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Inequality in Good and Bad Times: A Cross-Country Approach

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Abstract

This paper provides evidence of a strong relationship between the short-term dynamics of growth and inequality in developing economies. We find that reductions in inequality during growth upswings are largely reversed during growth slowdowns. Using a new methodology (mediation analysis), we identify unemployment, and youth unemployment especially, as the main channel through which fluctuations in growth affect future dynamics in inequality. These findings suggest that both the quality of jobs created and labor market policies are important to ensure that growth outcomes are conducive to inequality reduction.

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I. INTRODUCTION

Over the last three decades, real GDP per capita nearly tripled in developing economies, while inequality as measured by the Gini coefficient fell by about 20 percent. Could we expect future growth upswings to offer an ultimate remedy to inequality in the developing world? If growth downturns largely undo reductions in inequality earned during upswings, then volatility would pose a risk to reduced inequality and, as several studies have shown, to future growth itself.[2] Understanding the link between short-term fluctuations in growth and inequality is important to help identify targeted policies to mitigate any adverse impact of these fluctuations.

The relationship between inequality and economic growth has generally been studied as a long-term relationship (Barro, 2000; Berg and Ostry, 2017), implying that we still know very little as to how policies could affect both inequality and growth in the short-term. Our paper contributes to the literature on growth and inequality by providing evidence of a relationship between short-term fluctuations in growth and inequality for developing countries, using a novel methodology.

We investigate two main issues: (i) does inequality worsen during growth slowdowns and/or improve during growth upswings; (ii) what are the main channels through which short-term growth and inequality dynamics are intertwined? To answer these questions, we use data on inequality over the period 1981-2014 from the World Bank's PovcalNet database. Our main measure for inequality is the Gini index, but we also analyze the income (consumption) share of the bottom 50 percent and of the top 10 percent of households, respectively. Variations in growth are captured using a polytomous variable that takes on different values, depending on the size of the deviation between a country's growth rate in any given year and its mean growth rate.

[2] Berg, Ostry and Zettelmeyer (2012), for example, show that countries with lower inequality experience longer periods of sustained growth, while Dabla-Norris and others (2015) find that lower inequality is associated with higher growth rates.

To examine these issues empirically, we apply mediation analysis techniques, commonly used in other disciplines such as epidemiology, sociology and psychology (McKinnon, 2008). Mediation analysis is fairly novel in macroeconomics studies but is relevant as it enables us to assess in a rigorous manner through what mechanisms good and bad times affect inequality. Importantly, relative to traditional instrumental variables estimation, it allows us to quantify the relative importance of potential transmission channels and to highlight areas where policy interventions may be needed.

First, we investigate whether there exists a systematic relationship between growth upswings and downturns and inequality in the subsequent year. Results from panel regression suggest that for developing economies, growth upswings tend to be associated with lower inequality, while growth downturns tend to be associated with higher inequality. Reductions in inequality during upswings are largely undone by slowdowns. This relationship between growth fluctuations and inequality is robust to measures of inequality (Gini coefficients, or shares of income/consumption of the bottom 50 percent and top 10 percent of households, respectively).

Further analysis into potential causal mechanisms show that unemployment, especially among young people, is a key transmission channel from growth to inequality. Specifically, in our sample of developing countries, during periods of positive growth (good times), 41.3 percent of the effect of growth fluctuations on inequality occurs through the unemployment channel. However, during periods of negative growth (bad times), only 28.4 percent of the effects of growth fluctuations on inequality is transmitted through the unemployment channel. The bulk of these effects comes from youth unemployment. These findings suggest that the quality of jobs created and labor market policies, including those targeted to younger workers, are important to ensure that growth outcomes translate into reductions in inequality.

The rest of this paper is organized as follows. Section II reviews the literature linking inequality to economic growth. Section III discusses the data used for the analysis and documents some stylized facts. The empirical strategy is presented in section IV and results are discussed in section V. Concluding remarks are provided in section VI.

II. Related Literature

Early studies of the relationship between inequality and growth have focused on the long-term interaction between inequality and economic growth. Broadly, these studies can be categorized into two groups (i) how growth affects inequality and (ii) how inequality affects growth. Given that these have been studied for various country groups, over different time periods and employing varying measures of inequality, the inequality-growth literature remains inconclusive with mixed evidence.

The building block of the first strand is the Kuznets curve, which states that as an economy grows, inequality first increases and then decreases. Some early studies support this inverse-U-shaped pattern, though they disagree on the timing (Williamson and Lindert, 1980; Goldin and Katz, 1999). However, the Kuznets curve hypothesis is more often disproved than not with more recent data (Barro, 2000; Piketty, 2015). Acemoglu and Robinson (2002) illustrate this for the "East Asian Miracle" while studying the relationship between development and inequality.

The second strand of literature focuses on the impact of inequality on growth, first in the long-run and then in the medium term. Papers that study the long-term trends argue that countries with more equal income distributions grow faster (e.g. Alesina and Rodrik, 1994; Berg and Ostry, 2017). To document the dynamics between inequality and growth, a number of studies use panel data to examine how changes in equality affect growth in the following years, i.e. in the medium-run (Forbes, 2000; Banerjee and Duflo, 2003). Results point to a negative impact of inequality on growth. Dabla-Norris et al. (2015) document evidence on the importance of inequality for growth in emerging and developing countries by focusing on changes in the share of the poor and the middle classes of the income distribution.

