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## The elasticity of substitution between native and immigrant labor: A meta-analysis

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# THE ELASTICITY OF SUBSTITUTION BETWEEN NATIVE AND IMMIGRANT LABOR: A META-ANALYSIS

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IES Working Paper 8/2025

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# The Elasticity of Substitution between Native and Immigrant Labor: A Meta-Analysis

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## Abstract:

This paper presents the first comprehensive meta-analysis of the elasticity of substitution between native and immigrant labor. Drawing on 1,091 estimates from 41 studies, we examine whether immigrants and natives compete in the same labor markets, and to what extent published estimates are shaped by methodological choices and publication bias. We find strong evidence of small-study effects: less precise estimates are associated with lower elasticities, which is consistent with selective reporting. Correcting for these biases using a wide array of techniques (linear, nonlinear, and selection models) raises the mean implied elasticity from 13 to approximately 20. Model averaging techniques reveal that data features, such as experience level, wage definition, and region, explain much of the heterogeneity in reported results. Notably, the often-cited discrepancy between using  $\log(\text{mean wages})$  and  $\text{mean}(\log \text{ wages})$  largely disappears once publication bias is accounted for. Our findings imply that immigrants and natives are imperfect substitutes but more substitutable than is commonly assumed.

**JEL:** J15, J61, C83

**Keywords:** elasticity of substitution, immigration, native labor, metaanalysis, publication bias



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An online appendix with data and code is available at <https://meta-analysis.cz/migrant/>.

# 1 Introduction

The labor market impacts of immigration continue to spark intense policy debates and scholarly controversy. At the heart of these discussions lies a central economic question: to what extent are immigrant and native workers substitutes in production? This relationship, captured by the elasticity of substitution between native and immigrant labor, directly shapes how immigration affects wages, employment, and broader economic outcomes.

Estimates of this elasticity, however, vary dramatically across studies. Work by Borjas (2003) and Card (2001) sparked a now long-running debate. While Card (1990) famously found little evidence that immigration reduced native wages in the Mariel Boatlift case, Borjas (2017) challenged these findings with alternative subgroup analyses. Other studies, such as Ottaviano & Peri (2012) and Manacorda *et al.* (2012), suggest imperfect but meaningful substitutability. Yet the range of reported elasticities spans from 6 to over 500, and different modeling assumptions, data sources, and wage definitions yield conflicting results.

In practice, it is not always feasible for primary studies to estimate the elasticity of substitution between native and immigrant labor directly. Data limitations, model complexity, or identification concerns often lead researchers to estimate related labor market effects, such as the wage or employment impacts of immigration, without recovering the structural elasticity itself. In such cases, the elasticity is frequently parametrized, drawing on values from existing studies. However, this practice introduces substantial risk, as reported elasticities vary widely across the literature and are often sensitive to methodological choices. As a result, miscalibrated parameters may distort empirical conclusions and policy simulations. This highlights the need for a systematic synthesis of the empirical literature, one that not only corrects for publication bias but also explains the heterogeneity behind reported estimates.

Despite the centrality of this parameter in immigration economics, no meta-analysis offers a comprehensive synthesis of the evidence. Meta-analysis provides a formal framework for distilling patterns from fragmented empirical findings, especially in fields where results vary widely across contexts and methods (Stanley, 2001). Existing meta-analyses tend to focus on broader wage effects of immigration without isolating the underlying elasticity. As a result, policymakers and researchers often rely on a few influential studies to calibrate economic models, potentially embedding biased or unrepresentative values.

This paper addresses that gap. We conduct a comprehensive meta-analysis of the elasticity of substitution between native and immigrant labor, based on 1,091 estimates from 41 primary studies. We apply a wide range of publication bias correction techniques, including linear, nonlinear, and selection models, and systematically investigate sources of heterogeneity using both Bayesian and frequentist model averaging. Consistent with the empirical literature, we focus on estimates of the negative inverse elasticity,  $-\frac{1}{\sigma}$ , as these are the most commonly reported and are typically derived from specifications where relative labor supply is the main source of exogenous variation. This approach is generally more credible for causal inference than directly modeling wage responses, which are often confounded by demand-side shocks and endogeneity. Our analysis explores how methodological choices, data characteristics, and study contexts shape the magnitude and direction of reported results.

Our findings reveal three key insights. First, the literature is affected by substantial publication bias. Smaller, less precise studies tend to report systematically lower elasticities, likely reflecting a combination of selective reporting and modeling flexibility. After correcting for this bias, the implied elasticity rises from an uncorrected average of 13 to approximately 20, with nonlinear corrections suggesting even higher values. Second, much of the variation in reported estimates is driven by identifiable factors. Studies using annual data, focusing on low-experience workers, or measuring wages at the hourly level tend to report more negative estimates of the elasticity (lower substi-

tutability). Meanwhile, higher substitutability is associated with more granular data (higher number of cells), larger immigrant shares, and male samples. Third, we revisit the methodological debate over the use of  $\log(\text{mean wages})$  versus  $\text{mean}(\log \text{wages})$  in estimating wage effects. While uncorrected estimates differ markedly, consistent with critiques by Borjas *et al.* (2012), the gap largely disappears after adjusting for publication bias, suggesting that earlier disagreements may reflect selective reporting more than fundamental measurement flaws.

This is the first meta-analysis to assess the elasticity of substitution between natives and immigrants. The results suggest that immigrants and natives are imperfect substitutes, but more substitutable than commonly believed. This has important implications for how we model labor markets, estimate the wage effects of immigration, and inform evidence-based policy. The remainder of the paper proceeds as follows. Section 2 describes the data collection process and presents descriptive statistics. Section 3 quantifies publication bias and corrects for small-study effects. Section 4 explores heterogeneity using model averaging techniques. Section 5 contextualizes the findings and concludes.

## 2 Data

### 2.1 Previous Surveys

The effects of immigration on native labor market outcomes have been extensively studied, but the results are often varied and sometimes conflicting. This section synthesizes the data and methodologies used in key studies to understand the elasticity of substitution between native and immigrant labor.

Dustmann *et al.* (2016) and Edo (2019) both explore the reasons behind the differing results in studies on immigration’s labor market effects. Edo (2019) summarizes findings from over 50 studies, classifying them into structural approaches (education-experience cells), spatial correlation approaches (immigrant inflows across regions), and national

skill-cell approaches. These variations in methodologies contribute significantly to the diversity in results. Additionally, Pekkala Kerr & Kerr (2011) reviews literature focusing on the economic impacts of immigration, concluding that less-educated natives and earlier immigrant cohorts are the most affected groups.

A study by Borjas *et al.* (2011) highlights that the wage impact of immigration depends on two key elasticities: the elasticity of substitution between similarly skilled immigrants and natives, and the elasticity between high school dropouts and graduates. U.S. data suggests that skilled immigrants and natives are perfect substitutes, while high school dropouts and graduates are imperfect substitutes. Contrarily, Peri & Sparber (2011) finds that highly educated natives and immigrants are imperfect substitutes due to differing skill focuses, with immigrants concentrating on quantitative and analytical skills, and natives on interactive and communication skills. Further, Peri (2011) demonstrates that natives and immigrants within the same education and experience group are not perfect substitutes.

In a comprehensive meta-analysis, Aubry *et al.* (2022) investigate whether immigration affects wages by collecting 2,146 estimates from 64 studies published between 1972 and 2019. However, many primary studies do not accurately account for the elasticity of substitution between immigrant and native labor. Our focus is on this critical parameter, as it is fundamental for estimating the broader effects of immigration.

A related meta-analysis by Havranek *et al.* (2024) examines 682 estimates of the elasticity of substitution between skilled and unskilled labor from 77 studies. Although focused on a different skill dimension, their analysis offers important methodological guidance, particularly in the identification of attenuation and publication bias, which also affect studies estimating immigrant-native elasticities.

## 2.2 Definition and Interpretation of the Elasticity of Substitution

The elasticity of substitution between immigrant and native labor is mathematically defined as:

$$\sigma = \frac{d \log \left( \frac{L_i}{L_n} \right)}{d \log \left( \frac{w_i}{w_n} \right)}$$

where  $L_i$  and  $L_n$  are the quantities of immigrant and native labor employed, and  $w_i$  and  $w_n$  are their respective wages. This definition shows how the ratio of immigrant to native labor changes in response to changes in their relative wages (Borjas & Van Ours, 2010).

The nonnegativity of the elasticity of substitution is intuitively understandable. The general definition of the elasticity is that  $\sigma > 0$ , however, it is possible to obtain negative estimates of the elasticity. It is rare and typically considered implausible. A negative value suggests that a fall in the relative wage of immigrants would decrease their relative employment, a counterintuitive result under standard economic theory. Such values might arise due to estimation issues or data irregularities rather than genuine substitution behavior. Kearney (1997) critiques negative estimates, stating that they contradict established economic theory. Similarly, Bowles (1970) disregards negative estimates, considering them implausible from the outset. On the other hand, according to Ribó & Vilalta-Bufí (2020), the negative values of the elasticity suggest strong complementarity.

## 2.3 Collecting the Elasticity Dataset

Selecting appropriate primary studies is crucial for a meta-analysis. To gather our estimates of the elasticity of substitution between immigrant and native labor, we used keywords such as "elasticity of substitution," "immigrant," "labor," and "native" in Google Scholar. By January 31, 2025, we reviewed over 900 studies and collected 1,091 estimates from 41 studies (see Appendix A, which includes the list of all included studies and the PRISMA diagram). Our analysis focuses on the negative inverse elasticity,  $-\frac{1}{\sigma}$ ,

rather than the direct elasticity. This choice is motivated by the fact that relative labor supply is generally more exogenous than wage outcomes, making the inverse specification more reliable for causal inference. However, only a few studies report direct elasticity estimates, mostly without standard errors.

We focus on the negative inverse elasticity,  $-\frac{1}{\sigma}$ , as relative labor supply variations are more exogenous than wage changes. The base is the CES production function:

$$Y = [\alpha(aL_n)^\rho + (1 - \alpha)(bL_i)^\rho]^{\frac{1}{\rho}}, \quad (1)$$

where  $L_n$  and  $L_i$  are the native and immigrant labor inputs, respectively,  $a$  and  $b$  are factor-augmenting technologies, and  $\alpha$  represents the share of labor allocated to natives. From this,  $\sigma = \frac{1}{1-\rho}$ . The estimated equation in the primary studies is then:

$$\ln\left(\frac{w_n}{w_i}\right) = A - \frac{1}{\sigma} \ln\left(\frac{L_n}{L_i}\right), \quad (2)$$

where  $\frac{w_n}{w_i}$  is the native wage premium,  $\frac{L_n}{L_i}$  is the relative labor supply, and  $A$  includes other factors. Thus, as discussed earlier, we exclude studies reporting the (negative) elasticity of substitution instead of the inverse as those two types of estimates are not comparable with each other. Of the 41 studies in our dataset, 26 adopt the log of mean wages, while 18 use the mean of log wages.<sup>1</sup> Among the latter, key examples include Borjas *et al.* (2010), Borjas *et al.* (2012), and Card (2009), who argue that this specification better captures individual-level wage variation. In contrast, Ottaviano & Peri (2012) use log of mean wages, which Borjas *et al.* (2012) critiques for overstating negative impacts

We also collected 32 dummy variables concerning data characteristics, structural variations, estimation techniques, fixed effects, and publication characteristics. In the data, we also include the percentage of foreign-born population in respective country, the number of citations, journal impact factor, and publication year. Table C1 describes these variables, and Table 1 presents summary statistics for the sample, showing simple

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<sup>1</sup>The resulting number does not equal to 41 as three studies uses both measures.

means without correcting for publication bias, and provides valuable insights into the elasticity of substitution between immigrant and native labor across various subsamples and characteristics. To ensure robustness and avoid misleading inference, we tested for multicollinearity among explanatory variables and excluded dummy variables with insufficient variation (i.e., means below 0.03 or above 0.97), following standard practice. We also examined the impact of potential outliers by applying winsorization at the 1%, 2.5%, and 5% levels. Since the results remained stable across all levels, no winsorization was ultimately applied.

The overall mean of the negative inverse elasticity is -0.07, translating to an implied elasticity of 13.3. To correct for the influence of studies reporting multiple estimates, a weighted mean elasticity is also computed, with estimates weighted by the inverse of the number of estimates reported per study. When weighted by the inverse number of estimates per study, the mean slightly decreases to -0.077, implying an elasticity of 12.9. These results indicate a moderate level of substitutability between immigrant and native labor, with the 95% confidence intervals suggesting a robust range of estimates. However, substantial variation exists across different subsamples, suggesting that factors such as data characteristics, worker type, estimation techniques, and publication sources significantly influence elasticity estimates.

**Data characteristics.** Among the data characteristics, studies with a *high number of cells* report a less negative mean inverse elasticity (-0.065), indicating greater substitutability, whereas studies with a *low number of cells* show a more negative mean inverse elasticity (-0.081), i.e., lower substitutability. This suggests that a more granular analysis might reveal higher substitutability as one compares individuals with similar characteristics. Studies using *annual frequency data* yield a significantly more negative inverse elasticity (-0.108), possibly due to capturing more short-term fluctuations compared to *lower frequency data*, which show a less negative inverse elasticity (-0.048),



Table 1: Summary statistics for different subsets of the literature

Variable	N	Unweighted				Weighted			
		Mean	impl. el.	95% conf. int.		Mean	impl. el.	95% conf. int.	
Elasticity	1,091	-0.07	13.3	-0.08	-0.07	-0.08	12.9	-0.08	-0.07
<b>Subsamples</b>									
<i>Data characteristics</i>									
High number of cells	398	-0.07	15.3	-0.07	-0.06	-0.06	17.1	-0.07	-0.05
Low number of cells	693	-0.08	12.4	-0.09	-0.07	-0.10	10.5	-0.11	-0.08
Annual frequency data	488	-0.11	9.2	-0.12	-0.10	-0.11	9.4	-0.12	-0.09
Lower frequency data	603	-0.05	20.8	-0.05	-0.04	-0.05	22.1	-0.05	-0.04
<i>Structural variation</i>									
All workers	603	-0.09	11.4	-0.10	-0.08	-0.09	10.9	-0.10	-0.08
Full-time workers	488	-0.06	16.8	-0.06	-0.05	-0.06	17.3	-0.06	-0.05
High level of experience	42	-0.06	17.0	-0.07	-0.05	-0.04	22.6	-0.06	-0.03
Low level of experience	79	-0.12	8.4	-0.16	-0.08	-0.12	8.3	-0.16	-0.08
High level of education	106	-0.08	13.0	-0.09	-0.06	-0.05	19.8	-0.07	-0.04
Low level of education	171	-0.06	15.5	-0.07	-0.06	-0.07	13.7	-0.08	-0.06
English	735	-0.07	13.6	-0.08	-0.07	-0.09	11.7	-0.10	-0.07
Non-English	356	-0.08	12.8	-0.09	-0.07	-0.06	15.6	-0.07	-0.05
Bilingual	131	-0.04	26.4	-0.05	-0.03	-0.06	17.3	-0.07	-0.05
Non-biling	960	-0.08	12.5	-0.09	-0.07	-0.08	12.5	-0.09	-0.07
Top 6 languages	916	-0.07	14.4	-0.08	-0.06	-0.08	12.7	-0.09	-0.07
Male	449	-0.05	20.1	-0.06	-0.04	-0.04	24.8	-0.05	-0.03
Female	98	-0.07	14.5	-0.08	-0.05	-0.09	11.6	-0.11	-0.06
Both	544	-0.10	10.3	-0.11	-0.09	-0.11	9.2	-0.12	-0.10
Farmers	34	-0.52	1.9	-0.55	-0.49	-0.52	1.9	-0.55	-0.49
Non Farmers	1,057	-0.06	16.5	-0.07	-0.06	-0.05	18.3	-0.06	-0.05
North America	710	-0.07	14.0	-0.08	-0.06	-0.08	12.0	-0.09	-0.07
Other region	381	-0.08	12.3	-0.09	-0.07	-0.07	14.8	-0.08	-0.06
<i>Estimation characteristics</i>									
DV: log mean wage	865	-0.08	12.2	-0.09	-0.07	-0.11	9.1	-0.12	-0.10
DV: mean log wage	226	-0.05	20.3	-0.05	-0.04	-0.03	36.1	-0.03	-0.02
Annual wage	102	-0.05	20.3	-0.06	-0.04	-0.03	29.5	-0.05	-0.02
Monthly wage	107	-0.11	8.8	-0.14	-0.08	-0.09	10.7	-0.12	-0.07
Weekly wage	491	-0.05	19.0	-0.06	-0.05	-0.07	14.7	-0.07	-0.06
Daily wage	54	-0.06	16.2	-0.07	-0.05	-0.06	16.0	-0.07	-0.05
Hourly wage	352	-0.11	9.4	-0.12	-0.09	-0.12	8.7	-0.13	-0.10
National	846	-0.07	13.4	-0.08	-0.07	-0.08	12.6	-0.09	-0.07
Regional	245	-0.08	13.1	-0.09	-0.07	-0.07	14.0	-0.08	-0.06
OLS	794	-0.07	14.1	-0.08	-0.07	-0.08	13.2	-0.09	-0.07
IV	297	-0.08	13.0	-0.09	-0.06	-0.08	12.1	-0.09	-0.07
<i>Fixed effects</i>									
Time	777	-0.09	11.7	-0.09	-0.08	-0.09	10.7	-0.10	-0.08
Person	249	-0.14	7.2	-0.16	-0.12	-0.12	8.1	-0.15	-0.10
Skill	955	-0.07	14.3	-0.08	-0.06	-0.07	14.4	-0.08	-0.06
<i>Publication characteristics</i>									
Published	781	-0.07	14.2	-0.08	-0.06	-0.06	15.4	-0.07	-0.06
Unpublished	310	-0.09	11.5	-0.10	-0.07	-0.12	8.6	-0.14	-0.10
Unpublished old	242	-0.06	15.8	-0.07	-0.05	-0.08	13.0	-0.09	-0.06
Top 5 journals	64	-0.04	26.0	-0.05	-0.03	-0.04	26.3	-0.05	-0.03
Top 20 journals	257	-0.05	18.7	-0.06	-0.05	-0.04	26.1	-0.05	-0.03

*Notes:* The exact definition of the variables is available in Table C1. Weighted = estimates are weighted by the inverse of the number of estimates reported per study. The column impl. el. depicts implied elasticity computed as  $\theta = -1/\sigma$ , where  $\theta$  is the negative inverse elasticity and  $\sigma$  is the implied elasticity. N is the number of observation per each sample. No winsorization needed.

which translate to higher substitutability between immigrants and natives.

