Income and Corruption: A meta-analysis on the effect of foreign direct investment on income inequality

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Abstract

This study examines the empirical evidence on the relationship between FDI and income inequality by conducting a meta-regression analysis of 616 primary studies from 71 papers spanning 1951-2021. The analysis highlights the pivotal roles of corruption and GDP per capita in shaping the economic consensus. Findings indicate a positive FDI-inequality relationship for low-income countries, a negligible relationship for middle-income countries, and a negative relationship for high-income countries. Higher corruption levels are found to reduce the absolute strength of the FDI-inequality relationship in both low- and high-income countries. Notably, the control variables explain over *twice* the observed heterogeneity compared to the other 10 study characteristics *combined*, underscoring the importance of contextual factors. These results hold crucial policy implications, emphasising the need for targeted policies to harness the benefits of FDI while mitigating adverse effects on inequality. By shedding light on the complex interplay between FDI, corruption, and development, this meta-analysis contributes to the literature, informs both academic & policy discussions and probes deeper philosophical questions of morality over returns to investment.[1]

[1]I would like to thank my dissertation supervisor, Diego Battiston, for his continued support and guidance throughout this paper.

Contents

1 Introduction

Inequality—in its truest form of an unequal distribution—has long predated capitalism, the rise and fall of ancient civilisations, money in its early iterations as the shekel in the Mesopotamian civilisation c.2150 BC, and even Homo erectus little over 2 million years ago. Historically—and continually for other life forms—an inequible distribution of food and consumption was necessary to ensure survival. Since the inception of money and trade, this is no longer necessary. Since the inception of money and trade, aggregate inequality has only been exacerbated (Milanovic, 2016; Piketty, 2014).

Piketty (2020) estimates that in 1900 85% of property in Britain was held by the top decile. Today, it stands around 55%. He stipulates that India's top decile comprised 32% of all income in 1980. Today, that stands at 55%. In the Middle East, the top decile accounts for nearly 200% the income of the bottom 90% (Alvaredo et al., 2019; Piketty, 2020).

Simon Kuznets (1955) introduced the Kuznets' inverted-U curve describing the theoretical relationship between economic development and income inequality, stipulating that lower economic levels (measured in terms of real GNI) were corollary with lower Gini coefficients (higher inequality), while middle-income countries were associated with higher Gini coefficients (lower inequality) before tailing off again for higher-income countries. In the wake of this seminal paper there has been extensive economic debate on the relationship between economic development and income inequality with a litany of opinions and a drought of consensus (Robert J. Barro, 2000; Galor, 2009; Huang et al., 2020; Voitchovsky, 2005). The relationship between foreign direct investment and income inequality is a parallel area of contention, with economists divided on the direction and magnitude of the relationship (Huang et al., 2020).

Whether the discourse is on sub-group divides or aggregate impacts, the literature is rife with conflicting opinions. North-South divides (Feenstra et al., 1997; Wood, 1995), 'clubs' of countries (Canova et al., 1995; Suárez-Arbesú et al., 2023), population size (Milanovic, 2005, 2015), development levels & technology (Acemoglu, 2002; Acemoglu, S. Johnson, and J. Robinson, 2003), skill differences (Goldin et al., 2007; Katz et al., 1999), and the prevalence of international trade and search &

matching models (Helpman, 2010, 2017), amongst many others, are all factors that have been sought to explain the variety in the outcomes (Dabla-Norris et al., 2017). With the policy and economic implications of these relationships being so vast, it is imperative that we understand the true relationship between FDI and income inequality. Economic growth (Robert J Barro, 2003, 2015), political stability (Acemoglu, S. Johnson, and J. A. Robinson, 2005; Acemoglu, S. Johnson, J. A. Robinson, and Thaicharoen, 2003), and social cohesion (Easterly, 2001, 2007) are all at stake. The implications of the relationship between FDI and income inequality are far-reaching.

From Pan-Long (1995) to Soto et al. (2024), this paper conducts a meta-analysis of the empirical papers assessing the relationship between Foreign Direct Investment and income inequality. Using a meta-regression analyses (MRA) (Stanley, 2008; Stanley, Doucouliagos, et al., 2013), this paper empirically analysis 616 primary studies from 71 papers that are built on research periods spanning 70 years from 1951 to 2021. The paper aims to provide a comprehensive understanding of the relationship between FDI and income inequality, and to provide a robust analysis of the factors that may influence the relationship.

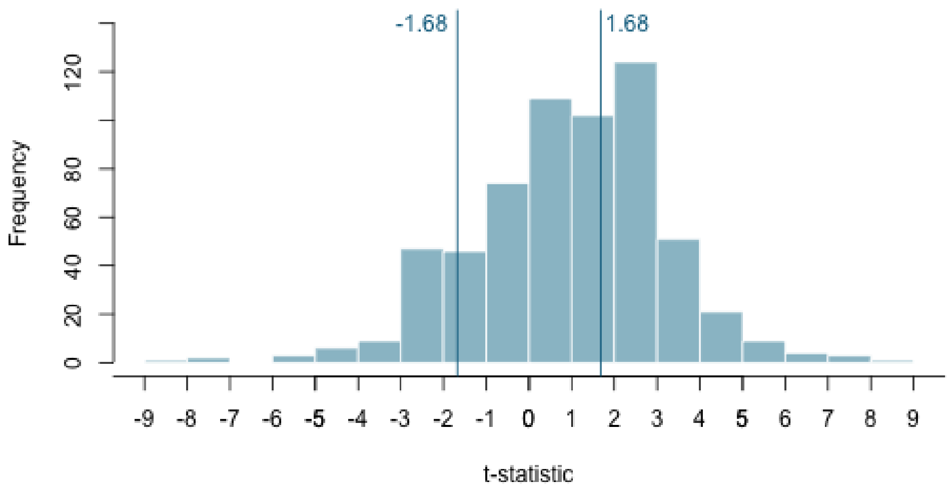


Figure 1: t-statistic of the estimated correlation coefficient between FDI and income inequality across the 616 primary studies in the 71 papers.

Figure 1 represents the initial t-statistics of the 616 primary studies. It illustrates a mean of 0.98 with a standard deviation of 2.47. We see that 427 primary studies reported positive values of effects of FDI on income, with 270, 223, and 127 of those being significant at the 10%, 5% and 1% level, respectively. There were 186 negative effects reported, with 90, 61, and 31 of those being significant at the 10%, 5% and 1% level, respectively. 256 of the 616 primary studies reported insignificant results.

Following the structure of common MRAs (Stanley, 2008), I will first construct the common and unit-free effect size for each study—to equalise study-specific differences—before regressing the effect size against a series of study characteristics in an effort to ascertain an underlying effect as well as an explanation of any and all impacts that may explain the disagreement across the literature. Of the 12 study characteristics explaining the observed differences in the primary studies, corruption and GDP per capita account for more than twice that of the other 10 characteristics combined. An analysis of studies characterised by income levels indicates that the relationship between FDI and income *in*equality is positive for low-income groups, negligible for middle-income groups, and negative for high-income groups.

The observations in the study are consistent with the broader economic literature, indicating a nuanced relationship of FDI and income inequality that is dependent on (relative) income levels. C.-C. Lee et al. (2022), for example, find the impact of FDI on income inequality negative but is negative (harmful) as financial development increases to a certain threshold, after which it is possible to improve the income distribution. Conflictingly, Nguyen (2023) finds that FDI increases income inequality in developed countries but decreases it in developed nations, while digitialisation, including financial, reduces income inequality in both groups.

It should be noted that Huang et al. (2020), which is the only found meta analysis on the relationship between FDI and income inequality is a paper that has been leant on throughout the process, providing insight, structure details, and a more-specified MRA for the foucs of this paper. Our similar findings are unsurprising given the similar data sets and the similar focus of the papers.

The paper is structured as follows: Section 2 outlines the data collection and methods used in the meta-analysis; Section 3 provides a discussion of the results; Section 4 concludes.

2 Data Collection and Methods

In conducting a thorough analysis of the available papers and mitigating systematic bias introduced by authors, it is standard to follow the MAER-NET criterion (Stanley, Doucouliagos, et al., 2013). As such, this section will begin with (1) outlining the search parameters and inclusion criteria, (2) provide summary statistics of the primary studies, (3) outline the meta-analysis methods, and (4) provide a discussion of the results.

2.1 Search parameters and inclusion criteria

The explicit question posed was *'an assessment of the impact of foreign direct investment (FDI) (inflows) on income inequality between 1951 and 2021'.* A systematic search was conducted across a variety of databases and search engines. It required a strict exclusion criteria to ensure the papers held reliable data, were of a high quality, and were not biased in their findings. This further provided a *de facto* rule book with which one could refine the number of papers.

The results, from over 2800 retrieved papers, were funnelled down to 71 selected articles[2]. The articles (that can be found in Appendix 18) were selected on the following criteria:

1. *Econometric study*

   The article[3] must have conducted an individual econometric analysis that assessed the relationship between FDI and income inequality in host nation(s). Theoretical papers were removed for their lack of founding

[2]The search was conducted across Google Scholar, EconStor, EconLit, DiscoverEd (the University of Edinburgh's library service), JSTOR, Scopus, SSRN, Elsevier and other prominent publisher's websites. Search terms included, in varied combinations, FDI, foreign direct investment, inequality, income inequality, income, wealth, Gini, openness, investment, income/wealth share, income/wealth distribution, foreign firm, Theil index, Atkinson index, liberalisation, and corruption. Additionally, I leant of the meta analysis research of Huang et al. (2020) for papers that I had previously missed. It should be noted that whilst the number of articles used for the analysis is equal to that of Huang et al. (2020), some of the articles differ for reasons including more stringent meta analysis criterion and for including papers released since 2021, as opposed to their 2019.

[3]Top-funnel literature research extended to books and other non-journal publications. However, these were ultimately excluded from the final analysis as their data were found to be duplicative of included articles.

and replicate articles were removed so as to mitigate against biases that lead to overweighting.

2. *Effect on host country of FDI*

   Assessment of the income inequality in the host country of FDI (inflows) as opposed to outflows from government/firm expenditure. We are not concerned with the impact of income inequality on donor countries.

3. *Aggregate, national-level income inequality*

   This was to mitigate against differences pertaining to alternative measures (i.e., gender, age, racial, education, etc.). Appropriate income inequality measures included Gini, income shares, etc.

   We focus on national inequality (overall Gini, for example) as opposed to inter-state inequality or other general sub-group inequality. Without more granular FDI data, sub-group inequality may not be accurately representative, nor is it easily mapped to corruption estimates derived later in the paper.

4. *Available common effect size*

   It is imperative to be able to measure a common effect size.[4].

5. *Country listing*

   The papers required an availability of information on which countries were assessed in each regression. Whilst the country listing is less pertinent for the meta analysis itself, it was pivotal in measuring the FDI on income inequality regression against externally-sourced data on government corruption levels and the later machine learning model test(s).[5]

[4] This requires being bale to calculate the t-statistic and degrees of freedom for every given coefficient on FDI; which, at a minimum requires reporting of one of the z-statistic, P-value, or standard error. It also required an understanding of the number of observations and its respective limiters (so as to calculate the degrees of freedom).

[5] I reached out to authors of five papers with unavailable data on countries run in each regression. Despite the obligations under publication in the *Journal of Economic Modelling*, one author did not respond to my request for information. This paper was excluded from the final analysis.

2.2 Summary statistics of the primary studies

The search resulted in 71 papers that provided us with 616 individual regression estimates of FDI on income inequality. The number of individually reported coefficients in any given paper ranged between 1 and 88 across all 71 papers included. Tables 1 and 2 below provide a non-exhaustive list of the primary and multiple country studies, respectively. The observed popularity of some countries is likely attributable to an amalgamation of factors, including the availability of robust datasets, significant economic growth since the 1950s, and the influx of comparatively substantial FDI. Across both individual- and multiple-country studies, there were a total of 18,238 country assessments.

Table 1: Frequency of countries in individual-country studies

Country Name	**Frequency**	**Country Name**	**Frequency**
United States	94	...	
South Korea	37	Spain	2
United Kingdom	28	Sweden	2
Mexico	26	Uruguay	2
Thailand	8	Brazil	1
Egypt	8	Hungary	1
...		South Africa	1
Total			252

Table 2: Frequency of countries in multiple-country studies

Country Name	**Frequency**	**Country Name**	**Frequency**
Chile	232	...	
Bangladesh	228	Tonga	3
India	228	São Tomé & Príncipe	2
Sri Lanka	228	Liberia	2
Thailand	228	Marshall Islands	1
...		Antigua & Barbuda	1
Total			17,986

The 616 primary studies span from 1951 to 2021, with the mean and median study years being 1992 and 1991, respectively. The cumulative density of the average study year is depicted in Figure 2. The economic development levels, both *within* and *across* studies, exhibit significant variation, which is later addressed.

Table 3 provides a synopsis of the general study focus, using OECD countries as a proxy for 'developed' nations. Of course this is a slightly myopic view of development levels. Regardless, it shows that there is more of a general focus on less-developed nations, which account for $\approx 79.48\%$ of the studies. This is perhaps due to the focus on *inflows* as opposed to *outflows*, where, typically, cash flows from wealthier nations to less-developed nations; therefore the policy implications of studies following the flow of money is likely to be greater when attention is on the recipient nation(s).

Given the broad range of time across studies, we expect to see a shift in economies progressing from lower to higher-income, with fewer developing countries in more recent studies. Empirically, this hold for all data and models built.

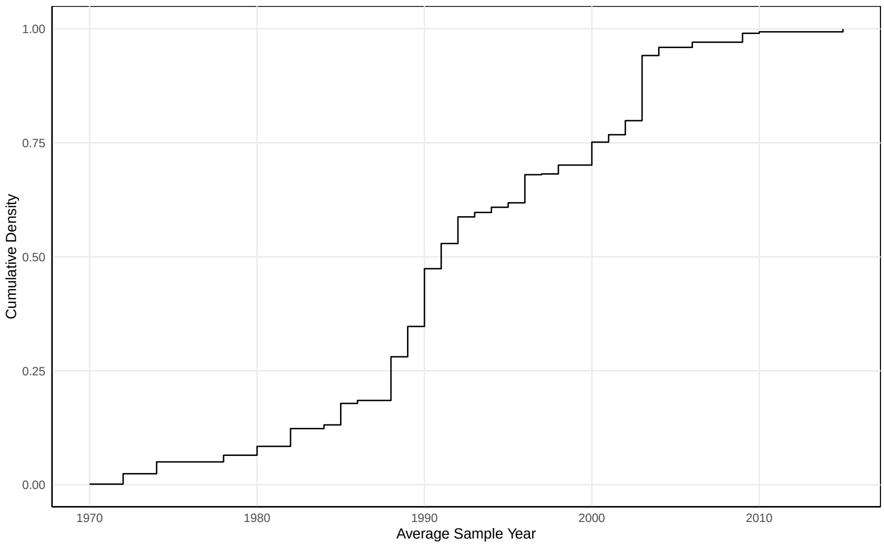


Figure 2: Average year of primary studies cumulative density

Following Stanley and Doucouliagos (2012), a Partial Correlation Coefficient (PCC) is claculated to assess impacts of FDI on income inequality. It is a unit-free measure that allows us to reliably compare the strength of the relationship across studies that have employed different measurement techniques. Whilst it is a unit-free measure, it is not a directionless measure.[6] Here, the PCC is a measure of

[6] A higher (lower) *positive* PCC indicates a stronger (weaker) relationship between FDI and income *in*equality, i.e., lower equality or a higher Gini coefficient. A greater (smaller) *negative* PCC indicates a stronger (weaker) negative relationship between FDI and income *in*equality, i.e.,

Table 3: Summary Statistics of OECD countries and non-OECD countries

Category	
Proportion of OECD- to non-OECD focused studies (%)	20.52
OECD-focused studies	
Count	188
Proportion of single- to multi-country (OECD-focused, %)	88.29
PCC mean	-0.022
PCC standard error	0.069
Multi-country studies	
Count	22
PCC mean	-0.089
PCC standard error	0.076
Single-country studies	
Count	166
PCC mean	-0.013
PCC standard error	0.068
Non-OECD focused studies	
Count	428
Proportion of single- to multi-country (non-OECD focused, %)	19.46
PCC mean	0.138
PCC standard error	0.116
Multi-country studies	
Count	342
PCC mean	0.156
PCC standard error	0.100
Single-country studies	
Count	86
PCC mean	0.066
PCC standard error	0.181

the strength of the relationship between FDI and income inequality. The PCC is calculated as follows:

$$r_i = \frac{t_i}{\sqrt{t_i^2 + df_i}}$$

Where t_i is the t-statistic of the coefficient of FDI on income inequality and df_i is the degrees of freedom of the regression. Given not all primary studies reported the t-statistic, many t-statistics were calculated from the reported P-values or z-scores[7].

The standard error of the partial correlation coefficient is given by:

$$SE_{r_i} = \frac{r_i}{t_i} = \sqrt{\frac{(1 - r_i^2)}{df_i}}$$

The initial mean of the aggregate PCC, r_i, is 0.089, with a standard deviation, SE_{r_i}, of 0.101. The standard deviation indicates a considerable dispersion of correlation values across the studies, reflecting the divided opinion in the literature on the effect of FDI on income inequality (Huang et al., 2020). This heterogeneity is visually demonstrated in Figure 3, plotting the PCC against the inverse of the standard error, $\frac{1}{\sqrt{r_i}}$, showing studies with lower precision levels tending to have broader ranges of PCC values. It would be premature to dismiss the relationship between FDI and income inequality based solely on the mean PCC value.

Funnel plot asymmetry can be indicative of the presence of publication bias, which is further corroborated by the Egger's test indicating its presence at an interval of 0.924, yielding a p-value of $3.563 \times 10^{-13} \approx 0$. Whilst not definitive proof of publication bias, it suggests the studies with lower precision levels may be more likely to be published if they report a statistically significant result. It could, however, also be a result of between-study heterogeneity (the funnel plot assumes effect sizes are the result of the studies' sampling error, but it could be different true sizes), different study methods, lower-quality studies could show greater effect

higher equality or a *lower* Gini coefficient.

[7] t-statistics are often imprecisely reported as positive values for negative effects (Stanley and Doucouliagos, 2012), so careful data collection was essential to correctly measure the direction of effect.