More recently there has been increasing interest on the impact of crises and growth fluctuations over shorter horizons (e.g. at business cycle frequencies) on inequality and vice versa. One driver of this growing interest in shorter term interactions between inequality and growth has been the increasing impact of economic crises on inequality (and vice versa), especially heightened during the recent Great Recession. As the transmission channels strengthened over time, we have started to observe a more visible effect on inequality and the probability of crises. This two-way relationship implies that higher inequality leads to a higher probability of economic crisis, and that economic fluctuations (i.e. crises) have adverse effects on inequality. Heathcote, Perri and Violante (2010a and 2010b) and Stiglitz (2012) have identified three main transmission channels spearheading this shorter-term phenomenon, namely labor markets, financial markets, and fiscal policy. The labor market channel works through changes in unemployment directly affecting income, while the financial channel has a stronger impact through wealth. The fiscal channel is shown to be effective especially through automatic stabilizers and countercyclical fiscal policy.

Reflecting data constraints, the focus of this more recent literature is almost exclusively on advanced economies, the US in particular (e.g. Krueger, Pistaferri and Violante (2010), Parker and Vissing-Jorgensen (2009), Heathcote, Perri and Violante (2010b)). The first paper finds, for 9 countries, that consumption inequality tends to increase much less than earnings and income inequality during recessions. The latter two papers find that the Great Recession has initially reduced inequality due to the pronounced reduction of the top 10 percent with higher sensitivity to aggregate fluctuations. Similarly, Atkinson and Morelli (2011) look at the behavior of inequality around consumption disasters (large drops in consumption) for 25 countries, including 6 developing countries. They find that financial crises are followed by an increase in inequality, but consumption/GDP collapses have no such effects.

The study by Calderón and Levy-Yeyati (2009), which analyzes a broad sample of developing countries, is an important exception and is also most closely related to our work. The authors investigate the effects of aggregate volatility on income distribution at five-year intervals over the period 1970-2005 for 75 developing countries. They focus on the effects of cyclical variability of output and of extreme output events on unemployment, poverty and inequality. Their findings suggest the existence of a robust regressive, asymmetric and non-linear relationship which is mitigated, to some extent, by personal wealth, public expenditure and labor protection.

III. WHAT DOES THE DATA SAY?

A. DATA

In our analysis, we use several data series. The main series include a measure of inequality and a measure of fluctuations in real GDP growth. As additional explanatory variables, we employ proxies for the fiscal stance, unemployment, financial wealth/assets and inflation. Finally, we use a number of control variables based on earlier literature, including GDP per capita (to capture the level of development) and demographic variables such as the population size and age structure.[3] Appendix I provides details on the variables used.

To measure inequality, we use the World Bank's PovcalNet database.[4] This database is primarily used to generate global estimates of "dollar-a-day" poverty (Chen and Ravallion, 2010), but it also reports inequality data for 111 advanced and developing countries based on microdata from household surveys.[5]

The broad country coverage of the PovcalNet database comes at the cost of slightly lower comparability. The estimates of inequality for developing countries in PovcalNet are based on household consumption data, with the notable exception of countries in Latin America and the Caribbean and in Europe for which inequality measures are based on household income. In a few of these latter cases, due to methodological changes, the measure switches from consumption to income or vice-versa (Appendices II and III). Moreover, the database does not specify whether, in the case of income-based inequality, income is before or after taxes and transfers (Ferreira, Lustig and Teles, 2015).[6]

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[3] See, for example, Calderón and Levy-Yeyati (2009); Ostry, Berg and Tsangarides (2014) for a detailed discussion of control variables.

[4] We choose to use PovcalNet over SWIID database, since SWIID contains imputed data points for missing observations, which might distort our results.

[5] This figure is based on the July 2017 vintage of the database. Data from rural household surveys were also reported for China, India, Indonesia and Uruguay.

[6] Consequently, we are not able to run our analysis separately for market Ginis to study the role played by taxes and transfers. The redistributive role of taxes and transfers is discussed in the October 2017 Fiscal Monitor.

To the extent that markets are for the most part incomplete in these economies, we expect a positive and strong link between consumption and income inequality, as shown by Alvaredo and Gasparini (2015). Nevertheless, to deal with breaks and heterogeneity, we control for these difference across and within countries in our empirical analysis through the inclusion of dummy variables and/or country fixed effects as appropriate.

Restricting our sample to include only developing countries with at least 5 rounds of household surveys during the period 1980-2014, we end up with an unbalanced panel of 71 countries. Within this category, we identify a sub-sample of 28 Emerging Market Economies (EMEs), broadly using the definitions in the IMF's Fiscal Monitor and Global Financial Stability Report (Appendix IV).

Table 1 provides a summary of the inequality data, including a breakdown by sub-region and by type of source data (household consumption or income).

