhi et al. (2005) found a semi-elasticity of –0.119 with a standard deviation of 1.028.

Second, our benchmark meta-regressions show that not only the quality of a study influences the estimates, but also both context heterogeneity and methodological heterogeneity do. Leading academic journals report significantly smaller estimates. Our regressions indicate that study period and the country analysed, play significant roles. Particularly, post-1973 study periods and samples focused on the U.S. yield significantly different estimates. Panel data produce larger and more negative estimates. In addition, the selected estimators and the use of individual-level data are relevant primarily when we examine sub-samples of significant estimates, estimates from non-leading academic journals, and IV-2SLS estimates.

Besides, we investigate the presence of publication bias and find no evidence of its existence. We also show that studies using an IV-2SLS estimator and employing a shift-share instrument tend to yield smaller and more negative estimates compared to those using other types of instruments.

We contribute to the literature in several aspects. Firstly, we employ a comprehensive, state-of-the-art meta-analysis methodology (Havránek et al., 2020; Stanley et al., 2013). While the results obtained with our expanded sample are consistent with main conclusions of Longhi et al. (2005), we find a smaller (closer to zero) impact of immigration on native wages. Notably, unlike this earlier meta-analysis, we evidence that the average wage effect is not statistically significant. Secondly, our sample incorporates many recent studies, allowing us to explore contemporary data characteristics and methodologies as determinants of the estimated wage effect. Recent contributions to the field often use disaggregated data, such as individual-level data from administrative sources, spanning long time 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). Importantly, our sample includes estimates from these recent studies, allowing us to determine to what extent methodological choices contribute to the observed variance and accuracy in the estimates.

This meta-analysis has two primary implications for future research. Firstly, we show that context heterogeneity plays a role in the estimation of the wage effect of immigration. This finding underscores the necessity of replication studies focusing on a variety of case studies to ensure external validity.

[1] Notable 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.

Secondly, we show that methodological 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 (Goldin et al., 2011), 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 and provide a meta-estimate of the wage effect of immigration. 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 Blau and Kahn, 2015; Dustmann et al., 2016). These studies typically relate labour market outcomes to changes in immigration as follows:

$$\ln w_{ct} = \beta \ln M_{ct} + \Gamma A'_{ct} + FE + \varepsilon_{ct} \tag{1}$$

In this equation, M_{ct} denotes the immigration stock (or flow) 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. These fixed effects typically consist in time and skill-cell fixed effects, although additional fixed effects may be included to account for worker characteristics such as their age, geographical location, or sector of employment.

The coefficient of interest, β, represents the elasticity 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 ($\beta < 0$) when natives and immigrants are close substitutes within a cell *c*. Conversely, when they act as complements, the wage effect might be positive. The value of β could also be null if other factors were to play a significant role in influencing the outcome.

The degree of competition between native and immigrant workers depends on the definition of the cell. Different levels of cell aggregation yield varying wage elasticities. In the national skill-cell approach, *c* denotes to the skill level of the workers. Consequently, β captures the relative impact of immigration on native wages within specific skill groups at the national level. In the mixed approach, the cell combines both the skill level and the geographic location of the workers. The pure spatial approach omits the skill dimension, diverting discussions on the complementarity between immigrants and natives. This is the reason we exclude estimates derived from pure spatial approaches.

A number of 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, neither w_{ct} nor M_{ct} are log-transformed, causing β to become a point estimate. In our analysis, we concentrate exclusively on elasticities and semi-elasticities, given that only a few studies report point estimates. Importantly, point estimates cannot be converted into relative effects, making them unsuitable for comparative analysis.

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 mid-2000s, the main method to infer causality in a reduced-form specification has been to use an Instrumental Variable (IV)-2SLS setting, typically a shift-share instrument, as originally proposed by Card (2001) in the field.

Our analysis excludes studies calibrating structural models of the labour market, like Ottaviano and Peri (2012). 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 as well as the degree of complementarity between natives and immigrants. In contrast, estimations of reduced-form models allow a more agnostic stance regarding these aspects. In addition, the analytical statistic employed to evaluate predictions from structural models differ from those used for assessing the quality of estimates from reduced-form models, making direct comparisons difficult.

We further omit studies leveraging natural experiments that harness exogenous sources of immigration, like the Mariel boatlift episode (see Card, 1990). Natural experiments rely on difference-in-differences (DiD) methods, capturing the immigration shock through the interaction of a treatment and a time dummy variable. In contrast, reduced-form estimations use a direct measure of immigration. As a result, estimates of the wage effect of immigration obtained from a DiD design are not comparable to wage elasticities. To include such a study into our analysis, one would need to determine the magnitude of the supply shock (the treatment) to convert the DiD coefficient into a wage elasticity. However, the magnitude of the supply shock is often not reported in studies using natural experiment designs.

3 Data and Empirical Strategy

We adopt a two-stage state-of-the-art methodology (Havránek et al., 2020; Stanley et al., 2013). In the first stage, we detail the collection of the estimates of interest. Then, we analyse the distribution of collected estimates. We show sampling errors account for only a small portion of the variation in the estimates. This highlights the need to investigate other sources of heterogeneity using meta-regressions. In the second stage, we perform meta-regressions to pinpoint the regularities observed in empirical studies.

3.1. Data Collection

We collected a set of empirical studies estimating a direct wage effect of immigration. The methodology for selecting the studies is detailed in Appendix A. We performed a systematic search for English-language studies using the EconLit search engine, focusing on journal articles, working papers, books, and collective volumes. We targeted studies with titles containing a combination of two keywords, such as *immigration* and *native*.[2] Altogether, we employed 47 keyword combinations. Our sample includes papers listed in EconLit up to May 15, 2019.

Then, we assessed the representativeness of our sample with respect to the existing literature. 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)[3]. In line with the principles of systematic and automated search, we abstained from adding any other studies to our sample (Havránek et al., 2020; Stanley et al., 2013).[4]

We refine our sample to include only those studies that estimate a reduced-form model, specifically those using a national skill-cell approach or a mixed approach. From each study, we identified all regressions yielding estimates of the wage effect of immigration, together with the associated standard errors. Whenever possible, we collected information on the magnitude of the immigration shock, as well as the p-value, t-statistic, and R^2. We also collected information on the study itself (such as publication year and number of authors), the sample (for instance, the country under study and the time period), and the estimation techniques (like the estimator and the set of fixed effects). Our dataset includes 1,165 estimates from 42 studies.

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, those originally reported as semi-elasticities were converted into elasticities. This conversion enables a uniform comparison of estimates. Our dataset contains 716 elasticities and 1,031 semi-elasticities after conversion. Our benchmark analysis is conducted on the sample of elasticities, because these coefficients are comparable across studies. This comparability stems from the normalisation of the immigration shock, a normalisation not provided by semi-elasticities.

3.2. Data Analysis

Descriptive statistics are presented in Appendix A. Our sample includes studies published from 1987 to 2019. 19% 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 14 countries, as well as data from groups of countries such as the OECD. The U.S. labour market is the focus of 30% of the estimates. Other countries analysed include Australia, Canada, Costa Rica, Denmark, France, Germany, Ireland, Israel, Norway, South Africa, Spain, the Netherlands, and the United Kingdom. 16% of the estimates were derived

[2] In line with Longhi et al. (2005) and Disdier and Head (2008), we favoured keyword searches over JEL classification codes, as these codes have changed over time. Additionally, not all studies, especially books and collective volumes, include JEL codes.

[3] We excluded studies adopting natural experiment and structural approaches. See section A for more details on the sample.

[4] We intentionally left out studies added to EconLit after May 15, 2019, and did not incorporate subsequent publications of working papers already present in our sample.

