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Has Democracy reduced Inequalities in Child

Mortality?

**An analysis of 5 million births from 50
developing countries since 1970**

A thesis submitted in partial satisfaction
of the requirements for the degree
Master of Science in Statistics

by

Antonio Pedro Ramos

2013

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ABSTRACT OF THE THESIS

**Has Democracy reduced Inequalities in Child
Mortality?
An analysis of 5 million births from 50
developing countries since 1970**

by

Antonio Pedro Ramos

Master of Science in Statistics

University of California, Los Angeles, 2013

Professor Mark Handcock, Chair

This paper offers the first large scale analysis of the effects of democratization on the rich- poor gap in child mortality across the developing world. Theories predict that democratic institutions should help those at the bottom of the income distribution more than those at the top. Yet, previous cross-national studies on democracy and child mortality have not focused on the rich-poor gap in health outcomes. Using an unique data set with more than 5 million birth records from 50 middle and low income countries, this study is the first one to test whether those at the bottom of the income distribution benefit more from the democratic transitions than those at the top. Although the rich and poor gap in child mortality is reducing over time, this change does not seem to be driven by regime type. Yet, there is remarkable heterogeneity on the effects of democratization on health that deserves further investigation.

The thesis of Antonio Pedro Ramos is approved.

Ying Nian Wu

Nicolas Christou

Mark Handcock, Committee Chair

University of California, Los Angeles

2013

I dedicate my Master of Science work to my father-in-law. He strongly supported and encouraged me to take my first systematic training in statistical methods. This training led me to my Graduate Certificate at Universidade Federal de Juiz de Fora and, eventually, to my degrees in Statistics and Political Science at UCLA. He did so in a very difficult time for me, when many others told me that what I needed was a "real job". Yet, as an engineer working in the steel industry, he knows the value of data analysis; and as someone who also struggled to get his own degree, he also knows the value of education. Now that I am approaching the end of this road, I envision many exciting career paths for me. Obrigado, Jose Luiz Brandao!

TABLE OF CONTENTS

1	Introduction	1
2	Democracy, Redistribution and Infant Death	5
2.1	Can Premature Infant Deaths be Prevented by Poor Governments?	6
2.2	Regime Type, Redistribution and Health Provision for the Poor	8
2.3	Previous Empirical Studies on Regime Type and Health	10
2.3.1	Measures of Regime Type	12
3	Limitations of Studies Using National Averages of Child Mortality	13
3.1	Inequality in Child Mortality Within Countries	14
3.1.1	Overall Inequities	14
3.1.2	Inequities Across Income Levels	14
3.2	Demographic Compositional Effects	15
4	Data	17
4.1	Time Trends in Mortality Rates by Income Level Within Countries	19
4.2	Covariates	21
5	Methods	22
5.1	Goals and Limitations of the Statistical Analysis	22
5.2	Measuring the Rich and Poor Gap in Child Mortality?	26
5.3	Random Effects, Fixed Effects and Clustered Data	26
5.3.1	Country Level Clustering	27

5.3.2	Within-Country Clustering	28
5.3.3	Modelling Time Trends	29
5.3.4	Country Level Logistic Regressions	29
5.3.5	Generalized Additive Models	30
5.4	Using Contrasts To Estimate the Poor-Rich Gap	32
5.5	Combining Information from Contrasts from the Country-by-Country Regressions using Meta Analysis	33
6	Results	36
6.1	Basic Models Fit: Comparing GAM and GLM	36
6.2	Baseline Differences	38
6.3	Overall Rate of Change	40
6.4	Does Democratization Changed Previous Levels of Child Mortality?	42
6.5	Does Democratization Changed Previous Rate of Change in In- equality in Child Mortality?	43
6.6	Relaxing the Lineary Assumption for Time Trends: Generalized Additive Models for the Time Trends	45
6.6.1	Illustration of the Heterogeneity of the Effects in The Prob- ability Scale	45
6.6.2	Summary of the Findings	46
7	Discussion and Conclusions	49
8	Appendix	53
	References	57

LIST OF FIGURES

4.1	Empirical distribution of Child Mortality Rates for rich and poor across all countries and years. Each line is a simple GAM model which the only predictors is the time trend. The black lines in the centers of each distribution are the overall averages time trends and the shaded areas are the confidences interval around them.	20
5.1	Hypothetical scenario describing the effect of democratization on the inequality in child mortality.	24
6.1	Predictions from the linear time trends models in detail for 4 types of countries. Always democracies, India; Always Dictatorships, Rwanda; One time transitions, Malawi; and, finally, multiple transitions countries, Pakistan. The Dark grey represent dictatorial periods, while light gray democracies. Dotted lines with read shades, are conditional mortality rates for the poor, while solid lines for blue shade are for the poor. The shades are 95 confidence intervals.	37
6.2	Baseline levels on inequality in the rich and poor gap in child mortality. These contrasts were estimate using the linear time trends models.	39
6.3	Overall time trends for the rich-poor gap in child mortality. These contrasts were estimate using the linear time trends models. . . .	41
6.4	Meta-analysis for the changes in the level of inequality in child mortality between births from the rich and poor mothers after democratization episodes. These contrasts were estimate using the linear time trends models.	43

6.5	Meta-analysis on the effects of the democratization on time trends for the rich-poor gap. These contrasts were estimate using the linear time trends models.	44
6.6	An ilustration of the effects of democratic transitions and their heterogeneity on the rich and poor gap in child mortality. Transition countries only. The light gray areas are dictatorial periods while the dark grays are democratic ones. The solid lines are the actual, in sample predictions in the gap in child mortality. The dotted lines are counterfactual scenarios where the bent lines where set to zero.	48
8.1	Conditional predictions from the linear time trends models	54

LIST OF TABLES

8.1	Results from the Mixed Effects Meta-Analysis for the baseline differences in the rich-poor gap in child mortality. The outcome variable is in the log-odds scale and is a contrasts from the country-by-country logist regression models with linear time trends. Income per capita is in the log-scale. All 50 countries were included. Reduce Model include no moderators (covariates) to account for the baseline differences. The log-likelihood ratio test is 5.64 (p-value:0.2274), indicating no statistically significant models' improvement after the inclusion of the moderators, which is also corroborated by very little change in the residual heterogeneity across models (see I^2).	55
8.2	Results from the Mixed Effects Meta-Analysis investigating over time trends in the rich-poor gap in child mortality. The outcome variable is in the log-odds scale and is a contrast from the country-by-country logist regressions models with linear time trends. Income per capita is in the log-scale. All 50 countries were included. Reduce Model include no moderators (covariates) to account for the baseline differences. Number of transitions refer to number of democratic transitions. The log-likelihood ratio test is 65.6859 (p-value:0.0001), indicating strong and statistically significant model improvement after the inclusion of the moderators, which is also corroborated by the large decline in heterogeneity across models (see I^2).	56

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CHAPTER 1

Introduction

This thesis is about the relationship, if any, between democracy and equality. Theories of democracy lead to the expectation that democratic governments will provide more welfare enhancing goods for the poor than autocracies [MR81, AR00, LB01, Sen99, Kud12, PAC00]. I test this argument using the gap in child mortality between the rich and the poor as a measure of the government delivery of welfare enhancing goods [Ros06, VWS03]. Although governmental policies are not the only influence on infant mortality rates, they do make a substantial contribution, for example, for the delivery of clean water, vaccination campaigns and by creating health clinics for the poor [BMB03, JSB03, BAP03]. More specifically, the introduction of the democracy should make a difference in the previous, pre-transition trends and levels of child mortality reduction across different income levels within previously authoritarian countries.

The median voter theorem [MR81] and its extensions [AR00] predicts that democratic institutions move the median voter downward towards the poor, which forces governments to provide better services for those outside the rich elites as otherwise they will loose electoral support. Other political economy models predict that under competitive elections with universal suffrage, politicians will be forced to provide more public goods for the population [DMS02, LP01]. These theories have implications for the provision of health, including the reduction of infant death: since those at the bottom of the income distribution suffer disproportionately from child mortality rates [BMB03] and relatively inexpensive policy

interventions could prevent most infant deaths [JSB03]. Therefore it follows from standard political economy models that democracy, by producing more public goods, should help the poor, and reduce overall child mortality.

To date, there is an extensive cross-national literature on regime type and infant death [GTA12, Kud12, BL03, Ros06, NZ03, PAC00]¹. These studies use national averages of child mortality and investigate whether lower child mortality rates are associated with democracy ². And national averages of child mortality are an important quantity and are often used as a proxy for the well-being of the poor in connection with theories of redistribution. Yet, this is not necessarily the case. Political economy theories are about re-distribution across groups and therefore must consider child mortality for each income level for each country.

By focusing on *national averages*, inequalities in child mortalities across sub-populations cannot not be captured. Indeed, it is well-known that countries with same national averages of child mortality may have totally different populations at risk [GK02]. Thus, by looking at national averages of child mortality, one cannot know whether these overall rates are declining due to improvement across the poor strata or further improvement among those with middle or upper income levels [VWS03]. Therefore, national averages of child mortality are not high resolution enough to test many political economy models. Instead, when working with national averages of child mortality, scholars in political science are implicitly assuming that changes in these quantities are due to improvements across the

¹Child mortality is a measure that is sensitive to many other conditions, including access to clean water and sanitation, indoor air quality, female education and literacy, prenatal and neonatal health services, caloric intake, disease, income, that are hard to measure among the very poor [Sen99, VWS03]. Other commonly used measures of well-being, such as poverty rates, school enrollment rates, and access to primary health care, tend to be less reliable (and less comparable) since their definitions vary from country to country and over time [Ros06]. In addition, focus on child health offers us insight into future dimensions of well-being in the developing world. For example, [Hat13], using height as a measure of well-being improvement across Europe, found that the main factor improved heigh in these continent was the decline of the disease environment as reflected by the fall of infant mortality.

² [Kud12] is an important exception as it uses individual level data. Yet, it still focuses on the *mean* effects of democracy on child health

lower income strata, which is not in general true, particularly in high-mortality places.

Secondly, national averages of child mortality might mistake change in the demographic composition of the population for well-being improvements. For example, the age of the mother, her level of education, whether she lives in a rural or urban area, all have an impact on children's probability of survival. National averages of child mortality fluctuate as a function of all these and other demographics and so do mortality rates across income levels. Thus to test the impact of democracy on well-being provision we, ideally, want to control for those changes at each income level within each country. We want to exploit over time variation within fixed demographic groups — i.e. young low income mothers from rural areas — within each country to make inferences about the effect of democracy on well-being provision. And these are not minor points. As suggested by Modernization Theory [Lip59], these demographic changes can be confounded with both democratization and child mortality reductions, and thus they need to be controlled for³.

I investigate the effect of democracy on child mortality rates at an unprecedented level of detail. I analyze records of 5.5 million births from over 50 middle and low income countries that account for over 75 % of the infant death toll in the world. With these data, I can investigate changes in trends and levels of mortality rates over time for births from each income level within countries while controlling for changes in the demographic composition of the population. Doing so allows us to test whether democracy actually improves health outcomes for the poor, using the rich as a point of comparison, while controlling for previous levels and trends in child mortality as well as demographic composition effects. Even

³This, of course, raises the question of whether democracy is acting indirectly, by reducing the number of births from more vulnerable subgroups. While this is possible, it is important to be able to have a research framework that separate out direct and indirect effects, which is not possible by looking at national averages of child mortality only

though this is not an experimental design, as political regime cannot be randomly assigned across countries, these data and this research design allow us to test political economy theories at a much more fine-grained level that was previously possible.

I show that a rich and poor gap in child mortality does exist around the developing world, even controlling for individual level demographic factors. I also show that these inequalities are reducing over time. Yet, I find complex linkages between political factors and health care provision. On average, political regimes do not affect either countries' initial levels of inequality nor their over time rate of change. Also, on average, the introduction of democracy in countries that made the transition to democracy does not systematically change the previous rates of reduction in the rich and poor gap. Yet, there is remarkable heterogeneity in the effects of the democratic transitions across countries that deserves further investigation. For example, the introduction of democracy in Pakistan is always associated with an increased gap in child mortality between the rich and the poor. On the other hand, in most Sub-Saharan countries the introduction of democracy is associated with a reduction in the rich and poor gap in child mortality.

The paper is organized as follows: first, I review previous literature on democracy, redistribution and child mortality, showing that (1) the gap between rich and poor have not been analyzed before and (2) that this is a quantity of major theoretical interest. Secondly, I discuss how the focus on national averages of child mortality, though important, may not be a good proxy for well-being improvements for the poorest in the developing world. Then I present the new data set, briefly describe how it can help us to answer questions about the rich and poor gap⁴. Then I discuss the methodological challenges and how tools such as meta-analysis can help us to get reliable answers. I then present my results. Finally, I conclude with the discussion of the theoretical implications of these results and

⁴A detailed discussion is presented in the data appendix

future line of research.

