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Population growth and economic development: a meta-analysis

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Abstract

The effect of population growth on economic development is a topic widely discussed in economics, concerning both low-income countries facing high population increases and developed regions experiencing population stagnation. I collect and synthesize 573 estimates of the effects of total population growth on GDP per capita growth from 66 studies to conduct a meta-analysis – a quantitative literature review. Using both linear and non-linear tests, I detect consistent publication bias favoring negative effects. To examine heterogeneity in the estimated effects, I utilize Bayesian model averaging and analyze 37 variables related to data characteristics, structural variation, model specifications, estimation techniques, and publication characteristics that could explain why the estimates differ. I found additional evidence indicating publication bias and uncovered specific study settings that consistently affect the estimates: the choice of data type, scope and length of data, and choice of controls in the regressions used to generate the estimates. The results also suggest regional differences: effects of population growth on GDP per capita growth are less adverse in African countries than in other regions. Based on this, the thesis demonstrates that the effects are likely to be less negative than presented, highlights the opportunities in African countries with high population growth, and emphasizes the importance of the study setting for the final estimates.

Kurzfassung

Das Thema des Einflusses des Bevölkerungswachstums auf die wirtschaftliche Entwicklung wird in der Volkswirtschaft intensiv diskutiert, sowohl in Niedriglohnländern mit hohen Bevölkerungszuwächsen als auch in entwickelten Regionen mit stagnierenden Bevölkerungszahlen. Für eine Meta-Analyse – eine quantitative Literaturübersicht – habe ich 573 Schätzungen der Auswirkungen des gesamten Bevölkerungswachstums auf das BIP-Wachstum pro Kopf aus 66 Studien gesammelt und synthetisiert. Sowohl lineare als auch nicht-lineare Tests zeigen einen konsistenten Publikationsbias zugunsten negativer Effekte. Um die Heterogenität der geschätzten Effekte zu untersuchen, verwende ich das Bayesian Model Averaging und analysiere 37 Variablen im Zusammenhang mit Datenmerkmalen, strukturellen Unterschieden, Modell-Spezifikationen, Schätzungstechniken und Publikationsmerkmalen, die erklären könnten, warum die Schätzungen variieren. Ich fand zusätzliche Beweise für einen Publikationsbias und entdeckte spezifische Studiensettings, die die Schätzungen konsistent beeinflussen: die Wahl des Datentyps, Umfang und Länge der Daten sowie die Wahl der Kontrollvariablen in den Regressionen, die zur Generierung der Schätzungen verwendet wurden. Die Ergebnisse deuten auch auf regionale Unterschiede hin: Die Auswirkungen des Bevölkerungswachstums auf das BIP-Wachstum pro Kopf sind in afrikanischen Ländern weniger negativ als in anderen Regionen. Basierend darauf zeigt die Masterarbeit, dass die Auswirkungen wahrscheinlich weniger negativ sind als dargestellt, hebt die Chancen in afrikanischen Ländern mit hohem Bevölkerungswachstum hervor und betont die Bedeutung des Studiensettings für die endgültigen Schätzungen.

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1. Introduction

Analyzing the effects of population growth on economic growth has received much attention in the literature. The motivation for analyzing in which direction the increased population growth affects economic growth if at all, is two-fold. In 2020, 8.44% of the people still lived in extreme poverty, and 25% of people lived in poverty defined by a poverty line of lower-middle-income countries (Hasell et al., 2022). Concurrently, the population growth rates in many of the poorest countries remain well above the high-income countries' average (World Bank, n.d.). One can theorize that higher population growth hinders economic growth through detracted human capital from investment, increased health risks for children and their mothers, and higher environmental threats (World Bank, 2010). These topics are often the focus of development economists aiming at, for example, reducing fertility rates in low-income regions, such as the famous Matlab experiment (Phillips et al., 1982). At the same time, many developed countries face rising dependency ratios (World Bank, n.d.) and low population growth (World Bank, n.d.), which can also pose risks to economic growth (Carone and Costello, 2006) and increase the burden on the economy. The direction of the effects of population growth on economic development thus not only concerns the ways to lift countries out of poverty but is also of great importance for current policies in developed countries with aging populations.

Whether population growth causes or hinders economic development is therefore a crucial question. However, the consensus about the overall effects of population growth is lacking in the literature and economic theory. One of the most popular related theories dating back to the 18th century – Malthusian theory (Malthus, 1798) – predicts negative effects on economic development. Some of the more recent well-known models such as Solow (1956) or Swan (1956) similarly predict a negative effect of increases in population growth on GDP per capita growth. On the other hand, models such as Romer (1986) assume a positive effect on economic growth thanks to increased population growth via higher stock of knowledge. Empirical papers do not present a clear view either. For example, a popular and cited paper by Kuznets (1967) did not find consistent effects of population growth. Others, such as Bloom and Williamson (1998) or Bloom and Malaney (1998) present a negative relationship, while Williamson and Mathers (2011) or Asimakopoulos and Karavias (2016) found a positive effect of population growth. The overall agreement of the academic literature on the effects is missing.

Therefore, with the intention to harmonize the evidence, I conduct a meta-analysis, a quantitative literature review on the topic of population and economic growth. Such a review collects empirical estimates and presents a synthesis of the overall evidence. This also allows me to detect potential publication bias, a situation in which certain results are preferred and more likely reported, while other estimates are discarded, leading to exaggerated and biased evidence (Stanley, 2005). Detecting publication bias can offer valuable insight by informing the reader about the attitude present in the literature, otherwise difficult if not impossible to detect. In addition, the heterogeneity analysis can uncover consistent patterns affecting the estimates, usually hidden from the eye of the reader. These patterns might include useful information and implications for policymakers as well as guidance for future research, identifying study settings and choice of methods employed by researchers significantly impacting the final estimates, and warning about specific sensitivities.

To perform a meta-analysis, I collect 573 estimates from 66 studies capturing the estimated effects of population growth on economic growth. The data demonstrate substantial variance: approximately 11% of these estimates indicate significant positive effects, 41% are insignificant, and 48% suggest significant negative effects of population growth on economic growth. I utilize advanced methods used in recent prominent meta-analyses to detect publication bias and to treat for model uncertainty in heterogeneity analysis.

My findings suggest that consistent and substantial publication bias favoring negative results is present in the literature, indicating that the evidence is likely to be exaggerated and the effects are less negative than commonly presented. The mean corrected estimate lies between -0.17 and -0.45, which would mean a reduction of 25-70% as compared to the mean estimate. The heterogeneity analysis uncovered specific sensitivities to the study design, including the choice of data type, scope and length of data, and choice of controls in the primary regressions. In addition, contrary to popular beliefs, the analysis suggests that the effects are less adverse in African countries. Lastly, the effects were found to be more adverse in the 1980s compared to other periods. Overall, the analysis should warn the reader about prevalent publication bias and offer guidance to policymakers as well as future researchers. The rest of the thesis is structured as follows: Chapter 2 presents the most popular population growth theories, empirical literature review, and highlights my contribution to the existing literature. Chapter 3 describes the process of data collection and offers both numerical and graphical descriptions of data. Chapter 4 explains the problem of publication bias, models used to detect publication bias, and the main results of the tests. Chapter 5 analyzes the heterogeneity in the estimates, methodology, and presents the main drivers. Chapter 6 concludes.

2. Literature review

2.1. Theoretical background

The economic theory provides several channels through which population growth could both hinder and promote economic development. The classical Solow-Swan Growth model, introduced more than 6 decades ago (Solow, 1956, Swan, 1956), predicts that higher population growth leads to lower steady-state capital and steady-state income per capita. Following Malthus (1798), his theory of demographic transition was introduced to the model, which enables the so-called "Malthusian poverty trap" to arise. According to this model, the population grows exponentially, whereas resources follow a linear trend, leading to lower standards of living. This phenomenon was also discussed in development theory by for example Leibenstein (1954) or Nelson (1956), which argues that a poor country's growth rate must be higher than the growth rate of population in order to escape the poverty trap. Coale and Hoover (1958) proposed several channels through which higher population growth hinders economic development such as resource-dilution effects where the capital is split between more persons, or resource diversion, where resources are shifted into rather indirectly productive health and education areas. Some studies, on the other hand, argued that population growth promoted agricultural innovation and adoption of new technologies (Boserup, 1981; Simon and Steinmann, 1981). More recently, several researchers focused on increasing returns to scale (Kremer, 1993; Romer, 1986), similarly suggesting that population growth can under certain conditions lead to economic growth through a higher stock of knowledge.[1]

To test the validity of economic models and estimate the effects of population growth on economic development, empirical studies using cross-sectional data define the estimation equation as follows:

$$\textit{Economic growth}_i = \alpha + \beta \cdot \textit{Population growth}_i + \sum_{k}^{K} \delta_k \cdot X_{ik} + \epsilon_i, \tag{2.1}$$

where the dependent variable is a measure of economic development, usually the growth rate of real GDP, real GDP per capita, or real GDP per worker. The main explanatory variable is a measure of population growth, usually the growth in total population, growth in working-age population, or fertility rates. X includes other independent variables that help explain economic development, such as investment or human capital, and ϵ_i denotes

[1] More detailed reviews of economic models are available, for example, in Shapirov (2015) or Pietak (2014).

the error term.

If a study utilizes the panel data structure instead of cross-sections, the equation is slightly modified:

$$\textit{Economic growth}_{it} = \alpha + \beta \cdot \textit{Population growth}_{it} + \sum_{k}^{K} \delta_k \cdot X_{itk} + \omega_i + \mu_t + \epsilon_{it}, \quad (2.2)$$

where ω_i denotes country-fixed effects, μ_t denotes the time-fixed effects, and ϵ_{it} is the error term that varies both over time and countries.

In this work, my focus lies on the estimates of β in the aforementioned equations. Moreover, I decided to focus solely on studies using the growth rate of real GDP per capita as a dependent variable, and the growth rate of the total population as an explanatory variable. These measures seem to be the most common choice for the researchers, as shown in Headey and Hodge (2009). This way, the collected data are directly comparable and do not require any recalculation, which can lead to imprecision. As presented in Headey and Hodge (2009), the estimated relationship between population growth and economic development can vary greatly, depending on different measures of population growth. Thus, in order not to mix uncomparable effects, I only consider studies estimating the effects of the total population growth. Note that in this case, the interpretation of the coefficients becomes straightforward: if total population growth increases by 1%, the economic growth will increase or decrease by β%, depending on the sign of the coefficient.

