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Population Diversity and Economic Growth: A Meta-Regression Analysis

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ABSTRACT

In this study, we apply meta-regression techniques to 1537 estimates derived from 83 studies that investigate the effect of population diversity on economic growth. We find a subtle inclination toward publishing results that assert a negative correlation between diversity and economic growth, indicating a mild publication bias. However, the extent and direction of this bias vary according to the specific diversity dimension considered. After adjusting for both publication bias and the methodological quality of the underlying studies, our results indicate that while ethnic and linguistic diversity exhibit a small and statistically insignificant positive effect on economic growth, the remaining diversity dimensions—namely religious, genetic, birthplace, and other forms of diversity—exert a significant positive impact on growth, with effect sizes ranging from moderate to large. Additionally, our findings reveal that the reported estimates are influenced by several factors, including the methodologies employed by researchers in measuring economic growth and diversity, the characteristics of the data and estimation techniques utilized, and the consideration of other growth-related factors.

1 | Introduction

Population diversity, characterized by the heterogeneity of a population in terms of attributes like ethnicity, linguistic background, religious beliefs, ancestral origins, place of birth, and cultural background, stands as a cornerstone in the architecture of societal structure. Each of these facets contributes uniquely to the tapestry of societal functionality, fostering a milieu where multiple perspectives coalesce to enrich the social fabric. The significance of population diversity within the economic sphere is multifaceted. It encourages a more comprehensive understanding of varied consumer needs and preferences. Businesses that harness this understanding are better positioned to tailor their offerings, resonating with a broader customer base (Peracchio, Bublitz, and Luna 2014). This adaptability is especially crucial in a globalized economy, where understanding and catering to diverse markets can spell the difference between success and obsolescence. In addition, population diversity can enhance international trade and investment (Lee, Lim, and Meng 2019). A diverse population often has stronger connections to different parts of the world, which can facilitate trade and attract foreign investment. Moreover, diversity plays a significant role in expanding the labor market. It brings together individuals from different backgrounds, increasing the pool of talent and skills available in the workforce (Bakens and De Graaff 2020). This diversity in the workforce enables industries to tap into a broader range of competencies, thus improving productivity and competitiveness (Ng and Metz 2015). Furthermore, population diversity often correlates with increased levels of entrepreneurship and innovation (Nathan and Lee 2013). Diverse communities provide a breeding ground for new business ideas and models, driven by the unique experiences and insights of their members.

This entrepreneurial spirit contributes significantly to economic dynamism and growth, as new businesses generate employment, foster competition, and drive technological advancements.

It is incontrovertible that the multifaceted nature of diversity exerts a profound influence on economic growth through various transmission channels. On one hand, diversity has the potential to hinder economic growth by engendering inefficiencies in the provision of public goods, leading to policies marred by ethnic biases, and precipitating conflicts or disagreements regarding the allocation and governance of common public goods and policies (e.g., Easterly and Levine 1997; Alesina et al. 2003; Montalvo and Reynal-Querol 2005; Chan, Dang, and Li 2018). On the other hand, diversity acts as a catalyst for economic enhancement by fostering productivity through the infusion of innovation, the synergy of varied skills, the stimulation of creativity, and the expansion of trade and product diversity (e.g., Ashraf and Galor 2013; Ying et al. 2017; Docquier et al. 2020; Zhu and Grigoriadis 2022; Peng et al. 2024). In light of these perspectives, the academic discourse exhibits a wide array of findings, ranging from positive to negative, significant to insignificant, concerning the nexus between diversity and economic growth. Moreover, the magnitude of the estimated coefficients exhibits considerable variability. Such marked heterogeneity prompts the question: What underlying factors contribute to this considerable heterogeneity within the existing literature? In pursuit of an answer, we engage in a comprehensive meta-analytical approach. This entails a quantitative synthesis of the existing literature, aiming to unravel the underlying causes of variation across studies and to ascertain a more accurate estimate of diversity's mean effect on economic growth, thereby adjusting for potential biases present in the current body of research.

Meta-analysis represents a sophisticated array of quantitative methodologies purposed for the critical assessment and synthesis of empirical studies (Stanley and Jarrell 2005). Recent meta-analyses of economic development encompass the studies by Cazachevici, Havranek, and Horvath (2020), investigating the influence of remittances on economic growth, Minasyan et al. (2019) exploring the nexus between educational gender disparity and economic growth, Heimberger's (2022) examination of the repercussions of economic globalization on economic growth, Stanley, Doucouliagos, and Steel (2018) examining the growth implications of Information and Communication Technologies (ICT), and Balima and Sokolova (2021) assessing the impact of International Monetary Fund (IMF) programs on economic growth. However, to date, there appears to be a lacuna in the existing body of literature regarding a meta-analytical exploration of how population diversity influences economic growth. In addressing this gap, our meta-analytical approach is directed toward elucidating several pivotal questions: What constitutes the typical influence of diversity on economic growth? Are the effects reported in existing literature subject to a publication bias, wherein certain estimates are preferentially highlighted due to their statistical significance or the direction of their results? How do various factors such as research methodology, data selection, and analytical approaches exert a systematic effect on the outcomes reported in the literature?

We adopt both linear and nonlinear methodologies to adjust for the presence of publication bias in a meta-sample of 1537 estimates derived from 83 peer-reviewed publications. Our findings indicate the presence of a mild publication bias favoring results that suggest a negative association between diversity and economic growth. However, the extent and direction of this bias appear to vary based on how diversity is defined and measured. Adjusting solely for publication bias, our analysis reveals that the overall effect of diversity on economic growth is positive, albeit quantitatively minor. Disaggregating diversity into ethnic, linguistic, religious, birthplace, genetic, and a residual category, we find that genetic diversity has a moderate positive impact on economic growth. Birthplace diversity also positively influences growth, with effects ranging from small to moderate, while the influence of other diversity dimensions remains relatively small. However, these initial findings do not fully encapsulate the complexity of the relationship between diversity and economic growth. By further adjusting for both publication bias and the methodological quality of the primary studies included in our meta-analysis, our best-practice estimates indicate a more nuanced relationship. Specifically, while ethnic and linguistic diversity demonstrates a small and statistically insignificant positive effect on economic growth, the remaining dimensions of diversity—religious, genetic, birthplace, and the residual category—demonstrate a significant positive impact on economic growth, with effect sizes spanning from moderate to large. These findings suggest that the positive growth effect of diversity is more nuanced and, at the same time, more substantial than previously recognized, contingent upon a comprehensive assessment that accounts for both publication bias and the methodological quality of the underlying studies.

To elucidate the systematic heterogeneity, we employ Bayesian model averaging estimation techniques to manage model uncertainty effectively. Our analysis reveals several factors contributing to this notable heterogeneity. Among the key findings of our investigation are the following: first, the impact of diversity varies markedly depending on the developmental stage of the countries under examination, with diversity demonstrating a more potent facilitation of growth in nations categorized as developing or emerging economies. Second, we observe that extant studies that neglect to incorporate variables such as initial income levels, governmental expenditure, and incidents of violence mismeasure the impact of diversity. Last, our findings indicate that studies using panel data or focusing solely on a single country tend to report a systematically reduced influence of diversity on economic growth.

The present study adopts an exclusively empirical approach, concentrating on a comprehensive quantitative analysis and critical assessment of the existing body of econometric evidence. For an expansive and comprehensive review of pertinent literature exploring the nexus between diversity and economic growth, notable references include the works of Collier (2001), Alesina and La Ferrara (2005), Campos and Kuzeyev (2007), Fedderke, Luiz, and De Kadt (2008), Alesina, Harnoss, and Rapoport (2016), and Bove and Elia (2017). Furthermore, a thorough definition and measurement of diversity are rigorously examined in the seminal works of Alesina et al. (2003), Fearon (2003), Posner (2004), Montalvo and Reynal-Querol (2005), Okediji (2005), Ashraf and Galor (2013), Alesina, Harnoss, and Rapoport (2016), and Steele et al. (2022).

The structure of this manuscript is methodically arranged in a subsequent manner. Section 2 elucidates the methodology employed in our data-gathering process. Section 3 expounds upon the findings derived from our rigorous examination of selective publications. Thereafter, Section 4 is dedicated to expounding upon the findings pertaining to the significance of diverse estimate characteristics. The discourse culminates with Section 5, which provides the concluding remarks.

2 | Data

Following the recent guidelines by Havránek et al. (2020) and Irsova et al. (2024) for conducting meta-analyses in economic research, our methodological framework adheres to systematic inquiry for relevant studies, careful data collection, rigorous coding methodologies, and thorough dissemination of results. The preliminary stage of this meta-analytical study involves the aggregation of extant estimates derived from the available body of literature. Google Scholar was used to identify relevant academic papers. When searching for pertinent studies, we used one of the terms "diversity," "population diversity," "ethnic diversity," "linguistic diversity," "religious diversity," "genetic diversity," "birthplace diversity," and "cultural diversity" in combination with "economic growth" or "economic development." Moreover, we conducted a thorough screening of the references cited in the retrieved studies to identify additional potentially relevant studies. The search concluded on November 15, 2023, with no studies added beyond that date.

To ensure the consistency and comparability of our meta-study sample, we applied the following inclusion criteria:

I. **Measurable Effect Size**: Studies were only included if they provided sufficient information to quantify a comparable effect size. This required reporting key metrics, including regression coefficients, sample sizes, and statistical indicators such as *t*-statistics, standard errors, or *p* values. Studies lacking this essential information were excluded from the analysis.

II. **Numerical Estimation of Diversity's Effect**: Research works aimed to provide a quantitative assessment of the effect of diversity on economic growth through the utilization of regression analysis. Notably, studies were delimited to those offering numerical estimations and were thus exclusive of works centered solely on presenting descriptive statistics, theoretical constructs, or systematic reviews.

III. **Peer-Reviewed Journal Publication**: To ensure the quality and rigor of the included studies, we exclusively considered articles published in peer-reviewed journals. Peer review is a vital quality control process, ensuring manuscripts are evaluated by field experts before publication. Manuscripts that had not undergone this rigorous peer review process were purposefully omitted from consideration due to their limited peer review process.[1]

IV. **English Language Requirement**: For practical reasons, only research conducted in English was included in the sample of the meta-analysis.

Our meta-analysis extends beyond studies examining a direct linear relationship between diversity and growth to include those incorporating quadratic diversity terms and interaction variables with diversity. In cases where supplementary information is accessible, we calculated the average marginal effect of diversity on growth and estimated the associated standard error using the delta method, as exemplified by the methodology outlined in Cazachevici, Havranek, and Horvath (2020). Ultimately, our inclusion criteria were met by eighty-three scholarly journal articles, resulting in the aggregation of 1537 estimations for a comprehensive meta-study dataset. The Supporting Information Appendix offers a detailed catalogue of the 83 included studies, alongside a schematic representation (Figure SA1) delineating the methodology employed in the assembly of the meta-dataset.

All estimates encompassed within our sample were derived from regression models specifically designed to examine the effect of a diversity indicator (D) on economic growth (G), while accounting for a set of control covariates (X):

$$G = \alpha_1 + \alpha_2 D + \alpha_3 X + \upsilon \tag{1}$$

The extant body of scholarly work has utilized diverse measures in assessing both diversity and economic growth, a fundamental consideration in meta-regression analysis aimed at elucidating variations in reported findings. Noteworthy, indicators of economic growth encompass metrics such as the growth rate of real GDP per capita, the growth rate of nominal GDP per capita, real GDP per capita (in logarithmic expression), and nominal GDP per capita (in logarithmic expression). Correspondingly, measures of diversity encompass multifaceted dimensions including ethnic, linguistic, religious, genetic, birthplace, and other diversity measures. Hence, to ensure comparability of findings across various studies, a conversion of these estimates into partial correlation coefficients (PCCs) is undertaken (Stanley and Doucouliagos 2012).[2] The computation of the PCC follows this procedure:

$$PCC_{is} = \frac{t_{is}}{\sqrt{t_{is}^2 + df_{is}}} \tag{2}$$

In the context under consideration, the partial correlation coefficient (PCC), symbolized as PCC_{is}, serves as an indicator delineating the magnitude and orientation of the correlation existing between diversity and growth while holding other variables constant, as examined within regression i of study s. t_{is} represents the relevant t-statistic, while df_{is} stands for the number of degrees of freedom. PCC values span from −1 to 1, wherein a positive value signifies a positive association between diversity and growth, while a negative value indicates a negative correlation.