CHAPTER 2

Democracy, Redistribution and Infant Death

How does democracy affect public health, specially children's health? The implicit assumption of political economy models is that government can indeed change levels and/or trends in child mortality, especially for the poor. Once that is assumed, one can discuss the conditions under which governments will have incentive to provide better health care across income levels. If child mortality is largely a function of factors beyond governmental control, however, political incentives introduced by democratization will likely not change health outcomes. For example, suppose tropical climate is a major vector illness and thus a major factor behind child mortality; or, similarly, suppose that the prevention of premature deaths is simply beyond the resources of the poor governments. The point is that it is far from obvious that poor governments have the resources to reduce child mortality within their own countries. Thus I will review the public health literature to present evidence in favor of the assumption that low-resources governments actually have the ability to reduce child mortality. I will also review the political economy literature, which focus on the incentives created via political mechanisms.

2.1 Can Premature Infant Deaths be Prevented by Poor Governments?

In a series of studies published by The Lancet in 2003, a set of related questions central to political economy models were investigated: Where are children were dying and why? Could these deaths be prevented with current medical technology and resources available for poor countries? If yes, how these deaths are not been averted? What can be done to improve health systems capacity?

[BMB03] review myriad of studies and a wealth of data on the causes of premature death in the developing world in recent decades. They find that 90% of all premature infant deaths were concentrated in 42 countries and half of them in only six (in order of the death toll: India, Nigeria, China, Pakistan, Congo and Ethiopia). Common challenges across different countries include undernutrition, infectious diseases, and particularly the effect of multiple concurrent illness, such as diarrhea, pneumonia, measles and malaria. For example, measles is often complicated by pneumonia and diarrhea. Undernutrition is the underlying cause of a substantial proportion of all child deaths. For example, for infants aged 0-5 months, lack of breastfeeding is associated with five-fold to seven-fold increase in death risk while non-exclusive breastfeeding is associated with a two-fold increase. Vitamin A deficiency increases death risk from diarrhea, pneumonia, measles and malaria by 20-25 %. Likewise, zinc deficiency increases the risk of death from malaria, diarrhea, pneumonia by 13-21 %¹. AIDS is a more localized cause of infant death: it is responsible for only 3 % of deaths and it only accounts for more than 10% of the infant deaths in 3 of the 42 countries with the highest level of mortality. Yet, in Zimbabwe and Botswana, it accounts for over 50 % of the under 5 deaths.

¹Estimates and uncertainty bounds for the main causes are the following: 22% of deaths attributed to diarrhea (14-30%), 21% to pneumonia (14-24%), 9% to malaria (6-13%), 1% to measles (1-9%), 33% to neonatal causes (29-36%), 9% to other causes, and fewer than 1% to unknown causes.

[JSB03] investigate whether public health interventions can be delivered at high coverage in low income countries, where governments have limited resources. That analysis also focused on the 42 countries that concentrate 90% of premature infant deaths in the world. Instead of focusing on the role played by distal determinants of child mortality such as poverty or physical environment, it only looks at the more proximal determinants that can be delivered by the health sectors. Also, they do not consider determinants that are assumed to be implemented by sectors other than health but with a known impact on child mortality, such as maternal education. Within the health sector, however, it investigates interventions that reduced both exposure to diseases as well as those that will reduce the likelihood that a disease will eventually result in death. In their calculations, they only included interventions with known effects and thus the estimates from their studies are somewhat conservative.

The study concludes that roughly two-thirds of the under 5 deaths in these 42 countries could be prevented with interventions that matched the above criteria. For example, in most cases diarrhea can be treated with simple oral rehydration therapy. Malaria may be avoided with simple measures such as insecticide-treated bed nets or treated with available cheap anti-malarials. Measles, another common disease, can be treated with a very cheap and effective vaccine. A group of effective nutrition interventions including breastfeeding, complementary feeding, vitamin A, and zinc supplementation could save about 24 million children each year (25% of total deaths at the year of the study). Effective and integrated case management of childhood infections (diarrhea and dysentery, pneumonia, malaria, and neonatal sepsis) could save 32 million children each year (33% of total deaths). Other interventions include breastfeeding promotion and immunizations. Hence, there is no need for expensive new drugs, technologies or vaccines to achieve large further reductions in child mortality in poor.

[BAP03] discuss the reasons for such low coverage and possible remedies.

For instance, in Brazil, Egypt, Philippines and Mexico, diarrhea-control programs and oral rehydration therapy were followed by mortality reductions that could not be accounted for other factors. In Latin America, governmental programs irradiated polio and made measles quite rare. The main point that emerges from its investigation is that, while community based initiatives are important to deliver health services, specially in places of hard access, strengthening national health systems are the ultimate long term aim.

Thus there exists plenty of evidence that governments from poor regions of the world do have the resources to greatly reduce child mortality. The political question is under which conditions are they willing to do so.

2.2 Regime Type, Redistribution and Health Provision for the Poor

There are many ways in which politics, health and redistribution are linked. In a series of studies on famine, poverty and deprivation, [Sen99] and [SD02] describe electoral competition and free press as political devices that force governments to provide for the poor, specially in periods of crises. Yet, perhaps the most influential approaches linking politics and well-being focused on the provision of health as a redistributive issue. The central idea in these studies is that democracies help the poor by providing them with more redistribution than non-democracies. Because child mortality is mostly concentrated among the poor [Ros06, YJH10], targeting the poor with basic health services would have the effect of reducing child mortality.

One of earlier arguments on redistribution is from [MR81]². Here, the key players are a wealth elite, the remaining of the citizenry, and the government. The leaders seek political support from the wealth political elite under dictatorships.

²See also [Mul03] for a comprehensive, if somewhat dated, review of the literature.

The introduction of democracy expands suffrage such that the poor are included among the electorate. As a consequence, democratization moves the median voter downward the income distribution as the richest are no longer the only ones voting. To see this, consider the following: suppose income is unequally distributed in the society before the democratization. If so, the median voter, immediately after the democratization (i.e, the suffrage expansion), will earn less than the median income. Hence, the median voter will support policies that tax the wealthy and redistribute to middle and low income classes. According to this logic, democracy should favor redistribution from the rich to the low income strata³.

[Boi03] builds on this model by adding the effect of capital mobility and exploring the strategic interaction of an elite, that control the state under authoritarian rule and the mass public, who controls power under democracy. It also suggests that democracy favor redistribution toward the poor. [AR00] explore the conditions in which states transit from authoritarian rule to the democratic rule; it suggests that authoritarian government favors the interest of the elite, while democracy supports redistribution for a large fraction of the electorate. [LP04] and [DMS02] consider that under contested elections with universal suffrage, providing public goods for the mass electorate is a lower cost strategy for politicians to win elections than the distribution private goods to specific groups of voters. This is so because under democratic elections politicians need to appeal to a large number of votes. Though there is nothing inherently pro-poor in providing public goods, most of child mortality averting measures such as vaccination campaigns, public health clinics, and clean water would be provided as public goods.

None of these works focus on health issues, let alone child mortality. Yet

³Though this is the standard presentation on the literature, it is not entirely descriptively accurate. In fact, most modern dictatorships held elections. The problem though, is not so much that the poor don't vote, but instead no one's votes choose who rules. Possibly the rich choose who rules in some other way, or maybe rulers and their allies become rich and aren't forced to share power in order to maintain their rule. Yet the basic final outcomes are similar for my purposes: under non-democratic elections, government don't have incentives to design policies that reach those outside the elite groups.

all these models suggest that the introduction of democracy should provide redistribution for the poor, where the child mortality is concentrated. Also, all these works focus on election as the main channel in which the government will redistribute for the poor.

2.3 Previous Empirical Studies on Regime Type and Health

Previous empirical studies have provided contradictory findings on the effect of regime type and health. [PAC00] reported that democracy do provide better health outcomes, including lower infant mortality. [LB01] found that a move from complete autocracy to complete democracy substantially reduces infant mortality. [BK06] found a link between democracy and better health outcomes, such as life expectancy and infant mortality. Focusing on transitions in sub-Saharan Africa, [Kud12] found that democracy did reduce infant mortality. Yet, recently, some of these results have been challenged. [Ros06] found that once high income dictatorships are included and missing data is accounted for, there is no evidence that democracy is beneficial to the poor infants. [GTA12] did not find contemporaneous effects of democracy on health, though they argue that the accumulate stock of democracy is important for current level of child mortality. Focusing on caloric intake [BK11] find that democracy and hybrid regimes are better into translating economic growth into higher calorie intake, which was used as a proxy for redistribution.

The view that democracy produces superior health outcomes was challenged by an influential empirical study by [Ros06]. Based on its empirical findings — no effect of democracy on child mortality — it challenges this theoretical literature by providing an alternative theory. According to [Ros06], infant mortality averting goods are relatively inelastic: as long as households don't suffer from severe budgets constraints, they will buy those goods anyway. In order to be consumed

by the middle and upper income strata, these goods don't need to be provided as public goods. Only, or mostly, the poor needs them as a public good in order to have access to them. Thus the demand of mortality averting goods as a public goods is specific from the lowest income strata. Similarly, the impact of the government reducing child mortality is largely a function of its ability, or desire, to reach low income households, the ones which don't have access to mortality averting goods.

Assuming that the demand for mortality averting public goods is monotonic in income, the median voter in a sufficiently wealth country may not demand those mortality averting public goods from the government. Thus by pursuing the median voter, new democratic elected governments will not necessarily have incentives to provide mortality averting public goods. The most general and basic point is not that the median voter theorem does not have empirical support but, instead, that the common interpretations could be mistaken. Accordingly, theory does not imply improvements for those at the bottom of income, as is often assumed. Instead, it implies improved for those at the middle income levels.

To that I would add that is an empirical and context specific question whether the middle income groups will be actually demanding mortality averting goods. It might be true in some very poor places but not be the case in middle income countries.

[Ros06] is not the only one to challenge the view that democracy will produce more redistribution. As [Nel07] discusses, elections might not provide better services for the poor. Reviewing a series of empirical and theoretical studies, he concludes that often the introduction of democracy is not associated with better health outcomes and, in some cases, electoral pressures actually represent an impediment to improved outcomes. Typical pathologies of new democracies may diverge governmental efforts and societal demands, even in a context of competitive elections. Electoral rules, social cleaves, party ideology and the natural

difficulties for ordinary citizens to understand large scale complex institutional and policy reforms may all conspire against the provision of better health services. Moreover, other non-electoral channels such as special interest groups and decentralization might hinder improvements as well. Still others such as [IS06] also call attention to the role played by other variables, such as race, ethnicity and religion, that might force voters in democratic elections to focus on voting along these lines, further hindering general well-being improvements.

Thus whether democracy and elections actually redistribute for the poor is an open and active debate. I hope this paper can further advance this debate by focusing on an important but overlooked issue, the child mortality gap between rich and poor.

2.3.1 Measures of Regime Type

Recent scholarships provide us with a various and often highly correlated measures of democracy. Yet, these measures are often highly correlated. While one could compare results across different measures, here I focus on a well-established measure of democracy that are based on country observable characteristics and focused on elections. In fact, one of the core assumptions from the theoretical literature is that the introduction of free elections is enough to trigger redistribution⁴. I employ the measure of democracy developed by [PAC00] and extended by [CG10]. The advantage of this measure is that it is highly comparable across countries. Thus we can investigate what happen in the different places of the developing world when the same new democratic electoral rules were introduced.

⁴Popular measures of democracy include Polity IV and Freedom House. There are at least two important problems associated with these in the context of my study: (1) they do not focus on elections (2) they are not based on countries' observable characteristics.

CHAPTER 3

Limitations of Studies Using National Averages of Child Mortality

National averages of child mortality are only one of the many ways to measure premature death. They measure the total premature death toll in a given society in a given year. They also address a very specific and important question: how many children born at a given year made it to the age of, say, 5 years old? Our ability to measure this important quantity has improved remarkably [RMF10]. Yet, it is often mistakenly used as a proxy for well-being of the poor or as an indication of the rich and poor gap. For example, changes in the national averages of child mortality will not necessarily reflect changes in these rates among the poor, specially in high mortality places, as it has been assumed by previous studies. Moreover, national averages of child mortality ,by construction, cannot tell us the difference in rates across income levels, for example, the gap between the rich and the poor, which is a major quantity of theoretical interest. Finally, by using national averages of child mortality one cannot control for over time changes in demographic factors associated with both democratization and reduction in child mortality, as the ones highlighted by modernization theory. Thus, by using individual level data, one can have much more leverage in estimating the *causal* effect of democracy on infant health [Kud12].