**Structural variation.** Structural characteristics of the data reveal several interesting patterns. Estimates for *full-time workers* (-0.059) appear less negative than those for *all workers* (-0.088), suggesting that part-time or irregular employment may reduce the substitutability between native and immigrant labor. There are also notable differences across experience levels: estimates restricted to *high-experience workers* yield a mean inverse elasticity of -0.059, while those for *low-experience workers* are substantially more negative (-0.119). This pattern may suggest that immigrants are more easily substituted for experienced native workers, but the small number of observations in both categories (42 and 79, respectively) calls for caution in interpretation. In terms of education, natives with *lower education levels* seem somewhat more substitutable by immigrants, as shown by a slightly higher implied elasticity (16 vs. 13 for *high-educated workers*). This aligns with theoretical expectations that immigrants often compete more directly with lower-skilled natives in the labor market (Borjas *et al.*, 2011; Manacorda *et al.*, 2012). However, the difference is of small magnitude. Language and regional characteristics generally yield similar substitution patterns, with implied elasticities between 12 and 14 across *English-speaking*, *non-English-speaking*, *non-bilingual*, *top 6 language countries*, *North America* (Canada and the United States), and *other regions* (the rest of the world). However, studies from *bilingual countries* show notably higher substitutability, with a mean inverse elasticity of -0.038 (implied elasticity of 26). This might reflect greater labor market flexibility or adaptability in multilingual settings. Regarding gender, *female-specific* estimates ( $n = 98$ ) show an average inverse elasticity of -0.069, while *pooled* samples yield a more negative estimate of -0.097. Estimates for *males* suggest even higher substitutability (implied elasticity of 20). These patterns may reflect gendered differences in occupational concentration or labor market integration between natives and immigrants. Finally, estimates for *farm workers* are markedly more negative (-0.519,

implied elasticity of 2), likely due to segmentation in the agricultural labor market where immigrants and natives perform structurally distinct tasks, as highlighted in studies using U.S. farm data by Wei *et al.* (2016, 2019).

**Estimation characteristics.** Estimation decisions, including data frequency, wage definition, fixed effects, and estimation strategy, play a crucial role in shaping the reported elasticity of substitution between immigrant and native labor. One important distinction lies in the level of wage aggregation. Studies using *hourly wage* data report the lowest elasticity estimates (approximately 9 unweighted and weighted), implying stronger wage effects of immigration and lower substitutability. In contrast, *annual wage* measures yield much higher elasticities (20 unweighted, and 30 weighted), suggesting that longer time horizons may better capture labor market adjustments and attenuate short-run noise. This contradicts the concern raised by Borjas *et al.* (2012), who argued that annual earnings may conflate wage rates with labor supply and hence understate substitutability. In our sample, the pattern runs in the opposite direction, hourly earnings imply lower substitutability, whereas annual measures suggest higher elasticities.

The choice of dependent variable transformation also significantly influences the estimated elasticity. Most studies use either the *log of mean wages* ( $\log(\text{mean wage})$ ) or the *mean of log wages* ( $\text{mean}(\log \text{ wage})$ ). While the two may seem similar, they differ in important ways due to Jensen’s Inequality:

$$\text{mean}(\log(X)) \leq \log(\text{mean}(X))$$

which implies that  $\log(\text{mean wage})$  typically yields higher (i.e., more negative in our scenario) estimates of  $-1/\sigma$  than  $\text{mean}(\log \text{ wage})$ . This matters because most studies estimate the negative inverse elasticity, meaning a more negative value corresponds to lower substitutability. Accordingly, in our sample, studies using  $\log(\text{mean wage})$  report

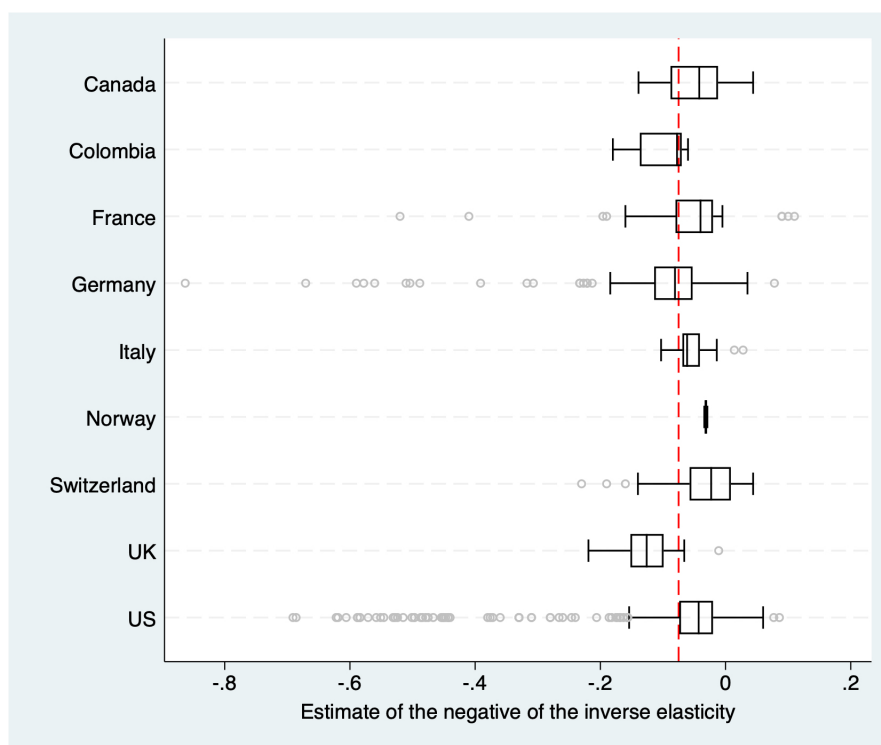
much lower elasticities: 12 (unweighted), 9 (weighted), and those using  $\text{mean}(\log \text{ wage})$  yield significantly higher elasticities: 20 (unweighted), 36 (weighted). This stark contrast echoes the debate between Borjas *et al.* (2012) and Ottaviano & Peri (2012). Borjas *et al.* critique the use of  $\log(\text{mean wage})$ , arguing it overstates the wage impact of immigration by downplaying within-group wage variation. They advocate for  $\text{mean}(\log \text{ wage})$ , which is more common in labor economics (e.g., Card, 2001; Katz & Murphy, 1992), better aligned with production theory, and less sensitive to outliers. Borjas *et al.* (2011) reinforces this preference, noting that  $\text{mean}(\log \text{ wage})$  provides a consistent marginal product index, whereas  $\log(\text{mean wage})$  lacks a direct theoretical interpretation. While our meta-analysis does not claim one transformation is universally superior, it confirms that the choice materially affects the estimated elasticity and should not be overlooked in policy interpretation.

Regarding estimation methods, we observe only modest differences between *ordinary least squares* (OLS) and *instrumental variable* (IV) estimates. OLS produces an average implied elasticity of 14 (unweighted), while IV estimates average 13. Lastly, *national* vs. *regional data* yield similar average estimates. National-level analyses produce a slightly less negative inverse elasticity (-0.075) compared to regional analyses (-0.076), implying similar substitution patterns.

**Publication characteristics.** Finally, publication characteristics reveal that *published studies* report less negative inverse elasticities (-0.070) compared to *unpublished studies* (working papers, or PhD theses; -0.087). This could indicate potential publication bias, where studies reporting higher substitutability estimates are more likely to be published. Studies *published in top-tier journals* (top 5 and top 20) report the least negative elasticities (-0.038 and -0.054, respectively), indicating that higher-quality studies might find higher substitutability, potentially due to more rigorous methodologies and peer review processes.

Overall, these findings underscore the variability in the estimated elasticity of substitution between immigrant and native labor, influenced by data characteristics, structural variations, estimation techniques, and publication quality. These differences highlight the complexity of labor market interactions and the importance of context-specific analyses in understanding the impacts of immigration on native wages and employment. Figure 1 shows a box plot of the negative inverse elasticity estimates across countries, revealing that the UK has the least substitutability, while Switzerland has the highest. However, it is important to note that the estimate for the UK is based on a single study, and conclusions drawn from it should be treated with caution. The corresponding summary statistics are quantified in Table 2.

Figure 1: Box plot of negative inverse elasticity across countries



*Notes:* The length of each box represents the interquartile range (P25-P75), and the dividing line inside the box is the median value. The whiskers represent the highest and lowest data points within 1.5 times the range between the upper and lower quartiles. The dots show the outlying estimates with extreme values stacked at the values denoted as 'outliers'. The red vertical line presents the mean of all estimates (-0.07).

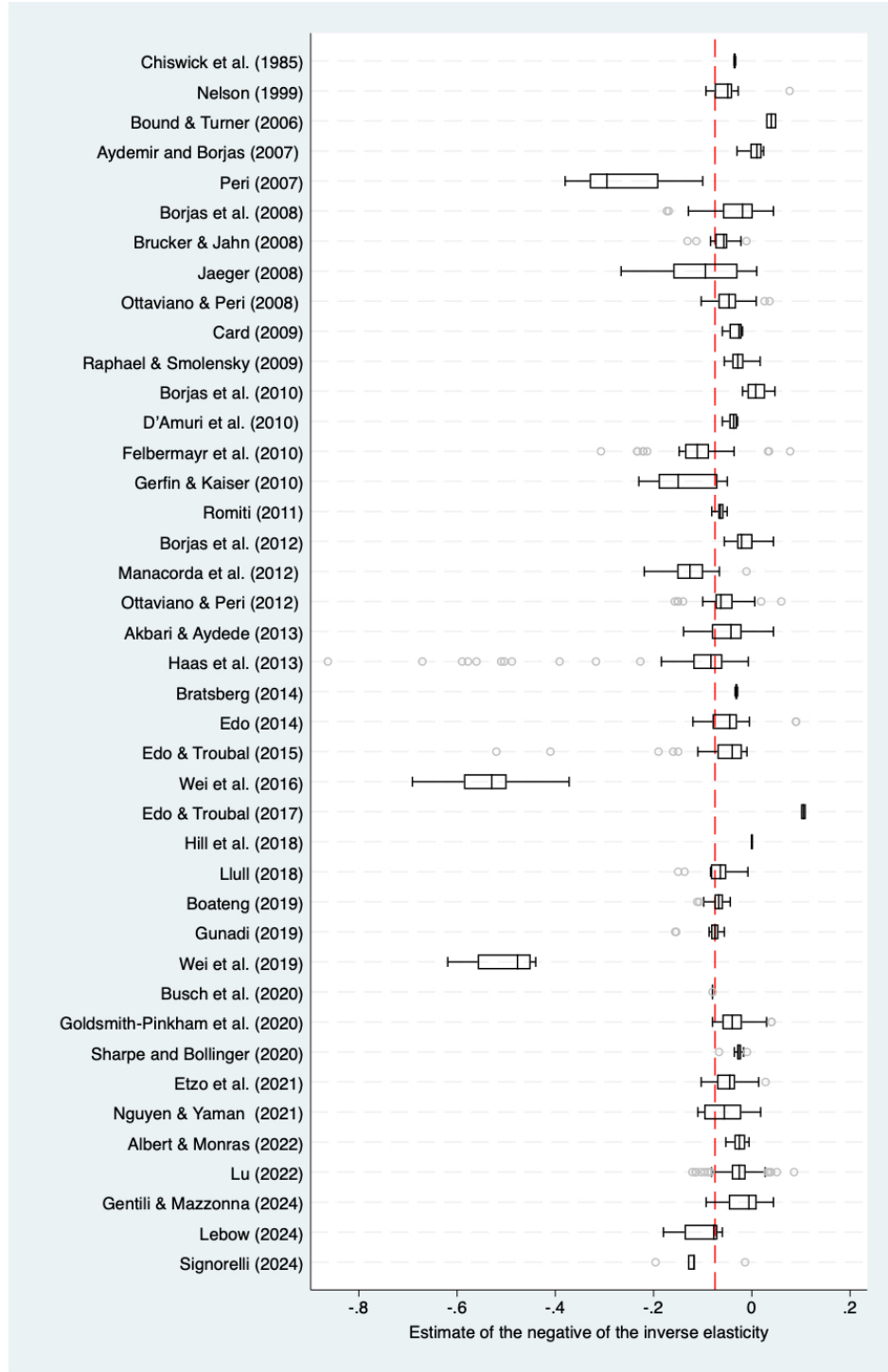
Table 2: Summary statistics for different countries

Country	Studies	Obs.	Unweighted			Weighted		
			Mean	Impl. el.	95% conf. int.	Mean	Impl. el.	95% conf. int.
Australia, Britain, Canada, US	1	4	-0.03	28.6	-0.04 -0.03	-0.03	28.6	-0.04 -0.03
Canada	3	63	-0.05	21.1	-0.06 -0.04	-0.04	24.7	-0.05 -0.03
Colombia	1	30	-0.10	10.3	-0.11 -0.08	-0.10	10.3	-0.11 -0.08
France	4	83	-0.06	17.1	-0.08 -0.04	-0.03	33.9	-0.05 -0.01
Germany	5	136	-0.12	8.5	-0.14 -0.09	-0.09	11.3	-0.10 -0.07
Italy	2	35	-0.06	18.1	-0.06 -0.05	-0.06	17.8	-0.06 -0.05
Norway	1	4	-0.03	31.7	-0.04 -0.03	-0.03	31.7	-0.04 -0.03
Switzerland	2	68	-0.03	34.6	-0.04 -0.02	-0.08	12.6	-0.10 -0.06
UK	1	25	-0.13	7.9	-0.15 -0.11	-0.13	7.9	-0.15 -0.11
US	21	643	-0.07	13.5	-0.08 -0.06	-0.09	11.0	-0.10 -0.08
US without farmers	19	609	-0.05	20.3	-0.05 -0.04	-0.05	21.4	-0.05 -0.04
	41	1,091						

*Notes:* In four cases (Australia–Britain–Canada–US combined, Colombia, Norway, and the UK), only one study is available for the country; hence, weighted and unweighted means are identical. Weighted = estimates are weighted by the inverse of the number of estimates reported per study. No winsorization needed.

Figure 2 shows a box plot of negative inverse elasticity estimates across individual studies, sorted by publication year, illustrating variations not only across countries but also across studies. Notably, studies by Wei *et al.* (2016) and Wei *et al.* (2019) focus on farm workers, explaining their distinct estimates. The distinctiveness in these estimates arises from the specific nature of farm work, which often involves labor-intensive tasks requiring particular physical endurance and skills typically found among younger workers (Wei *et al.*, 2016, 2019).

Figure 2: Box plot of negative inverse elasticity across studies



*Notes:* The length of each box represents the interquartile range (P25-P75), and the dividing line inside the box is the median value. The whiskers represent the highest and lowest data points within 1.5 times the range between the upper and lower quartiles. The dots show the outlying estimates with extreme values stacked at the values denoted as 'outliers'. The red vertical line presents the mean of all estimates (-0.07).

