Income Inequality and Trust: Evidence from Emerging Economies

Thesis submitted by

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Abstract

In this course of this project, I explore the relationship between income inequality and trust across emerging economies. Previous studies have analysed this relationship across OECD countries or at either country or individual level. In this project, I test this in the context of key emerging economies, which have witnessed an increase in income inequality in the last few decades.

I create a country level and an individual level panel dataset from combining data from the World Values Survey, Solts Income Inequality Database and World Bank Governance Indicators. I then use a country-level fixed effects panel regression with the country-level data, multilevel models with the micro data. In the last part of the analysis, I examine if trust levels are changing across demographics in emerging economies by using Age-Period-Cohort models.

I find three key results. First, while there is no macro-level relationship between trust and Gini levels, there is an individual level relationship between

the relative income position of the respondent and their trust levels. These results are similar for alternate indicators of both trust and income inequality. Second, factors like life satisfaction, political participation and freedom of choice have a mediating effect on trust. Third, the model finds a strong relationship between age and trust level and indicates that older people are less likely to trust others often. However, unlike similar studies, I fail to find a relationship between trust levels and periods and cohorts

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Chapter 1

Income Inequality and Trust

The motivation for this project comes from the vast literature examining the role of cultural factors in economic development. While earlier research on economic development focused on factors like trade, institutions, access to public goods etc., there is now an increasing interest in the role of behavioural and cultural factors like trust and social capital [3].These stem from the idea that the nature of transactions and the level of social cohesion in a society is essentially based on how differently individuals expect others to behave, or in other words, 'trust' others.

Research on trust generally focuses on individuals who are not bound by any familial or social ties, though as a concept it encompasses trust in institutions

(like political parties) or mechanisms (like elections). In essence, it relates to intentions of individuals and their beliefs about the expected behaviour of others. Thus, it can be defined as a relationship where an individual *"places resources at the disposal of another party without any legal commitment from the latter, but with the expectation that the act of trust will pay off"* [11]. Moreover, "trusting" not only depends on expected behaviours but underlying this are norms and sanctions associated with reciprocal behaviour. In situations where there is no transparency about the expected behaviors of others, the level of trust becomes especially significant [3] . Through these shared norms and cultural meanings, trust levels could shape cooperation in a society and explain differences in economic development. For example, increased trust levels could lead to openness and willingness to close deals with other members of a society, reducing transaction costs and lessening dependency on checks and balancing mechanisms. Differences in trust levels, have been linked not only to stronger labour and financial markets but also to collective and public goods like taxation and common natural resource management [3, 26]. This correlation with various aspects of economic, social and political development underscores the importance of trust and forms the basis of this study.

Given that trust levels are integral to an economy, I want to examine the role of one the key factors that have been associated with trust: Income Inequality. I focus specifically on the role of economic or income inequality, and relative in-

come position, as a determinant of trust. In this section, I outline some causes and effects in income inequality and mechanisms through which this has been thought to affect trust levels.

There is growing evidence that there is increasing inequality in income both across and within countries, and that this is in turn connected to trust and social cohesion. While the U-shaped connection between income inequality and indicators like happiness and life satisfaction has been well-documented, its connection with trust remains ambiguous, more so due of the role of contextual and historical factors. [3]

Recent advances in inequality research provide an opportunity to explore trends in income across a society in detail. These include, for example, modifications to the frequently used Gini coefficients and new measures of identifying inequality. The availability of longer and more complete data on both inequality and income levels, along with data on related indicators like well-being, participation and views on key economic and political events in the same questionnaire, presents a useful method to track changes.

Studies using these data point to rising trends in inequality in the last century albeit at varying levels [29, 41]. Arguably, in emerging economies, a major factor linked to inequality is globalization, and increasing movement of financial and technological factors. This relates to the concept of skill based technolog-

ical change (SBTC), which posits that there is a change in production technology favouring the more skilled, and thereby creating a wage inequality [9]. This relationship between globalization and inequality is particularly relevant in economies where liberalization and de-regulation policies were put in place relatively recently compared to other countries [13]. Another factor relating to inequality and particularly relevant to emerging economies are demographic shifts or the increase in share of young population as a fraction of total population [38].

Changing inequality levels have in turn been linked to indicators of well-being. Perceived legitimacy of distributive outcomes and procedures are theorized to play an important role in affecting individual sense of well-being and affect societal cohesion [20]. While its effects range from health to crime to poverty, I am interested particularly in its effect on social cohesion. Inequality can play a major role in citizens losing trust in institutions, eroding social cohesion and general confidence. Previous research has shown that income inequality affects social trust in a variety of ways [5, 30, 37, 45]

My primary hypothesis is that increasing income inequality in emerging countries is connected to changing generalized trust levels. Specifically, income inequality or changing relative position in the income distribution is an important factor in determining trust levels. Following the results of related studies

of countries across OECD countries, I hypothesize that this relationship is mediated by changing life satisfaction and well-being rates. My study sample consists of emerging economies from across different continents for which most data (more than four waves) is available, which have experienced a recent increase in income inequality levels. These includes countries from the BRICS consortium along with other economies for which data is most available. Appendix 2 outlines the list of countries and number of observations across waves for which trust data is available for each. While the sample is arguably is heterogeneous in nature, the WVS data also has a long enough time frame for these countries in order for us to control for country effects. (A)

Most studies on income inequality and trust focus on the relationship in OECD countries. With this project, I want to fill this gap by studying this relationship (both individual and macro level) in the case of emerging economies. In the process, I want to explore the changing levels of trust and income inequality and the role of related factors like life satisfaction, freedom of choice and political participation.

Chapter 2

Literature Review

In this section, I briefly cover how trust is measured. I then outline evidence from across different countries and contexts, and focus on the case of emerging economies.

2.1 Measuring Trust

As a concept, trust can be broadly classified into three types: trust in strangers, or organizations/institutions or trust in a group of people. Research in social sciences generally focuses on the latter. Methods used to study trust in strangers include empirical survey research, behavioural or public goods ex-

periments, or field based measures.

Empirical research investigating the link between growth and trust usually draw from answers to survey questions which cover a large number of countries and begin from the 1980s. The expansion of World Values Survey and European Social Surveys across multiple countries provides an opportunity to study changing cultural and social factors. I use the generalized social trust (GSS measure), since it measures trust in strangers.

The GSS measure was first introduced in a study of civic culture in post-war Europe [4]. This question runs as follows: *"Generally speaking, would you say that most people can be trusted, or that you can't be too careful when dealing with others?"* Possible answers are either "Most people can be trusted" or "Need to be very careful." Related surveys like the European Values Survey, General Social Survey and the European Social Surveys also use the same question. Studies also consider a three-item index combining response to the trust question. Apart from the GSS question, they take into account responses to questions such as whether "most of the time people try to be helpful" and "most of the time people try to be fair." These three items together provide a strong measure of latent generalized trust. However, these indicators are not available across all countries or across all waves uniformly, and therefore not used frequently.

Nevertheless, there are debates about difficulties in interpretation of these measures. Besides ambiguities arising from the structure of the questions, it is unsure if the individuals who declare to have strong trust in others actually behave more cooperatively.

Another method of measuring trust is through public good games in laboratory settings. In general, these use variants of the 'trust game'. Broadly, two subjects A and B decide how much to give to each other in turns. Generally, one measures "trust in others" by the amount sent initially by subject A. Trustworthiness is measured by the amount sent back by subject B [11].

Given the inadequacies of the trust measure, studies often compare the results of the survey measure to lab experiments. A study using investment games in India in comparison to the trust survey question in WVS, finds that responses to the question hold with long term beliefs. However, this method may not be appropriate short term psychological perturbations. Other studies show that their experimental measures of trust are clearly correlated with questions on past trusting behaviour [1, ächter2004Trust]. Holm and Danielson (2005) find a positive correlation between behaviour in games and answers to the trust question in Sweden, but not in Tanzania [27]. While Fehr et al. (2002) find that the trust question does predict trusting behaviour but not trustworthiness, Ermish et al. (2009) find exactly the opposite results on a representative

sample of the British population [14, 17]. These results are, however, difficult to compare, as the designs of the games are not perfectly identical between the different experiments. A study on the SOEP trust questionnaire concludes that the trust measure is not correlated with "trust in institutions" or "trust in known others", but rather with trust in strangers [39].

