Estudios Gerenciales
Journal of Management and Economics for Iberoamerica

Research article

Gender wage gap in emerging markets and developing economies

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Abstract
The last decade has witnessed a rapid expansion of empirical work on gender wage gaps. This meta-analysis synthesizes 40 estimates for emerging and developing economies (1999–2021) using random-effects models, tests for publication selection, and a restricted maximum likelihood meta-regression with country-year covariates. The pooled underlying proportional gap is 28.5% in favor of men, with pronounced regional variation (about 18% in Latin America, 43% in Asia, and 30% in emerging Europe). Cross-study variation is systematically related to gender development, female unemployment, and article publication year.

Keywords: gender wage gap; meta-analysis; publication bias; developing countries.

Brecha salarial de género en mercados emergentes y economías en desarrollo

Resumen
En la última década se ha expandido con rapidez la evidencia empírica sobre brechas salariales de género. Este metaanálisis sintetiza 40 estimaciones para economías emergentes y en desarrollo (1999–2021) mediante modelos de efectos aleatorios, pruebas de selección de publicación y una meta-regresión por máxima verosimilitud restringida con covariables país-año. La brecha proporcional subyacente agrupada es de 28,5% a favor de los hombres, con marcada variación regional (18% en América Latina, 43% en Asia y 30% en Europa emergente). La variación entre estudios se relaciona con el desarrollo de género, el desempleo femenino y el año de publicación del artículo.

Palabras clave: brecha salarial de género; metaanálisis; sesgos de publicación; países en desarrollo.

Diferença salarial entre homens e mulheres em mercados emergentes e economias em desenvolvimento

Resumo
Na última década, a evidência empírica sobre as diferenças salariais entre homens e mulheres expandiu-se rapidamente. Esta meta-análise sintetiza 40 estimativas para economias emergentes e em desenvolvimento (1999-2021) utilizando modelos de efeitos aleatórios, testes de viés de publicação e uma meta-regressão de máxima verossimilhança restrita com covariáveis país e ano. A diferença proporcional subjacente agrupada é de 28,5% a favor dos homens, com variação regional acentuada (18% na América Latina, 43% na Ásia e 30% na Europa emergente). A variação entre os estudos está relacionada ao desenvolvimento de gênero, à taxa de desemprego feminino e ao ano de publicação do artigo.

Palavras-chave: diferença salarial entre os sexos; meta-nálise; viés de publicação; países em desenvolvimento.

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JEL classification: J23; J31; C83.

How to cite: Herrera, D. Y. and Mora, J. J. (2025). Gender wage gap in emerging markets and developing economies. *Estudios Gerenciales, 41*(177), 481-491. https://doi.org/10.18046/j.estger.2025.177.7513

DOI: https://doi.org/10.18046/j.estger.2025.177.7513

Received: 10-06-2025
Accepted: 23-02-2026
Available online: 13-04-2026

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1. Introduction

Equal pay between men and women is a long-standing objective of the International Labour Organization (ILO, 1951) and constitutes one of the United Nations Sustainable Development Goals (United Nations, 2015). Becker's (1957) seminal work, The Economics of Discrimination, formally analyzed labor market discrimination and laid the foundation for subsequent research on wage inequality. Since then, researchers have increasingly focused on gender wage differentials, making it a central issue in labor economics.

For decades, researchers have relied on the Blinder (1973) and Oaxaca (1973) decomposition techniques to estimate wage differences between men and women and to separate the share of the gap attributable to productivity-related factors from those related to discrimination. Scholars commonly analyze gender discrimination by comparing male and female earnings while holding productivity constant. One method simply includes a sex dummy in the wage regression model, directly capturing the average wage differential between men and women after controlling for observable characteristics. More generally, these econometric approaches aim to isolate the portion of the wage gap that human capital or job characteristics cannot explain, thereby identifying potential evidence of labor market discrimination.

More recently, scholars have developed meta-analysis as a powerful statistical tool to synthesize empirical evidence across multiple studies. Meta-analysis provides a systematic and quantitative framework for summarizing research findings on a common topic, allowing scholars and policymakers to make more informed, evidence-based decisions (Weichselbaumer & Winter-Ebmer, 2005). Although researchers originally popularized meta-analysis in the medical and psychological sciences, its application in economics has expanded notably. For example, Card and Krueger (1995a, 1995b) employed meta-analytical methods to examine the effects of minimum wages, Dalhuisen et al. (2003) analyzed the income elasticity of water demand, and Mora and Muro (2020) investigated the wage–employment elasticity in Colombia.

The empirical study of gender wage disparities has also increasingly benefited from this methodological approach. Stanley and Jarrell (1998) made one of the earliest and most influential contributions to this literature by pioneering the application of meta-regression analysis (MRA) to quantify the extent and determinants of gender wage discrimination. Drawing on 41 estimates from U.S. studies, they provided one of the first systematic syntheses of empirical evidence in this field. Their results showed broad consensus on the existence of gender-based wage discrimination but revealed substantial variation in its estimated magnitude across studies. Crucially, they demonstrated that methodological choices—such as correcting for selection bias or including experience—significantly affected estimated wage gaps, underscoring the importance of model specification and the potential for omitted-variable bias in measuring discrimination.

Building on this foundation, Weichselbaumer and Winter-Ebmer (2005) conducted a comprehensive international meta-analysis encompassing 263 studies across 64 countries. Their work provided a global perspective, showing that the raw gender wage differential declined considerably over time, largely due to improvements in women's labor market endowments rather than a complete reduction in discrimination. They introduced quality-weighting procedures to account for methodological heterogeneity and assessed data restrictions and specification errors—such as using potential instead of actual experience—that can bias estimates of the gender wage gap.

Complementing these contributions, Kunze (2008) reviewed the econometric consistency and decomposition approaches used in gender wage gap studies. Her analysis emphasized that endogeneity in variables such as work experience and time out of the labor market can yield inconsistent estimates and complicate causal interpretation. She advocated the use of fixed effects and instrumental variable estimators to address these biases and enhance the reliability of empirical evidence on gender wage disparities.