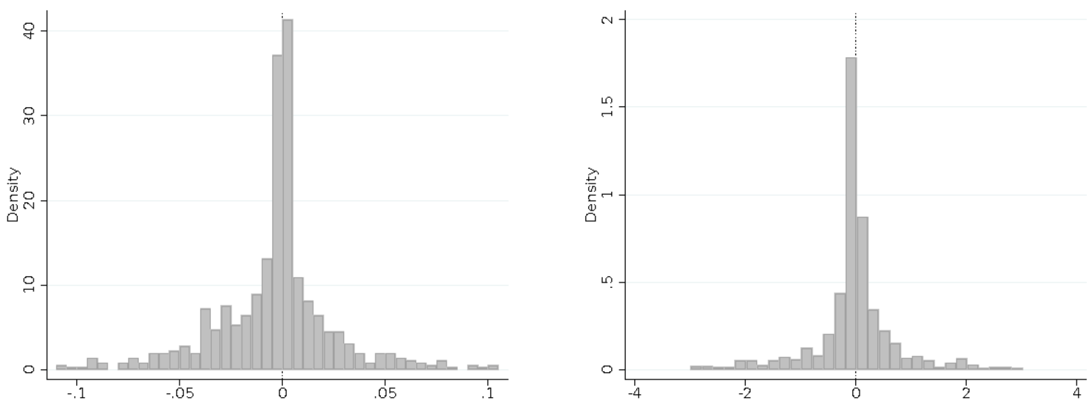
from panel data, 35.5% used an IV-2SLS estimator in contrast to OLS, 8.8% employed a shift-share instrument à la Card (2001), and 19.7% leverage individual-level data, which aligns with the recent surge of administrative data.

Figure 2 shows the distribution of estimates. Panel (a) depicts the distribution of elasticities. A notable characteristic of the sample is the small magnitude of the estimates, predominantly centred around zero. The average wage elasticity is −0.004, with a range from –0.110 to 0.104 (see Appendix A, Table A.1). This suggests that a 1% surge in the immigrant labour force corresponds, on average, to a 0.004% decline in native wages. Panel (b) displays the distribution of semi-elasticities. The mean effect of immigration on native wages stands at −0.025, with values ranging from −2.981 to 2.900. These statistics are in line with the findings presented by Longhi et al. (2005).

Figure 2: Density of the Estimates

(a) Elasticities

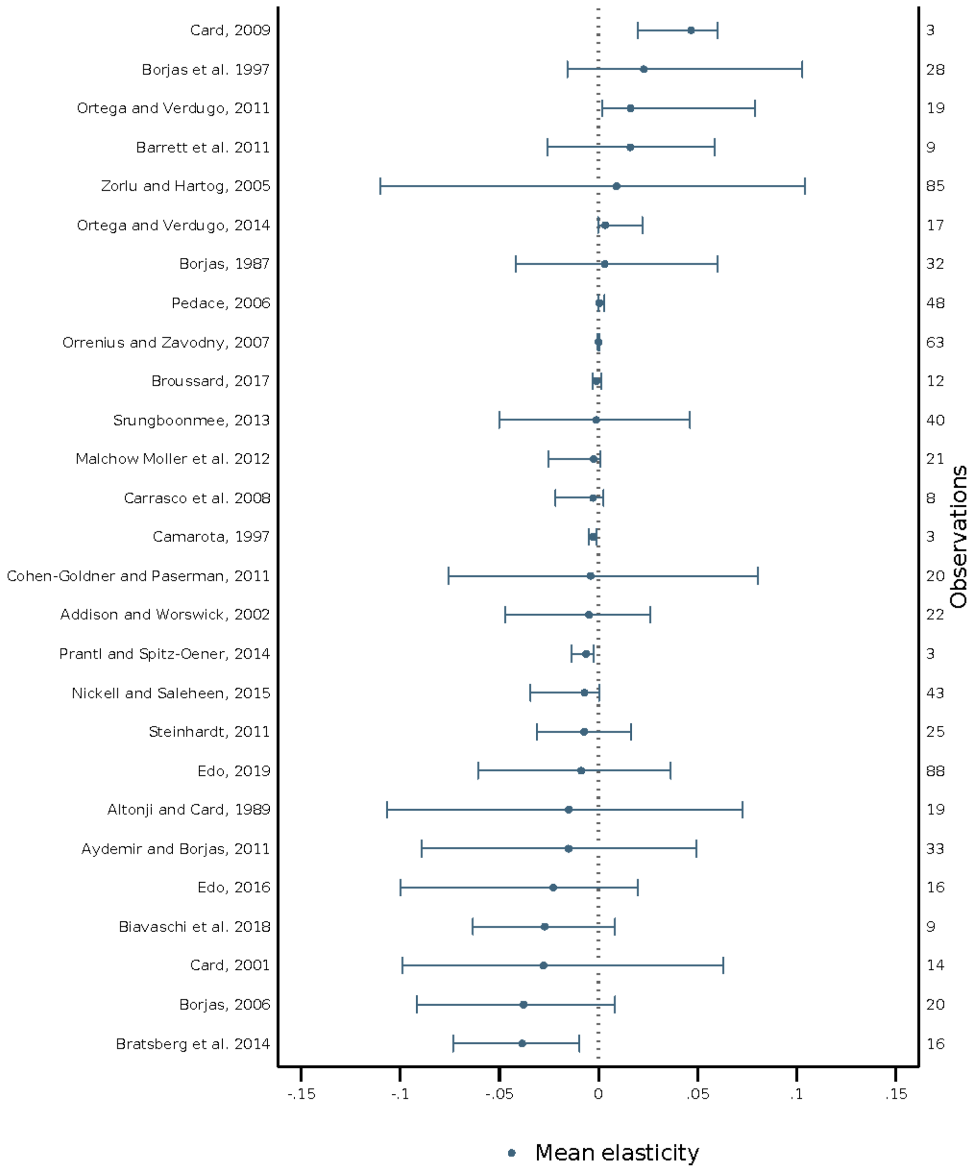
(b) Semi-Elasticities



Note: Densities of elasticities and semi-elasticities are presented in Figures 2a and 2b respectively. The dotted line on the vertical axis indicates a value of zero for the estimate. Both samples indicate that estimates are predominantly concentrated around zero.

In Figure 3, we present a forest plot to further examine the between- and within-study variance in elasticities, as elasticities will serve as our benchmark sample. The plot illustrates both the average wage effect of immigration and its corresponding 95% confidence intervals for each study. These intervals are determined either using the standard error of each estimate or by dividing the estimate by its t-statistic. Additionally, Figure 3 shows the number of estimates identified within each study.

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



Note: Forest plot showing the between- and within-study variation of the elasticities. For each study, the figure presents the average estimate along with the minimum and maximum estimates per study. The right axis indicates the number of estimates reported in each study.

3.3. Sampling Errors

The observed variance in the wage effect of immigration, as previously discussed, might result from coefficients estimated using data from differing countries and time periods, or from different methodologies. If all sub-samples were drawn from a population with a unique wage effect of immigration, the deviation of the estimates from the true 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 $z_i = \left(\hat{\beta}_i - \tilde{\beta}\right)/\sigma$, 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, $\hat{\beta}_i/se\left(\hat{\beta}_i\right)$.

Figure C.2 in Appendix A depicts the distribution of observed t-statistics, alongside the Normal distribution serving as a benchmark for the hypothesis of a unique population mean. This figure suggests that the observed t-statistics exhibit greater dispersion than expected from a Normal distribution. Consequently, sampling errors only marginally account for the observed variance in estimates of the wage effect of immigration.

Lastly, we follow Higgins et al. (2003) and compute the I^2 statistic. This metric indicates the fraction of observed variance that does not originate from sampling errors. This statistic amounts to 97%. Therefore, both Figure C.2 and the I^2 statistic underscore the need to investigate other sources of heterogeneity beyond mere sampling errors.

3.4. Empirical Strategy

In our meta-analysis, we investigate two primary sources of heterogeneity: *context* and *methodological* heterogeneity. Context heterogeneity relates to the structural characteristics of the data at hand. It includes factors such as the geographical region, the time period, and the skill-level of both native and immigrant populations. Nonetheless, even when holding context attributes constant (or when analysing identical datasets), choices made in data analysis can have significant effects. Decisions such as leveraging the panel dimension of the data, using individual-level data, or using specific econometric models can influence the direction, magnitude, and statistical significance of the wage effect estimates.

To delve deeper into these sources of heterogeneity, we propose the following benchmark meta-model:

$$\hat{\beta}_{i,s} = \Theta_1 Quality'_s + \Theta_2 Context'_{i,s} + \Theta_3 Method'_{i,s} + \lambda + \varepsilon_{i,s} \tag{2}$$

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

The first vector of variables, $Quality'_s$, controls for the quality of the study. 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 a binary variable equal to one if the study incorporates a theoretical model. The latter variable indicates whether the underlying mechanisms have been thoroughly considered by the authors and whether the empirical analysis is grounded in theoretical foundations. In addition, we control for the standard error of the estimate to account for its level of precision and thereby for the presence of publication bias.