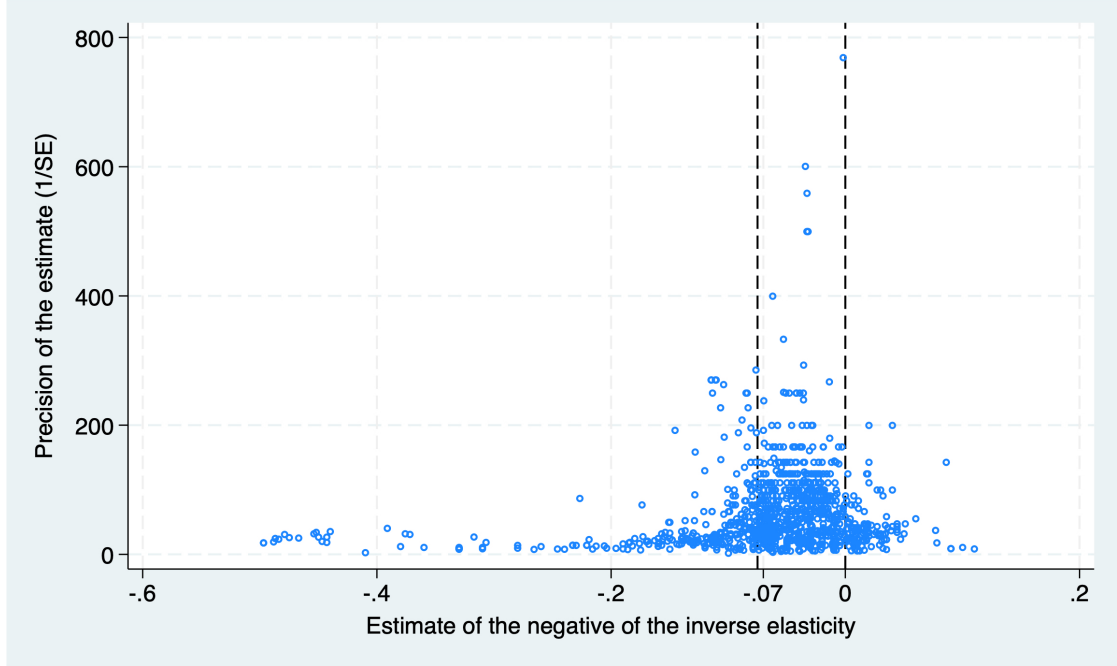
### 3 Publication Bias

Publication bias poses a major challenge in any meta-analysis, particularly when studies with significant or expected results are more likely to be published than those with null or unexpected findings. This can lead to systematic under- or overestimation of the true effect size—in this case, the elasticity of substitution between immigrant and native labor. To assess and correct for such bias, we apply a wide array of graphical, linear, and nonlinear meta-regression techniques. Our goal is to quantify the impact of publication bias and recover bias-adjusted estimates that better approximate the true underlying elasticity.

A funnel plot, developed by Egger *et al.* (1997), is a scatter diagram that plots the size of a study’s effect estimate horizontally against its inverse standard error (a proxy for precision) on the vertical axis. Funnel plots are a widely used visual tool for detecting publication bias (Stanley & Doucouliagos, 2010), and Figure 3 illustrates this relationship for our dataset of negative inverse elasticities. In the absence of publication bias, the plot should be symmetric around the mean estimate because studies with smaller sample sizes (and thus larger standard errors) are expected to scatter widely at the bottom of the plot, while those with larger sample sizes (and smaller standard errors) cluster narrowly at the top. Figure 3 reveals noticeable asymmetry, indicating potential publication bias. The vertical lines at -0.07 and zero indicate the mean of all collected estimates and the point of positive values of the negative inverse elasticity, respectively. The asymmetry, particularly the longer left tail, suggests that studies with negative estimates are overrepresented in the literature.



Figure 3: Funnel plot suggests publication bias among elasticities



*Notes:* The first vertical line from the left at -0.07 represents the mean of all collected estimates (1,091), while the second vertical line at zero indicates some positive values of the negative inverse elasticity, implying a negative implied elasticity. In the absence of publication bias the funnel plot should be symmetrical. Studies used in the analysis are listed in Table A1. SE = standard error. For clarity, we drop 26 estimates, which are lower than -0.5. In reality, there is a longer left tail. We include all estimates in the following analysis.

### 3.1 Methodology

To quantify the publication bias, we perform linear meta-regression models such as the Funnel Asymmetry Test (FAT) and Precision Effect Test (PET), along with the PEESE and PET-PEESE models. These methods rely on regressing elasticity estimates on their standard errors to detect systematic patterns in reported results.

$$\hat{\theta}_i = \beta_0 + \beta_1 \cdot SE(\hat{\theta}_i) + \epsilon_i \quad (3)$$

Here,  $\hat{\theta}_i$  is the reported negative inverse elasticity estimate from study  $i$  (i.e.,  $\hat{\theta}_i = -1/\hat{\sigma}_i$ , where  $\hat{\sigma}_i$  is implied elasticity from study  $i$ ),  $SE_i$  is its standard error, and  $\epsilon_i$  is an error term. If  $\beta_1$  is statistically significant, it suggests publication bias (smaller studies report systematically different effects). The intercept  $\beta_0$  represents the true effect size corrected for bias. PEESE works similarly, it corrects for heteroskedasticity and adjusts for bias in reported estimates with regression model:  $\hat{\theta}_i = \beta_0 + \beta_1 \cdot SE_i^2 + \epsilon_i$ .

To account for within-study dependence and between-study heterogeneity, we estimate fixed-effects (FE), between-effects (BE), and weighted meta-regressions. Following best practices in meta-analysis, we apply alternative weighting schemes also based on inverse variance, often recommended as the optimal weight in meta-analysis (Stanley & Doucouliagos, 2015). In addition to linear approaches, several nonlinear and advanced methods are employed, including Weighted Average of Adequately Powered Estimates (WAAP) proposed by Ioannidis *et al.* (2017), which corrects for publication bias by averaging estimates with sufficient statistical power; Stem-Based Method developed by Furukawa (2020), which adjusts for publication bias by examining the distribution of study results; Endogenous Kink (EK) introduced by Bom & Rachinger (2019), which accounts for nonlinear publication bias; and Selection Model (SM) proposed by Andrews & Kasy (2019), which estimates the probability that non-significant results are published relative to significant ones.

These methods allow for richer correction of publication bias, especially when its functional form is not linear. Moreover, instrumental variable (IV) methods are widely employed in meta-analyses to address potential endogeneity between reported estimates and their standard errors, which may arise due to selective reporting or model specification choices. In theory, valid instruments can isolate exogenous variation in the standard error and recover unbiased estimates of the true effect. However, in our setting, attempts to implement IV strategies were unsuccessful due to weak instrumentation. Specifically, we tested standard instruments used in meta-analysis, such as the square root of the

inverse number of observations (as a proxy for precision), (log) citations per year, and journal impact factor. However, none of these instruments passed standard relevance thresholds, resulting in weak instrument problems. Weak instruments can exacerbate bias rather than mitigate it, producing highly unstable estimates with inflated standard errors. Given these limitations, and in line with best practices for meta-analytic inference under instrument weakness, we do not report results from IV estimations.

### 3.2 Results

To assess the extent of publication bias in the empirical literature on the elasticity of substitution between native and immigrant labor, we apply the code developed by Havráňková *et al.* (2023), which includes four estimators: FAT-PET, PEESE, PET-PEESE, and EK. Table 3 presents the  $\beta_0$  (corrected effect size) estimates across these methods under three different weighting schemes: unweighted (0), standard inverse-variance weights (1), and adjusted weights (2). The main estimate, highlighted in bold, comes from FAT-PET under standard weighting (1), which we identify as the most appropriate weighting scheme based on robustness and model consistency.

Table 3: Corrected effect estimates ( $\beta_0$ ) from FAT-PET, PEESE, PET-PEESE, and EK under different weighting schemes

Method	No Weights (0)	Standard Weights (1)	Adjusted Weights (2)
<b>FAT-PET</b>	-0.052*** (0.004)	<b>-0.038*** (0.005)</b>	-0.051*** (0.004)
PEESE (Robustness)	-0.071*** (0.003)	-0.046*** (0.004)	-0.071*** (0.003)
PET-PEESE (Alternative)	-0.071*** (0.003)	-0.046*** (0.004)	-0.071*** (0.003)
EK (Sensitivity)	-0.052*** (0.004)	-0.038*** (0.005)	-0.051*** (0.004)

*Notes:* The table reports corrected effect sizes ( $\beta_0$ ) from each estimator. The standard errors are reported in parantheses. The main specification (bold) uses standard inverse-variance weights. PET-PEESE follows a decision rule based on the FAT-PET slope.

All methods detect publication bias, with standard weights yielding our preferred baseline. The FAT-PET intercept is statistically significant at  $-0.038$  ( $p < 0.001$ ), indicating a small and negative average elasticity in the absence of publication bias. The slope is also significantly negative ( $\beta_1 = -0.703$ ,  $p = 0.009$ ), suggesting that smaller, less

precise studies tend to report stronger negative effects, a classic sign of small-study bias. These results are corroborated by wild bootstrap tests. According to the PET-PEESE decision rule (Stanley & Doucouliagos, 2014), in our case the corrected effect size should be taken from the PEESE regression. In this literature the PET and PEESE estimates are identical, which supports the robustness of the result.

The choice of weighting scheme also affects the results. Unweighted estimates are consistently more negative, suggesting small-study bias, where low-precision studies disproportionately report large negative effects. Standard weighting reduces the magnitude of the effect and is statistically more stable, making it the preferred approach. Adjusted weights (2) attempt to account for selection bias in reported estimates, but the corrected effects are similar to the unweighted results, implying that this scheme does not fully mitigate small-study bias.

To further investigate publication bias, we employ both linear and nonlinear meta-regression methods. To address heteroskedasticity, we also apply weights based on inverse variance, following the methodologies of Stanley (2008), Doucouliagos & Stanley (2013), and Stanley & Doucouliagos (2014). A statistically significant slope on the standard error indicates the presence of small-study effects or publication bias. Under the assumption that publication selection is linearly related to study precision and that heterogeneity is negligible, the intercept can be interpreted as the true, bias-corrected elasticity of substitution. However, the linearity assumption does not always hold, as explained by Andrews & Kasy (2019). Thus, in addition to the linear tests, we employed several advanced (nonlinear) techniques to correct for publication bias.

Table 4 presents the results from these linear tests (Panel A) and compares them with several advanced nonlinear methods (Panel B), including WAAP, the Stem method, the Selection Model, and the Endogenous Kink (EK) estimator. Across the table, both linear and nonlinear methods suggest statistically significant publication bias and yield higher corrected elasticities than those reported in the unadjusted literature.

Table 4: Linear as well as nonlinear techniques suggest publication bias

<b>Panel A: linear</b>			
	OLS	FE	BE
SE	-0.703*** (0.270)	-0.654*** (0.219)	-0.881 (0.710)
Constant	-0.0515*** (0.0102)	-0.0531*** (0.00732)	-0.0472 (0.0303)
impl.el.	19.4	18.8	21.2
Observations	1,091	1,091	1,091
Number of idstudy		41	41
R-squared	0.060	0.097	0.038
	Precision	Study	
SE	-1.083** (0.458)	-0.785* (0.465)	
Constant	-0.0388*** (0.00817)	-0.0505*** (0.0128)	
impl.el.	25.8	19.8	
Observations	1,091	1,091	
R-squared	0.068	0.047	
<b>Panel B: nonlinear</b>			
	WAAP	Stem method	EK
SE			-1.1176*** (0.1651)
Constant	-0.0454*** (0.00153)	-0.0268 (0.0206)	-0.0383*** (0.0018)
implied el.	22.0	37.3	26.1
	SM		
SE	P = 0.752 (0.065)		
Constant	-0.044*** (0.002)		
implied el.	22.7		

*Notes:* The table presents results of regression  $\theta_{ij} = \beta_0 + \beta_1 SE_{ij} + \epsilon_{ij}$ , and  $SE(\theta_{ij})$  are the i-th estimates of the negative inverse elasticity and their standard errors reported in the j-th study. The standard errors clustered at the study level are reported in parantheses. Implied elasticity ( $\sigma$ ) is calculated as  $\sigma = -1/\theta$ . OLS = ordinary least squares. FE = study-level fixed effects. BE = study-level between effects. Precision = the inverse of the reported estimate's variance is used as the weight. Study = the inverse of the number of estimates reported per study is used as the weight. WAAP = the weighted average of adequately powered estimates by Ioannidis *et al.* (2017). The stem-based technique by Furukawa (2020). EK = endogenous kink by Bom & Rachinger (2019). SM = selection model, the method by Andrews & Kasy (2019), P denotes the probability that estimates insignificant at the 5% level are published relative to the probability that significant estimates are published (normalized at 1). N = 1,091. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

To interpret these magnitudes, consider that a higher elasticity implies weaker wage effects of immigration. For instance, an elasticity of 13 (uncorrected mean) implies that a 10% increase in immigrant labor leads to about a 0.77% decrease in native wages, whereas an elasticity of 20 (corrected for publication bias) reduces that impact to just

0.5%.<sup>2</sup> Thus, moving from an elasticity of 13 to 20 reflects a nearly 35% reduction in the estimated wage pressure from immigration.<sup>3</sup> This pattern, though seemingly counterintuitive, reflects the distinction between two different types of labor market adjustments. When the elasticity of substitution is high, it means that immigrants and natives are close substitutes—they perform similar tasks and can readily replace each other in production. In such cases, employers can easily switch to cheaper labor (e.g., immigrants), but because substitution is efficient (without major frictions or losses in productivity), the average wage for those who remain employed declines only modestly.

However, the limited average wage decline does not imply no impact: the burden may fall on the extensive margin—some natives may exit employment or be displaced to other sectors. In other words, displacement rather than wage compression may become the dominant channel. This distinction is emphasized by Borjas (2003), who note that average wage effects may understate the true economic pressure from immigration if substitution is high. Similarly, Smith (2003) explains that partial equilibrium models often show wage declines, while general equilibrium frameworks highlight the role of reallocation and sectoral mobility.

Moreover, Ottaviano & Peri (2012) argue that immigration’s wage impact depends critically on the degree of substitutability. In contexts where immigrants and natives are not perfect substitutes, the effects are more diffuse and may involve complementarities in production. But when substitutability is high, as our corrected elasticity of 20 suggests, wages become less responsive, while employment composition adjusts more sharply. Therefore, the finding that a 10% increase in immigrant labor reduces native wages by only 0.5% when elasticity is 20 does not imply an absence of labor market pressure. Rather, it suggests that labor markets adjust via both wages and employment, with the wage margin being muted under high substitutability.

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<sup>2</sup>This is based on the standard relationship  $\Delta w/w = -1/\sigma \cdot \Delta L/L$ .

<sup>3</sup>Difference in impact:  $0.77\% - 0.50\% = 0.27\%$ . Relative reduction:  $0.27\%/0.77\% \approx 0.35$ , or 35%.

**Linear Tests.** The results from OLS and fixed-effects (FE) meta-regressions confirm publication bias, with significantly negative slopes on the standard error term. The between-effects (BE) model, however, yields an insignificant slope, likely due to its inability to capture within-study variation. The FE model is supported by a high intra-class correlation ( $\rho \approx 0.78$ ), indicating that much of the variance is driven by study-level characteristics, making it a more appropriate specification than BE. Weighted regressions amplify the signal of bias. Weighting by precision produces a larger bias estimate than OLS, whereas weighting by the inverse number of estimates per study still yields significant results, though somewhat attenuated. All linear models (except BE) produce statistically significant intercepts, which can be interpreted as the corrected effects. For instance, the FE regression suggests a corrected elasticity of approximately 19, compared to the unweighted mean of 13.

**Nonlinear Corrections.** Panel B shows that nonlinear correction methods largely corroborate the findings from linear models, often producing even higher implied elasticities. The WAAP estimator yields a corrected elasticity of 22, while the EK method estimates 26. These methods are particularly useful because they do not rely on the linearity assumption and can better accommodate the non-random selection of statistically significant estimates. The Stem-based method by Furukawa (2020) produces a higher corrected elasticity (37), although the estimate is not statistically significant. The Selection Model (SM) of Andrews & Kasy (2019) estimates that studies with insignificant results at the 5% level are about 75.2% as likely to be published as significant ones, suggesting a moderate degree of selection bias. The SM also returns a corrected elasticity of 23, aligning well with the WAAP and linear methods.

### 3.3 Results: Subsamples

To assess how publication bias varies across study contexts and methodological choices, we conduct a detailed subsample analysis. By disaggregating the data, we explore whether corrected elasticities differ by region, estimation strategy, sample characteristics, and model specification. This approach complements the heterogeneity analysis presented in the next section and helps validate whether the main findings hold in distinct subsets of the literature.

Table 5 summarizes the comparison of uncorrected and corrected mean implied elasticities across various subsamples. The last column reports the difference between these values, providing an estimate of how much publication bias may have affected each subgroup. Most subsamples display a positive correction, suggesting that the literature tends to underreport the elasticity of substitution between native and immigrant labor. The results of the linear tests (OLS, FE, weighted by precision, weighted by the number of estimates per study) for all subsamples can be found in the Appendix, Table B1 depicts the results for different countries, Table B2 shows the results for all other subsamples. The results reveal several important patterns.