2.2. Empirical literature

The empirical literature on the topic of population and economic growth lacks a unified stance on the overall relationship. Kuznets (1967), in a widely cited and popular article, did not find a consistent relationship between population growth and development and noted substantial differences between developed and underdeveloped countries as well as different population groups within individual countries. Bloom and Williamson (1998), Bloom and Malaney (1998), and Bloom et al. (2000) found a mostly negative and significant relationship between population and economic growth with an average estimate ranging between -1.4 and -1.7, meaning that 1% increase in population growth has more than proportional effect on economic growth – it is expected to decrease by 1.4-1.7%. In other popular empirical studies from 1990s and 2000s, as in Klasen (2002) and Mauro (1995), a negative relationship of similar magnitude was found, although not always significant. More recently, Williamson and Mathers (2011), Baskaran and Feld (2013), or Asimakopoulos and Karavias (2016), found mostly a positive association, but similarly to previous studies, the significance was often missing. X. Li and Liu (2005), Aisen and Veiga (2013), or Malikane and Chitambara (2017) presented negative coefficients, but of somewhat smaller magnitude compared to older studies, suggesting less than proportional effects.

Apart from the effects of different magnitudes, researchers also often present results for different regions or countries. Ogundari and Awokuse (2018), Malikane and Chitambara (2017), Tumwebaze and Ijjo (2015), Zghidi et al. (2016), Ndoricimpa (2017), Savvides (1995), or Zahonogo (2016) analyzed the relationship between population and economic growth in African countries, whereas others such as Chu (2012), Levendis and Lee (2013), or Golley and Zheng (2015) focused on Asian region. Brander and Dowrick (1994), Were (2015), Hayat (2018), Ruiz (2018), Asimakopoulos and Karavias (2016), S. M. Miller and Russek (1997), X. Li and Liu (2005), Moreira (2005), Filipovic (2005), Ahsan and Haque (2017) analyzed the effects separately for developing countries, often lacking significance. Baskaran and Feld (2013), Brkić et al. (2020), and Mencinger et al. (2014) used data for Europe and OECD countries, possibly suggesting a positive relationship, but in most cases insignificant. The estimated effects for developed countries can be found in Brander and Dowrick (1994), Klasen (2002), Were (2015), Hayat (2018), Ruiz (2018), Asimakopoulos and Karavias (2016), S. M. Miller and Russek (1997), or X. Li and Liu (2005), with mean effect being negative and smaller than proportional. Substantial heterogeneity in the estimated effects is present.

Several literature reviews on the topic are available. To mention a few, some can be found for instance in McNicoll (1984), Birdsall (1988), Dasgupta (1995), or more recently, in Menike (2018). However, the paper most closely related to this work can be found in Headey and Hodge (2009), which conducted a quantitative meta-regression of the literature on the topic of population and economic growth. They found that the age patterns matter significantly for the overall effects – the increase in the young population has a negative effect on economic growth, whereas the increase in the adult population has a positive effect. The overall effect of population growth was found to be typically insignificant. They also found weak evidence for the aforementioned dilution and resource-diversion effects. The effects of population growth were found to be increasingly adverse since the 1980s. The meta-regression did not provide much evidence suggesting that the effects are more adverse in developing countries. In fact, in some cases, they found contradictory evidence. Lastly, they present some evidence implying that certain data characteristics such as different time coverage or the use of panel data rather than cross-sections and econometric methodologies, for instance, the use of weighted least squares, might affect the final estimates as well. Nonetheless, it is important to keep in mind that this quantitative review of the literature failed to address some important issues.

2.3. Contribution

Most importantly, the previously conducted meta-regression analysis (Headey and Hodge, 2009) did not address two main issues: potential publication bias and model uncertainty. Firstly, the publication bias is a problem prevalent in the literature. If certain results are preferred and reported while others are omitted, the collected evidence will be biased. The meta-analysis allows me to test for the so-called selective reporting and it is

possible to estimate the mean corrected effects. Although the analysis in Headey and Hodge (2009) works with t-statistics, they did not perform rigorous publication bias tests. Secondly, model uncertainty is a problem typical for meta-regression analyses. With many collected explanatory variables, it is likely that some of them are highly correlated among themselves, giving rise to collinearity and consequently, imprecise estimates. Moreover, many of the collected variables will prove to be redundant and unimportant in the analysis, exaggerating the imprecision in the analysis even further. Thus, the researcher usually faces significant model uncertainty (Irsova et al., 2023). However, Headey and Hodge (2009) did not control for this. In addition, the sample used in Headey and Hodge (2009) is by now outdated – it covers the literature only up to 2007. In more than 10 years, the approaches and the quality of the data used in the primary studies may have advanced. Thus, enlarging the dataset might provide different, robust results and question the previous findings (Irsova et al., 2023). Therefore, I also aim to update the dataset and include the most recent studies.
My contribution is therefore three-fold:

1. I address the problem of selective reporting and perform rigorous publication bias tests. Besides linear specifications, I utilize non-linear models that allow for non-linear breaks at certain data points. I also present the estimated mean corrected effects that take into account potential publication bias.

2. I address model uncertainty by utilizing Bayesian model averaging. The model averaging techniques are becoming more prevalent in meta-analyses, as they treat for model uncertainty and allow researchers to identify the most important and relevant explanatory variables (Havránek et al., 2020).

3. I update the dataset and include the most recent studies. As the dynamics of the relationship might change over time, such an enlarged dataset might offer more insights and new answers to the questions concerning population and economic growth. Additionally, an enlarged dataset with significantly more observations, using new papers utilizing advanced approaches and potentially higher quality data should lead to a more robust analysis and results.

In this work, I want to build on the previous MRA and use rigorous, state-of-the-art techniques to improve quantitative analysis to address the aforementioned issues, following most recent prominent meta-analyses such as Gechert et al. (2022), Cazachevici et al. (2020), Matousek et al. (2022), or Zigraiova et al. (2021). I will also revisit the main hypotheses formulated in the previous meta-regression analysis (see Chapter 5) using a larger sample, providing additional evidence and answers to the hypothesis questions. The obtained results should identify potential publication bias, give guidance to future researchers, and highlight sensitivities of estimates to primary study settings, as well as advice to policymakers concerned with the question of population growth. Especially, the results can be useful for less developed countries that seek ways to adopt growth-promoting solutions, or developed countries facing stagnation.

3. Data collection

3.1. Search query

As a first step, I consider 29 studies used in the previous meta-regression conducted by Headey and Hodge (2009). To enlarge this dataset and include also most recent studies, I continue my search in Google Scholar. Given the large amount of studies, I define the following inclusion criteria that a study needs to satisfy in order to be included in my final sample:

- a study must use the growth rate of real GDP per capita as a dependent variable.
- a study must use the growth rate of the total population as an independent variable. As shown in Headey and Hodge (2009), this is a common approach in the literature.
- following Headey and Hodge (2009), I excluded studies that include nonlinear relationships between population and economic growth to ensure data consistency.
- a study must report a numerical estimate of β in Equation 2.1 or Equation 2.2.
- a study must report a measure of the precision of an estimate such as standard errors or t-statistics.
- a study must be clear about the number of observations, number of countries, and time period of the data used for the estimation.
- a study must be clear about the methodology used to estimate the relevant coefficients.

The first three inclusion criteria lead to a substantial decrease in the number of relevant studies, which makes the data collection feasible and ensures data homogeneity by making the estimates directly comparable. In this approach, I can avoid recalculating the estimated effects into the same metric and retain all the information contained in the data. To search for the relevant studies, I use the following keywords in Google Scholar: "population growth" AND "economic growth", "population growth" AND "economic development", and "population growth" AND "on economic development". I pay special attention to studies published after 2007 as the previously conducted meta-regression provides the literature up to the year 2007 and repeat the search while omitting studies published earlier. In each case, I examine the first 500 results to identify all potentially important papers and focus on 206 empirical studies containing the estimates of the population growth effects. The search was terminated in February 2024. Taking into account all of the inclusion criteria, 573 empirical estimates and their standard errors from 66 studies were included in the final dataset. Note that the dataset in Headey and Hodge (2009) included several working papers. Therefore, I did not limit myself only to published articles, following closely their approach. Nonetheless, the defined criteria led to the omission of most working papers that were found. In the end, my final sample included 64 studies and 2 working papers. Additionally, next to the effect estimates and the standard errors, I collected 36 other explanatory variables that might be later important in explaining heterogeneity in the estimated effects. These variables are listed and explained in more detail in Chapter 5.

3.2. Data

The collected sample covers 3 decades of research, and the time coverage in the data used by primary studies covers the period from the 1950s until the 2020s, almost seven decades. The complete list of all studies included in the meta-analysis can be found in Table 3.1. The collected data can now be described both numerically and graphically. I start with the numerical description which is shown in Table 3.2. Both unweighted and weighted mean estimated effects of population growth on economic growth are equal to -0.72. This would suggest that if population growth increases by 1%, the economic growth is expected to decrease by 0.72%. The median estimated effect is somewhat smaller and equal to -0.52, suggesting that the means are to some degree driven by a few outliers. The same applies to standard errors of the estimates. While the means are relatively large compared to the mean effect estimates, the median standard error is equal to 0.29. Substantial heterogeneity is present in the data: approximately 11% of the estimates suggest positive effects, 41% are insignificant, and 48% suggest negative effects. Overall, 59% of the estimates have t-statistics larger than 1.96 in the absolute value, which would correspond to the commonly used p-value of 5%.

Because extreme outliers might drive the summary statistics, I use the winsorization process to replace these effect estimates and standard errors with more plausible values, as done for instance in Gechert et al. (2022) or Zigraiova et al. (2021), and defined in J. N. Miller (1993). As opposed to trimming, this does not lead to the exclusion of data from the dataset and is thus preferred. Formally speaking:

$$\beta_w = min[max(\beta, \beta_p), \beta_{1-p}] \tag{3.1}$$

$$SE(\beta)_w = min\{max[SE(\beta), SE(\beta)_p], SE(\beta)_{1-p}\}, \tag{3.2}$$

where p is the proportion of the data that we want to replace from both sides, β_p and $SE(\beta)_p$) are the lower thresholds, and β_{1-p} and $SE(\beta)_{1-p}$ denote the upper threshold. In this work, I use $p = 0.025$. In other words, I replace the extreme lower and upper 2.5% of the data. The summary statistics for the winsorized dataset can be found in the bottom part of Table 3.2. The values are less spread out, and the means are somewhat closer to the median estimates.