More recently, Iwasaki and Satogami (2023) expanded the meta-analytical framework to examine the gender wage gap in emerging European markets. Synthesizing 670 estimates from 53 studies covering post-communist Central and Eastern European economies, they found persistent yet declining wage inequalities during the transition to market economies. Their findings indicate that EU membership reduces gender wage gaps, suggesting that institutional transformation, democratization, and European integration have played a crucial role in shaping gendered labor market outcomes in the region.

Taken together, these meta-analytical studies provide a comprehensive foundation for understanding the evolution and determinants of gender wage disparities across diverse economic and institutional contexts. They underscore the importance of methodological rigor, cross-country comparability, and sensitivity to institutional and cultural heterogeneity. Building on this tradition, this article applies a meta-analytic framework to examine gender wage inequalities in developing and emerging economies.[1]

However, systematic evidence for emerging and developing economies remains comparatively limited and highly heterogeneous. Relative to Iwasaki and Satogami (2023), who focus on European emerging markets, we extend the evidence base to emerging and developing economies across regions. We also go beyond regional comparisons by explicitly modeling between-study heterogeneity using country-year structural and institutional moderators (female unemployment rate, gender development, and governance/market environment), alongside a methodological control for Blinder–Oaxaca estimates. Finally, we parameterize ILO Convention No. 100 using an exposure measure (years since ratification), which helps separate ratification status from post-ratification

1 We define European emerging markets broadly as the post-communist economies of Central and Eastern Europe that transitioned from Soviet-style planned systems to market-oriented economies in the late 1980s and early 1990s. These countries continue to undergo economic convergence and adapt their institutions to narrow the gap with the advanced industrial economies of North America and Western Europe.

dynamics. This extension clarifies how institutional correlates relate to wage-gap variation in contexts where the empirical literature is predominantly observational and cross-country evidence remains fragmented.

Gender wage inequality remains one of the most persistent barriers to achieving inclusive and sustainable economic growth. Beyond its ethical implications, the gender pay gap has measurable economic and social costs, including lower household income, reduced productivity, and the inefficient allocation of human capital. Addressing these disparities is therefore essential not only for advancing gender equality but also for fostering overall economic performance.

Our results show that, despite notable progress in recent decades, significant wage differentials persist in emerging and developing economies. On average, men earn about 28.5% more than women, with regional variations ranging from 18% in Latin America to over 40% in Asia. These findings highlight the ongoing challenges of achieving pay equity and reinforce the importance of implementing effective institutional and policy measures to reduce gender-based wage disparities.

2. Estimates of wage differentials

Before conducting the meta-analysis, it is essential to summarize the econometric foundations for estimating gender wage gaps in empirical literature. Understanding the construction of these estimates clarifies the types of measures synthesized in this study and ensures comparability across different methodologies.

Researchers have developed several econometric approaches to quantify gender-based wage disparities. Among the most influential are the decomposition methods proposed by Blinder (1973) and Oaxaca (1973), which provide a framework to distinguish the portion of the wage gap explained by observable productivity-related characteristics from the portion that remains unexplained. In empirical applications, gender wage differentials are often estimated either through these decomposition techniques or by including a gender indicator variable in wage regressions that control for factors such as education, experience, occupation, and sector of employment. Both approaches yield estimates of the wage differential between men and women; however, the degree of covariate adjustment differs by method, and decomposition-based headline gaps are not strictly equivalent to gender-dummy coefficients.

Building on this framework, the Blinder–Oaxaca decomposition allows the observed wage gap to be divided into two components: one explained by differences in workers' characteristics (such as education, experience, or occupation) and an unexplained component associated with differences in the returns to these characteristics.

Formally, the first step consists of estimating the wages for individuals *i* for men and women *(g)*.

$$\mathrm{w_{gi}} = \beta_{\mathrm{g}} \mathrm{x_{gi}} + \varepsilon_{\mathrm{gi}} \quad (1)$$

where, *g=(men,women)*, w_i is the logarithm of the wage, X_i contains the variables that affect the productivity of workers, therefore, their wages, and ε_i is a random error term assumed to be normally distributed with mean zero and variance σ_2.

In this sense, the difference in average wages can be written as follows:

$$\left(\overline{\mathrm{w}}_{\mathrm{m}} - \overline{\mathrm{w}}_{\mathrm{w}}\right) = \left(\overline{\mathrm{X}}_{\mathrm{m}} - \overline{\mathrm{X}}_{\mathrm{w}}\right)\hat{\beta}_{\mathrm{m}} + \left(\hat{\beta}_{\mathrm{m}} + \hat{\beta}_{\mathrm{w}}\right)\overline{\mathrm{X}}_{\mathrm{w}} \quad (2)$$

where, $\bar{w}_g$ and $\bar{X}_g$ are the mean of the logarithm of the wages and the control characteristics of group *g*, respectively, and $\hat{\beta}_g$ is the estimated parameter of Equation (1). The first term is called the "endowment effect," and the second is the "remuneration effect." Thus, the first term represents the effect of different productive characteristics, and the second term represents the unexplained residual due to differences in the estimated coefficients for both groups (Galvis, 2011).

3. Methodological approach

Meta-analysis is a methodology used for systematic and quantitative research review (Weichselbaumer & Winter-Ebmer, 2005). Meta-analysis can provide objective and comprehensive summaries of economic research (Stanley et al., 2013), and more precise estimates of effect sizes by synthesizing data from numerous studies.

When estimating meta-regressions, detecting the existence of publication bias is crucial. If there is publication bias, any meta-regression estimates will be biased. For example, Card and Krueger (1995a) and Stanley (2005) argue that there are at least three different sources of publication bias: 1) reviewers and editors may be predisposed to accept articles consistent with the conventional view; 2) researchers can use a conventionally expected outcome as a test for model selection; and 3) individuals may be predisposed to treat "statistically significant" results more favorably.