Table 1. Summary Statistics for the Gini Index: 1981-2014

		Observations	Mean	S.D	Min	Max
Advanced Economies		288	31.6	4.3	19.4	42.8
Developing Countries						
All		879	41.6	10.2	16.2	64.8
By Region						
East Asia & Pacific	EAP	104	37.8	6.1	17.8	49.2
Europe and Central Asia	ECA	292	32.0	5.5	16.2	53.7
Latin America and Caribbean	LAC	333	51.6	5.1	34.4	63.3
Middle East and Northern Africa	MENA	37	39.9	3.0	34.0	47.4
South Asia	SOA	32	33.3	3.8	25.9	41.0
Sub-Saharan Africa	SSA	81	44.1	7.7	28.9	64.8
By measure of Inequality						
Income	I	378	48.8	9.2	17.8	63.3
Consumption	C	501	36.2	7.1	16.2	64.8

Source: Authors' calculations using the World Bank's PovcalNet database.
The summary statistics are reported for all countries in the PovcalNet database as of July, 2017. Sub-national (rural) observations for China, India, Indonesia and Uruguay are excluded as are countries with less than 5 rounds of survey results.

The explanatory and control variables are obtained from standard macroeconomic databases such as the IMF's *World Economic Outlook* (WEO) and the World Bank's *World Development Indicators* (WDI).

B. Stylized Facts

In this section, we document a few stylized facts on inequality in good and bad times for the developing countries in our sample.

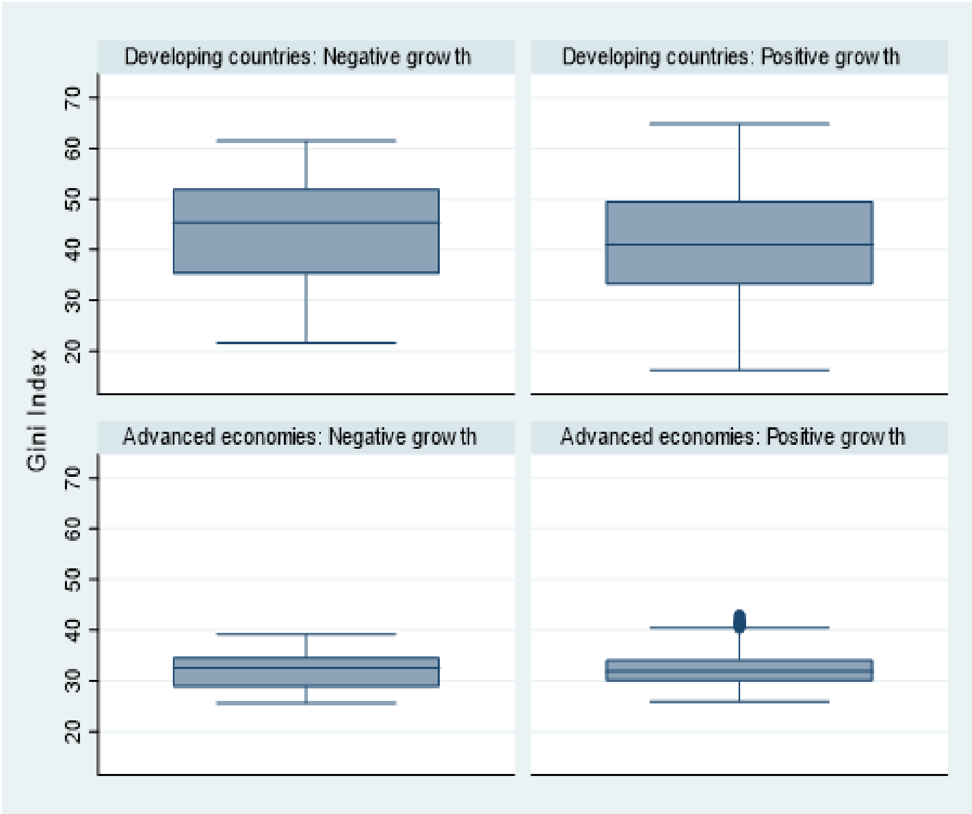
- The average Gini coefficient declined by about 20 percent in our sample of developing countries over the period 1981-2014.

- In about 30 percent of these country cases, the change in the Gini index from one comparable survey to another exceeded ± 2 points.[7] Large declines were more prevalent than large increases and, on average, there is much more dispersion or volatility in the within-country Gini index in developing countries than in advanced economies. The standard deviation of the Gini coefficient in the developing countries' sample is about twice that of advanced economies.

- A preliminary comparison of average Gini coefficients across growth conditions (positive or negative growth) using box and whisker plots suggests that inequality may be more sensitive to growth conditions in developing countries than in advanced economies in our sample (Figure 1).

[7] The threshold of 2 points is similar to that used in the October 2017 Fiscal Monitor and is based on the idea of salience or economically significant changes as discussed in Atkinson (2015).

Figure 1. Box Plots of Inequality



Source: Authors' calculations based on the World Bank's PovcalNet and World Economic Outlook databases.