The formula delineating the standard error (SE) associated with each partial correlation coefficient (PCC) is hereby presented as follows:

$$SE(PCC)_{is} = \sqrt{\frac{1 - PCC_{is}^2}{df_{is}}} = \frac{PCC_{is}}{t_{is}} \tag{3}$$

The meta-dataset under examination includes 1537 observations, derived from 83 studies. The methodology for calculating partial

TABLE 1 | Summary statistics for standardized diversity coefficients (PCC).

	Number of estimates	Unweighted average	Standard deviation	Median	UWLS	95% CI (UWLS)	
All estimates	1537	−0.010	0.217	−0.003	0.009	0.001	0.018
Ethnic diversity	375	−0.107	0.169	−0.112	−0.071	−0.084	−0.057
Linguistic diversity	512	−0.076	0.216	−0.042	−0.035	−0.050	−0.020
Religious diversity	124	−0.018	0.159	0.010	0.001	−0.021	0.023
Genetic diversity	119	0.044	0.170	0.094	0.077	0.053	0.101
Birthplace diversity	280	0.178	0.133	0.168	0.167	0.152	0.181
Residual category diversity	127	0.083	0.267	−0.012	0.050	0.008	0.092

Note: UWLS: Unrestricted Weighted Least Squares, using the inverse of the variances as precision weights; 95% CI: 95% Confidence Interval.

correlation coefficients uses t-values and df. The t-values have an average of 0.154 and a median of −0.060, ranging from −7.123 to 12.314. The df variable has an average of 363.592 and a median of 124 and ranges from a minimum of 3 to a maximum of 11,814. The presence of outliers in these statistics requires careful consideration due to their influence on the PCC, which is crucial for determining standard error and consequently influences the weighting in meta-analyses, as described in Equation (3). To attenuate the potential influence of outliers, we implement a winsorization process at the 1.5% level for the t-values and df. Notably, our primary results remain robust irrespective of the specific level of winsorization applied. Detailed comparisons of the winsorized and original distributions for t-statistics, degrees of freedom, and PCC values are available in the Supporting Information Appendix (Table SA1).[3]

Table 1 delineates a comprehensive overview of findings derived from the meta-analysis, presenting both the median and unweighted average of the partial correlations. Additionally, outcomes from the application of an Unrestricted Weighted Least Squares (UWLS) model,[4] inclusive of the corresponding 95% confidence interval, are provided. In the first row of Table 1, outcomes pertaining to the entirety of estimates ($n = 1537$) are documented. The findings indicate that, on average, the influence of diversity on economic growth is notably negligible, approaching zero. Adhering to Doucouliagos' (2011) guideline, a partial correlation is deemed diminutive when its absolute value falls below 0.07. The calculated precision-weighted average effect stands at 0.009 (as derived from the UWLS approach). When considering the entire sample of estimates through descriptive statistics reinforces the observation that the impact of diversity on economic growth manifests as exceedingly trivial and lacks substantive economic relevance.

Furthermore, we disaggregate the sample based on various dimensions of diversity. Specifically, we present comprehensive summary statistics encompassing median values, standard deviations, unweighted averages, and precision-weighted averages for estimates within sub-samples categorized by ethnic, linguistic, religious, genetic, birthplace, and residual category diversity. Regarding religious diversity, both unweighted average and precision-weighted average effects approximate zero. Additionally, linguistic diversity manifests a negative effect, while residual category diversity demonstrates a positive effect. Both effects are small, estimated at −0.076 and 0.083, respectively, as indicated by an unweighted average. The precision-weighted averages portray these effects as −0.035 and 0.050, respectively. Ethnic diversity exerts a small negative effect on growth, with an unweighted average of −0.107 and a precision-weighted average of −0.071. Genetic diversity yields a positive albeit small effect on growth, as denoted by an unweighted average of 0.044, while the precision-weighted average effect assumes a larger magnitude at 0.077. Finally, birthplace diversity portrays a medium-sized positive growth effect, as per Doucouliagos' (2011) classification, evidenced by an unweighted average of 0.178 and a precision-weighted average effect of 0.167.[5]

Nevertheless, these simple estimators (Table 1) fail to consider the potential ramifications of publication bias and the influence arising from data and specification choices. Consequently, they need to be treated with caution. In the subsequent sections, we delve into both concerns, elaborating on our estimation methodology to delineate the fundamental impact of diversity on economic growth.

3 | Publication Bias

The phenomenon of publication selection pertains to a systematic procedure in which the choice of results to be published is contingent upon their statistical significance or their congruence with established theoretical frameworks or antecedent empirical evidence (Andrews and Kasy 2019). This phenomenon manifests through a predilection among authors, reviewers, and editorial boards toward the dissemination and publication of findings that demonstrate statistical significance. Researchers might exhibit an inclination to acknowledge statistically significant outcomes that corroborate specific theoretical constructs. Moreover, there exists a prevalent tendency to accord preferential treatment to statistically significant results over those deemed non-significant. As a result, the literature may not accurately reflect the true nature of the relationships being studied, which can distort our understanding of economic phenomena and compromise the reliability of statistical conclusions. Consequently, identifying and rectifying this publication selection bias is imperative and constitutes a fundamental objective in the conduct of meta-analyses.

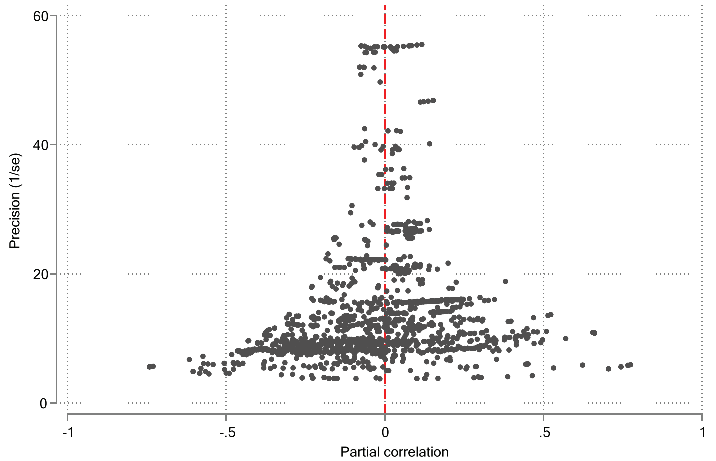

FIGURE 1 | Funnel plot, partial correlations of diversity and economic growth (All estimates, $n = 1537$). Precision is calculated as 1/standard error of the partial correlation coefficient. The dotted line represents position of a zero partial correlation. [Colour figure can be viewed at wileyonlinelibrary.com]

The funnel plot is a simple yet effective visual tool for assessing publication bias. It plots precision, defined as the inverse of the standard error, on the vertical axis, and the partial correlation on the horizontal axis. Estimates with higher precision (smaller standard errors) appear at the top, while those with lower precision (larger standard errors) are positioned at the bottom. In scenarios devoid of publication bias, the funnel plot is characterized by its symmetrical nature. However, in the presence of publication bias, this symmetry is disrupted, resulting in an asymmetrical formation of the plot.

Figure 1 presents a funnel plot incorporating all estimates ($n =$ 1537). Upon examination of this plot, it becomes evident that there exists a significant divergence in the primary studies concerning both the magnitude and the direction of the impact exerted by diversity on economic growth. Notably, although there is a more concentrated distribution of data points toward the left segment of the graph, it remains ambiguous as to whether this pattern indicates the presence of any publication bias.

In Figure 2, we present funnel plots delineated according to various diversity categories, including ethnic, linguistic, religious, genetic, birthplace, and a residual category. Notably, the left-hand side of the funnel plots, particularly for ethnic and linguistic diversity, exhibits a pronounced density. This observation intimates a possible bias in the scholarly discourse, favoring the publication of findings that suggest a detrimental effect of ethnic and linguistic diversity on economic growth. In other words, there seems to be a scholarly inclination toward endorsing studies that associate these forms of diversity with a decrease in economic growth. Conversely, a significant concentration of data points on the right-hand side of the funnel plot for genetic diversity is observed. This pattern is indicative of a preferential reporting bias toward studies that posit a positive correlation between birthplace diversity and economic growth, implying that the extant literature is more inclined to publish studies supporting the notion that birthplace diversity contributes positively to economic growth. In the case of the other categories of diversity, namely religious, genetic, and the residual category, the funnel plots do not exhibit any overt indications of publication bias. These plots encompass a balanced representation of both positive and negative findings, suggesting a more equitable distribution of published studies in these domains.

The utilization of funnel plots facilitates a visual assessment that is predominantly subjective in nature. Consequently, it is imperative to undertake a more formalized evaluation to ascertain the existence of publication bias in the underlying effect of diversity on economic growth.

In order to rigorously assess the presence of publication bias, our study incorporates the application of the Funnel-Asymmetry and Precision-Effect Test (FAT-PET). This approach encompasses a meta-regression analysis where the PCCs are regressed against their respective standard errors. The formula for this regression is expressed as:

$$PCC_{is} = \alpha_0 + \alpha_1 SE(PCC_{is}) + e_{is} \tag{4}$$

Here, PCC_{is} and $SE(PCC_{is})$ denote the partial correlation coefficients and their respective standard errors, as previously defined. The term e_{is} represents the regression error term. Within this framework, the coefficient α_0 is interpreted as the true effect, adjusted for publication bias under the pivotal assumption that publication selection bias is linearly related to the standard error. Meanwhile, the coefficient α_1 delineates the direction and magnitude of the publication bias. To mitigate the influence of potential within-study correlation, our meta-study adopts a strategy of clustering standard errors at the study level. Complementing the standard errors, we also incorporate wild bootstrap confidence intervals (Roodman et al. 2019).

Table 2 provides a detailed presentation of the results derived from our comprehensive meta-analysis, as outlined in Equation (4), encompassing all estimates ($n = 1537$). These estimates are further categorized across various dimensions of diversity, including ethnic, linguistic, religious, genetic, birthplace, and a residual category. Initially, our methodology includes a distinct statistical specification on unweighted samples, with an estimation of the between-effect at the study level.[6] To address heteroskedasticity, we employ two weighted least squares (WLS) methods. The first approach, WLS: Precision, weights estimates

TABLE 2 | Linear tests for publication bias.

	All estimates (n = 1537)		
Estimation:	**BE**	**WLS: Precision**	**WLS: Study**
Publication bias (Standard error)	−0.835**	−0.838**	−0.700**
	(0.335)	(0.367)	(0.303)
		[−1.689, −0.081]	[−1.476, −0.067]
Effect beyond bias (Constant)	0.005	0.067**	−0.009
	(0.034)	(0.029)	(0.021)
		[−0.003, 0.126]	[−0.053, 0.038]
	Ethnic diversity (n = 375)		
Estimation:	**BE**	**WLS: Precision**	**WLS: Study**
Publication bias (Standard error)	−0.871**	−1.053***	−0.805*
	(0.357)	(0.323)	(0.480)
		[−1.736, −0.313]	[−2.041, 0.199]
Effect beyond bias (Constant)	−0.027	−0.005	−0.031
	(0.034)	(0.023)	(0.028)
		[−0.057, 0.060]	[−0.090, 0.035]
	Linguistic diversity (n = 512)		
Estimation:	**BE**	**WLS: Precision**	**WLS: Study**
Publication bias (Standard error)	−0.068	−1.645***	−0.008
	(0.517)	(0.614)	(0.471)
		[−3.249, −0.094]	[−1.802, 0.970]
Effect beyond bias (Constant)	−0.095*	0.084*	−0.114**
	(0.055)	(0.050)	(0.047)
		[−0.088, 0.193]	[−0.220, 0.010]
	Religious diversity (n = 124)		
Estimation:	**BE**	**WLS: Precision**	**WLS: Study**
Publication bias (Standard error)	−0.536	−0.797	−0.638*
	(0.526)	(0.860)	(0.328)
		[−2.939, 2.045]	[−1.698, 0.363]
Effect beyond bias (Constant)	0.056	0.048	0.049**
	(0.047)	(0.033)	(0.024)
		[−0.032, 0.182]	[0.003, 0.116]
	Genetic diversity (n = 119)		
Estimation:	**BE**	**WLS: Precision**	**WLS: Study**
Publication bias (Standard error)	−5.532***	−1.352	−3.837**
	(1.492)	(0.856)	(1.642)
		[−8.900, 8.100]	[−27.786, 21.932]

(Continues)