Publication bias distorts meta-analyses by skewing results, leading to an overestimation of the overall effect size. Studies reporting statistically significant or "positive" findings are more likely to be published and included than those with null or negative outcomes. Consequently, a meta-analysis that disproportionately includes positive studies will fail to reflect the true effect. This bias can inflate the magnitude—or even the apparent existence—of an effect, thus making the conclusions of such meta-analyses unreliable and potentially leading to misguided policy decisions.

An objective statistical test to model publication bias involves a meta-regression analysis (MRA) between a study's reported effect and its standard error. Card and Krueger (1995a) popularized this approach in economics as a way to diagnose selection in empirical literature. Subsequent applications and extensions in economics include Ashenfelter et al. (1999) and Görg and Strobl (2001), among others (see also Mookerjee, 2006).

$$\mathrm{eff_i} = \beta_1 + \beta_0 \mathrm{Se_i} + \varepsilon_i \quad (3)$$

where, eff_i is the estimated proportional gender wage differential reported in study ε_i, is its standard error, and ε_i is an error term. In the absence of selection bias, the true effect of the differential will be β_1. Following Stanley (2005, 2008), publication selection is assessed via a meta-regression of reported effects on their standard errors (the funnel-asymmetry test, FAT). Because heteroskedasticity[2] is inherent in this relationship, the equation is re-estimated after scaling by Se_i, yielding the Precision-Effect Test (PET) specification in Equation (4). The intercept provides a test for publication bias (FAT), while the slope provides an estimate of the underlying effect net of selection (PET).

$$\mathrm{t_i} = \beta_0 + \beta_1 \left(\frac{1}{\mathrm{Se_i}} \right) + \nu_i \quad (4)$$

t_i is the t conventional value for estimating differential .

In other words, the t conventional test of the intercept of Equation (4), β_0 is a test for publication bias, and its estimate, $\hat{\beta}_0$, indicates the direction and magnitude of this bias (Egger et al., 1997; Stanley 2008; Doucouliagos & Stanley, 2009). Therefore, the β_0 test can be considered the funnel plot asymmetry test. If literature is free of publication bias, the intercept will not be statistically significant.

The β_1 test considers the true differential that goes beyond the systematic "contamination" that arises from publication biases. Therefore, β_1 is the "true" value of the differential (Stanley, 2008).

3.1 Data

The search and coding process for the studies followed the Meta-Analysis of Economics Research Network (MAER-Net) protocols (Stanley et al., 2013). In this context, studies were retrieved from JSTOR, SCOPUS, ISI, Web of Science, EBSCO, and Google Scholar using keywords such as "Blinder–Oaxaca decomposition", "wage gap", "gender discrimination", "labor market inequalities", "emerging markets", and "developing countries". The search covered the period from 1999 to 2021[3]. The sample covers research conducted in Latin America, Asia, and Europe.

The inclusion criteria required that studies provide empirical estimates of the gender wage gap, employ econometric techniques, and report sufficient statistical information (e.g., standard errors or t-values) to allow for the computation of comparable effect sizes. Peer-reviewed journal articles, working papers, and book chapters with a rigorous empirical framework were considered, while studies with limited methodological transparency or incomplete statistical reporting were excluded from the final sample.

The search strategy initially applied no restrictions regarding geography or time, thereby allowing for broad coverage of the existing literature. In cases where duplicate entries or overlapping datasets were detected, careful consideration was given to retain only the most relevant or methodologically robust versions of the studies. This filtering reduced mechanical dependence arising from duplicate entries and overlapping datasets. In several cases, researchers calculated the gender wage gap across multiple countries or time periods within a single publication. We treat these estimates as separate effect-size observations to retain relevant variation within the literature. Because multiple estimates may originate from the same author(s), we report clustered standard errors by author as a sensitivity check to dependence across estimates. We also estimate random-effects models to account for between-study heterogeneity.

Moreover, to mitigate publication bias, unpublished working papers and institutional reports that met methodological standards were also included in the dataset. This inclusive strategy ensured that the database captured not only statistically significant findings, which are more likely to be published, but also a broader range of evidence that reflects the field's diversity of research outcomes. By combining both published and unpublished studies, our analysis provides a more balanced and comprehensive overview of gender wage disparities.

We examined the empirical studies to determine whether authors reported regression-adjusted gender wage gaps (e.g., a gender dummy in a wage regression with covariates) or decomposition-based measures. For studies using the Blinder–Oaxaca framework, we extract the total differential as the headline gap reported by the authors. We treat this measure as a summary of the overall wage differential reported in that study and do not interpret it as strictly equivalent to a fully regression-adjusted gender-dummy coefficient. To account for potential methodological differences, we include a Blinder–Oaxaca indicator as a moderator in the meta-regression so that institutional and structural associations are not confounded by estimation approach.

From this search, we selected forty estimates based on the availability of information regarding standard errors and sample sizes[4]. Table 1 presents the descriptive statistics of the dataset.

Accordingly, ten estimates were considered for Latin America[5], thirteen for Asia[6], and seventeen for Europe[7]. The mean wage differential was 0.20 in Latin America, 0.34 in Asia, and 0.23 in Europe. Moreover, the share of published studies among the estimates reached 100% for Latin America, 77% for Asia, and 65% for Europe.

Conversely, to identify the extent to which the variance is false or real, we used the index I_2 developed by Higgins et al. (2003)[8]. This index is defined on a relative scale from 0 to 100, independent of the number of studies. If I_2 is close to

2 In economics, research studies use different sample sizes and different econometric models and techniques. Therefore, the random estimation errors of this MRA model, ε_i in Equation (1), are likely to be heteroscedastic.

3 All studies included in this meta-analysis are listed in the References section.

4 Although a substantial number of studies from Latin America, Europe, and Asia were identified, they were excluded due to the lack of reported standard errors.