IV. Empirical Strategy

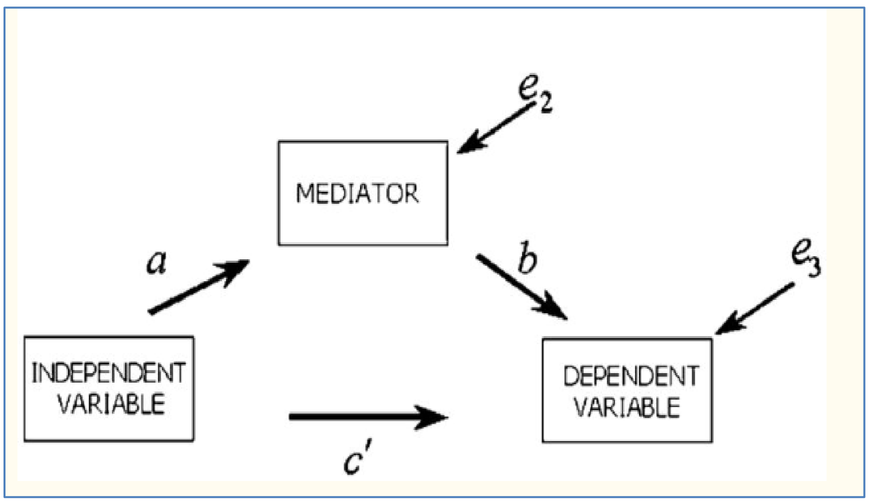
A. Methodology: Causal Mediation Analysis

We design our empirical analysis around two main questions: (i) is there a statistically meaningful relationship between growth fluctuations and inequality? (ii) through which economic and policy channels do growth fluctuations affect inequality? To this end, we utilize causal mediation analysis, which is a relatively novel approach in economics.

Traditionally, the instrumental variables (IV) approach has been used in economics and other fields to identify causal effects when an explanatory or treatment variable is suspected to be endogenous. The instrument is assumed to be correlated with the explanatory variable but not the outcome variable (the exclusion restriction). The existence of any causal mechanisms other than the hypothesized one is ruled out by assuming the direct effect of the treatment to be zero (Imai, Keele, Tingley and Yamamoto, 2011). Causal mediation analysis overcomes this limitation.

By using mediation analysis, we are able to relax the exclusion restriction as it allows for both an indirect (mediated) and a direct effect, as well as for the possibility of multiple mediated effects for the same treatment variable. As a result, we can identify and quantify the main causal mechanisms through which growth conditions affect inequality. This methodology is borrowed from the field of psychology where it is widely used by researchers to decompose observed associations into components that uncover causal mechanisms. For example, Conger et al. (1990) use mediation analysis to investigate whether parental unemployment has negative effects on children's behavior through its effect on the quality of parenting. However, the use of this methodology in economics is relatively more recent (see Dippel, Gold and Heblich, 2015; Huber, 2016). Figure 2 illustrates the basic framework.

Figure 2: Illustration of Mediation Analysis[8]



[8] MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S.,2007.

The widely used causal steps approach (Baron and Kenny, 1986; Kenny et al., 1998) is based on a linear structural equations model as follows:

$$\boldsymbol{Y = i_1 + cX + e_1} \qquad (1)$$
$$\boldsymbol{Y = \ i_2 + c'X \ + bM + e_2} \qquad (2)$$
$$\boldsymbol{M = i_3 + aX + e_3} \qquad (3)$$

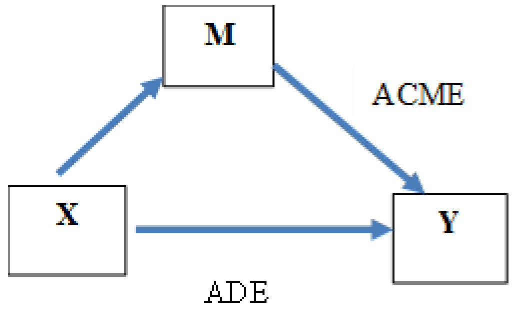
where Y is the dependent variable. M is the mediator and X is the independent variable with residuals denoted as e_1, e_2, e_3.

The four steps under this approach are as follows:

1. Establishing a significant relation of the independent variable (X) to the dependent variable (Y) (Eq.1).
2. Documenting a significant relation of the independent variable (X) to the hypothesized mediating variable (M) (Eq.3).
3. Showing that the mediator is significantly related to the dependent variable when both the independent variable and mediator are predictors of the dependent variable (Eq.2).
4. Verifying that the absolute value of the coefficient ***c*** in Eq 1 is larger than ***c'*** in Eq.2. This step allows to assess whether the relationship between the independent variable and dependent variable has been significantly reduced after inclusion of the mediator.

Mediation models report a breakdown of the total effect of a treatment (or intervention) into its direct and indirect components. These are namely the ***average causal mediation effects*** (ACME), which transits through a mediator variable, M, and the ***average direct effects*** (ADE), which combine the remaining effects (i.e. the unmediated effects). In other words, the ADE includes effects transmitted through all other channels. These results help assess the strength of the mediator (Figure 3).