**Geographic and Linguistic Variation.** One of the most striking findings concerns regional differences. Prior to correcting for publication bias, the mean implied elasticities for North America and other regions are relatively close (14 vs. 12). However, after correction, the implied elasticity in North America jumps to 38 compared to just 15 for other regions, a difference of 23 points. This substantial divergence suggests that immigrants and natives are significantly more substitutable in North American labor markets. A similar pattern appears when we consider language, English-speaking countries show a much larger correction (from 14 to 38) than non-English-speaking countries (from 13 to 16). The larger correction in English-speaking countries indicates stronger publication bias in that context, possibly due to editorial preferences or academic norms. The smaller



Table 5: Comparison of uncorrected and corrected mean implied elasticity

Variable	n	Uncorrected el.	Corrected el.	Difference	Variable	n	Uncorrected. el.	Corrected. el.	Difference
Elasticity	1,091	13.3	24.4	11.1	Monthly wage	107	8.8	12.9	4.1
<b>Data characteristics</b>					Weekly wage	491	19.0	18.3	-0.7
High number of cells	398	15.3	21.9	6.6	Daily wage	54	16.2	12.4	-3.8
Low number of cells	693	12.4	22.1	9.7	Hourly wage	352	9.4	14.9	5.5
Annual frequency data	488	9.2	10.9	1.7	National	846	13.4	18.6	5.2
Lower frequency data	603	20.8	46.3	25.5	Regional	245	13.1	10.1	-3.0
<b>Structural variation</b>					OLS	794	14.1	13.5	-0.6
All workers	603	11.4	17.5	6.1	IV	297	13.0	17.7	4.7
Full-time workers	488	16.8	26.1	9.3	<i>Fixed effects</i>				
High level of experience	42	17.0	15.6	-1.4	Time	777	11.7	14.9	3.2
Low level of experience	79	8.4	44.2	35.8	Person	249	7.2	11.8	4.6
High level of education	106	13.0	16.3	3.3	Skill	955	14.3	15.2	0.9
Low level of education	171	15.5	25.2	9.7	<b>Publication characteristics</b>				
English	735	13.6	37.6	24	Published	781	14.2	18.9	4.7
Non-English	356	12.8	15.5	2.7	Unpublished	310	11.5	15.8	4.3
Bilingual	131	26.4	27.0	0.6	Unpublished old	242	15.8	13.7	-2.1
Non-biling	960	12.5	20.2	7.7	Top 5 journals	64	26.0	19.2	-6.8
Top 6 languages	916	14.4	21.6	7.2	Top 20 journals	257	18.7	18.6	-0.1
Male	449	20.1	33.6	13.5	<b>Countries</b>				
Female	98	14.5	19.3	4.8	Canada	63	21.1	24.4	3.3
Both	544	10.3	14.2	3.9	Colombia	30	10.3	22.3	12
Farmers	34	1.9	2.4	0.5	France	83	17.1	172.7	155.6
Non Farmers	1,057	16.5	23.6	7.1	Germany	136	8.5	11.8	3.3
North America	710	14.0	38.3	24.3	Italy	35	18.1	16.2	-1.9
Other region	381	12.3	14.9	2.6	Norway	4	31.7	22.6	-9.1
<b>Estimation characteristics</b>					Switzerland	68	34.6	44.2	9.6
DV_log mean wage	865	12.2	17.7	5.5	UK	25	7.9	12.5	4.6
DV_mean log wage	226	20.3	21.0	0.7	US	643	13.5	48.5	35
Annual wage	102	20.3	22.7	2.4	US wo farmers	609	20.3	45.2	24.9

Notes: The exact definition of the variables is available in Table C1. The results from the linear tests can be found in Table B1 and Table B2.

correction in non-English-speaking countries may reflect less selective reporting, but also lower underlying substitutability, potentially linked to language and institutional barriers between natives and immigrants. Moreover, there are notable differences between national and regional data sources. While uncorrected mean elasticities appear nearly identical (approximately 13), publication bias adjustments reveal a striking divergence. The corrected mean elasticity rises to 19 for national-level analyses but declines to just 10 for regional-level ones. These findings caution against treating the two approaches as interchangeable and underscore the importance of accounting for estimation context when comparing results across studies.

**Experience and Education.** The corrected elasticity varies significantly by experience level. Low-experience workers show a sharp increase in elasticity (from 8 to 44), while high-experience workers display a negligible change (from 17 to 15). This difference implies that younger or less experienced native workers face stronger substitution pressures from immigrants. These results resonate with the BMA findings, where “low experience” had a high posterior inclusion probability ( $PIP = 1.00$ ) and negative marginal effect, indicating stronger effects in this group. In contrast, education level shows a more modest effect. The corrected elasticities for low-educated (25) and high-educated (16) workers differ by 9 points. While suggestive of some heterogeneity, the difference is less pronounced than for experience.

**Log Mean vs. Mean Log Wages.** The transformation of the dependent variable plays a pivotal role in shaping elasticity estimates. Studies using the log of mean wages yield a corrected elasticity of 18, whereas those using the mean of log wages report a similar corrected elasticity of 21, a modest difference of just 3 points. While the uncorrected estimates differ more substantially (12 vs. 20), the correction narrows this gap. This finding is particularly important in light of prior critiques. According to Borjas *et al.* (2012), the log of mean wages tends to produce more negative effects, potentially

overstating the adverse wage impact of immigration. Conversely, the mean of log wages, endorsed by Borjas and others as the standard approach, yields more conservative and theoretically sound results. Our corrected results suggest that once publication bias is accounted for, the difference in effect size between these two transformations becomes negligible, implying that previous disputes may have been driven in part by selective reporting rather than fundamental differences in measurement.

**Other Noteworthy Patterns.** *Frequency of Data:* Studies using lower-frequency data (e.g., decennial census rounds) show a substantial correction in implied elasticity, from 21 to 46, compared to a smaller increase in studies using annual data (from 9 to 11). This suggests that publication bias is more severe in studies relying on infrequent data collection. Notably, this pattern appears driven by U.S. and Canadian studies, which often rely on census data and also exhibit large corrected elasticities. *Gender:* Male samples see a large correction (from 20 to 34), while female-only samples show a more modest change (15 to 19), consistent with BMA results where the male variable had a strong positive effect ( $PIP = 1.00$ ). *Published vs. Unpublished Studies:* Both published and unpublished studies show substantial corrections ( $\approx 4.5$  points), indicating that publication bias affects the entire literature, not only journal articles. Interestingly, top 5 journals show a negative correction, possibly reflecting more rigorous identification strategies or selectivity.

The subsample analysis reinforces the core finding of this paper: publication bias leads to systematic underestimation of the elasticity of substitution between native and immigrant labor. Most subsamples show significant upward corrections once bias is addressed, particularly among low-experience workers, North American and English-speaking countries, and studies using lower-frequency data. Moreover, the relatively small difference between corrected elasticities across different dependent variable transformations suggests that the choice between log mean and mean log, while important,

does not fully explain the variation in the literature. Rather, much of the observed heterogeneity is driven by structural differences in populations, contexts, and estimation methods, as supported by the BMA.

## 4 Heterogeneity

While publication bias distorts meta-analytic results by favoring significant estimates, heterogeneity reflects genuine differences across studies due to variation in data, methodology, and context. Identifying the key drivers of heterogeneity is critical for understanding when and why studies report higher or lower elasticities of substitution between immigrant and native labor. In this section, we explore the extent and sources of heterogeneity using Bayesian Model Averaging (BMA) and Frequentist Model Averaging (FMA), supported by results from the publication bias subsample analysis.

The literature on the elasticity of substitution spans multiple countries, time periods, data types, and estimation strategies. As such, estimates are likely to reflect not only underlying economic relationships but also structural and methodological variation. We categorize sources of heterogeneity into four domains: data characteristics, structural variation, estimation characteristics, and publication characteristics. Table 6 summarizes the variables used in our heterogeneity models. For each, we coded 1,087 observations from 40 studies.<sup>4</sup>

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<sup>4</sup>The number of observations differ from the publication bias analysis. We had to drop 4 observations (1 study) due to lack of the data.

Table 6: Characteristics used to explain heterogeneity

Category	Variables
Data characteristics	Number of cells (log), Annual frequency data
Structural variation	All workers, High level of experience, Low level of experience, High level of education, Low level of education, Top 6 languages, Male, Female, Immigrant population
Estimation characteristics	log(mean wage), Annual, Monthly, Weekly, Daily, Hourly, National, OLS
<i>Fixed effects</i>	Time FE, Personal FE, Skill FE
Publication characteristics	Impact factor, Citations/year (log), Published study, Top 5 journal, Publication year (log)

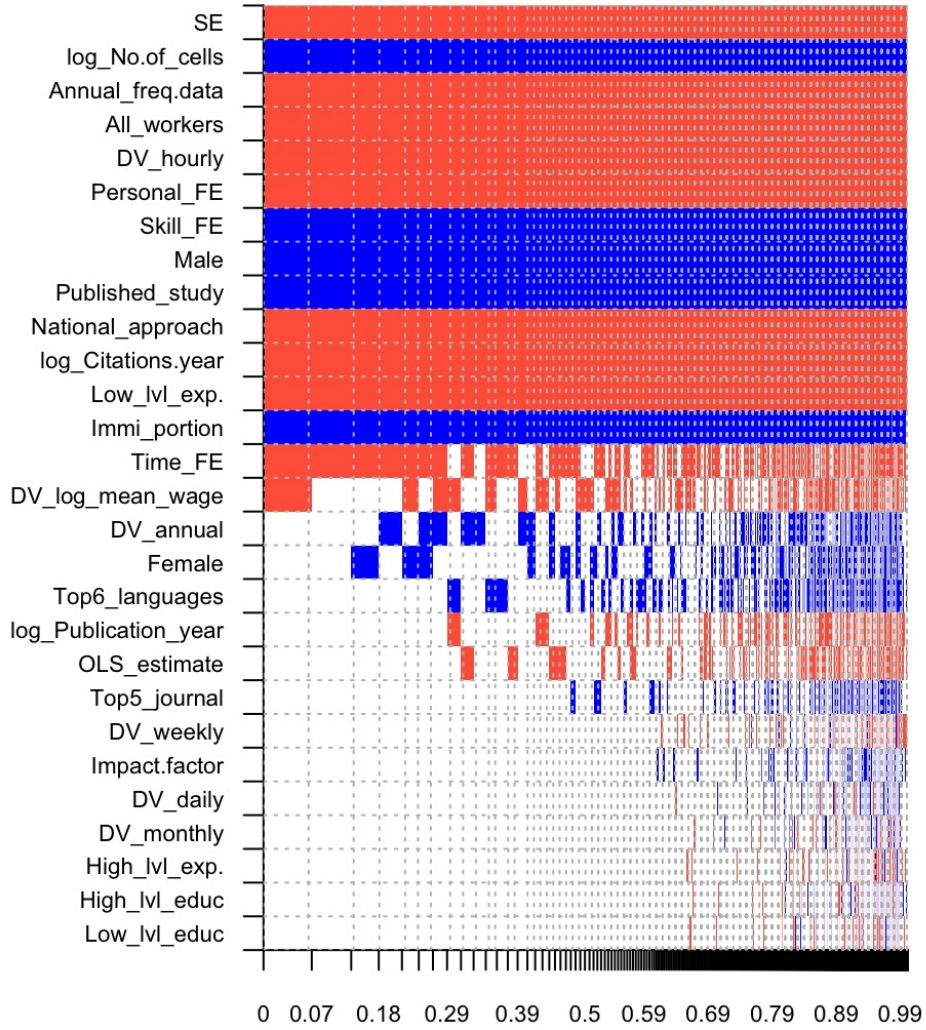
*Notes:* Details on each variable, including definition and summary statistics, are available in Table C1.

To account for model uncertainty, we estimate both BMA and FMA models, using the inverse of the elasticity (i.e.,  $\theta = -1/\sigma$ ) as the dependent variable. We implement BMA using the UIP prior (unit information prior assumes a unit-information prior centered around zero) for the  $g$ -prior and a uniform prior over model space as the baseline specification. This combination reflects standard practice in economic meta-analyses and balances parsimony with flexibility. To ensure robustness, we perform a series of additional estimations using alternative prior settings, including BRIC, EBL, and hyper- $g$  priors, combined with both uniform and random model priors. The results of these robustness checks are consistent with the baseline model and are presented in Appendix C. All BMA specifications were estimated using Markov Chain Monte Carlo (MCMC) sampling with 3 million iterations (after a 1 million burn-in), and the full model space was explored up to 10,000 models. Figure 4 shows posterior inclusion probabilities (PIPs) across all variables, while Table 7 reports corresponding coefficient estimates.

#### 4.1 Key Drivers of Elasticity Estimates

Firstly, it is essential to clarify how to interpret the dependent variable used in our analysis. All primary studies report the negative inverse of the elasticity of substitution ( $-1/\sigma$ ). As a result, a more negative value of  $-1/\sigma$  indicates a lower elasticity ( $\sigma$ ), meaning weaker substitutability between native and immigrant labor. Conversely, less negative (closer to zero) values imply higher elasticity and thus greater substitutability.

Figure 4: Model inclusion in Bayesian model averaging.



*Notes:* The response variable is the estimate of the elasticity of substitution. Columns denote individual models; variables are sorted by posterior inclusion probability in descending order. The horizontal axis denotes cumulative posterior model probabilities. Blue color = the variable is included and the estimated sign is positive. Red color = the variable is included and the estimated sign is negative. No color = the variable is not included in the model. Numerical results of the BMA exercise are reported in Table 7, detailed description of all variables is available in Table C1.

Table 7: Why do estimates of the elasticity of substitution differ?

	Bayesian model averaging			Frequentist check		
	PIP	Post. mean	Post. SD	Coef.	SE	<i>p</i> -value
Constant	1.00	5.4	NA	30.12	12.72	0.02
SE	1.00	-0.49	0.08	-0.53	0.08	0.00
<b>Data characteristics</b>						
Number of cells (log)	1.00	0.06	0.01	0.07	0.01	0.00
Annual frequency data	1.00	-0.09	0.01	-0.08	0.01	0.00
<b>Structural variation</b>						
All workers	1.00	-0.05	0.01	-0.05	0.01	0.00
High level of experience	0.03	0.00	0.00	0.01	0.01	0.67
Low level of experience	1.00	-0.05	0.01	-0.04	0.01	0.00
High level of education	0.03	0.00	0.00	0.00	0.01	0.74
Low level of education	0.03	0.00	0.00	0.00	0.01	0.81
Top 6 languages	0.29	0.01	0.01	0.04	0.02	0.02
Male	1.00	0.04	0.01	0.04	0.01	0.00
Female	0.32	0.01	0.01	0.02	0.01	0.04
Immigrant population	1.00	0.38	0.09	0.35	0.09	0.00
<b>Estimation characteristics</b>						
DV: log mean wage	0.44	-0.01	0.01	-0.01	0.01	0.12
DV_annual	0.33	0.01	0.02	0.01	0.02	0.56
DV_monthly	0.04	0.00	0.00	0.01	0.02	0.38
DV_weekly	0.06	0.00	0.00	-0.01	0.01	0.69
DV_daily	0.04	0.00	0.00	0.02	0.02	0.37
DV_hourly	1.00	-0.06	0.01	-0.06	0.01	0.00
National	1.00	-0.05	0.01	-0.04	0.01	0.00
OLS	0.20	0.00	0.01	-0.02	0.01	0.02
<i>Fixed effects</i>						
Time FE	0.71	-0.02	0.01	-0.01	0.01	0.10
Personal FE	1.00	-0.08	0.01	-0.09	0.01	0.00
Skill FE	1.00	0.07	0.01	0.07	0.01	0.00
<b>Publication characteristics</b>						
Impact factor	0.05	0.00	0.00	0.00	0.01	0.69
Citations/year (log)	1.00	-0.02	0.01	-0.03	0.01	0.00
Published study	1.00	0.05	0.01	0.06	0.01	0.00
Top5 journal	0.11	0.00	0.01	0.02	0.02	0.25
Publication year (log)	0.21	-1.69	3.73	-9.18	3.85	0.02
Studies	40			40		
Observations	1,087			1,087		

*Notes:* PIP = posterior inclusion probability. For the interpretation of the posterior inclusion probability, we follow the guidelines offered by Kass & Raftery (1995) to be able to evaluate the importance of each explanatory variable:  $0.5 < PIP < 0.75$ : weak effect,  $0.75 < PIP < 0.95$ : substantial effect,  $0.95 < PIP < 0.99$ : strong effect,  $0.99 < PIP$ : decisive effect. SD = standard deviation. The table shows unconditional moments for BMA. Detailed description of all variables is available in Table C1.

Several variables emerge as consistent predictors of the estimated elasticity of substitution. Larger *standard errors* are associated with more negative  $-1/\sigma$  estimates, confirming the presence of small-study effects consistent with our publication bias findings. This implies that smaller, less precise studies tend to report lower substitution elasticities ( $\sigma$ ), likely due to selective reporting or overfitting. *Annual frequency data* studies report more negative  $-1/\sigma$ , implying lower elasticities and less substitutability. This may be driven by U.S. and Canadian studies or due to short-term noise in annual data masking longer-term labor market adjustments. Studies focusing on *low-experience* workers yield more negative  $-1/\sigma$  values, indicating lower  $\sigma$  and hence lower substitutability between immigrants and natives in this group. This aligns with the subsample findings showing low-experience workers are more exposed to competition from immigrants. Studies focusing on *male samples* tend to report less negative  $-1/\sigma$  estimates, implying higher elasticities and greater substitutability between immigrant and native male workers. This aligns with the subsample results, where male-only samples had a high corrected elasticity (34), indicating stronger substitution effects compared to female or mixed-gender samples. Higher *immigrant shares* are associated with less negative  $-1/\sigma$  estimates, which implies higher elasticity and greater substitutability. This suggests that labor markets with more immigrants may be more integrated or better structured for immigrant-native substitution. Including *personal fixed effects* results in more negative  $-1/\sigma$  values, suggesting lower elasticity and less substitutability, possibly because controlling for individual-level heterogeneity reveals greater differences between native and immigrant workers. Conversely, including *skill fixed effects* produces positive  $-1/\sigma$  values, indicating higher elasticity and greater substitutability across skill groups once this variation is controlled for. While the BMA model suggests that *national-level* studies are associated with more negative  $-1/\sigma$  estimates (i.e., lower elasticity), the publication bias analysis yields a different result. Once corrected, national-level studies yield higher elasticities than *regional ones* (19 vs. 10), indicating greater substitutabil-



ity. This suggests that the more negative estimates from national studies may partly reflect bias or methodological differences rather than genuine differences in substitution patterns. One possible explanation is that national data may appear less substitutable due to aggregation, but once bias is corrected, their estimates reflect more integrated labor markets compared to the more localized, and possibly more segmented, regional analyses. *Published* studies tend to be less negative  $-1/\sigma$ , implying higher elasticities and greater substitutability. This is consistent with the idea that peer review helps reduce exaggerated or extreme estimates. More highly *cited* studies tend to report more negative  $-1/\sigma$  values, implying lower elasticity and thus weaker substitutability. This may reflect a preference in the literature for studies that highlight imperfect substitution, possibly due to theoretical alignment or greater perceived novelty. Alternatively, it could indicate that influential studies are more likely to focus on labor market segments where substitution is particularly limited. Notably, the choice of *dependent variable* transformation (log mean vs. mean log wages) receives a moderate PIP (0.44). This supports the subsample analysis, where the uncorrected estimates differed, but the corrected elasticities were quite similar across the two transformations, suggesting that prior debates may have been exaggerated by publication bias.