Table 3.1.: Studies used in the meta-analysis

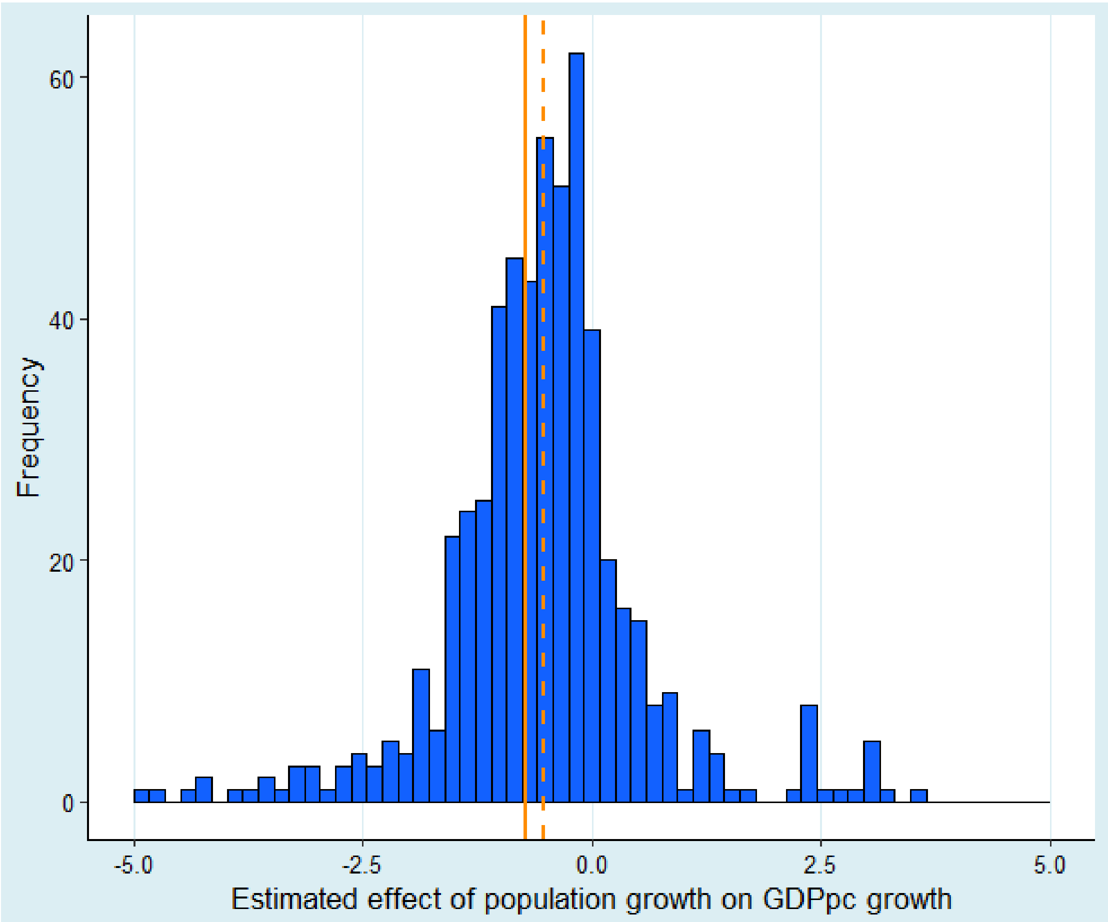
Ahsan and Haque (2017)	Aisen and Veiga (2013)
Alimi et al. (2021)	Asimakopoulos and Karavias (2016)
Baskaran and Feld (2013)	Bloom and Williamson (1998)
Bloom and Malaney (1998)	Bloom et al. (2000)
Bloom and Finlay (2009)	Brander and Dowrick (1994)
Brkić et al. (2020)	Castells-Quintana and Wenban-Smith (2020)
Chee and Nair (2010)	Cho (1996)
Chu (2012)	Cui (2017)
Durham (2004)	Easterly et al. (1997)
Epaphra and Kombe (2017)	Filipovic (2005)
Fincke and Greiner (2015)	Galor and Zang (1997)
Golley and Zheng (2015)	Hajamini (2015)
Hakim et al. (2016)	Hayat (2018)
Ihnatov and Căpraru (2012)	Imi (2005)
Jayasuriya and Burke (2013)	Jetter (2017)
A. C. Kelley and Schmidt (2005)	Klasen (2002)
Klasen and Lawson (2007)	Klasen and Lamanna (2009)
Kurzman et al. (2002)	Lai and Yip (2022)
Lee and Lin (1994)	Levendis and Lee (2013)
Levine and Renelt (1992)	X. Li and Liu (2005)
H. Li et al. (2000)	Malikane and Chitambara (2017)
Mauro (1995)	Mencinger et al. (2014)
S. M. Miller and Russek (1997)	Moreira (2005)
Naudé (2004)	Ndoricimpa (2017)
Obamuyi and Olayiwola (2019)	Ogundari and Awokuse (2018)
Okada and Samreth (2014)	Papapetrou and Tsalaporta (2020)
Ruiz (2018)	Sangkhaphan and Shu (2019)
Savvides (1995)	Shabbir et al. (2016)
Shabbir (2017)	Song (2013)
Sultana et al. (2022)	Thao (2018)
Tumwebaze and Ijjo (2015)	Were (2015)
Williamson and Mathers (2011)	Zahonogo (2016)
Zergawu et al. (2020)	Zghidi et al. (2016)

Table 3.2.: Numerical description of the estimated effects

	Mean	Weighted mean	Median	Min.	Max.	SD
Estimated effect	-0.72	-0.72	-0.52	-24.28	11.35	2.19
Standard error	1.59	0.55	0.29	0.00	32.93	2.04
Winsorized data						
Estimated effect	-0.61	-0.60	-0.52	-4.23	2.41	1.16
Standard error	0.43	0.43	0.29	0.02	2.41	0.46

Notes: The table reports the mean and median reported estimate of the effect of population growth on GDPpc growth. Weighted = estimated effects are weighted by the inverse of the number of estimates per study so that each study is assigned the same weight. Winsorization process utilizes p=0.025. Min. = minimum, Max. = maximum, SD = standard deviation, GDPpc = gross domestic product per capita.

Figure 3.1.: Distribution of the estimated effects



Notes: The figure shows the distribution of the estimated effects of population growth on GDPpc growth. The solid vertical line denotes the mean estimated effect, the dashed vertical line denotes the median estimated effect. Estimates smaller than -5 and greater than 5 are excluded from the figure for ease of exposition. GDPpc = gross domestic product per capita.

The estimates are graphically depicted in Figure 3.1. The histogram of the effect estimates also depicts the mean estimated effect, denoted by the solid vertical line, and the median estimated effect, denoted by the dashed vertical line. Clearly, most of the estimates are negative - in fact, around 79% of all the estimates are smaller than 0. The histogram is rather skewed, and instead of peaking at the mean estimate, it peaks noticeably closer to 0. This might, however, suggest that publication bias is present in the literature. Therefore, I continue with a detailed publication bias analysis in the following section.

4. Publication bias

4.1. Defining publication bias

Publication bias is a common problem that arises if researchers or publishers favor, consciously or unconsciously, specific results and only a certain part of the overall evidence gets published. As a consequence, the evidence collected from the studies gets distorted and biased, being no longer a good representation of actual knowledge (Thornton and Lee, 2000). There are two main types of publication bias. Type I publication bias arises if the researchers and publishers only focus on intuitive results, discarding the estimates that are clearly faulty and unexpected (Thornton and Lee, 2000). However, the evidence is also likely to contain exaggerated estimates that are much harder to recognize and discard from the analysis. Because seemingly faulty estimates are omitted and the overestimated ones are kept, the evidence is distorted and bias arises (Gechert et al., 2022). On the other hand, type II publication bias refers to a situation when statistically significant results are preferred, whereas estimates that are not significantly different from zero are discarded. In other words, the authors and publishers prefer to find some supporting evidence, rather than the non-existence of the effects (Stanley, 2005).

In my case, both publication bias of type I and type II might be present in the literature. As already shown in the previous chapter and Headey and Hodge (2009), the effects of population growth on economic growth are rather negative. Presumably, negative results might be therefore preferred to positive estimates, giving rise to a type I publication bias. Moreover, given the large amount of various economic theories focusing on the importance of population growth as one of the determinants of economic development, researchers might be tempted to omit the insignificant results. This would lead to type II publication bias.

Although Headey and Hodge (2009) discusses the t-statistics of the estimated population growth effects, their study lacks a thorough and rigorous publication bias analysis. Therefore, I now turn my attention to novel techniques to detect publication bias in the literature. The following sections discuss the methodologies and results in detail.

4.2. Methodology

To detect publication bias, I follow other recent meta-analyses that can be found in Gechert et al. (2022), Cazachevici et al. (2020), Matousek et al. (2022), or Zigraiova et al. (2021), and conduct several linear and non-linear tests, including tests that allow for endogeneity in the standard errors. As a first step, I plot the so-called funnel plot proposed by Egger et al. (1997). This simple graphical test originally plotted the estimated effects against the inverse of the sample size, used as a proxy for precision. Alternatively, the inverse of the standard errors can also be used as an approximation of precision. Because I have the standard errors of the estimated effects at hand, as in the aforementioned papers, this work uses the latter proxy. If there is no selective reporting in the literature, this plot should be symmetric and the estimates should be distributed around the true mean. However, if publication bias is present, the funnel plot will be asymmetrical and skewed (Egger et al., 1997).

Then I will continue with more rigorous regression-based linear tests as described in Stanley and Doucouliagos (2010). These regression-based techniques assume that if there is no publication bias, standard errors should be statistically independent of the estimates. The equation to be estimated is:

$$\beta_{ij} = \beta_0 + \gamma SE(\beta_{ij}) + \epsilon_{ij}, \tag{4.1}$$

where β_{ij} is the i^{th} estimated effect of population growth on economic growth from the j^{th} study, $SE(\beta_{ij})$ is the corresponding standard error, and ϵ_{ij} is the error term. The statistical significance of the coefficient γ can be seen as a statistical funnel asymmetry test for publication bias. The estimated intercept denotes the true effect beyond the bias.

I estimate the baseline Equation 4.1 using simple OLS. In addition, I also estimate the between-effects model, which uses the between-study differences and allows for more balanced study weights (Viechtbauer, 2010). As an alternative, I use weighted least squares and weight the Equation 4.1 by the inverse of the study size (number of estimates per study). This way, each study gets the same weight. Lastly, to address endogeneity in the standard errors, I employ the instrumental variable regression. Naturally, the differences in standard errors and estimates might be driven by the estimation techniques and different study designs. The instrument that I chose to use is the inverse of the number of observations used to estimate the population growth effects, as common in other papers (Gechert et al., 2022). This instrument is likely to be correlated with the standard errors, but at the same time, it should be independent of the study design. Thus, it should satisfy the exclusion restriction and treat for the hypothetical endogeneity of the standard errors. In all these specifications, I use winsorized data and I cluster the standard errors at the study level to also control for potential correlation within individual studies.