We explore the *context heterogeneity* across studies through a vector of covariates, denoted as $Context'_{i,s}$. It controls for the characteristics of the sample of observations that the authors used to derive the estimate. It includes a binary variable equal to one for the U.S., given the bias of the literature towards this country. Estimates on the U.S. account for 30% of our benchmark sample. This variable may capture some country-specific and structural features, such as the high level of flexibility of the U.S. labour market and the limited worker protection in U.S. legislation. This vector also includes a binary variable set to one when the mid-year of the sample period is after 1973, the year marking the first oil crisis. Additionally, it features another binary variable equal to one when the mid-year of the sample period is after 2007, to account for the sub-prime crisis and its economic consequences.

We explore the *methodological heterogeneity* across studies through a vector denoted as $Method'_{i,s}$. It includes a binary variable equal to one for panel data estimations. Besides, it includes a binary variable equal to one when the authors used disaggregated data at the individual level. This variable controls for the fact that the use of individual-level data can provide better quality estimates and ease causal inference. Finally, it includes a binary variable for the use of an IV-2SLS estimator (as opposed to OLS) to derive the estimate, allowing for the consideration that studies addressing endogeneity tend to yield more causal outcomes. In Appendix A, Table A.2 shows the categorical variables used in the analysis and the corresponding number of observations in each category.

We include a set of year dummies (capturing e.g., the year of publication of the study and the time trend), and standard errors are clustered at the year of publication level to control for correlation and dependence across errors over time.

4 Results

4.1. Benchmark Results

Estimates of the wage effect of immigration. We present the results of the benchmark meta-regressions in Table 1, using the sample of elasticities. In columns (1) to (3), we examine the determinants of the wage effect of immigration across studies. In column (4), we attempt to account for potential publication bias by incorporating the standard error of the estimates into our regressions, in line with the approaches of Card and Krueger (1995) and Longhi et al. (2005).[5] When this variable is missing, we compute an implicit error by dividing the estimate by its t-statistic. Lastly, in column (5), we control for the time trend by incorporating year dummies. Note the R-squared value increases as an additional block of variables and as time dummies are introduced into the analysis.

The main results of Table 1 are the following. The quality of the study, proxied by its publication in a leading academic journal and the backing of a supporting theoretical model, appears to have a negative impact on the estimates across studies. We find no effect of the standard error of the estimates, suggesting an absence of publication bias.

Context heterogeneity helps rationalise the variance of the estimates. The impact of immigration on native wages in the U.S. is significantly different from the one in other countries. In addition, differences across study periods account for a large disparity in the estimated wage effects of immigration across studies. This is true for studies leveraging data after the 1973 oil crisis.

[5] The tests conducted by Card and Krueger (1995) and Longhi et al. (2005) examine the correlation between the estimates and their standard errors. In the presence of publication bias, a disproportionately high number of published t-statistic just above certain significance thresholds would be expected, suggesting a direct proportionality between the estimates and their standard errors.

We also identify heterogeneity in the methodologies. The between-study analysis shows that panel data lead to significantly different estimates than cross-sectional data. However, the use of individual-level data and the econometric model implemented by the authors (IV-2SLS *versus* OLS) do not explain the observed variance in the estimated wage effect of immigration.

Lastly, the estimated average effect of immigration on native wages is negative but insignificant (column 5)[6]. The effect amounts to –0.005, with a standard deviation of 0.022. Our findings corroborate the conclusions from the earlier meta-analysis of Longhi et al. (2005): the effect of immigration on native wages, if existent, is negative and relatively small.

Magnitude, sign and significance of the wage effect. One limitation of our analysis is that our estimates combine both the effect of the magnitude (measured as the absolute value) and the sign of the estimate, since the sample of elasticities ranges from negative to positive values.

We address this limitation in Table 2. Results for the magnitude of the estimate are reported in column (1). In this specification, the dependent variable is the absolute value of the estimate. We find that the quality of the study, captured by its publication in a leading academic journal and the backing of a supporting theoretical model, have a significant impact on the magnitude of the wage effect. High-quality studies report systematically larger coefficients. Additionally, the use of panel data is associated with larger wage effects.

Results for the sign of the estimate obtained from a probit model are reported in column (2). In this specification, the dependent variable is a dummy equal to one if the estimated wage effect is positive and zero otherwise. We do not find any effect of the quality of the study on the sign of the estimate. Nonetheless, estimates for the U.S. are consistently more negative. Periods of study also significantly impact the sign of the wage effect. We find that studies conducted after the crisis of 1973 and 2007 tend to yield negative estimates. Finally, the use of panel data is also associated with negative wage effects.

In columns (3) and (4), we report the results of our benchmark model using two sets of elasticities: those with negative values (reported in absolute terms) and those with positive values. The size of the two sub-samples is not markedly different (364 negative elasticities and 286 positive elasticities). The results again emphasise the significant roles played by the quality of the study and context heterogeneity in influencing the magnitude of the estimates, regardless of whether these estimates are negative or positive. Notably, samples focusing on the U.S. consistently yield smaller estimates, irrespective of their positive or negative sign. As opposed to our benchmark results, the set of negative elasticities shows a significant average effect of –0.020, while the set of positive elasticities indicates a significant average effect of 0.013.

Finally, one limitation of our benchmark analysis is that we aggregate estimates of varying quality. While some estimates may be accurate and relevant, they are averaged with potentially lower-quality estimates. In column (5), we focus on a set of elasticities that are significant at a minimum of the

[6] To compute the ’estimated average effect of immigration, we first predict the effect of immigration on native wages after performing our meta-regression, as detailed in equation 2. We then collect the mean and standard deviation of this predicted effect. Subsequently, we bootstrap the mean of the predicted effect using 50 replications and calculate the associated standard error. The bootstrapped mean of the predicted effect is what we refer to as the ’estimated average effect’ or ’meta-estimate’.

10% level. Doing so, we acknowledge that the magnitude and sign of non- significant coefficients should not be interpreted. At most, these coefficients might be considered indicative of zero effects. Therefore, we exclude these non-significant coefficients from our analysis, reducing our sample to a total of 399 elasticities. We find that reducing the sample does not affect our benchmark findings presented in Table 1.

Results across skill groups. In Table 3, we investigate the heterogeneity of the wage effect of immigration across native workers taking into account the skills of both immigrants and native workers. Scholars have extensively studied the impact of immigration on wages for both groups, yet the debate is primarily centred on the effects of unskilled immigration on the labour market. As emphasised by George Borjas, in the U.S. context, immigrants often share similar characteristics with unskilled U.S. workers, who are likely to be the most affected by an immigration shock in the short term.

In columns (1) and (2), we include an additional categorical variable controlling for the skill level of the immigrant population. While some studies use the education attainment of individuals, others use their occupation to define them as high-skilled, medium-skilled (such as clerks), or low-skilled workers. For the purpose of our meta-analysis, the term 'high-skilled workers' is defined as workers who have attained higher education or hold a white-collar position. This category is defined in relation to other workers, namely the low-medium skilled category that serves as the reference. Additionally, we include a categorical variable controlling for the skill level of the affected native population, again using the low-medium skilled native workers as the reference category. In column (1), the dependent variable is the estimated wage effect of immigration. In column (2), the dependent variable is a dummy equal to 1 if the estimate is positive and zero otherwise. The results suggest that the wage impact of high-skilled immigration is significantly larger and more likely to be positive compared to that of low-skilled immigration. Furthermore, the wage effect on high-skilled native workers is significantly smaller yet more likely to be positive when compared to their low-skilled counterparts. These findings are consistent with the existing literature, which indicates larger substitution effects among unskilled workers.

We restrict our sample to estimates associated with low-skilled native workers in column (3), and to estimates associated with high-skilled native workers in column (4). Although the number of studies is reduced, we find that high-skilled immigration has a significantly different wage effect compared to low-skilled immigration on low-skilled native workers. The coefficient is positive, which is in line with our previous findings.