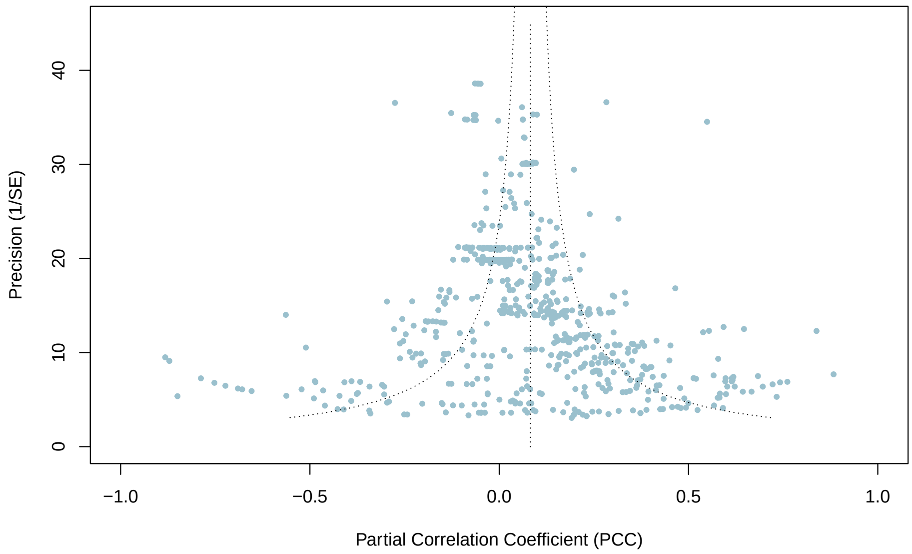


Figure 3: Funnel plot of partial correlation coefficients

sizes as a result of greater bias risk, or it could have occurred by chance—although the latter is unlikely given the number of studies and low p-value (Page et al., 2021). Funnel plot asymmetry was witnessed in all funnel plots for different control groups and income levels other than single-country focused and unpublished papers, see Appendix A.3 Table 26.

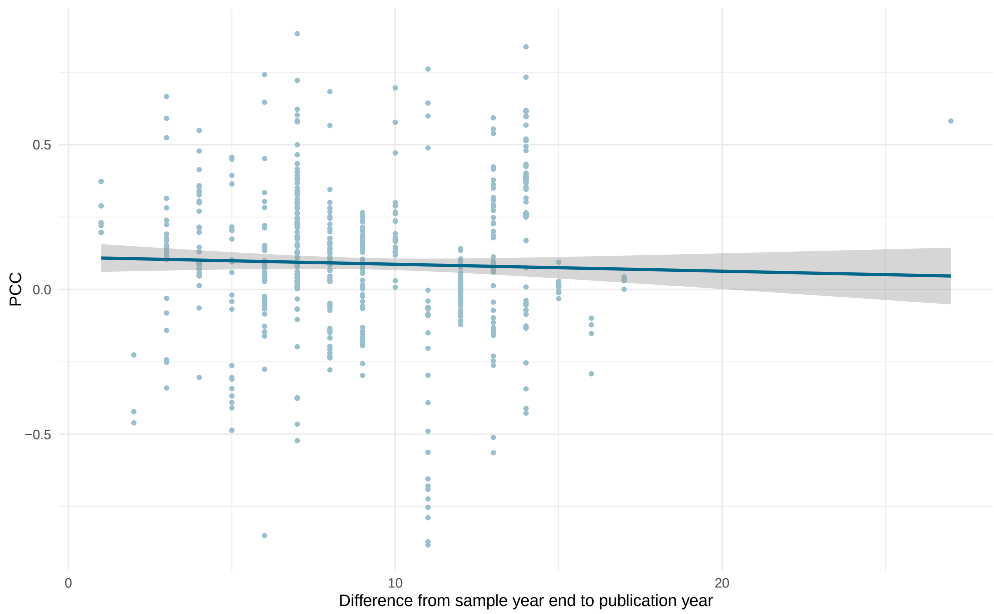


Figure 4: $|r_i| - SE_{r_i}$ against the time lag between study completion and publication

Further, funnel plot asymmetry could be the result of time-lag bias, where belief-conforming or statistically significant studies are more likely to be reported earlier than other papers (Page et al., 2021). Figure 4 shows an incredibly linear relationship, suggesting that there is unlikely to be a time-bias across the primary studies. A more robust analysis linear regression analysis reveals no statistically significant relationship between the time lag from study completion to publication and the adjusted partial correlation coefficient, with a p-value of 0.985 indicating the absence of time-lag bias across the primary studies. This finding, supported by an extremely low adjusted-R^2 value, suggests that the time lag does *not* meaningfully influence the adjusted PCC, aligning with initial observations of no apparent time-bias. The results of this analysis are in Appendix A.3 Table 12. Similar tests using both 3-year moving averages and more lags yielded similar results.

Table 4 presents a summary of statistics that may help to explain the heterogeneity observed in the funnel plot. Study characteristics are employed as binary variables to distinguish findings, with the objective of discovering a true underlying effect size amidst the heterogeneity.

2.2.1 Measures of FDI and inequality

The majority of studies used the total value of FDI that has accumulated in the host country (*stock*, 445), as opposed to the value of FDI that has entered the host country in a given year (*flow*, 171). The Gini coefficient was the most commonly used measure of income inequality (413), followed by income share ratios of the top/bottom decile or quintile(s) (91).

2.2.2 Measures of economic development

The mean value of the GDP per capita was mapped to each country in each year across all studies individually.[8] This approach was adopted to account for the heterogeneity in the economic status of countries across the studies and to facilitate subsequent corruption modelling. The mean of the (log) real GDP per capita across all studies, in their respective years, was $9.493 \approx \$13,267$ (2011 US$).

[8] I.e., a single-country study on Portugal from 1960 to 1970 would yield a different real GDP per capita than an identical study on Portugal conducted from 1990 to 2000.

Table 4: Definition and Summary Statistics

		Summarise	
Variable name	**Variable description**	**1**	**0**
Measures of FDI and inequality			
FDI	The *stock* of inward FDI	445	171
Gini	Gini coefficient	413	203
Income Share	Income share ratios of the top/bottom decile or quintile(s)	91	525
Wage/income disparities	Income share distributions	67	549
Other inequality measure*	Theil index, Atkinson index, EHHI Gini coefficient, etc.	45	571
Measure of economic development			
GDP per capita	Natural log of GDP per capita	Mean = 9.493	
		Median = 9.189	
Measures of controlling endogeneity			
Estimation methods	Methods that accounted for endogeneity (2SLS, IV, GMM)	153	463
GDP	Control for GDP	375	241
Education	Control for school enrolment	301	313
Country	Single country study	252	364
Trade	Control for trade	176	440
Population	Control for population	167	449
Inflation	Control for inflation	162	454
Unemployment	Control for unemployment	115	501
Government expenditure	Control for government expenditure	98	518
Publication bias			
Published	Published work	566	50
Standard error of the PCC		Mean = 0.101	

Note: all values, other than the means, are provided as dummy variable counts
* Measures of the bottom decile/quintile were excluded from the analysis given an increase in the income share of the bottom decile/quintile would be indicative of a decrease in inequality.

2.2.3 Publication bias

Economics, among other academic disciplines, has been historically prone to publication bias (Andrews et al., 2019; Bausell, 2021; Stanley, Doucouliagos, et al., 2013). Publication bias occurs when studies with statistically significant results and/or studies that conform to preconceived beliefs are more likely to be published (Stanley, Doucouliagos, et al., 2013). Such a bias can result in an overestimation of the true effect size (Rothstein et al., 2005). 566 of the 616 studies were published.

In the absence of publication bias, the mean PCC value would serve as a reliable estimate of the true effect size, and no significant difference would be observed between the results of published and unpublished works. This is to say there should be no correlation between the PCC and the dummy variable representing publication status. In our results, we see that published studies were more likely to report positive PCCs. While it cannot be independently attributed to publication bias, the asymmetry in the funnel plot (Figure 3) suggests a likely presence of publication bias.

2.3 Measuring economic development over time

There has been extensive research over recent decades assessing the significant economic and income growth since the 1950s (Chancel et al., 2022; Morawetz, 1977). Figure 6 depicts this with incomes between 1951 and 2021[9] clearly depicting a positive trend in countries' GDP per capita.

To account for the heterogeneity in the economic status of countries across the studies over time, I implemented the World Bank's income classifications.[10] I further utilised the Maddison Project's (Bolt et al., 2020) data to calculate the average GDP per capita for each study on a more granular level. The values were mapped to the countries featured in each study for each time period within the study's time frame.[11] The methodology employed accounted for temporal economic

[9] Maddison Project data collected from Bolt et al. (2020)

[10] As ordinal datapoints of low-income, lower-middle-income, upper-middle-income, and high-income. These classifications, which are specific to each year, were assigned numerical values of LI = 1, LM = 2, UM = 3, and HI = 4, respectively. More accurately, they are Atlas method-derived datapoints, smoothing exchange rate fluctuations using a three-year moving average, price-adjusted conversion factor (World Bank, Accessed: 2024).

[11] The mathematical intuition for how this was achieved is displayed in Appendix A.1. The

progression of countries, enabling a comparative analysis of study outcomes in relation to relative economic development level(s).[12]

Correlation analysis was conducted to examine the similarities between the World Bank and Maddison Project data, some results of which are shown in Figure 5. The analysis yielded a robust positive correlation of approximately 0.91 between the two datasets.[13] While both datasets employ PPP-adjusted data, the World Bank data generally surpasses the Maddison Project data. This discrepancy may arise from differences in the specific PPP adjustments used or other methodological differences. Additionally, the World Bank data exhibits greater volatility than the Maddison Project data, likely arising from the World Bank's inclusion of a wider array of countries, encompassing those with lower development levels. A portion of the observed difference could also be attributable to the 'bins' of the World Bank data, where the largest bin (HI = 4) encompasses all countries with a GDP per capita exceeding a certain threshold, thereby offering limited differentiation between countries such as the UK and Qatar.

It is highly regarded that economic convergence occurs over time, with a majority of countries transitioning from low(er)- to high(er)-income status (Berry et al., 2017; Morawetz, 1977; Webber et al., 2001). This economic transition is illustrated in Figure 6, using the Maddison Project data (Bolt et al., 2020), showing the log of GDP per capita for all countries (in the dataset, which comprises 169 countries) in each year between 1951 and 2018.

Unsurprisingly, we see a positive correlation between the log of GDP per capita and the year of publication,[14] further showing the economic development of countries, particularly across the literature. Figure 7 shows more recent publications—which have lent on more recent studies—have used more developed countries in their analysis.

average income category from these calculations were then used to classify the study as low-income, lower-middle income, upper-middle income, or high-income.

[12]Both datasets were employed as the World Bank's categorisations for countries only went as far back as 1989 and were linearly extrapolated to 1951, while the Maddison Project's Data only came up to 2018, and had more missing countries. These are both limitations, and mitigating these issues is outlined in Appendix A.1.

[13]This finding aligns with expectations given the World Bank's utilisation of Maddison Project data for its own classifications.

[14]More recent papers are capable of using recent studies. This both holds in our data, and is obvious, in that older papers are unable to report true values of future studies, and I have purposefully excluded theoretical papers.

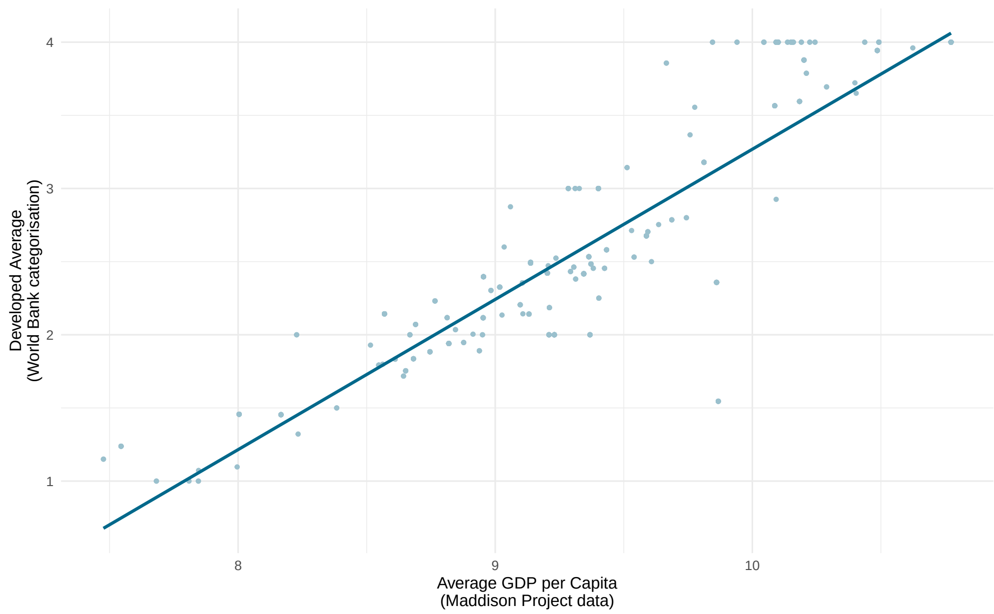


Figure 5: World Bank and Maddison Project data comparison

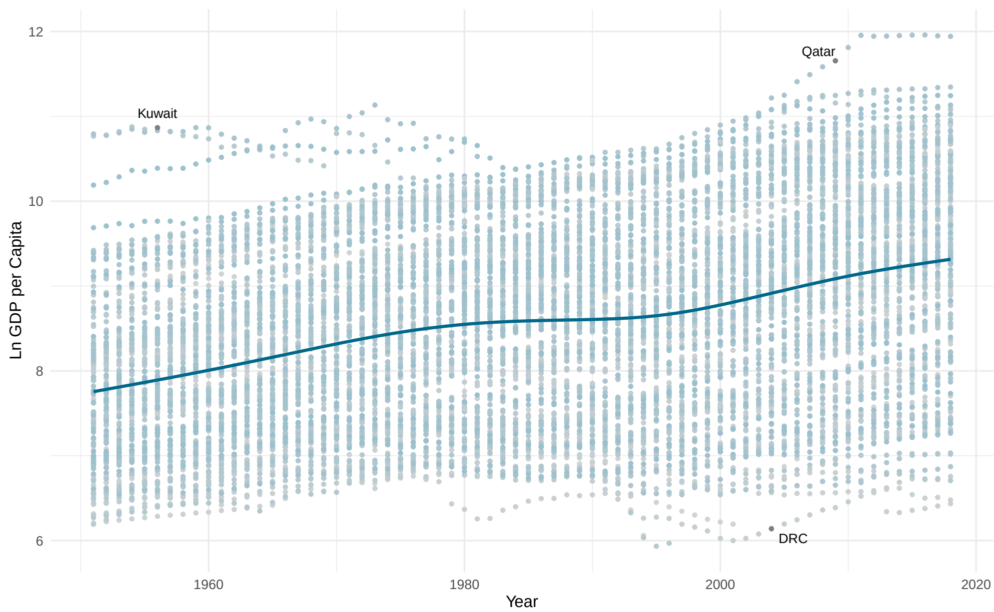


Figure 6: Log GDP per capita over time by country

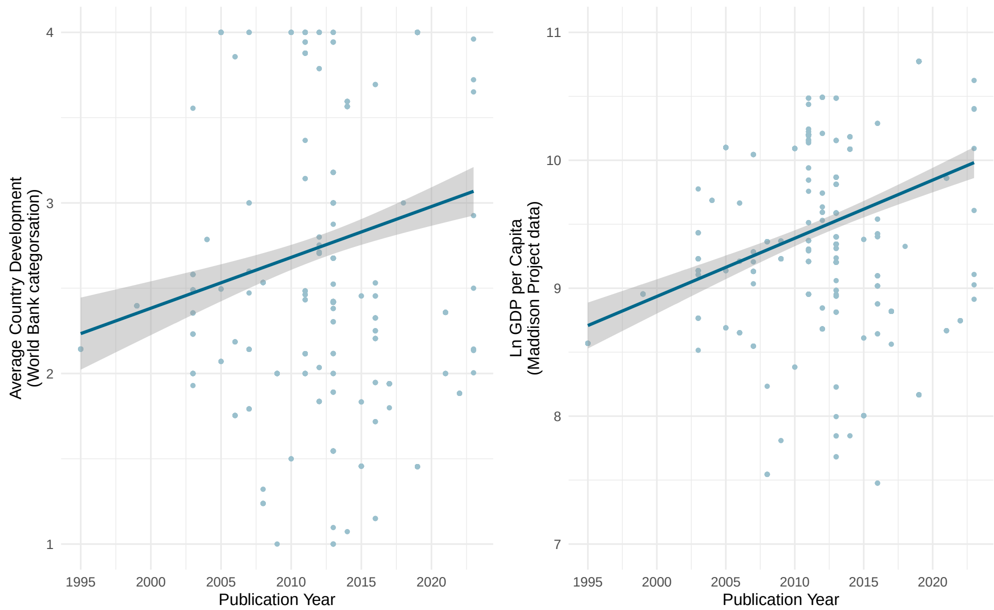


Figure 7: Economic development over time against publication year

3 Meta-Analysis

3.1 Meta-Analysis Methods

A meta regression analysis (MRA), fundamentally, is an empirical methodology employed to systematically review a vast array of studies, with the objective of retrieving the true underlying effect(s) (Stanley, Doucouliagos, et al., 2013). The standardised effect sizes, the PCCs, are regressed against the core factors outlined in Table 4. The coefficients corresponding to these factors are intended to signify their capacity to account for the observed heterogeneity in the effect sizes.

The MRA model is as follows:

$$r_i = \alpha_0 + \beta_0 SE_i + \sum \boldsymbol{\beta_k Z_{ki}} + \epsilon_i \tag{3.1}$$

where r_i is the PCC of the study with unique id, $\boldsymbol{Z_{ki}}$ is a vector of k study characteristics (shown in Table 4), SE_i is the standard error of the PCC, and ϵ_i is the error term

In Equation 3.1, the presence of a statistically-significant α_0 would indicate that—

after taking account of the study characteristics—there remains an underlying effect between foreign direct investment and income inequality. Further, a statistically-significant β_0 would suggest the presence of publication bias.

Running a *funnel-asymmetry and precision-effect (FAT-PET)* test, which plots Figure 3, is a simple regression that removes $\sum \boldsymbol{\beta_k Z_{ki}}$ from Equation 3.1:

$$r_i = \alpha_0 + \beta_0 SE_i + \epsilon_i. \tag{3.2}$$

The results of a FAT test attempt to detect publication bias, as discussed earlier (Stanley and Doucouliagos, 2012). In the presence of publication bias, r_i is expected to be correlated with SE_i, *ceteris paribus* (Stanley and Doucouliagos, 2012). This suggests that $\alpha_0 \neq 0$ in the presence of publication bias. As we expect the variance of the effect, r_i, and therefore the error, ϵ_i, will likely vary from study to study and that ϵ_i is unlikely to be independently and identically distributed (i.i.d.). This is to say that the error term is likely to be heteroskedastic and, as a result, we should not estimate the effect size using OLS,[15] but rather a weighted least squares (WLS) regression, where the weights are the inverse of the standard error, $\frac{1}{SE_i}$ (Stanley and Doucouliagos, 2012)[16].

By not requiring atheoretical assumptions on the error residuals, the WLS estimate is more robust to the heteroskedasticity of the error term (Stanley and Doucouliagos, 2012). In order to obtain a WLS estimate of the effect, we can weight the standard errors by the inverse of the respective estimate's standard error, $\frac{1}{SE_i}$. This was earlier referred to as the 'precision'. Following on from 3.1, we get:

$$t_i = \frac{r_i}{SE_i} = \alpha_0 \frac{1}{SE_i} + \beta_0 + \sum \boldsymbol{\beta_k} \frac{\boldsymbol{Z_{ki}}}{SE_i} + \nu_i, \tag{3.3}$$

where $\nu_i = \epsilon_i \frac{1}{SE_i}$.