## 4.2 Interpretation and Synthesis

The two core approaches, publication bias correction and BMA, deliver mutually reinforcing conclusions. The publication bias analysis shows that the literature systematically underreports the elasticity of substitution. The uncorrected mean implied elasticity is 13, while the corrected mean rises to 20, indicating that native and immigrant workers are more substitutable than raw estimates suggest. This upward adjustment is particularly pronounced in studies using low-frequency data, low-experience samples, and North America-based estimates, with corrections of up to 36 points in implied elasticity. This pattern is echoed in the BMA results, which independently confirm the role of bias and

structural heterogeneity. The standard error, a proxy for study precision, is the most decisive predictor ( $PIP = 1.00$ ) of reported elasticity estimates. Its negative effect confirms that imprecise studies, typically smaller in sample size, report systematically lower elasticities, aligning with the FAT-PET-PEESE logic of small-study bias.

BMA identifies several structural and methodological factors that systematically shape reported elasticities, many of which correspond closely with subsamples that exhibit large publication bias corrections. For instance, low-experience samples yield both more negative uncorrected estimates and larger bias-corrected elasticities, and BMA confirms that this group has a decisive negative effect on the estimate. Other key variables, such as personal fixed effects, national-level data, and published study status, also show consistent patterns across both methods. This convergence reinforces the credibility of our findings. Subsamples with the most pronounced corrections are also those identified by BMA as systematically associated with more negative reported effects. The implication is that both selection bias and real structural variation co-determine observed results in the literature.

An additional contribution of this meta-analysis is its re-examination of the long-standing methodological debate over the choice between  $\log(\text{mean wages})$  and  $\text{mean}(\log \text{wages})$  as the dependent variable. The literature has been sharply divided. Borjas *et al.* (2012) argues that  $\log(\text{mean})$  overstates wage effects (i.e., more negative inverse elasticities, implying lower substitutability) by ignoring within-group variation, while Ottaviano & Peri (2012) defend its use as conceptually valid in production settings. Our findings offer a nuanced perspective. In uncorrected data, the difference is sizable: 12 ( $\log \text{mean}$ ) vs. 20 ( $\text{mean log}$ ). This pattern is consistent with Borjas *et al.* (2012). Yet after correcting for publication bias, the gap narrows significantly to 18 vs. 21. This suggests that much of the earlier divergence may have been driven by selective reporting rather than fundamental methodological flaws. BMA confirms this by assigning only moderate importance to the transformation choice ( $PIP = 0.44$ ), indicating that while

it matters, it is not a primary source of variation once bias is controlled for.

## 5 Conclusion

This meta-analysis offers a comprehensive reassessment of the substitutability between native and immigrant labor. Drawing on 1,091 estimates from 41 studies, we demonstrate that published research systematically understates the elasticity of substitution due to publication bias and methodological variation. After applying a range of robust bias-correction techniques and accounting for heterogeneity via model averaging, we find that the true elasticity is considerably higher than the literature implies.

The average corrected elasticity is approximately 20 (with nonlinear corrections being slightly higher), compared to an uncorrected mean of 13. This difference is substantial and has important interpretive implications. In theory, a higher elasticity of substitution reduces the wage sensitivity of natives to immigration. Moving from an elasticity of 13 to 20 reduces the implied wage impact of a 10% immigration increase from 0.77% to 0.5%, a 35% decline. However, this smaller wage effect should not be interpreted as evidence of negligible labor market disruption. Rather, as emphasized by Borjas (2003), and Smith (2003), high substitutability may result in reallocation of employment: natives who remain in the labor force may face limited wage pressure, while others may exit employment or shift sectors entirely.

In this sense, the measured wage effect captures only part of the story. This distinction echoes the broader shift in labor economics from focusing solely on wage effects to examining broader market equilibria, including labor force participation, sectoral sorting, and occupational mobility. As Dustmann *et al.* (2016) note, understanding the full impact of immigration requires looking at both the intensive margin (wages) and the extensive margin (employment and sectoral flows). Moreover, our BMA and Frequentist Model Averaging analysis shows that variation in reported estimates is driven by identi-

fiable factors: study precision, frequency of data, experience level, gender composition, estimation strategy, and publication characteristics.

These findings offer new clarity on a literature often characterized by fragmented and conflicting results. While earlier studies such as Peri (2007), Manacorda *et al.* (2012), and Ottaviano & Peri (2012) have emphasized imperfect substitution, especially among low-skilled immigrant and native workers, others like Borjas *et al.* (2010) and Borjas *et al.* (2012) argue for more segmented labor markets. Our results suggest that both perspectives capture parts of the truth, but that average effects are likely less negative than reported, and substitutability is higher than previously believed. Importantly, our results align with newer studies like Aubry *et al.* (2022) and Gentili & Mazzonna (2024), which emphasize the methodological heterogeneity and role of researcher choices in driving reported outcomes. Our combined approach, correcting for publication bias and modeling heterogeneity jointly, helps resolve these tensions and provides a more robust estimate of the average elasticity of substitution.

From a methodological standpoint, our findings underscore the value of applying multiple bias-correction techniques in meta-analysis. The convergence of linear (FAT-PET-PEESE), nonlinear (EK, WAAP, SM, Stem method), and model-averaging (BMA/FMA) approaches enhances the credibility of our corrected estimates and provides nuanced insight into both bias and heterogeneity. Despite the methodological rigor of this meta-analysis, certain limitations persist. Country-specific effects, such as institutional differences or regional labor market conditions, are only partially addressed through subsample analysis. Related concerns about false positives and low statistical power in economics have prompted calls for broader replication and retrospective power analysis (Stanley *et al.*, 2022). This study demonstrates the value of meta-analysis not only as a tool for clarifying empirical uncertainty but also for guiding more evidence-based, context-specific policy design. By systematically correcting for bias and modeling heterogeneity, we provide a clearer, more reliable benchmark for understanding the labor

market impacts of immigration.

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## Appendix

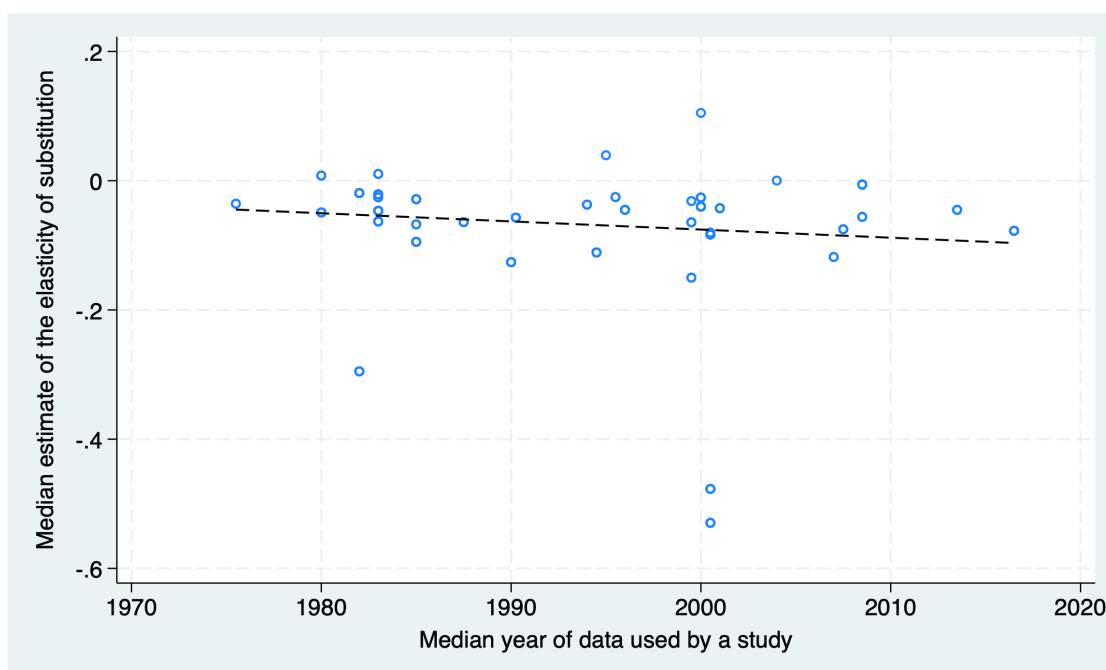
### A Data

Table A1: Studies included in the meta-analysis

Akbari & Aydede (2013)	Albert & Monras (2022)	Aydemir & Borjas (2007)
Boateng (2019)	Borjas <i>et al.</i> (2008)	Borjas <i>et al.</i> (2010)
Borjas <i>et al.</i> (2012)	Bound & Turner (2006)	Bratsberg <i>et al.</i> (2014)
Brücker & Jahn (2008)	Busch <i>et al.</i> (2020)	Card (2009)
Chiswick <i>et al.</i> (1985)	D’Amuri <i>et al.</i> (2010)	Edo (2014)
Edo & Toubal (2015)	Edo & Toubal (2017)	Etzo <i>et al.</i> (2021)
Felbermayr <i>et al.</i> (2010)	Gentili & Mazzonna (2024)	Gerfin & Kaiser (2010)
Goldsmith-Pinkham <i>et al.</i> (2020)	Gunadi (2019)	Haas <i>et al.</i> (2013)
Hill <i>et al.</i> (2018)	Jaeger <i>et al.</i> (1996, revised 2008)	Lebow (2024)
Llull (2018)	Lu (2023)	Manacorda <i>et al.</i> (2012)
Nelson (1999)	Nguyen & Yaman (2021)	Ottaviano & Peri (2008)
Ottaviano & Peri (2012)	Peri (2007)	Raphael & Smolensky (2009)
Romiti <i>et al.</i> (2011)	Sharpe & Bollinger (2020)	Signorelli (2024)
Wei <i>et al.</i> (2016)	Wei <i>et al.</i> (2019)	

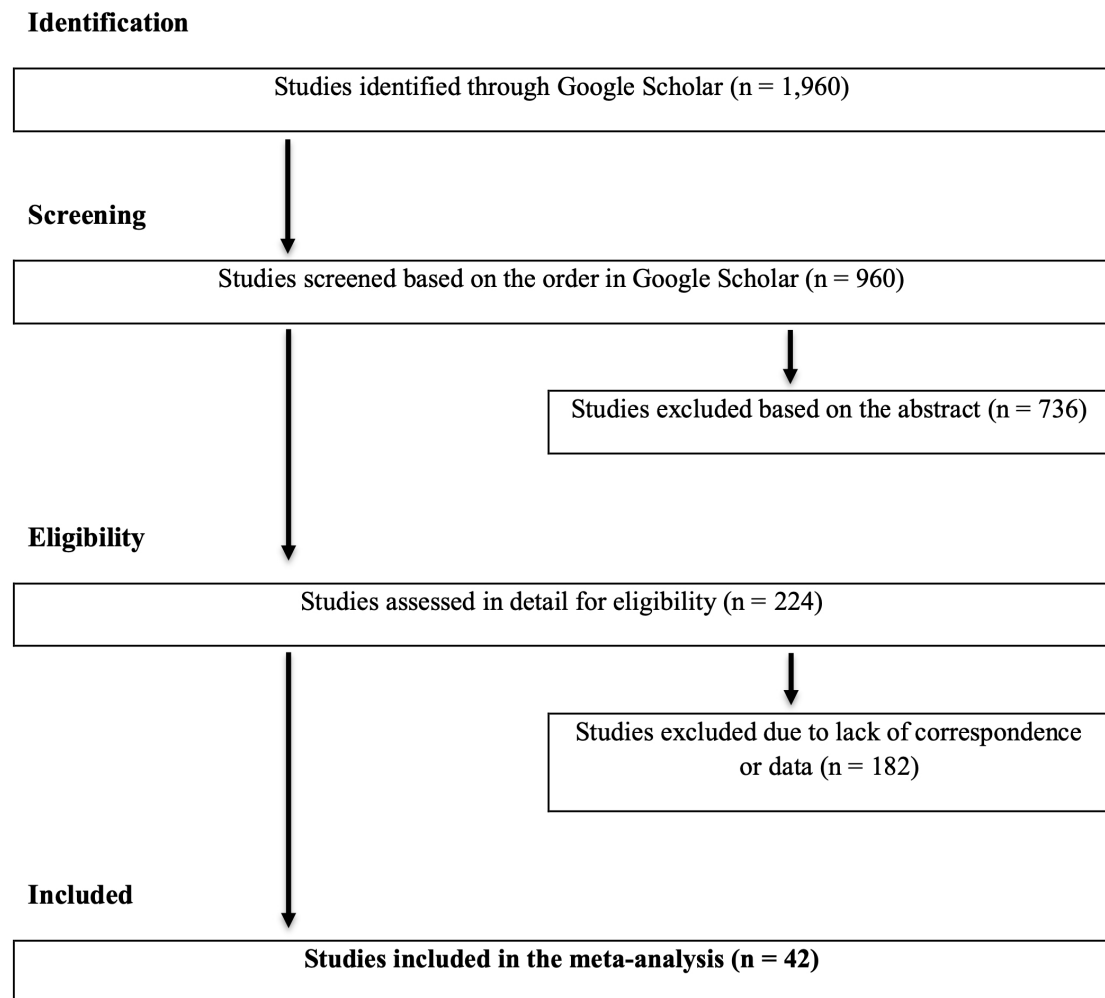
In Figure A1 we can see the decreasing trend of the negative inverse elasticity over the years, meaning that the substitutability between natives and immigrants slightly decreased over the years. The trend might be driven to more negative numbers (lower substitutability) by two studies, Wei *et al.* (2016) and Wei *et al.* (2019), which are dealing only with farmers.

Figure A1: Trend over the years: negative inverse elasticities



*Notes:* The vertical axis shows the median estimate of the negative inverse elasticity of substitution reported in individual studies. The horizontal axis shows the median year of the data used in the studies. Mean of all estimates is -0.072.