2.2 Literature Review: Income Inequality and Trust

Studies across countries and regions point to a negative correlation between social capital, trust and income per-capita levels. While much of the earlier studies focus on cross-sectional relationship between income inequality and trust, the availability of data across time periods present an opportunity to study this relationship at a longitudinal level. Recent research uses causal inference methods like historical fixed effects or instrumental variables approach to infer if income inequality directly has an effect on trust. However, given that trust and perception of income inequality depends heavily on social, cultural and contextual factors, the results of these studies are prone to problems with external validity, and suffer from omitted variables bias.

On the one hand of the spectrum of studies are within country studies which

have low external validity but account for contextual or country specific effects because of the directed focus. In a cross sectional study of the localities within US, Alesina and Ferrera (2002) use individual level data drawn and find that recent history of traumatic experience, belonging to a historically discriminated race and being economically unsuccessful are more likely make an individual less trustworthy [2]. In a similar study but accounting for both individual and country level variables, Uslaner and Brown (2005) use the American National Election Study to show that trust is strongly affected by economic inequality. They show that this in turn also affects civic and communal participation [45]. Using data from a longer time period from the General Social Survey, Fairbrother and Martin (2011) show that declining social trust is related to income inequality, cross sectionally but not longitudinally, thereby indicating that claims for a causal relationship are unsubstantiated. They conclude that while inequality does seem to influence generalized social trust; the declining trust of recent decades certainly cannot be attributed to rising inequality [16]. In one of few within country studies outside of US, Gustavsson and Jordahl (2008) use individual panel data from Sweden to show that household inequality erodes trust especially when it is concentrated at the bottom of the distribution. Hence, they indicate that the concentration of incomes among top earners is a reason for erosion of trust [22]. These studies generally conclude that economic inequality, along with other factors, are correlated with

trust levels.

On the other hand are studies which look at a cross sectional relationship between inequality and trust but across a number of countries. This effectively accounts for the effects of major global events, like the 2008 financial crisis for example, but not country level factors. Bjornskov (2007) explores the determinants of generalized trust across countries to find that both income inequality and ethnic diversity reduces trust [**?**]. Fischer and Torgler (2006), study the relationship between the relative position of income on social capital using micro-data from the ISSP 1998 microdata across 25 countries and along four dimensions. They find both relative and absolute position of income to be a significant determinant of trust [18].

While these cross country studies find a negative relationship between income inequality and trust, they use data from the same point in time and hence are often biased. This could be due to the presence of omitted variables, reverse causality, or possible measurement errors. However, studies using a panel approach yield similar results. Gould and Hijzen use panel data for EU and US with a fixed effect regression, and find a significant effect between income inequality and trust [19]. Kyriacou, and Trivin (2018), in a study of 89 countries across time, argue that the positive effect of economic development on generalized trust is likely to be affected by income inequality [32]. Mikucka et al

(2017) study well-being in developing, transition and developed countries to explicitly distinguish cross-country differences over time. They use the World Values Surveys and European Values Surveys along with macro-level indicators of economic growth and income inequality. Their results indicate different effects for developed and other types of countries, and find significant effects in the former but not in transition and developing countries [35].

Recent studies use causal inference methodologies to point to a direct effect between inequality and trust. Of this, those studying the effect of historical and cultural factors tend to concentrate around a single country or region. In a comprehensive study using data from around 250 years in Italy, Tabellini (2010) uses an Instrumental Variable approach to show that regions with regions with higher illiteracy rates and worse political institutions are likelier to have lower generalized trust levels. Moreover, trust levels are in turn correlated with income differences [43]. Guiso et al (2008) also undertake a similar study in Italy. They instrument today's trust with past history of independence of certain cities and exploit the historical variation of independence of cities to show that cities that experienced independence earlier have higher social capital, which in turn is linked to higher income per capita. Using historical data to study trust has also been used in the countries which have recent experiences with immigration [21]. Uslaner (2014) shows that the descendants of immigrants to the US have a strong tendency to show the same level of trust

as the current inhabitants of the countries from which their ancestors came generations ago [45].

Using an instrumental variable (IV) is another way to examine this causal relationship. This becomes especially useful since there are a number of endogenous variables influencing trust and income inequality, and IVs offer a way to separate these and directly identify the relationship. Leigh (2006) use an IV - the relative size of mature cohorts - to measure the same relationships and using data from 59 countries, and find that a rise in inequality reduces trust [34]. Barone and Mocetti 2016 use data from the World Value Survey to study the relationship between income inequality and generalized trust using an indicator of exposure of ICT as an instrumental variable for OECD countries. They find this relationship to be higher than the OLS estimates, and also when using different measurements of inequality like top income shares [5]. In a meta study, Bergh and Bjornskov (2014) examine direction of causality in cross country studies on trust, social capital and inequality. Reviewing literature and using prisoners dilemma games, they find that income inequality has an effect on trust, but also that welfare states do not affect the final trust levels. Further they also find that trust has an effect on income distribution [7].

A range of studies have examined the role of possible mediators. Graafland (2011) conjecture that relationship of income inequality to trust depends on

how income inequality affects inequality of life satisfaction. They conduct a panel analysis across 25 OECD countries and show that panel analysis shows that income inequality increases life satisfaction inequality and that both income inequality and life satisfaction inequality have a significant negative impact on social trust [20]. In a similar study, Oishi (2011) examines the relationship with an indicator for happiness. Using General Social Survey data from 1972 to 2008, they find that Americans are on average happier in the years and lack of trust. Other studies have linked this with other political and civic indicators like community and political participation [37]. Uslaner (2014) argues that trust is not determined by the level of economic inequality but rather by the type of functioning government, re distributive policies, markets, and presence of corruption [45]. In a later study, Uslaner (2005) examines the relationship between income inequality, trust and community participation with American state level data between 19070s and 1990s. The findings indicate that inequality is the strongest determinant of trust and that trust has a greater effect on communal participation than on political participation [44].

Another strand of literature looks at the role of inequality perceptions. Hauser and Norton show that people on average misperceive current levels of inequality, typically underestimating the extent of inequality in their country and that this in turn drives their preferences for redistribution [25]. Knell and Stix's work extends from this. They posit that low (high) income individuals overesti-

mate (underestimate) their own position and that subjective estimates increase with own income position. Moreover, people from high and low income position have different perceptions of income inequality [31]. In line with these models, Reyes et al analyze perceptions of inequality for 17 countries to conclude that unfairness perceptions are more correlated with relative than absolute measures of income inequality and that individual characteristics influence this perception. [**?**]

In the case of emerging economies, results of similar studies have been more ambiguous. Barone and Mocetti (2018) conduct an initial study using macro level data from all countries from the World Values Surveys, including developing countries and find no relationship between trust and income inequality in developing countries [5]. Lee (2020) conduct a study on trust across Asian countries. They employ a multilevel analysis using Asia Barometer Survey's fourth wave. They find individual's perception of their economic well-being is a significant determinant of trust, and that macro-level income inequality functions as a moderator for the relationship between perceived income inequality and trust [33]. Chi and Kwon (2016) use their own survey data on trust in East Asian democracies to conclude that citizens' perceived salience of inequality has a trust-eroding effect [10]. Zmerli and Castillo (2015) analyze data from the Latino-barometer survey across 18 countries to conclude that of inequality are negatively associated with political trust but that higher levels of macro-

level inequality attenuate rather than increase the strength of the negative association between distributive fairness perceptions and political trust [46]. Hu (2015) uses age period cohort models to study effects of reform-era in China on generalized trust. The findings show a declining trend in generalized trust and there are significant differences in trusting behaviour across age groups and cohorts [28].

Chapter 3

Data

3.1 Data

In order to study trends in income inequality and trust, and analyse the relationship between the two, I use data from three different sources. My main outcome variable is generalized trust. Generalized trust is a widely used trust measure that seeks to understand the level of trust, and has been used in multiple studies as a survey measure of trust. Data on generalized trust measure and related indicators like life satisfaction, well-being and civic participation is available from the World Values Survey for different countries across five waves. However, a major limitation is the lack of absolute income data. For

this, I make use of Solt's Income Inequality Database which measures Gini coefficients for countries and while accounting for missing values. For the control variables, I use data from the World Bank Governance Indicators. I merge these with the start year of each WVS wave for each country with the respective observations in the other two data sets. I outline this in detail in this section.