Eventually, I will allow for non-linear publication bias. All these methods are explained in an easy manner in works such as Simpartl (2023), Čala (2021), or Kamenická (2021). I start by using the stem-based method developed by Furukawa (2019). This method works only with the stem of a funnel plot – a certain proportion of studies that suffer from less bias. The number of studies is chosen by minimizing the mean squared error determined by the bias-variance trade-off. The more imprecise estimates I discard in the analysis, the smaller the bias. However, at the same time, I also discard the information in the data and the sample will suffer from high variance. This can be written as:

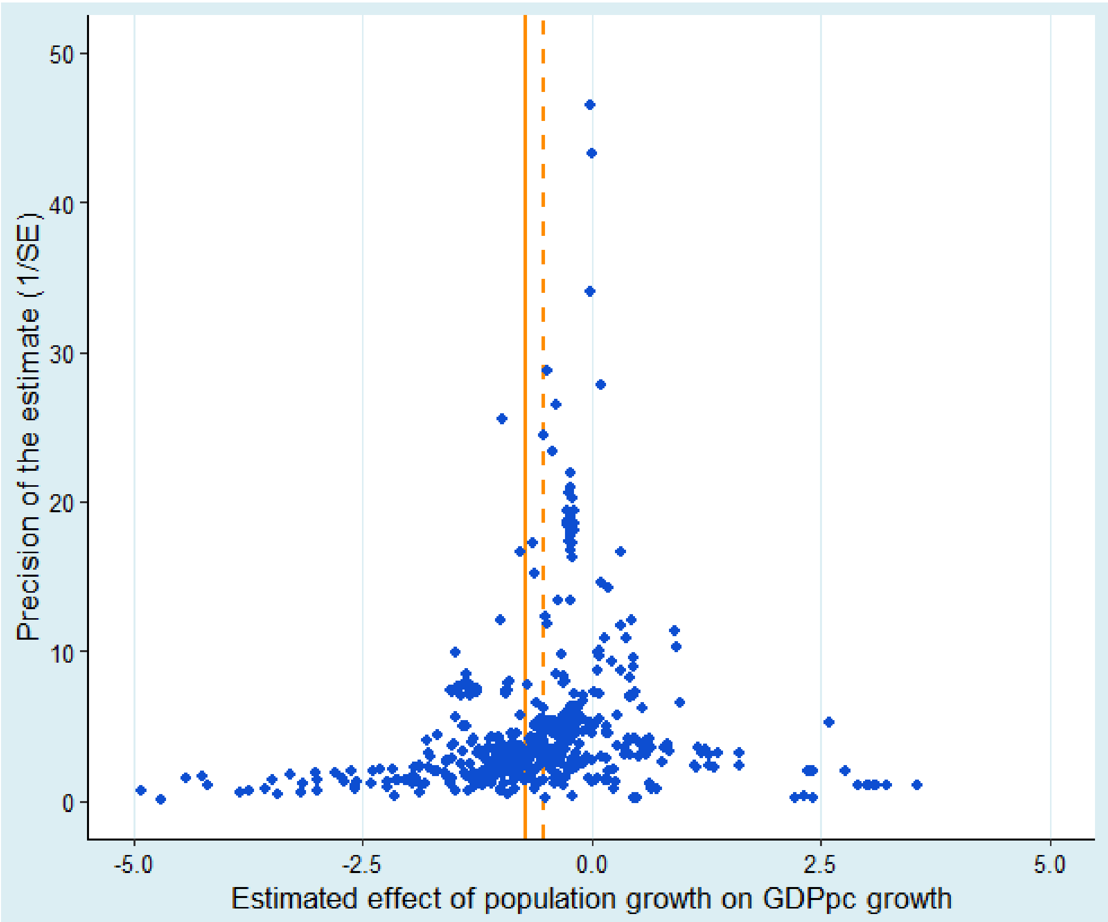
$$minMSE(n) = Bias^2(n) + Var(n), \tag{4.2}$$

where MSE denotes the mean squared error and Var denotes the variance.
Next, I adopt the so-called Selection model developed by Andrews and Kasy (2019) that utilizes conditional publication probability – the probability of a study being published conditional on its results. A parametric model for the publication probability is assumed and fitted by maximum likelihood. Using the identified conditional probabilities, the method estimates the bias-corrected estimate. Unlike remaining non-linear techniques, this model does not discard any estimated effects. Instead, it assumes a specific distribution function of the published estimates given the true effects. Using this function, it reweights the estimates by applying different weighting schemes to different intervals of the reported significance levels. I chose the intervals by looking at the histogram of t-statistics of the estimates, which can be found in Figure A.1. Assuming that certain estimates are overreported, these receive smaller weights, whereas estimates that are specified to be underreported receive larger weights. Nonetheless, the Selection model rests on an assumption that the estimates of the effects and the corresponding standard errors should be statistically independent if there is no publication bias present – the correlation between the estimates and standard errors should be approximately zero. However, even in the absence of publication bias, it is likely that the standard errors are endogenous for various reasons (Gechert et al., 2022). Normally, the true distribution of the estimates of the effects is unknown. In the case of the Selection model, it is possible to weight the estimates by the inverse of the estimated publication probability to identify the assumed distribution function (Kranz and Pütz, 2022) and test whether the correlation is significantly different from 0. Following Havranek et al. (2022), I report the results of this test in Table A.1, suggesting that the correlation is not zero. Therefore, we must keep in mind that a crucial assumption is not satisfied when interpreting the main results.
Then, I use the Weighted Average of Adequately Powered (WAAP) method, proposed by Ioannidis et al. (2017). This technique uses only the estimates that have adequate statistical power – above 80%. This accounts mainly for the non-linear break point where the absolute value of t-statistics is equal to 1.96, translating to a commonly used p-value of 5%.
Lastly, I utilize the p-uniform* method (van Aert and van Assen, 2021) from psychology. Similarly to the IV regression, this method also relaxes the exogeneity assumption. The p-uniform* test assumes that in the absence of publication bias, the p-values at the mean underlying effect should follow a uniform distribution. Therefore, the mean corrected effect is estimated by searching for such a subset of estimates and their standard errors, of which the p-values approximate the uniform distribution (Gechert et al., 2022). The model specifies densities for the effect sizes as a function of the true mean, assuming the uniform distribution of p-values, and is fitted by maximum likelihood.

4.3. Results

The funnel plot, utilizing unwinsorized data, can be found in Figure 4.1. The plot is hardly symmetrical, providing the first evidence for the presence of publication bias. Most estimates in my sample are negative, and the stem of the funnel plot is noticeably closer to 0 than the mean or median estimate, suggesting that negative estimates might be preferred. However, as already noted, this is a simple graphical test and the interpretation might be subjective.

Figure 4.1.: Funnel plot suggests publication bias



Notes: The figure depicts the funnel plot for the estimated effects of population growth on GDPpc. If there is no publication bias, estimates should be symmetrically distributed around the mean, denoted by the solid vertical line (Egger et al., 1997). The dashed vertical line denotes the median estimated effect. Estimates smaller than -5 and greater than 5 are excluded for ease of exposition. GDPpc = gross domestic product per capita.

The results from rigorous, regression-based linear techniques using winsorized data are

Table 4.1.: Linear techniques suggest publication bias

	OLS	BE	Study-size	IV
Standard error	-0.714***	-0.920***	-1.012***	-1.220
Publication bias	(0.210)	(0.136)	(0.204)	(0.972)
Constant	-0.300***	-0.227***	-0.170*	-0.085
Mean beyond bias	(0.072)	(0.078)	(0.406)	(0.389)
Mean of the dependent variable	-0.605	-0.605	-0.605	-0.605
Observations	573	573	573	573
Studies	66	66	66	66
Weak instruments				12.029***

Notes: The table reports results of the regression $\beta_{ij} = \beta_0 + \gamma SE(\beta_{ij}) + \epsilon_{ij}$. β_{ij} and $SE(\beta_{ij})$ denote the i^{th} estimate of the effect of population growth on GDPpc growth and its standard error, respectively. BE = between-effects model. Study size = the inverse of the number of estimates reported per study is used as the weight. IV = the inverse of the sample size used to generate the estimate is used as an instrument for the standard error. The standard errors are clustered at the study level and reported in parentheses. ***, ** and * denote statistical significance at 1%, 5% and 10% level. The data used for linear tests are winsorized at 2.5%.

depicted in Table 4.1. The baseline OLS specification produces a statistically significant estimate of the coefficient γ, suggesting that publication bias in favor of negative results is present. The estimated intercept is also statistically significant at 1% level, and it is substantially closer to zero than the mean estimated effect. The results from the between-effects model are of a similar magnitude. Both the estimated coefficient γ and the intercept are statistically significant at 1% level. The weighted specification also suggests publication bias, with the coefficient γ being highly statistically significant. The estimated intercept is also statistically significant, but only at 10% significance level. The IV regression produces only imprecise estimates, although F-statistics testing for weak instruments is large enough to reject the null hypothesis. The estimates are of a similar magnitude as the previous specifications, however, given the relatively large standard errors, we must stay cautious with the interpretation. Overall, the estimated statistically significant γ is close to 1. Following the interpretation of Doucouliagos and Stanley (2013), $|\gamma| < 2$ suggests that publication bias is modest to substantial. The mean beyond bias is estimated to lie between -0.30 and -0.17. This would mean that the absolute value of the mean beyond bias could be approximately 50-70% smaller than the evidence from the literature tells us.

Finally, the results of the non-linear techniques, using winsorized data, are shown in Table 4.2. The estimated mean beyond bias is statistically significant in all four cases, and it is noticeably closer to zero than the mean estimated effect. The estimates range from -0.30 and -0.45. In the absolute values, these estimated means are approximately 25-50% smaller than the mean estimated effect.

Table 4.2.: Non-linear techniques suggest publication bias

	Stem-based	Selection model	WAAP	p-uniform*
Constant	-0.452***	-0.370***	-0.360***	-0.304***
Mean beyond bias	(0.023)	(0.061)	(0.050)	
p-value	<0.001	<0.001	<0.001	0.007
Mean of the dependent variable	-0.605	-0.605	-0.605	-0.605

Notes: The table depicts the results of non-linear techniques to test for the presence of publication bias. Stem-method developed by Furukawa (2019) works with a certain proportion of the estimates, chosen by minimizing the mean squared error determined by the trade-off between bias and variance. The Selection model introduced by Andrews and Kasy (2019) estimates the mean corrected effect by assigning different weighting schemes to different intervals of the reported p-values based on the conditional publication probability. WAAP model developed by Ioannidis et al. (2017) focuses only on estimates with adequate power. P-uniform* test, developed by van Aert and van Assen (2021), assumes that the p-values follow the uniform distribution at the mean underlying effect. For the WAAP method, the standard-errors are clustered at the study-level. ***, ** and * denote statistical significance at 1%, 5% and 10% level. The data used for non-linear tests are winsorized at 2.5%.

Overall, both linear and non-linear techniques consistently suggest that publication bias is present in the literature – negative effects are likely to be preferred over positive or insignificant ones. The linear tests found a statistically significant correlation between the estimates and their standard errors that would suggest modest or substantial publication bias and the mean corrected effects are considerably closer to zero than the mean estimated effect. In the absolute value, the non-linear methods produced somewhat larger estimates of the mean beyond bias than the linear tests, but nonetheless, they are much smaller than the unconditional mean. The results indicate that the true effects of population growth on economic development could lie between -0.17 and -0.45 – a reduction of 25-70%.