Table 1: Benchmark Results

	(1)	(2)	(3)	(4)	(5)
Quality of the study and estimate					
Leading academic journal	-0.007	-0.025***	-0.026***	-0.024***	-0.026***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.002)
Theoretical model	-0.010**	-0.014***	-0.014***	-0.015***	-0.022*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.012)
Estimate S.E.				-0.009	-0.004
				(0.005)	(0.003)
Context heterogeneity					
The U.S.		0.004	0.003	0.006	0.012***
		(0.004)	(0.004)	(0.004)	(0.000)
Sample mid-year after 1973		-0.032***	-0.032***	-0.038***	-0.068***
		(0.009)	(0.010)	(0.010)	(0.001)
Sample mid-year after 2007		0.002	0.005	0.006	-0.001
		(0.004)	(0.008)	(0.008)	(0.003)
Method heterogeneity					
Panel data			-0.003	-0.000	-0.029***
			(0.005)	(0.005)	(0.002)
Individual-level data			0.001	0.003	0.014
			(0.006)	(0.005)	(0.012)
IV-2SLS estimator			0.003	0.005	0.006
			(0.005)	(0.004)	(0.005)
Observations	716	716	716	655	655
Studies	27	27	27	27	27
Estimator	OLS	OLS	OLS	OLS	OLS, FE
Year dummies	no	no	no	no	yes
R^2	0.046	0.116	0.119	0.158	0.300
Meta-estimate	-0.004	-0.004	-0.004	-0.005	-0.005
S.E.	0.005	0.005	0.007	0.005	0.004
S.D.	0.006	0.010	0.010	0.011	0.022

Note: This table presents the results of meta-regressions using the sample of elasticities. The dependent variable is the estimated wage effect of immigration. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors, clustered at the publication-year level, are reported in parentheses. For each meta-regression, a meta-estimate is reported with the corresponding bootstrapped standard error as well as the standard deviation.

Table 2: Magnitude and Sign of the Estimates

	Magnitude	Sign (1 if>0)	Negative	Positive	Signif.
	(1)	(2)	(3)	(4)	(5)
Quality of the study and estimate					
Leading academic journal	0.019***	-0.264	0.021***	0.015***	-0.027***
	(0.002)	(0.928)	(0.002)	(0.001)	(0.001)
Theoretical model	0.030**	0.469	0.023	0.014***	-0.016***
	(0.012)	(0.767)	(0.014)	(0.002)	(0.003)
Estimate S.E.	0.005	0.078	0.004	0.004	-0.003
	(0.004)	(0.117)	(0.004)	(0.004)	(0.003)
Context heterogeneity					
The U.S.	-0.013***	-1.614**	-0.016***	-0.005***	0.018***
	(0.000)	(0.754)	(0.001)	(0.001)	(0.000)
Sample mid-year after 1973	-0.033	-1.826***	0.039***	-0.046***	-0.036***
	(0.023)	(0.310)	(0.002)	(0.013)	(0.010)
Sample mid-year after 2007	0.005*	-4.124***	0.006**		
	(0.002)	(0.637)	(0.002)		
Method heterogeneity					
Panel data	0.022***	-9.572***	0.016		-0.007***
	(0.002)	(1.251)	(0.010)		(0.000)
Individual-level data	-0.021	-0.566	-0.013	-0.003*	-0.005*
	(0.012)	(0.761)	(0.014)	(0.002)	(0.002)
IV-2SLS estimator	0.001	0.475	0.004	-0.001	-0.001
	(0.005)	(0.354)	(0.005)	(0.002)	(0.005)
Observations	655	939	364	286	399
Studies	27	35	25	21	25
Estimator	OLS, FE	Probit, FE	OLS, FE	OLS, FE	OLS, FE
Year dummies	yes	yes	yes	yes	yes
R^2	0.394		0.482	0.538	0.216
Meta-estimate			0.020	0.013	-0.005
S.E.			0.004	0.002	0.002
S.D.			0.016	0.027	0.013

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

Table 3: Skills of Immigrants and Native Workers

	Magnitude	Sign (1 if>0)	Unskilled	Skilled
	(1)	(2)	(3)	(4)
Quality of the study and estimate				
Leading academic journal	-0.026***	-0.261		
	(0.002)	(0.827)		
Theoretical model	-0.021*	0.442		
	(0.012)	(0.696)		
Estimate S.E.	-0.004	0.057	0.002	-0.001
	(0.003)	(0.116)	(0.003)	(0.001)
Context heterogeneity				
The U.S.	0.012***	-2.013**		
	(0.000)	(0.824)		
Sample mid-year after 1973	-0.068***	-1.831***	-0.063***	
	(0.001)	(0.310)	(0.003)	
Sample mid-year after 2007	0.001	-4.452***	-0.017	0.005***
	(0.004)	(0.544)	(0.012)	(0.000)
High-skilled immigration (ref.: low-med)	0.008**	1.129***	0.016**	0.014
	(0.003)	(0.248)	(0.006)	(0.009)
All or undefined immigration (ref.: low-med)	-0.000	-0.443	-0.002	0.004
	(0.006)	(0.293)	(0.004)	(0.002)
High-skilled affected native workers (ref.: low-med)	-0.005**	0.284***		
	(0.002)	(0.102)		
All or undefined affected native workers (ref.: low-med)	0.002	-0.413		
	(0.004)	(0.303)		
Method heterogeneity				
Panel data	-0.029***	-10.129***		
	(0.002)	(1.161)		
Individual-level data	0.013	-0.564		
	(0.012)	(0.735)		
IV-2SLS estimator	0.006	0.500	-0.012	-0.000
	(0.005)	(0.350)	(0.012)	(0.000)
Observations	655	939	129	49
Studies	27	35	10	6
Estimator	OLS, FE	Probit, FE	OLS, FE	OLS, FE
Year dummies	yes	yes	yes	yes
R^2	0.303		0.334	0.301
Meta-estimate	-.005		-.004	-.003
S.E.	.004		.007	.004
S.D.	.022		.018	.006

Note: This table presents the results of meta-regressions using the sample of elasticities. In columns (1), (3) and (4), the dependent variable is the estimated wage effect of immigration. In column (2), the dependent variable is a dummy equal to 1 if the estimate is positive and zero otherwise. In column (3), results are obtained using a sub-sample of estimates for unskilled native workers. In column (4), results are obtained using a sub-sample of estimates for skilled native workers. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors, clustered at the publication-year level, are reported in parentheses. For each meta-regression, a meta-estimate is reported with the corresponding bootstrapped standard error as well as the standard deviation.

4.2. Robustness Tests

We present a set of robustness tests in Appendix B. Table B.3 reports results from alternative estimation strategies. Table B.4 presents the results for the benchmark model based on a sample of elasticities. Finally, we compare our results to the meta-analysis conducted by Longhi et al. (2005) in Table B.5.

Alternative estimation strategies. We use two alternative econometric models commonly found in the meta-analysis literature, and we present the results in Table B.3. Columns (1) to (4) present the results obtained using weighted least squares (WLS). It is a common practice in meta-regression analyses to explore the heterogeneity in results across studies by employing a linear regression model estimated with WLS that takes into account the precision and quality of the estimates (e.g., see Longhi et al. (2005)).

Column (1) presents the results obtained from a WLS estimation using weights defined as the inverse of the standard errors of the estimate. This approach increases the weight of more accurate estimations. In column (2), we present the results from a WLS estimation with a composite quality index as the weighting scheme, following the approach of Longhi et al. (2005). The weight for each estimate is defined as the sum of two quality indices. The first index assigns a higher weight (equal to 2) to studies published in leading academic journals and a lower weight (equal to 1) to other studies. The second index assigns a higher value (equal to 2) to estimates produced by sophisticated econometric techniques such as IV-2SLS, and 1 otherwise. By summing these two indices, the quality weight ranges from 2 to 4. Columns (1) and (2) confirm part of our benchmark results. High-quality studies display smaller elasticities. Both context heterogeneity and methodological heterogeneity matter, and we find no evidence that using individual-level data and the type of estimator has an impact on the wage effect of immigration.