Figure 3: ACME and ADE in Mediation Analysis



In our analysis, we follow the mediation approach suggested by Imai, Keele and Yamamoto (2010) (*IKY*, *henceforth*), which assumes 'sequential ignorability'. Sequential ignorability implies non-existence of an omitted covariate which can affect: (i) the variable of interest and the dependent variable; and/or (ii) the dependent variable and the mediator. If sequential ignorability is a valid assumption and the system is linear, the IKY methodology is numerically equivalent to the traditional linear structural equations model approach described previously.[9]

One important advantage of the IKY framework, however, is its transparency regarding the underlying identifying assumption of sequential ignorability. Given that this condition cannot be tested with observed data, IKY proposes a correlation parameter (ρ) reflecting the existence of omitted variables that are related to the mediator and outcome even after conditioning on treatment, and the parameter is incorporated into the calculations of ACME.[10] Specifically, ρ is the correlation between the error term for the mediation equation

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[9] Notably, it produces unbiased estimates of the ACME.

[10] Formally, the sequential ignorability conditions are expressed as:

$$\{Y_{it}(t',m), M_{it}(t)\} \perp\!\!\!\perp T_{it} | X_{it} = x$$

$$Y_{it}(t',m) \perp\!\!\!\perp M_{it}(t) |\, T_{it} = t, X_{it} = x$$

The first equation implies that treatment status is ignorable, conditional on covariates, i.e., there are no unobserved confounding variables that change with growth conditions which affect the mediator (M_{it}) and inequality outcomes (Y_{it}). The second equation shows that the mediator (M_{it}) is ignorable, conditional on treatment status and covariates. Specifically, this condition requires that no unobserved variables affect both the considered inequality outcomes (Y_{it}) and the mediator (M_{it}), after conditioning on observable variables that affect both Y_{it} and M_{it}.

in Eq.3, e_3, and the error term for the outcome equation in Eq.2,e_2. If sequential ignorability holds, ρ equals zero. Hence, non-null values of ρ suggest that unobserved factors confound the ACME estimate. Although the true value of ρ is unknown, it is possible to calculate values of ρ for which the confidence interval of the ACME contains 0. Thus, the IKY procedure allows for a sensitivity analysis to infer how strongly the sequential ignorability assumption would have to be violated to reverse the analytical conclusion about the estimated ACME.

B. EMPIRICAL ANALYSIS: IMPLEMENTATION

We start by testing for the first question and estimate panel regressions to identify correlations between growth conditions/fluctuations (good or bad times) and inequality, conditioning on several control variables. For this purpose, we construct a polytomous variable to measure good and bad times, as our main explanatory variable: $\boldsymbol{GC_{it}}$. Specifically, we run the following regression with the lagged growth conditions ($\boldsymbol{GC_{it-1}}$) and control variables identified in the literature.[11]

$$Y_{it} = \alpha + \boldsymbol{\beta GC_{it-1}} + \boldsymbol{\gamma_2 X_{it}} + \theta_i + \vartheta_t + \varepsilon_{it}, \qquad (4)$$

where Y_{it} is the dependent variable, namely inequality as measured by the Gini index.[12]

GC_{it-1} refers to the lagged value of a polytomous variable which captures growth conditions and allows us to define good and bad times, for which we run separate regressions. The computations are explained below.

[11] We use the lagged values of growth conditions to ensure that the mediator variables lie in between the independent (treatment) and the dependent (outcome) variables. To borrow terminology from the treatment-control literature, mediator variables are post-treatment variables which occur before the outcome (Imai, Keele and Yamamoto, 2010).

[12] We also use alternatively the share of income (or consumption) of the bottom 50 percent and the share of income (or consumption) of the top 10 percent of households to test the robustness of our results.

X_{it} is a vector which comprises standard control variables which have been shown in the literature to be correlated with inequality. These include the size of the population and the level of GDP per capita which we use to test for the existence of a Kuznets curve, that is the existence of an inverse-u shape in the relationship between inequality and the level of per capita income.

In addition, in some specifications, the vector X_{it} also includes potential mediator variables such as access to finance, unemployment and the share of government spending in GDP, which we include to check if they capture the statistical significance of growth conditions.

$\theta_i \; and \; \vartheta_t$ are country and time fixed effects, respectively.

Defining 'good times' and 'bad times'

For each country, we define 'good times' as any year in which the growth rate of GDP per capita is strictly positive; and 'bad times' as any year in which the growth rate of GDP per capita is zero or negative. We further classify good times and bad times, for each country, into three different regimes depending on the distance, measured in standard deviations, between its per capita GDP growth rate in any given year and its period average per capita GDP growth rate. The polytomous growth conditions variable is thus determined by country-specific thresholds, and is defined as follows:

GC_{it-1}= 1 if the real growth rate of GDP per capita is >0 *(≤0 for bad times)* and the deviation from the mean growth rate ≤ 1.5;

GC_{it-1} =2 if the real growth rate of GDP per capita is >0 *(≤0 for bad times)* and the deviation from the mean growth rate > 1.5 and ≤ 2.0;

GC_{it-1} =3 if the real growth rate of GDP per capita is >0 *(≤0 for bad times)* and the deviation from the mean growth rate > 2.0.