3.1 Inequality in Child Mortality Within Countries

3.1.1 Overall Inequities

Within developing nations, there are enormous variations in child mortality across subpopulations. And countries with the same national averages can and often do have different distribution populations at risk. For example, [GK02] compare Benin and Central Africa Republic, showing that while both countries have quite similar average probability of death, they also present markedly different distribution of the actual survival time around their means and hence divergent health inequality. In the Central African Republic, about 25% of children have a probability of death lower than three percent. In contrast, children in Benin have risks of death more closely distributed around the mean, with only 4% of its children having a probability of death lower than three percent. Clearly, at the lower end of the distributions, Benin has a worse performance, but it does much better at the higher extreme. For example, in Benin, less than 1% of children have a probability of death greater than forty percent, contrasted with the Central African Republic, where more than 4% of children have that probability of death.

3.1.2 Inequities Across Income Levels

[VWS03] document wide disparities between rich and poor not only across countries but also *within the same country*. They also find that the poor are more likely to be exposed to health risks. Inadequate water and sanitation, indoor air pollution, crowding and exposure to diseases vectors are common problems for the poor. Also, the poor have less resistance to diseases because of undernutrition and other hazards typical in poor communities. These inequalities are most likely the results of unequal access to preventive and curative interventions. The poorest children are least likely to be vaccinated, to receive vitamin A or to sleep under a

treated net. They also note that public subsidies often go to middle class or even to the richest. In countries such as Guinea (1994), Ecuador(1998) and India(1995-6) most government subsidies to the health sector goes to the 20 % richest, while places like Costa Rica (1992) and Sri Lanka(1995-6) do better in reaching the poor.

As a consequence, the mortality gap between rich and poor children are not only wide but they are also becoming wider in some places [VWS03]. In Indonesia, for example, under-5 mortality is nearly four times higher in the poorest fifth of the population than in the richest fifth. These gaps exist within all regions. In Bolivia, under-5 mortality decreased during the 1990s by 34% in the richest quintile but only by 8% among the poorest quintile. In Vietnam, poor children saw no appreciable improvement in their survival prospects during the late 1980s and early 1990s. A policy intervention that eliminated these inequities - e.g., by bringing rates in the poorest 80% of the population down to those prevailing in the richest 20% - would have a major effect on the under-5 mortality rate for the country as a whole, even in low-inequality regions. Worldwide, about 40% of all under-5 deaths could be prevented this way. In several African countries, mortality rates among poor children actually rose during the 1990s, even though they fell among better-off children.

3.2 Demographic Compositional Effects

In addition to avoiding the mentioned problems, individual level data on infant death also has clear advantages in helping us to have a more causal interpretation of the effects of democracy on infant health¹. Even though there is no random assignment of political regimes to countries (and hence causal inference is problematic), by using individual level data on child mortality one can control for over

¹This point will be discussed in more details in the methods section.

time changes in demographic factors that might be influencing both democracy and child mortality reductions. In fact, modernization theory [Lip59] holds that democratization is a consequence of an overall societal process where more traditional social structures are substituted by more westernized, urban life styles with widespread use of modern technology and medicine. These processes also imply a change in cultural and moral values. For example, modernization is often associated with an increase in maternal education, and with a reduction in the number of families living in rural areas. It is also implied a more equalitarian position for women in society, and a widening in political participation. Since some of these factors are strong predictors of child mortality, modernization also changes demographic factors that are relevant for child survival.

The data I employ allow us to exploit over time changes within very specific demographic groups within countries, instead of only trusting cross-country or within country comparisons. For example, one can look at the changes in levels and rates of change of child mortality for poor, low aged mothers from rural areas. Further, one can compare and contrast trends in subgroups of theoretical interests, such as rich versus poor, while controlling for other demographic variables. As a consequence, the results are robust to changes in the demographic composition of the population over time that drive both democratization and changes in level of child mortality, but with no direct relationship between the two. Of course, one should also consider whether the effect of democracy is *indirect*, via changes on the demographic composition of the population. In that case, instead of reducing, say, mortality rates from low aged mothers, democracy would be acting indirectly, by reducing the fraction of mothers that belong to this high risk group. While this is an important question, it can only be answered with individual level data. National averages of child mortality cannot separate out net (marginal) and conditional effects of democracy².

²I am using “marginal” in the probability of summing over all demographic levels.

CHAPTER 4

Data

The data set used in this study come from the Demographic and Health Surveys (DHS) (<http://www.measuredhs.com/>). These are comparable nationally representative surveys that have been conducted in more than 85 countries since 1984 [CNF12, FCB12]. These surveys collect a great deal of information from these countries, particularly on the fertility and reproductive health of their population. Low income countries and international agencies have long relied on it to monitor the health of their population. For example, the national averages of child mortality are often estimated from DHS [RMF10]. DHS has a standards of procedures which makes their data highly comparable across countries and thus easier to use in cross national studies [GK02].

DHS also collect information on indicators of permanent income for each household, such as ownership of car, radios and TVs; whether the household has electricity and running water; type of the materials of the walls, floor and the roof of the house is made of; and the type of the toilet of the household. This information is used to construct an indicator of the permanent income of the household. Details of the model to construct this indicator are discussed by [Rut08], but they are also discussed in the data appendix.

DHS data are based on *retrospective surveys* that can be used to form *retrospective panels*, which are a common source of information in demography and health sciences, particularly from the developing countries. Some countries were surveyed

only once, such as Brazil, while others have multiple waves, such as India¹. Taken together the data contain information for approximately 5.5 births. But the sample size varies considerably from country to country. While Kazakhstan has the records of less than 15 thousands births, India has over a million of births in it. Retrospective panels are constructed from these surveys as follows: at the year in which the survey is conducted, mothers of reproductive age (usually 15-45) from a sample of representative households in the country are interviewed. These mothers answer several questions, including ones about their complete birth histories — how many children they had and when. These answers are use to form retrospective panels where each observation represent a child born to a given mother in a given year. Additionally, interviews collect objective information from the household, such as the ones used to contract the wealth index. These surveys are representative at the national level, but sometimes they are also representative of subnational levels, such as in India.

One main advantage of using these data over conventional sources, such as official government reports, is that these data are largely immune to political manipulation. It is an USAID-funded project currently implemented by a private company ICF International [CNF12,FCB12]. The data itself has been used and validated by thousands of researches all over the globe. Thus most of the previous concern about miss reporting due to political reasons [Ros06] are greatly minimized here ².

These data are subject to several problems, such as recall bias, lack of representatives of some subpopulations, and a few types of censoring and measurement error in the variables that were not collected by the time of the interview. I discuss all of these issue in detail in the appendix. I point out to some evidence against most of these concerns, including evidence from the relevant literature. Overall,

¹Detailed information is available on the online appendix.

²Though this is also true for more recent estimates of National Averages of Child Mortality

there are very few disadvantages in using these data as opposed to using national averages of child mortality, *even if one only cares about national averages*. In fact, at least for the sample of countries I have included here, the best national averages of child mortality closely match smoothed versions of the proportion of children from the DHS sample³. Even for catastrophic events, such as the genocide episode in Rwanda, the DHS data follows quite well the best national averages of child mortality.

In using these surveys, I have tried to maximize the number of countries included in the analysis. Yet, I needed to include countries for which the data coverage was long enough that I could construct a representative panel of low and middle income countries over time. I decided to include any countries for which the wealth information was available, excluding the first wave of the survey, from the mid 1980's. Thus, I have included all countries with data available since the second wave of the surveys. This included information from 50 low and middle income countries (see data appendix). Within these countries, I have excluded all births before 1970. Before 1970, most countries had very few birth documents, and they did not represent their population, as we can see when this information is compared with the national averages of child mortality.

The sample of countries included in my sample are quite representative of the premature, infant death toll in the world. Even with the exclusion of China, the countries used account for more than the 75% of infant deaths in the world, from 1970 to 2010. Details in the data appendix.

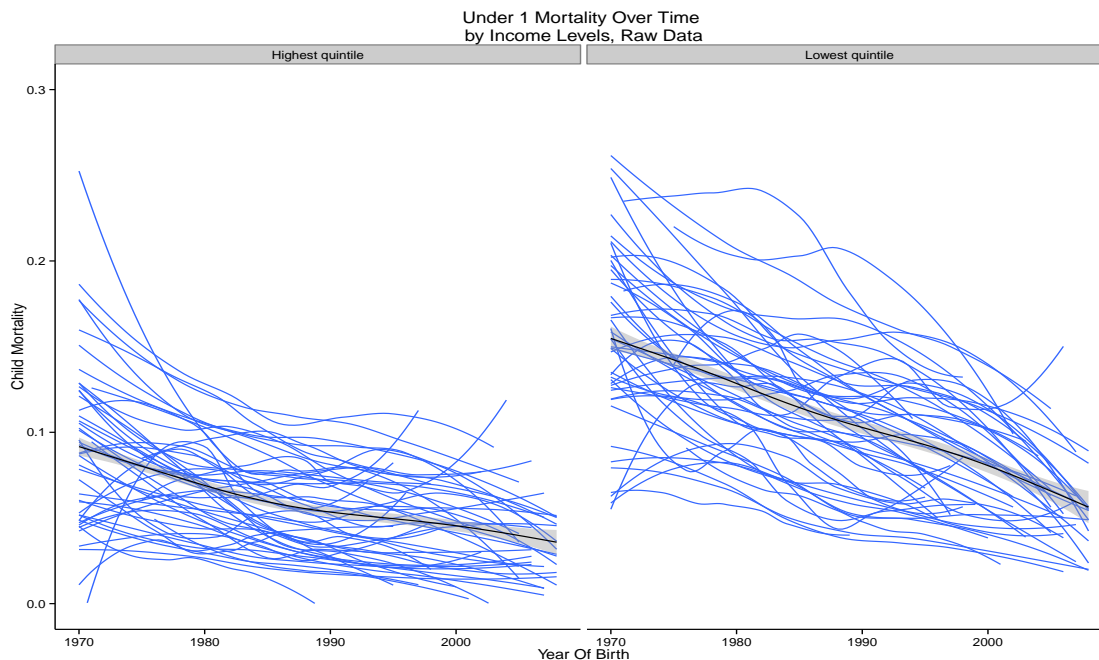


Figure 4.1: Empirical distribution of Child Mortality Rates for rich and poor across all countries and years. Each line is a simple GAM model which the only predictors is the time trend. The black lines in the centers of each distribution are the overall averages time trends and the shaded areas are the confidences interval around them.

4.1 Time Trends in Mortality Rates by Income Level Within Countries

Figure 4.1 describes the overtime change in child mortality for rich and poor children in my sample. Each line represents a country. The right panel reflects poor within each country while the left panel represents the richest⁴. Child mortality is declining for both the rich and the poor strata of the population. The gap between them are mostly closing over time. Yet, the poor suffer from disproport-

³This is shown graphically on the appendix.

⁴In the appendix, country-by-county plots are available for a very detail look the data.

tionally higher death rates than the rich. There is also more variance among the poor across countries, even though infant deaths among the poor is also falling over time. Careful investigation of this overtime trends via statistical modeling offer us the opportunity to disentangle long term over time trends from changes introduced by political factors.

4.2 Covariates

The covariates come from 3 levels: (1) child, (2) mother/household and (3) country. At the child level, I have included the basic demographic variables: gender, birth order, year of birth and the age of the mother at birth. At the mother level, I have included their highest level of education and household income. At the country level, I have included time and income. These are well-known predictors of child mortality. All models include covariates that are standard in the health literature.

CHAPTER 5

Methods

Before the formal presentation of the statistical machinery I will discuss the goal, objectives and limitations of the statistical analysis on this study. Given available data, the challenge is to find out a research design that can help us achieve leverage on the causal effect of democracy on child mortality gap between rich and poor. Following that, I will discuss the statistical tools available to us to pursue our scientific objective.

5.1 Goals and Limitations of the Statistical Analysis

The causal effect of a treatment on an unit can be simply defined as the difference in an outcome between two conditions — with and without the treatment. The fundamental problem of causal inference, however, is that a unit cannot be observed both with and without the treatment [Hol86]. Suppose that a democratization episodes can be considered a treatment. Thus at any given point in time, a country, say Brazil, is either democratic or not, but never both. Thus, we cannot observe the child mortality rates for Brazil under both conditions, democracy and dictatorships, simultaneously. Therefore we cannot calculate the difference in these rates between political regimes. This would be the causal effect of democracy on child mortality. In some situations, however, the same country can be observed at different treatment states but *at different point in time*. If time had no effect, one could use this information to calculate causal effects of interest as the difference in the outcome between the treatment time and the control time.