5 Including Argentina, Chile, Costa Rica, Ecuador, El Salvador, Uruguay and Paragua

6 Including Bangladesh, India, Indonesia, Kazakhstan, Malaysia, Thailand, and Uzbekistan.

7 Including Belarus, Bulgaria, Croatia, Hungary, Serbia, and Ukraine.

8 If there is notable heterogeneity in the study, the random effects method should be used. Several studies in different parts of the world show that there is great heterogeneity among studies. Therefore, the random effects method should be used for the analysis.

zero, the observed variance is largely false, but if it is close to 100, it makes sense to make assumptions about the variance and the factors that might explain it. In this context, the value of the test (I^2) was 98.49%, 99.40%, and 99.89% for Latin America, Asia, and Europe (Figure 1), respectively.

To visually assess potential publication bias, a funnel plot was constructed following Sutton et al. (2000). This graphical method plots study precision against estimated effects and allow for the detection of asymmetries that may indicate the presence of publication bias. In this plot, precision is proxied by the standard error.

As the name suggests, if publication bias is absent, the shape should be an inverted funnel, and estimates should vary randomly and symmetrically around the "true" population effect.

The funnel plots (Figure 2) suggest asymmetry consistent with potential publication selection. Because visual inspection can be sensitive to small samples and heterogeneity, we complement this evidence with formal FAT–PET tests reported in Table 3.

Table 1. Descriptive statistics

Region	Number of estimates *(K)*	Mean – Wage Differential	% Published
Latin America	10	0.20	100
Asia	13	0.34	76.9
Europe	17	0.23	64.7

Source: own elaboration.

4. Results

Paldam (2015) proposes a simple rule of thumb to approximate the underlying effect by dividing the mean reported differential by two. Table 2 reports the values obtained from this informal approximation. Given the limitations of this rule of thumb, we proceed with formal estimations using multiple approaches to identify the underlying differential and assess publication selection and dependence across estimates.

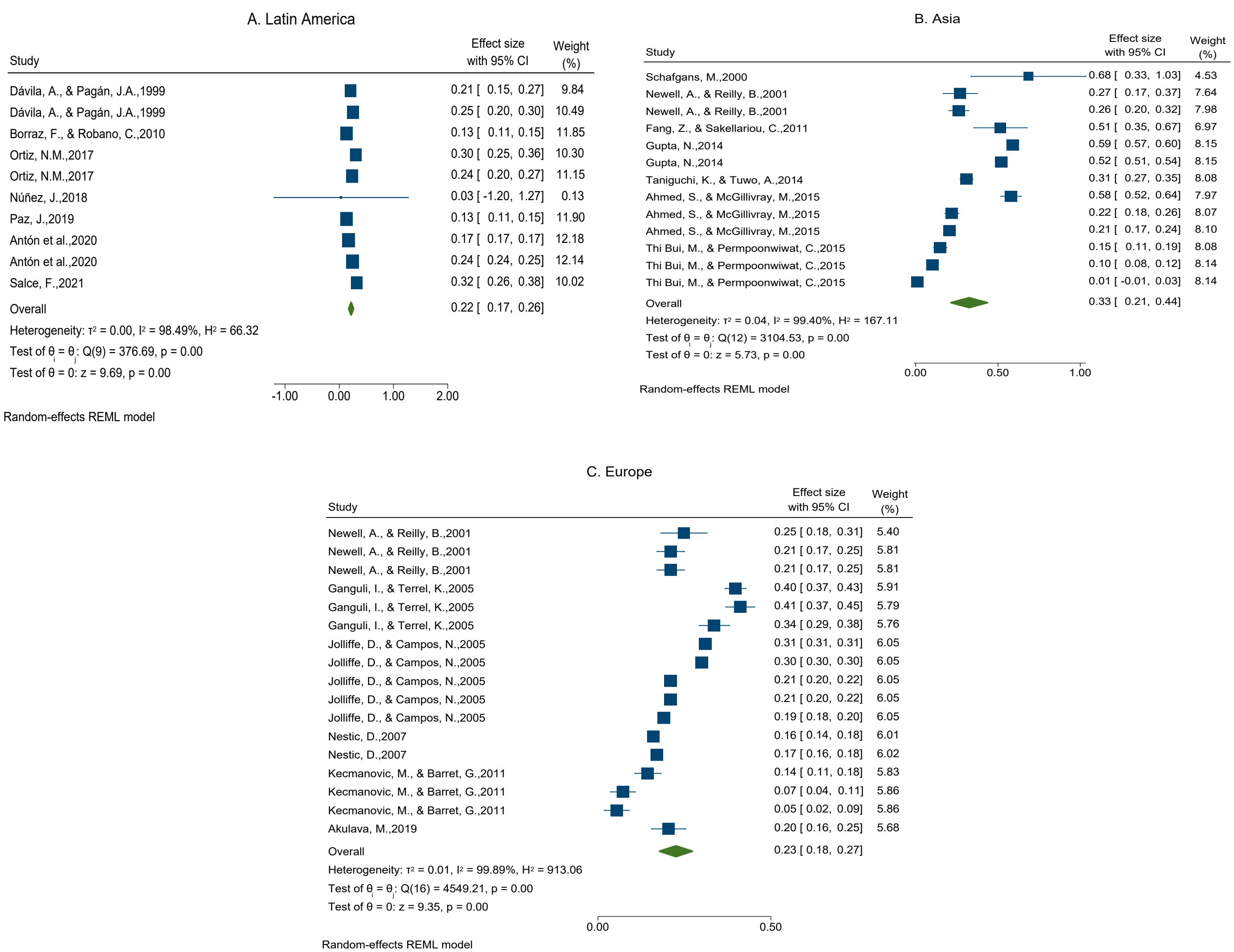

Figure 1. Forest plot
Source: own elaboration.