Finally, we present the results using a random-effect model in column (3). This specification follows the methodology proposed by Borenstein et al. (2010) and Disdier and Head (2008). In this model, it is assumed that the *true* estimate varies across studies, and the sample of observations is a *random* sample of estimates that could have been observed. The advantage of a random-effect model is its ability to estimate the mean of a distribution of estimates, in which each study matters because it provides unique information about a wage effect of immigration that no other study has estimated. The results confirm our benchmark findings, especially on the quality of the study and the context heterogeneity.

Semi-elasticities versus elasticities. In our benchmark analysis, we use a set of elasticities. Using elasticities allows for easy interpretation due to the normalisation of the immigration shock, and for more straightforward comparison across different studies. However, a large part of the existing literature estimates semi-elasticities. While it is theoretically feasible to convert semi-elasticities into elasticities, many studies do not provide sufficient information on the magnitude of the immigration shock to make this conversion possible. Consequently, we replicate our analysis using a sample of estimates expressed as semi-elasticities. Our sample of semi-elasticities contains 1,031 coefficients.

In Table B.4, we present the results of our analysis using a sample of estimates in the form of elasticities (column 1) and in the form of semi-elasticities (column 2). In these regressions, only observations for which we have both the elasticity and the semi-elasticity are included. First, the results obtained with this smaller set of elasticities, compared to our benchmark sample, are highly consistent with our benchmark findings. Second, we find consistent results across the two sub-samples of elasticities and semi-elasticities. However, the result associated with the use of U.S. data is poorly significant. In column (3), we replicate our analysis on the full set of elasticities, including 1,031 coefficients. Apart from the results pertaining to quality of the study, the findings align with both our baseline results and those derived from the reduced sample of semi-elasticities (presented in column 2).

Comparison with the sample of Longhi et al. (2005). In Table B.5, we further explore the differerences between our sample and the sample used in the meta-analysis of Longhi et al. (2005). Our sample includes 11 of the 18 studies used by Longhi et al. (2005). However, only five of these 11 studies report semi-elasticities along with other variables of interest for our analysis. In column (1), we narrow our analysis to these five studies (comprising 79 estimates) that overlap with the meta-analysis of Longhi et al. (2005). Our aim is to assess whether our results would be significantly affected by restricting our analysis to the studies investigated in this previous meta-analysis. Given the small number of studies included in this sub-sample and the structure of fixed effects we impose, only four variables remain to be studied.

We find that studies focused on the U.S. yield smaller or more negative estimates. This result diverges from our benchmark findings. It also diverges from Longhi et al. (2005) who found that the wage effect of immigration tends to be smaller for European countries compared to the U.S. Then, the use of individual-level data and the use of an IV-2SLS estimator does not have a significant impact on the wage effect, which also fits our benchmark findings.

In this initial meta-analysis of the wage effect of immigration, Longhi et al. (2005) used a sample of studies published until 2003. In column (2), we therefore restrict our sample to studies published until 2003. This sample includes some studies used by Longhi et al. (2005), but not exclusively. Here, the size of the sample reduces to 134 estimates and 9 studies. The between- study analysis confirms that studies published before 2003 on the U.S. yield smaller estimates. It confirms that this result is specific to the period under analysis rather than the specificity of the sample used by Longhi et al. (2005). Nevertheless, the results related to the sample period, the use of panel data, and individual-level data, align with our benchmark results.

5 Extensions

We now present two additional extensions to our analysis. Firstly, we further investigate the presence of publication bias in the data used for our analysis. Secondly, we examine whether employing a shift-share instrumental variable influences the estimated wage effect of immigration. Results are reported in Appendix C and described below.

5.1. Publication Bias

A general concern in meta-analyses is the potential for selective reporting and the publication of significant coefficients, known as publication bias. This bias suggests that the likelihood of a study being published is influenced by the statistical significance of its results. Consequently, the array of published findings might not accurately reflect the entire spectrum of research. Therefore, we undertake an examination of the presence of publication bias within our sample.

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, with the expectation that a lack of positive correlation might signal publication bias.

For this exercise, we restrict our sample to estimates where both the associated sample size and standard error are known. Following the approach used by Card and Krueger (1995), we retain only one estimate per study. We then calculate the t-statistic by dividing the estimate by its standard error and subsequently regress the statistic on the sample size.

Figure C.2a presents the relationship between t-statistics and sample size, using the first estimate reported in each study. We observe a positive correlation between the significance of the first estimates and the sample size, suggesting the absence of a publication bias in our sample. However, Figure C.2b, which presents the results using the median estimate of each study, reveals a negative correlation. This indicates the potential presence of publication bias in our data.

P-hacking. We use next a method outlined by Brodeur et al. (2020) to assess the presence of publication bias by scrutinising the clustering of reported t-statistics around conventional significance levels (1.64 for 10%, 1.96 for 5%, and 2.32 for 1%). An excess of observations immediately above these thresholds could indicate publication bias or "p-hacking", assuming a continuous underlying distribution of t-statistics.

The results are presented in Figure C.3. The distribution of the t-statistic (in absolute terms) around the significance thresholds does not indicate the presence of publication bias (Figure C.3a). This analysis is replicated for articles in leading academic journals (Figure C.3b, where we notice a peak at the 10% significance level. However, since peaks of similar size occur at other points of the distribution, the evidence of publication bias remains inconclusive for our benchmark sample.

Regression results. In Table C.6, columns (1) and (2), we incorporate the number of estimates reported in each study. This approach accounts for the fact that some studies report more estimates than others. In addition, we introduce the logarithm of the sample size used to derive each estimate as an additional covariate in column (2). This allows us to further examine the influence of publication bias on our findings. Our results remain robust to these alternative specifications.

In Table C.7, we replicate our analysis using two sub-samples of data. In column (1), we limit our analysis to studies published in leading academic journals. All these studies include a theoretical model and use recent data; thus, these covariates are omitted from the regressions. Differing from our benchmark findings, we find that the use of an IV-2SLS estimator significantly and positively impact the estimated wage effect of immigration. Furthermore, the average wage elasticity identified in these studies is –0.012 and significant, while our benchmark average elasticity is equal to –0.005 and not significant. Consequently, we can infer that studies published in leading academic journals tend to report more negative estimates of the impact of immigration on native wages.

There are two possible interpretations to this result. On the one hand, it might indicate that the true effect of immigration is more negative than what the average effect suggests. This inference is based on the premise that estimates published in journals with larger audiences and higher quality standards could be more reliable. On the other hand, the observed difference between estimates from leading journals and other sources should not be attributable to differential quality standards, methodological issues, or other observable determinants that we have considered.

In column (2), we restrict our analysis to a set of studies, excluding those published in leading academic journals. The results obtained with this sub-sample corroborate our benchmark findings. Additionally, they support the idea that the benchmark average elasticity is largely driven by this sub-sample, as we estimate a mean elasticity of –0.003 which is not statistically significant. Finally, in column (3), we limit our sample to a set of working papers. Here again, the results obtained with this sub-sample confirm our benchmark findings.

5.2. Shift-Share Instrumental Variables

In a second extension, we investigate whether the use of shift-share instrumental variables has any impact on the estimated wage effect of immigration. This type of instrument was introduced in the field by the seminal paper of Card (2001) and is widely used in the literature. Other types of instruments include lagged values of immigration as well as some additional external variables. Our identification relies on the inclusion of a binary variable equal to one if the estimate has been produced using a shift-share instrument *à la* Card (2001), and zero otherwise.

We present the results using our benchmark sample of elasticities in Table C.8, columns (1) and (2). Neither the use of an IV-2SLS estimator nor the use of a shift-share instrument appears to impact the estimated wage effect of immigration (column 1). Nonetheless, when we restrict our sample to studies using an IV-2SLS estimator (column 2), we find that studies using a shift-share instrument yield smaller (or more negative) estimates.

To conclude, we find no definitive results associated with the use of an instrumental variable strategy unless we narrow our focus to the use of shift-share instruments. In that respect, our results are in line with Longhi et al. (2005), who find that estimates obtained from linear regressions using no instrument are significantly larger. Note that our sample spans a longer period, allowing us to include a large number of studies employing shift-share instruments. In contrast, the sample in Longhi et al. (2005) ends in 2003, which is too early to investigate thoroughly the specificity of this type of instrument.

5.3. Fixed Effects and Displacement

Second, we explore difference between studies that use a national skill-cell approach and those employing a mixed approach. As explained by Dustmann et al. (2016), these two approaches may yield different results. Specifically, the mixed approach typically controls for effects across different areas and/or sectors by employing fixed effects. Consequently, this approach holds constant the wage effects that arise from the spatial (or sectoral) reallocation of workers.