The FAT test then simply becomes a hypothesis test:

$$H_0 : \alpha_0 = 0 \quad \text{vs.} \quad H_1 : \alpha_0 \neq 0. \tag{3.4}$$

[15]As r_i can have different estimated variances, often in multiple orders of magnitudes

[16]The mathematical derivation for the WLS estimate of an MRA is found in Appendix A.2

From Stanley (2005, 2008), we can test, through the PET test of $H_0 : \beta_0 = 0$, whether there is an underlying exogenous effect between FDI and income inequality. From our initial results in column (1) of Table 5, we would reject the null hypothesis of $H_0 : \beta_0 = 0$ in favour of the alternative hypothesis of $H_1 : \beta_0 \neq 0$, with a significant intercept of 0.033. We could further reject the null hypothesis of $H_0 : \alpha_0 = 0$ in favour of the alternative hypothesis of $H_1 : \alpha_0 \neq 0$, with a coefficient of 0.583 on the standard error of the PCC, which is significant at the 95% confidence interval.

Deeper analysis after accounting for specific study characteristics and stripping the model to a baseline version[17], as shown in column (3) of Table 5, reveals a significant intercept of 0.392 and a coefficient on the standard error of the PCC of 0.366. This would mean that we continue to reject the null in favour of the alternative with respect to both $H_0 : \beta_0 = 0$ and $H_0 : \alpha_0 = 0$.

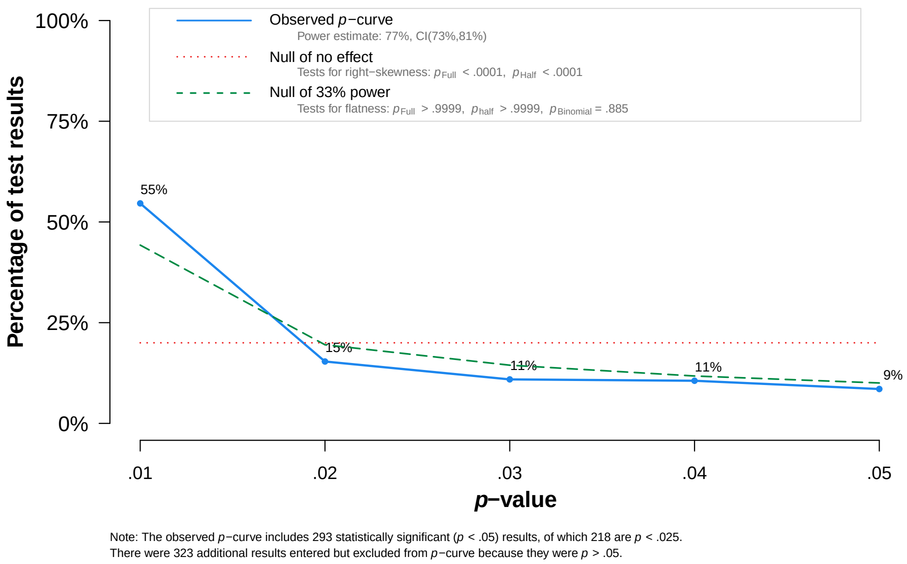


Figure 8: p-curve of primary studies

Figure 8 presents the results of the p-curve test, which plots statistically significant ($p < 0.05$) values and evaluates the presence of evidential value in the underlying impact of foreign direct investment on income inequality. 47.6% of the results are statistically significant. The flatness test and the right-skewness test suggest that the data is not flat and rather exhibits a right-skewed distribution. This finding aligns with the expected pattern when a true underlying effect exists. An

[17]How this is achieved is covered in Section 3.2 but follows the steps outlined by Stanley and Doucouliagos (2012).

equivalent test was run on countries by income level for robustness and the outputs are shown in Appendix A.3 Figure 28. They show the asymmetrical presence is more prevalent in middle- and low-income country focused studies.

While additional factors—such as study heterogeneity and quality—must be taken into account, the p-curve analysis provides compelling evidence for the existence of an underlying effect. To draw definitive conclusions, however, it is crucial to consider these results in conjunction with a comprehensive examination of other relevant studies in the field.

3.2 Discussion of the Results

The FAT-PET test, as shown in column (1) of Table 5, yields a significant intercept of 0.033 and a coefficient of 0.583 on the standard error of the PCC.[18] This intercept suggests a discernible correlation between FDI and income inequality, while the coefficient on the standard error of the PCC points to potential publication bias. These preliminary controls—devoid of controls for other study characteristics—are not definitive and likely encompass heterogeneity across studies.

Incorporating the study characteristics, the comprehensive meta-regression analysis in column (2) of Table 5 reveals a statistically significant intercept of 0.348 and a coefficient on the standard error of the PCC of 0.323 at the 95% confidence interval level. This analysis offers a more detailed understanding of the effects of FDI on income inequality, taking into account the heterogeneity across studies.

Moreover, the Gini coefficient (0.144), income share ratios (0.250), and wage/ income disparities (0.197) have significant and positive impacts on the PCC. Given the binary nature of these measurements in the regression analysis, when income inequality is measured via the Gini coefficient, a more robust positive relationship between FDI and income inequality is observed. This does not imply that using the Gini coefficient as a measure *increases* income inequality, rather that a stronger relationship between FDI and income inequality is observed when the Gini coefficient is used as the measure of income inequality over other income measures.

The results further indicate the log of GDP per capita is negatively associated

[18] To reiterate, the Partial Correlation Coefficient is a measure of the *relative strength of the relationship between FDI and income inequality*; it is unit-free but directional.

Table 5: Initial meta-regression analysis results on all 616 studies.

Dependent variable: PCC	(1) FAT-PET	(2) FULL	(3) SPECIFIC	(4) SPECIFIC (median)
Intercept	0.033**	0.348*	0.392**	0.224
	(0.016)	(0.200)	(0.180)	(0.168)
Measures of FDI and inequality				
FDI (stock)		0.019		
		(0.027)		
Gini		0.144***	0.140***	0.144***
		(0.033)	(0.031)	(0.031)
Income share		0.250***	0.194***	0.177***
		(0.067)	(0.043)	(0.042)
Wage/income disparities		0.197***	0.192***	0.192***
		(0.041)	(0.039)	(0.039)
Economic development				
GDP per capita (Log)		−0.056***	−0.059***	−0.043***
		(0.018)	(0.017)	(0.015)
Controlling for endogeneity				
Estimation methods		0.018		
		(0.021)		
GDP control		0.019		
		(0.022)		
Education control		−0.008		
		(0.024)		
Single country		−0.106***	−0.102***	−0.094***
		(0.026)	(0.023)	(0.024)
Trade control		−0.007		
		(0.023)		
Population control		0.000		
		(0.033)		
Inflation control		−0.029		
		(0.034)		
Unemployment control		−0.036		
		(0.043)		
Government control		−0.015		
		(0.030)		
Publication bias				
Published		0.128***	0.124***	0.132***
		(0.040)	(0.038)	(0.038)
Standard error of the PCC	0.583***	0.323	0.366**	0.410**
	(0.165)	(0.198)	(0.182)	(0.182)
Observations	616	616	616	616
Adjusted-R^2	4.36%	24.96%	26.09%	24.89%

Note: Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

with the PCC, with a coefficient of −0.056. Across the results, this is the only continuous variable, implying that higher levels of GDP per capita (richer countries) are associated with a weaker relationship between FDI and income inequality. Specifically, a 1% increase in the log of GDP per capita is associated with a 0.056 percentage point *decrease* in the PCC. The results of the MRA provide a more nuanced understanding of the impacts of FDI on income inequality, accounting for the heterogeneity across the studies.

In the 'full' model (column (2) of Table 5) which accounts for endogeneity, it is observed that among the various factors—estimation method, GDP, education, single-country controls, etc.—only single country studies exert a significant influence on the PCC, with the rest showing a small and insignificant effect on the relationship between FDI and income inequality.

Studies concentrated on a single country tend to exert a negative impact on the PCC, as evidenced by a statistically significant coefficient of −0.106. This suggests that research with a geographically-singular focus tend to report a weaker (stronger) positive (negative) correlation between FDI and income inequality.

One plausible explanation for this observation could be the propensity for single-country studies to be conducted in developing nations. This hypothesis is empirically supported by the average 'development level' in the primary studies for single-country and multi-country studies being 3.5 and 2.7, respectively. The availability of data and the academic interest in these regions, where the relationship between FDI and income inequality is more pronounced, could be contributing factors.

Furthermore, it could be reasonable to presume that that multi-country studies often concentrate on specific clusters of countries or 'clubs' such as OECD members, developed nations, MENA, *et cetera*. These studies are likely to be subject to unobservable or immeasurable between-country heterogeneity, which could influence the observed relationship between FDI and income inequality.

Table 5 Column (3)[19] present the results of the baseline model.[20]

In the specific model, we witness an underlying effect between FDI and income

[19] and all *'SPECIFIC'* models henceforth.

[20] The baseline model employs a general-to-specific selection approach, iteratively restricting the model until the only regressors left are those over a specified confidence interval, namely 90% (Stanley and Doucouliagos, 2012).

inequality, with a significant intercept of 0.392 and a coefficient of 0.366 on the standard error of the PCC. The significant positive intercept, α_0, indicates that there is a positive relationship between FDI and income *in*equality (negative social benefit) after controlling for the study characteristics.

Gini reports a significant and positive impact on the PCC, with a coefficient of 0.140. Income share ratios and wage/income disparities also exhibit significant and positive impacts on the PCC, with coefficients of 0.194 and 0.192, respectively and single-country studies continue to exert a significant negative impact on the PCC, with a coefficient of −0.102.

Similarly to the full model, we witness a continuation in publication bias, with a significant coefficient of 0.124, suggesting that published studies tended to report a stronger (weaker) positive (negative) relationship between FDI and income inequality.

Column (4) of Table 5 presents the results of the median model, which is a robustness check on the specific model. By employing the *median* of the log of GDP per capita as opposed to the *mean*, we observe that the intercept, and thus the underlying effect of FDI on income inequality falls from 0.392 to 0.224, and no longer remains significant at any reasonable confidence interval. This is likely the result of a right-skewed distribution of GDP per capita, where (ultra-)rich countries (outliers) pull the mean up. Despite using the logarithm to mitigate impacts, as is the case with wealth the absence of outliers on the lower end of the curve[21] prevents the distribution from conforming to a normal distribution, and rather more of a Pareto distribution. As such, the median is a more robust measure of central tendency and has been used in relevant models henceforth.

Under the specific (median) model, the results suggest that the binary use of the Gini coefficient to measure income inequality has a greater impact on the PCC than in the specific model with use of the mean. Further, we see that there is a stronger presence of publication bias in the specific model of the median than in the specific model of the mean, while all of the income share(s), wage/income disparities, log GDP per capita, and single country effects have a reduced impact on the PCC, the relationship between FDI and income inequality.

[21]There is a theoretical bound for GDP per capita if we imagine a country is worthless with \$0 GDP per capita, and marginally richer with a GDP per capita of \$1, $ln(0) = -\infty$, and $ln(1) = 0$. Wealth is not random.

Table 6: Baseline results for different income groups.

Dependent variable: PCC	(1) Low Income	(2) Middle Income	(3) High Income
Intercept	0.083***	−0.027	−0.325***
	(0.034)	(0.100)	(0.061)
Measures of FDI and inequality			
FDI			0.089*
			(0.046)
Wage/income disparities			0.303***
			(0.053)
Controlling for endogeneity			
Estimation methods		−0.060**	
		(0.030)	
GDP control	0.149***		−0.206***
	(0.036)		(0.054)
Education control			−0.306***
			(0.071)
Trade control			0.555***
			(0.093)
Population control			0.688***
			(0.107)
Inflation control	−0.229***		0.504***
	(0.058)		(0.075)
Unemployment control			−0.465***
			(0.073)
Government control			0.656***
			(0.080)
Publication bias			
Published		0.049	0.121***
		(0.083)	(0.033)
Standard error of the PCC	−0.124	0.856***	−0.298
	(0.248)	(0.307)	(0.399)
Observations	157	260	199
Adjusted-R^2	26.36%	10.19%	82.47%

Note: Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

3.3 Economic Development

3.3.1 Differences in economic development level(s)

Ordinal categorisation, as previously outlined, resulted in 157 low-income countries, 260 middle-income countries, and 199 high-income countries.[22] The average development level for the low-, middle-, and high-income countries was 1.76, 2.46, and 3.90, respectively. Results of the FAT-PET test, full, and baseline regressions for each respective income group are presented in Appendix Tables 14, 15, and 15. Table 6 presents just the baseline results for the different income groups for ease of comparison. GDP per capita is dropped from the models as we have already accounted for the economic development level of the countries in the grouping. To include the log of GDP per capita would be to double-count the economic development level of the countries.

Table 6 reveals a positive and significant relationship between FDI and income inequality in low-income countries, despite a small impact on the PCC of just 0.083 percentage points. In middle-income countries, the relationship is slightly negative and insignificant, with a PCC of −0.027. High-income countries, on the other hand, exhibit a negative and significant relationship with a PCC of −0.325.

Ceteris paribus, the relationship between FDI and income inequality is positive in low-income countries, ambiguous (and insignificant) in middle-income countries, and large and significant in higher-income countries. This is to say that in poorer countries FDI, in aggregate, has *increased* income inequality between 1951 and 2021, while in richer countries, FDI has *decreased* income inequality. Moreover, the relationship between FDI and income inequality is not uniform across countries of varying economic development levels, explaining much of the heterogeneity in the results, and providing an empirical derivation of the Kuznets (1955) inverted-U curve. These empirical results contribute significantly to the ongoing economic debate among academics regarding the true underlying impacts of foreign direct investment on income inequality. Consistent with the literature, these findings suggest that the relationship between FDI and income inequality is contingent on the economic development level of the host country (Huang et al., 2020).

[22]Despite a misalignment between categorisations—which likely impacts the variances—the implementation of the WLS regression meant smaller studies are be penalised. Further, it ensured conformity to global relativity in economic development levels over time.

Across the primary studies, we further see a fall in the PCC over publication time, see Figure 9, indicating that there may have been a non-linear trend over time in the relationship between FDI and income inequality for given countries. This is expected with low-income countries having positive relationships in the PCC that fall as economic development advances. One such example of rapid economic growth is in *'China miracle'* in the wake of the *Open Door Policy* of Deng Xiaoping, 1978 (J. Y. Lin et al., 1997; Zhang et al., 2016).

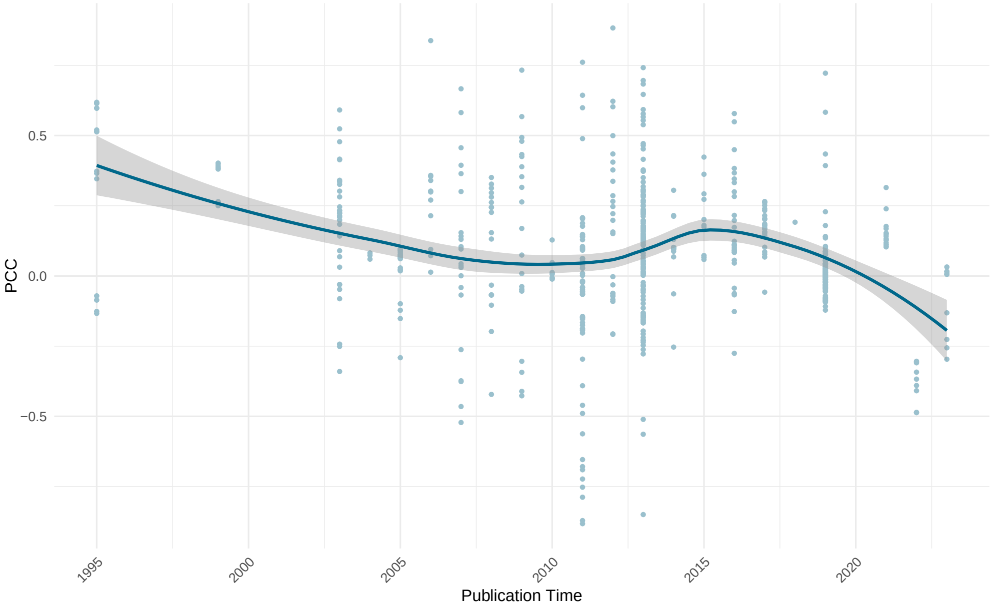


Figure 9: PCC over time.

Interestingly, we see large differences in the predictability of controls between the different income groups. In low-income countries, GDP and inflation controls are significant predictors of the PCC, while in middle-income countries only estimation methods are a significant predictor of PCC variation. In high-income countries, FDI (*stock*), wage/income disparities, GDP, education, trade, population, inflation, unemployment, and government controls are all significant predictors of PCC variation. The dummy variable of *published* drops off for the low-income group, indicating that the difference in the relationship between FDI and income inequality between published and unpublished studies in low-income countries is either already accounted for or irrelevant to the specific subset of countries in this study.

The coefficient on the standard error of the PCC is only significant (both large and positive) in middle-income countries, with a coefficient of 0.856, with the other two groups showing a negative and insignificant relationship, lessening the likely presence of publication bias in the respective studies. An Egger's test for the presence of funnel plot asymmetry in the three studies reveals that there is no presence of asymmetry in the high-income countries study, but there is the presence of (positive) funnel plot asymmetry in both the low- and middle-income countries studies, see Appendix A.3 Figure 27.

Both unemployment and education controls are significant and negative predictors of the PCC in high-income countries, with coefficients of -0.465 and -0.306, respectively. This suggests that high-income focused studies which took account of years of schooling and/or unemployment levels, a weaker relationship between FDI and income inequality was seen. FDI, wage/income disparities, trade, population, and government controls are all significant and positive predictors of the PCC in high-income countries, with coefficients of 0.089, 0.303, 0.555, 0.688, and 0.656, respectively.

Comparing low-income focused studies to high-income focused studies, we see that the impact of GDP controls and inflation controls reverses. GDP controls in low-income countries are significant and positive predictors of the PCC, while in high-income countries they are significant and negative predictors of the PCC. Inflation controls in low-income countries are significant and negative predictors of the PCC, while in high-income countries they are significant and positive predictors of the PCC.

It is well documented that developing nations tend to exhibit higher levels of income inequality compared to developed nations (Osakwe et al., 2023). One could argue that income inequality is a larger relative issue in lower-income compared with higher-income countries.

Paradoxically, the results seen in Table 6 show to present an economic chasm whereby an increase in foreign direct investment, *ceteris paribus*, leads to an *increase* in the income inequality of developing nations and a *decrease* in income inequality in higher-income countries.