Figure A2: PRISMA diagram



# Online Appendix

## B Publication Bias

Table B1: Linear test for different countries

	OLS	FE	Precision	Study
<b>PANEL A</b>				
<i>Canada</i>				
SE	-0.241***	-0.229*	-0.708***	-0.178
(publication bias)	(0.0489)	(0.0754)	(0.123)	(0.134)
Constant	-0.0410***	-0.0413***	-0.0285***	-0.0356***
(effect beyond bias)	(0.00308)	(0.00202)	(0.00164)	(0.0121)
impl.el.	24.39	24.21	35.09	28.09
Observations	63	63	63	63
Number of idstudy		3		
R-squared	0.033	0.031	0.089	0.010
<i>France</i>				
SE	-0.667***	-0.695***	-0.536***	-0.250
(publication bias)	(0.0524)	(0.0388)	(0.135)	(0.460)
Constant	-0.00579	-0.00358	-0.0161***	-0.00972
(effect beyond bias)	(0.00540)	(0.00306)	(0.00350)	(0.0338)
impl.el.	172.71	279.33	62.11	102.88
Observations	83	83	83	83
Number of idstudy		4		
R-squared	0.373	0.462	0.190	0.017
<i>Germany</i>				
SE	-1.097	-1.989	-1.619	-0.857
(publication bias)	(1.086)	(1.914)	(1.138)	(0.628)
Constant	-0.0851***	-0.0583	-0.0694***	-0.0665***
(effect beyond bias)	(0.0156)	(0.0577)	(0.00793)	(0.0152)
impl.el.	11.75	17.15	14.41	15.04
Observations	136	136	136	136
Number of idstudy		5		
R-squared	0.073	0.149	0.100	0.072
<i>Italy</i>				
SE	0.300	0.369	0.0953	0.265
(publication bias)	(0.275)	(0.343)	(0.468)	(0.300)
Constant	-0.0616***	-0.0630*	-0.0573***	-0.0616***
(effect beyond bias)	(6.48e-05)	(0.00713)	(0.00404)	(0.000441)
impl.el.	16.23	15.87	17.45	16.23
Observations	35	35	35	35
Number of idstudy		2		
R-squared	0.010	0.017	0.001	0.008
<i>Switzerland</i>				
SE	-0.0866*	-0.131**	-0.0471	0.0703
(publication bias)	(0.0499)	(0.00953)	(0.169)	(0.101)
Constant	-0.0226	-0.0194**	-0.0255***	-0.0839*
(effect beyond bias)	(0.0176)	(0.000695)	(0.00164)	(0.0496)
impl.el.	44.25	51.55	39.22	11.92
Observations	68	68	68	68
Number of idstudy		2		
R-squared	0.008	0.033	0.002	0.001
<i>US</i>				
SE	-2.100**	-0.486	-2.302**	-2.605**

Continued on next page

Table B1 – continued from previous page

	OLS	FE	Precision	Study
(publication bias)	(0.973)	(0.337)	(1.062)	(1.068)
Constant	-0.0206	-0.0617***	-0.0155	-0.0161
(effect beyond bias)	(0.0157)	(0.0086)	(0.0115)	(0.0179)
impl.el.	48.46	16.20	64.50	62.11
Observations	643	643	643	643
Number of idstudy		22		
R-squared	0.170	0.028	0.159	0.192
<i>US without farmers</i>				
SE	-1.121**	-0.297	-0.860**	-1.377*
(publication bias)	(0.541)	(0.318)	(0.402)	(0.752)
Constant	-0.0221*	-0.0421***	-0.0284***	-0.0100
(effect beyond bias)	(0.0107)	(0.0077)	(0.0073)	(0.0132)
impl.el.	45.23	23.76	35.21	99.84
Observations	609	609	609	609
Number of idstudy		20		
R-squared	0.211	0.011	0.077	0.254
<b>PANEL B</b>				
<i>Colombia</i>				
SE	-2.754***	-2.754	-2.799***	-2.754***
(publication bias)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.0449***	-0.0449	-0.0441***	-0.0449***
(effect beyond bias)	(0.00)	(0.00)	(0.00)	(0.00)
impl.el.	22.27	22.27	22.68	22.27
Observations	30	30	30	30
Number of idstudy		1		
R-squared	0.942	0.942	0.917	0.942
<i>Norway</i>				
SE	0.667***	0.667	0.667***	0.667***
(publication bias)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.0442***	-0.0442	-0.0442***	-0.0442***
(effect beyond bias)	(0.00)	(0.00)	(0.00)	(0.00)
impl.el.	22.62	22.62	22.62	22.62
Observations	4	4	4	4
Number of idstudy		1		
R-squared	0.941	0.941	0.940	0.941
<i>UK</i>				
SE	-0.836***	-0.836	-0.642***	-0.836***
(publication bias)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.0802***	-0.0802	-0.0908***	-0.0802***
(effect beyond bias)	(0.00)	(0.00)	(0.00)	(0.00)
impl.el.	12.47	12.47	11.01	12.47
Observations	25	25	25	25
Number of idstudy		1		
R-squared	0.103	0.103	0.050	0.103

Table B2: Linear test for different subsamples

	OLS	FE	Precision	Study
<b>Panel A: Data characteristics</b>				
<i>High no. of cells</i>				
SE	-0.446***	-0.529***	-0.539***	-0.162
(publication bias)	(0.109)	(0.155)	(0.202)	(0.412)
Constant	-0.0457***	-0.0421***	-0.0416***	-0.0521***
(effect beyond bias)	(0.0101)	(0.00677)	(0.00639)	(0.0112)

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Table B2 – continued from previous page

	OLS	FE	Precision	Study
impl.el.	21.88	23.75	24.04	19.19
Observations	398	398	398	398
Number of idstudy		26		
R-squared	0.094	0.160	0.065	0.007
<i>Low no. of cells</i>				
SE	-1.290	-0.847	-1.746**	-2.106**
(publication bias)	(0.906)	(0.702)	(0.882)	(0.960)
Constant	-0.0452**	-0.0573***	-0.0326***	-0.0323
(effect beyond bias)	(0.0192)	(0.0193)	(0.0118)	(0.0210)
impl.el.	22.12	17.45	30.67	30.94
Observations	693	693	693	693
Number of idstudy		26		
R-squared	0.089	0.070	0.096	0.150
<i>Annual frequency</i>				
SE	-0.380	-0.706***	-1.078*	-0.369
(publication bias)	(0.240)	(0.249)	(0.647)	(0.520)
Constant	-0.0913***	-0.0767***	-0.0600***	-0.0914***
(effect beyond bias)	(0.0228)	(0.0112)	(0.0109)	(0.0260)
impl.el.	10.95	13.04	16.67	10.94
Observations	488	488	488	488
Number of idstudy		22		
R-squared	0.016	0.125	0.060	0.009
<i>Lower Frequency</i>				
SE	-1.094**	-0.258	-0.745*	-1.292*
(publication bias)	(0.539)	(0.316)	(0.406)	(0.756)
Constant	-0.0216**	-0.0418***	-0.0300***	-0.0109
(effect beyond bias)	(0.0107)	(0.0076)	(0.0072)	(0.0129)
impl.el.	46.30	23.94	33.33	91.93
Observations	603	603	603	603
Number of idstudy		20		
R-squared	0.204	0.009	0.060	0.233
<b>Panel B: Structural variation</b>				
<i>All Workers</i>				
SE	-0.995	-0.843	-1.689*	-1.273
(publication bias)	(0.845)	(0.582)	(0.997)	(0.895)
Constant	-0.0572**	-0.0619***	-0.0361**	-0.0514**
(effect beyond bias)	(0.0184)	(0.0177)	(0.0142)	(0.0211)
impl.el.	17.47	16.15	27.71	19.45
Observations	603	603	603	603
Number of idstudy		26		
R-squared	0.055	0.089	0.093	0.065
<i>Full-time workers</i>				
SE	-0.571***	-0.520***	-0.546***	-0.441*
(publication bias)	(0.063)	(0.174)	(0.186)	(0.225)
Constant	-0.0383***	-0.0402***	-0.0392***	-0.0413***
(effect beyond bias)	(0.0068)	(0.0064)	(0.0052)	(0.0065)
impl.el.	26.10	24.88	25.51	24.21
Observations	488	488	488	488
Number of idstudy		21		
R-squared	0.184	0.134	0.074	0.072
<i>High-Experienced</i>				
SE	0.306	-0.502	0.378	1.598
(publication bias)	(0.991)	(0.463)	(1.031)	(1.017)
Constant	-0.0641***	-0.0505***	-0.0653***	-0.0791***
(effect beyond bias)	(0.0126)	(0.00782)	(0.0136)	(0.0140)

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Table B2 – continued from previous page

	OLS	FE	Precision	Study
impl.el.	15.60	19.80	15.31	12.64
Observations	42	42	42	42
Number of idstudy		4		
R-squared	0.007	0.018	0.006	0.236
<i>Low-Experienced</i>				
SE	-4.851***	-4.641***	-4.495***	-4.779***
(publication bias)	(0.343)	(0.432)	(1.523)	(0.312)
Constant	-0.0226	-0.0268**	-0.0297***	-0.0204
(effect beyond bias)	(0.0324)	(0.00859)	(0.0111)	(0.0329)
impl.el.	44.25	37.31	33.67	49.02
Observations	79	79	79	79
Number of idstudy		5		
R-squared	0.387	0.429	0.221	0.375
<i>High-Educated</i>				
SE	-0.313**	0.101	-0.872***	-0.342**
(publication bias)	(0.129)	(0.293)	(0.240)	(0.148)
Constant	-0.0612***	-0.0822***	-0.0328***	-0.0342
(effect beyond bias)	(0.0158)	(0.0149)	(0.00902)	(0.0249)
impl.el.	16.34	12.17	30.49	29.24
Observations	106	106	106	106
Number of idstudy		12		
R-squared	0.037	0.002	0.125	0.030
<i>Low-Educated</i>				
SE	-1.008*	-0.446*	-1.074**	-1.750**
(publication bias)	(0.610)	(0.239)	(0.446)	(0.805)
Constant	-0.0396***	-0.0534***	-0.0380***	-0.0287*
(effect beyond bias)	(0.0123)	(0.00585)	(0.00847)	(0.0150)
impl.el.	25.25	18.73	26.32	34.84
Observations	171	171	171	171
Number of idstudy		14		
R-squared	0.194	0.033	0.121	0.391
<i>English</i>				
SE	-1.768**	-0.412*	-2.099**	-2.292**
(publication bias)	(0.722)	(0.211)	(0.847)	(0.869)
Constant	-0.0266**	-0.0625***	-0.0178*	-0.0195
(effect beyond bias)	(0.0124)	(0.0056)	(0.0090)	(0.0146)
impl.el.	37.59	16.00	56.09	51.22
Observations	735	735	735	735
Number of idstudy		26		
R-squared	0.151	0.028	0.159	0.176
<i>Other language</i>				
SE	-0.288	-0.719**	-0.181	-0.0246
(publication bias)	(0.200)	(0.280)	(0.262)	(0.412)
Constant	-0.0646***	-0.0440***	-0.0696***	-0.0628***
(effect beyond bias)	(0.0195)	(0.0134)	(0.00919)	(0.0126)
impl.el.	15.48	22.73	14.37	15.92
Observations	356	356	356	356
Number of idstudy		15		
R-squared	0.023	0.130	0.004	0.000
<i>Bilingual</i>				
SE	-0.0173	-0.158**	-0.106	-0.273
(publication bias)	(0.0417)	(0.0456)	(0.240)	(0.358)
Constant	-0.0370***	-0.0298***	-0.0324***	-0.0452***
(effect beyond bias)	(0.0100)	(0.00231)	(0.00168)	(0.0127)
impl.el.	27.03	33.56	30.86	22.12
Observations	131	131	131	131

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Table B2 – continued from previous page

	OLS	FE	Precision	Study
Number of idstudy		5		
R-squared	0.000	0.030	0.005	0.025
<i>No Bilingual</i>				
SE	-0.985***	-0.834***	-1.391***	-0.905
(publication bias)	(0.344)	(0.265)	(0.534)	(0.560)
Constant	-0.0495***	-0.0542***	-0.0369***	-0.0501***
(effect beyond bias)	(0.0116)	(0.0082)	(0.0092)	(0.0140)
impl.el.	20.20	18.45	27.09	19.96
Observations	960	960	960	960
Number of idstudy		37		
R-squared	0.094	0.122	0.091	0.055
<i>Top 6 Languages</i>				
SE	-0.676***	-0.521***	-1.143**	-0.783
(publication bias)	(0.272)	(0.144)	(0.527)	(0.493)
Constant	-0.0462***	-0.0516***	-0.0302***	-0.0496***
(effect beyond bias)	(0.0106)	(0.0049)	(0.0062)	(0.0163)
impl.el.	21.64	19.38	33.12	20.16
Observations	916	916	916	916
Number of idstudy		33		
R-squared	0.063	0.127	0.085	0.045
<i>Male</i>				
SE	-0.627***	-0.621***	-0.542**	-0.566***
(publication bias)	(0.080)	(0.080)	(0.208)	(0.165)
Constant	-0.0298***	-0.0300***	-0.0325***	-0.0238***
(effect beyond bias)	(0.0060)	(0.0025)	(0.0062)	(0.0059)
impl.el.	33.56	33.34	30.77	42.02
Observations	449	449	449	449
Number of idstudy		25		
R-squared	0.202	0.211	0.048	0.106
<i>Female</i>				
SE	-0.596	-0.323	-0.896	-0.768
(publication bias)	(0.440)	(0.237)	(0.569)	(0.754)
Constant	-0.0517***	-0.0596***	-0.0430***	-0.0576***
(effect beyond bias)	(0.00992)	(0.00688)	(0.0109)	(0.0134)
impl.el.	19.34	16.78	23.26	17.36
Observations	98	98	98	98
Number of idstudy		9		
R-squared	0.063	0.018	0.093	0.060
<i>Both Genders</i>				
SE	-0.748	-0.738	-1.462*	-0.749
(publication bias)	(0.627)	(0.531)	(0.803)	(0.836)
Constant	-0.0703***	-0.0707***	-0.0450***	-0.0803***
(effect beyond bias)	(0.0179)	(0.0188)	(0.0123)	(0.0271)
impl.el.	14.22	14.14	22.22	12.45
Observations	544	544	544	544
Number of idstudy		29		
R-squared	0.036	0.072	0.086	0.027
<i>Farmers</i>				
SE	-2.154***	-2.119*	-2.448***	-2.164***
(publication bias)	(0.133)	(0.247)	(0.426)	(0.120)
Constant	-0.417***	-0.419**	-0.403***	-0.416***
(effect beyond bias)	(0.00511)	(0.0118)	(0.0207)	(0.00461)
impl.el.	2.40	2.39	2.48	2.40
Observations	34	34	34	34
Number of idstudy		2		
R-squared	0.352	0.311	0.245	0.364

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Table B2 – continued from previous page

	OLS	FE	Precision	Study
<i>No Farmers</i>				
SE	-0.554**	-0.635**	-0.582**	-0.497
(publication bias)	(0.196)	(0.221)	(0.227)	(0.378)
Constant	-0.0424***	-0.0398***	-0.0415***	-0.0380***
(effect beyond bias)	(0.0071)	(0.0073)	(0.0075)	(0.0076)
impl.el.	23.57	25.13	24.08	26.29
Observations	1,057	1,057	1,057	1,057
Number of idstudy		39		
R-squared	0.079	0.094	0.037	0.053
<i>North America</i>				
SE	-1.783**	-0.393*	-2.120**	-2.353**
(publication bias)	(0.793)	(0.218)	(0.937)	(0.957)
Constant	-0.0261**	-0.0615***	-0.0175*	-0.0186
(effect beyond bias)	(0.0128)	(0.0056)	(0.0098)	(0.0149)
impl.el.	38.28	16.26	57.00	53.78
Observations	710	710	710	710
Number of idstudy		25		
R-squared	0.145	0.026	0.150	0.176
<i>No North America</i>				
SE	-0.299	-0.720**	-0.247	-0.0553
(publication bias)	(0.196)	(0.276)	(0.259)	(0.406)
Constant	-0.0670***	-0.0467***	-0.0695***	-0.0653***
(effect beyond bias)	(0.0181)	(0.0133)	(0.00907)	(0.0125)
impl.el.	14.93	21.41	14.39	15.31
Observations	381	381	381	381
Number of idstudy		16		
R-squared	0.024	0.130	0.008	0.001
<b>Panel C: Estimation technique</b>				
<i>DV log(mean())</i>				
SE	-0.698**	-0.666**	-1.103**	-1.028**
(publication bias)	(0.279)	(0.229)	(0.514)	(0.405)
Constant	-0.0565***	-0.0577***	-0.0419***	-0.0684***
(effect beyond bias)	(0.0134)	(0.0082)	(0.0099)	(0.0212)
impl.el.	17.69	17.32	23.85	14.62
Observations	865	865	865	865
Number of idstudy		26		
R-squared	0.058	0.101	0.067	0.072
<i>DV mean(log())</i>				
SE	-0.069	-0.378	-0.695**	1.142**
(publication bias)	(0.382)	(0.457)	(0.345)	(0.367)
Constant	-0.0477***	-0.0405***	-0.0331***	-0.0560***
(effect beyond bias)	(0.0100)	(0.0106)	(0.0073)	(0.0107)
impl.el.	20.96	24.69	30.17	17.86
Observations	226	226	226	226
Number of idstudy		18		
R-squared	0.001	0.032	0.051	0.282
<i>Annual Wage</i>				
SE	-0.378	-0.271	-0.670**	-0.728
(publication bias)	(0.230)	(0.184)	(0.201)	(0.623)
Constant	-0.0362***	-0.0399***	-0.0263***	-0.0093
(effect beyond bias)	(0.0082)	(0.0063)	(0.0058)	(0.0157)
impl.el.	22.67	25.12	15.32	13.54
Observations	102	102	102	102
Number of idstudy		7		
R-squared	0.068	0.042	0.119	0.133

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Table B2 – continued from previous page