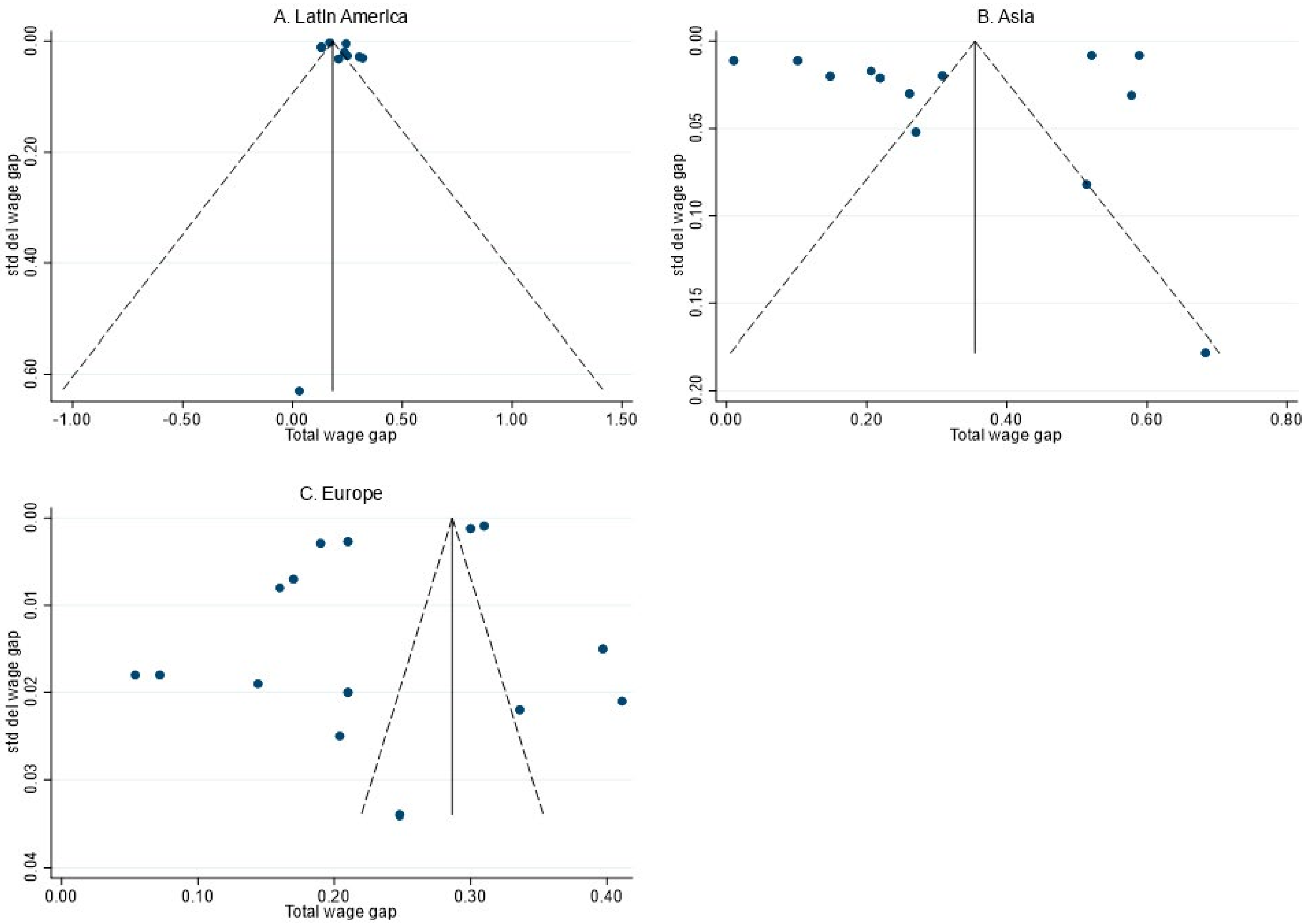

Figure 2. Funnel plot
Source: own elaboration.

Table 2. Informal rule of Paldam

Continent	Average wage differential	Effect
Latin America	0.203	10.2%
Asia	0.339	16.9%
Europe	0.226	11.3%

Source: own elaboration.

However, given the informal nature of this rule of thumb, we rely on a set of formal estimators to identify the underlying effect. First, we estimate Equation (4) as the baseline specification. Second, we re-estimate Equation (4) with heteroskedasticity-robust inference. Third, we estimate Equation (4) using the author as the clustering unit (Doucouliagos & Stanley, 2009) as a sensitivity check to dependence across estimates contributed by the same author(s). Fourth, we estimate Equation (4) as a random-effects meta-regression with the between-study variance estimated by restricted maximum likelihood, which accounts for unobserved heterogeneity across effect sizes. Fifth, we report an empirical Bayes estimator to obtain shrinkage estimates that reduce the influence of outliers and reflect differences in precision. Finally, we apply instrumental-variables estimation to address potential endogeneity between effect sizes and their standard errors; the inverse of the standard error is instrumented using the square root of the sample size for each estimate (Mora & Muro, 2020). Table 3 reports the results.

The pooled estimates in Table 3 indicate sizeable regional heterogeneity in reported wage differentials. In Latin America, the estimated underlying proportional differential is approximately 18% in favor of men. In Asia, the corresponding estimate is about 43%, while in Europe's emerging and developing economies, it is approximately 30.3%. For the pooled sample of emerging and developing economies, the underlying differential is 28.5%.