The outcomes probe a deeper philosophical question of whether the benefits in opportunities and growth are worth the trade-off with income inequality on an individual level in developing nations.[23] It further calls for deeper questioning

[23]The impacts of FDI on economic growth are outside the scope of this paper, but it has been deeply studied by the likes of Almfraji et al. (2014), J.-W. Lee et al. (1994), and Pegkas (2015),

around the ethical implications of investment strategies and economic policies, particularly in the context of richer nations, companies, or individuals investing in poorer countries. Moreover, it simultaneously prompts a reevaluation of the moral dimensions of effective altruism, and a reconsideration of whether the desired outcomes should be measured in terms of individual social well being or the aggregate economic prosperity of a given nation.

3.4 Moderating variables and their explanatory power

Table 7 extends the analysis from column (4) of Table 5. It simplifies the median baseline model by sequentially eliminating three elements: (1) the controls for publication bias, (2) the controls for endogeneity, and (3) the measures of inequality. The resulting model uses the median (natural) log of GDP per capita as the sole control variable.

The elimination of controls for publication bias is not intended to enhance the model's predictive power—it in fact reduces its robustness, given the significant publication bias identified in the studies. The objective is to quantify the extent to which different factors account for the heterogeneity observed in the primary studies. This is to say that by iteratively removing the controls in groups, we can see the extent to which study-specific controls have an impact on the observed differences across outcomes.

Column (1) of Table 7 reveals a notable increase in the impact of FDI on income inequality, with the intercept rising to a significant 0.593 from an insignificant 0.224 in the 'specific' median model. This does not, however, imply a sudden intensification in the underlying effects of FDI on income inequality or an underestimation in previous models.

By examining the adjusted-$\boldsymbol{R}^2$, we can assess the influence of specific estimators on the heterogeneity in the primary studies. The baseline model, which accounts for publication bias, explains 24.89% of the heterogeneity. Removing the controls for publication bias reduces this to 21.71%, suggesting that these controls account for 12.78% of the observed heterogeneity.[24]

etc.

[24] $\left(\frac{24.89-21.71}{24.89}\right)\times 100 \approx 12.78\%$. Publication bias explains 3.18% of the heterogeneity, but 12.78% of the *observed* heterogeneity.

Table 7: Moderating variables' explanatory power.

Dependent variable: PCC	(1) Drop Publications	(2) Drop Endogeneities	(3) Drop Inequalities
Intercept	0.593***	0.758***	0.816***
	(0.138)	(0.134)	(0.091)
Measures of inequality			
Gini	0.141***	0.122***	
	(0.031)	(0.031)	
Income share	0.202***	0.142***	
	(0.042)	(0.040)	
Wage/income disparities	0.170***	0.120***	
	(0.039)	(0.038)	
Economic development			
GDP per capita	−0.066***	−0.084***	−0.078***
(Log, median)	(0.014)	(0.014)	(0.010)
Controlling for endogeneity			
Single country	−0.094***		
	(0.023)		
Publication bias			
Published			
Standard error of the PCC			
Observations	616	616	616
Adjusted-R^2	21.71%	21.01%	16.84%

Note: Column (1) shows a baseline model using the median of GDP per capita, removing controls for publication bias; column (2) strips back column (1) to remove the controls for endogeneity; column (3) further removes the measures of inequality to control only for GDP per capita.
Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Further elimination of the controls for endogeneity, where only single-country focused studies significantly predict the PCC, results in an explained heterogeneity of 21.01%. This implies that the controls for endogeneity explain a marginal 0.70% of the heterogeneity in the primary studies.

Finally, removing the measures of inequality allows us to explain 16.84% of the heterogeneity in the primary studies. Consequently, we can infer that the median of the log of GDP per capita explains 67.66% of the *observed* heterogeneity across the primary studies. Stated differently, GDP per capita accounts for more of the heterogeneity in the primary studies than *twice* that of the other ten controls *combined*.

What is largely unaccounted for is any significant association between a nation's wealth and its estimated level of corruption. Increased social tensions resulting from rapid economic growth (Anwar et al., 2012), disruptions between skilled and unskilled labour (Deng et al., 2013; Feenstra et al., 1997), education (Roser and Cuaresma, 2016), amongst other factors, have all been shown to impact the relationship between FDI and income inequality, in varying ways. Moreover, there has been extensive research into the relationship between corruption and its impacts on FDI flows (Bénassy-Quéré et al., 2007; Pan-Long, 1995). Empirically, however, there has been a scarcity of research directly addressing the potential for malfeasance and misappropriation of funds by people—or groups—in power.

Economies with higher levels of development, larger service sectors, and greater per capita GDP typically display lower levels of corruption (Treisman, 2000). This observation, however, is not universally applicable, as evidenced by the Watergate scandal in the United States during the 1970s. Several factors contribute to this pattern, but a fundamental argument posits that those in power can more easily maintain control over less-developed nations with lower GDP per capita and smaller service sectors (Blackburn et al., 2006).

4 Corruption

Across the primary studies, we see that the relationship between foreign direct investment and income inequality is contingent on the level of GDP per capita of a given country or set of countries. In all 616 primary studies, just 10 assessed the impact of differences in democratic states against non-democratic states (Bussmann et al., 2005; Reuveny et al., 2003). Despite this, many of the papers alluded to corruption being a likely impactor on the relationship between FDI and income inequality, with GDP typically acting as a de-facto proxy for corruption levels given their correlation.[25] Corruption levels have only been broadly assessed and measured since 1995 from Transparency International's Corruption Perceptions Index (CPI) (Transparency International, 2024). The Worldwide Governance Indicators (WGI), developed in 1996, measure the quality of governance in a given country, with one

[25]Some papers, such as Baek et al. (2016) and Bannerman (2007), used corruption in part through a proxy of political risk.

of the six indicators being control of corruption (Kaufmann et al., 2010).[26]

The CPIs are considered the 'gold standard' of global corruption estimators and the WGIs have come under scrutiny at multiple points over the past decades for ineffective research in generating their estimates. The correlation between the CPIs and WGIs is approximately 0.989.

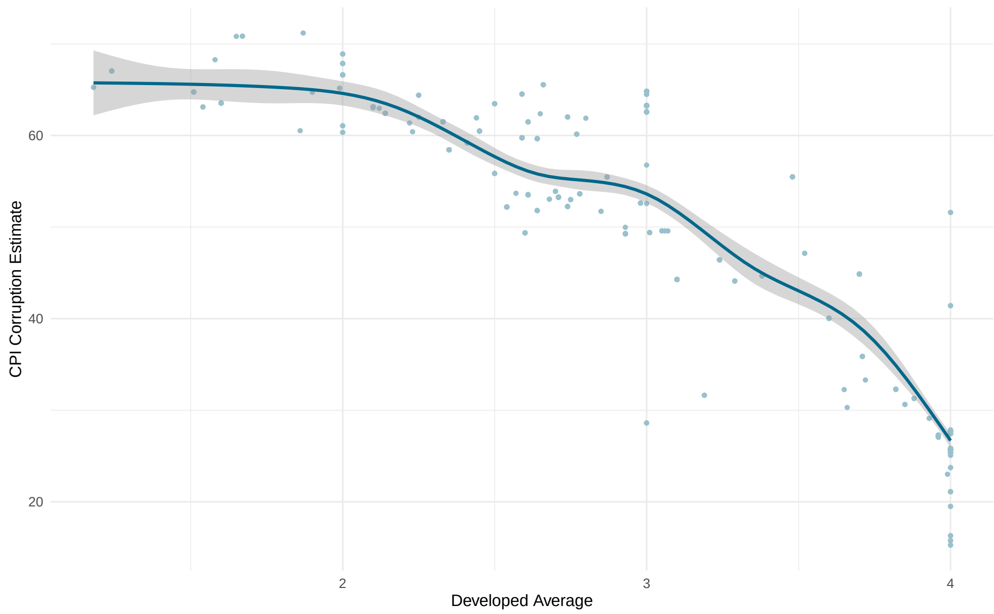


Figure 10: Corruption estimates and (ordinal) GDP per capita

I hypothesise that whilst GDP per capita accounts for 67.66% of the observed heterogeneity across studies, see Table 7, by introducing a corruption term in a similar manner (i.e., by matching both years and countries to the respective studies), we will see an increase in the explained heterogeneity and a likely reduction in the observed heterogeneity from GDP per capita as a result of omitted variable bias.

4.1 Summary Statistics

Across the decade of officially-reported corruption estimates, the most corrupt nation was Somalia, on average, with a corruption value of 83.89. The least corrupt was Denmark with a value of 2.15. The Seychelles and Palau fell the most (became less corrupt), while Antigua and Barbuda and the Cayman Islands rose

[26]The others are *Voice and Accountability, Regulatory Quality, Political Stability and Absence of Violence/Terrorism, Rule of Law,* and *Government Effectiveness.*

the most (became more corrupt). The mean yearly change between 2012 and 2022 is 0.014 with a standard deviation of 0.628. Figure 11 shows the distribution of the corruption estimates between 2012 and 2022 while Figure 12 shows the average annual change for given countries between 2012 and 2022.

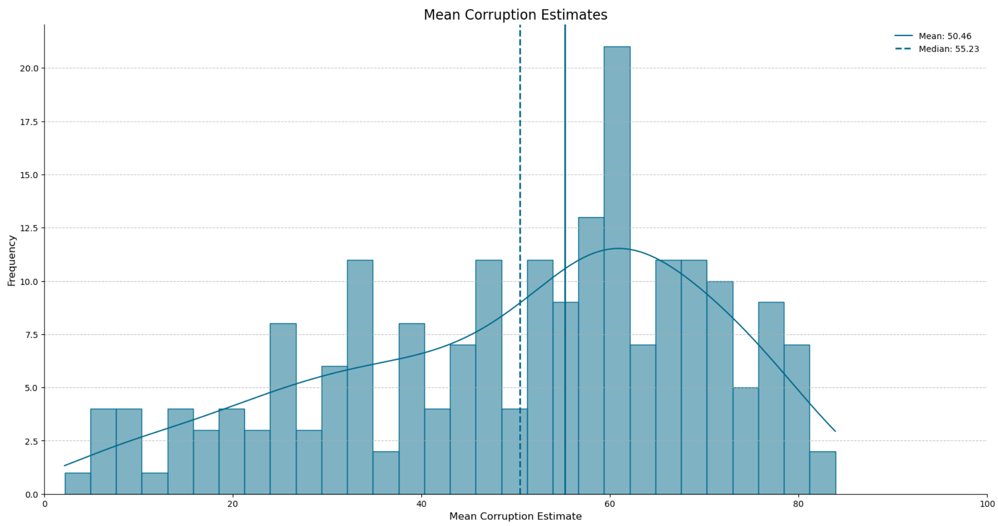


Figure 11: Histogram of the corruption estimates between 2012 and 2022. The World Bank (2024)

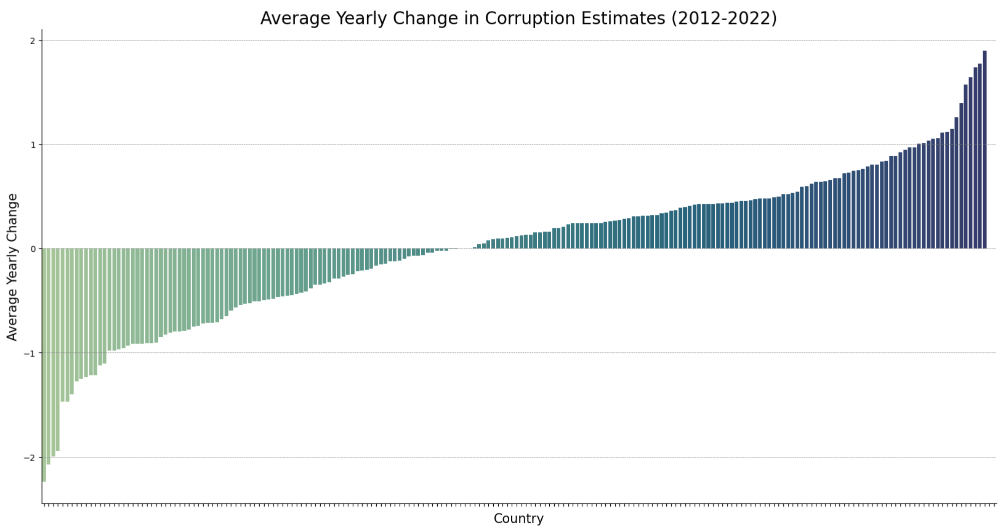


Figure 12: Average change in corruption estimates between 2012 and 2022. The World Bank (2024)

4.2 Methodology

To build the machine learning model, I have utilised the World Bank's API to pull development indicators for each country between 1960 and 2023. This led to a dataset of 23,832,470 data points. The data was cleaned and preprocessed to increase the accuracy and intuition of the model.[27]

Due to the questions around the calculation of the WGI, and for initial estimates only being reported biannually, I removed all values prior to 2012 so as to preserve the integrity of the foundations with which the model is built on. Further, with regards to the CPI, prior to 2012 all time-country values reported were immeasurable both across years and countries, rendering the data unusable for the model. This provided 2012 with a good base year and meant the backcasting model was built on 2012-2022 data.

The purpose of the machine learning model was to use development indicators to make predictive estimates of corruption levels in a given country for a given year. The model will have an error rate and is unlikely to pick up individual cases of corruption—e.g., Watergate—but will rather give a generalised estimate of government corruption through the years based on their economic conditions and other development indicators. Model 3, for example, was able to predict a fall of corruption in Ireland in the 1990s, Figure 21b, which is likely the case with the ceasefire from the IRA in 1994, although it was unable to predict a reasonable increase in corruption levels during the 1990s in Nigeria under the dictatorship of Sani Abacha (Cox, 1997; Ige, 2002). The models lean heavily on later (more recent) CPI and WGI values, where it has extrapolated on the presumption that corruption levels are unlikely, at least on an aggregate level, to have changed drastically in the 62 years between 1960 and 2022. This presumption is myopic in the case of outliers, but is essential to mitigate overfitting of the data.

To train the model, missing corruption estimate country-year rows were removed. For all models, the data was split into a 80:20 training-test set which meant that

[27]I.e., the WGI corruption estimate is a reported value between -2.5 and 2.5, with -2.5 being the most corrupt and 2.5 being the least corrupt. To make this more intuitive, the data is transformed to be between 0 and 100, with 0 being the least corrupt and 100 being completely corrupt, i.e., a greater corruption estimate is now seen as higher corruption. The same was done for the CPI values.

the model was trained on years 2015-2022 and tested on years 2012-2013.[28]

I will briefly discuss each model and but a more comparable summary table is outlined in Appendix A.4 Table 17. Model 3 & 4 are used for further analysis.

4.3 Model 1

Model 1 is a rudimentary model minimising the squared error in the absolute difference between the predicted corruption estimate and the actual corruption estimate.[29] An RMSE of 0 would suggest that all points perfectly predicted the corruption estimated in the test set. All values above the 45-degree line suggest that the model is over-predicting the corruption estimate ($\hat{y}_i > y_i$), and vice versa. Figure 13 shows the actual vs. predicted values for the model with each individual graph representing a difference in the imputed values used for predicting the model in an effort to reduce both the computational complexity and demand of the model, and to reduce the over-fitting of values. Variances in the absolute differences typically indicate that it is harder to reliably estimate corruption levels in the middle of the distribution, while it is better at predicting the extremes. This is likely due to the model being trained on the extremes of the distribution, where the corruption estimates are more reliable, and less so in the middle of the distribution where the corruption estimates are less reliable.

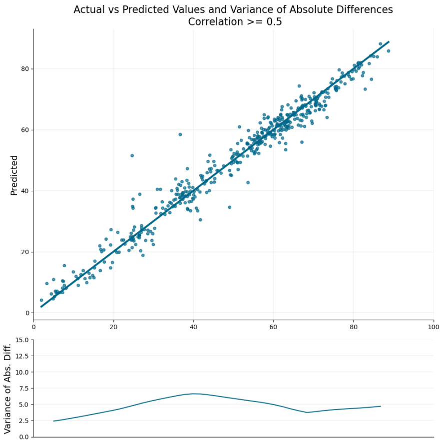
Figure 10 illustrates the negative correlation between GDP per capita—as ordinal datapoints—and corruption estimates. Economic prosperity arises from cooperation and collectivism both within and among nations, population growth, technological

[28]Models were built in *Python* using the the *XGBoost* library with a modified optimiser that builds on the standard squared error approach, which is a scalable and accurate implementation of the gradient boosting framework. The custom optimiser was largely similar to the squared error optimiser where I penalised large deviations between years as well as large deviations from the average values officially reported by the WGI and CPIs. It further penalised an over-reliance on single predictive features in favour of a more balanced model. This was required as the World Bank's Development Indicators can be spotty in missing values, so lack of a penalty term on feature over-reliance, missing values had large predictive power in the corruption estimates, increasing overfitting, thereby reducing reliability.

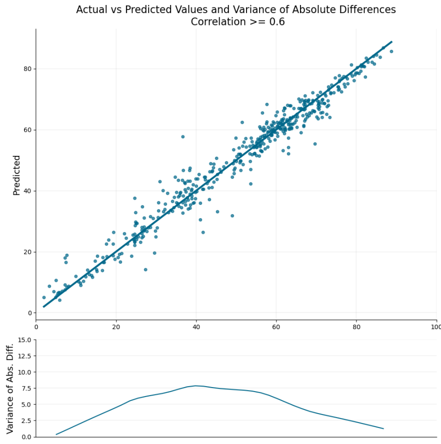
[29]Here, the objective is to minimise the root mean squared error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{4.1}$$

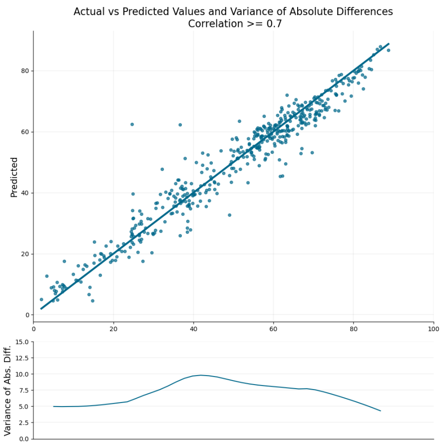
where y_i is the actual corruption estimate and $\hat{y}_i$ is the predicted corruption estimate.