Still, it is important to keep in mind that the estimates and their standard errors can be correlated with other aspects of the study design such as estimation techniques, data characteristics, or the use of controls in primary studies. These variables could also explain the differences in the estimated effects. The next Chapter 5 is thus devoted to a detailed analysis of the sources of heterogeneity.

5. Why do estimates differ?

5.1. Methodology

In this section, I aim to uncover the potential drivers that could influence the effect estimates. The baseline regression to be estimated can be formally written as:

$$\beta_{ij} = \beta_0 + \sum_j \gamma_j X_{ij} + \epsilon_{ij}, \tag{5.1}$$

where β_{ij} denotes the i^{th} effect estimate from the j^{th} study, and X_{ij} denotes the vector of all explanatory variables that could potentially explain the heterogeneity in the estimates. β_0 stands for the intercept, ϵ_{ij} is the error term.

Given the large amount of explanatory variables, meta-analytic regressions often suffer from substantial model uncertainty. In my case, I collected 37 explanatory variables, many of which might prove to be redundant, irrelevant, and correlated, causing the estimates to be imprecise (Irsova et al., 2023). However, identifying a single suitable model is practically infeasible – with 37 explanatory variables, there are 2^{37} possible models with different combinations of explanatory variables that are impossible to analyze manually. Recently, the use of Bayesian Model Averaging (BMA) has become common in meta-analyses (Havránek et al., 2020, Irsova et al., 2023), for instance in Cazachevici et al. (2020) or Gechert et al. (2022). Because this method addresses the model uncertainty, I follow the aforementioned meta-analyses and utilize the BMA method to identify the most important drivers of heterogeneity.

To treat model uncertainty, BMA estimates a large number of possible specifications with different posterior model probabilities (PMP). Following the classification in Gechert et al. (2022), PMP can be seen as an information criterion, depicting how well the model performs. Additionally, BMA results also include posterior inclusion probabilities (PIP) for each explanatory variable. This metric is calculated as a sum of the PMPs of all the models where the corresponding variable is included. Thus, PIP reflects the importance of the corresponding variable in the model. The BMA estimation also produces the posterior mean (PM) and posterior standard deviation (PSD) of the coefficients. As with other Bayesian methods, this model averaging technique aims to identify the best approximation of the distribution of the regression parameters γ_j, conditional on our dataset and our set of possible models.

The process is explained in detail in Hoeting et al. (1999). Formally speaking, let $D =$ sampled data, $N =$ the number of possible explanatory variables, $K =$ the number of all possible specifications, or 2^N. Then set of all possible models will be denoted as $M = M_1, M_2, ..M_K$. PMP, based on Bayes' theorem, can now be defined as:

$$PMP = P(M_K|D) = \frac{P(D|M_k)P(M_k)}{P(D)} = \frac{P(D|M_k)P(M_k)}{\sum_{k=1}^{K} P(D|M_k)P(M_k)}, \tag{5.2}$$

where $P(D|M_k)$ stands for the marginal likelihood of model M_k. $P(M_k)$ is the prior model probability, which requires us to formulate our beliefs about the probability distribution of all models. The denominator is a sum of all marginal likelihoods for models from the set M. The marginal likelihood of model M_K can be derived as

$$P(D|M_k) = \int P(D|\gamma_k, M_k)P(\gamma_k|M_k)d\gamma_k, \tag{5.3}$$

where γ_k denotes the vector of regression parameters of model M_k, $P(\gamma_k|M_k)$ is the prior density of γ_k under model M_k and $P(D|\gamma_k, M_k)$ is the likelihood.
Finally, the PM for the i^{th} variable can be derived as:

$$PM = E(\gamma_i|D) = \sum_{k=1}^{K} \hat{\gamma_{ik}} P(M_k|D), \tag{5.4}$$

where $\hat{\gamma_{ik}}$ is the regression coefficient for the variable i, estimated by the model M_k. Posterior variance can be calculated as (Raftery, 1993; Draper, 1995):

$$Var(\gamma_i|D) = \sum_{k=1}^{K}(Var(\gamma_i|D, M_k) + \hat{\gamma_{ik}})P(M_k|D) - E(\gamma_i|D)^2 \tag{5.5}$$

As noted, I need to first make some assumptions about the prior model probability $P(M_k)$ as well as the prior density of the parameters $P(\gamma_k|M_k)$ (Hoeting et al., 1999). I choose the priors following recent papers such as Bajzik et al. (2020), Matousek et al. (2022), or Zigraiova et al. (2021). For the prior model probability, I choose dilution prior suggested by George (2010) which treats for multicollinearity among models. For the prior distribution of the coefficients, I use popular unit information prior (Eicher et al., 2011), which assigns the prior the same weight as one observation in the data – this prior lets the data speak for themselves.

As discussed in Hoeting et al. (1999), the model averaging seems to be easy to implement on the surface. However, researchers often face large model spaces using more than 30 variables where deterministic methods are usually too computationally expensive or do not revisit all the models. Thus, the BMA is typically implemented using Markov chain Monte Carlo (MCMC) stochastic methods. For the estimation, I use the Bayesian model selection package for R software developed by Zeugner and Feldkircher (2015) (Havranek et al., 2018).

Moreover, as a robustness check, I perform a frequentist check following Cazachevici et al. (2020). I estimate ordinary least squares with the variables from BMA of which the posterior inclusion probability is larger than 0.50. This threshold is chosen based on the classification provided in Jeffreys (1998). According to him, variables with $0.50 < PIP < 0.75$ are weakly significant, variables with $0.75 <= PIP < 0.95$ are substantially significant, variables with $0.95 <= PIP < 0.99$ are strongly significant, and lastly, variable with $PIP >= 0.99$ are decisively significant. I include all the variables that are significant in the robustness check.

5.2. Explanatory variables

The previous meta-regression (Headey and Hodge, 2009) formulated 8 main research hypotheses that were investigated and provided the baseline set of explanatory variables that could be considered:

1. The total population or the working-age population growth should have less adverse effects on economic development than the growth in the dependent population.
2. The effects of population growth are more adverse in the presence of land scarcity (heterogeneity in the estimates if the primary study controls for the population density).
3. The effects of population growth are less adverse if the primary study controls for investment (resource-dilution effects).
4. The effects of population growth are less adverse if the primary study controls for education (resource-diversion effects).
5. The effects of population growth are more adverse if the primary study excludes education and health due to multicollinearity problems.
6. The effects of population growth are less adverse if the primary study controls for institutions (institutional interactions hypothesis).
7. The effects of population growth have been more adverse since the 1980s.
8. The effects of population growth are more adverse in developing countries.
9. The estimated effects of population growth are influenced by the choice of econometric methods and data characteristics.

The hypothesis number 1. can only be tested indirectly, by checking if including working population growth, in addition to total population growth, leads to different estimates of β. The land scarcity hypothesis is derived from the theory of Malthus (1798) who stated that while the population grows exponentially, the food resources only follow a linear trend, leading to a decrease in standards of living. However, this should not be seen as a direct test of his theory. The resource-dilution and resource-diversion effects hypotheses are based on Coale and Hoover (1958), proposing that population growth has negative effects on economic development because the capital is spread between more people and the resources are shifted into rather indirectly productive health and education areas. The institution interactions hypothesis stems from A. Kelley and Schmidt (2001). As argued, public spending or trade barriers might hinder labour-absorption and thus, population growth could only have positive effects on economic growth if it interacts with functioning institutions. Hypothesis number 7. rests on the fact that the population growth effects were found to be more adverse since the 1980s, although not clearly explained (for example Bloom and Freeman (1988), Brander and Dowrick (1994), also supported by Headey and Hodge, 2009). Hypothesis number 8. presents a popular belief that negative effects of population growth are more pronounced in developing countries, compared to developed regions. Lastly, answering hypothesis number 9. should offer guidance to future research and highlight the sensitivity of estimated effects to the primary study setting. I collected a set of variables that allowed me to re-test all of these previously analyzed hypotheses but one. Unfortunately, given the lack of studies controlling for health or public health expenditure, hypothesis number 5. will not be considered further. However, many other factors could affect the final estimates. Besides the standard errors of the estimates to account for publication bias, I collected 36 other explanatory variables, among these also some that can be used to test the aforementioned hypotheses. Note that I also performed multicollinearity tests to ensure that the variables are not highly correlated with each other and possibly capturing the same information. The explanatory variables were then divided into 5 main categories. Apart from the effect estimates and their standard error, I will discuss the data characteristics, structural variation, different model specifications, estimation techniques, and publication characteristics.

Table 5.1.: Explanatory variables

Variable	**Description**	**Mean**	**SD**
Effect estimate	Estimate of the effect of the population growth on the real GDPpc growth	-0.605	1.163
Standard error	Standard error of the estimate	0.425	0.464
Data characteristics			
Cross-sections	=1 if the study uses cross-sectional data for the estimation	0.253	0.435
Panel data	=1 if the study uses panel data for the estimation	0.747	0.435
Annual data	=1 if the study uses annual data from the estimation	0.358	0.480
Data length	=logarithm of the number of years captured by the data used for the estimation	3.084	0.557
1960s	=1 if the study uses data from 1960s or earlier	0.016	0.124
1970s	=1 if the study uses data from 1970s	0.161	0.367
1980s	=1 if the study uses data from 1980s	0.202	0.402
1990s	=1 if the study uses data from 1990s	0.295	0.456
2000s	=1 if the study uses data after 1990s	0.326	0.479

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Table 5.1.: Explanatory variables (continued)

Variable	Description	Mean	SD
Penn Table	=1 if the population data come from the Penn Table	0.141	0.349
World Bank database	=1 if the population data come from the WB database	0.681	0.467
Other data source	=1 if the population data come from other source	0.178	0.383
Structural variation			
Number of countries	=logarithm of the number of countries used for the estimation	3.514	1.371
Developed	=1 if the study uses data for developed countries for the estimation	0.120	0.326
Developing	=1 if the study uses data for developing countries for the estimation	0.211	0.408
Africa	=1 if the study uses data for African countries for the estimation	0.134	0.341
Asia	=1 if the study uses data for Asian countries for the estimation	0.134	0.341
Heterogeneous	=1 if the study uses data for a heterogeneous set of countries for the estimation	0.401	0.490
Specifications			
Initial level of development	=1 if the study controls for the initial level of economic growth in the regression	0.815	0.389
Dependency ratio	=1 if the study controls for dependency ratios in the regression	0.103	0.304
Working population	=1 if the study controls for the working population growth in the regression	0.096	0.295
Employment	=1 if the study controls for employment in the regression	0.077	0.266
Life expectancy	=1 if the study controls for life expectancy in the regression	0.072	0.258
Population density	=1 if the study controls for population density in the regression	0.052	0.223
Financial development	=1 if the study controls for financial development in the regression	0.223	0.417
Institutions	=1 if the study controls for the quality of institutions in the regression	0.284	0.452
Democracy	=1 if the study controls for democracy in the regression	0.138	0.345
Education	=1 if the study controls for human capital in the regression	0.607	0.489
Government consumption	=1 if the study controls for government consumption in the regression	0.272	0.446
Trade openness	=1 if the study controls for trade openness in the regression	0.628	0.484
Investment	=1 if the study controls for investment in the regression	0.698	0.459
Region dummies	=1 if the study includes individual region dummies in the regression	0.148	0.356