Table 3. FAT–PET estimates of publication selection (intercept) and underlying wage differentials (slope)[9][10]

	Variable	Baseline	Robust	Cluster (by author)	Random effects [REML]	Empirical Bayes	IV
Latin America	Wage differential	0.18***	0.18***	0.18***	0.18***	0.18***	0.18***
		(0.014)	(0.016)	(0.002)	(0.014)	(0.014)	(0.013)
	Constant	2.12	2.12	2.12	2.12	2.12	2.12
		(2.65)	(1.55)	(1.79)	(2.65)	(2.65)	(2.37)
	No. estimates	10	10	10	10	10	10
Asia	Wage differential	0.43***	0.43**	0.43*	0.43***	0.43***	0.43***
		(0.119)	(0.149)	(0.209)	(0.119)	(0.119)	(0.109)
	Constant	-6.42	-6.42	-6.42	-6.42	-6.42	-6.42
		(8.15)	(5.64)	(6.96)	(8.15)	(8.15)	(7.49)
	No. estimates	13	13	13	13	13	13
Europe	Wage differential	0.3031***	0.3031***	0.3031***	0.3031***	0.3031***	0.3031***
		(0.012)	(0.013)	(0.010)	(0.012)	(0.012)	(0.011)
	Constant	-10.40**	-10.40**	-10.40	-10.40**	-10.40**	-10.40**
		(4.52)	(3.59)	(7.00)	(4.52)	(4.52)	(4.25)
	No. estimates	17	17	17	17	17	17
Emerging and Developing Economies	Wage differential	0.285***	0.285***	0.285***	0.285***	0.285***	0.285***
		(0.012)	(0.021)	(0.018)	(0.012)	(0.012)	(0.012)
	Constant	-4.59	-4.59*	-4.59	-4.59	-4.59	-4.59
		(3.18)	(2.56)	(3.89)	(3.18)	(3.18)	(3.10)
	No. estimates	40	40	40	40	40	40

Note. ***statistically significant at the 0.01 level; **statistically significant at the 0.05 level. Standard errors appear in parentheses ( ).
Source: own elaboration.

Regarding publication selection, the FAT intercepts provide the formal test. The intercept is statistically significant only for Europe, thus suggesting stronger evidence of selection in that regional sub-sample.

To further investigate the sources of heterogeneity in reported gender wage gaps, we introduce an institutional moderator linked to equal pay legislation: the International Labour Organization (ILO) Equal Remuneration Convention, 1951 (No. 100). It establishes the principle of equal remuneration for men and women for work of equal value (ILO, 2006). Ratification can be read as a clear, formal signal of commitment to equal pay norms, even though the strength of enforcement, administrative capacity, and the pace of effective implementation can differ widely across countries—and often change only gradually over time.

In the meta-regression, we operationalize Convention No. 100 in two complementary ways, both referenced to the year of the underlying data used to estimate each wage gap: (i) a binary indicator that takes the value one if the country had ratified Convention No. 100 by that year, and (ii) the number of years since ratification as of that year. This setup lets us distinguish a "step" effect associated with ratification status from a more incremental relationship that may emerge as time passes and institutions adapt after ratification.

Equal pay plays a fundamental role in women's lives by increasing their economic independence and improving their status and decision-making power both at home and in their communities. Likewise, it reduces the risk of poverty and ensures an adequate standard of living for elderly women. Equal remuneration promotes the well-being of families, increases the competitiveness of companies, and encourages the development of economies.

To better account for structural and institutional differences across the country–year settings from which the primary estimates are drawn, our specification includes a set of moderators grounded in standard labor-market theory. One of them is the female unemployment rate, which we use as a proxy for labor-market slack and, more specifically, for the relative difficulty women face in accessing and keeping employment. Movements in unemployment can influence observed gender wage gaps through several channels. A key one is composition and selection among employed women: when unemployment rises, the women who remain employed may be, on average, more positively selected on observed and unobserved productivity characteristics, which can mechanically compress the measured wage gap. At the same time, higher unemployment can drive sectoral and occupational reallocation and alter wage-setting, shifting measured gaps even if discrimination itself does not change (Mulligan & Rubinstein, 2008).

9 "Wage differential" is the estimated underlying gap. "Constant" captures funnel asymmetry consistent with publication selection bias. Columns report baseline, robust, clustered (author), random-effects (restricted maximum likelihood), empirical Bayes, and instrumental-variables estimates.

10 Several studies were excluded from the sample because they did not provide sufficient statistical information—specifically, standard errors or sample sizes. Although this reduced the number of available observations, it was necessary to ensure methodological consistency and reliability of the meta-regression analysis (Stanley et al., 2013). The omitted studies lacked detailed econometric reporting, and their exclusion does not appear to introduce systematic regional or methodological bias. The robustness of the results across alternative estimation methods (robust, clustered, REML, and IV) further suggests that the main conclusions are not sensitive to this selection criterion, although this limitation may slightly restrict the representativeness of the overall sample.

We introduce the Gender Development Index (GDI) as a broad proxy for the development conditions that shape gender inequality, capturing gaps between women and men in basic capabilities and access to economic resources. A substantial literature suggests that countries with stronger overall gender development tend to display better labor-market outcomes for women and smaller disparities in economic opportunity (Klasen & Lamanna, 2009; UNDP, 2020). By controlling GDI, we can better separate the role of explicit institutional commitments from more general structural progress in gender equality.

Broader institutional quality is captured through Government Effectiveness, which approximates state capacity and policy implementation quality (Kaufmann et al., 2010), and the Index of Economic Freedom, which reflects characteristics of the regulatory and market environment that may shape wage-setting mechanisms and labor-market performance (Hall & Lawson, 2014). These variables help distinguish the role of gender-specific development from overall institutional and market conditions.

To control for methodological heterogeneity, we include an indicator for whether the primary estimate is obtained using a Blinder–Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973). This helps prevent systematic differences in estimation strategy from confounding institutional or structural associations.

Given the dispersion in reported effect sizes and persistent between-study heterogeneity, we estimate a random-effects meta-regression (Table 4).

Table 4. Random-effects meta-regression (REML)[11]

Variable	Coef.
Year of publication	-0.00755*
	(0.00381)
Ratified (year of data)	-0.05226
	(0.08170)
Years since ratification	0.00230**
	(0.00104)
Blinder-Oaxaca	0.01196
	(0.04744)
Female unemployment rate	-0.01046 **
	(0.00389)
Gender Development Index	-1.30385***
	(0.31979)
Government Effectiveness	-0.01114
	(0.03930)
Economic Freedom Index	-0.00154
	(0.00283)
Constant	16.80883**
	(7.58122)
No. estimates	40

Note. ***statistically significant at the 0.01 level; **statistically significant at the 0.05 level. Standard errors appear in parentheses ( ).
Source: own elaboration.