	Genetic diversity ($n = 119$)		
Estimation:	**BE**	**WLS: Precision**	**WLS: Study**
Effect beyond bias (Constant)	0.543***	0.183***	0.347***
	(0.157)	(0.041)	(0.120)
		[−0.319, 0.866]	[−1.712, 1.131]
	Birthplace diversity ($n = 280$)		
Estimation:	**BE**	**WLS: Precision**	**WLS: Study**
Publication bias (Standard error)	3.513***	2.688***	3.150***
	(0.643)	(0.790)	(0.171)
		[−3.552, 10.529]	[2.207, 4.062]
Effect beyond bias (Constant)	−0.063	−0.018	−0.036***
	(0.056)	(0.033)	(0.013)
		[−0.442, 0.152]	[−0.114, 0.138]
	Residual category diversity ($n = 127$)		
Estimation:	**BE**	**WLS: Precision**	**WLS: Study**
Publication bias (Standard error)	−0.394	1.814*	−0.186
	(1.125)	(0.938)	(0.855)
		[−2.533, 3.538]	[−1.993, 3.319]
Effect beyond bias (Constant)	0.016	−0.085	0.019
	(0.107)	(0.058)	(0.058)
		[−0.173, 0.881]	[−1.601, 2.810]

Note: The table presents the results of regression $PCC_{is} = \alpha_0 + \alpha_1 SE(PCC_{is}) + e_{is}$, where PCC_{is} and $SE(PCC_{is})$ are the i-th estimated partial correlation coefficient (*pcc*) and its standard error reported in the s-th study. BE = study-level between effects. WLS = weighted least squares. WLS: Precision = model is weighted by the inverse of the estimate's standard error. WLS: Study = model is weighted by the inverse of the number of estimates per study. Standard errors are reported in parentheses; 95% confidence intervals obtained using wild bootstrap are shown in square brackets. Significance level is denoted by *** (1%), ** (5%), and * (10%).

based on their precision, giving greater importance to more accurate results and directly reducing heteroskedasticity. The second approach, WLS: Study, uses the inverse of the number of observations per study as the weighting factor, ensuring equal treatment of studies regardless of size and balancing the influence of both smaller and larger studies in the analysis.

In the results presented in the upper section of Table 2 where all estimates are incorporated, it is observed that all employed models consistently demonstrate that the coefficient α_1 is negative and exhibits statistical significance, diverging notably from zero. The categorization framework of Doucouliagos and Stanley (2013) classifies the observed selectivity magnitude as "little to modest" ($|\alpha_1| < 1$). Consequently, the findings derived from the FAT-PET test provide empirical support for the presence of a slight to moderate bias in published research, particularly favoring outcomes that suggest a negative correlation between diversity and economic growth.

Delving into specifics, the analysis of estimates focusing on ethnic diversity consistently shows that α_1 is negative and bears statistical significance across all models. This reinforces the presence of a minor to moderate publication bias, as indicated by the FAT-PET test, wherein negative estimates, correlating ethnic diversity with reduced economic growth, are preferred. In the specific context of linguistic diversity, only the WLS: Precision approach, which compensates for heteroskedasticity, produces a negative and statistically significant ($p < 0.05$) α_1. This outcome points to a substantial publication bias favoring negative estimates ($1 \leq |\alpha_1| \leq 2$). Regarding genetic diversity, both the BE estimator and the WLS: Precision approach yields a negative and statistically significant α_1, indicating a severe publication bias toward negative estimates ($|\alpha_1| \geq 2$). Conversely, the analysis of birthplace diversity presents a distinct scenario. Here, the estimated α_1 across all models is positive and possesses high statistical significance, suggesting a severe publication bias favoring positive estimates. Last, the results of the FAT-PET tests for religious diversity and the residual category diversity exhibit less significance. This aligns with the insights drawn from funnel plots, suggesting that current literature employing measures of religious diversity and other diversity metrics, does not appear to be influenced by publication selectivity.

The limitations of the regression models presented in Table 2 stem from an underlying assumption of a linear correlation between publication selection and standard error, an assumption

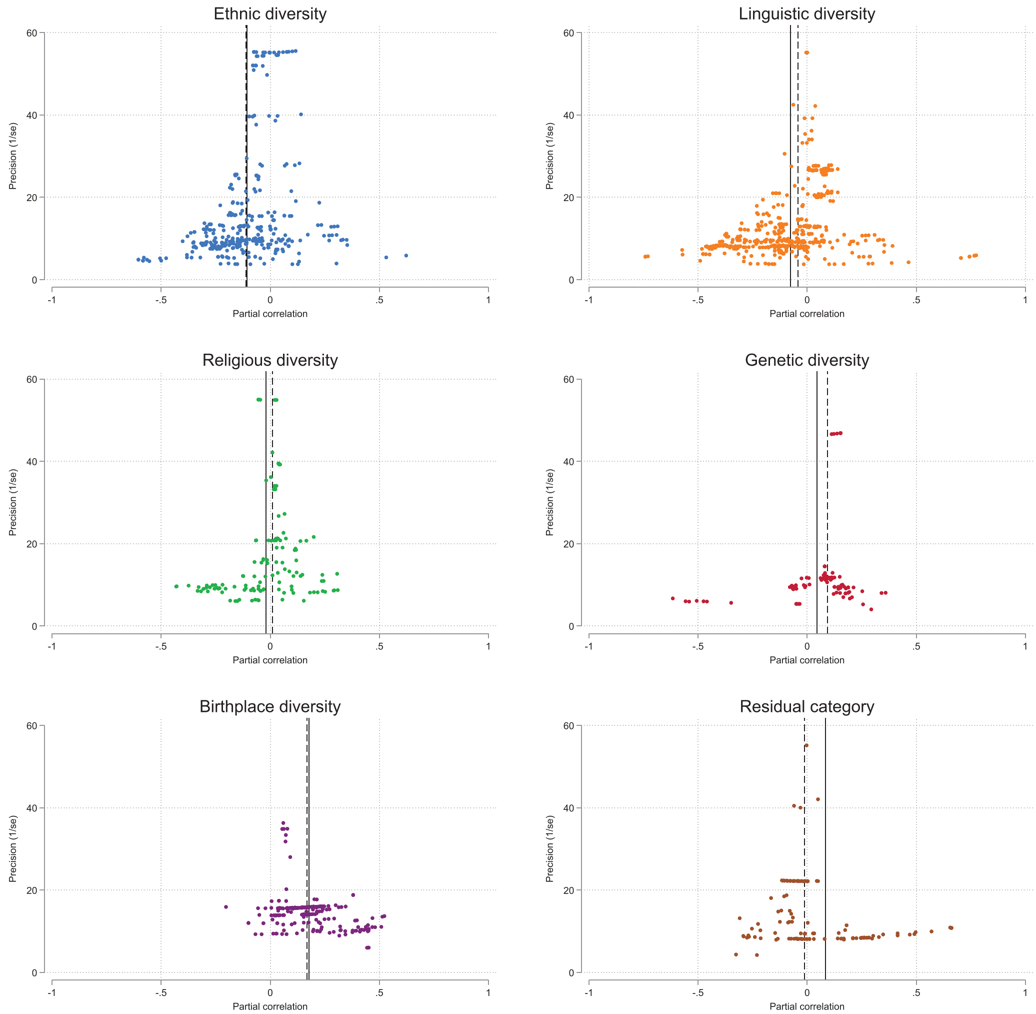

FIGURE 2 | Funnel plots by diversity category. Funnel plots based on the category of diversity: Ethnic diversity ($n = 375$), Linguistic diversity ($n = 512$), Religious diversity ($n = 124$), Genetic diversity ($n = 119$), Birthplace diversity ($n = 280$), Residual category diversity ($n = 127$). Precision is calculated as 1/standard error of the partial correlation coefficient. For each diversity category, the dotted vertical line represents the sample median; the solid vertical line depicts the sample mean. [Colour figure can be viewed at wileyonlinelibrary.com]

that may not accurately reflect real-world scenarios. Empirically, it has been observed that estimates demonstrating sufficient precision to achieve statistical significance at a 5% level (or below) are generally less susceptible to the influence of publication bias. In such instances, a linear model may excessively adjust for publication bias, inadvertently introducing a reverse bias, namely a downward bias. To address this limitation, the study incorporates alternative methodologies that accommodate a non-linear relationship between the selection process and standard errors. These methodologies and their corresponding outcomes are comprehensively delineated in Table 3.

The initial methodology under examination is the "Top10" approach, pioneered by Stanley, Jarrell, and Doucouliagos (2010). This approach advocates for the exclusion of 90% of results characterized by the least precise estimates, significantly diminishing publication bias. This method significantly mitigates publication bias and frequently surpasses traditional methods in accurately estimating the true effect. Additionally, we incorporate the Weighted Average of Adequately Powered Estimates (WAAP) developed by Ioannidis, Stanley, and Doucouliagos (2017). This technique selectively employs estimates exhibiting a minimum of 80% statistical power, calculating the mean of these estimates, weighted by inverse variance.[7] Further analysis by Stanley, Doucouliagos, and Ioannidis (2017) using Monte Carlo simulations reveals that this approach often outperforms conventional meta-analysis estimators. Our study also integrates the novel selection model introduced by Andrews and Kasy (2019). This model assesses the likelihood of reporting negative and insignificant estimates, subsequently adjusting the reported estimates based on these probabilities. Additionally, our analysis incorporates the Endogenous Kink (EK) model, introduced by Bom and Rachinger (2019). This model postulates a linear relationship between an estimate and its standard error, but only up to a certain threshold, acknowledging that beyond this point, the presence of publication bias in reported coefficients becomes implausible. This leads to an endogenously determined "kink" or threshold where this relationship alters. Finally, our analysis includes the stem-based bias correction method developed by Furukawa (2019). Furukawa's approach navigates the trade-off between publication bias and variance, noting that while the most precise studies are less affected by selective reporting,

TABLE 3 | Nonlinear tests: Bias-corrected effect of diversity on economic growth.

	All estimates (n = 1537)				
	Top10	**WAAP**	**Kinked model**	**Selection model**	**Stem method**
Effect beyond bias	0.030	–	0.033***	0.007**	0.101
	(0.005)		(0.006)	(0.003)	(0.085)
	Ethnic diversity (n = 375)				
	Top10	**WAAP**	**Kinked model**	**Selection model**	**Stem method**
Effect beyond bias	−0.010	–	0.006	−0.070***	0.101
	(0.010)		(0.007)	(0.008)	(0.095)
	Linguistic diversity (n = 512)				
	Top10	**WAAP**	**Kinked model**	**Selection model**	**Stem method**
Effect beyond bias	0.047***	–	0.105***	0.007**	−0.008
	(0.007)		(0.010)	(0.003)	(0.057)
	Religious diversity (n = 124)				
	Top10	**WAAP**	**Kinked model**	**Selection model**	**Stem method**
Effect beyond bias	0.010	–	0.023*	0.012*	−0.052
	(0.011)		(0.013)	(0.007)	(0.055)
	Genetic diversity (n = 119)				
	Top10	**WAAP**	**Kinked model**	**Selection model**	**Stem method**
Effect beyond bias	0.138***	0.144***	0.146***	0.136***	0.151***
	(0.007)	(0.005)	(0.008)	(0.008)	(0.026)
	Birthplace diversity (n = 280)				
	Top10	**WAAP**	**Kinked model**	**Selection model**	**Stem method**
Effect beyond bias	0.174***	0.093***	−0.008	0.148***	0.064
	(0.021)	(0.028)	(0.025)	(0.013)	(0.067)
	Residual category diversity (n = 127)				
	Top10	**WAAP**	**Kinked model**	**Selection model**	**Stem method**
Effect beyond bias	−0.070***	–	−0.096***	0.101***	−0.005
	(0.015)		(0.031)	(0.028)	(0.105)

Note: The table presents the results of regression $PCC_{is} = \alpha_0 + \alpha_1 SE(PCC_{is}) + e_{is}$, where PCC_{is} and $SE(PCC_{is})$ are the i-th estimated partial correlation coefficient (*pcc*) and its standard error reported in the s-th study. Top 10 (Stanley, Jarrell, and Doucouliagos 2010), WAAP (Ioannidis, Stanley, and Doucouliagos 2017), Kinked model (Bom and Rachinger 2019), Selection model (Andrews and Kasy 2019), Stem method (Furukawa 2019). Standard errors are reported in parentheses. Significance level is denoted by *** (1%), ** (5%), and * (10%).

disregarding less precise studies can be inefficient. His nonparametric method determines the proportion of the most precise studies that should be utilized to compute the corrected mean.