Yet, in this study, time clearly has an effect. Not only have mortality rates declined over time, but the number of democracies has increased. Brazil in the 1970s is authoritarian and is plagued by high levels of child mortality. In the late 1990s, it is a working democracy with much better health outcomes. Yet, it would be naive simply assume that in the absence of democracy Brazil would still be plagued by child mortality. In fact, something else may have caused both phenomena in Brazil but without any direct relation between the two. For example, suppose that modernization theory [Lip59] is correct in that lower child mortality and democracy are functions of modernization of the society. Or suppose that something else, not democracy, causes reduction in child mortality but we cannot observe it. In fact, many countries reduce child mortality under dictatorships, most notably perhaps China, which reduced it a factor of three in a few decades [Cal86]. Yet, if we are able to assume that infant mortality evolves in a predictable way, then it is possible to use the longitudinal structure of the data to estimate what would have been in Brazil in the late 1990s without democracy. To do so, we need to have enough information from the pre-democratization time trends so that we can extrapolate them into the future and then ask the question: what would have been Brazil in the absence of democracy? Comparing counterfactual scenarios with actual scenarios would give an estimate of the causal effect of interest.

While this approach does help with the non-random selection nature of the "treatment", the democratization episodes, it does not help with whether the timing of the treatment is endogenous. For example, suppose something else such as income or maternal education is causing both child mortality reduction and democratization. As modernization theory suggests, democracy might very well be endogenous to countries' mechanism of child mortality reduction [Lip59]. And we know that maternal education is one of the strongest predictors of child mortality [GCL10]. One way to tackle this problem is to control for the demo-

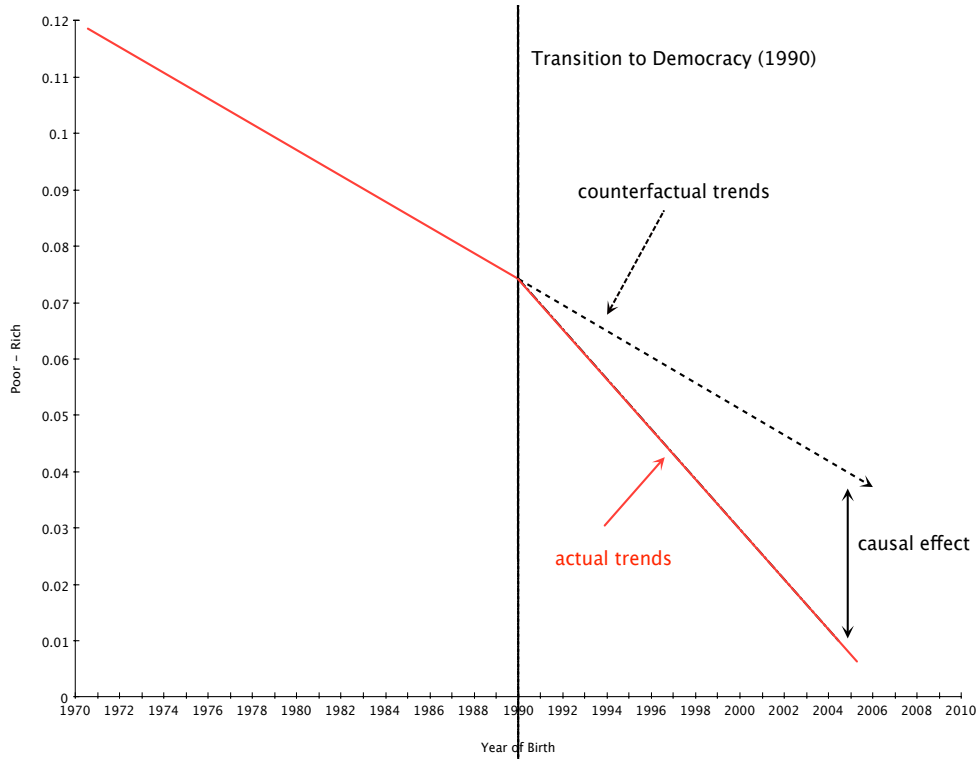


Figure 5.1: Hypothetical scenario describing the effect of democratization on the inequality in child mortality.

graphic covariates that were suggested to be causing both [Kud12]. This strategy will help to account for societal demographic changes that are associated with both child mortality reduction and democratization. By focusing on time trends within demographic groups within countries, I account for many unobserved characteristics that not only make countries different from each other but, even more importantly, make people across income levels different from each other. All these unobserved characteristics are absorbed by the time trends across demographics within countries.

Figure 5.1 illustrates the issue. The goal is to estimate the degree in which the democratization episodes shifts previous trends and level and rates of change in inequality in child mortality. This strategy is related to interrupted time series

models, which have extensive use in social sciences [MW07, GH06]. It is related to the more recent approaches of synthetic case control studies [ADH10, AH12].

The primary weakness of this approach is that previous time trends might not be good predictors of future time trends. There are a few ways to address that. First, I am using several covariates that may impact time trends. Secondly, I am experimenting with different time trend extrapolations and I am allowing time trends for each demographic group within countries. This is a quite a flexible approach. Finally, I am using several countries in the analysis simultaneously, such that I am borrowing strength across countries.

Another issue is that this approach does not take advantage of the information from countries that never experienced democratic transitions. Yet, I am keeping these non-transition countries so that I can compare countries which made the transition with countries that never did it. Also, I can compare always democracies with always dictatorships to analyze whether this makes a difference in over time changes in trends and levels in inequality.

Thus, my goal is to measure over time trends, investigating whether democratizations have affected them. In order to test for that, I am focusing on two major approaches: The first is to check whether countries' trends in the rich and poor gap are related to regime type. For example, are transition countries reducing the gap faster than dictatorships? Does the number of transitions in a country affect time trends? The second is related to the introduction of democracy in previously authoritarian places. Does democratization change previous, pre-democratization levels and rates of changes?

I propose to answer the following questions:

- Are baseline differences in child mortality driven by regime type?
- Are overtime trends in child mortality driven by regime type?

- Does democratization change levels of inequality in child mortality?
- Does democratization change the previous rate of change in child mortality?

That said, the collection here is far from an experimental situation and therefore causal inference is always problematic. Perhaps, the best way to describe what I am doing is prediction and inference but with an eye in the underlying causal scientific question of interest.

5.2 Measuring the Rich and Poor Gap in Child Mortality?

As discussed, health disparities varies widely across subpopulations within the same country. Race, ethnicity and income levels are only of the few possible grouping variables. Here I want to focus on the inequalities that are linked to the theoretical expectations from the political economy theories. These are inequalities between income levels, specially the rich and poor gap. One approach is to define inequality as the *ratio* between death probabilities from rich and poor children: how more likely to premature death are poor children compared to rich ones? Yet, ratios can become unstable when the rich children approaches zero probability of death. A simple alternative is to calculate the predicted difference between rich and poor. This is a simple contrast from regression equations. Thus I am defining inequality here as the rich-poor gap in predicted mortality rates, controlling for standard demographic variables:

$$\text{INEQUALITY} = \widehat{\text{CH}}_{\text{poor}} - \widehat{\text{CH}}_{\text{rich}}$$

5.3 Random Effects, Fixed Effects and Clustered Data

The response variable is a binary outcome at the level of children: whether a child born in a particular country and year, with certain characteristics (mothers's age, sex, place of residence, etc) live to the age of one or not ¹. The source of political variation, the democratization episodes, take action at the country level.

The data also exhibit complex clustered structure and a longitudinal profile. For example, children born from the same mother, in the same countries and in the same years may have correlated risk of death. Years are also correlated in the sense that the probability of death in any given year is in general more similar to that of proximal years. It is important to account for this clustering for both statistical and substantive reasons. From a statistical perspective, not accounting for the clustering will produce wrong standard errors and therefore risks incorrect statistical inferences.

5.3.1 Country Level Clustering

The data are clustered at the country level and by year, with at least several thousand of observations in each cluster. Because of clustered nature of the data, a simple approach would be to fit a full random coefficients' model using data from all countries [SBK07, GSB07, PGB04, Pan10b, Pan10a, Par12, WJ94, Wes98, BK07] ². Random Effects Models display superior statistical properties, such as smaller mean square error than alternative approaches [Rob91, Bat10, SBK07]. These models can be easily extended for the case of generalized linear models, such as logistic and probit regression for binary outcomes. This would allow us to model the heterogeneity across countries. Yet, given the size of the data, it is not

¹I am focus on mortality under 1 (Neonatal and Posneonatal), because it reduces the censoring regarding the children that did not have the chance to die, thus increasing sample size, which is helpful in estimating post-transition trends.

²See also Autumn 2005 edition of *Political Analysis* devoted to the analysis of multilevel data set.

computationally feasible to fit a full random effects model to the entire data set. An alternative, easy and simple approach is to run separate regressions for each country and then to combine the results using meta-analysis.

5.3.2 Within-Country Clustering

In addition to the between country clustering, there is also within country clustering. For example, children born from the same mothers or from the same village or state. In previous research, some attention has been paid to the within-mother clustering. Some of the previous literature in social and health sciences that worked with this data suggested controlling for “mothers unobserved effects”. The flavor of the control strategy varies: “fixed effects” in development economics [Kud12] or random effects in health sciences [GK02] ([BFS11] also uses DHS data but without mothers effects). I formally test for whether mothers effects helps the models’ fit. For a subset of countries in which the number of kids per mother was higher than total sample averages, I actually fit models with and without mother effects, comparing models’ fit using several statistics (AIC, BIC, deviance, etc). The results do not show any significant improvements by modeling mothers effects (they are available upon request). Given the computation complexity of adding mothers effects in the context of a logistic regression, I do not include these effects here ³.

³The lack of improvement after accounting for mothers effects actually makes sense. First, most mother have only one child. The median number of children per mother in my sample is 3, but it varies from only 2 to up to 6 for very few countries. This is already very low figure to estimate mother effects but when one investigates how many infant deaths each mother experienced the figures are even lower: 76 % of the mother experienced no death of their children, 15 % one death and only the remaining more than one death. Furthermore, mother effects would be unlikely to be useful in a longitudinal context, even if enough data was available. The age of the mother at birth is one of the most important predictors of the child probability of survival. In fact, mothers’ abilities to give birth to a health child varies widely over their age. Thus even if enough children were available per mother, we will only be able to estimate some type of time invariance unobserved characteristic of the mothers, which likely would not inform us much about latent factors related to their fertility. Finally, and perhaps most importantly in the context of this study, the inclusion of mothers’ effects will reduce my ability to use covariates at the mother level, such as income and education, which are key for the scientific question here

5.3.3 Modelling Time Trends

As previously discussed, modeling time trends in the decline of child mortality for children born from mothers at different income levels is the key component of my analysis. Though there are many observations, the outcome is binary and therefore each observation does not contain a great deal of information about the underlying individual probabilities of death. And I am actually calculating $5 * 50 = 250$ time trends, one for each quintile of income for each country. This is specially challenging for countries with large variability over time. Moreover, for the transitional countries, we want to decompose the trends after and before the transition so that we can investigate whether democratic transition changes previous trends.

Increasingly complex time trends such as higher order polynomials and B-splines would be able to capture more details in the over time changes. Yet, these models are harder to estimate, and they suffer from higher risk of capturing sampling variability as opposed to actual changes in the true underlying population. Finally, these models are more difficult to summarize across countries. On the other hand, simple time trends such as a low order polynomials are easier to summarize and interpret. They also allow for very easy decomposing of time trends after and before the democratic transitions and can also calculate overall time trends over the entire period more efficiently.

I estimate the basic specification using linear time trends at each income level from each country (see details below). This is quite flexible approach already. However, I will also use Generalized Additive Models (GAM) to check the robustness of my findings to deviations from linearity.

addressed. These is so because these variables are strongly correlated with mothers' effects.

5.3.4 Country Level Logistic Regressions

For each country, I fit a logistic regression with linear time trends:

$$\begin{aligned} Pr(y_i = 1) &= \text{logit}^{-1}(\mathbf{X}_i\beta) \\ &= \beta_1 \text{wealth} * (\beta_2 \text{time} + \beta_3 \text{new.time} + \beta_4 \text{democracy}) \\ &\quad + \beta_5 \text{Maternal.Education} + \beta_6 \text{household.income} + \\ &\quad + \beta_7 \text{Country.Income} \\ &\quad + \beta_8 \text{new.time.genocide} + \beta_9 \text{new.intercept.genocide} \\ &\quad + \beta_{10} \text{residence} + \beta_{11} \text{sex} + \beta_{12} \text{birth.order} \\ &\quad + \beta_{13} \text{age.mother.at.birth} + \beta_{14} \text{age.mother.at.birth}^2 \end{aligned}$$

All key variables are interacted with the wealth of the mothers. Time is a linear time trends; new time is a linear slope deviations in the time trends after the introduction of democracy; and democracy is a binary variable that equals to one after the introduction of democracy. While linear in the logit scale, these variables are no longer linear on the probability scale, which adds additional flexibility to the model in the scale of the data. The variables are centered so that they have an easier interpretation. This model has the advantage of being easy to fit to meta-analysis upon: time is described by only a few coefficients which are exactly the same across countries.