My study sample consists of emerging economies from across different continents for which most data (more than four waves) is available, and which have experienced a recent increase in income inequality levels. These includes countries from the BRICS consortium along with other economies for which data is most available. Appendix 2 outlines the list of countries and number of observations across waves for which trust data is available for each. While the sample is arguably is heterogeneous in nature, the WVS data also has a long enough time frame for these countries in order for us to control for country effects. (A)

3.1.1 World Values Survey (Trust)

The World Value Survey (WVS) is conducted across multiple countries for every five year period (wave). Mainly, it seeks to measure behavioural attitudes, cultural cohesion and personal views. Repeated Cross Sections like the WVS

are also pseudo-panel datasets due to their longitudinal nature, but unlike actual longitudinal data where the same individuals are surveyed across multiple years, in RCS data different individuals are surveyed across multiple rounds. A characteristic of RCS data is that it has a large number of observations and a small waves/years unlike a typical longitudinal data, which has a lesser observations but across a larger number of years. In WVS, not all countries are repeated across waves, and while data from each wave is representative at the country level, it is conducted with the same sample.

My main outcome variable is generalized trust. Generalized trust is a widely used measure to identify the level of trust, and has been used in multiple studies as a survey measure of trust. Our measure of trust is constructed using the WVS, covering five waves from the 1980s to the mid-2000s. This is the response to the question - *"Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?"* Respondents who said *"most people can be trusted"* were coded as 1, while those who said, *"you need to be very careful in dealing with people"* were coded as 0. I also use related measures of "trust" from the WVS like life satisfaction, community participation and trust in institutions. While there have been concerns about the accuracy of the trust measures, there is general consensus that it is accurate long term measure of trust, and that it is correlated to experimental measures of trust. For the macro level analysis, I collapse this individual level

indicator to country level. Hence, the resultant observation is the share of individuals in each country-wave combination responding that they are more likely to trust others. This has been used in similar macro-level studies on trust.

3.1.2 Income Inequality

The main dependent variable I use is income inequality. There are three income inequality measures that I use:

- Gini Data from Solts Standardized Income Inequality database. This captures inequality at a macro-level. This is the ratio of mean absolute difference between all income pairs to twice the mean income. It captures inequality across the whole income distribution.

- Data on concentration of income of the top 1%, obtained from World Bank PovCal database. This captures inequality in the form of concentration of income at the very top of the distribution.

- Relative income level using self-rated Income levels from the WVS data. Respondents were asked to choose the scale of income they belonged to in out of ten categories in the WVS data. I subtract their actual income level from the median across each country-wave to get their position on the income scale. I use this as a measure of income inequality.

The Gini data from Solt's Standardized World Income Inequality Database (SWIID) incorporates data on inequality from across different data sources while using a custom missing-data algorithm to standardize. This maximizes the comparability for our set of countries, along with coverage across years. SWIID contains data on two Gini indices – disposable income (income after transfers and taxes) and market income (total income before transfer and taxes). We use the former in our analysis, though the trends between the two are quite similar in all the countries.

3.1.3 Control Variables

For the other control variables, I obtain data from World Bank Governance Indicators. These include log of GDP per capita and unemployment rates, mean education rates, age structure (ratio of total individuals over 65 years / Total individuals between 0 and 14 years), Town Size and Corruption ranking. GDP and unemployment levels signify the economic scenario, mean education rates and age structure are variables capturing the social and demographic structure. I include Town Size to capture the effect of groups. Like in similar studies, I expect that people with smaller town sizes are more likely to form informal social networks. However, these variables are highly correlated, so that economic interpretation of the expected signs should be taken with caution.

Appendix 1 outlines the key descriptive statistics. (A)

Chapter 4

Methods

In this section, I explain the methodologies that I use to study the relationship between inequality and trust. I explore three methods with panel datasets created from WVS, Solts Income Inequality Index and World Bank Governance Indicators. I first test if the relationship is valid at a macro-level after collapsing the trust variable into country level. I then use a multi-level or nested model to test if this is also the case with individual level microdata. Finally, in the third part, I employ age-cohort-period models to understand change in trust levels across demographics.

In order to derive a causal inference, my main source is fixed effects in a panel data structure. Income inequality has been found to affect trust through loss

of social capital and perception of comparatively worse life. Hence, I test if this relationship is valid using three possible mediators - life satisfaction, political participation and freedom of choice and control.

First, I test if there is a significant difference across years and countries in the data. To do this, I make use of a one way ANOVA. I use one-way analysis of variance to test the effect of gini on trust levels, and whether there is a significant difference in mean trust levels across countries and across waves. The results (Appendix 3) show that there is a considerable variation in trust across waves. (A)

4.1 Aggregate Fixed Effects

At a macro level, I use a fixed effects study with aggregated panel data at the country level on trust and income inequality. Since WVS is representative at a country level, this creates a panel dataset of country level indicators. With this, we introduce country fixed effects to capture any time-invariant unobserved factor at country level. The panel approach that we are using allows us to hold constant both stable country-to-country differences and changes in trust that equally affect all countries in the same year. The empirical specification is:

$$\text{trust}_{c,t} = \alpha + \beta \text{ineq}_{c,t} + \gamma \, \text{X}_{c,t} \; + \text{Y}_c + \text{P}_{t\$} + \mu_{c,t}$$

Where trust is the level of trust in a country c, at time t, inequality is the measure of income inequality in the same country at the same year, and X$_{\$}c, t\}$ include time varying controls and Y_c and P$_t$ are the fixed effects a the country and year level and $\mu_{c,t}$ is the error term.

Among control variables, I include log of GDP (as capturing economic growth and dimensions of well-being), Mean Education Rates, Unemployment Rates, Age Structure (total population above 64/age less than or equal to 14) and corruption ranking indicating the political climate. All the controls that I use are aggregated at a country level, making it suitable to use in a fixed effects model. Moreover, the small sample size limits the possibility of using many controls. Here the trust indicator for each country measures the percentage of respondents who responded affirmatively to the trust question. This method has been followed in other macro-economic studies on trust [5, 20] and has the advantage of better indicators on income inequality and country level indicators like exports, unemployment and demographic structure. Previous research on aggregation of individual indicators shows that temporal aggregation does not have any influence in a static setting (which is our case) but can be expected to affect dynamic panels, due to possible auto-correlation [40].

Since there are now seven waves of WVS data, there is a sufficiently deep longitudinal dimension to identify country specific trends in trust and inequality.

If subjects change little, or not at all, across time, a fixed effects model may not work very well or even at all. There needs to be within-subject variability in the variables if we are to use subjects as their own controls. This does not seem to be case with our data set. There is considerable variability in both income inequality and trust level across emerging economies. For example, our focus on these countries reflects the effect of globalization or technological change for example on possible income inequality.

There is significant loss of data in our case due to aggregation.The presence of time varying heterogeneity could bias the effects of the fixed effects model.This small sample limits the use of multiple predictors and the type of analysis that can be done [12].

4.2 Multilevel Models

Given that values and attitudes towards authorities are interlaced between individual and societal levels, the next step is to adopt analysis techniques that consider simultaneously variance across individuals and contexts. Multilevel regression is appropriate in this case because it allows combination of individual- and aggregate-level variables, thereby maximizing the use of the available information. We are able to test simultaneously the relationships

between trust and income and the cross-national equivalence of these relationships. This strategy also increases the number of observations, the degrees of freedom, and allows more accurate estimates [36].

The WVS data follows a nested structure, where individuals are situated within waves which are in turn situated within countries. Given this nested structure, Multilevel models presents a useful inferential method that take into account individuals and their contexts. This is the case with our survey since it is not conducted among same individuals in each wave. This also provides a means to quantify the extent to which countries matter for outcomes – the extent to which differences in outcomes reflect differences in the effects of country-specific features of demographic structure, labour markets and other socio-economic institutions such as tax-benefit systems that are distinct from the differences in outcomes associated with variations in the characteristics of the individuals themselves. The variance component model implies random effects, in that the variation in the intercepts is captured by the variance in the level 2 residuals. The model is repeated below with the assumption of normally distributed errors. Residuals can be correlated within levels but not across levels.

I choose the same subset of countries as in the linear fixed effects model. The dependent variable used in this study is the binary GSS variable from WVS, which takes the value of 1 if the respondents trust strangers often, and 0 oth-

erwise. The main independent variable is income inequality. In order to fit this on an individual level, I use the income scale from WVS. The scale asks the respondent to rate his/her income level across ten categories (different across countries). In order to find the relative position of the respondent, I find the median income level for each country-wave combination and subtract the actual income level of the respondent from the median. The resultant variable "relative income position" gives us an idea about the income position of respondent in that particular country during a particular period. The other controls that I use are log of GDP (as capturing economic growth and dimensions of well-being), Respondent Employment Status, Respondent Education Rate, Respondent Age, Corruption ranking (as capturing political scenario). Of this, only the log of GDP and corruption ranking are defined at an aggregate level, and the other controls are defined at an individual level.