Table 4 presents the REML meta-regression results[12]. The model is jointly significant ($F(8,31)=3.88$; $p=0.0029$) and explains approximately 43.2% of the between-study variation, while residual heterogeneity remains very high ($I^2 = 99.06$). Relative to baseline specification, the inclusion of structural and institutional moderators increases explanatory power and reduces unexplained heterogeneity, although substantial dispersion remains.

Regarding institutional exposure, the number of years since ratification is positive and statistically significant. Since the dependent variable is expressed as a proportion, this coefficient implies that each additional year since ratification is associated with an increase of approximately 0.23 percentage points in the reported wage gap. Importantly, this result should be interpreted as a cross-context association that may reflect gradual post-ratification structural and compositional changes, rather than causal policy effect. Consistent with this interpretation, ratification status itself is not statistically significant, indicating no evidence of a discrete shift at the time of ratification in the pooled data.

Among the structural moderators, the Gender Development Index displays a large and highly significant negative coefficient, indicating systematically smaller wage gaps in contexts with higher gender development. Female unemployment is negative and statistically significant, implying that higher female unemployment rates are associated with smaller reported wage gaps. A plausible interpretation is compositional: in weaker labor markets, the subset of women who remain employed may be more positively selected into higher-paying jobs or sectors, mechanically narrowing observed differentials. This result should be interpreted as a cross-context association rather than a causal effect.

Year of publication is negative and significant, suggesting that more recent studies tend to report smaller differentials. Government Effectiveness and the Index of Economic Freedom are not statistically significant once the remaining controls are included. The Blinder–Oaxaca dummy is also not statistically significant, indicating no systematic differences in reported effect sizes by estimation approach conditional on the included moderators.

Given the substantial residual heterogeneity ($I^2 = 99.06\%$), the pooled effect should be interpreted as an average across highly diverse contexts. Using the estimated between-study variance ($\tau^2 = 0.01011$), we compute a 95% prediction interval for the wage-gap effect evaluated at sample-average covariates. The predicted mean wage gap is 0.2505, while the corresponding 95% prediction interval ranges from 0.0425 to 0.4586.

This wide interval indicates that gender wage differentials in emerging and developing economies can vary considerably across institutional and structural environments. While the average differential is precisely estimated, the magnitude observed in a new country or study may differ substantially depending on underlying contextual factors.

11 All continuous moderators are entered in their original scales. The female unemployment rate is measured in percentage points (0–100). The Gender Development Index follows the UNDP definition. Government Effectiveness corresponds to the Worldwide Governance Indicators scale – World Bank. The Economic Freedom Index follows its original index scale – The Heritage Foundation.

12 As a robustness check, we added an Asia dummy; results are unchanged—the dummy is statistically insignificant and model fit does not improve, while the main coefficients remain stable.

4.1. Regional differences in the gender wage gap

Meta-analysis reveals substantial regional disparities in gender wage differentials across emerging and developing economies. Specifically, men earn, on average, 18% more than women in Latin America, approximately 30% more in Europe, and a markedly higher 43% in Asia. These findings suggest that structural, institutional, and cultural characteristics of labor markets strongly influence the variation in observed wage gaps across regions. The particularly high disparity in Asia may reflect the persistence of traditional gender norms, lower female labor force participation in some countries, and limited access to leadership positions and formal employment opportunities for women, consistent with recent evidence for the region (Yenilmez & Darici, 2025).

In Europe, women have long maintained high labor force participation, rooted in the legacy of the socialist era. During this period, state authorities treated women as an essential economic resource and implemented policies to systematically integrate them into the national workforce (Fodor & Balogh, 2010; Iwasaki & Satogami, 2023). Socialist regimes widely promoted the notion that the Communist Bloc had resolved gender inequality in the labor market, emphasizing women's full integration into productive employment. Women's educational attainment and access to professional occupations increased markedly, and opportunities for highly educated women to participate in skilled professions expanded significantly. However, despite these advances, many of these nations—originally underdeveloped economies on Europe's periphery—retained strong traditional gender norms and a persistent division of labor within households. As Fodor and Balogh (2010) observe, women continued to bear a "double burden" of productive and reproductive work: although governments established childcare services and public nurseries, domestic labor and caregiving remained primarily women's responsibilities, reinforced by labor legislation that defined parental leave as a right exclusively for female workers. This combination of high female participation and enduring traditional roles contributed to a persistent gender wage gap, particularly through vertical occupational segregation and the "glass ceiling" that limits women's advancement into top managerial and better-paid positions (Becker, 1957; Weichselbaumer & Winter-Ebmer, 2005).

In contrast, in Latin America, female labor force participation has increased steadily in recent decades, but women remain predominantly concentrated in informal and low-wage sectors. Approximately half of all employed women work in the informal economy, and nearly 47.7% engage in precarious forms of employment (Organisation for Economic Co-operation and Development [OECD], 2017; Kugler, 2019). Female workers also disproportionately occupy low-paying jobs and less productive sectors, where career advancement opportunities are limited (OECD, 2017). This structural configuration reinforces a "sticky floor" effect, in which women remain trapped in low-wage, low-mobility positions (Galvis, 2011).

Consequently, the relatively smaller gender wage gap observed in Latin America does not necessarily reflect greater gender equity but instead reveals a segmented labor market in which female employment concentrates in sectors characterized by uniformly low pay and restricted upward mobility.