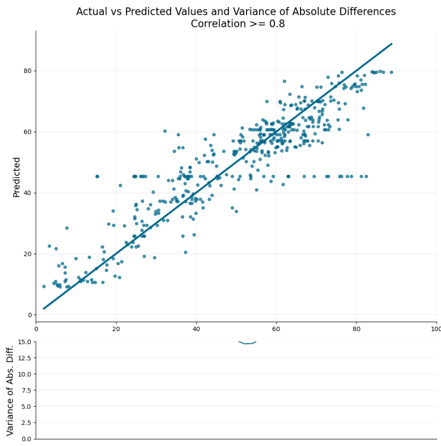
(a) Model 1 with correlation ≥ 0.5



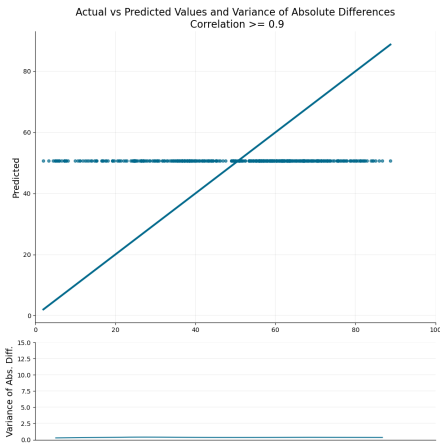
(b) Model 1 with correlation ≥ 0.6



(c) Model 1 with correlation ≥ 0.7



(d) Model 1 with correlation ≥ 0.8



(e) Model 1 with correlation ≥ 0.8

Figure 13: Actual vs. Predicted values for different correlations in Model 1

advancements, etc. (Aidt, 2003; Galor and Weil, 2000; Peterson, 2017; Sinding, 2009). As countries develop, corruption *tends* to decrease (Delabarre, 2021; Laffont, 2006). This is not to imply an absence of corruption in developed nations. Rather, it suggests that corruption is less widespread and has a smaller impact on the overall economy in these (Olken et al., 2012; Silva et al., 2001). Economic models may more accurately predict the extremes of the corruption distribution, where estimates are more reliable, compared to the middle of the distribution.[30]

Model 1*'s two top feature importances raise initial concerns as GDP per capita (current $) and GDP per capita (2015 $) are likely to be highly correlated. Moreover, CPIA transparency and CPIA property rights are apart of the World Governance Indicators, which come out in tandem with the corruption estimates, and therefore will provide no aid in backcasting the model for missing values of corruption.

For easier graphical representation of why Model 1* is a poor estimator see Figures 14a and 14b. Figure 14a shows the heatmap of the corruption estimates from Model 1*. A better time-corollary estimator would look like Figure 14g, given the safe assumption that there are time trends in the corruption estimates. All years to the right of 2011 are provided by the World Governance Indicators and all values to the left are backcasted using the Model 1*. The loss of colour across the Figure 14a indicates the model is unable to accurately predict the corruption estimates for the majority of countries in the dataset, tending towards average values as predictors (or 'features') become unavailable. A clear showing of this is the fictitious line seen at 1991, where a lot of the predictors in the model training set are no longer reported by the World Bank (or are unavailable using their API). Hence, prior to 1991, the heatmap becomes far paler in colour, and the darker colours (deep red for highly-corrupt countries and dark blue for low-corruption countries) lose their intensity as the model has to rely on fewer available datapoints. Perhaps a clearer representation of this is seen in Figure 14b, where countries (each row) can, within a matter of a few years, tend from being highly corrupt (dark red) to being lowly corrupt (dark blue). This is a strong limitation of the model.

[30]This is intuitive when you think about the marginal differences in economic factors can have significant aggregate impacts that models capture well, but may be less precise on an individual country basis where corruption estimates are less certain.

Model	Performance Metrics		Feature Importances	
	Training+Validation	Testing	Feature	Importance
Model 1*	R^2: 0.999 RMSE: 0.356 $\overline{CV}$: 0.955	R^2: 0.965 RMSE: 3.773	GDP per capita (current $)	0.592
			GDP per capita (2015$)	0.027
			CPIA transparity	0.017
			Wage and salaried workers, male (% of pop.)	0.012
			CPIA property rights	0.011
Model 2*	R^2: 0.999 RMSE: 0.545 $\overline{CV}$: 0.981	R^2: 0.984 RMSE: 2.481	Corruption lead 1	0.344
			Corruption lead 2	0.231
			Children out of school, male	0.115
			Government revenue (excluding grants)	0.017
			Time required to get electricity (days)	0.014
Model 3*	R^2: 0.999 RMSE: 0.034 $\overline{CV}$: 0.980	R^2: 0.980 RMSE: 2.837	Average corruption value, WGI (2012-2022)	0.859
			Corruption lead 1	0.015
			GDP per capita	0.009
			Population ages 0-14, female (% of female pop.)	0.008
			Population ages 0-14, male (% of male pop.)	0.006
Model 4*	R^2: 0.998 RMSE: 0.888 $\overline{CV}$: 0.984	R^2: 0.987 RMSE: 2.384	Average corruption value, CPI (2012-2022)	0.870
			Corruption lead 1	0.031
			Relative GDP per capita (*current US$*)	0.005
			Population ages 15-64, male	0.003
			CO_2 emissions from gaseous fuel consumption (kt)	0.002

Note: Where $\overline{CV}$ is the mean cross-validation score, $\overline{CV} = \frac{1}{k}\sum_{i=1}^{k} CV_i$.

Table 8: Model Performance and Feature Importances.

4.4 Model 2

Model 2 attempts to address Model 1's inability to perform trend analysis over time, Model 2 was developed with the inclusion of two lead variables for corruption estimates. These lead variables function similarly to lag variables, but are used for future values in a backcasting model.[31]

Theoretically, this modification should enhance the model's ability to predict corruption estimates for years with missing data, as it could utilise past values to forecast future ones. However, the practical application of this model revealed an overreliance on the lead variables, resulting in a model incapable of accurately predicting corruption levels across time or individual countries.

The suboptimality of Model 2* is evident in Figure 14c. The figure displays a significant discrepancy between the true data from 2012 onwards and the backcasted data from 1960-2011, which is not the desired outcome.[32]

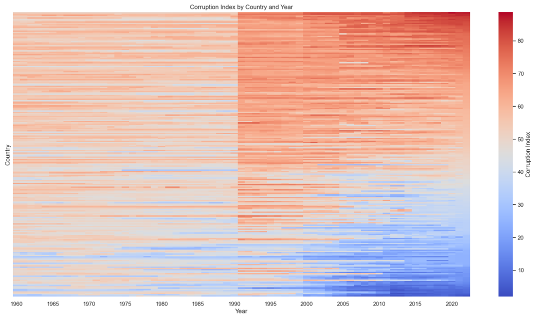
Due to overfitting in the training data, the model predicted that all countries, irrespective of their initial starting position, had a corruption estimate of approximately 81.5 by 1960. Somewhat comically, Figure 15 illustrates the histogram of the backcasted corruption estimates in 1960 from Model 2*, where all countries have a corruption estimate of c.81.5. The scale is identical to that in Figure 11.

4.5 Models 3 & 4

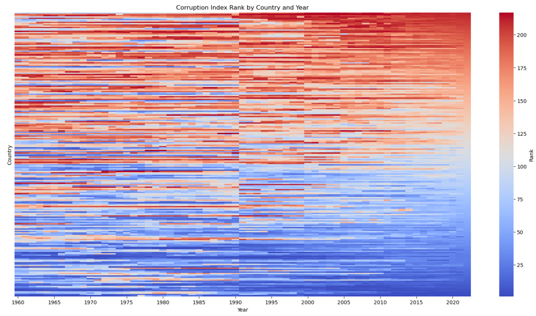
Model 3 builds upon the foundations of Models 1 and 2 by incorporating a strategy to impute missing values in the core predictors of the model, specifically GDP per capita. Rather than employing a simplistic linear extrapolation, this model employs the mean percentage change in GDP per capita over the subsequent five years to estimate missing values. It further introduces a resistance factor to mitigate error propagation in the model from extrapolation. Mathematically, for all instances of

[31] With *lead* variables having the same impact as *lag* variables, but for future values used in a backcasting model. I.e., lead 1 would be $t+1$, lead 2 would be $t+2$.

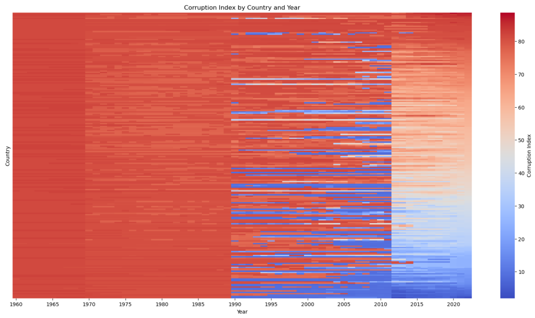
[32] Large 'blocks' of colours are visible prior to 1990. This is particularly problematic and is a consequence of the model iterating excessively on itself, causing it to converge all countries to an average as predictors are eliminated from the model.



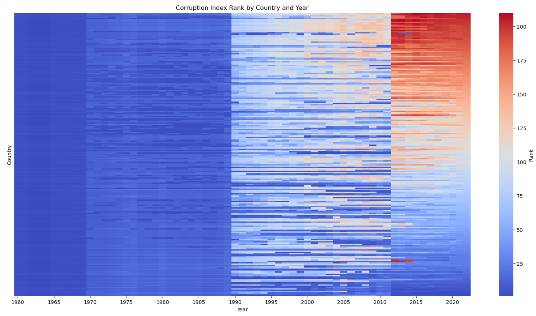
(a) Corruption estimates, Model 2*.



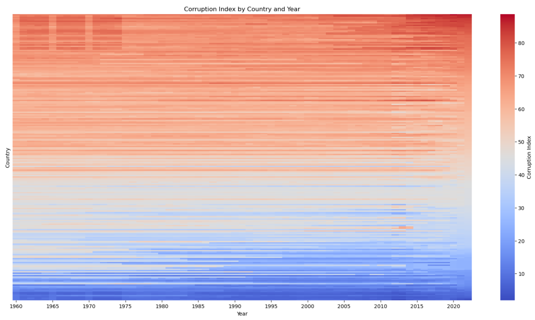
(b) Corruption ranks, Model 1*.



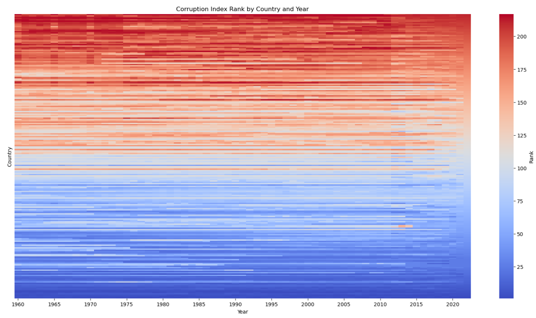
(c) Corruption estimates, Model 2*.



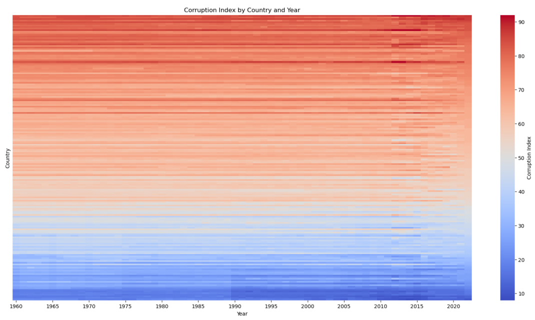
(d) Corruption ranks, Model 2*.



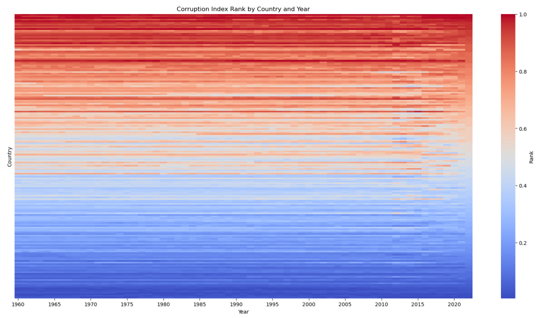
(e) Corruption estimates, Model 3*.



(f) Corruption ranks, Model 3*.



(g) Corruption estimates, Model 4*.



(h) Corruption ranks, Model 4*.

Figure 14: Heatmaps of corruption estimates and relative ranks.

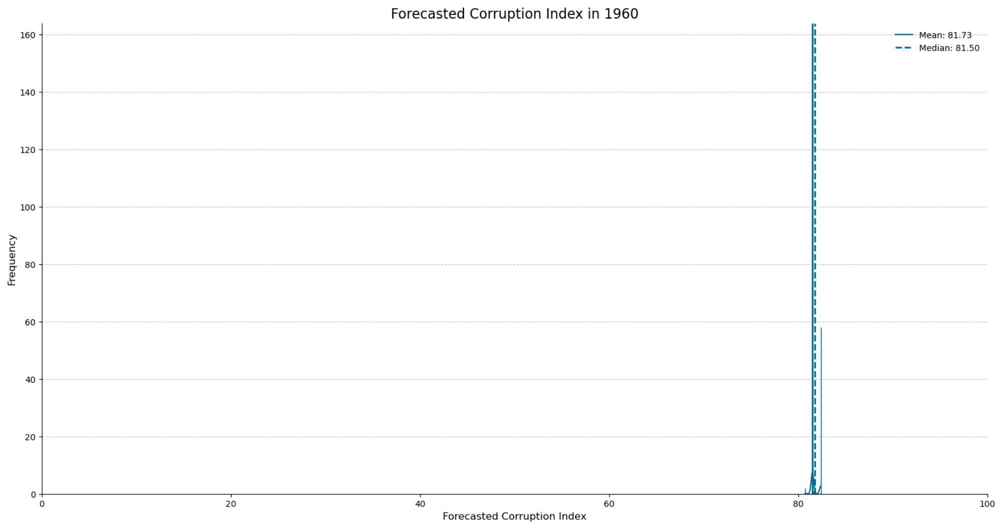


Figure 15: Histogram of the backcasted corruption estimates in 1960 from Model 2*.

missing values, the imputation is performed as follows:

$$GDP_t = GDP_{t+1} \times \left(1 - f\left(\frac{d\ln(GDP)}{dt}\right)\left[\frac{1}{10}\sum_{i=1}^{10}\frac{GDP_{t+i} - GDP_{t+1}}{GDP_{t+1}}\right]\right),$$

where

$$f\left(\frac{d\ln(GDP)}{dt}\right) = \begin{cases} \frac{1}{1+10\left(\left|\frac{d\ln(GDP)}{dt}\right|\right)} & \text{if } \left|\frac{d\ln(GDP)}{dt}\right| > 0.05, \\ \frac{1}{1+\left|\frac{d\ln(GDP)}{dt}\right|} & \text{otherwise.} \end{cases}$$

This method of imputation is more robust to the exponential growth often observed in economic indicators and provides a more accurate reflection of real-world economic dynamics.

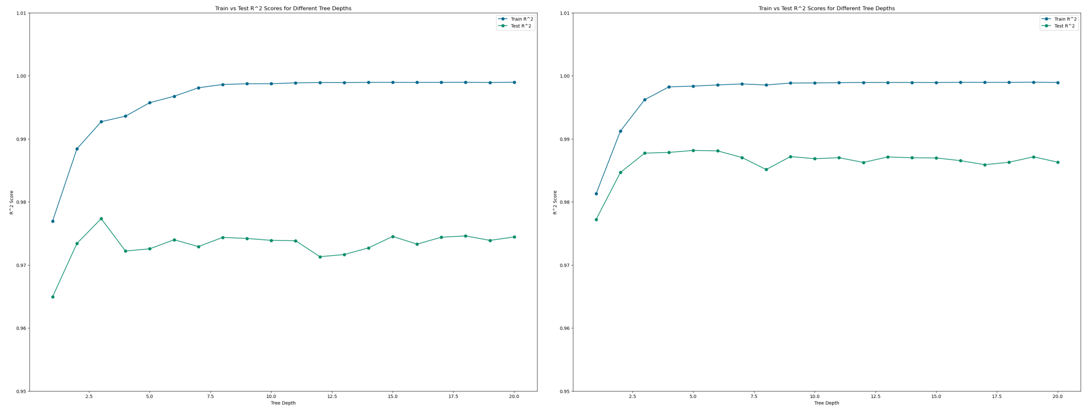
Traditional economics, and the Solow (1956) Model, employs the idea that smaller, less-developed economies grow at a faster rate than larger economies due to diminishing marginal returns. The extrapolation method is a reflection of this. Extrapolating in such a way can of course lead to individual errors which are especially noticed in cases where there is data missing from middle years, such as is the case with Afghanistan between the early 1980s and 2000s, shown in Figure 16 where the smoother aspects of the line are the extrapolation. The model incorrectly overshoots the GDP per capita fall from c.2002 to 1982, before the World Bank provides data again, resulting in a sharp spike. This is the result of severe cycles that Afghanistan seems to go through resulting in large year-to-year changes in waves. Over a longer horizon it looks to be a reasonable estimator, with the GDP per capitas tending towards similar values.

Figure 16: Imputed GDP per capita, Afghanistan 1960 to 2022.

Model 3 further seeks to identify missing data. To account for this in the model, I have removed all variables that have more than 50% missing data in the years prior to 2012. This reduced the number of predictors from 1,454 to 304 while ensuring that the training model was built on predictors that are available throughout the timeframe of the model.

To remove the over-reliance on lead estimates as was done in Model 2, Model 3 instead uses the average of the officially-reported corruption estimates so as to provide an 'anchor' for the estimates to be built on. This is done by taking the average of the corruption estimates from 2012 to 2022 and using this as the base for the backcasting model. Now, instead of two lead variables that hoped for increased stability between years, we now use just one lead variable alongside the initial average corruption level between 2012 and 2022.

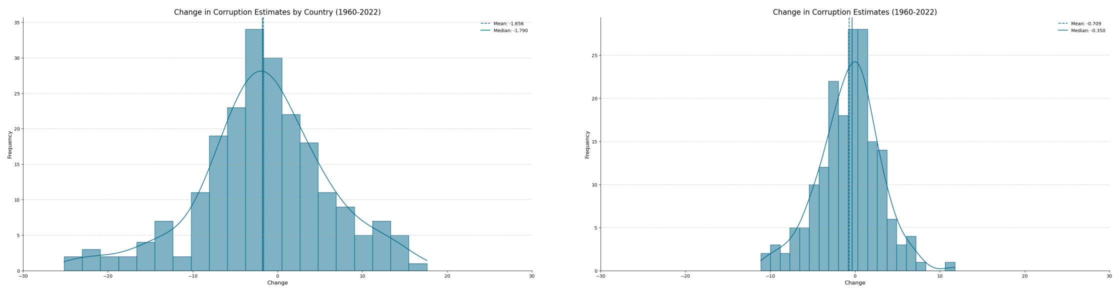
Figure 18a shows a histogram of the estimated change in the nominal corruption estimates between 1960 and 2022. The distribution approximates a normal distribution, albeit with a minor left skew, implying a potential model propensity towards higher corruption estimations. Model 4, later described, but shown in Figure 18b shows a tighter distribution around a similar mean. Both models follow



(a) Model 3. (b) Model 4.

Figure 17: Train vs. test R^2 Scores for different tree depths.

a similar rate of change as the WGI and CPI estimates of 2012-2022.



(a) Model 3. (b) Model 4.

Figure 18: Histograms of changes in nominal corruption estimates (1960-2022).