The empirical results delineated in Table 3, derived through the application of nonlinear methodologies to ascertain the bias-corrected influence of diversity on economic growth, indicate that the aggregate impact of diversity on economic growth (encompassing all estimates, $n = 1537$) is small and lacks significant economic pertinence. This assessment is further corroborated by the absence of a WAAP outcome, suggesting that the extant literature failed to detect the impact of population diversity on economic growth with a statistical power of 0.80 or higher, underscoring the minimal economic relevance of diversity's impact on growth. Specifically, the median estimate derived from these nonlinear techniques stands at 0.032. This observation holds consistent across various dimensions of diversity, including ethnic diversity (median estimate via nonlinear methods being −0.002), linguistic diversity (with a corresponding median estimate of 0.027), religious diversity (median estimate being

0.011), and the residual category (wherein the median estimate is −0.038). Pertaining to birthplace diversity, the median estimate procured through nonlinear techniques registers at 0.093. This value is approximately half of the unweighted mean (0.178) as presented in Table 1, thereby implying that while the impact of birthplace diversity on economic growth is positive, it turns small in economic terms. Conversely, in the context of genetic diversity, the median estimate obtained through the same nonlinear methodologies is 0.144, which is more than triple the unweighted mean (0.044) noted in Table 1. This finding posits that the influence of genetic diversity on economic growth is not only positive but also of a moderate magnitude.

It is imperative to acknowledge a notable limitation inherent in the use of the partial correlation coefficient and its standard error: the distribution deviates from normality as the partial correlation values verge on either −1 or +1. To mitigate this issue, the prevalent remedy employed is Fisher's z-transformation. In examining publication bias, our findings, delineated in the Supporting Information Appendix (Table SA2), align closely with those derived using the PCC (Table 2). Regarding the bias-corrected mean effect, as expounded in the Supporting Information Appendix (Table SA3), encompassing all estimates and specific estimates pertaining to ethnic, linguistic, religious, and residual category diversity, the bias-corrected effect remains small. In the realm of genetic diversity, the median estimate, as discerned through nonlinear methodologies, is quantified at 0.167. This value marginally surpasses the median estimate acquired using the PCC (0.144). Nonetheless, the influence of genetic diversity maintains a positive and moderate magnitude. In relation to birthplace diversity, the median estimate acquired through nonlinear approaches stands at 0.146, surpassing the median estimate derived using the PCC (0.093) and thereby categorizing it as having a moderate effect.

Moreover, we replicate our baseline analysis concerning publication bias and the bias-adjusted effect of diversity on economic growth, by utilizing the formula for the standard error of PCCs as delineated by Stanley and Doucouliagos (2023): $SE(PCC)_{is} = \frac{1-PCC_{is}^2}{\sqrt{df_{is}}}$. The results derived from utilizing this formula for the standard error, as presented in the Supporting Information Appendix (Table SA4), demonstrate substantial consistency with the outcomes observed in our initial analysis, as detailed in Tables 2 and 3.

Finally, we augment the FAT-PET analysis with the quadratic PEESE model (Precision-Effect Estimate with Standard Error), introduced by Stanley and Doucouliagos (2014). This model estimates the equation $PCC_{is} = \alpha_0 + \alpha_1[SE(PCC_{is})]^2 + e_{is}$, where α_0 and α_1 again denote the effect beyond bias and the degree of publication bias, respectively. The PEESE approach modifies the basic assumption of a linear relationship between the effect size estimate and its standard error, positing instead that the squaring of the standard error addresses the higher susceptibility of smaller studies, which are those with larger standard errors, to report inflated effects. This susceptibility is presumed to diminish as statistical power increases. While the PET method is notably effective when the true effect approximates zero, the PEESE approach generally outperforms it when the true effect deviates from zero. Our findings, detailed in the Supporting Information Appendix (Table SA5), reveal that results from PEESE regarding publication bias align with those from our initial analysis (Table 2). Similar consistency is observed with the bias-adjusted effects, except in the case of linguistic diversity where PEESE indicates an average effect beyond bias of −0.08, in contrast to 0.04 observed under more sophisticated methods, and in genetic diversity, where PEESE records an average effect of 0.23 compared to 0.14 in advanced methods. Despite these variations, we advocate for prioritizing the results derived from advanced methods concerning the bias-adjusted effect, as they have been demonstrated to surpass conventional approaches in meta-analyses, including PEESE, as evidenced by various simulations (e.g., Bom and Rachinger 2019; Furukawa 2019; Hong and Reed 2021; Stanley, Doucouliagos, and Ioannidis 2017).

4 | Heterogeneity

In this section, we delve deeper into the nuanced relationship between population diversity and economic growth by explicitly modeling the heterogeneity inherent in the reported estimates. Our analysis uses a comprehensive set of explanatory variables organized into categories such as economic growth and diversity measures, data characteristics, methodological approaches, and publication contexts. These variables are essential for a nuanced understanding of the diverse impacts on economic growth and are described in detail below. The goals of this section are threefold: first, to determine whether the publication bias result remains robust when controlling for various aspects of estimation context; second, to identify the underlying factors of study design that systematically influence the reported estimates; and third, to derive a mean estimate conditional on various characteristics and adjusted for publication, identification, and other potential biases in the literature.

4.1 | Variables

Table 4 provides a comprehensive overview of the variables extracted from the primary studies, encompassing their respective definitions, means, and standard deviations. To facilitate a structured presentation, these variables are categorized into distinct groups: economic growth metrics, diversity indices, data attributes, estimation techniques, a range of control variables, countries under investigation, and characteristics pertinent to publication.

Initially, the classification "Measure of economic growth" categorizes the assorted dependent variables employed by the primary research studies. Predominantly, this category includes the growth of real GDP per capita and the real GDP per capita (expressed in logs). Additionally, economic growth is quantified through the growth of nominal GDP per capita, accounting for 8% of instances, and the logarithmic expression of nominal GDP per capita, constituting 27% of the cases.

The classification "Diversity measures" categorizes various measures of diversity employed in primary research. A significant proportion, exceeding one-third (33%) of these studies, implement linguistic diversity measures, specifically focusing on indices that assess linguistic fractionalization and polarization. The linguistic

TABLE 4 | Variables used in the meta-regression analysis ($n = 1537$).

Variable	Definition	Mean	SD
Effect size			
PCC	Partial correlation coefficient	−0.010	0.217
SE	Standard error of the PCC	0.092	0.045
Measure of economic growth			
Growth of real GDP per capita	Dummy, 1 if dependent variable in primary regression is the growth rate of real GDP per capita, 0 otherwise	0.328	0.470
Growth of nominal GDP per capita (Ref.)	Dummy, 1 if dependent variable in primary regression is the growth rate of GDP per capita, 0 otherwise	0.077	0.267
Real GDP per capita	Dummy, 1 if dependent variable in primary regression is logarithm of real GDP per capita, 0 otherwise	0.327	0.469
Nominal GDP per capita	Dummy, 1 if dependent variable in primary regression is logarithm of GDP per capita, 0 otherwise	0.268	0.443
Diversity measures			
Ethnic diversity	Dummy, 1 if a measure of ethnic diversity used, 0 otherwise	0.244	0.430
Linguistic diversity	Dummy, 1 if a measure of linguistic diversity used, 0 otherwise	0.333	0.471
Religious diversity	Dummy, 1 if a measure of religious diversity used, 0 otherwise	0.081	0.272
Genetic diversity	Dummy, 1 if a measure of genetic diversity used, 0 otherwise	0.077	0.267
Birthplace diversity	Dummy, 1 if a measure of birthplace diversity used, 0 otherwise	0.182	0.386
Residual category diversity (Ref.)	Dummy, 1 if a measure other than Ethnic, Linguistic, Religious, Genetic, Birthplace diversity used, 0 otherwise	0.083	0.275
Joint	Dummy, 1 if more than one diversity indicator included in regression, 0 otherwise	0.308	0.462
Data characteristics			
Cross-sectional (Ref.)	Dummy, 1 if dataset is cross-sectional, 0 otherwise	0.400	0.490
Panel data	Dummy, 1 if dataset is panel, 0 otherwise	0.600	0.490
Single country	Dummy, 1 if the primary study uses data for a single country, 0 otherwise	0.278	0.448
Time span	Logarithm of number of years in the sample	1.339	0.749
Control for endogeneity	Dummy, 1 if the primary study controls for endogeneity of the diversity measure, 0 otherwise	0.137	0.344
Estimation methods			
OLS	Dummy, 1 if Ordinary Least Squares (OLS) used in the estimation, 0 otherwise	0.476	0.500
Fixed effects	Dummy, 1 if Fixed Effects used in the estimation, 0 otherwise	0.111	0.314
IV	Dummy, 1 if Instrumental Variable (IV) used in the estimation, 0 otherwise	0.199	0.399
SUR	Dummy, 1 if Seemingly Unrelated Regression (SUR) used in the estimation, 0 otherwise	0.129	0.336
Other estimator (Ref.)	Dummy, 1 if other estimator used (e.g., Random Effects, Generalized Method of Moments (GMM), and Three-Stage Least Squares (3SLS)), 0 otherwise	0.085	0.278
Control variables			
Initial income	Dummy, 1 if initial income included as explanatory variable, 0 otherwise	0.442	0.497
Investment	Dummy, 1 if investment included as explanatory variable, 0 otherwise	0.263	0.440
Education	Dummy, 1 if education variable included as explanatory variable, 0 otherwise	0.640	0.480

(Continues)

Variable	Definition	Mean	SD
Government spending	Dummy, 1 if government expenditures included as explanatory variable, 0 otherwise	0.254	0.436
Trade openness	Dummy, 1 if trade openness included as explanatory variable, 0 otherwise	0.323	0.468
Violence	Dummy, 1 if violence included as explanatory variable, 0 otherwise	0.144	0.352
Health	Dummy, 1 if health included as explanatory variable, 0 otherwise	0.204	0.403
Population	Dummy, 1 if population included as explanatory variable, 0 otherwise	0.504	0.500
Democracy	Dummy, 1 if democracy variable included as explanatory variable, 0 otherwise	0.150	0.357
Financial development	Dummy, 1 if financial development measure included as explanatory variable, 0 otherwise	0.148	0.355
Countries examined			
Developed	Dummy, 1 if only developed countries included in the sample, 0 otherwise	0.198	0.399
Developing	Dummy, 1 if only developing countries included in the sample, 0 otherwise	0.228	0.419
Mixed (Ref.)	Dummy, 1 if both developed and developing countries included in the sample, 0 otherwise	0.574	0.495
Publication characteristics			
Publication year	The year of publication of the study minus the average year of publication (2014.310) of the sample	0.000	5.496
Impact factor	Recursive impact factor of journal from RePEc	1.149	1.517
Non-economic journal (Ref.)	Dummy, 1 if published in non-economic journals (demography, development, political sciences, sociology, etc.), 0 otherwise	0.150	0.357
Economic journal	Dummy, 1 if published in economics journals, 0 otherwise	0.850	0.357
Citations	Logarithm of number of Google Scholar citations	4.831	1.637

Notes: The recursive impact factor of the outlet from RePEc was collected in October 2023.
Abbreviations: SD, standard deviation; Ref., reference category.

fractionalization index quantitatively assesses the probability that two randomly chosen individuals within a given population would have different mother tongues. Alternatively, this indicator reflects the probability that two randomly selected people from a population will not belong to the same linguistic group. The index ranges from 0 to 1, where: A value of 0 indicates no linguistic diversity, meaning the entire population speaks the same language. A value of 1 represents the highest possible linguistic diversity, where each individual speaks a unique language. Linguistic polarization, in simple terms, measures how distinct the language used by two or more groups is. Analogous to the fractionalization index, this measure also spans from 0 to 1, where escalating values are indicative of heightened linguistic diversity. It is important to note that variations exist in the total number of linguistic groups considered when deriving these indices, contingent upon the specific source of the data. For example, the research of Alesina et al. (2003) encompasses 1055 major linguistic groups. In contrast, the linguistic fractionalization indicator as proposed in Easterly and Levine (1997) encompasses up to 1600 groups. Moreover, Desmet, Ortuño-Ortín, and Wacziarg (2012) proffer a classification of languages across various levels of aggregation, compiling a dataset of 6912 global languages to assess both fractionalization and polarization. Hence, it is prudent to acknowledge that, although these source-specific fractionalization indices quantify probabilities, direct comparisons between them remain elusive due to the discrepancies in the number of linguistic groups taken into account across varying sources. An analogous divergence in the enumeration of major groups considered also applies to measures of polarization across disparate sources. In addition, an important reference in this context is the study by Zhu and Grigoriadis (2022), which utilizes the aforementioned indicators of linguistic diversity, but uniquely contextualizes them within the framework of regional dialects in China, thus contributing a distinctive perspective to the study of linguistic diversity.