The use of standard-deviation based thresholds to distinguish between ‘normal’ and ‘extreme’ events is common in the climate economics literature (e.g. Desbureaux and Rodella, 2017). In our analysis, this enables us to capture potential non-linearities between the growth rate of real GDP per capita and inequality. [13] Table 2 illustrates the distribution of good and bad times in our sample.

Table 2. Distribution of ‘Good’ and ‘Bad’ Times in Developing Countries

	GC_{it}=1	GC_{it}=2	GC_{it}=3
Good times			
Number of years	548	83	277
Percentage of observations	60.4%	9.1%	30.5%
Bad times			
Number of years	35	29	165
Percentage of observations	15.3%	12.7%	72.1%

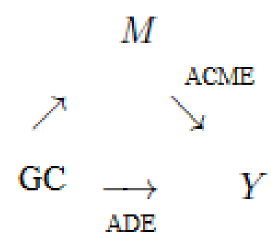
Note: The table shows distribution of years into each regime of good (bad) times for all years when inequality is also observed.
Source: Authors’ calculations.

Once we document a statistically significant relationship between growth conditions and inequality, we use mediation analysis to identify and quantify the main channels through which the effects of growth conditions affect inequality. In this paper, we are interested in the

[13] Hamilton (2017) warns against spurious dynamics from the HP filter when used to estimate business cycle dynamics, and instead suggests regressing the variable at date t+h on its four more recent values at date t. This approach is unfortunately not possible in this paper, given the sparsity of our dataset and especially given the limited number of time series observations that we have on a specific country. However, taking standard deviations of growth rates from country period averages as we do in this paper allows us to distinguish between normal and extreme events, and more so without resorting to any assumption on the specific nature of the trend in GDP growth. In doing so, we remain consistent with the finding of Aguiar and Gopinath (2007) that emerging markets are subject to extreme volatile shocks to the stochastic trend. The finding of Aguiar and Gopinath (2007) warrants against specifying the business cycles for emerging markets as fluctuations around a given trend, as it is typically done for more advanced economies.

causal relationship from growth conditions to inequality. Growth conditions (GC), however, can indirectly influence other factors or mediators (M) which in turn affect economic inequality (Y). Figure 4 illustrates this framework.

Figure 4: Implementation of Mediation Analysis



The choice of mediator variables for our study is informed by the existing literature. In particular, we use the conceptual framework of Heathcote, Perri and Violante (2010a) who decompose the monetary dimensions of economic inequality from the household budget constraint (Figure 5).[14]

Figure 5. Monetary Dimensions of Economic Inequality

This conceptual framework is useful to identify potential drivers of inequality. They are as follows: employment and labor force participation (for wages and earnings inequality); taxes

[14] We abstract here from wealth inequality on which we have limited data for the countries in our sample.

and transfers (for inequality in household disposable income); and, lending, borrowing, assets (for consumption inequality).

Based on available data for developing countries, we test the following mediator variables and priors:

- *Employment, or equivalently, unemployment.* When growth is strong, typically more jobs are created. Conversely, when it slows, some jobs are lost.

- *Access to finance.* The hypothesis is that in periods of strong growth, banks may be more willing to provide credit. On the other hand, during downturns, they may be more risk-averse and lend less.

- *Government spending*. In many countries, though not so much in the developing world, certain categories of spending (unemployment benefits and cash transfers, for example) tend to increase during economic downturns.

To implement mediation analysis, we follow the *IKY* approach which is based on a four-step algorithm:

- First, one structural equation model is specified for both the observed outcome and mediator variables using the following set of equations.

$$M_{it} = \alpha_1 + \boldsymbol{\beta_1 GC_{it-1}} + \boldsymbol{\tau_1 \breve{X}_{it}} + \mu_i + \sigma_t + \epsilon_{it}, \qquad (5)$$

$$Y_{it} = \alpha_2 + \varphi\, M_{it} + \boldsymbol{\beta_2 GC_{it-1}} + \boldsymbol{\gamma_2 \breve{X}_{it}} + \theta_i + \vartheta_t + \varepsilon_{it}, \qquad (6)$$

In equations (5) and (6), M_{it} are successive mediators; Y_{it} is inequality; growth conditions are captured by GC_{it-1}. $\boldsymbol{\breve{X}}_{it}$ is a vector of standard control variables from the literature on inequality, excluding mediator variables. μ_i and θ_i are country fixed effects, while σ_t and ϑ_t capture time effects

- Second, the model parameters in equations (5) and (6) are simulated from their sampling distribution by iteratively estimating the regressions using random sub-samples.[15]
- Third, all potential values of the mediator, conditional on treatment and covariates are modeled. The values are based on the distribution of the model parameters obtained in the previous step.
- In the fourth and final step, we use the distribution of parameters and the potential values of the mediators obtained above to compute summary statistics, point estimates, and confidence intervals for the ACME. This allows us to test whether the sequential ignorability assumption is reasonable.

V. Results

i. Linking Inequality and Growth Conditions

In this section, we report the results of panel regressions to estimate Eq.4. Table 3 shows the results for developing countries, while Table 4 shows the results for a subset of emerging market economies.