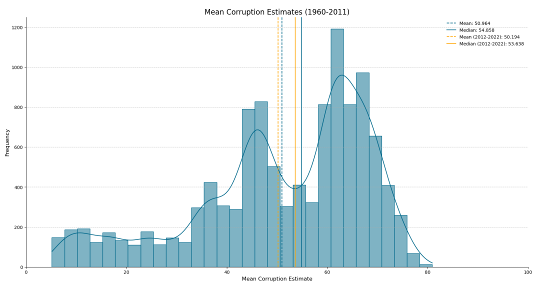
Model 4 is a replication of Model 3, where instead of the WGI's estimate of corruption we use Corruption Perceptions Index values. Matching the WGI estimates, the CPI estimates that Somalia is the most corrupt country with an average of 90 between 2012 and 2022 while Denmark is the least corrupt with a value of 10. As a note, CPIs only provide discrete integer estimations between 0 and 100.[33] Further, it estimates that the Seychelles has the largest fall in corruption while St. Lucia has the largest rise in corruption.

Notably, in Models 3 & 4, following the anchor of the 2012-2022 mean values and the 'lead' predictor, GDP and population measures emerge as the most significant predictors of corruption estimates. This aligns with broader economic literature demonstrating that larger economies generally exhibit lower corruption levels, and

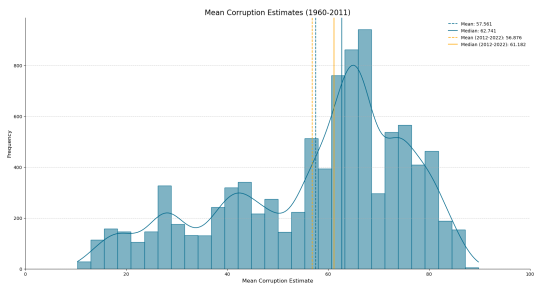
[33] I have not snapped predictions to the nearest integer, rather I have used the continuous values provided by the model.

that societies with greater provisions for female growth and prosperity typically observe reduced corruption (Holcombe et al., 2015; Mauro, 1997). Amin et al. (2019) found that moving from the 25^{th} to the 75^{th} percentile in the population size distribution is associated with a conservatively-estimated 0.23% increase in the mean corruption score, resulting from increased red-tape and it being harder to 'reach a consensus on growth-enhancing anti-corruption reforms.' Intriguingly, the fifth-largest predictor in Model 4 is CO_2 emissions from gaseous fuel consumption. Environmental economic papers (Abid et al., 2023; Akhbari et al., 2019) have shown that there is a positive relationship between corruption and environmental degradation, at least in low-income countries, while there is still debate over any significance in high-income countries.

In the same nature as the previous iterations between correlation levels (Figure 13), Figure 31 depicts the correlation between the actual and predicted values in Model 4. We are beginning to see a very tight prediction (low adjusted-R^2 of 0.987 with the optimal model using all variables) with a RMSE of 2.384, which is a significant improvement over Model 1 with an RMSE of 3.773. Moreover, the improvement in comparison with Model 3 is likely due to the greater reliability in the CPI estimates over the WGI estimates.



(a) Model 3.



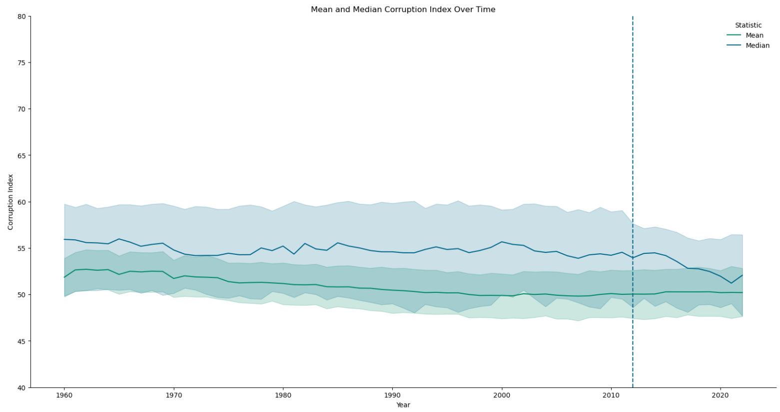
(b) Model 4.

Figure 19: Histograms of mean corruption estimates (1960-2011).

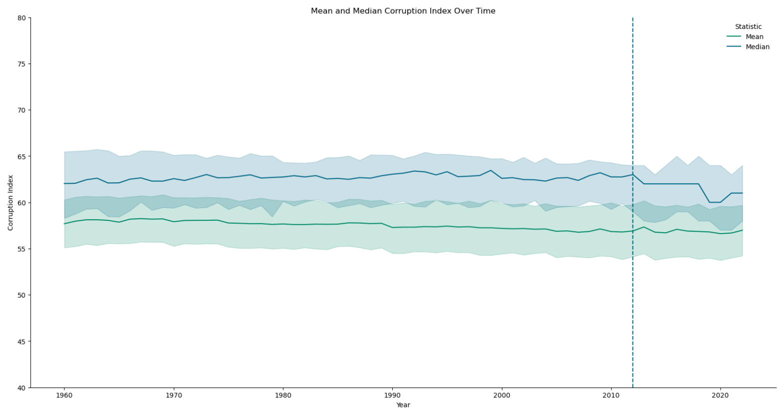
The mean corruption estimates forecasted by the models are presented in Figure 20. These estimates exhibit a relatively linear and stable trend over time and suggest a right-skewed distribution.[34]

Figure 24 illustrates the corruption estimates of the least corrupt countries in 2022 and their backcasted estimates to 1960. These countries demonstrate relatively stable corruption estimates across the time period, with a marginal tendency

[34]As the mean is greater than the median in both graphs.



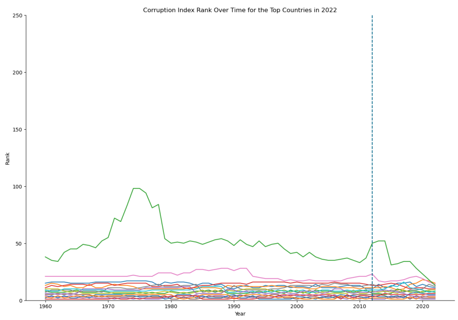
(a) Model 3.



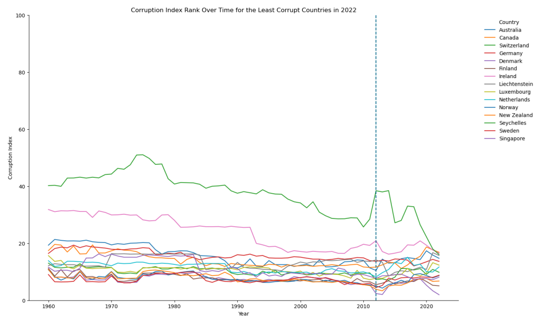
(b) Model 4.

Figure 20: Mean corruption estimates (1960-2022).

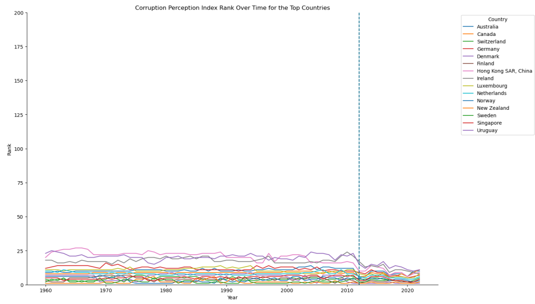
towards higher corruption levels in 1960.



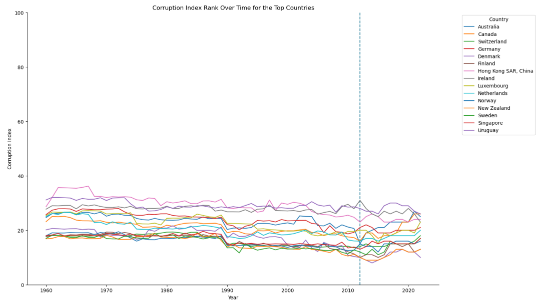
(a) Model 3 Rank.



(b) Model 3 Index.



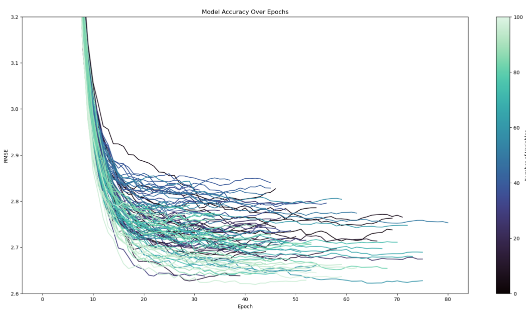
(c) Model 4 Rank.



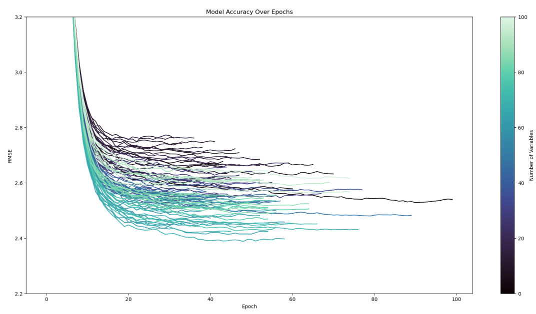
(d) Model 4 Index.

Figure 21: Corruption estimate backcasts.

The robustness of Models 3 and 4 is substantiated by optimal decision tree depths of 3 and 5, respectively, as indicated in Figure 17. The rapid fall in RMSE with escalating epochs and variables, depicted in Figure 22, attests to the models' learning efficacy, predictive refinement, and reliance on a small number of variables.



(a) Model 3.

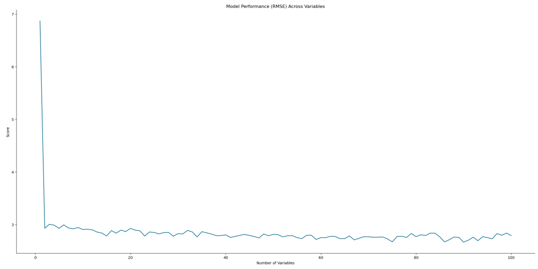


(b) Model 4.

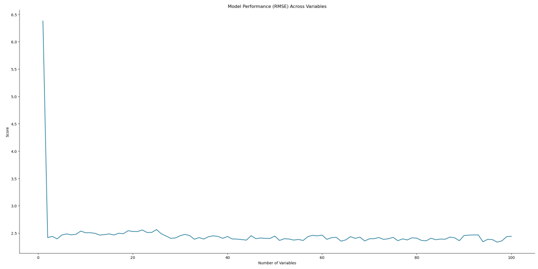
Figure 22: RMSE across epochs.

The quick convergence to a Poisson distribution with an increasing number of variables, observable in Figure 24, underscores the substantial predictive potency of early variables, typically 'leads' or averages. Figure 29 further corroborates this, revealing a pronounced influence of the initial variable on model predictions, a detail elaborated in Table 8.

These findings affirm the models' proficiency in backcasting corruption estimates to 1960 using World Bank explanatory variables, notwithstanding some overfitting propensities. The model, whilst not exact, should provide a strong estimate of corruption levels on a country-year basis.

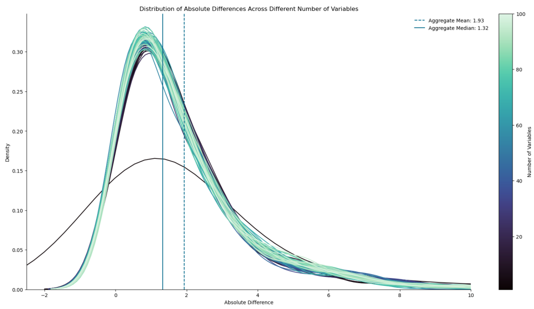


(a) Model 3.

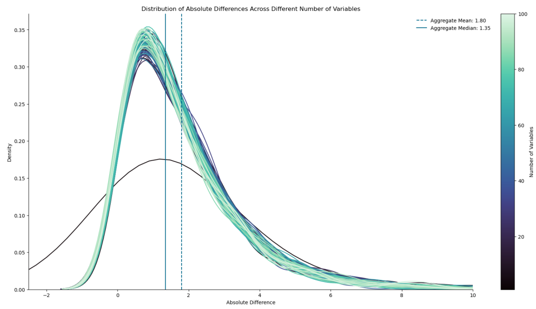


(b) Model 4.

Figure 23: Optimal variables.



(a) Model 3.



(b) Model 4.

Figure 24: Abs. differences across variables.

4.6 Corruption Effects on the Impacts of FDI on Income Inequality

Model 3 was used primarily for the following analysis and reported data so as to maintain a consistency across the paper.[35]

[35]Model 4 was tested in parallel and there were discernible differences between the model(s). Whilst the World Bank's Indicators only go as far back as 1960, and therefore reliable estimates of corruption were only available up until that point, I extrapolated linearly the corruption estimates for countries to 1950 (from their 1960 values). This of course introduces a small amount of error, but it was necessary to ensure that all studies were incorporated evenly and the overall impact is likely to have been negligible.

Rerunning the previous regressions shows the additional inclusion of a corruption variable in the regression model leads to a marginally-smaller adjusted-$\boldsymbol{R}^2$ of 25.82% compared to the 24.89% in the initial model. Moreover, we see that GDP per capita is no longer significant in the model, while the corruption estimate is significant at the 1% level. This implies that the significancy of GDP per capita seen in previous regressions is likely to have been the result of omitted variable bias, resulting in GDP per capita being a proxy for the omitted variable, namely corruption. The coefficient on the corruption estimate is 0.002, indicating that a one-unit increase in the corruption estimate leads to a 0.002 percentage point increase in the PCC.

Whilst nominally small, it is statistically significant and suggests that corruption has a positive impact on the relationship between FDI and income inequality, which is to say that the more corrupt a nation is, the more FDI will result in increased inequality, irrespective of GDP per capita,[36] see Table 9. There is a strong relationship between GDP per capita and corruption, which holds empirically and is more intuitively shown in Figure 10.

In the specific model we see the Gini coefficient, income share, and wage/income disparities all have positive coefficients. As previously mentioned, these are binary variables. Therefore, the results suggest that measurement of inequality in these ways lead to greater positive (or smaller negative) PCC estimates against a standard—*other inequality measures*—*ceteris paribus*.

The output shown in Table 10 shows the specific models for low-, middle-, and high-income countries. The resulting findings indicate that there is a negative relationship between corruption and the PCC in low-income countries, with a significant coefficient of -0.008; no impact of corruption on middle-income countries (corruption drops out of the model), and; a positive impact of corruption on the PCC in high-income countries with a coefficient of 0.015. With the respective intercepts being 0.684, 0.020, and -0.735, the results suggest that the PCC is higher and positive in low-income countries and lower (and negative) in high-income countries. Both low- and high-income counties are significant at the 1% level indicating a non-linear and decreasing trend in the impacts of foreign direct investment on income inequality. This is to say that for low-income countries, an increase in foreign direct investment inflows will *increase* inequality, whilst in high-income countries greater investment inflows *reduce* inequality, with corruption estimates

[36] Both GDP controls and GDP per capita drop out of the specific model.

Table 9: Initial meta-regression analysis results on all 616 studies.

	(1)	(2)	(3)
Dependent variable: PCC	FULL	FULL (WGI)	SPECIFIC (WGI)
Intercept	0.148	−0.402	−0.264***
	(0.179)	(0.298)	(0.050)
Measures of FDI and inequality			
FDI (stock)	0.047	0.040	
	(0.030)	(0.030)	
Gini	0.133***	0.123***	0.133***
	(0.033)	(0.033)	(0.032)
Income share	0.159**	0.169**	0.173***
	(0.070)	(0.070)	(0.041)
Wage/income disparities	0.196***	0.204***	0.203***
	(0.041)	(0.041)	(0.038)
Economic development			
GDP per capita (Log, median)	−0.037**	0.011	
	(0.016)	(0.027)	
Corruption Control			
WGI Corruption Estimate (Model 3)		0.003**	0.002***
		(0.001)	(0.001)
Controlling for endogeneity			
Estimation methods	0.017	0.022	
	(0.022)	(0.021)	
GDP control	0.088**	0.093*	
	(0.042)	(0.042)	
Education control	−0.015	−0.017	
	(0.023)	(0.023)	
Single country	−0.097***	−0.111***	−0.106***
	(0.026)	(0.027)	(0.023)
Trade control	−0.007	−0.011	
	(0.023)	(0.023)	
Population control	0.016	0.003	
	(0.030)	(0.031)	
Inflation control	−0.042	−0.050	
	(0.035)	(0.035)	
Unemployment control	−0.025	−0.031	
	(0.043)	(0.043)	
Government control	−0.004	−0.000	
	(0.030)	(0.030)	
Publication bias			
Published	0.140***	0.123***	0.116***
	(0.040)	(0.041)	(0.039)
Standard error of the PCC	0.308	0.427**	0.507***
	(0.198)	(0.204)	(0.175)
Observations	616	616	616
Adjusted-R^2	24.89%	25.82%	25.82%

Note:
GDP control drops out when following the general-to-specific iterative restriction method.
Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

from the machine learning model indicating that higher corruption estimates tend both low- and high-income countries toward a lower absolute impact of FDI on income inequality. This is further supportive evidence of Kuznets' (1955) stipulation on the prevalence of an inverted-U curve.

Table 10: Specific results for different income groups with corruption.

Dependent variable: PCC	(1) Low Income	(2) Middle Income	(3) High Income
Intercept	0.684***	0.020	−0.735***
	(0.212)	(0.158)	(0.086)
Measures of FDI and inequality			
FDI		0.065**	0.171***
		(0.039)	(0.042)
Wage/income disparities			0.472***
			(0.054)
Corruption Control			
WGI Corruption Estimate	−0.008**		0.015***
(Model 3)	(0.003)		(0.003)
Controlling for endogeneity			
Estimation methods		−0.061***	
		(0.031)	
Education control		−0.059**	−0.229***
		(0.028)	(0.062)
Single country control	−0.152***	−0.071*	
	(0.037)	(0.039)	
Trade control			0.281***
			(0.064)
Population control			0.605***
			(0.099)
Inflation control	−0.239***		0.330***
	(0.068)		(0.051)
Unemployment control	0.293***		−0.400***
	(0.086)		(0.070)
Government control			0.559***
			(0.072)
Publication bias			
Published		0.073	0.098***
		(0.084)	(0.032)
Standard error of the PCC	−0.127	0.665**	−0.103
	(0.331)	(0.322)	(0.385)
Observations	157	260	199
Adjusted-R^2	26.36%	10.19%	80.57%

Note: Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

This is a significant finding as it suggests that corruption has an impact on the relationship between FDI and income inequality, and that this impact asymmetrical across income classifications. Moreover, it holds in the presence of GDP-per-capita clustering,[37] and eradicates the significance of GDP per capita in the model without GDP classification, suggesting that GDP per capita is a proxy for corruption in the model where corruption fails to be accounted for. It also probes the idea that FDI policy implementation with an absence of corruption analysis is likely to lead to not only a an inefficient misallocation of resources but also adverse impacts on equality.