5.3.5 Generalized Additive Models

More complex alternative to the linear time trends models include B-Splines and higher order polynomials. These models have their own challengers, such as model selection for the optimal polynomial degree or where to place the knots for the splines. A more systematic approach is a Generalize Additive Model (GAM) over time trends by income levels. GAM's are generalization of Generalized Linear

Models, such as Logistic regressions, where the functional form of some or all covariates are estimate from the data, non-parametrically [BJ98]. These models use robust statistical procedures to estimate the exact functional form of the time trends at each income level from the data. Thus, instead of considering several different possibilities for, say, the basis function for the B-spline or the polynomial order, comparing the fits each time, we can fit a GAM with the smoother over time trends by income. Though not widely known in Political Science research, GAMs are routinely used in many scientific fields exactly to investigate the misspecification in parametric forms, such as the linear time trends models ⁴. GAMs include GLMs as special cases when linearity at the level of the predictors is assumed. If we want to test whether a GLM is well-specified, we can do so by comparing it to a GAM. This is especially useful in my case where we want to check the robustness of the linear time trends to different functional forms. Let's define $\mathbf{X}\beta$ as the matrix with all other covariates from the previous equation, including the intercept but excluding time trends. Thus we are allowing different time trends by different income levels to follow different non-linear trajectories for different countries ^{5 6}.

The biggest drawback of using GAM is that different countries have will have different sets of parameters summarizing their over time changes at each income level. Thus, one can no longer easily feed an exact set of coefficients into a meta-analysis and get an overall result. Still we can: 1) conduct statistical tests to compare overall fits across GAM and GLM; 2) get prediction from these GAM models, comparing them against those from the GLS; 3) have linear time trend for the bent line while keeping the GAM smoother for the overall time trends⁷.

⁴Recall that in this study GAM were also use to investigate the exact functional form of the effect of the age of the mother on mortality rates over time, due to the censoring of that variable.

⁵Smooth terms are represented using penalized regression splines (or similar smoothers) with smoothing parameters selected, in my case by GCV/UBRE/AIC/REML.

⁶gam in R package mgcv solves the smoothing parameter estimation problem by using the Generalized Cross Validation (GCV) or an Un-Biased Risk Estimator (UBRE)criterion. Please see the manual the R package for details.

⁷A still more flexible approach would be to use fixed effects for each years in every country

5.4 Using Contrasts To Estimate the Poor-Rich Gap

Once we fit a Logistic Regression or a GAM model to the data, we need to get the quantities of interest to feed into the meta-analysis. All of these are contrasts from the logistic regression models. We need an estimated difference between the rich and the poor, and its associated measure of uncertainty, while holding the other covariates at sensible values. A simple example helps to illustrate the issue. Suppose, children are either from rich or poor mothers, who either have primary or higher education. Further, suppose that \mathbf{X} is a vector of covariates that we want to hold constant, such as the sex of the children, birth order and place of residence of the mother. Let $\widehat{\text{Rich}}$ be the estimate baseline (at the beginning of the study) probability of death for the children from a rich mother with higher education while $\widehat{\text{Poor}}$ is the probability of death from a birth from a low income mother with only primary education. Using these facts we can estimate Δ as the difference between the probability of deaths as a linear contrast (in the logit scale):

$$\begin{aligned}\widehat{\text{Poor}} &= \hat{\alpha} + (\hat{\beta}_1 * \text{poor}) * 1 + (\hat{\beta}_2 * \text{primary}) * 1 + \mathbf{X}\hat{\beta} \\ \widehat{\text{Rich}} &= \hat{\alpha} + (\hat{\beta}_1 * \text{poor}) * 0 + (\hat{\beta}_2 * \text{primary}) * 0 + \mathbf{X}\hat{\beta} \\ \Delta &= \widehat{\text{Poor}} - \widehat{\text{Rich}} = \hat{\beta}_1 * \text{poor} + \hat{\beta}_2 * \text{primary}\end{aligned}$$

The standard deviation of these contrasts can be easily calculated using the formula of the variance of two correlated random variables:

- i.e. unstructured dummies' indicators for each year in every country logistic regression. I have experimented with this approach as well. While in expectation it would provide unbiased estimates of the changes in child mortality at every single year in every country for each income level it does not work in practice. Instead it produces estimates with huge standard errors and mean values that are inconsistent with the raw data, the other regression estimates, and even with the common sense, such as that the death rates being higher for rich than for *poor most of the time*. I would almost certainly erase any effect that democracy might have in child mortality, if any. Therefore I abandoned it, though a few country examples are available upon request.

$$\text{Var}(\Delta) = \text{Var}(\hat{\beta}_1) + \text{Var}(\hat{\beta}_2) - 2\text{Cov}(\hat{\beta}_1, \hat{\beta}_2)$$

These quantities are available in the variance-covariance matrices of the fitted logit or gam models.

5.5 Combining Information from Contrasts from the Country-by-Country Regressions using Meta Analysis

Suppose we have fitted the country-by-country regressions and calculated the desired contrasts. How do we go about estimating the effect jointly for all countries? Meta-analysis are common used procedures in health and statistical science when the goal is to combine information from several studies with similar targets. The simpler version of such procedure is the fixed effects meta-analysis. Let $i = 1, \dots, k$ independent effects size estimates, each corresponding to a true effect size, from example a contrast between rich and poor at the baseline for each i country, Δ_i . We shall assume that

$$y_i = \Delta_i + \varepsilon_i$$

where y_i is the observed level effect from i -th study independent effects size estimates, corresponding the the true effect and $\varepsilon_i \sim N(0, \nu_i)$. The y_i 's are the unbiased and normally distributed estimates of the true effects, Δ_i . The sampling variance is also assumed to be known and in my case is simply the estimate standard error of the contrasts, Δ_i .

The random effects models for meta-analysis builds upon these simpler fixed effect formulation by allowing for the possibility of variability among the true effects. This is especially useful here, where there are remarkable difference in the sample characteristics across countries Thus we have:

$$\Delta_i = \mu + v_i$$

where $v_i \sim N(0, \tau^2)$. Hence the true effects are assumed to be normally distributed with mean μ and variance τ^2 . Here the goal is to estimate μ , the average true effect and τ^2 , the total heterogeneity of the true effects. If $\tau^2 = 0$, implies homogeneity. Mixed effects meta-analytic models adds further modeling flexibility, by letting us to investigate the sources of heterogeneity across the true effects with one or more moderators. They are very similar to mixed effects regression models:

$$\theta_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip} + v_i$$

where β_{ip} is the value of the j -th moderator variable for the i -th study. Again we assume that $v_i \sim N(0, \tau^2)$ but now τ^2 is the amount of residual heterogeneity in the true effects not accounted by the moderators. In this study, moderators are simple country levels variables such as the income level of the baseline, political regime type (transition, democracy or dictatorships) or the number of democratic transitions it has experienced.

In the case of homogeneity among the true effects, the distinction among all these methods disappears as $\mu = \bar{\theta}_w = \bar{\theta}_v \equiv \theta$. I will present results from the random effects models, which have advantages. Yet, the results are also robust to that choice. Various measures have been proposed to interpret τ^2 . The I^2 statistics is a in percentage — how much of the total variability in the effects size estimates is due to heterogeneity among the true effects as oppose to sample variability ($\tau^2 = 0$ implies $I^2 = 0\%$).

The fixed effects meta-analysis provides information about *conditional inference*: What is the size of the true effects among the set of k studies included in the sample. On the other hand, the random/mixed effects models provide *uncon-*

ditional inferences about a set of larger studies in which the k included studies is considered to be a random sample. The later can answer questions such as how large is the true effect among the larger population, such as middle and low income countries.

CHAPTER 6

Results

I present the results in several steps. Hopefully the reader uninterested in all details will find the presentation of the results organized enough so that he or she can focus on the parts of most interest. Yet, to have a comprehensive sense of the results, all sections are essential. At the core of the analysis is the logit regression model described above. Thus they poses interpretation challenges. Meta-analysis and associate statistical inference will be conducted in the log-odds metrics but, whenever possible, I will illustrate the effects size in the probability scale.

First, I provide a sense of how well the model fits the data. Second, I will discuss the baseline difference and overall time trends for all 50 countries. I will presents results from a mixed effects meta-analysis to investigate whether these can be explained by political factors. Then I will turn to the analysis of the 22 transition countries. I will discusses the results from the bent line approach to investigate whether the introduction of democracy changed previous levels and trends in inequality. Finally, I will provide some illustration for the counterfactual scenarios in the probability scale.

6.1 Basic Models Fit: Comparing GAM and GLM

Both the GLS and the GAM models fit the data well at least in the sense of providing predictions that resemble important features of the raw data (more on that bellow). Confidence intervals are small enough so that in most cases the

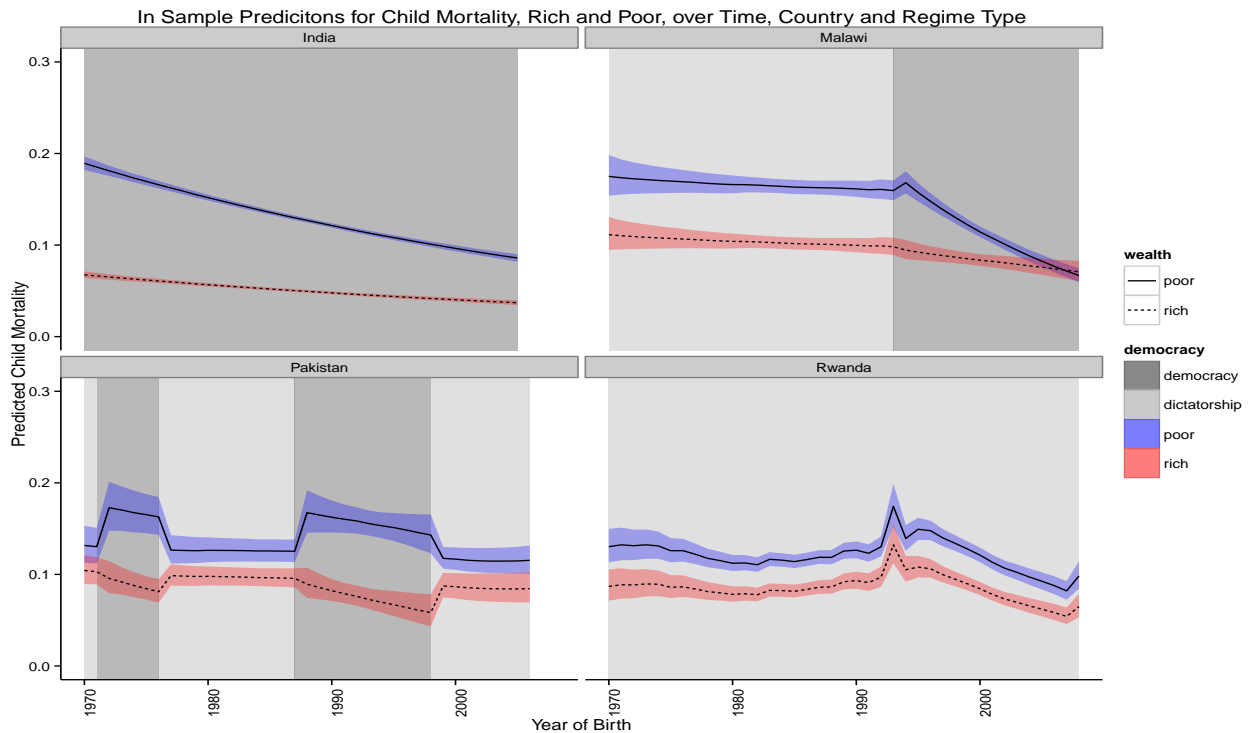


Figure 6.1: Predictions from the linear time trends models in detail for 4 types of countries. Always democracies, India; Always Dictatorships, Rwanda; One time transitions, Malawi; and, finally, multiple transitions countries, Pakistan. The Dark grey represent dictatorial periods, while light gray democracies. Dotted lines with read shades, are conditional mortality rates for the poor, while solid lines for blue shade are for the poor. The shades are 95 confidence intervals.

difference between the poor and the rich are statistically significant though the analysis.

Figure 6.1 presents basic predictions from the linear time trend models for the four basic (political) type of countries: always democratic, such as India; always dictatorships, such as Rwanda — which was also affected by a genocide episode; countries which endure one democratic transition, such as Malawi; and finally countries that experience many democratic transitions, such as Pakistan.

It is remarkable that the linear time trends models were able to capture several important features of the data, such as the genocide episode in Rwanda. Some patterns are quite amazing, such as in Pakistan. For this country each time that democracy was introduced, child mortality increased for the poor, thus widening the rich-poor gap. Figure 8.1, in the appendix, shows the results of the predictions for all countries using the linear time trends models.