In columns (1) and (2) of Table 3, we report the result for when the Gini coefficient is used as dependent variable and when demographic factors (size and age structure of population) are controlled for. The coefficient on good times is negative and statistically significant. The interpretation of this result is that, on average, good times are associated with lower Gini coefficients or less inequality in the subsequent year for the full sample of developing countries. Conversely, the coefficient on bad times is positive and statistically significant. This suggests that bad times are associated with an increase in the Gini coefficient, and thus inequality, in the subsequent period.

Next, we want to examine how the relationship between inequality and good and bad times changes when a mediator variable is included. Of the three candidates identified earlier

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[15] For our analysis, we used 1000 iterations.

(unemployment, access to finance and government spending), we only find a systematic and robust relationship with the unemployment variable. The lack of results on access to finance and government spending may seem at first glance counterintuitive. [16] However, in the majority of the developing countries in our sample, banking or financial systems and government spending play limited roles in stabilizing economic cycles. Thus, even though access to finance and government spending have been shown to matter for long-term inequality, we are not able to establish their significance as channels of transmissions of good and bad times to inequality over shorter horizons in our sample of countries.

Table 3. Developing Countries: Relationship between Inequality and Growth Conditions

Dependent Variable: GINI Index	(1)	(2)	(3)	(4)	(5)	(6)
Good times (lag 1 year)	*-0.690***		*-0.576**		*-0.627**	
	(0.313)		*(0.317)*		*(0.322)*	
Bad times (lag 1 year)		*0.676****		*0.388*		*0.419*
		(0.246)		*(0.265)*		*(0.265)*
Log of GDP per capita	3.288	2.892	-10.128*	-10.219*	-8.794	-8.876
	(5.612)	(5.660)	(5.517)	(5.574)	(5.514)	(5.578)
Log of GDP per capita squared	-0.145	-0.123	0.704**	0.704**	0.622*	0.622*
	(0.332)	(0.333)	(0.339)	(0.340)	(0.339)	(0.341)
Log of population	-6.208***	-6.480***	-0.423	-0.786	-0.485	-0.886
	(2.233)	(2.194)	(2.677)	(2.644)	(2.685)	(2.661)
Population structure	-0.211**	-0.220**	-0.085	-0.086	-0.070	-0.071
	(0.097)	(0.097)	(0.102)	(0.102)	(0.101)	(0.102)
Unemployment			*0.219****	*0.220****		
			(0.059)	*(0.060)*		
Youth Unemployment					*0.084****	*0.084***
					(0.032)	*(0.033)*
Constant	91.314***	96.028***	59.252*	63.872*	55.054*	60.089*
	(29.285)	(29.450)	(32.714)	(32.986)	(32.843)	(33.204)
Observations	854	854	771	771	771	771
Adjusted R-squared	0.897	0.897	0.913	0.913	0.912	0.912
rmse	3.244	3.234	2.915	2.917	2.928	2.930

Robust standard errors in parentheses. Standard errors are robust to autocorrelation and heteroskedasticity.
*** p<0.01, ** p<0.05, * p<0.1

The results of panel regressions of inequality on good and bad times, controlling for unemployment are shown in Table 3, columns (3) and (4). A couple of points are worth

[16]These results are not reported for the sake of brevity, but they are available from the authors upon request.

highlighting. The first is that the inclusion of unemployment reduces the statistical significance of good and bad times. This suggests that unemployment is a promising candidate for the mediation analysis. Second, the estimated sign on unemployment is intuitive. An increase in unemployment tends to increase inequality as measured by the Gini coefficient regardless of growth conditions. We also run regressions of inequality on good and bad times, controlling for youth unemployment.[17] Details are presented in columns (5) and (6) and confirm that youth unemployment is indeed a potential candidate for mediation analysis. The results obtained for the sub-sample of emerging market economies (Table 4) are consistent with those for the full sample.

Table 4. Emerging Market Economies: Relationship between Inequality and Growth Conditions

Dependent Variable: GINI Index	(1)	(2)	(3)	(4)	(5)	(6)
Good times (lag 1 year)	*-0.766**		*-0.658*		*-0.679*	
	(0.390)		*(0.420)*		*(0.423)*	
Bad times (lag 1 year)		*0.652***		*0.538***		*0.539***
		(0.267)		*(0.273)*		*(0.271)*
Log of GDP per capita	49.313***	48.636***	26.242*	27.033*	27.981**	28.782**
	(10.463)	(10.466)	(13.913)	(13.745)	(13.996)	(13.831)
Log of GDP per capita squared	-2.463***	-2.424***	-1.097	-1.145	-1.189	-1.239
	(0.589)	(0.588)	(0.785)	(0.770)	(0.790)	(0.775)
Log of population	-9.406**	-9.378**	2.111	1.675	1.606	1.138
	(4.149)	(4.063)	(5.523)	(5.319)	(5.531)	(5.323)
Population structure	-0.291	-0.296	-0.287	-0.284	-0.244	-0.242
	(0.186)	(0.188)	(0.248)	(0.245)	(0.248)	(0.246)
Unemployment			*0.192***	*0.190***		
			(0.075)	*(0.075)*		
Youth Unemployment					*0.086***	*0.083***
					(0.039)	*(0.040)*
Constant	9.025	10.694	-103.133	-99.474	-103.943	-99.610
	(63.842)	(63.567)	(81.098)	(80.101)	(81.753)	(80.779)
Observations	425	425	370	370	370	370
Adjusted R-squared	0.936	0.937	0.942	0.943	0.942	0.942
rmse	2.639	2.624	2.425	2.413	2.433	2.423