In Table C.9 column (1), we include a binary variable set to one for wage elasticities obtained from models incorporating area fixed effects. Similarly, another binary variable is set to one for elasticities derived from models that incorporate sector fixed effects. We find no effect from the use of area fixed effects.

We acknowledge that numerous studies in the literature also examine displacement effects, namely the potential movement of native workers to other occupations, sectors, or out of the labour force due to immigration. This aspect is particularly relevant in many European countries where minimum wage laws may prevent wage adjustments following supply shocks. Although our meta-analysis is solely focused on studies that provide estimates of the wage effect of immigration, we can control for whether a study addresses displacement effects or not.

In column (2), we introduce a binary variable set to one if the study discusses displacement effects. This variable serves as another proxy for the quality of the study. Our findings indicate that this variable does not play a significant role in explaining variations in the wage effect of immigration and does not alter our benchmark findings.

6 Conclusions

In this paper, we provide a meta-analysis of the literature on the wage effect of immigration, encompassing 42 studies published between 1987 and 2019. Our study expands on the work of Longhi et al. (2005) by using a more extensive literature corpus, which includes studies using panel and micro-level administrative data, and more sophisticated econometric methodologies. Moreover, the context of these studies have evolved over time, with more countries being analysed and longer time spans covered.

Specifically, our analysis aims at identifying the sources of variation in the estimated wage effects of immigration across studies, focusing on the quality of the study and the presence of both context and methodological heterogeneity. We observe an average wage effect of immigration that is close to zero and often not statistically significant; our benchmark meta-regression yields an insignificant elasticity of –0.005. This heterogeneity across studies appears to be attributed to both context and methodological heterogeneity. Our benchmark meta-regressions indicate that not only does the quality of a study influence its estimates, but context heterogeneity and methodological heterogeneity also play significant roles. Our findings indicate that leading academic journals are more likely to publish negative estimates, even after accounting for potential publication bias. Estimates for the U.S. are larger while those obtained with data after the first oil crises are smaller. Leveraging panel and individual-level data yields smaller estimates. Finally, among studies using an IV-2SLS estimator (as opposed to an OLS), using a shift-share instrumental variable produces smaller estimates.

While systematic reviews and meta-analyses are essential for synthesising evidence, they are prone to biases such as publication bias and evidence selection bias. Our study aims to control for these biases. We have investigated the presence of a publication bias but did not find any conclusive evidence about it. We have meticulously documented our paper collection process to minimise evidence selection bias, as detailed in Appendix A. Additionally, we acknowledge the potential for a systematic bias in the literature, as highlighted by Aydemir and Borjas (2011) and Peri and Sparber (2011), i.e. that many or all studies could be biased in a specific direction. Although averaging numerous estimates reduces the impact of sampling error and idiosyncratic methodological issues in individual studies, it does not necessarily reveal the *true* estimate in the presence of such a systematic bias.

Our meta-analysis suggests two main directions for future research. First, the findings emphasise the importance of context heterogeneity in estimating the wage effect of immigration: this highlights the importance of replication studies focusing on diverse case studies to ensure external validity.

Second, our results emphasise the importance of methodological heterogeneity. In this regard, economists should be encouraged to thoroughly discuss how their methodological choices impact their results. Additionally, there is a need for further methodological contributions, particularly in addressing endogeneity issues, as demonstrated by the work of Jaeger et al. (2018) and Adão et al. (2019). Finally, our results underscore that the ongoing methodological debate in the field is crucial, considering the impact of quantitative research on policy discussions about the costs and benefits of immigration, a point emphasised by Goldin et al. (2011).

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A. Additional Information on the Data

Data Collection

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

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

A final assessment enabled us to drop some remaining duplicates (e.g., working papers that have been published). In addition, we only kept empirical studies estimating a reduced-form model, and excluded structural approaches as well as natural-experiment designs. After excluding outliers, we obtained a sample of 1,165 estimates collected across 42 studies. We list these studies below.

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Table A.1: Summary Statistics

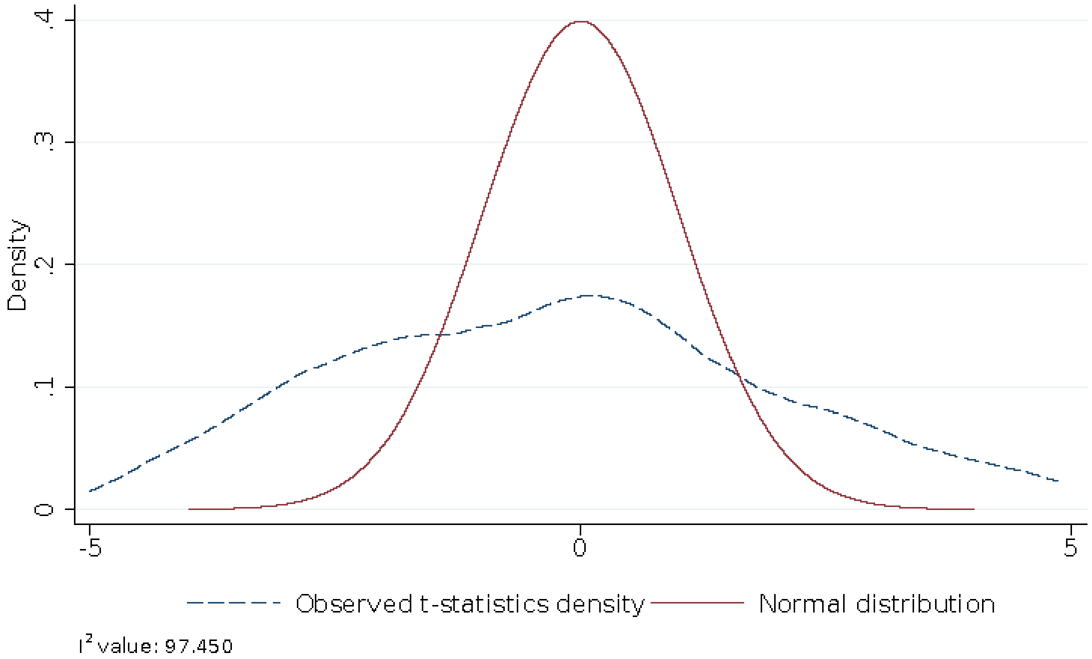
	Mean	S.D.	Min.	Max.	N
Study characteristics					
Journal article	0.833	0.377	0	1	42
Leading academic journal	0.190	0.397	0	1	42
Publication year	2008.405	7.991	1987	2019	42
No. of authors	1.833	0.881	1	4	42
Estimation characteristics					
Elasticity	-0.004	0.029	-0.110	0.104	716
S.E. (elasticity)	0.260	0.481	0	5.819	655
Semi-elasticity	-0.025	0.745	-2.981	2.900	1,031
S.E. (semi-elasticity)	0.308	0.611	0	11.967	1,031
Sample size	194,925	1,135,949	9	1.09e+07	810
The U.S.	0.302	0.459	0	1	1,165
First sample year	1984.902	13.754	1911	2004	1,165
Last sample year	1996.094	11.173	1941	2014	1,165
Panel data	0.161	0.368	0	1	1,165
Individual-level data	0.197	0.398	0	1	1,165
IV-2SLS estimator	0.355	0.479	0	1	1,165
Shift-share	0.088	0.283	0	1	1,165
National skill-cell approach	0.583	0.493	0	1	1,165
Mixture approach	0.417	0.493	0	1	1,165