Ethnic diversity is another dimension, accounting for approximately 24% of the studies. This domain encompasses metrics such as ethnic fractionalization and polarization (e.g., Gören 2014; Bove and Elia 2017), which are analogous to the indices employed for linguistic diversity but pertain to distinct ethnic groups. Notably, the number of ethnic groups varies across various datasets, rendering direct comparisons between them challenging. Moreover, the ethnic dualism ratio serves as another gauge of ethnic diversity (e.g., Crenshaw and Robison 2010). This ratio calculates the proportion of the second-largest ethnic group in relation to the predominant ethnic group within a population. A higher value of this ratio indicates a greater level of ethnic diversity within the population in question.

Approximately 8% of the research incorporates measures of religious diversity, encompassing indices of religious fractionalization and polarization, such as those posited by Alesina et al. (2003) and Montalvo and Reynal-Querol (2005). These indices are designed to quantify the degree of heterogeneity among various religious groups. A similar proportion, 8%, is observed in the context of genetic diversity, encompassing intrapopulation genetic heterozygosity as elucidated by Ashraf and Galor (2013). Birthplace diversity, representing studies that utilize measures to gauge the heterogeneity in individuals' places of birth (e.g., Alesina, Harnoss, and Rapoport 2016; Docquier et al. 2020), is evident in 18% of cases. Additionally, a dummy variable termed *Residual category diversity* is employed for studies incorporating alternative measures of diversity not encompassed within the previously specified categories. Furthermore, a binary variable, *Joint*, is designated for research that integrates more than one measure of diversity in their regression models, comprising about 31% of the cases.

The initial factors considered under data characteristics include the type of data employed in the primary study, specifically if it is cross-sectional or panel data, along with the sample's duration in years. To address data features within the regression model across various studies, we include a variable to indicate if the primary study's data pertains to a single country. Furthermore, we employ a dummy variable, assigned a value of one if the study includes measures to address endogeneity in the regression. Within our sample, approximately 14% of the estimates employ methods designed to address endogeneity.[8]

In the realm of estimation techniques, our focus is on the diverse methodologies employed by the primary studies to examine the impact of diversity on economic growth. We categorize these methods as follows: *Ordinary Least Squares (OLS), Instrumental Variable (IV), Seemingly Unrelated Regression (SUR)*, *Fixed effects*, and an additional variable, *Other estimator*. The *Other estimator* encompasses approaches like Random Effects, Generalized Method of Moments (GMM), and Three-Stage Least Squares (3SLS).

In order to consider a range of control variables that are often used in regression models in existing research (including those related to macroeconomics, socioeconomic factors, politics, and the country's context), we compile a list of dummy variables representing these common controls in our sample, labeled under "Control variables." Predominant among the macroeconomic factors identified in the primary literature are indicators such as initial income levels and the degree of trade openness. Further augmenting this framework, we integrate a quintet of dummy variables: *Education, Population*, Investment, *Government spending*, and *Democracy*. These variables help to assess whether primary studies consider demographic, socioeconomic, human capital, and democratic level factors. Additionally, researchers sometimes add variables to assess the development of the financial sector, violence (covering aspects like conflicts, assassinations, and civil wars used in primary studies), and health (covering aspects like fertility rates, life expectancy, mortality rates, and diseases used in primary studies).

The diversity-growth nexus may be influenced by the specific countries analyzed and their development status. Population diversity differs significantly across developed and developing nations (Amin 2021), potentially impacting primary study outcomes. Therefore, we consider whether an estimate originates from a sample of countries classified as advanced (developed), developing/emerging, or a combination of both, following the categorization by the International Monetary Fund (IMF 2022).

In the final category titled "Publication characteristics," detailed in Table 4, we introduce a series of variables to evaluate whether the publication traits in primary studies significantly influence the relationship between diversity and economic growth. We first examine the possibility of a time trend by considering the publication year of each study. In assessing the scholarly impact of the primary studies, we utilize two variables. The first variable is the recursive impact factor, as derived from the Research Papers in Economics (RePEc) database, herein denoted as *Impact factor*. The second variable is the cumulative count of citations, sourced from Google Scholar, which is hereafter referenced as *Citations*. Finally, we utilize a binary variable to ascertain the presence of divergent outcomes within research conducted in economic-oriented journals as compared to those published in non-economic journals.

The Supporting Information Appendix (Figure SA2) includes a figure illustrating the correlation matrix between the variables under examination. This figure illustrates key stylized facts within the body of research examined: for example, studies that use birthplace diversity are more likely to utilize the panel fixed-effects estimator, more recent studies tend to focus on a single country compared to older studies, and publications in high-impact factor journals often incorporate more than one measure of diversity in their regressions. Despite the fact that all variance-inflation factors remain under the threshold of 10, it is noteworthy that certain correlation coefficients surpass 0.60. This phenomenon potentially signals underlying collinearity issues. To address this concern, our methodology includes the utilization of the dilution prior, a technique specifically designed to accommodate and mitigate potential collinearity effects.

4.2 | Estimation

To evaluate the extent to which systematic differences among studies influence the correlation between diversity and economic growth, we augment Equation (4) by incorporating a range of study-specific attributes. These attributes are designed to capture the heterogeneity inherent in the primary studies under consideration:

$$PCC_{is} = \alpha_0 + \alpha_1 SE(PCC_{is}) + \sum_{k=1}^{K} \alpha_{k+1} X_{isk} + \varepsilon_{is} \quad (5)$$

In the proposed model, X_{isk} encompasses the regressors enumerated in Table 4, which capture specific attributes of regression i within study s. In order to address the presence of heteroskedasticity within the regression, we modify Equation (5) by dividing it by $SE(PCC_{is})$. This process yields a WLS adaptation of Equation (5), characterized by inverse variance weights:

$$\frac{PCC_{is}}{SE(PCC_{is})} = \alpha_0 \frac{1}{SE(PCC_{is})} + \alpha_1 + \sum_{k=1}^{K} \alpha_{k+1} X_{isk} \frac{1}{SE(PCC_{is})} + \varepsilon_{is} \frac{1}{SE(PCC_{is})} \quad (6)$$

The conventional method for modeling heterogeneity involves the regression of the estimated PCCs against the array of variables previously delineated. While the potential relevance of each variable in elucidating heterogeneity is acknowledged, it is pragmatically anticipated that a limited subset will demonstrate significant importance. The inclusion of an excessive number of variables within a singular regression framework is likely to diminish the precision of the overall estimation process. This, in turn, introduces complexities in drawing inferences, particularly regarding the variables of paramount importance. Such a scenario is indicative of pronounced model uncertainty, where the integration of non-contributory variables could lead to misspecification bias, which in turn undermines the validity of the inferential outcomes. This situation is further compounded by issues of collinearity. Opting for a simple OLS regression under these circumstances would yield inefficient estimates. In reality, a regression model that encompasses all variables represents merely one among a myriad of possible models. In addressing these multifaceted challenges, we adopt a strategy used in previous meta-analyses (for instance, Havranek and Sokolova 2020; Elminejad et al. 2023; Mandon and Woldemichael 2023) and implement Bayesian model averaging (BMA) as delineated in Hoeting et al. (1999).

The BMA technique undertakes the estimation of numerous regressions across varying combinations of variables within the designated model space. Given the incorporation of 33 distinct regressors in our analysis, the exhaustive evaluation of 2^{33} potential models would require an extensive duration, potentially spanning several days, when executed on a conventional personal computing system. To circumvent this computational challenge, we adopt the Markov chain Monte Carlo method, as delineated by Madigan, York, and Allard (1995), which efficiently navigates through the model space, prioritizing models with superior posterior probabilities. For the practical application of BMA, we utilize the "*bms*" package, a tool created by Zeugner and Feldkircher (2015). Within our foundational model specification, we integrate the dilution prior, an approach advocated by George (2010). This prior is particularly noteworthy for its consideration of the collinearity present among the covariates in each model. It operates by adjusting the model probabilities in proportion to the determinant of the correlation matrix corresponding to the variables. A heightened level of collinearity correlates with a determinant nearing zero, culminating in the diminution of the respective model's weight. Moreover, in alignment with the methodologies proposed by Eicher, Papageorgiou, and Raftery (2011), we also employ the unit information prior (UIP) in conjunction with Zellner's g-prior. This technique equates the prior probability, wherein all regression parameters are presumed to be null, with the evidential weight of a single observation within the data.[9] For further elucidation on the BMA process, refer to the Supporting Information Appendix (Table SA7 and Figure SA3).

We employ BMA incorporating the entirety of the available estimates (n = 1537), thereby leveraging the maximal number of observations at our disposal. This utilization facilitates the generation of a more holistic and aggregated representation of the heterogeneity inherent in the diversity-economic growth relationship. For instance, if we were to conduct a BMA exclusively on estimates utilizing religious diversity (n = 124), we would be confronted with a significantly reduced number of observations. In such a scenario, we would have less than one-third of the covariates available for capturing the multifaceted aspects of heterogeneity in the context under investigation. Consequently, this limited sample size would render it inadequate for conducting rigorous analysis.

4.3 | Results

Figure 3 provides a detailed graphical representation of the outcomes derived from the BMA estimation process. This figure arranges the regressors on the vertical axis, aligning them in a descending sequence based on their posterior inclusion probabilities (PIPs). It presents various regression models in columns, sequentially organized from left to right in accordance with their corresponding posterior model probabilities (PMPs). The graphical representation is limited to showcasing the top 5000 models. This deliberate selection accounts for the cumulative probability not extending to the full value of 1. In pursuit of achieving convergence within the estimation process, a rigorous computational approach is adopted, involving 3 million iterations complemented by a substantial phase of 1 million burn-ins. In addition, Figure 3 employs a color-coded system to signify the influence of each regressor, as denoted by the regression coefficient's sign. A blue-colored cell indicates that a variable is included in the model and its coefficient sign is positive, that is, it causes that the estimated effect of diversity on economic growth in the primary studies is larger. A red-colored cell indicates that the variable is included and has a negative effect. The absence or exclusion of a covariate from the estimated model is visually communicated through the presence of a blank cell within the figure.

Table 5 provides the numerical outcomes from BMA and specifically enumerates the posterior mean, standard deviation, and PIP for each covariate under consideration. Integral to all models is the intercept, serving as an indicator for the potential existence of publication bias. A thorough examination reveals that 21 covariates exhibit PIPs exceeding the threshold of 0.5, suggesting their relevance to the impact of diversity on economic growth in the primary studies examined. For the nuanced interpretation of PIP magnitudes, we align with the criteria established by Kass and Raftery (1995). According to Kass and Raftery, the scale of effect can be categorized as weak (PIPs ranging from 0.5 to 0.75), substantial (0.75 to 0.95), strong (0.95 to 0.99), or decisive (0.99 to 1). Adhering to these conventions, our analysis identifies 10 covariates that exhibit a decisive effect. These include

TABLE 5 | Explaining heterogeneity.