The multilevel design differs from the earlier fixed effects model in important ways apart from differences in data. Firstly, the variation in the intercept and/or the regression coefficients (slopes) is captured by variance components that constitute the random parameters in the multilevel model. Secondly, it allows for explanatory variables both at country level and individual level to be entered into the analysis. In our analysis we use country fixed effects and relative income random effects, which would indicate that people with different income levels behave differently with regard to trust across the sample

countries.

As mentioned previously, I use a total sample of 20 countries, with total observations around 70,000 varying across countries and waves. I choose countries for which more than 4 waves are available to preserve longitudinal variance and capture time effects.

However, this is a significant limitation associated with multi-level analysis in repeated cross section data like the WVS. A small number of countries in most multi-country data sets constrains the ability of such models to provide robust conclusions about the effects of country-level characteristics on outcomes. However, studies show that there is no concrete evidence on the exact number of groups that are required to avoid these problems. Studies sometimes cite rules of thumb (recommending anywhere between 10 and 50 groups as a minimum). This is also dependent on application specific factors [8]. Stegmueller (2013) caution using classical maximum likelihood methods with fewer than 10 or 15 groups, especially when the model includes cross-level interactions and random coefficients, while Moinuddin et al. (2007) recommend using at least 50 groups. [42]

Acknowledging that it is often difficult to find data for a high number of countries, Stegmueller (2013) recommends a two-step method with country levels and individuals levels, along with strong descriptive statistics to identify if this

presents as a problem [42].

An often used modification to multilevel models involves the simultaneous but separate analysis of cross-sectional and longitudinal relationships. As outlined by Fairbrother (2014), these have to do with calculating mean, and subtracting the mean from time-varying variable of interest, in our case the income level, thereby group-mean centring the covariates [15]. I do this by creating a new variable that measures mean income scale across all respondents across waves for each country - this is the cross sectional variable. For longitudinal relationships, I subtract this mean income scale from the actual income scale of each respondents. However, unlike his analysis which uses Gini across waves at county level for the US, the nature of WVS data limits us to using scales of income rather than absolute values [16]

4.3 Age-Period-Cohort Models

In the final part of our analysis, I use the individual level data from WVS to do an age period cohort (APC) analysis. APC models are commonly used in social sciences literature to understand the tendency of a variable to change across demographics. By simultaneously modelling age, period and cohort effects, we can establish if there were cohort and/or period-based changes in trust, and

related indicators.

Age reveals a life-course pattern, and sheds light on whether people who are older and generally more likely to trust, in line with the results of multiple studies. Period effect focuses on the role of certain historical events to affect trust levels, for example, economic recession or war. Finally, cohort effect marks out the differential levels of generalized trust across birth cohorts, and could possibly highlight for example, if those born after deregulation reforms are more or less likely to have trusting tendencies.

APC models have widely been used with WVS data. Hu (2015) examines the transition of generalized trust in mainland China from 1990 to 2007 using data from the WVS [28]. The APC models suggest a declining trend in the level of generalized trust across different periods from 1990 to 2007, net of age and cohort effects. Hajdu and Sik analyse work values across age, periods and cohorts. They use data from the WVS and EVS, to suggest that that the relative importance of work is significantly higher in the middle-age groups than among the younger or older groups [24]. While not explicitly following an APC mode, Beja (2018) tests the U-shaped relationship between happiness and age using the cross classified multilevel regression procedure and the World Values Survey data while accounting for period and cohort effects [6]

The key problem with using APC models in Repeated Cross Section data like

the WVS is that it is often difficult to extricate age, period and cohort effects and that there is multicollinearity between the three. Thus, age period and cohort measures cannot be simultaneously included in a standard regression model due to this dependency. Using a standard regression model can lead to divergent or even conflicting estimates. One way to get around this is by using a hierarchical APC model with cross-classified random effect models (CCREMs) which have generally been used with Repeated Cross Sectional data. When CCREMs are applied to APC analysis, effects of age and other individual-level variables are set as fixed effects at level 1, whereas period and cohort effects are set as random effects at level 2.

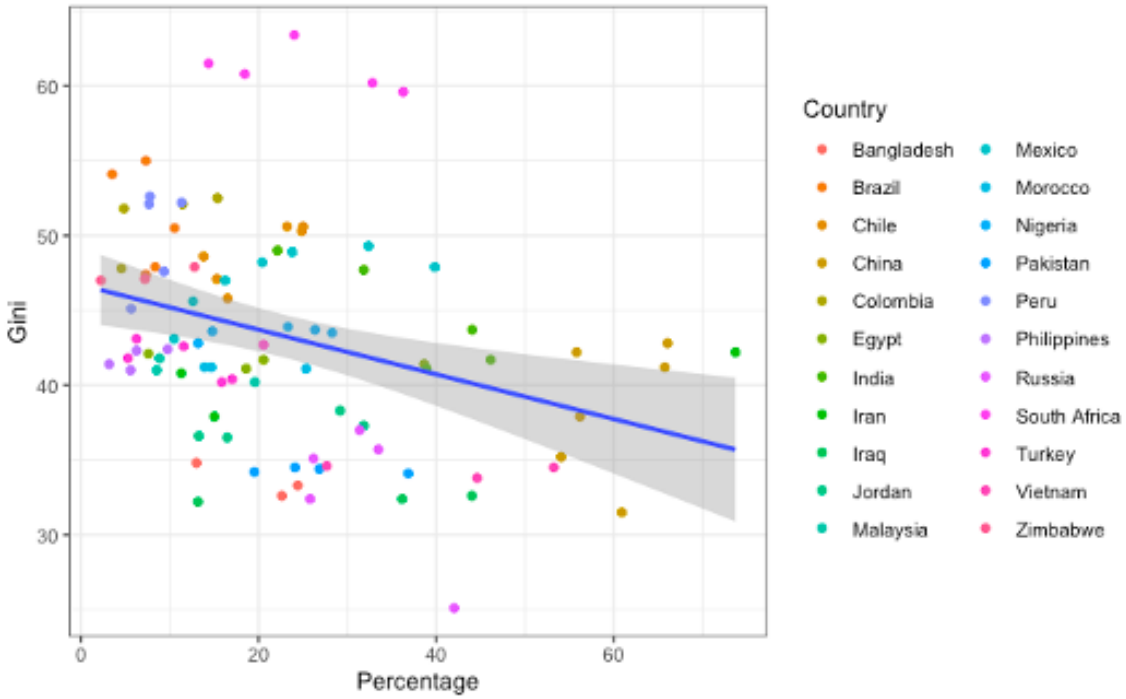
Chapter 5

Results

5.1 Cross Sectional Analysis

The figure below shows the relationship between the percentage of people who trust often and the Gini index, with each point representing a country-wave combination. A cross sectional analysis using all waves of countries indicates a moderate negative correlation between the two (r = -0.32). This is in line with our hypothesis. Moreover, dispersion between waves of the same country indicate the possibility of a longitudinal relationship. In order to explore this, I first use a fixed-effects panel regression.

Figure 5.1: Results of Cross Sectional Analysis



5.2 Fixed Effects Panel

The data for the fixed effects is collected from the World Values Survey, Solt's Income Inequality Database and the World Bank Governance Indicators. The percentage of trust levels in a country is represented as a logistic function of Gini displacement, and economic, social and political controls. They include data from 22 emerging economies which have more than 4 waves of data. Table 4.1 shows the results of our analysis.

Model 1 and Model 2 are OLS models that do not take into account heterogeneity across countries and years. While Model 1 regresses only income inequality

and trust, Model 2 includes a range of control variables. I pool the standard errors by countries, as followed in similar studies. Essentially, these results are similar to the cross sectional results we obtained above, and indicate that a one percent increase in Gini index leads to a 1.2 percent decrease in percentage of individuals who trust others often.

Models 3 through 6 are linear fixed effects models on panel data with within effects for country and waves. Model 3 is the baseline model, Model 4 includes Unemployment and GDP, Model 5 introduces the Age structure at the particular country-wave combination and Model 6 introduces Mean years of Education for each country wave.

Like in similar studies, I add the controls step-wise to show marginal effects on outcome. The results fail to find any relationship between trust and income inequality after accounting for fixed effects. This is in line with results from Barone et al (2016) and Graafland (2013), who do not observe a longitudinal relationship for developing countries but do for OECD countries. These studies take into account all countries, and hence have a more heterogeneous sample. In line with the results of similar studies, our results seem to indicate that trust seems to be correlated with the GDP level of a country [5, 20]. However, while these results do take into account some level of fixed effects, there is always the possibility of omitted variables and reverse causality between trust,

GDP and income inequality. Gini indicator using market income shows similar results.