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

Table A.2: Categorical Variables of Interest

Categorical variables of interest	Definition	Obs.
Leading academic journal: yes	Leading academic journals: AER, JPE, Restud, QJE, JEEA, JLE.	214
Leading academic journal: no (ref.)	Other outlets.	951
Theoretical model: no (ref.)	The study does not include a theoretical model.	771
Theoretical model: yes	The study includes a theoretical model.	394
The U.S.: yes	Estimation based on the U.S. labour market.	352
The U.S.: no (ref.)	Estimation based on other areas than the U.S. labour market.	813
Sample mid-year after 1973: no (ref.)	The mid-year of the sample period is prior to 1973.	105
Sample mid-year after 1973: yes	The mid-year of the sample period is after 1973.	1,060
Sample mid-year after 2007: no (ref.)	The mid-year of the sample period is prior to 2007.	1,142
Sample mid-year after 2007: yes	The mid-year of the sample period is after 2007.	23
High skilled immigration	High skilled immigrant workers.	74
Low-medium skilled immigration (ref.)	Low-medium skilled immigrant workers.	129
All or undefined immigration	No explicit reference to the skill level of the immigrant workers.	962
Affected skill group: All groups or undefined	No explicit reference to the skill level of the native workers.	815
Affected skill group: High	High skilled native workers.	116
Affected skill group: Low-Medium skills	Low-medium skilled native workers.	234
Panel data: yes	Estimation based on panel data or pooled cross-sectional data.	188
Panel data: no (ref.)	Estimation based on cross-sectional data.	977
Individual-level data: no (ref.)	Estimation based on aggregate data.	935
Individual-level data: yes	Estimation based on individual-level data.	230
IV-2SLS estimator: yes	2SLS estimation using instrumental variables.	413
IV-2SLS estimator: no (ref.)	OLS estimation without correction for endogeneity bias.	752
Shift-share: no (ref.)	The study uses another IV or no IV.	102
Shift-share: yes	The study uses a shift-share IV à la Card (2001a).	1,063
Mixture approach	Estimation of a reduced-form model using spatial and cell variation.	486
National skill-cell approach	Estimation of a reduced-form model using cell variation.	679
Fixed Effects: No area FE (Ref.)	The study does not include area FE	679
Fixed Effects: Area FE	The study includes area FE.	486
Fixed Effects: No sector FE (Ref.)	The study does not include industry FE	926
Fixed Effects: Sector FE	The study includes industry FE.	239
No discussion to study displacement (Ref.)	The study does not include a discussion about displacement effects.	809
Discussion to study displacement	The study includes a discussion about displacement effects.	356

Figure A.1: Distribution of the t-Statistics



Note: This figure has been produced using the full sample of coefficients, including elasticities and semi-elasticities. It depicts the observed distribution of the t-statistics and the Normal distribution.

B. Robustness Tests

Table B.3: Alternative Estimation Strategies

	Weighted least squares		R.E.
	(1)	(2)	(3)
Quality of the study and estimate			
Leading academic journal	-0.024***	-0.027***	-0.028***
	(0.001)	(0.002)	(0.009)
Theoretical model	-0.019*	-0.020	-0.019***
	(0.011)	(0.012)	(0.005)
Estimate S.E.	-0.012*	-0.003	-0.004
	(0.006)	(0.003)	(0.003)
Context heterogeneity			
The U.S.	0.002***	0.013***	0.010***
	(0.000)	(0.000)	(0.003)
Sample mid-year after 1973	-0.067***	-0.071***	-0.062***
	(0.009)	(0.002)	(0.003)
Sample mid-year after 2007	-0.003***	0.001	-0.002
	(0.001)	(0.003)	(0.003)
Method heterogeneity			
Panel data	-0.033***	-0.028***	0.003
	(0.001)	(0.002)	(0.007)
Individual-level data	0.010	0.012	-0.002
	(0.011)	(0.011)	(0.004)
IV-2SLS estimator	0.004	0.007	0.003
	(0.002)	(0.005)	(0.005)
Observations	652	655	655
Studies	27	27	27
Estimator	WLS [w: 1/S.E.]	WLS [w: quality]	OLS, R.E.
Year dummies	yes	yes	no
R^2	0.303	0.271	
Meta-estimate	-0.003	-0.007	-0.003
S.E.	.015	.004	.006
S.D.	.022	.023	.016

Note: This table presents the results of meta-regressions using the sample of elasticities. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors, clustered at the publication-year level, are reported in parentheses. For each meta-regression, a meta-estimate is reported with the corresponding bootstrapped standard error as well as the standard deviation.

Table B.4: Sub-Samples of Elasticities and Semi-Elasticities

	Elasticities	Semi-Elasticities	
	(1)	(2)	(3)
Quality of the study and estimate			
Leading academic journal	-0.021***	-0.310***	-0.224
	(0.002)	(0.093)	(0.151)
Theoretical model	-0.018	0.037	-0.164
	(0.012)	(0.175)	(0.103)
Estimate S.E.	-0.005	-0.187*	-0.063
	(0.003)	(0.091)	(0.072)
Context heterogeneity			
The U.S.	0.012***	0.034*	-0.245
	(0.000)	(0.018)	(0.171)
Sample mid-year after 1973	-0.068***	-0.862***	-0.827***
	(0.001)	(0.101)	(0.126)
Sample mid-year after 2007	-0.002	0.106	-0.003
	(0.003)	(0.115)	(0.074)
Method heterogeneity			
Panel data	-0.032***	-0.508***	-0.445***
	(0.002)	(0.015)	(0.141)
Individual-level data	0.014	-0.155	0.105
	(0.012)	(0.148)	(0.175)
IV-2SLS estimator	0.005	0.262	0.280*
	(0.006)	(0.221)	(0.138)
Observations	599	599	1,031
Studies	26	26	41
Estimator	OLS, FE	OLS, FE	OLS, FE
Year dummies	yes	yes	yes
R^2	0.311	0.143	0.200
Meta-estimate	-.005	-.101	-.025
S.E.	.002	.077	.047
S.D.	.024	.396	.330

Note: This table presents the results of meta-regressions using the sample of elasticities in column (1) and the sample of semi-elasticities in columns (2) and (3). In these regressions, only observations for which we have both the elasticity and the semi-elasticity are included. We report the results using the full sample of semi-elasticities in columns (5) and (6). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors, clustered at the publication-year level, are reported in parentheses. For each meta-regression, a meta-estimate is reported with the corresponding boot-strapped standard error as well as the standard deviation.

Table B.5: Studies Included in Longhi et al. (2005) and Until 2003

	Longhi et al. (2005)	Until 2003
	(1)	(2)
Quality of the study and estimate		
Estimate S.E.	-0.362	-0.384
	(0.318)	(0.298)
Context heterogeneity		
The U.S.	-1.077***	-0.839***
	(0.154)	(0.147)
Sample mid-year after 1973		-0.841***
		(0.074)
Method heterogeneity		
Panel data		0.004***
		(0.000)
Individual-level data	-0.661**	-0.366*
	(0.144)	(0.174)
IV-2SLS estimator	0.267	-0.193
	(0.342)	(0.438)
Observations	79	134
Studies	5	9
Estimator	OLS, FE	OLS, FE
Year dummies		yes
R^2	0.219	0.340
Meta-estimate	-0.199	-0.103
S.E.	0.220	0.161
S.D.	0.512	0.389

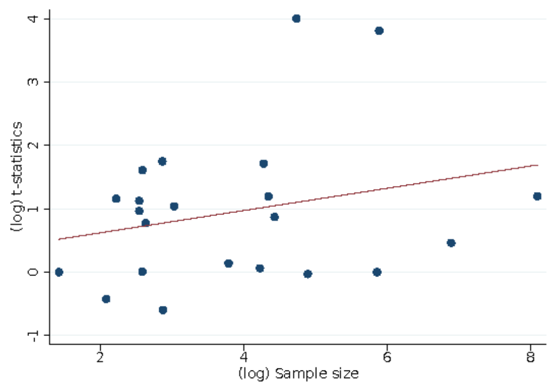
Note: This table presents the results of meta-regressions using the sample of semi-elasticities. The sample is limited to the studies used in the meta- analysis of Longhi et al. (2005) in column (1), and it is limited to studies published until 2003 in column (2). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors, clustered at the publication-year level, are reported in parentheses. For each meta-regression, a meta-estimate is reported with the corresponding bootstrapped standard error as well as the standard deviation.