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Table 5.1.: Explanatory variables (continued)

Variable	Description	Mean	SD
Time dummies	=1 if the study includes time dummies in the regression	0.115	0.320
Number of explanatory variables	=number of explanatory variables in the regression (excluding the intercept and country or time-fixed effects)	8.330	3.465
Estimation techniques			
OLS	=1 if the study uses OLS to estimate the regression	0.277	0.449
GMM	=1 if the study uses GMM (Arellano-Bond approach) to estimate the regression	0.285	0.452
FE/RE	=1 if the study uses fixed-effects or random-effects to estimate the regression	0.311	0.463
IV regression	=1 if the study uses instrumental-variable regression	0.066	0.249
Other estimation technique	=1 if the study uses other estimation technique	0.061	0.240
Publication characteristics			
Citations	=logarithm of number of citations per year since the study was published	2.614	1.226
Impact factor	=the recursive discounted impact factor from RePEc	0.614	2.032

Notes: The table shows the set of explanatory variables that are used for the heterogeneity analysis along with their means and standard deviations. SD = standard deviation, GDPpc = Gross domestic product per capita, OLS = ordinary least squares, GMM = generalized method of moments, FE = fixed-effects, RE = random-effects, IV = instrumental variable.

Data characteristics

This category includes information about the data used by the primary study to generate the estimates, allowing me to discuss hypothesis number 9, testing whether data characteristics affect the final effects. I control for data dimension and distinguish between the cross-sectional data and panel data. None of the reviewed studies used time-series data. 75% of the estimates are produced using use panel data, whereas 25% utilize cross-sections. Another important channel might be the frequency of the data. Only 36% of the estimates are produced utilizing annual data. The rest of the studies chose to utilize the averaged, low-frequency data in order to eliminate and smooth out short-term fluctuations (Démurger, 2001). This includes using for example 3-year averages such as in Ruiz (2018), 5-year averages as in Bloom et al. (2000), or 7-year averages as did for example Savvides (1995). This also includes studies using averages over longer time periods, just like in Galor and Zang (1997). Additionally, I control for the data length, which captures the number of years used to generate the estimates. The mean number of years equals approximately 24 years. I also create a separate dummy variable for studies using data from different decades, starting in the 1960s up till the 2000s or later. This allows me to test the 7th hypothesis formulated by Headey and Hodge (2009) and check if the effects have been more adverse since the 1980s. Lastly, I control for the data source, as macroeconomic data are often prone to measurement error. The most common data sources are the

World Bank database and Penn Table. Other data sources include OECD data (Baskaran and Feld, 2013), IMF data (Fincke and Greiner, 2015), or statistical yearbooks (Chu, 2012).

Structural variation

This category comprises variables related to sample variation. Firstly, I control for the number of countries in the dataset used to generate the estimates. Most studies employ datasets including a relatively large number of countries, with the mean number of countries captured in the data being approximately 55. Second, the effects of population growth might substantially differ across regions, as Headey and Hodge (2009) mentioned in hypothesis 8. Therefore, I distinguish between the estimates produced using only data for a heteregenous set of developed (12% of the estimates) or developing countries (21% of the estimates). The dataset allows me to additionally distinguish the estimates produced using only data for African or Asian countries. Because some studies used large heterogeneous datasets including mixture of both developed and developing countries (40% of the estimates), I also separate these estimates.

Specifications

Another likely source of heterogeneity in the estimates is the use of different controls in the regression. Given the vast theoretical and empirical background suggesting that the initial level of development is an important indicator of future economic growth (Durlauf et al., 2008), most primary studies use the initial level of development as one of the key explanatory variables. Nonetheless, there are some studies that omit the initial level of development in the regression, such as for example Klasen and Lawson (2007) or Ndoricimpa (2017). Other important controls are those connected to population growth such as controlling for increases in dependent populations (as in Papapetrou and Tsalaporta (2020)), or working population growth (see for example Bloom and Williamson (1998)). Distinguishing these studies from others allows me to indirectly test the hypothesis number 1 which states that the growth of the working-age population should have less adverse effects on economic growth than growth in dependent populations. One could assume that if the primary study controls for the dependent populations, the coefficient on total population growth should be more positive (less negative) because it mainly includes the positive effects stemming from an increase in the working population. On the other hand, controlling for growth in the working population should result in more negative effects of population growth, as it now primarily captures the burden of the non-working population. Other controls connected to population dynamics are employment and life expectancy. Other common controls used by primary studies include population density (hypothesis number 2. related to land scarcity following Malthus (1798)), financial development, institutions (hypothesis number 6. – institutional interactions hypothesis, following A. Kelley and Schmidt (2001)), democracy, education (hypothesis number 4. – resource-diversion effects, following Coale and Hoover (1958)), government consumption, trade openness, investment (hypothesis number 3. – resource-dilution effects, following Coale and Hoover (1958)), region dummies that allow for different intercepts, and time dummies that could be effective in capturing various structural breaks in the data unrelated to other explanatory variables. Lastly, I also control for the number of explanatory variables used in the regression.

Estimation techniques

The choice of econometric method can also greatly influence the final estimates, already recognized in Headey and Hodge (2009) and formulated in hypothesis number 9. Therefore, I distinguish between estimates produced using OLS (found in, for example, Bloom and Williamson (1998)), fixed-effects or random-effects models (Brander and Dowrick, 1994), or IV regressions accounting for endogeneity in the explanatory variables (Imi, 2005). The updated dataset also allows me to distinguish the GMM approach, which has become increasingly common in recent years (for instance in Aisen and Veiga, 2013, Ogundari and Awokuse, 2018, or Ruiz, 2018). Other estimation techniques are pooled into one group given the lack of observations for each separate methodology and include for example weighted least squares (Brander and Dowrick, 1994) or Pooled Mean Group estimation (Zahonogo, 2016).

Publication characteristics

Following other prominent meta-analyses such as Havranek et al. (2016) or Cazachevici et al. (2020), I also control for publication characteristics. One could assume that studies published in trusted journals utilize more suitable methodologies and statistical approaches, or, on the other hand, publishers might prefer certain results over others, giving rise to publication bias. Therefore, I control for the number of citations (in Google Scholar) per year and the recursive discounted impact factor for the journal where the primary study was published.

5.3. Results

The results for BMA are graphically presented in 5.1. The horizontal axis shows the cumulative PMP so that the models are sorted from the best-performing on the left to the worst-performing on the right. On the vertical axis, the explanatory variables are sorted by their importance captured by PIP, so that the most relevant variables are on the top and the least relevant are on the bottom. The colors indicate the direction of the relationship – blue color means that the variable has a positive impact on the effect estimate, red color indicates a negative impact on the effect estimates, and white color means that the variable is not included in the corresponding model (Cazachevici et al., 2020).

The most important explanatory variable is the standard error. This result can be seen as additional evidence that publication bias is present. Even after controlling for many different aspects and study designs, the standard errors are highly significant in the regression. This variable is followed by variables time dummies and financial development that have a negative impact on the estimates. Next, the variables Africa and the number of countries have a positive impact, followed by the 1980s with a negative impact. Similarly, citations are negative affecting the estimates, meaning that more cited studies report more negative estimates – providing more evidence suggesting publication bias. Another significant variable that is positively correlated with the estimates is data length. Cross-sections and working population are the last significant variables in the regression with negative impact, following the significance classification in Jeffreys (1998). The numerical results for BMA including PIP, PM, PSD, and results of the frequentist robustness check are shown in 5.2.

Table 5.2.: Explaining the heterogeneity in the estimates

Response variable: Estimated effect	Bayesian model averaging (baseline model)			Frequentist check (robustness check)		
	PIP	PM	PSD	Coef.	SE	t-statistics
Intercept	**1.00**	-1.03		-1.25	0.26	**-4.85**
Standard error	**1.00**	-0.67	0.10	-0.66	0.09	**-6.95**
Data characteristics						
Cross-sections	**0.80**	-0.41	0.25	-0.40	0.13	**-3.09**
Annual data	0.02	0.00	0.02			
Data length	**0.80**	0.28	0.17	0.34	0.09	**3.63**
1960s	0.18	0.15	0.35			
1970s	0.02	0.00	0.03			
1980s	**0.97**	-0.50	0.16	-0.56	0.12	**-4.67**
1990s	0.02	0.00	0.02			
Penn Table	0.03	-0.00	0.05			
Other data source	0.02	-0.00	0.05			
Structural variation						
Number of countries	**0.98**	0.20	0.06	0.20	0.04	**4.91**
Developed	0.01	-0.00	0.02			
Developing	0.06	-0.01	0.06			
Africa	**1.00**	0.69	0.15	0.66	0.13	**5.01**
Asia	0.02	-0.00	0.06			
Specifications						
Initial level of development	0.03	-0.00	0.04			
Dependency ratio	0.09	-0.07	0.19			
Working population	**0.79**	-0.43	0.26	-0.57	0.15	**-3.76**
Employment	0.01	0.00	0.02			
Life expectancy	0.01	-0.00	0.02			
Population density	0.02	-0.00	0.03			
Financial development	**1.00**	-0.76	0.15	-0.87	0.12	**-7.30**
Institutions	0.01	-0.00	0.02			
Democracy	0.07	0.02	0.07			
Education	0.02	0.00	0.02			
Government consumption	0.08	-0.02	0.07			
Trade openness	0.10	0.02	0.08			
Investment	0.07	-0.01	0.06			