Table 5.1: Fixed Effects Panel Regression

	Dependent variable:				
	Percentage				
	(1)	(2)	(3)	(4)	(5)
Gini Index	0.158	0.145	0.586	0.846	0.093
	(0.466)	(0.431)	(0.588)	(0.592)	(0.794)
Log of GDP		-4.664***	-4.093***	-6.919***	-6.120**
		(1.277)	(1.536)	(2.122)	(2.866)
Unemployment			-0.766	-0.711	-0.585
			(0.729)	(0.714)	(1.003)
Age				40.331*	17.151
				(21.363)	(31.096)
Mean Education					6.506
					(4.047)
Observations	96	96	85	85	66
R^2	0.002	0.158	0.160	0.208	0.154
Adjusted R^2	-0.299	-0.111	-0.176	-0.127	-0.409
F Statistic	0.115 (df = 1; 73)	6.740*** (df = 2; 72)	3.817** (df = 3; 60)	3.876*** (df = 4; 59)	1.425 (df = 5; 39)
Note:					*p<0.1; **p<0.05; ***p<0.01

5.2.1 Alternative Gini indicator : Top Income Shares

In Table 4.2, I repeat the analysis but for a different measure of inequality - top income indicators from the World Bank PovCal database. Top income share indicates the percentage of total income owned by top ten percent of the population. The sample size falls to 30 observations, due to nonavailability of data. The results are, however, similar.

Table 5.2: Fixed Effects Panel Regression: Top Income Shares

	Dependent variable:				
			perc		
	(1)	(2)	(3)	(4)	(5)
Top Income Share	0.847*	0.957*	1.636**	1.616*	0.542
	(0.486)	(0.519)	(0.714)	(0.762)	(1.269)
Unemployment		-1.273	-2.225	-2.194	-3.297
		(1.293)	(1.447)	(1.523)	(4.196)
Age			36.330	38.642	-8.463
			(26.948)	(35.311)	(105.502)
Log of GDP				-0.465	-2.040
				(4.378)	(9.092)
Mean Education					12.376
					(12.456)
Observations	35	33	33	33	24
R^2	0.132	0.184	0.267	0.267	0.271
Adjusted R^2	-0.476	-0.537	-0.466	-0.563	-1.794
F Statistic	3.037* (df = 1; 20)	1.912 (df = 2; 17)	1.942 (df = 3; 16)	1.369 (df = 4; 15)	0.447 (df = 5; 6)
Note:					*p<0.1; **p<0.05; ***p<0.01

5.3 Multilevel Models

In the second part of the analysis, I use a multi-level model with country level random intercepts. For this I use the unaggregated WVS data on trust. Multi-level models consider variance within both individuals and contexts (countries) thus taking into the account the nested structure of the data.

For the data on trust, I use the response to the GSS question – "Do you trust people often?". Hence, the outcome variable is binary in nature, where '1' is affirmative and '2' is not. For the income inequality variable, I use a relative income position variable, the difference between median income for each country-wave combination and the actual income level. I add controls from the WVS dataset on the individual education status, age and employment status apart from country level variables like log of GDP and export rates. The income variable in this section is not an actual inequality measure, as in the fixed effects model, but a relative measure based on country and year/wave.

Models 1 to 4 are multilevel generalized linear models with a logit function using maximum likelihood estimation. Model 1 (Baseline) is the direct relation between relative income position and trust with country level random intercepts. Model 2 includes the control variables. The AIC from Model 2 drops significantly denoting that controls do explain a significant portion of the vari-

ation. Model 3 includes wave fixed effects. Because there are only seven waves, I add time as a fixed effect (with time as a random effect the results are quite similar). Model 4 introduces the relative income position as also a random effect - this takes into account the fact that people with similar relative income positions across different countries behave differently. The results are presented in the Table 4.3 below.

The results indicate that relative income position is significantly associated with trust. An increase in relative income position leads to a 2.8 increase in probability of an individual trusting more. Other controls variables are significant as well, especially GDP and to a lesser extent, the demographic variables. Results also show that the wave fixed effects are significant, meaning that there are changes across time.

5.3.1 Separating Cross Sectional and Longitudinal Effects

Multilevel modelling in repeated cross sectional surveys (like in our case) has had many recent developments to account for small sample sizes and in order to distinguish better the difference between longitudinal and cross sectional variation. Fairbrother (2018) modifies the multilevel model in order to distinguish

Table 5.3: Multilevel Models

	Dependent variable:			
	f.trust			
	(1)	(2)	(3)	(4)
Relative Income	-0.027***	-0.016***	-0.017***	-0.028*
	(0.003)	(0.005)	(0.005)	(0.015)
Log of GDP		0.131***	-0.233***	-0.240***
		(0.017)	(0.043)	(0.043)
Unemployment		0.071***	0.075***	0.068***
		(0.009)	(0.009)	(0.009)
Age		-0.003***	-0.003***	-0.003***
		(0.001)	(0.001)	(0.001)
Education Levels		-0.014***	-0.017***	-0.015***
		(0.005)	(0.005)	(0.005)
Town Size		0.016***	0.027***	0.027***
		(0.005)	(0.005)	(0.005)
Wave			0.218***	0.227***
			(0.024)	(0.024)
Constant	1.477***	-2.272***	5.970***	6.167***
	(0.168)	(0.476)	(1.024)	(1.011)
Observations	154,781	66,109	66,109	66,109
Log Likelihood	-74,570.480	-31,622.810	-31,582.260	-31,510.220
Akaike Inf. Crit.	149,146.900	63,261.620	63,182.530	63,042.430
Bayesian Inf. Crit.	149,176.800	63,334.410	63,264.420	63,142.520
Note:				*p<0.1; **p<0.05; ***p<0.01

between cross sectional and longitudinal effects. He uses the similar method in his analysis of trust across counties in the US. Essentially, he converts the income inequality variable into a mean variable and a variable denoting longitudinal change.

I do the same in our case. I convert the income scale variable into two separate variables. In order to distinguish between possible causal mechanisms, I seek to identify separate longitudinal and cross-sectional associations between inequality and trust. To do so, I calculate the mean of all of a country's income scale levels for all waves, this overall average X captures the effect of enduring differences in country levels of inequality. To capture the effect of change in inequality over time, I subtract each overall average from each specific entry. Thus here, the cross sectional component is X, or the mean, while the longitudinal component is observation - X. According to Fairbrother (2018), they are thus orthogonal to each other by construction, and their effects can be estimated separately.

The results of the same are displayed in the table below. Here, I follow the same methods as followed in the earlier table. The results indicate that there is significant longitudinal variations relation between scale of income and trust. The final model containing random intercepts for countries and random effects for both types of income variation, indicating that individuals nested in the

same country are more likely to function in the same way than participants nested in different countries.

5.4 Age Period Cohort Models

In the final part of the analysis, I use an age-period-cohort model to understand if trust varies across Age, Periods or Cohorts. As in similar papers, I characterize Age as age of the respondent, Period as Wave years and cohort as the difference between the two. Since there is multicollinearity between the three, I use an extension of multilevel modelling called CCREMs, as outlined in the previous section, and treat age as level 1 effects and periods and cohorts as level 2.

Table 1 outlines the results of a multilevel model of the APC model where Age and other demographic factors are fixed effects and Period and Cohorts are random effects. Model 1 is the base logistic regression containing only age effects, Model 2 contains on period random effects, Model 3 only cohort random effects. Model 4 contains both period and cohort random effects and indicates that all individual values and cohort effects are significant. The models with period and cohort effects have a lower BIC which indicate that they are a better fit. The models indicate that Age is a significant factor in determining trust

Table 5.4: Separating Cross Sectional and Longitudinal Effects

	Dependent variable:			
	f.trust			
	(1)	(2)	(3)	(4)
Cross Sectional	-0.693**	-0.437	-0.524	-0.611**
	(0.339)	(0.420)	(0.385)	(0.300)
Longitudinal	-0.026***	-0.015***	-0.016***	-0.026*
	(0.003)	(0.005)	(0.005)	(0.014)
Log of GDP		0.132***	-0.233***	-0.221***
		(0.017)	(0.043)	(0.040)
Unemployment		0.064***	0.068***	0.083***
		(0.009)	(0.009)	(0.009)
Age		-0.003***	-0.003***	-0.003***
		(0.001)	(0.001)	(0.001)
Education Levels		-0.015***	-0.017***	-0.016***
		(0.005)	(0.005)	(0.005)
Town Size		0.016***	0.027***	0.028***
		(0.005)	(0.005)	(0.005)
Wave			0.219***	0.208***
			(0.024)	(0.023)
Constant	4.582***	-0.280	8.386***	8.268***
	(1.527)	(1.956)	(2.037)	(1.657)
Observations	154,781	66,109	66,109	66,109
Log Likelihood	-74,570.650	-31,623.100	-31,581.900	-31,535.390
Akaike Inf. Crit.	149,149.300	63,264.200	63,183.800	63,100.770
Bayesian Inf. Crit.	149,189.100	63,346.100	63,274.790	63,237.260
Note:				*p<0.1; **p<0.05; ***p<0.01

levels.