Further robustness checks shown in Appendix A.3 show that when regressing GDP per capita and the corruption alone on the PCC we are only able to account for 17.52% of the heterogeneity which is to say that, taken together, they are only able to account for 5.93% more of the heterogeneity than when individually regressed on the PCC. Deeper analysis on this through an interaction term:

$$\begin{aligned} \text{PCC} = \alpha_0 + \beta_1 \text{GDP per capita} + \beta_2 \text{Corruption} \\ + \beta_3 \left(\text{GDP per capita} \times \text{Corruption}\right) + \epsilon \end{aligned} \tag{4.2}$$

shows that the interaction term is significant, with a coefficient, β_3, of 0.002, indicating that the relationship between GDP per capita and the PCC is moderated by the level of corruption in a country, see Table 13. The significance of the coefficient on the interaction term corroborates our findings that the effect of corruption on the partial correlation coefficient is asymmetric across GDP.

When grouped by income level, corruption is able to explain 14.59%, 0%, and 4.50% of the *observed* heterogeneity for low-, middle-, and high-income studies, respectively.[38] This is significantly less than in the full specified model, further indicating the strong multicollinearity between GDP per capita and corruption.

Building on the initial analysis, comparative analysis between Tables 6—without corruption—and 10 show that an equivalent analysis method leads to vastly divergent results. Table 6 shows low-income countries having a positive PCC of 0.083, whilst high-income countries having a negative relationship with an intercept of -0.325 (both significant). Transitioning to Table 10, we see that the relationship between FDI and income inequality in low-income countries is now 0.684, whilst high-income countries have a negative relationship with an intercept of -0.735.

[37] See Appendix A.4 Tables 14, 15, and 16 for further data on this

[38] $\left(\frac{4.92}{33.70}\right) \times 100 \approx 14.59$; $\left(\frac{0.00}{13.53}\right) \times 100 = 0$; $\left(\frac{3.74}{83.06}\right) \times 100 \approx 4.50$, see Tables 16, 15, and 14.

Table 11: Corruption Impacts on different income levels.

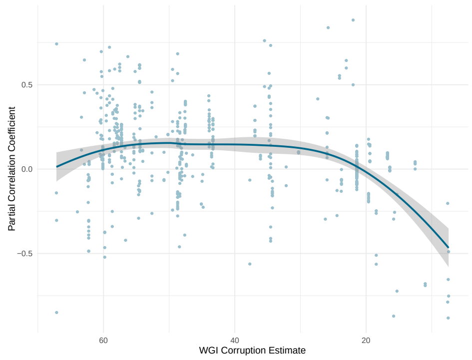
Dependent variable: PCC	(1) Low Income	(2) Middle Income	(3) High Income	(4) Full Model
Intercept	0.416***	0.180*	−0.190***	−0.091***
	(0.131)	(0.104)	(0.060)	(0.023)
Corruption Control				
WGI Corruption Estimate	−0.005**	−0.001	0.008***	0.004***
(Model 3)	(0.002)	(0.002)	(0.003)	(0.001)
Observations	157	260	199	
Adjusted-R^2	4.92%	0.00%	3.74%	16.54%

Note: Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

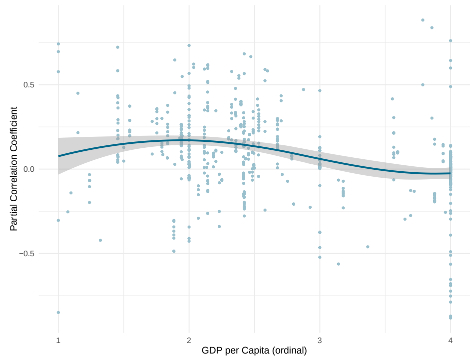
Empirically, they are not only statistically significant from 0, but also from one another. This implies a profound influence of corruption on the relationship between FDI and income inequality and highlights corruption's great influence on economic inequality and possible 'corruption tax' (Asongu et al., 2013; Finckenstein, 2021; Krasniqi et al., 2021). Moreover, it emphasises the importance of including anti-corruption strategies in policy development/implementation to promote fair economic advancement.

The data shows the relationship can perhaps best be described by the Kuznets' inverted-U curve, where FDI initially increases income inequality for exogenous increases in corruption in low-income countries, has a negligible impact in middle-income countries and decreases income inequality in high-income countries, see Figure 25a (Kuznets, 1955).

We previously found GDP per capita accounted for more of the heterogeneity in the primary models than twice that of the other ten controls *combined*. Huang et al. (2020) found similar results—although this is not surprising given the overlap in the primary studies. The inclusion of corruption estimates in the model, however, has a significant impact on the results. Given we can now say that there is omitted variable bias without a corruption control, we witness that corruption, *not GDP per capita*, accounts for more of the heterogeneity in the primary models than the other ten controls combined and that there has been severe myopia, or data restrictions, that has led to GDP per capita being the primary focus of the literature as opposed to corruption.



(a) Kuznet's curve of the PCC against the corruption estimate. *Note:* the x-axis is reversed to follow that of the Kuznets' curve with lower development to the left.



(b) Kuznet's curve of the PCC against the GDP per capita (ordinal).

Figure 25: *de-facto* Kuznets' inverted-U curves.

4.7 Limitations

While the aim of a meta-analysis is to provide a more robust understanding of the underlying relationship between variables of interest, its study is not without limitations Firstly, the data used in the MRA is subject to the limitations of the primary studies, including potential publication errors, and the possibility of omitted variable bias. Secondly, the machine learning model is constructed using aggregate and broad assumptions, which may not hold precisely in individual time-country cases. Thirdly, the model is likely to have been affected by multicollinearity, a common issue that is challenging to mitigate. Fourthly, the model may have been subject to endogeneity, a prevalent concern in economic studies, and while the model has attempted to control for this, the controls may not be exhaustive. Finally, error may have been introduced through the use of the World Bank's data, which frequently has null values or missing data, requiring generalised assumptions. Despite these limitations, the model(s) have been subject to the robustness checks outlined in Appendix A.3.

5 Conclusion

The relationship between foreign direct investment (FDI) and income inequality has been extensively debated, with conflicting findings on the direction and magnitude of its impact (J.-E. Lee, 2006b; Wu et al., 2012). This paper contributes to the ongoing discourse by introducing an empirical assessment of national-level corruption as a moderating factor in the FDI-income inequality nexus. The results suggest that the relationship between FDI and income inequality is complex and significantly influenced by corruption, economic development, publication bias and other endogeneity concerns, collectively explaining the heterogeneous conclusions across studies. Notably, relative corruption accounts for more than *twice* the explained heterogeneity compared to the other ten controls in the regression *combined*, underscoring its critical role in shaping the relationship's impact.

The meta-analysis, encompassing 616 primary studies from 71 papers published between 1951 and 2021, reveals that overall, FDI has a socially-beneficial negative relationship with income *in*equality. However, this relationship is asymmetric across levels of economic development. In low-income countries, greater FDI increases inequality, while in high-income countries, the reverse is observed, and middle-income countries witness no significant impact. After accounting for aggregate income, a one-unit increase in a country's corruption estimate is associated with a 0.008 percentage point decrease in the partial correlation coefficient in low-income countries, a negligible difference in middle-income countries, and a 0.015 higher relationship in high-income countries. This suggests that an increase in corruption weakens the *relative* strength of the relationship between FDI and income inequality, implying that greater corruption leads to a lower observed absolute impact of FDI on influencing inequality.

Paradoxically, the findings present an economic chasm, whereby low-income countries, typically characterised by higher levels of inequality, fail to use foreign investment to reduce income inequality, while high-income countries can readily receive FDI and witness a sizeable impact on reducing inequality. This raises important philosophical questions around the ethical implications of investment and economic policies, particularly in the context of less-developed countries. The outcomes of this study necessitate a deeper examination of the trade-offs between the benefits in opportunities and growth and the potential increase in income inequality on an individual level in developing nations. It calls for further reevaluation of the moral dimensions of effective altruism and a reconsideration of whether the desired outcomes should be measured in terms of individual social well-being or the aggregate economic prosperity of a given nation.

Corruption's influence underscores the need for policymakers to prioritise anti-corruption measures alongside efforts to attract FDI and promote economic development. Greater efforts to ascertain corruption levels would lead to improvements in the impact of each dollar invested in developing nations; in turn reducing income inequality. Economics remains blinkered by the flawed proxy of GDP per capita, overlooking the significant potential for progress through effective metric measurement and seeking to curb corruption in developing nations.

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Appendices

A Appendix A

A.1 Mathematical Intuition for Economic Development Level

An average income category was computed for each study. For instance, where an individual income level, IL, at time t for country c (with a unique identity number, i) is characterised by

$$IL_{i,c,t},$$

where

$$IL_{i,c,t} \in [1,4] \cap \mathbb{Z}$$

a study with a set of countries, over a study period of ts to tf would be characterised by

$$\sum_{c=1}^{C} \sum_{t=ts}^{tf} IL_{i,c,t}.$$

The study's average (mean) value would be

$$\overline{IL}_{i,c,t} = \frac{\sum_{c=1}^{C} \sum_{t=ts}^{tf} IL_{i,c,t}}{(tf - ts + 1)C}.$$

where C is the number of countries in the study, i.

Should

$$\overline{IL}_{i,c,t} \in [1,4] \cap \mathbb{R} \setminus \mathbb{Z},$$

it would be inferred that the study incorporated a mix of countries with varying economic development levels.

For the Maddison Project data, an adjustment of the calculation is required in order to get an average of the Log GDP per capita for each study, see Equation A.1.

$$\overline{\ln GDPpc}_{i,t} = \ln\left(\frac{\sum_{c=1}^{C}\sum_{t=ts}^{tf}\left[GDPpc_{i,c,t} \times I_{i,c,t}\right]}{\sum_{c=1}^{C}\sum_{t=ts}^{tf} I_{i,c,t}}\right) \tag{A.1}$$

$$\text{where} \quad I_{i,c,t} = \begin{cases} 1 & \text{if data for country } c \text{ is available at time } t \\ 0 & \text{otherwise} \end{cases}$$

For example, within the (Baek et al., 2016) study, only 114 of the 115 countries used in the study were available in the Maddison Project's database, $C = 114$ as opposed to 115. By adjusting both the numerator and the denominator, it takes the assumption that the missing country would have had a similar GDP per capita to the average of the other countries in the study. This is a limitation of the study, but one that is necessary to apply the data in a reasonable way.

A.2 Weighted Least Squares derivation

The WLS estimate of the effect size is derived from the minimisation of the weighted sum of squared errors, which reweight studies according to their effect size. For

$$\boldsymbol{r} = \boldsymbol{M\beta} + \boldsymbol{\epsilon} \tag{A.2}$$

Where $\boldsymbol{r}$ is the vector (of size $N \times 1$, where N is the number of estimates across the literature) of effect sizes (in our case PCCs); $\boldsymbol{M}$ is the matrix (of size $M \times K$, where K is the number of study characteristics) of moderator variables; $\boldsymbol{\beta}$ is the vector (of size $K \times 1$) of coefficients, and $\boldsymbol{\epsilon}$ is an $L \times 1$-sized vector of residuals of the errors (Stanley and Doucouliagos, 2012). The WLS estimate of β is thus given by:

$$\hat{\boldsymbol{\beta}} = \left(\boldsymbol{M'\Omega^{-1}M}\right)^{-1} \boldsymbol{M'\Omega^{-1}r} \tag{A.3}$$

where:

$$\mathbf{\Omega} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_N^2 \end{bmatrix} \tag{A.4}$$

and σ_i^2 is the variance of the i^{th} effect size, r, and its sampling error, ϵ_i (Stanley and Doucouliagos, 2012).

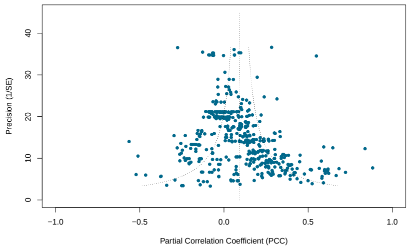
Equation A.3 is a Generalised Least Squares (GLS) estimator, with WLS being a special case where $\mathbf{\Omega}$ has this specific diagonal structure. When the parameters in $\mathbf{\Omega}$ are known, GLS is the best linear unbiased estimator (Greene, 2003). Even when consistent estimates of σ_i^2 are used in place of the true values, the feasible GLS version of Equation A.3 is consistent, asymptotically efficient, and asymptotically normal (Greene, 2003; Stanley and Doucouliagos, 2012).

A.3 Robustness checks

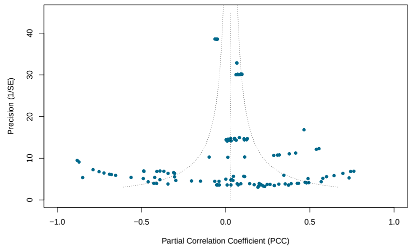
Intercept	0.091***
	(0.018)
Time Lag	-0.000
	(0.002)
Adjusted R^2	0.21%

Table 12: Regression Analysis of Time Lag and Adjusted PCC

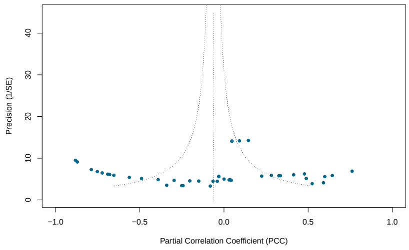
A.4 Machine Learning Robustness Checks



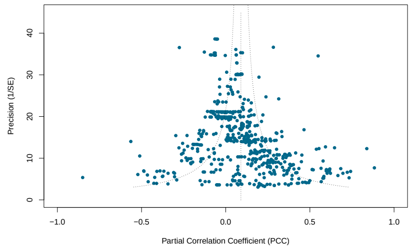
(a) Multi-country studies.*



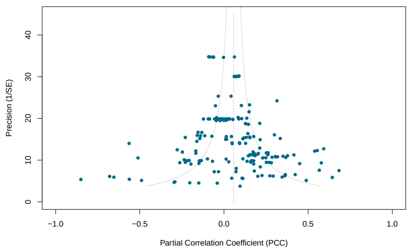
(b) Single-country studies.



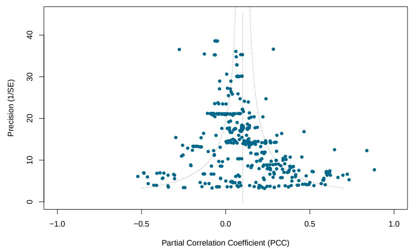
(c) Unpublished studies.



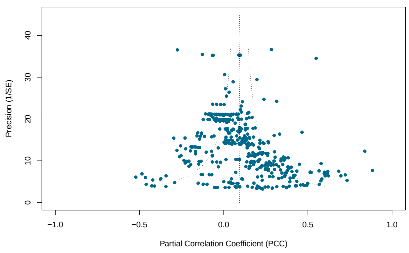
(d) Published studies.*



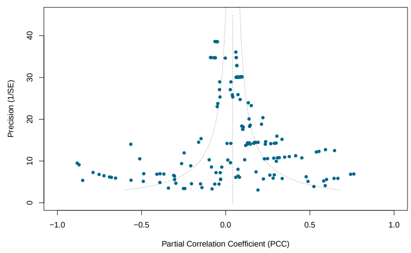
(e) Studies with endogeneity controls.*



(f) Studies without endogeneity controls.*



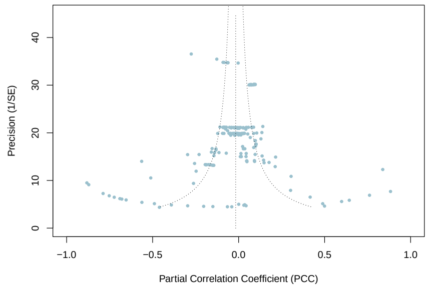
(g) Studies with core tests.*



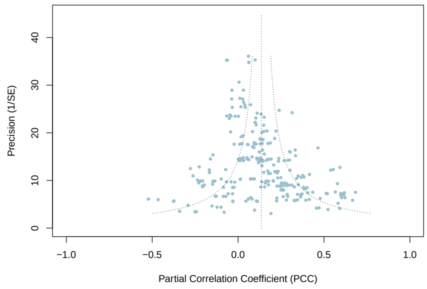
(h) Studies without core tests.*

Figure 26: Funnel Plots.

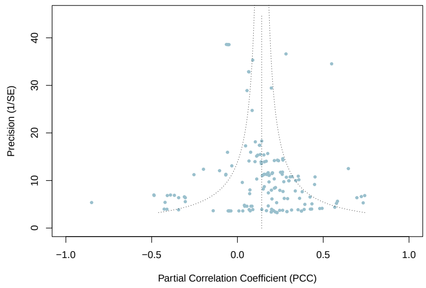
Note. * indicates the presence of funnel plot asymmetry, per the Eggers' test.



(a) High-income Countries.



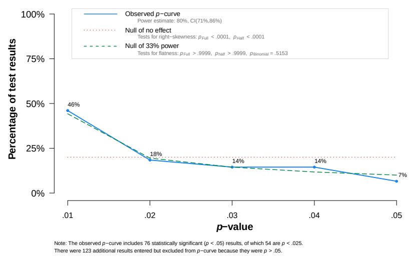
(b) Low-income Countries.*



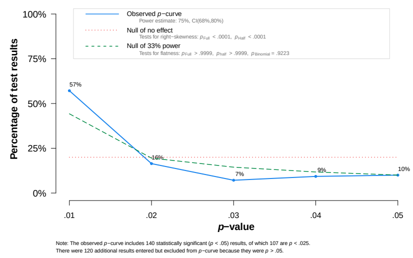
(c) Low-income Countries.*

Figure 27: Funnel Plots for Different Income Levels.

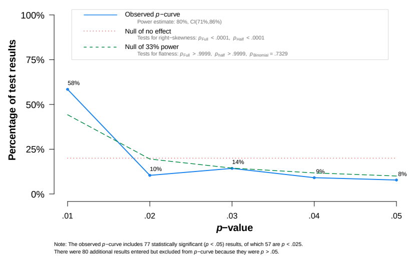
Note. * indicates the presence of funnel plot asymmetry, per the Eggers' test.



(a) High-income Countries.



(b) Low-income Countries.



(c) Low-income Countries.

Figure 28: p-curves for different income levels.

	Full Model	Interaction Model
Intercept	0.416*	1.452***
	(0.228)	(0.442)
GDP per capita	-0.045**	-0.148***
(ln, median)	(0.020)	(0.043)
WGI corruption estimate	0.002*	-0.021**
(Model 3)	(0.001)	(0.009)
GDP per capita ×		0.002***
WGI corruption estimate		(0.001)
Adjusted-R^2	17.52%	18.26%

Table 13: Heterogeneity of GDP per capita and Corruption

Table 17: Enhanced Comparison of Machine Learning Models for Corruption Estimation

Model	Description
Model 1: Basic RMSE Minimisation	
	Construction: Employs a regression approach focusing on minimising RMSE between predicted and actual corruption estimates. Feature set of 253 variables.
	Key Findings: — Achieves high R^2 values on training data, indicating strong fit. — Demonstrates significant overfitting, with a notable performance drop on unseen data.
	Strengths: — Simple and straightforward implementation. — Effective for baseline comparisons.