	OLS	FE	Precision	Study
<i>Monthly Wage</i>				
SE	-1.618	-3.215*	-1.792	-1.026*
(publication bias)	(1.420)	(1.336)	(1.620)	(0.546)
Constant	-0.0741***	-0.0344	-0.0697***	-0.0570**
(effect beyond bias)	(0.0129)	(0.0331)	(0.0072)	(0.0203)
impl.el.	12.89	34.98	21.35	17.54
Observations	107	107	107	107
Number of idstudy		5		
R-squared	0.094	0.285	0.076	0.085
<i>Weekly Wage</i>				
SE	-0.526	-0.277	-0.532	-1.422
(publication bias)	(0.583)	(0.177)	(0.509)	(0.732)
Constant	-0.0364***	-0.0441***	-0.0362***	-0.0179
(effect beyond bias)	(0.0107)	(0.0055)	(0.0083)	(0.0168)
impl.el.	18.29	15.92	20.41	24.91
Observations	491	491	491	491
Number of idstudy		17		
R-squared	0.075	0.030	0.047	0.309
<i>Daily Wage</i>				
SE	-1.180**	-0.953	-0.937**	-1.528***
(publication bias)	(0.399)	(0.544)	(0.458)	(0.237)
Constant	-0.0350***	-0.0401**	-0.0405***	-0.0221**
(effect beyond bias)	(0.0106)	(0.0123)	(0.0103)	(0.0095)
impl.el.	12.39	17.15	20.46	27.82
Observations	54	54	54	54
Number of idstudy		5		
R-squared	0.513	0.354	0.252	0.757
<i>Hourly Wage</i>				
SE	-0.695**	-0.645***	-1.815**	-0.425
(publication bias)	(0.275)	(0.123)	(0.882)	(0.616)
Constant	-0.0772**	-0.0793***	-0.0296**	-0.0976***
(effect beyond bias)	(0.0337)	(0.0052)	(0.0119)	(0.0380)
impl.el.	14.87	16.43	20.92	23.67
Observations	352	352	352	352
Number of idstudy		16		
R-squared	0.054	0.186	0.141	0.011
<i>National</i>				
SE	-0.629**	-0.714**	-0.933*	-0.527
(publication bias)	(0.283)	(0.250)	(0.556)	(0.491)
Constant	-0.0536***	-0.0507***	-0.0434***	-0.0603***
(effect beyond bias)	(0.0128)	(0.0083)	(0.0095)	(0.0172)
impl.el.	18.65	19.72	21.48	14.78
Observations	846	846	846	846
Number of idstudy		31		
R-squared	0.045	0.113	0.043	0.018
<i>Regional</i>				
SE	-1.081*	-0.310	-1.575***	-1.731**
(publication bias)	(0.568)	(0.339)	(0.442)	(0.712)
Constant	-0.0402***	-0.0661***	-0.0237***	-0.0227**
(effect beyond bias)	(0.0128)	(0.0114)	(0.0076)	(0.0131)
impl.el.	10.12	24.55	41.92	34.85
Observations	245	245	245	245
Number of idstudy		12		
R-squared	0.232	0.026	0.333	0.438
<i>OLS</i>				
SE	-1.321**	-0.876*	-1.443*	-0.811

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Table B2 – continued from previous page

	OLS	FE	Precision	Study
(publication bias)	(0.628)	(0.483)	(0.726)	(0.950)
Constant	-0.0374***	-0.0499***	-0.0340***	-0.0504**
(effect beyond bias)	(0.0108)	(0.0135)	(0.0100)	(0.0192)
impl.el.	13.49	17.89	21.82	15.91
Observations	794	794	794	794
Number of idstudy		39		
R-squared	0.083	0.074	0.080	0.027
<i>IV</i>				
SE	-0.465**	-0.445**	-0.675*	-0.771**
(publication bias)	(0.206)	(0.212)	(0.381)	(0.278)
Constant	-0.0544***	-0.0554***	-0.0443***	-0.0492***
(effect beyond bias)	(0.0151)	(0.0102)	(0.0097)	(0.0089)
impl.el.	17.72	17.53	22.34	15.89
Observations	297	297	297	297
Number of idstudy		22		
R-squared	0.072	0.056	0.062	0.168
<b>Fixed effects</b>				
<i>Person FE</i>				
SE	-1.360*	-0.707*	-2.874**	-0.945
(publication bias)	(0.724)	(0.335)	(1.127)	(1.196)
Constant	-0.0845***	-0.110***	-0.0242**	-0.0864**
(effect beyond bias)	(0.0316)	(0.0134)	(0.0120)	(0.0398)
impl.el.	11.83	9.09	41.32	11.57
Observations	249	249	249	249
Number of idstudy		16		
R-squared	0.089	0.106	0.263	0.036
<i>Skill FE</i>				
SE	-0.640**	-0.654**	-0.751**	-0.656
(publication bias)	(0.234)	(0.221)	(0.306)	(0.432)
Constant	-0.0468***	-0.0463***	-0.0428***	-0.0450***
(effect beyond bias)	(0.0084)	(0.0080)	(0.0094)	(0.0091)
impl.el.	15.21	16.89	18.45	14.73
Observations	955	955	955	955
Number of idstudy		39		
R-squared	0.070	0.100	0.048	0.049
<i>Time FE</i>				
SE	-0.707**	-0.715**	-1.136**	-0.743
(publication bias)	(0.296)	(0.260)	(0.537)	(0.506)
Constant	-0.0584***	-0.0581***	-0.0422***	-0.0646***
(effect beyond bias)	(0.0157)	(0.0099)	(0.0130)	(0.0192)
impl.el.	14.89	17.02	18.76	20.41
Observations	777	777	777	777
Number of idstudy		33		
R-squared	0.055	0.106	0.065	0.037
<b>Panel D: Publication characteristics</b>				
<i>Published Studies</i>				
SE	-0.510**	-0.654**	-0.882*	-0.414
(publication bias)	(0.221)	(0.242)	(0.476)	(0.436)
Constant	-0.0537***	-0.0490***	-0.0416***	-0.0521***
(effect beyond bias)	(0.0126)	(0.0079)	(0.0092)	(0.0138)
impl.el.	18.91	20.46	22.73	15.82
Observations	781	781	781	781
Number of idstudy		31		
R-squared	0.041	0.105	0.046	0.018

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Table B2 – continued from previous page

	OLS	FE	Precision	Study
<i>Unpublished Studies</i> (WP/PhD thesis)				
SE	-1.514*	-0.656	-1.652	-1.633*
(publication bias)	(0.815)	(0.410)	(0.989)	(0.846)
Constant	-0.0330*	-0.0634***	-0.0281**	-0.0419**
(effect beyond bias)	(0.0184)	(0.0145)	(0.0123)	(0.0318)
impl.el.	15.82	17.29	19.84	14.98
Observations	310	310	310	310
Number of idstudy		10		
R-squared	0.139	0.061	0.138	0.101
<i>Unpublished: Old</i>				
SE	-1.304*	-0.620	-1.008	-1.655**
(publication bias)	(0.686)	(0.491)	(0.606)	(0.879)
Constant	-0.0211	-0.0433**	-0.0307**	-0.0005
(effect beyond bias)	(0.0164)	(0.0159)	(0.0118)	(0.0280)
impl.el.	13.74	15.82	17.91	14.35
Observations	242	242	242	242
Number of idstudy		6		
R-squared	0.290	0.054	0.147	0.283
<i>Top 5 Journals</i>				
SE	0.0136	-0.131	-1.161	-0.0790
(publication bias)	(0.562)	(0.632)	(1.332)	(0.614)
Constant	-0.0386***	-0.0365***	-0.0214*	-0.0369***
(effect beyond bias)	(0.0069)	(0.0093)	(0.0122)	(0.0074)
impl.el.	19.25	21.78	22.64	16.82
Observations	64	64	64	64
Number of idstudy		5		
R-squared	0.000	0.001	0.052	0.001
<i>Top 20 Journals</i>				
SE	-0.798	-0.530	-0.958*	0.904
(publication bias)	(0.692)	(0.560)	(0.568)	(0.737)
Constant	-0.0374***	-0.0428***	-0.0341**	-0.0606***
(effect beyond bias)	(0.0129)	(0.0114)	(0.0091)	(0.0127)
impl.el.	18.62	20.89	22.93	16.25
Observations	257	257	257	257
Number of idstudy		13		
R-squared	0.080	0.030	0.067	0.163

## C Heterogeneity

Table C1: Description and summary statistics of regression variables

Variable	Description	Mean	Std. dev.	WM
Elasticity	Estimate of the negative of the inverse elasticity of substitution between the immigrant and native labor (response variable).	-0.08	0.11	-0.09
* Standard error (SE)	Standard error of the estimated inverse elasticity. The variable is important for gauging publication bias.	0.03	0.04	0.03
<b>Data characteristics</b>				
* Number of cells	The logarithm of the number of cells to which are individuals devided.	2.28	0.61	2.34
High number of cells	= 1 if the number of cells is higher or equal to 196 (median 192); = 0 otherwise.	0.37	0.48	0.47
* Annual frequency data	= 1 if annual frequency of the data is used in the estimation, reference category; = 0 if decennial or 5 year span.	0.45	0.50	0.52
<b>Structural variation</b>				
* All workers	= 1 if all workers included (including self-employed, in-school, or part-time workers), reference category; = 0 if only full-time workers included.	0.55	0.50	0.55
* High level of experience	= 1 if only high experienced workers included in the estimation (years of experience equal to or higher than 20).	0.04	0.19	0.02
* Low level of experience	= 1 if only low experienced workers included in the estimation (years of experience lower than 20).	0.07	0.26	0.03

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**Table C1 – continued from previous page**

Variable	Description	Mean	Std. dev.	WM
* High level of education	= 1 if only high educated workers included in the estimation (worker has some college degree).	0.10	0.30	0.11
* Low level of education	= 1 if only low educated workers included in the estimation (worker does not have any college degree, i.e. high school graduates as well as high school dropouts).	0.16	0.36	0.15
English	= 1 if English is official language in the country; = 0 otherwise.	0.67	0.47	0.63
Bilingual	= 1 if the country for which the elasticity is estimated has two or more official languages (multilingualism); = 0 otherwise.	0.12	0.33	0.10
* Top 6 languages	= 1 if one of the official languages of the country is in top 6 languages by total number of speakers (English, Mandarin Chinese, Hindi, Spanish, Standard Arabic, French), reference category; = 0 otherwise.	0.84	0.37	0.76
* Male	= 1 if only men included in the estimation.	0.41	0.49	0.47
* Female	= 1 if only women included in the estimation.	0.09	0.29	0.06
Both	= 1 if women and men (pooled) included in the estimation.	0.50	0.50	0.47
Farmers	= 1 if only farmers included in the estimation.	0.03	0.17	0.06
North America	= 1 if the country for which the elasticity is estimated is the United States or Canada; = 0 otherwise.	0.65	0.48	0.61
* Immigrants	The percentage of foreign-born population.	0.05	0.07	0.05
<b>Estimation characteristics</b>				

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**Table C1 – continued from previous page**

Variable	Description	Mean	Std. dev.	WM
* DV_log mean wage	= 1 if log mean wage used as dependent variable, reference category; = 0 if mean log wage.	0.79	0.41	0.63
* Annual wage	= 1 if the study uses annual wages to examine the elasticity of substitution.	0.09	0.29	0.11
* Monthly wage	= 1 if the study uses monthly wages to examine the elasticity of substitution.	0.10	0.30	0.10
* Weekly wage	= 1 if the study uses weekly wages to examine the elasticity of substitution.	0.45	0.50	0.35
* Daily wage	= 1 if the study uses daily wages to examine the elasticity of substitution.	0.05	0.22	0.13
* Hourly wage	= 1 if the study uses hourly wages to examine the elasticity of substitution.	0.32	0.47	0.37
* National	= 1 if national approach, reference category; = 0 if regional approach.	0.77	0.42	0.73
* OLS	=1 if the ordinary least squares method, its variations (LS, DOLS, WLS, GLS) or LASSO estimates are used for estimation, reference category; = 0 if instrumental variables are used, including 2SLS, 3SLS, and GMM.	0.73	0.45	0.73
<i>Fixed effects</i>				
* Time	= 1 if time fixed effects are included in the model.	0.71	0.45	0.73
* Person	= 1 if person fixed effects are included in the model (age, location, gender, ..).	0.23	0.42	0.31

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**Table C1 – continued from previous page**

Variable	Description	Mean	Std. dev.	WM
* Skill	= 1 if skill fixed effects are included in the model (education, experience).	0.87	0.33	0.84
<b>Publication characteristics</b>				
* Impact factor	The discounted recursive RePEc impact factor of the outlet (March 3, 2025).	0.59	0.91	0.78
* Citations	The logarithm of the number of per-year citations of the study in Google Scholar (March 3, 2025).	0.80	0.80	0.75
* Published	=1 if a study is published in a peer-reviewed journal, reference category; = 0 if a study is in a form of working paper or PhD Thesis.	0.71	0.45	0.72
Unpublished old	= 1 if WP was not published more than 10 years.	0.22	0.42	0.17
* Top 5 journals	= 1 if a study published in the top 5 economic journals (The American Economic Review, Econometrica, the Journal of Political Economy, the Quarterly Journal of Economics, and the Review of Economic Studies)	0.06	0.24	0.13
Top 20 journals	= 1 if a study published in the top 20 economic journals (according to citations on Google Scholar, <a href="https://scholar.google.com/citations?view_op=top_venues&amp;hl=en&amp;vq=bus_economics">https://scholar.google.com/citations?view_op=top_venues&amp;hl=en&amp;vq=bus_economics</a> )	0.24	0.43	0.31
* Publication year	The logarithm of the study's publication year.	3.30	0.00	3.30
Observations: 1,087				
Studies: 40				

Note that the heterogeneity analysis comprises of 1,087 observations (from 40 studies). The number of observations differ from the publication bias analysis. We had to drop 4 observations (1 study) due to lack of the data. The summary statistics of the whole dataset is in Table 1. SD = standard deviation, WM = mean weighted by the inverse of the number of estimates reported per study. \* indicates that the variable was used for heterogeneity analysis.

Table C2: Robustness of BMA results across different random-model priors

Random model prior	UIP prior			BRIC prior			Hyper-g prior			EBL prior		
	PIP	Post Mean	Post SD	PIP	Post Mean	Post SD	PIP	Post Mean	Post SD	PIP	Post Mean	Post SD
(Intercept)	1.00	7.66	NA	1.00	7.66	NA	1.00	25.42	NA	1.00	25.47	NA
SE	1.00	-0.49	0.08	1.00	-0.49	0.08	1.00	-0.51	0.08	1.00	-0.51	0.08
log_No.of_cells	1.00	0.06	0.01	1.00	0.06	0.01	1.00	0.07	0.01	1.00	0.07	0.01
Annual_freq.data	1.00	-0.09	0.01	1.00	-0.09	0.01	1.00	-0.08	0.01	1.00	-0.08	0.01
All_workers	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.05	0.01
High_lvl_exp.	0.05	0.00	0.00	0.05	0.00	0.00	0.46	0.00	0.01	0.46	0.00	0.01
Low_lvl_exp.	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.04	0.01	1.00	-0.04	0.01
High_lvl_educ	0.05	0.00	0.00	0.05	0.00	0.00	0.46	0.00	0.01	0.46	0.00	0.01
Low_lvl_educ	0.04	0.00	0.00	0.04	0.00	0.00	0.45	0.00	0.01	0.45	0.00	0.01
Top6_languages	0.37	0.01	0.02	0.37	0.01	0.02	0.91	0.03	0.02	0.91	0.03	0.02
Male	1.00	0.04	0.01	1.00	0.04	0.01	1.00	0.04	0.01	1.00	0.04	0.01
Female	0.38	0.01	0.01	0.38	0.01	0.01	0.86	0.02	0.01	0.86	0.02	0.01
Immi_portion	1.00	0.38	0.09	1.00	0.38	0.09	1.00	0.35	0.09	1.00	0.35	0.09
DV_log_mean_wage	0.49	-0.01	0.01	0.49	-0.01	0.01	0.80	-0.01	0.01	0.80	-0.01	0.01
DV_annual	0.36	0.01	0.02	0.36	0.01	0.02	0.60	0.01	0.01	0.60	0.01	0.01
DV_monthly	0.06	0.00	0.00	0.06	0.00	0.00	0.53	0.01	0.01	0.53	0.01	0.01
DV_weekly	0.09	0.00	0.01	0.09	0.00	0.01	0.55	-0.01	0.01	0.55	-0.01	0.01
DV_daily	0.06	0.00	0.00	0.06	0.00	0.00	0.53	0.01	0.01	0.53	0.01	0.01
DV_hourly	1.00	-0.06	0.01	1.00	-0.06	0.01	1.00	-0.06	0.01	1.00	-0.06	0.01
National_approach	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.04	0.01	1.00	-0.04	0.01
OLS_estimate	0.28	0.00	0.01	0.28	0.00	0.01	0.89	-0.01	0.01	0.89	-0.01	0.01
Time_FE	0.72	-0.02	0.01	0.72	-0.02	0.01	0.85	-0.01	0.01	0.85	-0.01	0.01
Personal_FE	1.00	-0.08	0.01	1.00	-0.08	0.01	1.00	-0.09	0.01	1.00	-0.09	0.01
Skill_FE	1.00	0.07	0.01	1.00	0.07	0.01	1.00	0.07	0.01	1.00	0.07	0.01
Impact factor	0.07	0.00	0.00	0.07	0.00	0.00	0.51	0.00	0.01	0.51	0.00	0.01
log_Citations/year	1.00	-0.03	0.01	1.00	-0.03	0.01	1.00	-0.03	0.01	1.00	-0.03	0.01
Published_study	1.00	0.05	0.01	1.00	0.05	0.01	1.00	0.06	0.01	1.00	0.06	0.01
Top5_journal	0.17	0.00	0.01	0.17	0.00	0.01	0.71	0.02	0.02	0.71	0.02	0.02
log_Publication_year	0.29	-2.37	4.26	0.29	-2.37	4.26	0.90	-7.75	4.47	0.90	-7.77	4.47
Studies	40											
Observations	1,087											

Notes: PIP = Posterior Inclusion Probability. SD = Standard Deviation. Results reflect Bayesian Model Averaging using random-model priors under four alternative  $g$ -prior formulations: UIP, BRIC, hyper- $g$ , and EBL. For definitions of included covariates, see Table C1.