Table 5.5: Age-Period-Cohort Model

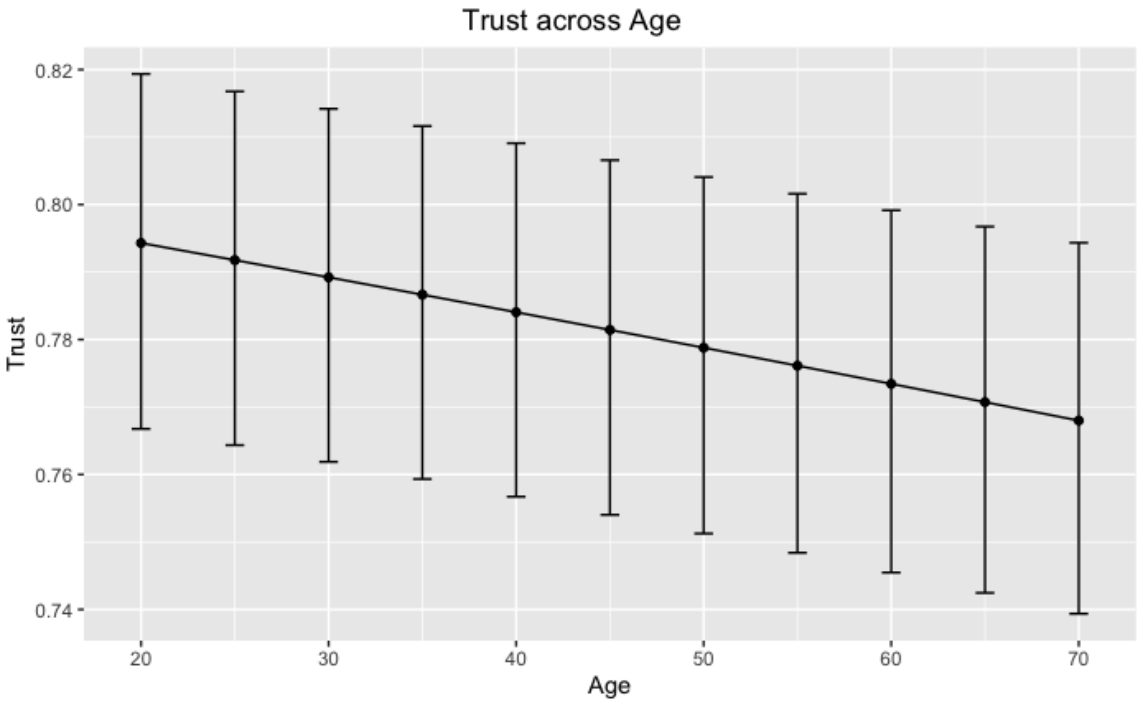
	Dependent variable:			
	Trust			
	Logistic		*Generalized Linear Mixed-Effects*	
	(1)	(2)	(3)	(4)
Age	-0.019***	-0.010	-0.032***	-0.031***
	(0.006)	(0.015)	(0.006)	(0.007)
Sex	0.098***	0.166***	0.091***	0.091***
	(0.014)	(0.033)	(0.014)	(0.014)
Education	-0.038***	-0.028***	-0.042***	-0.042***
	(0.003)	(0.008)	(0.003)	(0.003)
Married	0.027***	0.037***	0.024***	0.024***
	(0.004)	(0.009)	(0.004)	(0.004)
Constant	1.278***	0.897**	1.352***	1.344***
	(0.041)	(0.358)	(0.088)	(0.089)
Observations	118,879	20,982	118,879	118,879
Log Likelihood	-62,997.240	-11,062.400	-62,660.720	-62,654.620
Akaike Inf. Crit.	126,004.500	22,136.800	125,333.400	125,323.200
Bayesian Inf. Crit.		22,184.510	125,391.600	125,391.000
Note:				*p<0.1; **p<0.05; ***p<0.01

Specifically, it indicates that trust is negatively correlated with age, similar to the results of multiple other studies. Figure 1 is a graphical representation of this relationship.

However unlike similar studies, this study does not find a significant pattern

across periods or cohorts. A

Figure 5.2: Trust across Age



Chapter 6

Robustness

6.1 Alternate Indicator of Trust

Apart from the GSS question, I also consider an alternate indicator for trust. Generally, this has been a three-item index combining response to the trust question. Like other studies, I take into account the answers to questions "most of the time people try to be helpful" and whether "most of the time people try to be fair." Because of the unavailability of the former, I use the latter. Results of the macro-level model and the individual level micro-data (shown below) indicate similar results.

Table 6.1: Fixed Effects Panel Regression: Alternate Indicator

	Dependent variable:			
	f.freedom			
	(1)	(2)	(3)	(4)
Deviation from Median Income	0.189***	0.173***	0.173***	0.186***
	(0.007)	(0.014)	(0.014)	(0.038)
Log of GDP		0.517***	0.513***	0.442***
		(0.045)	(0.103)	(0.100)
Unemployment		-0.070***	-0.069***	-0.067***
		(0.019)	(0.020)	(0.019)
Age		-0.001	-0.001	-0.0004
		(0.002)	(0.002)	(0.002)
Education Levels		0.057***	0.057***	0.061***
		(0.013)	(0.013)	(0.013)
Town Size		0.015	0.015	0.011
		(0.012)	(0.012)	(0.012)
Wave			0.003	0.047
			(0.057)	(0.056)
Constant	3.357***	-9.365***	-9.257***	-7.651***
	(0.167)	(1.184)	(2.390)	(2.312)
Observations	129,859	55,267	55,267	55,267
Log Likelihood	-21,510.520	-6,822.523	-6,822.522	-6,794.088
Akaike Inf. Crit.	43,027.040	13,661.050	13,663.040	13,610.180
Bayesian Inf. Crit.	43,056.360	13,732.410	13,743.320	13,708.300
Note:				*p<0.1; **p<0.05; ***p<0.01

6.2 Mediation Analysis

Mediation is the process by which one variable transmits an effect onto another through one or more mediating variables. In their paper on mediation analysis, Baron and Kenny (1986, p.1176) defined a mediator as ”a given variable may be said to function as a mediator to the extent that it accounts for the relation between the predictor and the criterion. ” Mediation analysis with experimental data can be used to provide a causal inference. However, in our case, since WVS is a survey data, I use to study possible mechanisms that have been thought to play a role in the relationship between income and trust levels.

I examine three possible mechanisms: Life Satisfaction Levels, Community Participation, and freedom. I chose these because literature on trust and inequality often use these as possible mechanisms to understand the relationship between income inequality and trust.

Here, ACME stands for the average causal mediation effect which is the indirect effect of income inequality on trust that passes through life satisfaction. ADE or the Average Direct Effect is the direct effect of income inequality on trust. The total effect is the sum of both the direct and indirect effects. Similar

to the results of similar analysis, our results finds that all the indicators negatively mediate the effect of income inequality on trust. Of this, life satisfaction is most significant, mediating almost half of the total effect. The same is the case with political participation.