Continued on next page

Table 17 – continued from previous page

Model	Description
	Limitations: — High susceptibility to overfitting due to large feature set. — Inability to capture temporal trends or account for missing data effectively. — Potential overfitting, trends, or missing data (other than in the training set) unaccounted for. — The lack of penalty for missing data during the training phase likely leads to overfitting, as the missing values will significantly skew the datapoints for respective countries in their given years.
Model 2: Trend Analysis with Lead Variables	
	Construction: Enhances Model 1 by incorporating two lead variables for corruption, enabling the model to perform backcasting and trend analysis over time. **Key Findings**: — Reduced ability to capture temporal trends in corruption. — Tends to converge predictions towards the mean corruption level by 1960 due to severe overfitting. **Strengths**: — Attempts to model corruption dynamics over time. **Limitations**: — Overreliance on lead variables reduces accuracy in predicting actual corruption levels. — Struggles with missing data in middle years.
Model 3: GDP Imputation and Corruption Anchoring	

Continued on next page

Table 17 – continued from previous page

Model	Description
	Construction: Utilises mean 5-year growth rate for imputing missing GDP per capita data. Employs an average corruption anchor derived from 2012-2022 data to mitigate error propagation. **Key Findings**: — More robust imputation method improves model reliability. — Demonstrates extrapolation errors, particularly in countries with significant middle-year data gaps. **Strengths**: — Improved handling of missing data through sophisticated imputation techniques. **Limitations**: — Reliance on mean growth rates may not accurately reflect economic dynamics. — Removal of variables with over 50% missing data may omit critical information.
Model 4: CPI-Based Refinement	
	Construction: Adopts a similar approach to Model 3 but uses CPI values for corruption estimates, adding further refinement and additional lead variables. **Key Findings**: — Utilises CPI for more nuanced corruption predictions. — Shares limitations with Model 3 but offers slightly improved predictive accuracy. **Strengths**: — Leverages CPI data for enhanced corruption estimation.

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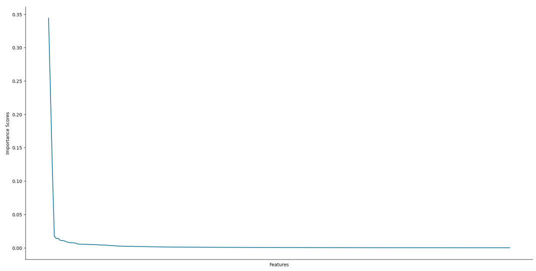
Table 17 – continued from previous page

Model	**Description**
	Limitations: — Similar to Model 3, struggles with data imputation and feature selection issues.



(a) Model 1.

(b) Model 2.

(c) Model 3.

(d) Model 4.

Figure 29: Feature Importances.

A.5 Primary studies used in the analysis

Table 14: Robustness checks on high(er)-income countries.

Dependent variable: PCC	(1) FAT-PET	(2) FULL MODEL	(3) SPECIFIC MODEL	(4) FULL (WGI)	(5) SPECIFIC (WGI)
Intercept	0.035	−0.339***	−0.325***	−0.767***	−0.758***
	(0.026)	(0.074)	(0.061)	(0.093)	(0.086)
Measures of FDI and inequality					
FDI		0.089*	0.089*	0.165***	0.164***
		(0.049)	(0.046)	(0.061)	(0.042)
Gini		0.009		0.071	0.065*
		(0.043)		(0.038)	(0.035)
Income share		0.110		0.120	
		(0.086)		(0.080)	
Wage/income disparities		0.357***	0.303***	0.564***	0.486***
		(0.076)	(0.053)	(0.084)	(0.054)
Corruption Control					
WGI Corruption Estimate (Model 3)				0.016***	0.016***
				(0.003)	(0.003)
Controlling for endogeneity					
Estimation methods		0.005		−0.022	
		(0.021)		(0.020)	
GDP control		−0.206***	−0.206***	0.012	
		(0.059)	(0.054)	(0.072)	
Education control		−0.313***	−0.306***	−0.209***	−0.201***
		(0.080)	(0.071)	(0.071)	(0.063)
Single country		−0.047		−0.060	
		(0.069)		(0.075)	
Trade control		0.559***	0.555***	0.239**	0.235***
		(0.121)	(0.093)	(0.106)	(0.067)
Population control		0.667***	0.688***	0.585***	0.608***
		(0.112)	(0.107)	(0.106)	(0.098)
Inflation control		0.489***	0.504***	0.297***	0.309***
		(0.094)	(0.075)	(0.078)	(0.052)
Unemployment control		−0.480***	−0.465***	−0.404***	−0.387***
		(0.081)	(0.073)	(0.077)	(0.070)
Government control		0.654***	0.656***	0.527***	0.521***
		(0.096)	(0.080)	(0.094)	(0.074)
Publication bias					
Published		0.116***	0.121***	0.089***	0.107
		(0.037)	(0.033)	(0.034)	(0.389)
Standard error of the PCC	−0.878*	−0.029	−0.298	−0.014	−0.271
	0.374	(0.451)	(0.399)	(0.423)	(0.389)
Observations	199	199	199	199	199
Adjusted-R^2	4.67%	80.35%	82.47%	82.04%	83.06%

Note. Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 15: Robustness checks on middle-income countries.

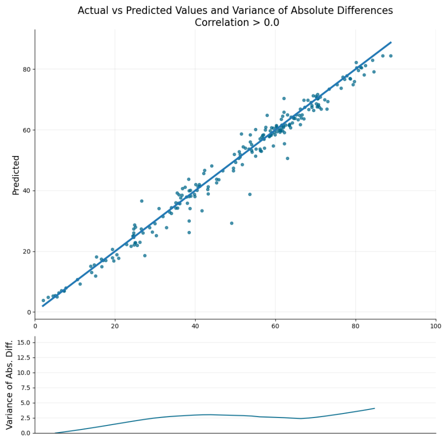
Dependent variable: PCC	(1) FAT-PET	(2) FULL MODEL	(3) SPECIFIC MODEL	(4) FULL WDI (WGI)	(5) SPECIFIC (WGI)
Intercept	0.058^{**}	-0.026	-0.027	-0.136	0.020
	(0.027)	(0.123)	(0.100)	(0.189)	(0.158)
Measures of FDI and inequality					
FDI		0.075^{*}	0.058	0.086^{**}	0.065^{*}
		(0.041)	(0.039)	(0.043)	(0.039)
Gini		0.057		0.077	
		(0.050)		(0.049)	
Wage/income disparities		0.067		0.077	
		(0.061)		(0.062)	
Corruption Control					
WGI Corruption Estimate (Model 3)				0.002	-0.000
				(0.003)	(0.002)
Controlling for endogeneity					
Estimation methods		-0.084^{**}	-0.060^{**}	-0.066^{*}	-0.061^{*}
		(0.039)	(0.030)	(0.039)	(0.031)
GDP control		-0.047		0.047	
		(0.030)		(0.079)	
Education control		-0.051		-0.032	-0.059^{**}
		(0.035)		(0.036)	(0.028)
Single country		-0.053		-0.038	-0.071^{*}
		(0.058)		(0.060)	(0.039)
Trade control		0.001		-0.013	
		(0.030)		(0.032)	
Population control		-0.022		-0.099	
		(0.072)		(0.079)	
Inflation control		-0.016		-0.037	
		(0.056)		(0.062)	
Unemployment control		-0.057		-0.070	
		(0.060)		(0.063)	
Government control		0.054		0.047	
		(0.047)		(0.049)	
Publication bias					
Published		0.080	0.049	0.054	0.073
		(0.089)	(0.083)	(0.091)	(0.084)
Standard error of the PCC	0.879^{***}	0.486	0.856^{***}	0.435	0.665^{**}
	(0.275)	(0.371)	(0.307)	(0.380)	(0.322)
Observations	260	260	260	260	260
Adjusted-R^2	9.19%	14.74%	10.19%	12.18%	13.53%

Note. Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

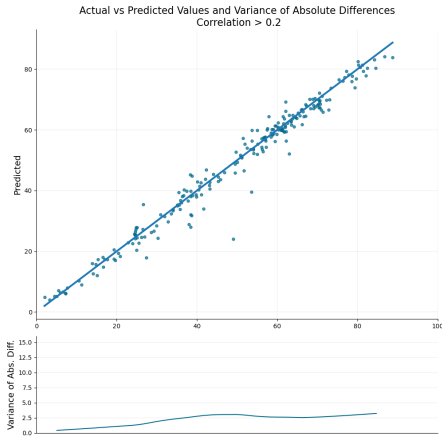
Dependent variable: PCC	FAT-PET	FULL MODEL	SPECIFIC MODEL	FULL (WGI)	SPECIFIC (WGI)
Intercept	0.124***	0.112	0.250***	0.729***	0.684***
	(0.034)	(0.103)	(0.039)	(0.241)	(0.212)
Measures of FDI and inequality					
FDI		0.074		0.062	
		(0.074)		(0.082)	
Gini		−0.024		0.099	
		(0.113)		(0.114)	
Wage/income disparities		−0.048		−0.012	
		(0.104)		(0.105)	
Corruption Control					
WGI Corruption Estimate				−0.010***	−0.008**
(Model 3)				(0.003)	(0.003)
Controlling for endogeneity					
Estimation methods		−0.088		0.098	
		(0.058)		(0.059)	
GDP control		0.126***	0.119***	0.005	
		(0.045)	(0.041)	(0.075)	
Education control		0.004		0.048	
		(0.052)		(0.063)	
Single country		−0.075	−0.137***	−0.098	−0.152***
		(0.059)	(0.044)	(0.063)	(0.068)
Trade control		0.035		0.024	
		(0.043)		(0.043)	
Population control		−0.073	−0.104**	−0.031	
		(0.063)	(0.043)	(0.066)	
Inflation control		−0.339***	−0.305***	−0.304***	−0.239***
		(0.072)	(0.065)	(0.074)	(0.068)
Unemployment control		0.146	0.255**	0.160	0.293***
		(0.115)	(0.089)	(0.115)	(0.086)
Government control		−0.054		−0.079	
		(0.062)		(0.062)	
Publication bias					
Published					
Standard error of the PCC	0.155	−0.164	0.201	−0.921*	−0.127
	(0.258)	(0.406)	(0.261)	(0.510)	(0.331)
Observations	157	157	157	157	157
Adjusted-R^2	0.00%	35.20%	37.97%	34.30%	33.70%

Note: Standard errors are in parentheses.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

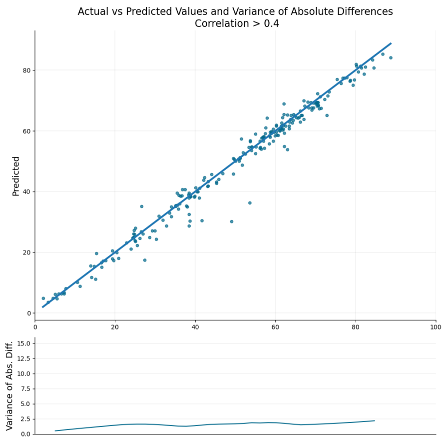
Table 16: Robustness checks on lower-income countries.



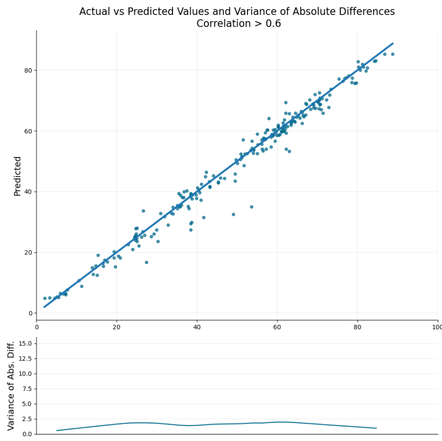
(a) Model 3 with all predictors



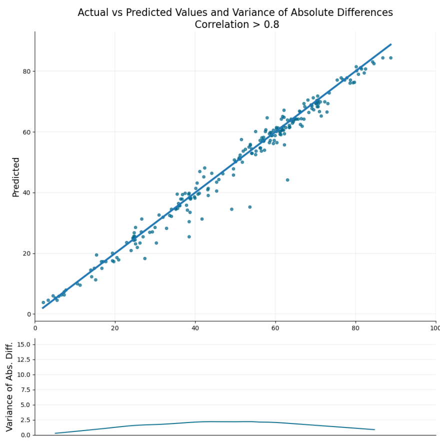
(b) Model 3 with correlation ≥ 0.2



(c) Model 3 with correlation ≥ 0.4

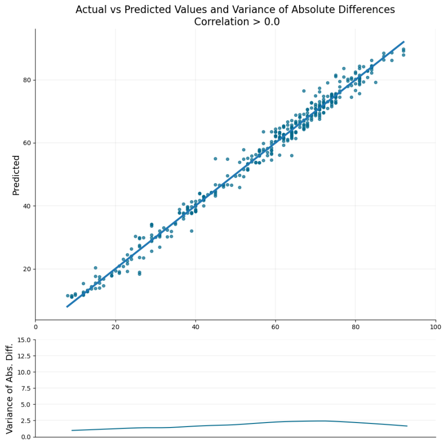


(d) Model 3 with correlation ≥ 0.6

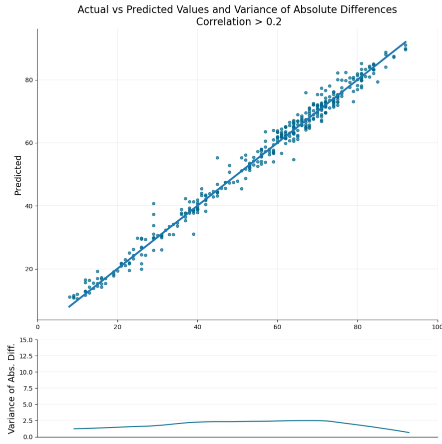


(e) Model 3 with correlation ≥ 0.8

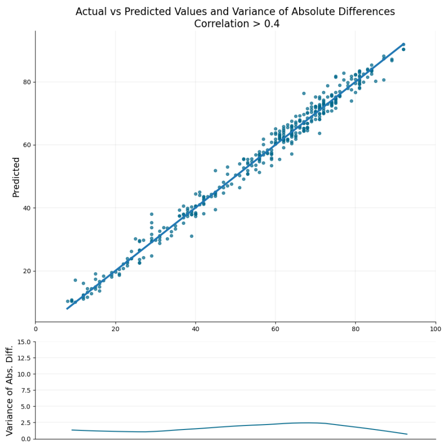
Figure 30: Actual vs. Predicted values for different correlations in Model 3



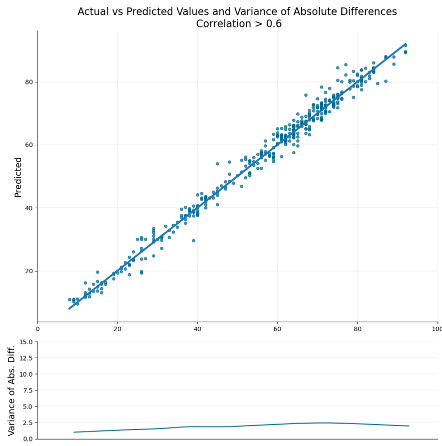
(a) Model 4 with all predictors



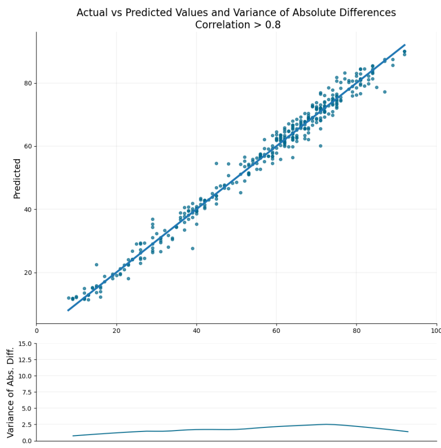
(b) Model 4 with correlation ≥ 0.2



(c) Model 4 with correlation ≥ 0.4



(d) Model 4 with correlation ≥ 0.6



(e) Model 4 with correlation ≥ 0.8

Figure 31: Actual vs. Predicted values for different correlations in Model 4

Table 18: Primary studies used

	Citation		**Citation**
1	Adams & Klobodu (2017)	37	Hussain *et al.* (2009)
2	Adams (2008)	38	Huynh (2021)*
3	Alam & Paramati (2016)	39	Jaumotte *et al.* (2013)
4	Ali *et al.* (2013)	40	Jensen & Rosas (2007)
5	Ali (2003)	41	Juarez Rivera-Castro (2013)
6	Angeles-Castro (2011)	42	Lee *et al.* (2013)
7	Anyanwu *et al.* (2016)	43	Lee (2006a)
8	Asteriou *et al.* (2014)	44	Lee (2006b)
9	Baek & Shi (2016)	45	Lin *et al.* (2013)
10	Bannerman (2007)	46	Lu & Yu (2015)
11	Basu & Guariglia (2007)	47	Mah (2003)
12	Beer (1999)	48	Mahutga & Bandelj (2008)
13	Benar (2007)	49	Majeed (2017)
14	Bhandari (2007)	50	Matallah (2019)
15	Bumann & Lensink (2016)	51	Morgan & Kelly (2013)
16	Bussmann *et al.* (2005)	52	Mushtaq *et al.* (2014)
17	Cai *et al.* (2010)	53	Ngwakwe & Dzomonda (2018)
18	Chaudhry & Imran (2013)	54	Pan-Long (1995)
19	Chen & Tsai (2012)	55	Reuveny & Li (2003)
20	Chintrakarn *et al.* (2012)	56	Roser & Cuaresma (2016)
21	Choi (2006)	57	Sato & Fukushige (2009)
22	Te Velde & Morrissey (2004)	58	Soto *et al.* (2023)*
23	Daumal (2013)	59	Sturm & De Haan (2015)
24	Deng & Lin (2013)	60	Suanes (2016)
25	Driffield *et al.* (2010)	61	Sylwester (2005)
26	Elmawazini *et al.* (2013)	62	Taylor & Driffield (2005)
27	Batuo & Asongu (2015)	63	Te Velde (2003)
28	Faustino & Vali (2011)	64	Tian *et al.* (2008)
29	Faustino & Vali (2013)	65	Tomohara & Yokota (2011)
30	Figini & Gorg (2011)	66	Ucal *et al.* (2016)
31	Georgantopoulos & Tsamis (2011)	67	Wang & Lee (2023)*
32	Groot (2014)*	68	Wang *et al.* (2019)
33	Ha (2012)	69	Wu & Hsu (2012)
34	Halmos (2011)	70	Rezk *et al.* (2022)*
35	Herzer & Nunnenkamp (2013)	71	Le *et al.* (2021)*
36	Herzer *et al.* (2014)		

* denotes papers that differ from Huang et al. (2020)