One may wonder whether these estimates were not artifacts of the models. Yet, the GAM, which include not information about political episodes, are remarkably similar to the Logistic regressions with linear time trends. For example, the gap introduced by democratization in Pakistan or the genocide episode in Rwanda are both captured by the GAM models, suggesting that these patterns are actually real. For some countries like Indonesia and Guatemala, it seems that the linear time trends represent actually a better fit. Detailed results comparison predictions from both models against the data are available upon request ¹.

6.2 Baseline Differences

Figure 6.2 — and with detailed numerical summaries in Table 8.1 in the appendix — collects and displays the contrast between the rich and the poor across

¹To formally compare the likelihood of all models from the GAM fit against all those from the GLM fit I have used the following χ test:

$$D = -2 * \sum_{i=1}^{50} \ell_{gam} + 2 * \sum_{i=1}^{50} \ell_{glm}$$

$$D \sim \chi_{df}$$

$$df = \sum df_{gam} - \sum df_{glm}$$

The statistical test indicates a better fit for the GAM, as one would expected. Yet, linear time trends allow us to decompose the trends in a more amenable manner to capture our scientific question of interest while producing overall similar results. Thus the point is that these models can reproduce important feature of the data and therefore should be able to capture discontinuities introduced by the political process.

Baseline Differences for the Poor–Rich Gap (Logit Scale)

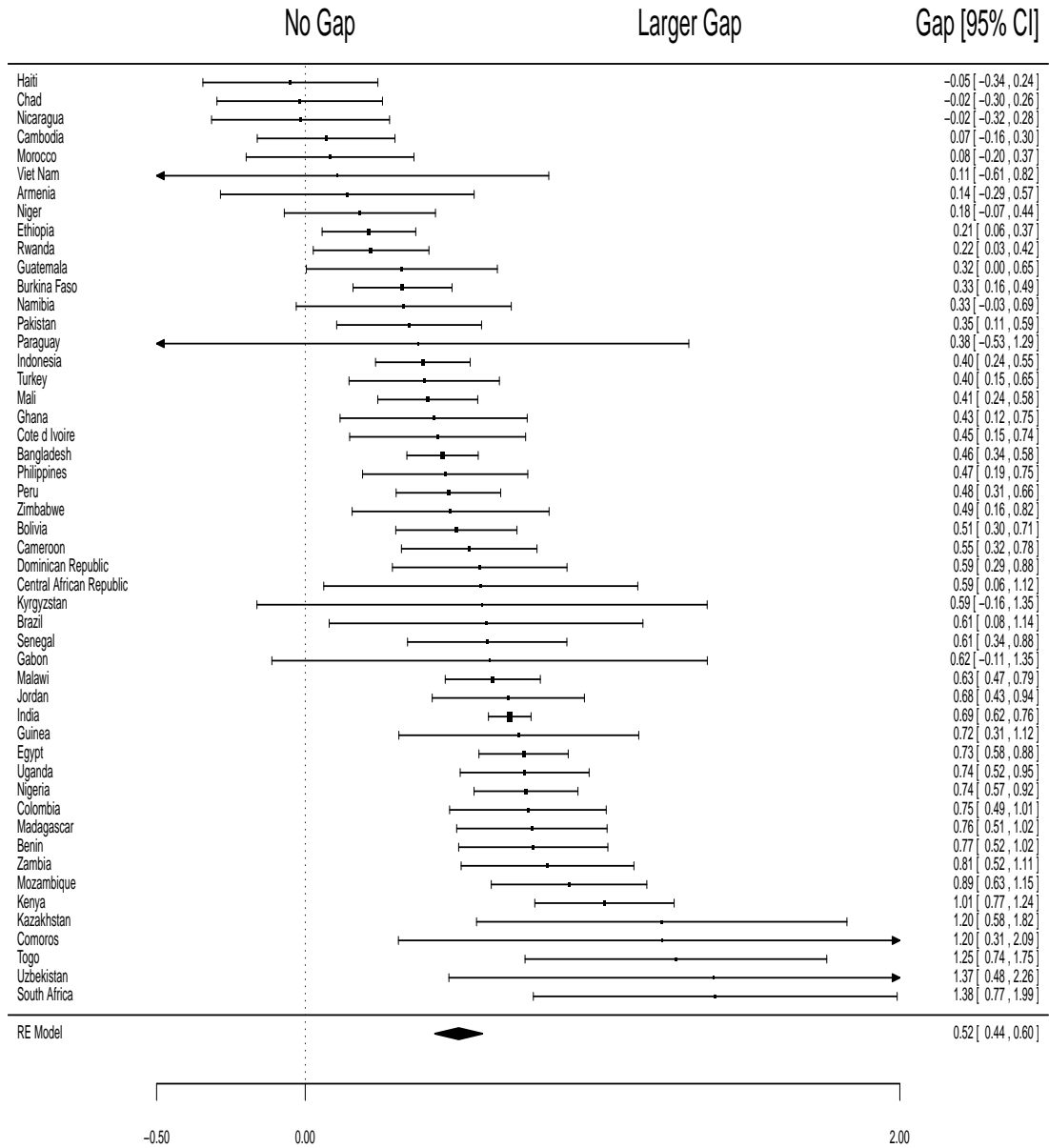


Figure 6.2: Baseline levels on inequality in the rich and poor gap in child mortality. These contrasts were estimate using the linear time trends models.

countries at the baseline year for each one of the 50 country studies ². As we can see in the figure 6.2, and except for a few cases, most countries exhibit a gap in child mortality for the rich and poor. The estimate difference in 5.1 log-odds with $se = .04$ which is highly statistically significant ($p_{\text{value}} < .0001$). As we can see in the figure, the exceptions are Haiti, Chad, Nicaragua, Cambodia. Morocco, Viet Nam, and Armenia. Some countries, such as Kazakhstan, Comoros, Togo. Uzbekistan, and South Africa exhibit big disparities. Accordingly, a test for heterogeneity finds that it exists and it is highly statistically significant. The I^2 statistic indicates that 81% of the heterogeneity is due to the actual differences across countries' baseline conditions, not sampling variability. This makes sense based on the contrasts presented in the Figure 6.2.

In order to explore the possible sources of heterogeneity across countries I fitted a mixed effects meta-analysis where I investigate the association between the baseline rich-poor gap and political factors — whether it is a transition country, a democratic country (for the entire period) or a dictatorship country (for the entire period). I have also controlled for per capita income at the baseline of the study. An alternative way to see what I am doing is to test that if controlling for income, these sets of countries display baseline differences in the inequality levels. Since none of variables explain countries' differences at the baseline, we know that baseline differences are not grouped by political factors.

6.3 Overall Rate of Change

Now I turn to changes over time. The main points to be investigated are: (1) whether countries changed inequality levels over time; (2) the heterogeneity across these changes and (3) and, if (1) and (2) are linked to political factors.

Figure 6.3 and (again, numerical details in the appendix, Table 8.2) display

²1971 for Bangladesh, 1975 for Comoros and 1976 for Vietnam ; all others were 1970.

Over Time Changes in the Poor-Rich Gap (Logit Scale from Linear Time Trends Models)

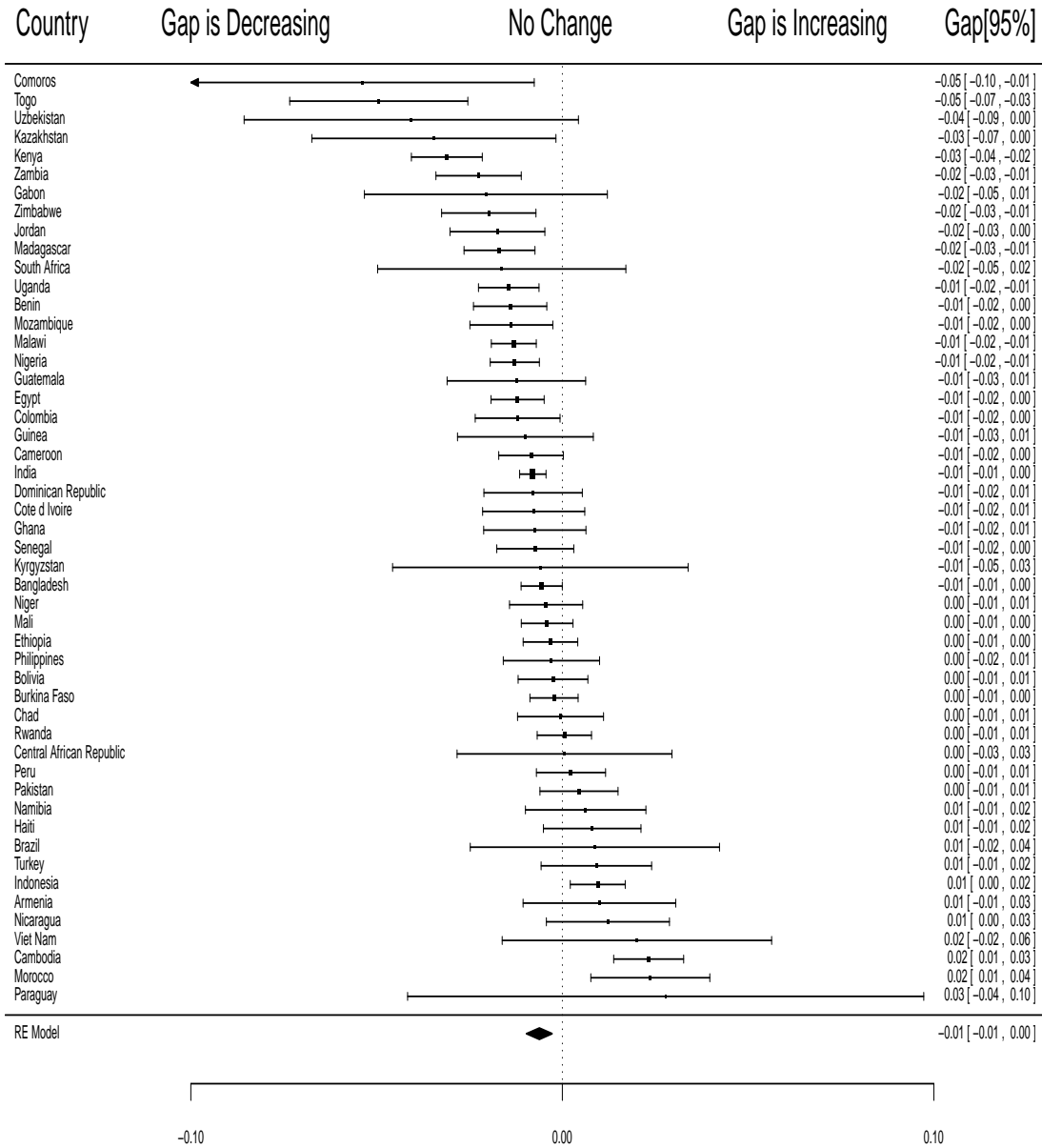


Figure 6.3: Overall time trends for the rich-poor gap in child mortality. These contrasts were estimate using the linear time trends models.

the rate of change in the log odds scale for each one of these countries. The actual numeric summaries of all those countries are also presented in the figure. For many the gap is decreasing, there is no statistically significant change for some and it is actually increasing for a few countries. Overall, the gap is decreasing: using meta analysis one can learn that the decreasing is statistically significant, $-.01$ log-odds for each additional yearly reduction in the gap between the rich and the poor, with $p_{value} = .0005$. Yet, the heterogeneity is very high: $I^2 = 80\%$ and statistically significant. It means that the variability in these yearly reduction in the gap that we see in figure 6.3 are real and not a product of sampling variability.

I fit a mixed effects meta-analysis to understand the forces driving the differential rates of change in the rich and poor gap for these 50 countries. I explain the over time changes in inequality by countries' regime type, income level at the baseline, inequality in child mortality at the baseline and the number of transitions endure by the country. Again, the political factors don't seem to matter. Yet, (1) higher income at the baseline is associated with lower reduction in child mortality, but (2) higher inequality at the baseline is associated with faster reductions.