	Bayesian model averaging (baseline model)			Weighted least squares (frequentist check)			Weighted-average least squared (WALS)		
	Post mean	Post St. Dev.	PIP	Coef.	St. error	*p* value	Coef.	St. error	*t*-value
Growth of real GDP per capita	−0.034	0.017	**0.865**	−0.045	0.018	0.017	−0.032	0.010	**−3.095**
Growth of nominal GDP per capita (Ref.)									
Real GDP per capita	0.026	0.036	0.405				0.023	0.018	**1.290**
Nominal GDP per capita	0.102	0.017	**1.000**	0.090	0.038	0.021	0.095	0.015	**6.432**
Ethnic diversity	−0.090	0.021	**1.000**	−0.092	0.044	0.039	−0.085	0.013	**−6.324**
Linguistic diversity	−0.092	0.024	**1.000**	−0.090	0.053	0.092	−0.079	0.013	**−5.948**
Religious diversity	−0.027	0.026	**0.577**	−0.037	0.051	0.472	−0.022	0.015	**−1.500**
Genetic diversity	0.033	0.033	**0.562**	0.045	0.065	0.485	0.033	0.019	**1.730**
Birthplace diversity	0.153	0.035	**1.000**	0.171	0.052	0.001	0.142	0.019	**7.650**
Residual category diversity (Ref.)									
Joint	0.062	0.010	**1.000**	0.061	0.021	0.006	0.056	0.008	**6.651**
Cross-sectional (Ref.)									
Panel data	−0.036	0.024	**0.753**	−0.055	0.026	0.037	−0.038	0.014	**−2.770**
Single country	−0.057	0.018	**0.999**	−0.062	0.028	0.026	−0.050	0.018	**−2.758**
Time span	0.020	0.012	**0.816**	0.025	0.008	0.004	0.016	0.006	**2.685**
Control for endogeneity	−0.002	0.006	0.101				0.006	0.013	0.450
OLS	0.003	0.008	0.184				0.004	0.010	0.426
Fixed effects	−0.031	0.022	**0.755**	−0.033	0.019	0.089	−0.033	0.015	**−2.273**
IV	−0.005	0.010	0.281				−0.019	0.011	**−1.789**
SUR	−0.010	0.017	0.303				−0.022	0.014	**−1.620**
Other estimator (Ref.)									
Initial income	0.050	0.013	**1.000**	0.042	0.016	0.010	0.042	0.009	**4.472**
Investment	0.004	0.010	0.167				0.019	0.011	**1.700**
Education	0.000	0.003	0.054				0.014	0.010	**1.427**
Government spending	0.078	0.013	**1.000**	0.086	0.023	0.000	0.058	0.011	**5.390**
Trade openness	0.002	0.007	0.121				0.007	0.010	0.687
Violence	−0.060	0.013	**1.000**	−0.069	0.024	0.006	−0.053	0.012	**−4.436**
Health	−0.039	0.015	**0.959**	−0.033	0.026	0.206	−0.052	0.012	**−4.418**
Population	−0.013	0.013	**0.602**	−0.020	0.013	0.117	−0.029	0.009	**−3.262**
Democracy	0.001	0.005	0.079				0.014	0.011	**1.216**
Financial development	0.000	0.004	0.039				0.002	0.015	0.146
Developed	0.006	0.016	0.148				0.017	0.019	0.871
Developing	0.032	0.017	**0.866**	0.039	0.020	0.052	0.031	0.012	**2.542**
Mixed (Ref.)									
Publication year	0.004	0.001	**0.983**	0.003	0.002	0.095	0.004	0.001	**3.364**
Impact factor	0.014	0.008	**0.768**	0.019	0.007	0.005	0.014	0.005	**2.903**
Non-economic journal (Ref.)									
Economic journal	−0.047	0.011	**1.000**	−0.048	0.022	0.031	−0.052	0.010	**−5.393**

(Continues)

	Bayesian model averaging (baseline model)			Weighted least squares (frequentist check)			Weighted-average least squared (WALS)		
	Post mean	**Post St. Dev.**	**PIP**	**Coef.**	**St. error**	***p* value**	**Coef.**	**St. error**	***t*-value**
Citations	0.004	0.006	0.401				0.003	0.004	0.674
Precision	0.027	0.039	0.392	0.069	0.060	0.253	0.047	0.030	1.586
Publication bias	−0.738	NA	1.000	−0.769	0.322	0.019	−0.735	0.147	−5.007
Observations		1537			1537			1537	
Number of studies		83			83			83	

Notes: The inverse of variance is used as the weight. The left-hand panel implements BMA utilizing the UIP g-prior and the dilution prior (Eicher, Papageorgiou, and Raftery 2011; George 2010). Regressors exhibiting a PIP exceeding 0.5 are highlighted in bold, indicative of their significance. The middle panel elucidates a frequentist check employing weighted least squares, encompassing variables with PIPs surpassing 0.5 in BMA. In the frequentist check, standard errors are clustered at the study level. The right-hand panel uses the weighted-average least squares (WALS) estimator. Regressors with a *t*-value (in absolute terms) greater than 1 are highlighted in bold to indicate their significance. A comprehensive description of all variables is presented in Table 4.

Abbreviations: Post mean, posterior mean; Post St. Dev., posterior standard deviation; PIP, posterior inclusion probability; Coef., coefficient, St. error, standard error.

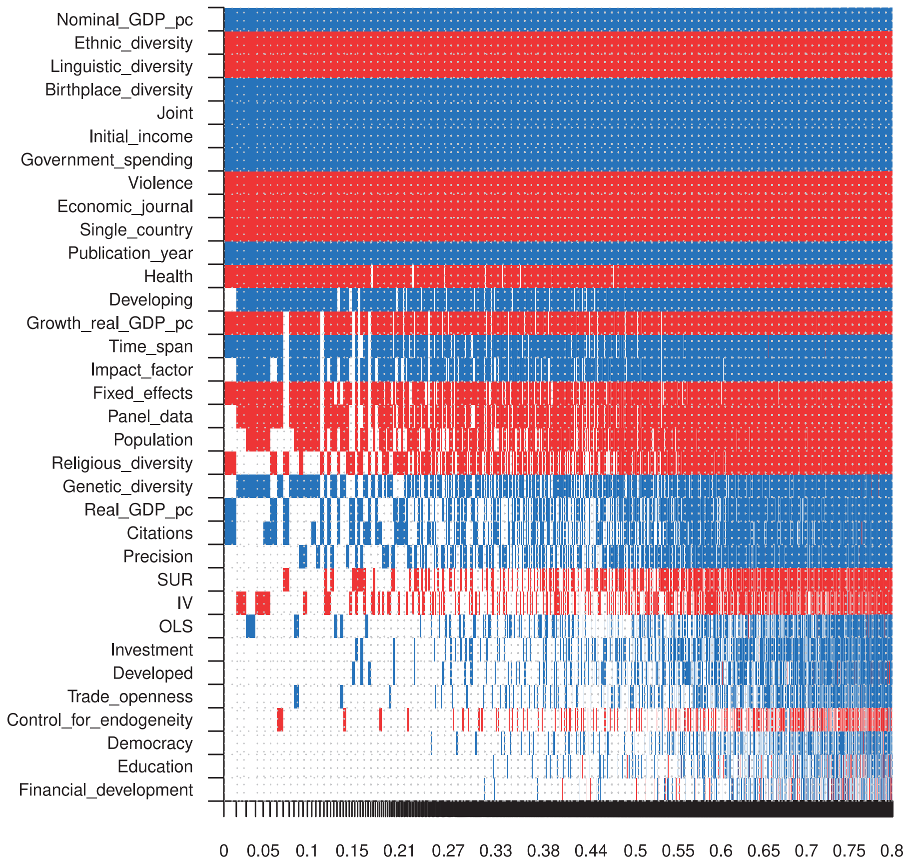

FIGURE 3 | Model inclusion in Bayesian model averaging. The figure presents the results of Bayesian model averaging (BMA). All regressors are explicitly detailed and defined within Table 4. The numerical results are documented in Table 5. Each column in the figure indicates individual models, and the variables are ordered by their posterior inclusion probability in descending order. The horizontal axis represents the cumulative posterior model probabilities. The estimation process integrates the unit information prior (UIP) recommended by Eicher, Papageorgiou, and Raftery (2011) and the dilution prior proposed by George (2010), specifically designed to address collinearity concerns. A blue color denotes that the variable has a positive estimated sign, while a red color denotes a variable with a negative estimated sign. The absence of color indicates the exclusion of the variable from the given model. [Colour figure can be viewed at wileyonlinelibrary.com]

Nominal GDP per capita, *Ethnic diversity*, *Linguistic diversity*, *Birthplace diversity*, *Joint*, *Single country*, *Initial income*, *Government spending*, *Violence*, and *Economic journal*. Furthermore, we observe a strong effect in two variables: *Health* and *Publication year*. Six regressors—*Growth of Real GDP per capita*, *Panel data*, *Time span*, *Fixed effects*, *Developing*, and *Impact factor*—display substantial effects. Last, the results indicate a weak effect in *Religious diversity*, *Genetic diversity*, and *Population*. A thorough elucidation of these findings is provided in the ensuing discussion.

The observed influence of publication bias in BMA results corroborates the evidence presented in the preceding section. Notably, the discernible negative and statistically significant coefficient of publication bias, even subsequent to the adjustment for a range of moderating variables, infers that the results presented in Table 2 are not merely an artifact of omitted variable bias. In this context, the extent of selectivity remains within a "little to modest" range, as indicated by the absolute magnitude of the publication bias coefficient being less than 1.

4.3.1 | Measure of Economic Growth

In examining the measures of economic growth, research employing real GDP per capita growth as the dependent variable typically presents a diminished estimate. Conversely, investigations utilizing nominal GDP per capita as the dependent variable tend to report a more favorable impact of diversity on economic growth. This outcome aligns with the insights delineated by Nordvik (2022), indicating that diversity fosters inflation, a component integral to nominal GDP.

4.3.2 | Diversity Measures

In consideration of the various diversity measures utilized in extant scholarly works, our findings indicate that studies employing measures of ethnic, linguistic, or religious diversity appear to diminish the perceived impact of diversity on economic growth. Conversely, investigations that employ genetic or birthplace diversity as proxies for diversity typically observe a more favorable influence of diversity on economic growth. In addition, investigations that incorporate multiple diversity measures into their regression frameworks typically observe an amplification in the estimated impact on economic growth. This observation is congruent with the findings of Fulford, Petkov, and Schiantarelli (2020), which demonstrate that the inclusion of dual diversity indices in regression analyses reveals a more marked positive correlation between ethnic diversity and economic growth, as opposed to the inclusion of a singular diversity measure.

4.3.3 | Data and Estimation Characteristics

In the realm of data attributes, the empirical evidence delineates a noteworthy correlation between an extended temporal scope in primary studies and the magnitude of estimated outcomes observed. Specifically, an increase in the number of years encompassed within these studies corresponds to an escalation in the reported estimates. Moreover, our analysis elucidates that studies concentrating on the impact of diversity on economic growth within a singular country context are inclined to report a more pronounced negative correlation. In contrast, investigations employing panel data, as opposed to the reference category of cross-sectional data, tend to yield diminished magnitudes of the reported impact. Concerning the estimation techniques prevalent in the existing literature, there is an indication that the employment of panel fixed-effects estimators in analyses tends to result in a lesser reported effect.

4.3.4 | Control Variables

In the context of the control variables under examination, the incorporation of the initial income covariate demonstrates a significant and positive influence, implying that its inclusion in regression analyses frequently results in an enhanced perceived impact of diversity on economic growth. Consequently, this intimates the pertinence of the convergence hypothesis in the nexus between diversity and economic growth. Moreover, this observation corroborates the findings of Alesina and La Ferrara (2005), underscoring that the detrimental impacts of both ethnic and linguistic diversity on economic growth diminish in the presence of elevated initial income levels. Furthermore, integrating a variable that accounts for government expenditure reveals an increase in the estimated coefficient, signifying that government spending plays a crucial role in moderating the effects of diversity on economic growth. This aligns with the insights presented by La Porta et al. (1999) and Zhu and Grigoriadis (2022), who postulate that heightened government consumption can mitigate intra-country ethnic tensions, fostering a more favorable relationship between diversity and economic growth. Conversely, the inclusion of a variable accounting for violence leads to a reduction in the estimated coefficient. Violence, encompassing elements such as conflicts, assassinations, and civil wars, exerts a direct deleterious effect on economic growth (e.g., Kang and Meernik 2005; Bodea and Elbadawi 2008). Tangerås and Lagerlöf (2009) provide further insights, indicating a heightened risk of civil war at intermediate levels of ethnic diversity, thereby elucidating the rationale behind the negative effect observed upon the inclusion of violence in regression models. In the same vein, the inclusion of a health-related variable tends to reduce the estimated coefficient. Brander and Dowrick (1994) illustrate that countries with higher fertility rates generally experience reduced per capita income growth. Given that ethnically diverse societies often exhibit higher fertility rates, as indicated by Janus (2013), this could elucidate the observed reduction in the estimated coefficient when health measures are factored into the regression analysis. Last, controlling for population also appears to decrease the estimated coefficient. This can be attributed to the interconnectedness of ethnic competition and rapid population growth with an increased incidence of internal warfare, as discussed by Goldstone (2016), thereby further attenuating the impact of diversity on economic growth.