Table C3: Robustness of BMA results across different uniform-model priors

Uniform model prior	UIP prior			BRIC prior			Hyper-g prior			EBL prior		
	PIP	Post Mean	Post SD	PIP	Post Mean	Post SD	PIP	Post Mean	Post SD	PIP	Post Mean	Post SD
(Intercept)	1.00	5.42	NA	1.00	5.42	NA	1.00	16.40	NA	1.00	16.45	NA
SE	1.00	-0.49	0.08	1.00	-0.49	0.08	1.00	-0.50	0.08	1.00	-0.50	0.08
log_No.of_cells	1.00	0.06	0.01	1.00	0.06	0.01	1.00	0.06	0.01	1.00	0.07	0.01
Annual_freq.data	1.00	-0.09	0.01	1.00	-0.09	0.01	1.00	-0.08	0.01	1.00	-0.08	0.01
All_workers	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.05	0.01
High_lvl_exp.	0.03	0.00	0.00	0.03	0.00	0.00	0.13	0.00	0.01	0.13	0.00	0.01
Low_lvl_exp.	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.05	0.01
High_lvl_educ	0.03	0.00	0.00	0.03	0.00	0.00	0.13	0.00	0.00	0.13	0.00	0.00
Low_lvl_educ	0.03	0.00	0.00	0.03	0.00	0.00	0.13	0.00	0.00	0.13	0.00	0.00
Top6_languages	0.29	0.01	0.01	0.29	0.01	0.01	0.67	0.02	0.02	0.67	0.02	0.02
Male	1.00	0.04	0.01	1.00	0.04	0.01	1.00	0.04	0.01	1.00	0.04	0.01
Female	0.32	0.01	0.01	0.32	0.01	0.01	0.62	0.01	0.01	0.62	0.01	0.01
Immi_portion	1.00	0.38	0.09	1.00	0.38	0.09	1.00	0.36	0.10	1.00	0.36	0.10
DV_log_mean_wage	0.44	-0.01	0.01	0.44	-0.01	0.01	0.62	-0.01	0.01	0.63	-0.01	0.01
DV_annual	0.33	0.01	0.02	0.33	0.01	0.02	0.42	0.01	0.02	0.42	0.01	0.02
DV_monthly	0.04	0.00	0.00	0.04	0.00	0.00	0.17	0.00	0.01	0.17	0.00	0.01
DV_weekly	0.06	0.00	0.00	0.06	0.00	0.00	0.24	0.00	0.01	0.24	0.00	0.01
DV_daily	0.04	0.00	0.00	0.04	0.00	0.00	0.17	0.00	0.01	0.17	0.00	0.01
DV_hourly	1.00	-0.06	0.01	1.00	-0.06	0.01	1.00	-0.06	0.01	1.00	-0.06	0.01
National_approach	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.05	0.01	1.00	-0.05	0.01
OLS_estimate	0.20	0.00	0.01	0.20	0.00	0.01	0.60	-0.01	0.01	0.60	-0.01	0.01
Time_FE	0.71	-0.02	0.01	0.71	-0.02	0.01	0.74	-0.01	0.01	0.74	-0.01	0.01
Personal_FE	1.00	-0.08	0.01	1.00	-0.08	0.01	1.00	-0.08	0.01	1.00	-0.08	0.01
Skill_FE	1.00	0.07	0.01	1.00	0.07	0.01	1.00	0.07	0.01	1.00	0.07	0.01
Impact factor	0.05	0.00	0.00	0.05	0.00	0.00	0.19	0.00	0.00	0.19	0.00	0.00
log_Citations/year	1.00	-0.02	0.01	1.00	-0.02	0.01	1.00	-0.03	0.01	1.00	-0.03	0.01
Published_study	1.00	0.05	0.01	1.00	0.05	0.01	1.00	0.06	0.01	1.00	0.06	0.01
Top5_journal	0.11	0.00	0.01	0.11	0.00	0.01	0.40	0.01	0.02	0.40	0.01	0.02
log_Publication_year	0.21	-1.69	3.73	0.21	-1.69	3.73	0.61	-5.02	5.05	0.61	-5.04	5.06
Studies	40											
Observations	1,087											

Notes: PIP = Posterior Inclusion Probability. SD = Standard Deviation. Results reflect Bayesian Model Averaging using uniform-model priors under four alternative  $g$ -prior formulations: UIP, BRIC, hyper- $g$ , and EBL. For definitions of included covariates, see Table C1.

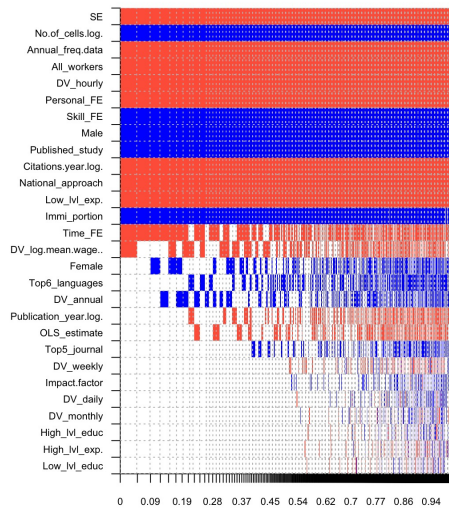


Figure C1: BMA: UIP and random priors

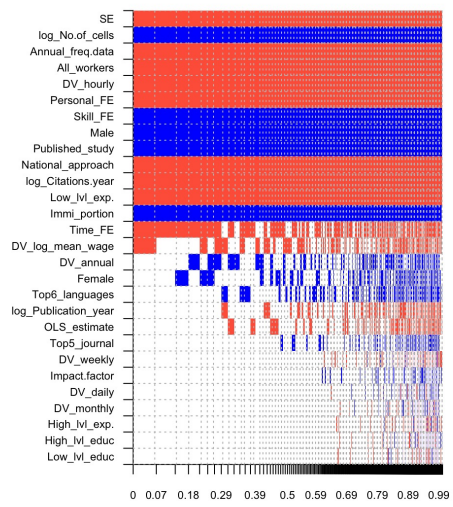


Figure C2: BMA: UIP and uniform priors

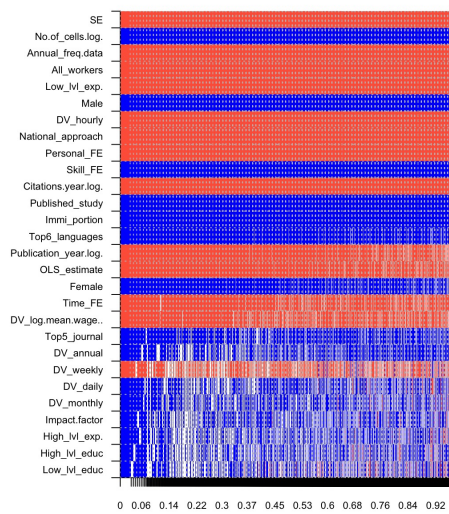


Figure C3: BMA: hyper-g and random priors

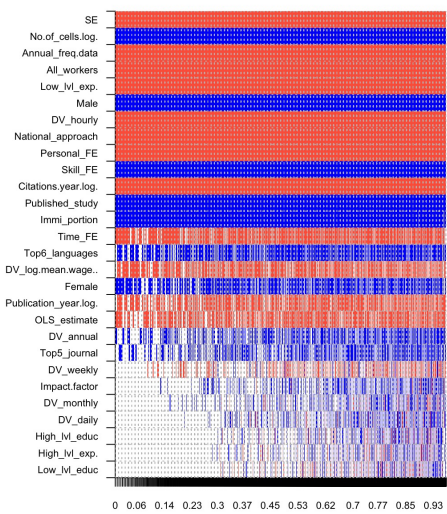


Figure C4: BMA: hyper-g and uniform priors

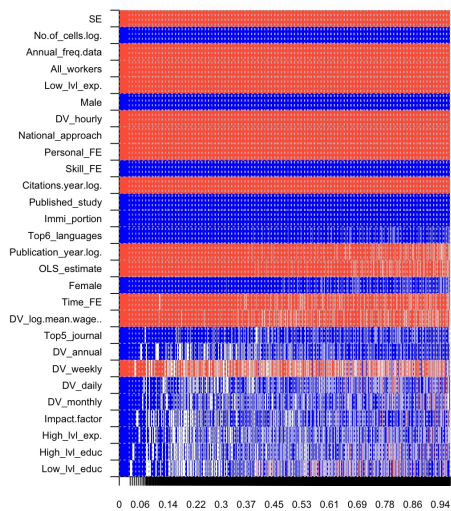


Figure C5: BMA: EBL and random priors

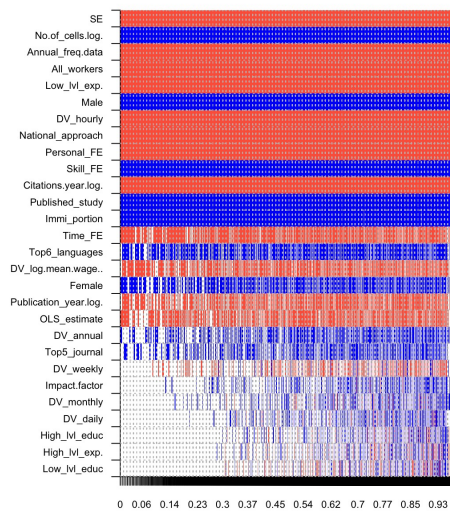


Figure C6: BMA: EBL and uniform priors

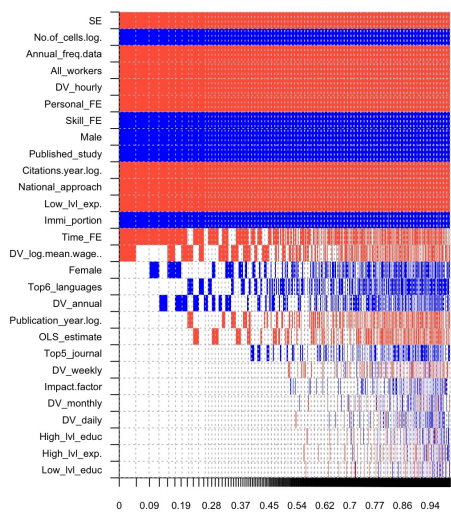


Figure C7: BMA: BRIC and random priors

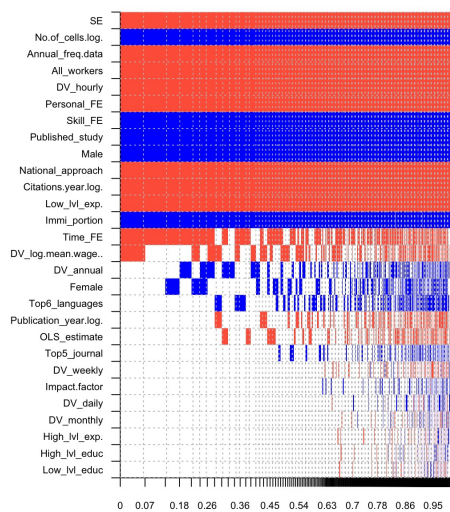


Figure C8: BMA: BRIC and uniform priors

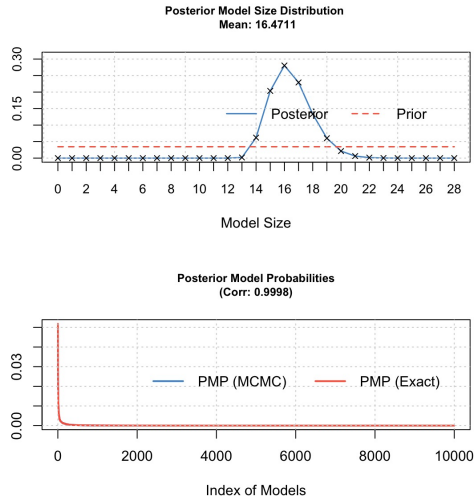


Figure C9: UIP and random priors

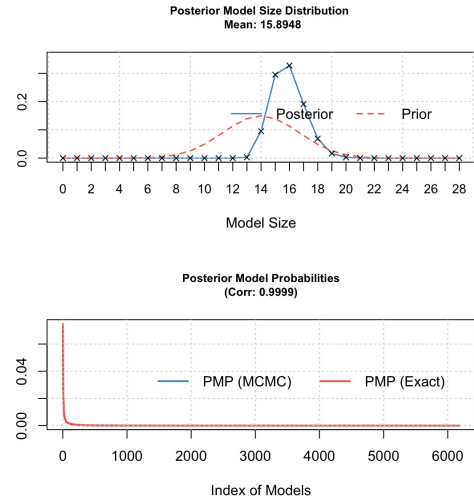


Figure C10: UIP and uniform priors

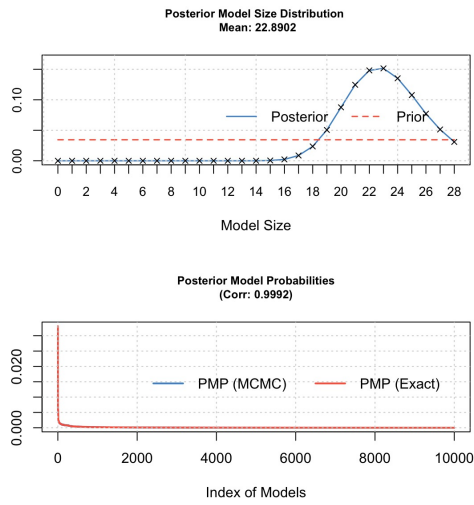


Figure C11: hyper-g and random priors

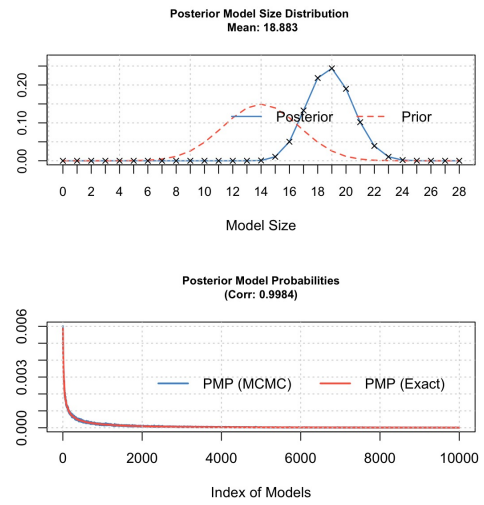


Figure C12: hyper-g and uniform priors



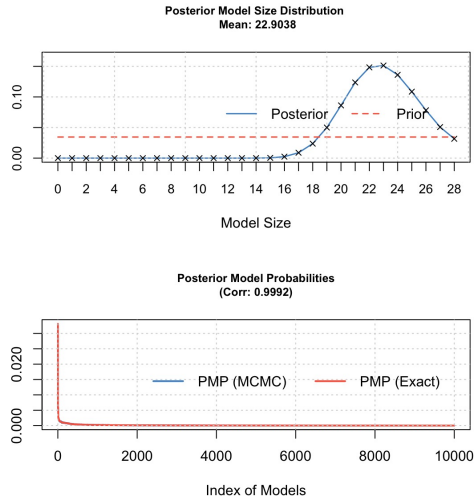


Figure C13: EBL and random priors

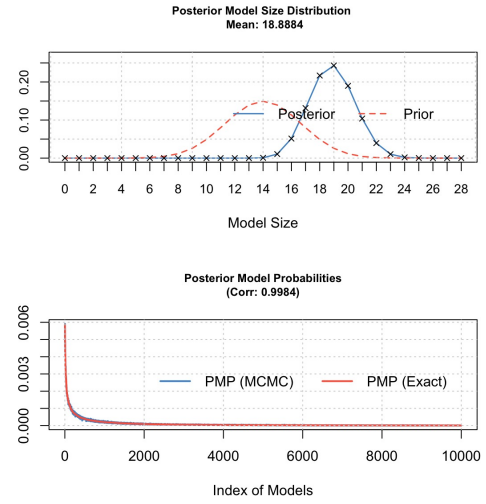


Figure C14: EBL and uniform priors

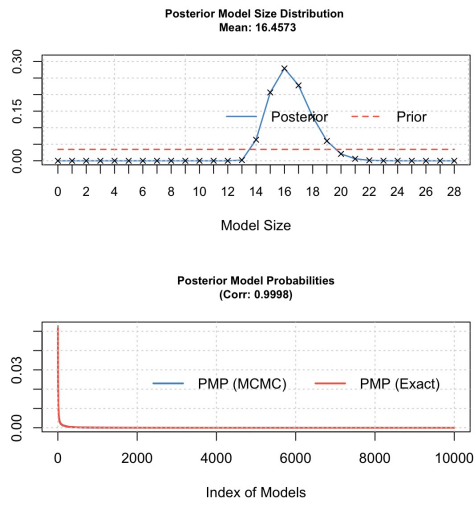


Figure C15: BRIC and random priors

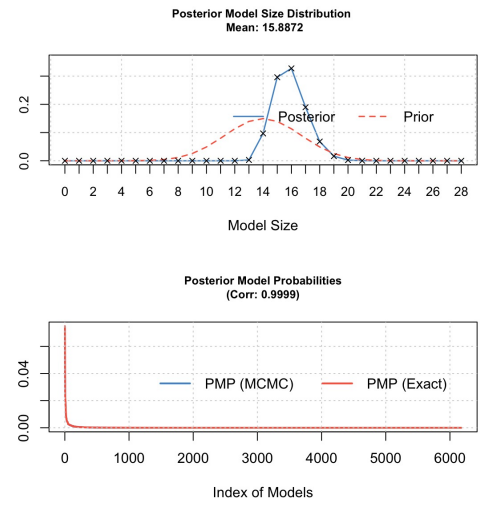


Figure C16: BRIC and uniform priors



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