6.4 Does Democratization Changed Previous Levels of Child Mortality?

Now we focus on the 22 transition countries and ask the question of whether democratic transitions changed previous level of inequality between rich and poor. The contrasts for each one of the 22 countries are displayed in Figure 6.4 as well as the overall effect. As we can see, for almost all countries, the effect are not significant and nor is the main effects — a 95% CI for the log-odds $(-.04, .08)$ includes zero. Corroborating the visual inspection in the plot, the heterogeneity is low, $I^2 < 1\%$. This means that democratic transitions did not impact previous inequality levels, period. The only exceptions are Brazil, where the transition did

Change in Levels of Inequality in Child Mortality After the Democratization (Linear Time Trends Models)

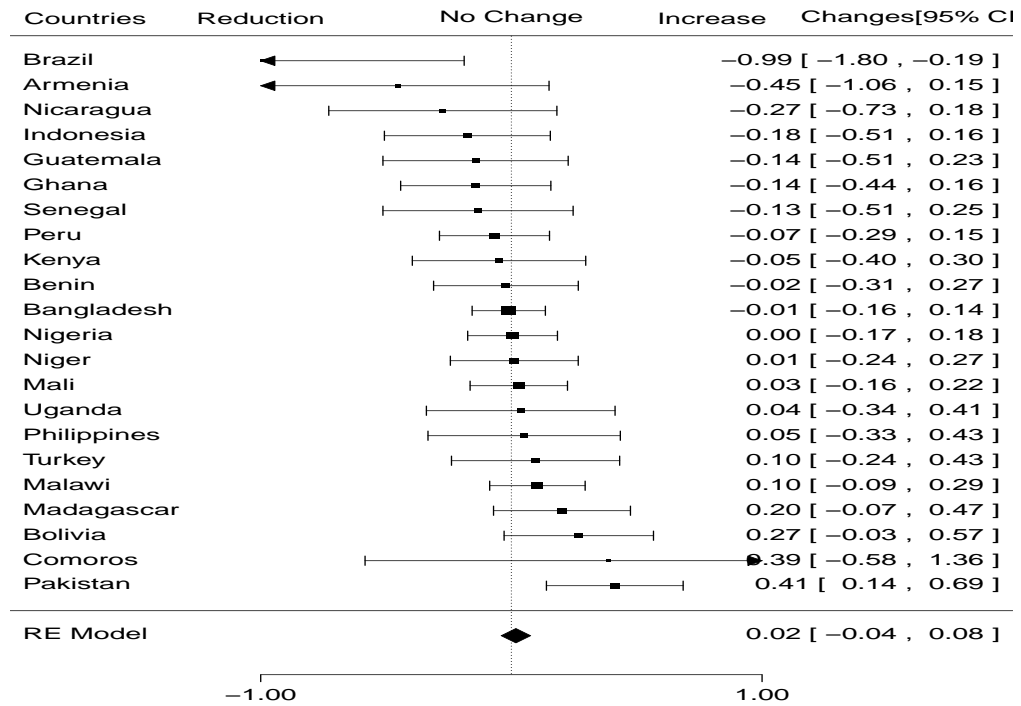


Figure 6.4: Meta-analysis for the changes in the level of inequality in child mortality between births from the rich and poor mothers after democratization episodes. These contrasts were estimate using the linear time trends models.

reduce inequality child mortality, and Pakistan, where the opposite happened.

6.5 Does Democratization Changed Previous Rate of Change in Inequality in Child Mortality?

Finally we want ask: do democratic transitions accelerate the rate of reduction in child mortality gap? Figure 6.5 display the results of the meta-analysis. The answer is no, though we still have a lot of heterogeneity across transitions - much more so than in it level effects. On average, each additional year after the demo-

**Additional Changes in the The Poor–Rich Gap after the Democratization
(Logit Scale from the Linear Time Trends Models)**

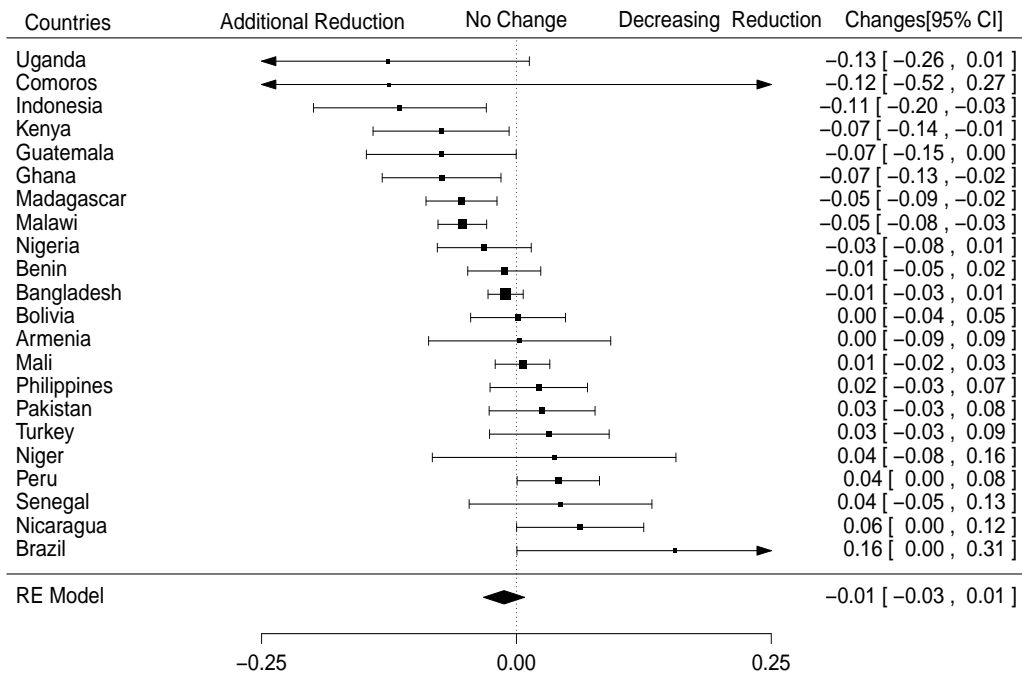


Figure 6.5: Meta-analysis on the effects of the democratization on time trends for the rich-poor gap. These contrasts were estimate using the linear time trends models.

cratic transition further closes gap in child mortality that was already in place before democratic transitions by -0.01 log-odds with 95 % confidence intervals of $(-0.03, 0.01)$, which is not significant. Still, the statistics of $I^2 = 72\%$ indicates that the effects are heterogeneous.

Since the main effects are not statistically significant, I am not fitting a mixed effects meta-analysis. Yet, we can still look at the forest plots to investigate whether the democratic transition further accelerate the reduction in the child mortality gap. Most of the countries in which democratization close the rich and poor gap in premature death are in Africa: Kenya, Ghana, Madagascar, Malawi

but also Indonesia from South-East Asia. On the other hand, for some countries it seems that the democratization slowed down the previous rate of reduction or even increased it, even though the effects are not quite statistically significant.

6.6 Relaxing the Lineary Assumption for Time Trends: Generalized Additive Models for the Time Trends

To test the robustness of my main findings to the linearity assumptions for the time trends, I use the already mentioned GAM models. Here the main time trends by income levels are estimated using a GAM and new time after the democratization is a linear deviation from it. The results are quite similar either in terms of the lack of significant for the effects of the transition and for the heterogeneity of the effects. Details are available upon request.

6.6.1 Illustration of the Heterogeneity of the Effects in The Probability Scale

While it is easy to do inference and hypothesis tests on the logit scale, it is much harder to have a sense of the actual effects size and their heterogeneity on that scale. Thus I made counterfactual predictions for all transitions countries, country-by-country. These are the same models used in the meta-analysis but now I am using them to make *conditional* predictions over time: I am comparing births from rich and poor mother, holding constant gender (female), place of residence (urban for rich and rural for poor), birth order (first birth) and the age of the mother at the birth of the child (18 years old). The education of the mother is a more complicated covariate to be kept constant. For example, for some Sub-Saharan countries, even rich mothers rarely have superior education, let alone higher; for some former communist countries, even even the poor has higher education. Also, while for some countries there are huge educational disparities

across income levels, that is not true for others. Thus “holding education constant” both across income levels within and across countries produces unrealistic, outside the ranges of the data, comparisons. A simple solution is use the typical (modal) value of the maternal education at each income level for each country. Thus I am letting education follow income, as the later is the major focus of this study ³.

Figure 6.6 illustrates the size and the heterogeneity of the effects of the transitions on the scale of the data - the probability scale. For each country, both counterfactual and actual predictions come from the same model. The difference between the factual and the counterfactual scenarios is that for the later I set the bent lines (the slopes shifts after democratization) and the intercepts shifts after democratization both to zero, as if democracy never happened. In the probability scale not only the effects size but also the heterogeneity was clear. For some countries, such as Uganda, there is a big reduction on the level of child mortality after the (ephemeral) democratic. Pakistan also has a huge increase in the inequality level every time a democratization happen, even though it does not affect its over time change. Many countries in Sub-Saharan Africa undergo fast declines in child mortality after the introduction of democracy, such as Ghana, Madagascar and Kenya.

6.6.2 Summary of the Findings

In brief, the main findings are as follows:

- Almost all countries exhibit a wide gap in child mortality rates between the rich and the poor quintiles of income. These are not only substantively but also statistically significant. At the baseline, the overall average difference is around 5% of excess of deaths for the poor in relation to the richest, though

³An interesting complementary analysis, will be to let education be the main driver and let income follow it.

it can vary from almost zero to over 10% for some countries. These baseline differences are not explained by either income per capita or regime type.

- Most countries in the world are decreasing the rich-poor gap in child mortality and the overall decrease is statistically significant. On average, the difference in mortality rates for the rich and the poor decreased from 5% to 2%, though there is heterogeneity across countries. Higher income per capita at the baseline is associated with lower rate of reduction, but a higher gap is associated with faster reduction. Again regime type and other political factors don't seem to affect these trends.
- Democratization episodes did not change previous level of inequality. This is uniformly true, being Pakistan and Brazil the only outliers.
- Overall democratization episodes don't seem to impact the previous trends in the reduction of child mortality. Yet, there is heterogeneity in these effects. Thus for some subsets of countries, such as few Sub-Saharan countries, it seems that democratic transitions did reduce the gap, however the opposite is true for countries such as Brazil and Pakistan (though not quite statistically significant at the conventional levels).
- All these results are robust to using either linear time trends or GAM's.

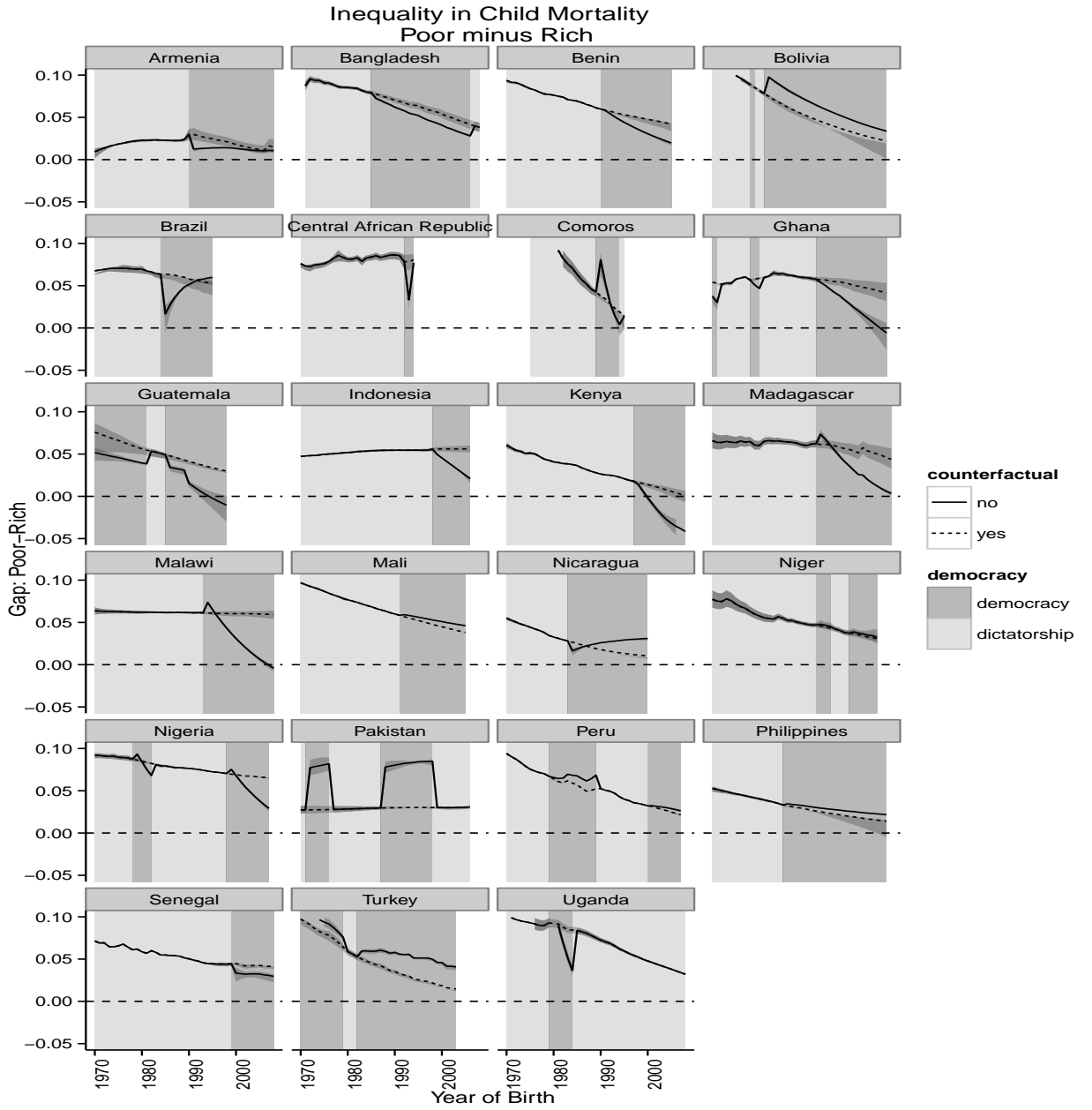


Figure 6.6: An illustration of the effects of democratic transitions and their heterogeneity on the rich and poor gap in child mortality. Transition countries only. The light gray areas are dictatorial periods while the dark grays are democratic ones. The solid lines are the actual, in sample predictions in the gap in child mortality. The dotted lines are counterfactual scenarios where the bent lines were set to zero.