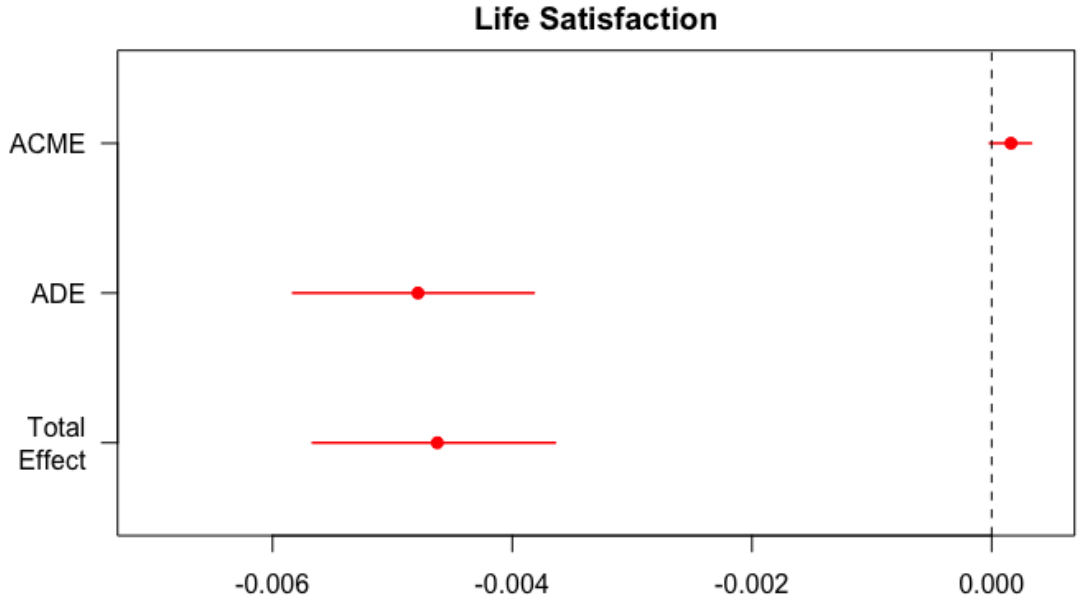


Figure 6.1: Life Satisfaction as a Mediator

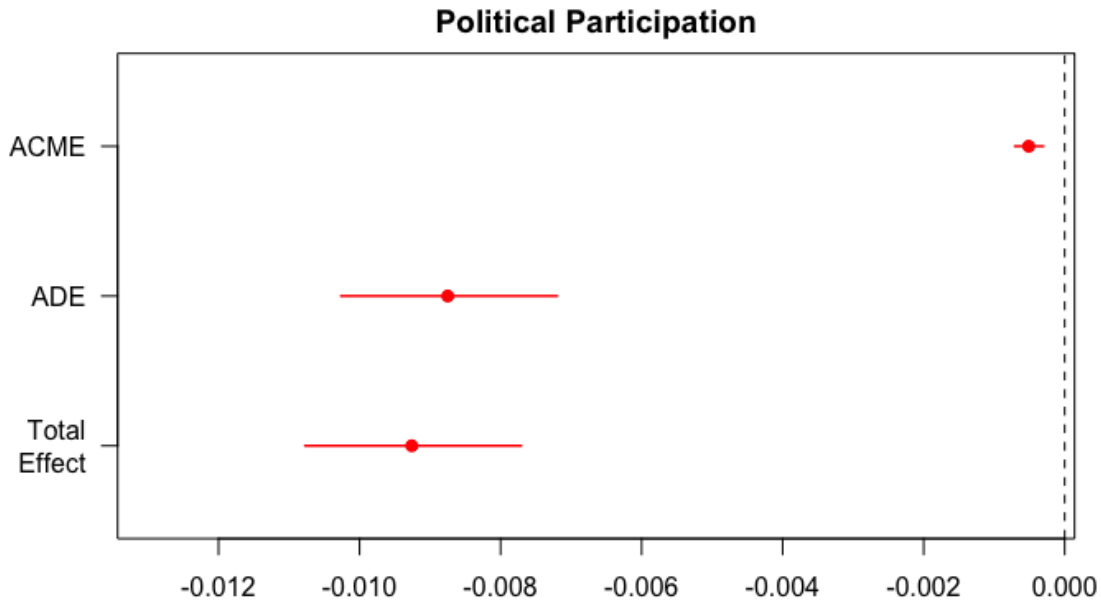


Figure 6.2: Political Participation as a Mediator

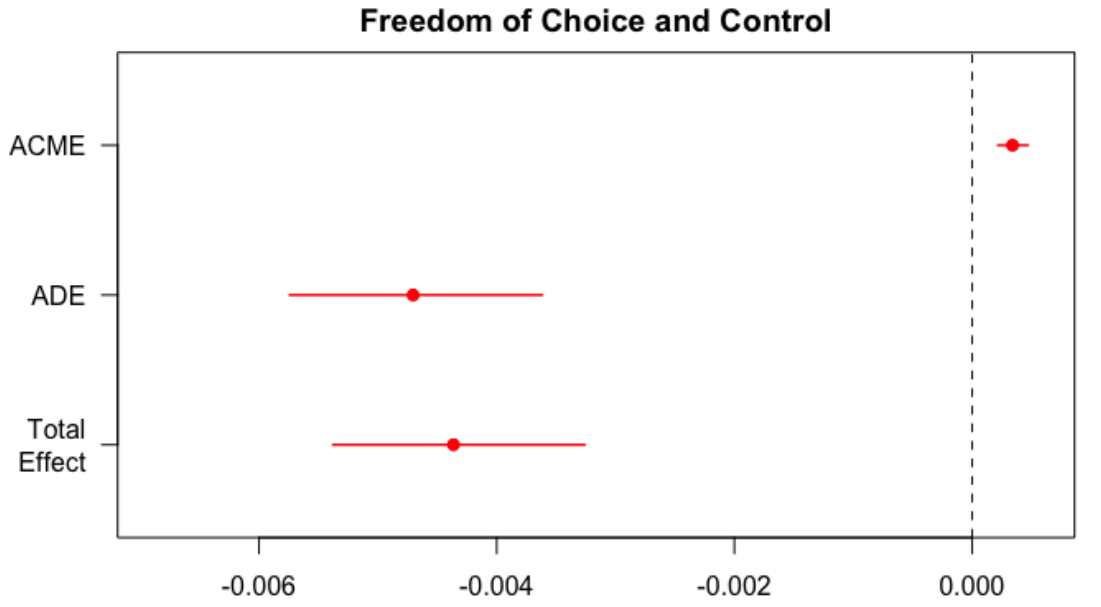


Figure 6.3: Freedom of Choice and Control as a Mediator

Chapter 7

Conclusions

This study is an attempt to understand the relationship between income inequality and trust levels in emerging economies. While similar studies have looked at the role of trust in OECD and American contexts, I use similar methods to study trends in key emerging economies. In order to do this, I adopt both a micro and macro approach, using aggregated and individual versions of the same dataset. The results from these methods show differing results, however. There is a high cross sectional variation in trust levels across countries, underscoring the importance of social, cultural and historical factors in determining trust. Even after accounting for this, and given the limited data, some countries, like China, India, Mexico for example, have witnessed a wide variation in their general trust levels over the last twenty years. This is also

accompanied by changing rates of income inequality. However, with the limitations of our dataset and with the general nonavailability of aggregated data for our country sample, it is difficult to infer a causal relationship between the two. While using a fixed effects panel dataset controls some variables, it does not preclude the possibility of reverse causality between the two.

The difference in the results between fixed effects and multi-level models show that while income inequality and trust do not seem to be related at a macro level, the idea still holds at an individual level. The relative income position of the respondent is correlated with the possibility of trusting meaning that an individual who earns less than the median is less likely to trust others. This is broadly in line with the results of similar micro level studies. At an individual level, trust is significantly related to the income position of the respondent. The analysis also finds GDP and unemployment rates (state of the economy) to be significant factor as well. This follows from the results of multiple micro-level studies that find social trust only to be significant at an individual level and not at macro level. Moreover, trust is also affected by related factors to income inequality, like unemployment levels or the state of the economy.

In order to explore the last point further, I use a mediation analysis of factors that have been thought to play an important role in this relationship. I use life satisfaction levels, political participation (voting at the local or national

elections), and freedom to exercise own choice and control as mediating mechanisms. I find that all these three factors have an significant opposite effect on the relationship between income inequality and trust. Specifically, life satisfaction is significantly associated with trust levels.

Finally, in order to understand how trust changes across demographics, I also use an Age-Period-Cohort analysis. This shows changing trust levels across ages, periods (survey waves) and cohorts (difference between age and period). Our results show that as people grow older they are significantly less likely to trust others. However, unlike the results of similar studies, our study fails to find a relationship across periods and cohorts. A next step would be to examine this relationship separately for each of the countries for which all waves of survey data are available.