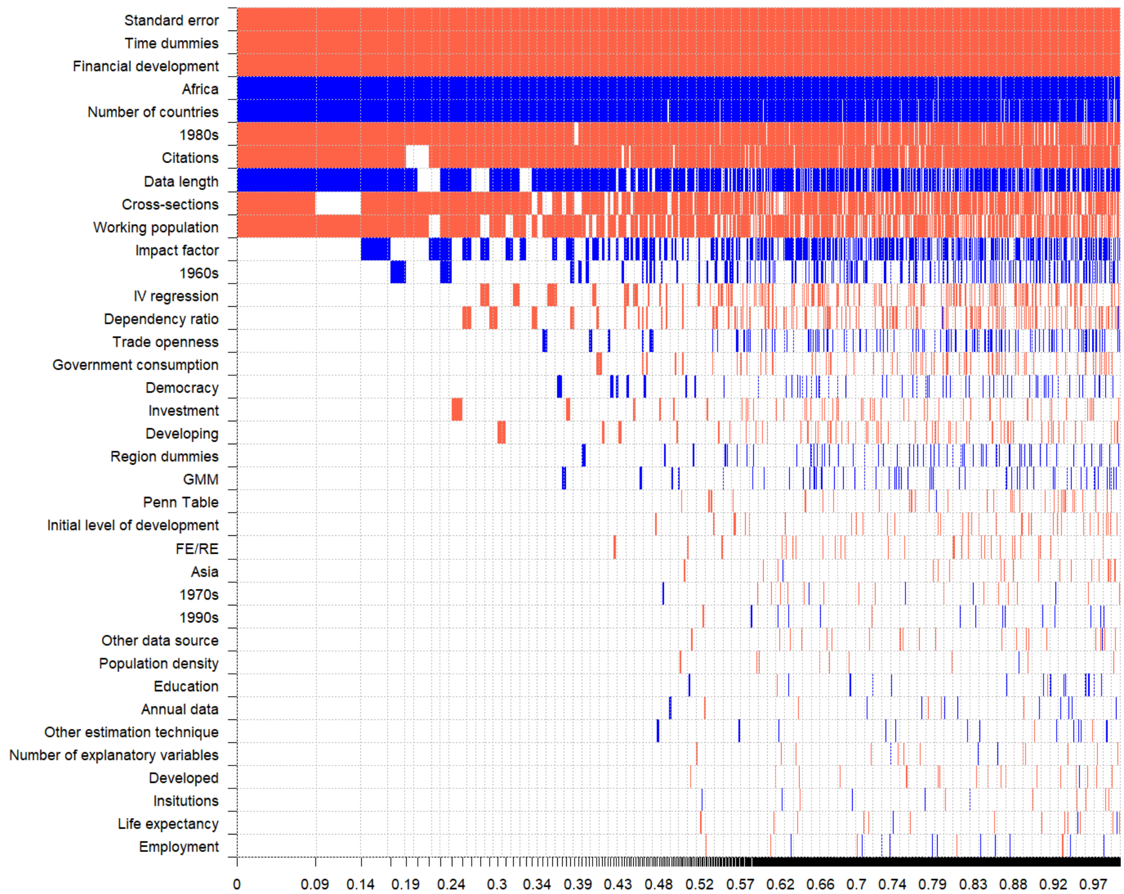
Continued on next page

Table 5.2.: Explaining the heterogeneity in the estimates (continued)

Response variable: Estimated effect	Bayesian model averaging (baseline model)			Frequentist check (robustness check)		
	PIP	PM	PSD	Coef.	SE	t-statistics
Region dummies	0.05	0.01	0.06			
Time dummies	**1.00**	-0.76	0.15	-0.77	0.14	**-5.56**
Number of explanatory variables	0.01	-0.00	0.00			
Estimation techniques						
GMM	0.05	0.01	0.05			
FE/RE	0.03	-0.00	0.03			
IV regression	0.18	-0.07	0.17			
Other	0.02	0.00	0.03			
Publication characteristics						
Citations	**0.94**	-0.16	0.07	-0.13	0.04	**-3.43**
Impact factor	0.43	0.03	0.04			
Studies	66			66		
Observations	573			573		

Notes: The table shows numerical results for the BMA estimation on the left-hand side and the OLS (robustness) check that includes significant variables as per BMA on the right-hand side. The dependent variable is the estimate of the effect of the population growth on GDPpc growth. The variables with PIP$>$ 0.5 that can be considered as significant are highlighted in bold. PIP = posterior inclusion probability, PM = posterior mean, PSD = posterior standard deviation, Coef. = estimated coefficient, SE = standard error, OLS = ordinary least squares, GMM = generalized method of moments, FE = fixed-effects, RE = random-effects, IV = instrumental variable.

Figure 5.1.: Model inclusion in Bayesian model averaging



Notes: The figure shows the results for BMA estimation. The dependent variable is the estimate of the effect of population growth on GDPpc growth. Each column can be seen as a model; the horizontal axis depicts cumulative posterior model probabilities with the best models with the highest PMP on the left-hand side; the vertical axis depicts the explanatory variables sorted by importance so that variables with the highest PIP are at the top. Blue color (darker in grayscale) means that the variable has a positive effect on the estimates; red color (lighter in grayscale) means that the variable has a negative effect on the estimate; white color means that the variable is excluded from the model. Numerical results of the BMA estimation are presented in Table 5.2. OLS = ordinary least squares, GMM = generalized method of moments, FE = fixed-effects, RE = random-effects, IV = instrumental variable.

Data characteristics

Data characteristics seem to be the first important category, giving support to hypothesis number 7 and 9. Three variables related to data characteristics are found to be significant – 1980s, with PIP=0.97, making this variable strongly significant, followed by cross-sections and data length with PIP=0.80, meaning that these two variables are substantially significant. Firstly, the use of data in 1980s, associated with a negative coefficient, was already found to be important in Headey and Hodge (2009). Although their analysis only included a dummy indicator equal to 1 if a study used data for the post-1980 period, updating the dataset which covers a longer period allowed me to distinguish between the decades. Interestingly, only the dummy indicator equal to 1 if a study uses data for the 1980s is significant [1]. Because most studies cover heterogeneous sets of countries, it is hard to pinpoint a specific event that would rationalize this. This stylized, even if puzzling fact has been already recognized (Bloom and Freeman, 1988, Brander and Dowrick, 1994), although not clearly explained. The insignificance of other dummies could, however, shed some light on this finding, as it could be a consequence of a particularly turbulent period. The increased inflation, consequent rising interest rates, and fiscal tightening in the US (Labonte et al., 2002), the oil crisis in the 1970s (Merrill, 2007), and the energy crisis in the 1980s (Painter, 2014) affected the economic development around the world. It is not unlikely that these events and consequent economic hardship are also connected to the more pronounced link between population growth and economic development. In addition to the 1980s dummy, using cross-sectional data leads to lower estimates. On the other hand, data length is associated with a positive coefficient, which would bring the estimates closer to 0. This was also mentioned in Headey and Hodge (2009), who suggested that the use of longer panels might reduce the effects. One might suggest that the effects are heterogeneous over time (Ehrlich and Lui, 1997), supported by the significance of the 1980s dummy. Then, using a longer time span might reduce the estimates and neutralize the effects of population growth.

Structural variation

In this category, two variables are found to be significant – a decisively significant variable Africa indicator equal to 1 if a study uses data for African countries only, and a substantially significant number of countries. Interestingly, using African data is associated with a positive coefficient, bringing estimates closer to 0. This speaks against hypothesis number 8, which suggests that the effects are more adverse in developing regions. The meta-regression in Headey and Hodge (2009) did not find much supporting evidence for this either, and they also found contradictory evidence similar to this in certain cases. Namely, they found that the effects of working-age and labor-force population growth on economic growth are less adverse in Africa. Even though my focus lies on total population growth instead of the working-age population, it is important to note that none of the studies using African data controlled for the working-age population growth, and total population growth is often considered to be a proxy for the labor force. Thus, it is

[1] Note that I tried including a dummy equal to 1 if a study uses post-1980s data as done in the previous meta-regression. This alternative did not yield significant results.

not unlikely that the estimates include mainly the positive effects of the increase in the labor force. The results can be therefore seen to be somehow in line with the findings of Headey and Hodge (2009). A similar picture is presented in Alimi et al. (2021), who find more positive effects of total population growth in the long run, stemming from the consequent increase in productivity. One might suggest that Africa finds itself on the concave part of the well-known classical production function, with a large positive marginal product of labor. Another possible explanation would be that dependent populations might not represent such a significant burden to the economy, compared to developed countries. This would mean that increases in total population, followed by increases in productivity, might indeed have positive effects on economic development, compensating for the negative effects stemming from increases in dependent populations. The next strongly significant variable is the number of countries with a positive impact on the coefficient, reducing the effects. Similarly to data length, this might be caused by heterogeneous effects of population growth across countries, bringing the estimated coefficient closer to zero as we increase the number of countries included in the primary dataset. This was also noted in Ehrlich and Lui (1997), who noticed different patterns in fertility, longevity, as well as economic development across different economies. Other meta-analyses concerning economic growth determinants, such as Cazachevici et al. (2020) or Valickova et al. (2015), find similar results suggesting that increasing the number of countries leads to coefficients that are smaller in the absolute value. This finding is of particular importance for future researchers, as most of the studies use rather heterogeneous sets of countries, and the mean number of countries used for the estimation is approximately 55. Only 16% of the estimates are generated using a sample of 10 countries or less.

Specifications

The inclusion of several controls is found to be substantially significant. Firstly, controlling for financial development and including time dummies in the regression is decisively significant. Both variables are associated with a negative coefficient, but it is not straightforward to say whether this is expected or not. In the case of financial development, previous meta-analyses found an overall positive effect of financial development on economic growth (Valickova et al., 2015, Bijlsma et al., 2018). However, the direction of correlation between the financial development and population growth is not quite clear. "Old-age security" theory popularized by Neher (1971), Caldwell (1976) and Caldwell (1982) suggests that if financial markets do not function properly, household transfer their wealth and income to old age via the children. On the other hand, increased access to credit might relax a household's budget and encourage higher fertility (Razin and Sadka, 1995). This is supported by empirical findings in Filoso and Papagni (2015), who found that improved access to credit leads to higher fertility rates. Therefore, if we assume the correlation between financial development and fertility rates is positive, the population growth coefficients in primary regression suffer from upward bias if financial development control is omitted. Controlling for financial development then causes the population growth coefficient to be more negative. The time dummies might be correlated both negatively and positively with economic growth, depending on whether they primarily capture a positive or negative economic shock. Because fertility rates are often found to be pro-cyclical (Sobotka et al., 2011), the correlation with population growth can be expected to be of the same sign. If the time dummy captures a negative economic shock, the population growth can be assumed to also decrease and vice versa. Similarly to the previous case, if the study omits time dummies, the estimates of population growth effects are biased upward whereas including time dummies will lead to more negative estimates. Overall, it seems that the estimates of population growth effects are sensitive to the choice of some control variables. Moreover, controlling for the working-age population growth is found to be substantially significant with negative effects on the estimates. This is in line with hypothesis number 1. If the primary study controls for labor-force growth, the coefficient on population growth should primarily capture the burden of increasing dependent populations, leading to more adverse effects and more negative estimates. This is consistent with the reasoning in Headey and Hodge (2009). However, I found no evidence for hypothesis number 2., which states that the estimates are expected to be more adverse in the presence of land scarcity, as the variable population density is not a significant explanatory determinant. Similarly, I find no support for hypothesis number 3., 4., and 6. Controlling for investment, education, and institutions does not seem to significantly affect the estimates.

Estimation techniques
None of the estimation characteristics is found to be a significant explanatory variable, which is in line with the results of meta-regression in Headey and Hodge (2009). These findings are related to hypothesis number 9., suggesting that while data characteristics might be important, there is a lack of evidence implying that estimation techniques are relevant determinants.