C Extensions

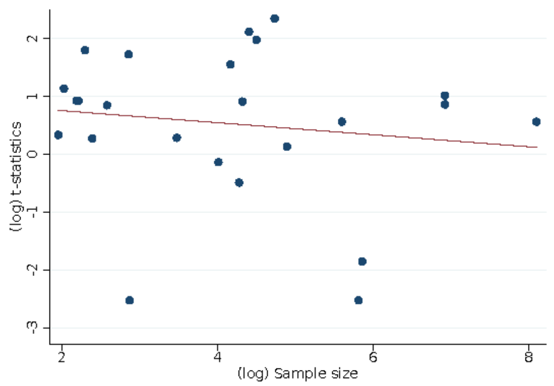
Publication bias

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

(a) First elasticity



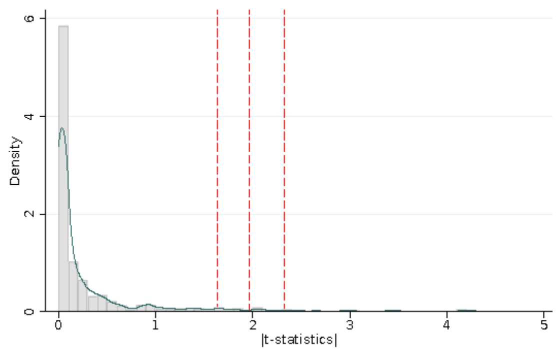
(b) Median elasticity



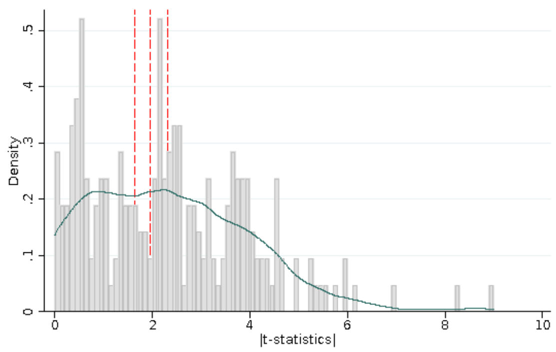
Note: These figures have been produced using the benchmark sample of elasticities. Figure C.2a has been produced using the first elasticity reported in each study. Figure C.2b has been produced using the median elasticity of each study. These figures depict the relationship between the significance of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

Figure C.3: Distribution of t-Statistics

(a) Benchmark sample



(b) Sub-sample of leading journals



Note: This figure reports the distribution of t-statistics. Figure C.3a shows the distribution for the benchmark sample of elasticities, and Figure C.3b shows the distribution for the sub-sample of elasticities reported in leading academic journals. Note that the t-statistics are in absolute values.

Table C.6: Publication Bias - Additional Controls

	(1)	(2)
Quality of the study and estimate		
Leading academic journal	-0.026***	-0.057***
	(0.002)	(0.004)
Theoretical model	-0.019*	-0.028*
	(0.010)	(0.015)
Estimate S.E.	-0.004	-0.003
	(0.003)	(0.003)
Nr of estimates	0.004	0.005
	(0.009)	(0.009)
Sample size		-0.000
		(0.003)
Context heterogeneity		
The U.S.	0.012***	0.024***
	(0.000)	(0.006)
Sample mid-year after 1973	-0.068***	-0.067***
	(0.002)	(0.002)
Sample mid-year after 2007	-0.001	-0.000
	(0.003)	(0.013)
Method heterogeneity		
Panel data	-0.031***	-0.025*
	(0.003)	(0.013)
Individual-level data	0.013	0.021*
	(0.010)	(0.011)
IV-2SLS estimator	0.005	0.004
	(0.005)	(0.006)
Observations	655	567
Studies	27	25
Estimator	OLS, FE	OLS, FE
Year dummies	yes	yes
R^2	0.301	0.277
Meta-estimate	-0.005	-0.006
S.E.	0.004	0.006
S.D.	0.023	0.024

Note: This table presents the results of meta-regressions using the sample of elasticities. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors, clustered at the publication-year level, are reported in parentheses. For each meta-regression, a meta-estimate is reported with the corresponding bootstrapped standard error as well as the standard deviation.

Table C.7: Publication Bias - Sub-Samples

	Leading journals	Leading journals excl.	Working papers
	(1)	(2)	(3)
Quality of the study and estimate			
Theoretical model		-0.031**	
		(0.014)	
Estimate S.E.	-0.015*	-0.002	-0.121**
	(0.005)	(0.002)	(0.026)
Context heterogeneity			
The U.S.	0.014***		
	(0.000)		
Sample mid-year after 1973		-0.068***	-0.049***
		(0.002)	(0.004)
Sample mid-year after 2007		-0.005**	-0.010*
		(0.002)	(0.004)
Method heterogeneity			
Panel data		-0.028***	
		(0.002)	
Individual-level data	0.000	0.022	
	(0.000)	(0.014)	
IV-2SLS estimator	0.022***	-0.002	-0.006
	(0.001)	(0.004)	(0.008)
Observations	135	520	84
Studies	3	24	4
Estimator	OLS, FE	OLS, FE	OLS, FE
Year dummies	yes	yes	yes
R^2	0.193	0.359	0.607
Meta-estimate	-0.012	-0.003	-0.004
S.E.	0.005	0.003	0.008
S.D.	0.014	0.022	0.023

Note: This table presents the results of meta-regressions using the sample of elasticities. The sample is limited to leading academic journals in column (1), while it excludes these journals 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, clustered at the publication-year level, are reported in parentheses. For each meta-regression, a meta-estimate is reported with the corresponding bootstrapped standard error as well as the standard deviation.

Shift-Share Instrumental Variables

Table C.8: Shift-Share Instrumental Variable

	Benchmark sample	IV-2SLS only
	(1)	(2)
Quality of the study and estimate		
Leading academic journal	-0.025***	-0.026***
	(0.002)	(0.000)
Theoretical model	-0.024*	
	(0.012)	
Estimate S.E.	-0.004	0.001
	(0.003)	(0.002)
Context heterogeneity		
The U.S.	0.012***	0.015***
	(0.000)	(0.000)
Sample mid-year after 1973	-0.068***	
	(0.001)	
Sample mid-year after 2007	-0.003	
	(0.003)	
Method heterogeneity		
Panel data	-0.028***	
	(0.002)	
Individual-level data	0.016	0.007***
	(0.012)	(0.002)
IV-2SLS estimator	0.002	
	(0.006)	
Shift-share IV	-0.007	-0.016***
	(0.008)	(0.002)
Observations	655	279
Studies	27	19
Estimator	OLS, FE	OLS, FE
Year dummies	yes	yes
R2	0.303	0.323
Meta-estimate	-0.005	-0.004
S.E.	0.003	0.002
S.D.	0.023	0.016

Note: This table presents the results of meta-regressions using the sample of elasticities. The sample is further limited to IV-2SLS estimators in column (2). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors, clustered at the publication-year level, are reported in parentheses. For each meta-regression, a meta-estimate is reported with the corresponding bootstrapped standard error as well as the standard deviation.

Fixed Effects and Displacement

Table C.9: Fixed Effects and Displacement

	Fixed effects	Displacement
	(1)	(2)
Quality of the study and estimate		
Leading academic journal	-0.025***	-0.033***
	(0.004)	(0.009)
Theoretical model	-0.013*	-0.027**
	(0.007)	(0.013)
Estimate S.E.	-0.003	-0.004
	(0.003)	(0.003)
Displacement effects discussed		-0.007
		(0.010)
Context heterogeneity		
The U.S.	0.012***	0.012***
	(0.001)	(0.000)
Sample mid-year after 1973	-0.068***	-0.069***
	(0.001)	(0.001)
Sample mid-year after 2007	-0.004	-0.001
	(0.009)	(0.003)
Method heterogeneity		
Panel data	-0.026***	-0.023***
	(0.008)	(0.008)
Individual-level data	0.001	0.013
	(0.006)	(0.012)
IV-2SLS estimator	0.005	0.006
	(0.006)	(0.005)
Area FE	-0.003	
	(0.010)	
Sector FE	0.022	
	(0.013)	
Observations	655	655
Studies	27	27
Estimator	OLS, FE	OLS, FE
Year dummies	yes	yes
R^2	0.310	0.301
Meta-estimate	-0.005	-0.005
S.E.	0.003	0.004
S.D.	0.022	0.021

Note: This table presents the results of meta-regressions using the sample of elasticities. The dependent variable is the estimated wage effect of immigration. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standard errors, clustered at the publication-year level, are reported in parentheses. For each meta-regression, a meta-estimate is reported with the corresponding bootstrapped standard error as well as the standard deviation.