A major limitation of this study is its inability to infer a causal relationship between income inequality and trust. My main source of identifying a causal relationship is using fixed effects panel data set. Other causal inference methods, like Instrumental Variables, or Regression Discontinuity, which have been used in similar studies, are less applicable to this study due to the lack of appropriate data. Another limitation is the heterogeneous sample in our study.

However, even with these limitations, this study offers some important results on trust levels in emerging economies. First, while there is no macro level rela-

tionship between trust and Gini levels, there is an individual level relationship between the relative income position of the respondent and their trust levels. These results are similar for alternate indicators of both trust and income inequality. Second, factors like life satisfaction, political participation and freedom of choice have a mediating effect on trust. Third, the model finds a strong relationship between age and trust level, and indicates that older people are less likely to trust others often. However, unlike similar studies, it fails to find a relationship between trust levels and periods and cohorts.

Appendix A

Appendix

Figure A.1: Trust and Income Inequality across Sample

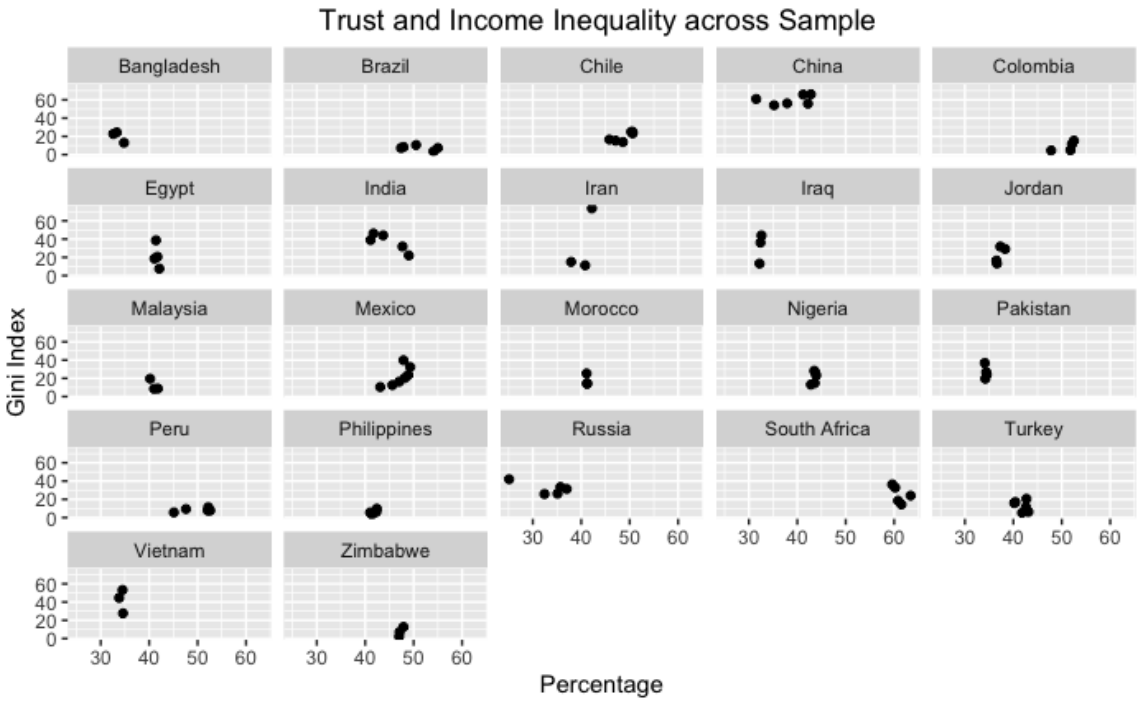


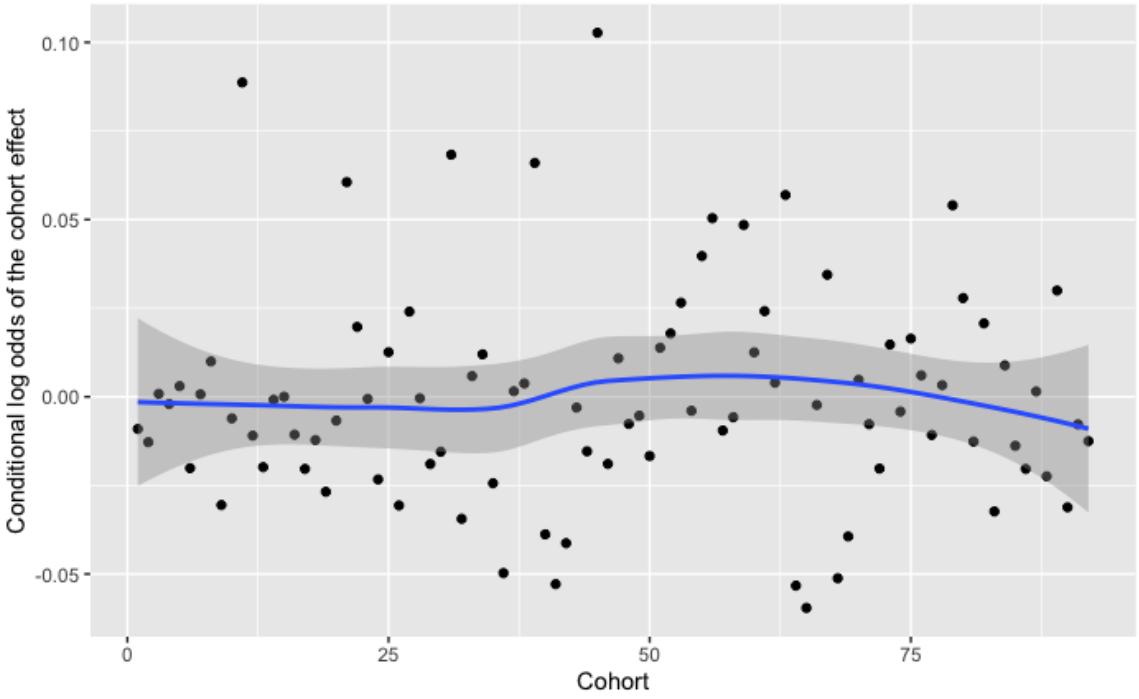
Table A.1: Descriptive Analysis

	Total (N=97)
Gini (Disposable)	
Mean (SD)	43.3 (7.42)
Median [Min, Max]	42.4 [25.1, 63.4]
Missing	1.00 (1.0%)
Age (years)	
Mean (SD)	0.203 (0.164)
Median [Min, Max]	0.151 [0.0622, 0.911]
Log of GDP	
Mean (SD)	26.0 (1.39)
Median [Min, Max]	26.1 [22.6, 30.1]
Missing	1.00 (1.0%)
Exports	
Mean (SD)	28.0 (18.6)
Median [Min, Max]	24.9 [7.02, 113]
Unemployment	
Mean (SD)	7.56 (5.40)
Median [Min, Max]	5.94 [0.621, 30.3]
Missing	11.0 (11.3%)
Percentage	
Mean (SD)	23.2 (16.1)
Median [Min, Max]	19.5 [2.22, 73.7]

Table A.2: Data Sample

	Waves						
	1	**2**	**3**	**4**	**5**	**6**	**7**
Argentina	1005	1002	1079	1280	1002	1030	1003
Bangladesh	0	0	1525	1500	0	0	1200
Brazil	0	1782	1143	0	1500	1486	1762
Chile	0	1500	1000	1200	1000	1000	1000
China	0	1000	1500	1000	1991	2300	3036
Columbia	0	0	6025	0	3025	1512	1520
Egypt	0	0	0	3000	3051	1523	1200
India	0	2500	2040	2002	2001	4078	0
Iran	0	0	0	2532	2667	0	1499
Iraq	0	0	0	2325	2701	1200	1200
Jordan	0	0	0	1223	1200	1200	1203
Korea	970	1251	1249	1200	1200	1200	1245
Morocco	0	0	0	1251	1200	1200	0
Mexico	1837	1531	1510	1535	1560	2000	1739
Malaysia	0	0	0	0	1201	1300	1313
Nigeria	0	1001	1996	2022	0	1759	1237
Pakistan	0	0	733	2000	0	1200	1995
Peru	0	0	1211	1501	1500	1210	1400
Philippines	0	0	1200	1200	0	1200	1200
Russia	0	1961	2040	0	2033	2500	1810
Turkey	0	1030	1907	3401	1346	1605	2415
Taiwan	0	0	780	0	1227	1238	1223
Vietnam	0	0	0	1000	1495	0	1200
South Africa	1596	2736	2935	3000	2988	3531	0
Zimbabwe	0	0	0	1002	0	1500	1215

Figure A.2: Trust across Cohorts



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