Publication characteristics
The last category identified one important explanatory variable. The number of citations per year is found to be substantially significant, providing additional evidence implying that publication bias is consistently present in the literature. This variable is associated with a negative coefficient, which means that more cited studies report more adverse (negative) effects of population growth. This would suggest that more negative estimates of the population growth effects are preferred in the empirical literature, giving rise to type I publication bias.

5.4. Implications

A few implications for future research and policy recommendations that can be drawn based on this analysis are in order. Firstly, note that I found prevalent publication bias favoring negative estimates to be present. The overall effects of population growth are likely to be less adverse than the literature would suggest, and the extent to which population growth prevents economic growth is most likely to be exaggerated. Nonetheless, the mean corrected for bias remains negative, suggesting that the question of population growth should remain important to policymakers. Next, I provide a short review of the hypotheses formulated at the beginning of the chapter.

1. Controlling for the working-age population leads to more adverse effects of population growth effects, implying that it is likely the dependent population that is hindering economic development. This means that the increases in the labor force are essential for offsetting the negative effects, and policies promoting labor absorption and employment should be implemented to account (at least partially) for overall population growth, namely the growth in dependent populations.

2. I found no evidence suggesting that population growth effects are more adverse in the presence of land scarcity, tested by controlling for population density. Thus, there is no reason to assume that economic development is more hindered by population growth in highly populated areas and vice versa.

3. I found no evidence supporting the resource-dilution effects hypothesis, as controlling for investment was not found to be an important driver of heterogeneity in the estimates. Therefore, it does not seem that the thinly spread capital is the reason behind the adverse effects of population growth.

4. I found no evidence supporting the resource-diversion effects hypothesis (resource-diversion effects). Controlling for education does not significantly affect the final estimates, implying it is also not the shift of resources into unproductive areas that is hindering economic development.

6. I found no evidence for the institutional interactions hypothesis, suggesting that the quality of institutions is not a relevant determinant. Better-functioning countries do not seem to experience less adverse effects of population growth.

7. My results suggest that the effects of population growth were more adverse in the 1980s. Nonetheless, since then, the trend is unclear. I did not find significant differences in more recent periods as compared to earlier decades. Arguably, these results could be driven by the turbulent events in the 1970s and 1980s such as increasing inflation, monetary and fiscal tightening in the US, or the oil and energy crisis, strengthening the negative link between economic and population growth around the world. Consequently, this might imply that recessions and difficult market conditions require prompt actions to address the question of population growth and corresponding adverse effects.

8. There is no evidence suggesting that developing countries experience more adverse effects of population growth, as compared to the developed regions. In fact, the results suggest that the effects are less adverse in Africa, implying that the region might profit especially from increases in productivity and enough space for labor absorption should be ensured. Thus, implementing policies promoting labor participation and employment could be particularly beneficial for economic development in this area.

9. While there is no evidence suggesting that econometric methods matter, the data characteristics are important determinants. Namely, datasets capturing longer periods or more countries produce less negative estimates, bringing the estimates closer to 0, whereas the use of cross-sections leads to more negative estimated effects. This could point to certain heterogeneity in the effects across regions and countries, as well as across time that is rather difficult to detect in case of pooled, large datasets. Thus, researchers should carefully consider the choice of data and their scope. This finding is especially relevant in light of the fact that most estimates are generated using heterogeneous datasets using data of a large number of countries. The future research should therefore consider estimating the effects of population growth on GDP per capita growth using smaller, homogeneous set of countries, or individual country data. Moreover, they should also give proper thought to the choice of their control variables, as the inclusion of time dummies or financial development can also significantly affect the final estimates.

6. Conclusions

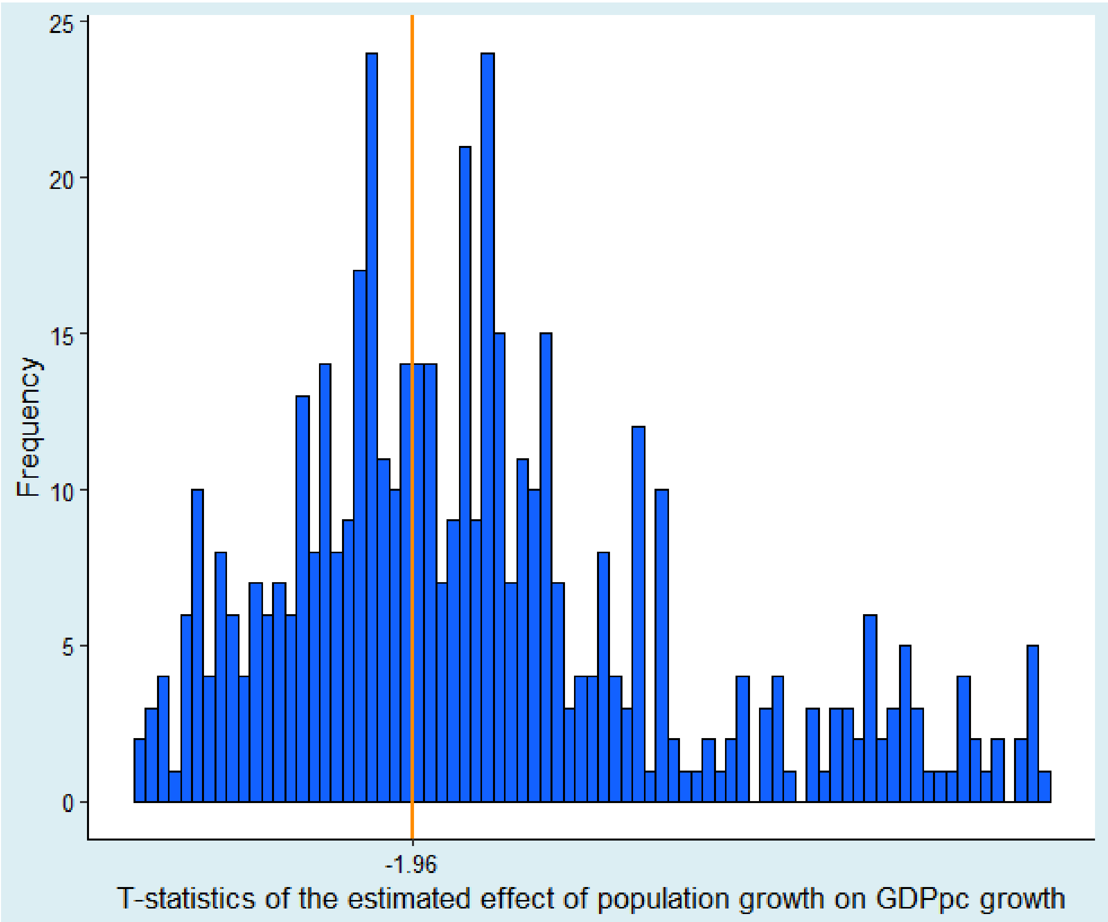
This thesis focuses on the effects of total population growth on GDP per capita growth. I conduct a meta-analysis of the literature and collect 573 estimates of the effects of population growth on GDP per capita growth from 66 empirical studies. This work follows a meta-regression that can be found in Headey and Hodge (2009) but addresses several important points that were missed in the previous work. Firstly, I test for publication bias – a problem often prevalent in the literature, arising if certain estimates are preferred, whereas others are omitted (Stanley, 2005). Secondly, I address model uncertainty in the heterogeneity analysis. Model uncertainty is commonly present in regressions containing a high number of explanatory variables, which is often the case when conducting a meta-analysis (Irsova et al., 2023). Therefore, I use a sophisticated Bayesian model averaging technique to treat for model uncertainty and identify the most important variables explaining heterogeneity in the estimated effects. Lastly, I update the dataset and include also most recent studies that were excluded from the analysis of Headey and Hodge (2009).

Using linear and non-linear publication bias tests, I detect consistent publication bias favoring negative effects in the literature. The mean corrected estimated effect lies between -0.17 and -0.45, suggesting a reduction of 25-70%. The effects are likely to be less negative than the literature reports. In addition, I examine the heterogeneity in the estimates of the population growth on the GDP per capita growth using 37 explanatory variables. These include variables related to data characteristics, structural variation, model specifications, estimation techniques, and publication characteristics. To treat for model uncertainty, I utilize the Bayesian model averaging technique as a main specification. As a robustness check, I use a simple OLS including only variables denoted as significant by the Bayesian model averaging. I find additional evidence for publication bias, which remains significant even after controlling for the other 36 explanatory variables. Moreover, I detect several study characteristics that significantly influence the final estimates, providing guidance for future research. These characteristics are mainly related to data type, scope and length of data, and the choice of controls in the primary regressions used to generate the estimates. Contrary to popular beliefs, but in line with the findings of Headey and Hodge (2009), I uncover some regional differences: effects are less negative in African countries in comparison with other regions. Similarly, in line with the analysis of Headey and Hodge (2009), I find that the effects were more negative in the 1980s. The findings of the thesis should therefore warn about the prevalent publication bias preferring negative estimates, highlight the potential opportunities in African countries, and emphasize the importance of study design for the estimated effects of population growth on the GDP per capita growth.

A few potential issues of this work should be mentioned. Firstly, any meta-analysis is highly dependent on the quality of the underlying studies. However, my inclusion criteria for studies to be included were designed such that the studies are of certain quality and data are directly comparable. In addition, if the studies employ incorrect techniques, the heterogeneity should uncover consistent patterns, highlighting also the importance of estimation methodology. I demonstrate the attempt to control for different estimation techniques including techniques accounting for endogeneity, and none of them was found to be significantly influential. Secondly, the endogeneity might be present in the tests used to detect publication bias. However, I present the results of IV regression and p-uniform* test to show also an attempt to account for endogeneity.

A. Appendix

Figure A.1.: Distribution of the t-statistics of the estimated effects



Notes: The figure shows the distribution of the t-statistics of the estimated effects of population growth on GDPpc growth. The solid vertical lines denote the cutoff that was passed to the Selection model developed by Andrews and Kasy (2019). Values of t-statistic equal to 1.96 translate to the commonly used p-value of 0.05 or 5%. The results of the model are reported in Table 4.2. T-statistics smaller than -5 and greater than 5 are excluded from the figure for sake of exposition.

Table A.1.: Specification test for the Selection model developed by Andrews and Kasy (2019).

Transformation	Correlation
level	0.272
	[0.099,0.428]
log	0.693
	[0.607, 0.757]

Notes: The table shows the test related to the Selection model Andrews and Kasy, 2019), following Kranz and Pütz (2022). Under the assumption of the Selection model, the correlation between both the level and the logarithm of the absolute value of the estimated population growth effect and the level and the logarithm of the corresponding standard error, weighted by the inverse publication probability estimated by the Selection model, should be zero. Otherwise, the crucial assumption is violated. Bootstrap confidence intervals are reported in the square brackets.

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