CHAPTER 7

Discussion and Conclusions

The rich and poor gap in child mortality does exist around the developing world, even controlling for individual level demographic factors. These inequalities are reducing over time. However, there is no evidence that either baseline differences or over time trends are systematically linked to political factors. I have also investigated the effects of the introduction of democracy on previous levels and rates of change in child mortality in transitional countries and find that neither the levels nor the previous rates of reduction in the rich and poor gap in child mortality are significantly affected by democratization episodes. While all of it points to an essentially null effect of democracy on health and equality, I also find a substantial heterogeneity in these effects, beyond what one would expect based on sampling variability only. This is especially true for the introduction of democracy in previously authoritarian countries. For example, in countries such as Pakistan, democratic transitions were always associated with the increasing gap between rich and poor while the opposite is true for a most Sub-Saharan countries. This is an important unexplained finding that deserves further investigation.

In understanding these results, it is worth revisiting theoretical ideas from [Ros06]. As previously discussed, [Ros06] provides a more subtle interpretation of the median voter theorem. He points to the fact that the median voter (likely around the median income) may have no more interest than the rich (top 20 %) do in providing policies that disproportionately benefit the poor (bottom 20%). Thus in seeking political support from a broader electorate, governments do not

need to appeal so much for the poor but instead mostly to the middle class. Thus median voter theories imply some redistribution, but from the rich to the middle class, and not necessarily for the poor.

Yet, sometimes democracy does reduce the mortality gap between the rich and the poor, particularly in poor countries ¹. We also know that it is not entirely correct that child mortality is concentrated among the poorest quintile within countries. For example, in some poor countries, child mortality maybe endemic across all income levels. In particular, it may very well affect the “middle class” in poor countries - and thus the median voter. Thus my hypothesis is that (1) when the median voter is actually affected by child mortality and (2) there exist enough disparities in child mortality across the middle class and the rich, democratization might reduce child mortality gap between these groups. Further, if health care is actually provided as a public good, it might be very well the case that democracy would also reduce child mortality across the poor as well. On the other hand, if all income levels are severely affected by child mortality, democratization might reduce it across all levels without necessarily reducing gaps. Currently, I am investigating whether my data allow for a more direct test of these hypotheses.

Additionally, it is worth remembering that the median voter theorem is a very simple model of democratic politics and as such it might be lacking elements to explain politics in some places. As [Nel07] points out, there are both theoretical and empirical evidence that elections alone are not necessary to produce social desirable outcomes. Party ideology, electoral systems and the natural difficulties of translating to the mass public the need of large scale complex reforms may all conspire against successful transitions. For example, there exist evidence that the ideology of the government might help increase redistribution from the rich to the poor. Thus future research should also consider these possibilities, though they

¹This finding is also corroborated by another study in which I have used more recent estimates of national averages of child mortality, with no missing data and less measurement error than it was previously available.

are often hard to be tested cross-nationally.

Another limitation of this study is the fact that I am looking at conditional effects of democracy upon child mortality — not its net (marginal) effects. To see the difference between the two consider the following: suppose democracy did not reduce child mortality for some high risk group, say, 18 year old low-income mothers with a low educational background. Still, democratization might have reduced the fraction of the population that belongs to this group, for example, by increasing levels of education, increasing urbanization or the age of the mother at her first birth in the general population. Thus by holding constant a certain demographic profile I might be underestimating the effect of democracy on the child mortality gap. In fact, one might argue that democracy acts indirectly, thus changing the demographic profile of the country but not necessarily improving well-being within demographic groups. Though my exploratory analysis did not indicate any big net (marginal) effects of this nature, I am currently investigating a way to test for that possibility more systematically. Even if these effects are salient, it would be difficult to provide a causal interpretation for those, as reduction on these high risk groups themselves might be associated with the emergency of democracy, as noted above.

There are other limitations. First, since democracy is not randomly assigned to countries, one cannot claim that we can establish the causal effect of democracy on the inequality of child mortality — or the lack of thereof — using this data alone. Theory and microlevel studies are needed to help with that. Finally, other measures of democracy based on countries' observable characteristics might be able to capture associations that I cannot capture here. Measures of the quality and the competitiveness of the elections are specially welcomed though they are much harder to compare across countries.

Future studies could explore the huge heterogeneity across countries found here. It would be especially interesting to investigate in more detail the effects

of political factors on sub-Saharan Africa child mortality and its inequities ². Another approach would be to focus on case studies where beneficial or deleterious effects of democratization were more pronounced. Some countries such as Brazil do have very detailed data on both child mortality and political variables [MMM11]. On the health science point of view, it would be a welcomed effort to include more countries in the analysis, using sources other than the DHS. Finally, it would be interesting to investigate other sources of inequalities beyond the rich and poor gap [GK02] and study whether these are linked to political factors.

²Another study found beneficial effects of democracy on mean child mortality across countries in these region [Kud12].

CHAPTER 8

Appendix

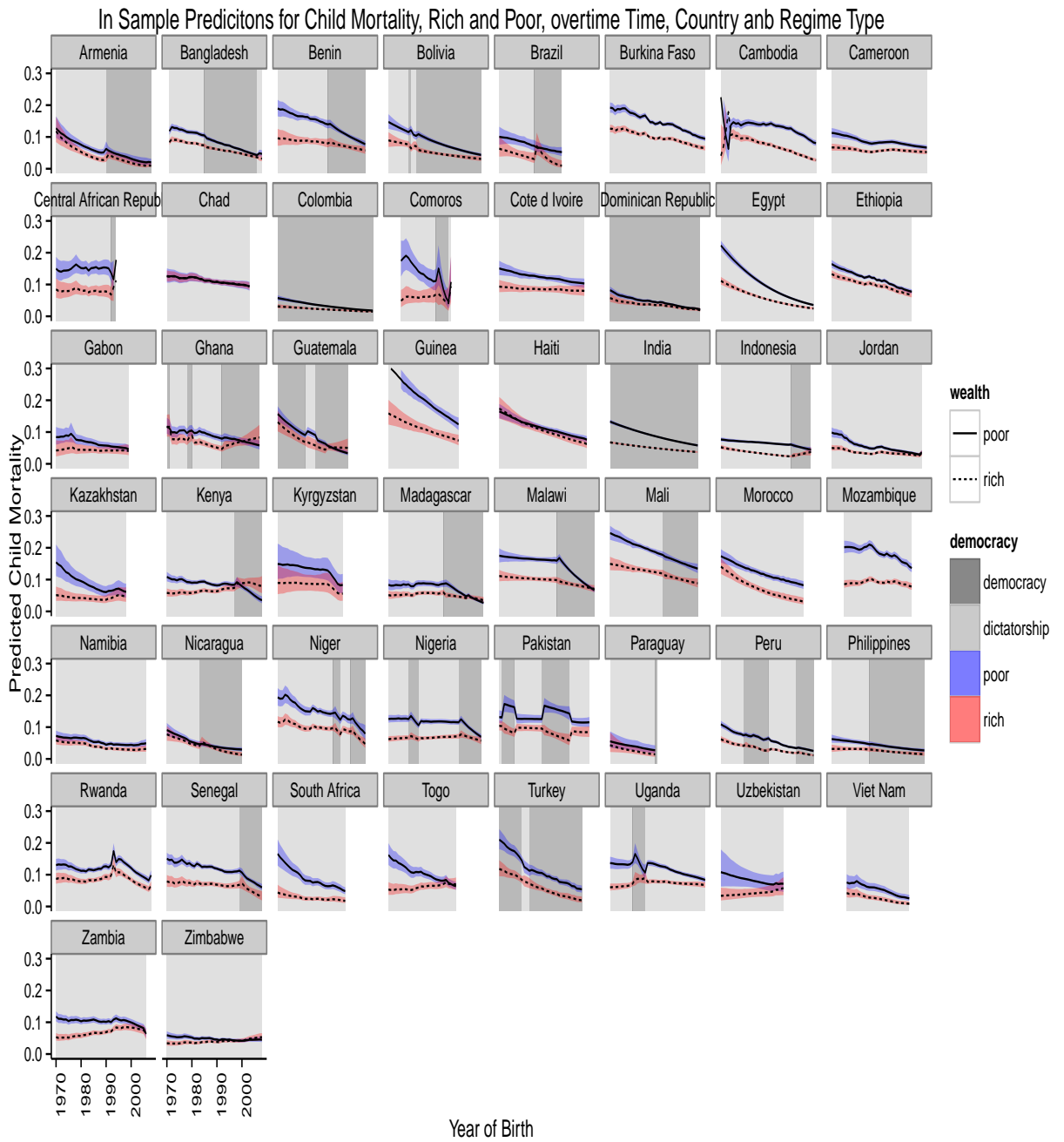


Figure 8.1: Conditional predictions from the linear time trends models

Baseline Differences in the Rich-Poor Gap in Child Mortality						
	Reduced			Full		
	Est.	SE	pval	Est.	SE	pval
Intercept	0.51	0.04	0.0001	0.29	0.43	.49
Dictatorship				0.01	0.08	0.9
Democracy				0.15	0.15	0.3
Genocide				0.15	0.15	0.3
Income per capita				0.03	0.06	.61
<i>N</i>		50			50	
<i>DF</i>		2			6	
<i>AIC</i>		30.5046			32.8614	
<i>BIC</i>		34.3287			44.3336	
log-likelihood		-13.2523			-10.4307	
<i>I</i> ²		81.19%			74.72 %	
Test for Heterogeneity		p-value=0.001			p-value=0.001	
Test for Moderators					0.1934	

Table 8.1: Results from the Mixed Effects Meta-Analysis for the baseline differences in the rich-poor gap in child mortality. The outcome variable is in the log-odds scale and is a contrasts from the country-by-country logist regression models with linear time trends. Income per capita is in the log-scale. All 50 countries were included. Reduce Model include no moderators (covariates) to account for the baseline differences. The log-likelihood ratio test is 5.64 (p-value:0.2274), indicating no statistically significant models' improvement after the inclusion of the moderators, which is also corroborated by very little change in the residual heterogeneity across models (see I^2).

Over Time Trends in the Rich-Poor Gap in Child Mortality						
	Reduced			Full		
	Est.	SE	pval	Est.	SE	pval
Intercept	-0.0062	0.0018	0.0001	0.0070	0.0094	0.4586
Dictatorship				0.0040	0.0028	0.1447
Democracy				0.0029	0.0029	0.3282
Genocide				0.0024	0.0041	0.5575
Baseline income per capita				0.030	0.0014	0.0308
Baseline rich-poor gap				-0.03357	0.0035	0.0001
number of transitions				0.0004	0.0011	.07212
<i>N</i>		50			50	
<i>DF</i>		2			8	
<i>AIC</i>		-333.7077			-280.0219	
<i>BIC</i>		-318.4115			-276.1978	
log-likelihood		174.8539			142.0109	
<i>I</i> ²		79.77%			1.85 %	
Test for Heterogeneity		p-value=0.0001			p-value=0.0982	
Test for Moderators					p-value=0.0001	

Table 8.2: Results from the Mixed Effects Meta-Analysis investigating over time trends in the rich-poor gap in child mortality. The outcome variable is in the log-odds scale and is a contrast from the country-by-country logist regressions models with linear time trends. Income per capita is in the log-scale. All 50 countries were included. Reduce Model include no moderators (covariates) to account for the baseline differences. Number of transitions refer to number of democratic transitions. The log-likelihood ratio test is 65.6859 (p-value:0.0001), indicating strong and statistically significant model improvement after the inclusion of the moderators, which is also corroborated by the large decline in heterogeneity across models (see I^2).

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