In summary, the smaller gender wage gap observed in Latin America appears to result from a combination of structural and institutional factors: (a) lower female participation in formal employment and greater concentration in low-mobility, low-wage sectors sustain the "sticky floor" effect; and (b) institutional and policy frameworks, including formal commitments such as the ratification of international agreements (e.g., ILO Convention No. 100), may be related to cross-country differences in wage gaps. Conversely, in Europe, higher female participation in formal and high-productivity sectors makes vertical discrimination—the "glass ceiling"—more visible, thereby widening the observed gender wage differential. In Asia, the largest wage gap among the three regions likely reflects persistent patriarchal norms, occupational segregation, and limited enforcement of equal pay legislation, which together perpetuate gender inequality despite significant economic and educational progress (Yenilmez & Darici, 2025).

Beyond the regional differences identified above, several mechanisms may help explain the persistence of gender wage disparities across countries. One key factor is statistical discrimination, in which employers form expectations about workers' productivity based on gender, treating it as a proxy for characteristics such as labor market attachment, family responsibilities, or expected career interruptions (Phelps, 1972; Arrow, 1973). This results in systematically lower wages or fewer promotion opportunities for women, even when they possess qualifications comparable to those of men.

Another important mechanism is occupational and sectoral segregation, both horizontal and vertical. Women are often concentrated in sectors or occupations characterized by lower pay and limited career progression – "sticky floors", while men are overrepresented in higher-paying managerial and technical positions – "glass ceilings" (Blau & Kahn, 2017). This segregation reflects not only market structures but also institutional and cultural factors that shape occupational choices and opportunities (Kunze, 2008; Galvis, 2011).

Additionally, social and cultural norms play a central role in reinforcing these disparities. In many emerging and developing economies, gender norms continue to influence women's access to formal employment, bargaining power, and the social value assigned to their work. Expectations related to caregiving, household responsibilities, and part-time employment often constrain women's labor market participation and earnings potential (Fodor & Balogh, 2010; Yenilmez & Darici, 2025). These cultural constraints interact with institutional settings—such as weak enforcement of equal pay legislation—to perpetuate wage inequalities even where legal frameworks for gender equality exist (Weichselbaumer & Winter-Ebmer, 2005).

Previous studies on the gender wage gap often face several limitations, including differences in methodological specifications, sample selection, and variable definitions, as well as the potential presence of publication bias. Moreover, many analyses focus on developed economies, leaving emerging and developing countries underrepresented in the empirical literature. The present meta-analysis addresses these limitations by systematically synthesizing results from a broad set of studies, applying statistical corrections for publication bias, and providing comparative evidence across regions. This approach allows for a more comprehensive and balanced assessment of the gender wage gap and its underlying determinants.

Although unpublished working papers and institutional reports were included to mitigate publication bias, the proportion of published studies varies notably across regions—100% for Latin America, 76.9% for Asia, and 64.7% for Europe. This heterogeneity may reflect differences in data accessibility, research funding, or publication incentives rather than genuine disparities in gender wage gaps. A qualitative sensitivity check confirms that the estimated effects remain consistent across robust, clustered, REML, and IV estimations, suggesting that the main regional patterns are not driven by publication status. Nonetheless, this difference constitutes a limitation to cross-regional comparability, as the higher share of published studies in Latin America may slightly inflate the average estimated wage gap due to the greater likelihood that statistically significant findings are published (Stanley, 2005; Doucouliagos & Stanley, 2009). Future research could expand the database by adding a larger set of unpublished studies, particularly from Latin America, to enhance balance and further minimize potential bias.

5. Conclusion

Women's participation in the labor market has expanded markedly since the mid-twentieth century (United States Bureau of Labor Statistics, 2018). Women also attain higher degrees and contribute more actively to the workforce than in previous generations. Yet gender-based wage differences persist across regions and occupational categories, keeping equal pay for work of equal value central to the international agenda and the Sustainable Development Goals.

This study contributes to that agenda by synthesizing empirical evidence on gender wage disparities in emerging and developing economies. Using forty estimates reported between 1999 and 2021 from peer-reviewed articles and working papers, we combine effect sizes using a random-effects meta-analysis and examine cross-study differences through an extended random-effects meta-regression estimated by restricted maximum likelihood. Results are supported by sensitivity checks using robust and clustered inference, empirical Bayes shrinkage, and instrumental-variables estimation.

The baseline synthesis confirms persistent gender wage differentials across regions. Among emerging and developing economies in the pooled sample, the underlying differential is approximately 28.5%, with sizeable regional variation: around 18% in Latin America, about 43% in Asia, and about 30% in Europe. These patterns underscore that gender pay inequality remains a significant challenge shaped by heterogeneous economic structures and institutional settings.

The extended random-effects meta-regression provides additional evidence on correlates of cross-study heterogeneity. Ratification of the International Labour Organization Equal Remuneration Convention, 1951 (No. 100) is not associated with an immediate reduction in the wage gap when defined at the year of measurement. By contrast, the time elapsed since ratification is statistically associated with the reported differential, which may reflect gradual post-ratification changes or other structural and compositional dynamics correlated with the post-ratification period rather than a discrete institutional break.

Among the structural moderators, the Gender Development Index shows a negative association with reported wage gaps, indicating that contexts characterized by higher gender development tend to exhibit smaller differentials. Female unemployment is negatively associated with reported differentials, consistent with compositional/selection effects among employed women, while year of publication is negatively associated with the wage gap, suggesting smaller differentials in more recent estimates.

Overall, the findings suggest that formal institutional commitments alone are insufficient to account for cross-country variation in gender wage gaps. Broader gender development conditions and labor market dynamics appear central to shaping observed differentials. Future research could incorporate additional moderators to further explain remaining heterogeneity and clarify the channels through which institutional commitments translate into labor-market outcomes.

Acknowledgement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of interest

The authors declare no conflict of interest.

Statement on the Use of AI

The authors declare that they used generative artificial intelligence (AI) tools solely as support in the manuscript writing process. Platforms such as ChatGPT were used for writing suggestions, idea organization, and style editing. All content was subsequently reviewed, validated, and edited by the authors, who assume full responsibility for the accuracy, originality, and validity of the work presented.

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