4.3.5 | Countries Examined

In the context of the examined nations and their respective stages of development, the BMA results reveal a notable trend:

investigations focused exclusively on developing or emerging nations tend to report an augmented coefficient in the correlation between diversity and economic growth. This outcome concurs with the work of Bove and Elia (2017), which posits that developing countries reap greater benefits from an increase in population diversity. Bove and Elia emphasize the paramount importance of diversity, characterizing it as a rich blend of human resources, particularly vital for developing countries. They assert that diversity fosters innovation and accelerates technological adoption, crucial for countries not yet at the technological frontier. This heterogeneity in human capital is especially beneficial in these contexts, as it amplifies the catch-up effect with advanced economies, leading to greater economic growth and development efficiency compared to more developed nations.

4.3.6 | Publication Characteristics

In the realm of publication characteristics, our analysis reveals an intriguing pattern: the diversity coefficient estimates reported in the literature demonstrate a progressive increase over time. This notable trend might be interpreted as a gradual shift away from the earlier inclination to align with the seminal works of Easterly and Levine (1997) and Alesina et al. (2003). These foundational studies, which stand as pillars in the initial corpus of literature, posited a detrimental impact of diversity on economic growth, a stance that has increasingly been questioned in recent literature. Furthermore, our investigation highlights a discernible pattern within economic-focused journals, where the diversity coefficient estimates tend to be lower. This pattern indicates a variance in reported effects based on the disciplinary focus of the publication outlet, with economic-oriented journals exhibiting more negative effects of diversity on economic growth compared to their non-economic counterparts. Last, our findings underscore the significance of the journal impact factor in this context. There exists a positive correlation between the impact factor of the publishing journals and the reported estimates of the diversity coefficient. This correlation suggests a qualitative dichotomy, where higher quality publications tend to report more positive effects of diversity on economic growth, in contrast to those in journals with a lower impact factor. This dichotomy raises critical questions about the influence of perceived scholarly prestige on the interpretation and reporting of research outcomes within the pertinent scholarly discourse.

To ascertain the reliability and consistency of our initial BMA findings, we conduct a series of rigorous robustness evaluations. Initially, an integration of Bayesian and frequentist methodologies is undertaken. This involves utilizing Bayesian principles for variable selection, coupled with frequentist approaches for the estimation process. The optimal model delineated through the BMA process incorporated the intercept and 21 influential explanatory variables, each surpassing a posterior inclusion probability threshold of 0.5, as per the criteria established by Kass and Raftery (1995), indicating their significant influence on the dependent variable. This model is re-evaluated utilizing the Weighted Least Squares (WLS) technique, with standard errors clustered at the study level. The WLS outcomes, juxtaposed alongside the BMA results in Table 5, demonstrate quantitative alignment with the BMA findings, albeit with marginally reduced significance. Moreover, the right-hand panel of Table 5 delineates the outcomes derived through the application of the weighted-average least squares (WALS) estimator (Magnus, Powell, and Prüfer 2010; De Luca and Magnus 2011).[10] The performance of WALS is comparable to that of the BMA approach, yet it demands significantly less computational effort (e.g., Magnus, Powell, and Prüfer 2010; Ugur, Churchill, and Luong 2020; Horie et al. 2025). Notably, the findings derived from the WALS estimator not only correspond closely with those obtained via the BMA method but also tend to demonstrate enhanced statistical significance. Furthermore, we explore alternative Bayesian model specifications by varying g-priors and model priors. This exploration includes employing a combination of the Bayesian Risk Inflation Criterion (BRIC) g-prior and the beta-binomial random model prior, which equitably distributes prior probability across all model sizes, as well as integrating the Hannan-Quinn (HQ) g-prior with the random model prior (Fernández, Ley, and Steel 2001; Ley and Steel 2009).[11] Figure 4 illustrates the PIPs for individual covariates under these varied priors within the BMA framework. The deviations observed are minimal, yet the combination of the HQ g-prior with the random model prior yields larger PIPs. Despite these variations, the ordinal ranking of variables by PIPs remains consistent, thereby leaving our primary conclusions unaltered. Detailed outcomes derived from these alternative BMA configurations are documented in the Supporting Information Appendix (Table SA8). Last, we apply Frequentist Model Averaging (FMA), a technique that obviates the necessity for explicit priors. Here, we utilize Mallow's weights (Hansen 2007) and the orthogonalization of covariate space as proposed by Amini and Parmeter (2012). The FMA results, delineated in the Supporting Information Appendix (Table SA8), display a broad concurrence with our initial BMA results, though they exhibit generally lesser statistical significance.

4.4 | Best Practice

In the final stage of our analysis, we utilize the results of BMA (as detailed in Table 5, left-hand panel) to derive a predicted value of the diversity impact based on the characteristics of an ideal study. We do so by computing the fitted values from the BMA exercise conditional on the definition of best practice. The construction of an idealized research scenario by meta-analysts necessitates the utilization of the maximum values of variables aligned with the exemplary practice, the minimum values for those diverging from this standard, and the mean values for variables whose optimal levels are indeterminate (namely, category moderators of equivalent desirability). While the delineation of "best practice" remains inherently subjective, it serves as an instrumental gauge to evaluate the cumulative effects of various analytical misalignments and publication bias. An a priori determination is selected to define what constitutes a best study—an ideal model conceived to accurately and reliably discern the influence of diversity on economic growth.

Our refined conceptualization of best practice encompasses the following principles: We approach economic growth measures (*Growth of real GDP per capita*, *Real GDP per capita*, and *Nominal GDP per capita*) with equal consideration, employing sample means as our evaluative standard. This objective stance extends similarly to variables including *Joint*, *Single country*, *Developed*,

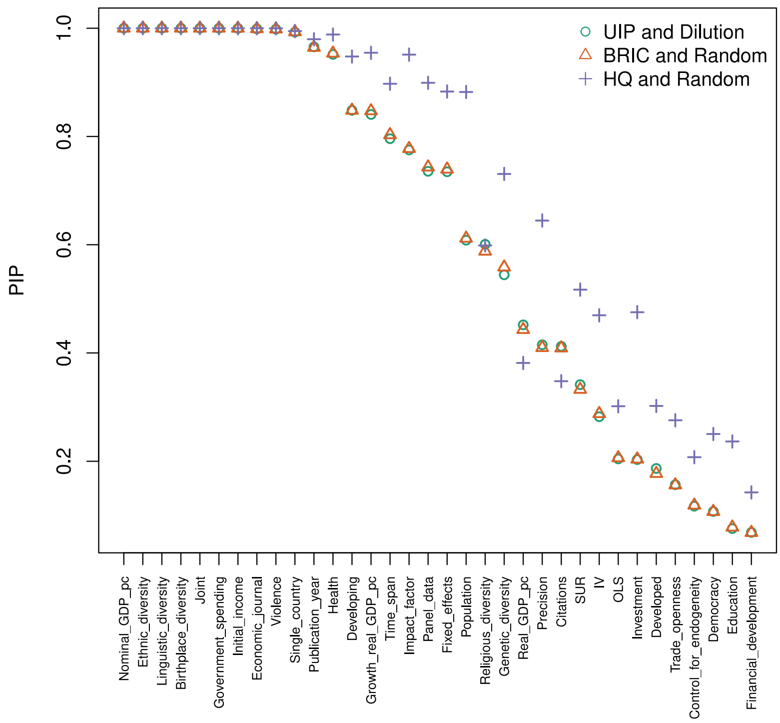

FIGURE 4 | Sensitivity of BMA to different priors. Posterior inclusion probabilities are consistent across different priors. PIP = posterior inclusion probability. UIP and Dilution = priors according to Eicher, Papageorgiou, and Raftery (2011) and George (2010). BRIC and Random = the benchmark g-prior for parameters with the beta-binomial model prior (each model size has equal prior probability). The HQ prior asymptotically mimics the Hannan-Quinn criterion. [Colour figure can be viewed at wileyonlinelibrary.com]

Developing, *Publication year*, and *Time span*. In the context of data categorization, no predilection is expressed between panel and cross-sectional data formats, hence the application of the sample mean for *Panel data*. Furthermore, in evaluating the estimation methods, a deliberate preference is exhibited toward studies that effectively address potential endogeneity issues between diversity and growth. This is achieved through the incorporation of an IV in the analytical framework. Consequently, the sample maxima are aligned for *IV* and *Control for endogeneity* variables, while the sample minima are utilized for *OLS*, *SUR*, *Fixed effects*, and *Other estimator*. Additionally, our approach encompasses the integration of sample maxima for variables indicative of academic influence and relevance, namely *Citations*, *Impact factor*, and *Economic journal*. Our comprehensive strategy also involves the inclusion of all relevant control variables, for which we also apply sample maxima, to adequately capture the multifaceted, country-specific characteristics influencing growth. These variables encompass *Initial income*, *Investment*, *Education*, *Government spending*, *Trade openness*, *Violence*, *Health*, *Population*, *Democracy*, and *Financial development*. Last, to counteract publication bias, we assign a value of zero to the standard error.

Based on the previously defined scenario, we present best practice estimates for different diversity aspects: ethnic, linguistic, religious, genetic, birthplace, and the residual category diversity. This involves integrating each diversity aspect into the diversity measure, assigning it a value of one, while assigning a value of zero to all others, as detailed in Table 6. When considering ethnic and linguistic diversity, the derived predictions do not exhibit statistical significance. Conversely, for the remaining dimensions—religious, genetic, birthplace, and the residual category diversity—all associated predictions are not only positive but also exhibit high statistical significance. Remarkably, these "best research practice" estimates substantially exceed the simple mean estimates delineated in Table 1 in absolute terms. This disparity suggests that there may be potential for methodological refinement in assessing the impact of various diversity dimensions on economic growth. Such advancements could potentially reveal profound economic implications related to the growth effects attributable to diversity.[12]

As previously outlined, our best-practice meta-analysis estimates, which adjust for both publication bias and methodological quality in the primary studies, indicate that while ethnic and linguistic diversity exhibit a small and statistically insignificant positive effect on economic growth, the remaining dimensions of diversity—specifically religious, genetic, birthplace, and the residual category—demonstrate a significant positive impact on economic growth, with effect sizes ranging from moderate to large. These findings imply a more intricate relationship between diversity and economic growth than previously indicated, highlighting the importance of a rigorous evaluation that accounts for both publication bias and methodological quality. Notably, the impact of birthplace diversity on economic growth presents a point of particular interest. According to Table 4, the effect of birthplace diversity, when adjusted solely for publication bias, appears to be small to moderate. In contrast, the best-practice estimates reveal a significantly larger effect. This discrepancy suggests that while publication bias may inflate estimates, methodological biases might conversely attenuate them. Moreover, in the cases of religious and residual category diversity, methodological biases tend to diminish the estimated

TABLE 6 | Best practice estimates.

	Ethnic diversity	Linguistic diversity	Religious diversity	Genetic diversity	Birthplace diversity	Residual category diversity
Baseline	0.072	0.077	0.159**	0.210***	0.380***	0.228**
Panel	0.047	0.051	0.133**	0.184***	0.355***	0.202*
Cross-sectional	0.104	0.108	0.190**	0.241***	0.411***	0.259**
Developed	0.077	0.081	0.163*	0.215**	0.385***	0.233*
Developing	0.099	0.103*	0.186***	0.237***	0.407***	0.254**
Growth real GDP per capita	0.015	0.019	0.101	0.153**	0.323***	0.171
Single & developed country	0.017	0.021	0.103	0.154**	0.325***	0.172
Single & developing country	0.048	0.052	0.135**	0.186**	0.356***	0.204**
No joint	0.055	0.059	0.141**	0.193***	0.363***	0.211*

Note: The table displays the mean partial correlation coefficients derived from the baseline Bayesian model averaging exercise, according to our subjective best practice criteria across various scenarios. The first row ("Baseline") employs the preferences described in the main text of our study (Subsection 4.4) for each distinct measure of diversity. In the subsequent rows, we modify only the relevant parts in accordance with the specified variables, while maintaining the remaining set of preferences. More specifically, in the second row ("Panel"), we set 1 for *Panel* and 0 for *Cross-sectional*. In the third row ("Cross-sectional"), we assign 0 for *Panel* and 1 for *Cross-sectional*. In the row ("Developed"), we plug in 1 for *Developed* and 0 for *Developing* and *Mixed*. In the row ("Developing"), we set 1 for *Developing* and 0 for *Developed* and *Mixed*. In the row ("Growth real GDP per capita"), we assign 1 for *Growth real GDP per capita* and 0 for *Growth of nominal GDP per capita*, *Real GDP per capita*, and *Nominal GDP per capita*. In the row ("Single & developed country"), we plug in 1 for *Single country* and *Developed*, and 0 for *Developing* and *Mixed*. In the row ("Single & developing country"), we assign 1 for *Single country* and *Developing*, and 0 for *Developed* and *Mixed*. In the last row ("No joint"), we set 0 for *Joint*. Standard errors are clustered at the study level. Significance level is denoted by *** (1%), ** (5%), and * (10%).

effect. However, after correcting for these biases, the impact of these diversity dimensions on economic growth is found to be moderate. In light of these considerations, we recommend prioritizing the comprehensive estimates derived from our best-practice analysis. These estimates offer a more robust and reliable assessment by addressing both publication and methodological biases, thereby providing a clearer and more accurate understanding of how different dimensions of diversity influence economic growth.

5 | Concluding Remarks

Through the utilization of meta-analysis and meta-regression techniques, this investigation examines the existing empirical evidence concerning the influence of population diversity on economic growth. While recent works have progressively focused on the growth implications of diversity, there remains a notable lack of consensus within the field, with existing studies yielding a broad range of findings. This study endeavors to enrich the academic discourse by conducting an extensive quantitative review of the accumulated evidence to date. Furthermore, it seeks to identify and analyze potential factors contributing to the observed variability in the empirical results documented in the current body of literature.

We examine a collection of 1537 estimates derived from 83 peer-reviewed publications. The meta-analysis conducted offers a plethora of key insights. Concerning the aspect of publication bias, a thorough examination of the entirety of estimates indicates a discernible inclination toward mild publication bias, predominantly favoring the dissemination of research that demonstrates a negative correlation between diversity and economic growth. The extent and direction of this bias, however, vary depending on the specific measure of population diversity utilized in the primary studies. When adjusting solely for publication bias, we find that diversity's overall effect on economic growth is positive but economically negligible. Disaggregating diversity into ethnic, linguistic, religious, birthplace, genetic, and a residual category, we show that genetic diversity has a moderate positive impact on economic growth. Similarly, birthplace diversity contributes positively, with effects ranging from small to moderate, while other dimensions of diversity demonstrate minor influences. However, these initial findings do not provide a complete understanding of the relationship between diversity and economic growth. After rigorously adjusting for both publication bias and the methodological quality of the primary studies included in our meta-analysis, our best-practice estimates provide a more nuanced picture. While ethnic and linguistic diversity shows a small, statistically insignificant positive impact on economic growth, the remaining dimensions—religious, genetic, birthplace, and other forms of diversity—demonstrate a significant positive influence on growth, with effect sizes that range from moderate to large. These findings underscore the importance of addressing both publication bias and methodological quality to achieve a more accurate picture of the relationship between diversity and economic growth. Once these factors are properly controlled, it becomes evident that certain forms of diversity have a markedly greater influence on economic growth than initially perceived. Our refined meta-analysis thus highlights the critical role of specific dimensions of diversity in enhancing economic performance, providing a more detailed and insightful understanding of how diversity drives economic advancement.

To explore the influence of distinct research attributes within primary investigations on the variance observed in the estimated impact of diversity, our approach involves an examination of over thirty candidate variables, employing Bayesian model averaging as a strategic approach to mitigate model uncertainty effectively. Our comprehensive quantitative analysis reveals that multiple factors significantly contribute to the observed heterogeneity in these primary studies concerning the nexus between diversity and economic expansion. First, we observe that primary studies utilizing the growth rate of real GDP per capita as a measure for economic growth, those employing panel data, focusing on a single country, and using the panel fixed-effects estimator, tend to report a diminished effect. Conversely, studies that rely on nominal GDP per capita as a measure report an amplified effect. The second layer of analysis highlights that research focusing on ethnic, linguistic, or religious diversity generally reports a reduced effect, in contrast to studies examining genetic or birthplace diversity, or those incorporating multiple diversity measures, which tend to indicate an increased effect. A further dimension of our analysis reveals that studies accounting for initial income levels and government expenditure are more likely to report augmented positive effects. In contrast, those incorporating factors such as the incidence of violence, health, and population measures tend to report a diminished effect. Notably, our findings also reveal that the diversity coefficient estimates reported in the literature demonstrate a progressive increase over time, and primary investigations, which encompass an extended temporal span in their regression analyses, consistently indicate an amplified effect. Moreover, the impact factor, an indicator of research quality, is found to enhance the estimated effect. Additionally, we find that studies exclusively focusing on developing countries tend to report an enhanced effect, whereas those published in economic-oriented journals typically report a reduced effect of diversity. Finally, our best practice estimates intimate the potential for methodological enhancements in estimating the impact of diversity on economic growth. Such advancements could unveil significant insights into the growth consequences of diversity, bearing substantial economic implications.

Prior to delving into potential directions for future research, it is incumbent upon us to acknowledge an inherent limitation within our study. Our meta-analysis employs partial correlation coefficients due to their feasibility in computation across various studies. Nevertheless, a notable critique of partial correlation coefficients is their inherent complexity in conveying the economic implications of the transformed partial correlation coefficients. As elucidated in our main discourse, even in instances where studies employ a common metric for assessing population diversity, such as the ethnic fractionalization index, discrepancies are evident in its calculation, dependent on the distinct data sources utilized. These variations lead to the source-specific fractionalization indices representing probabilities, but they pose a challenge for direct comparison, given the inconsistency in the number of ethnic groups considered in different sources. The issue extends to the assessment of polarization, where a similar disparity in the enumeration of major groups is observed across various sources. Moreover, the requisite statistics, particularly sample means essential for the computation of elasticities or semi-elasticities—quantitatively comparable effect sizes that can be interpreted in economic terms—are frequently omitted in numerous studies. Consequently, and with these considerations in mind, our choice to utilize partial correlation coefficients emerges as a contingency strategy (Irsova et al. 2024).

The present meta-analysis yields several pivotal directions for future research in the realm of the diversity-growth nexus. First, it is imperative for researchers, especially those offering statistically independent assessments, to closely examine the variables identified herein as significant moderators in the relationship between diversity and economic growth. Such examination is vital for a nuanced understanding of this complex interaction. Second, a rigorous examination should focus on explicating the causal pathways underlying the observed average effects of specific diversity dimensions—namely, religious, genetic, birthplace, and other variants—which manifest a positive and statistically significant influence on economic growth. Delving deeper into why these particular dimensions influence economic growth, in contrast to other facets of diversity that demonstrate minimal effect, is essential. Such inquiries not only enhance the theoretical framework surrounding the diversity-growth nexus but also inform policy interventions aimed at harnessing the potential of diversity to foster economic development. Prior research (e.g., Montalvo and Reynal-Querol 2005; Alesina, Harnoss, and Rapoport 2016; Amin 2021) has underscored the contingent and context-specific nature of diversity's effects on economic growth. Consequently, future studies should aim to elucidate the pathways through which diversity impacts economic growth. Our findings underscore the significance of factors such as initial income levels, government expenditure, and incidences of violence as pivotal moderating variables. An in-depth analysis of these factors could yield valuable insights. Last, while this meta-analysis has concentrated on economic growth as the primary dependent variable, there exists a corpus of theoretical and empirical evidence positing that population diversity exerts a direct influence on a range of policy-relevant outcomes, including trade, investment, and financial development. Thus, extending and adapting the meta-analytical approach outlined in this study could offer valuable insights into a broader spectrum of research questions concerning the effects of diversity.

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Conflicts of Interest

The author declares that there exist no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

Data and code files to replicate the results reported in the paper are available here: https://doi.org/10.7910/DVN/0FFF1U

Endnotes

[1] When the corpus of existing literature is substantial, well-established, and extensively developed, the omission of unpublished studies is not expected to significantly influence the results of a meta-analysis (Stanley and Doucouliagos 2012). Bearing this consideration in mind, our selection criteria were confined exclusively to studies that have undergone rigorous peer review. Consequently, our final dataset encompasses 83 peer-reviewed published studies, yielding a total of 1537 estimates derived from research spanning 27 years. This constitutes a considerably extensive sample size for a meta-analytical review, offering a robust basis for comprehensive synthesis and evaluation.

[2] In this meta-analysis, when we reference the logarithmic expression of real or nominal GDP per capita, it is crucial to clarify that this terminology specifically denotes the change in the logarithm of GDP per capita between two time periods, t and $t + k$, as utilized in the primary studies included in our meta-sample. Thus, despite the phrasing, the actual dependent variable consistently represents economic growth. This approach aligns with the standardized econometric practice of measuring growth through the differential in logarithmic values over time.

[3] Our original meta-sample, derived from 83 studies encompassing 1537 observations, predominantly consists of coefficient estimates and a minor portion of marginal effect estimates. It is important to note that both the coefficient estimates and the marginal effect estimates are not directly comparable, as their scales and measures differ. Therefore, although we initially calculated marginal effect estimates for a small portion of our meta-sample, we subsequently converted all 1537 estimates into partial correlation coefficients.

[4] Table SA6 in the Supporting Information Appendix offers detailed information for each primary study. It includes the mean and median partial correlation coefficients, median t-value, the number of estimates, measures of economic growth and diversity, data type, countries covered, estimation methods, journal name, and year of publication.

[5] We utilize the Unrestricted weighted least squares (UWLS) average method, as introduced by Stanley and Doucouliagos (2017), for synthesizing PCCs. This approach is demonstrated to be less prone to bias compared to conventional meta-regression techniques such as the fixed-effect and random-effects models used for calculating average PCCs. In the UWLS method, the effect size is synthesized as a point estimate from a regression model where the standardized effect size serves as the dependent variable, and estimation precision acts as the independent variable. Specifically, we apply the equation without an intercept term, utilizing the coefficient, α, to represent the synthesized value of the PCCs: $t_{is} = \alpha \frac{1}{SE(PCC_{is})} + \upsilon_{is}$, where υ_{is} is the residual term.

[6] Following the classification scheme proposed by Cohen (1988), which defines the magnitudes of correlations as small (0.10), medium (0.30), and large (0.50), our findings indicate that ethnic diversity has a small negative effect on growth. Conversely, birthplace diversity exhibits a small to medium positive effect. The effect of other diversity dimensions—linguistic, religious, genetic, and other forms—appears to be negligible.

[7] In our research design, we initially aimed to incorporate study-level fixed effects, a widely acknowledged method for enhancing robustness by controlling for unobserved characteristics unique to each study. However, this approach proved impractical due to the considerable imbalance present within our panel datasets, coupled with the occurrence of certain studies providing merely a singular observation. The effective application of the fixed-effect estimator is contingent upon the availability of multiple estimates from individual studies, a criterion not met in our current dataset configuration.

[8] The WAAP estimator exclusively discerns studies of adequate power pertaining to estimates in genetic and birthplace diversity.

[9] Within the examined sample of estimates, it is discerned that only two estimators, namely the GMM and IV approach, adequately address the endogeneity concern pertaining to the variable of diversity, and this is solely applicable in scenarios where diversity functions as the instrumented variable.

[10] It is important to acknowledge the methodological advancements in meta-regression analysis as demonstrated by Awaworyi Churchill, Luong, and Ugur (2022) in their study on the economic benefits of intellectual property protection. They introduce a multi-outcome meta-regression model that effectively addresses heterogeneity, publication selection bias, and data dependence across various economic outcomes. While this approach offers significant insights for studies with multiple dependent variables, our current meta-analysis focuses solely on economic growth as a single outcome. Therefore, we maintain our methodological approach using Bayesian model averaging and the dilution prior technique to address model uncertainty and potential collinearity. Nonetheless, the framework proposed by Awaworyi Churchill, Luong, and Ugur (2022) remains a notable contribution to the field of meta-regression analysis, guiding future research that involves multiple outcome variables.

[11] It is important to note that the models UWLS (Table 1), WLS: Precision (Table 2), BMA, and frequentist approaches (Table 5) all employ the same weighting scheme, specifically inverse variance weights.

[12] For further details on these alternative Bayesian model specifications, refer to the Supporting Information Appendix (Tables SA9 and SA10, and Figures A4–A7).

[13] We conduct a range of alternative best practice research scenarios, detailed in Table 6. The resulting predictions derived from these scenarios, both quantitative and qualitative, align closely with those derived from the baseline best practice research scenarios.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.