Robust standard errors in parentheses. Standard errors are robust to autocorrelation and heteroskedasticity.
*** p<0.01, ** p<0.05, * p<0.1

[17] Youth unemployment is based on the ILO's definition of youth employment which is the share of the labor force aged between 15 and 24.

Robustness to alternative measures of inequality

These results discussed above hold if the share of income (or consumption) of the bottom 50 percent of households is used as dependent variable to measure inequality in in the regressions (Appendix V, Tables 1 and 2). In this case, the coefficient on good times is positive and statistically significant, suggesting that good times are associated with an increase in the share of income (or consumption) of the poorest 50 percent of the households in the following year. By contrast, the negative and statistically significant coefficient on bad times suggests the share in income or consumption of the poorest 50 percent of households tends to decline in the following year.

For the share of income (or consumption) of the top 10 percent of households (Appendix V, Tables 3 and 4), a negative and statistically significant coefficient on good times suggests that years of high growth tend to be followed by redistributions away from the top 10 percent of households, which lower inequality. The coefficient of bad times for this measure of inequality is positive and statistically significant. As income typically declines in recessions, the increase in the share of income (or consumption) of the top 10 percent means that these households are able to maintain income (or consumption) or reduce it at a lower rate than the rest of the population.[18]

ii. Mediator Variables: Identifying the Transmission Channels

Based on estimation results of the relationship between growth conditions and inequality, we use mediation analysis to investigate the plausibility and significance of unemployment as a mediator or channel of transmission of growth conditions to inequality.

[18] A question of interest is whether the share of income follows a different path from the share of consumption during recessions for the top 10 percent. While capital and/or labor incomes can be expected to decline, consumption shares could still *increase*. Since we do not have both income and consumption shares for all countries, we are not able to make the distinction in our analysis.

Results confirm that unemployment is a key transmission channel of growth conditions to inequality as measured by the Gini coefficient. Notably, good times tend to reduce inequality in the subsequent period through changes in unemployment, while bad times increase it. For the full sample of developing countries, 41.3 percent of the effect of good times on inequality is mediated through the unemployment channel. By contrast, only 28.4 percent of the effects of bad times on inequality is transmitted through unemployment (Table 5, top panel).

The effect of good times on inequality through the employment channel is even larger if we restrict our sample to include only emerging market economies (Table 5, bottom panel). In this case, the effect of growth conditions on inequality explained by changes in unemployment are 51.1 percent for good times. We are not able to find however, a statistically significant link between bad times and unemployment for this sub-group of countries.

The asymmetry in the results may be due to the lower importance of self-employment and to the size of the informal sector in the sub-sample of emerging economies relative to the full sample which includes low-income countries. Lower self-employment and informal sector employment could mean that more jobs are created in good times and fewer jobs shed in bad times.

Table 5: Unemployment as Mediator

Variables	Mediator (1)	GINI coefficient (2)	ACME (3)	ρ at wich ACME = 0 (4)	Absolute Percentage mediated (5)
		Labor market effects (71 developing countries)			
Good time (lag 1yr.)	**-1.066***** **(0.326)**	0.175 (0.515)	-0.285	0.206	41.299%
Unemployment		**0.267**** **(0.118)**	[-0.631, -0.034]		
Bad time (lag 1yr.)	**0.578**** **(0.280)**	-0.330 (0.426)	0.153	0.208	28.359%
Unemployment		**0.268**** **(0.118)**	[-0.006, 0.412]		
		Labor market effects (28 emerging countries)			
Good time (lag 1yr.)	**-0.992***** **(0.479)**	0.959 (0.650)	-0.400	0.264	51.101%
Unemployment		**0.401*** **(0.208)**	[-1.109, 0.035]		
Bad time (lag 1yr.)	0.367 (0.375)	-0.335 (0.484)	0.141	0.261	22.290%
Unemployment		**0.395*** **(0.207)**	[-0.184, 0.601]		

Notes: Unweighted GINI coefficient from PovcalNet data. Standard errors in parenthesis are clustered at the country level. The full vector of covariates, inequality characteristics, country and year fixed effects are introduced. *** p<0.01, ** p<0.05, * p<0.1.

The ACME is calculated as the product of the estimated effect of the exogenous regressor (good/bad times) on the mediator (unemployment) in column (1) and the estimated effect of the mediator on the outcome (in column 2). For example, the ACME of -0.285 is obtained by multiplying -1.066 by 0.267.
The absolute percentage mediated by unemployment is the ACME divided by the total effect of good/bad times on inequality.
Confidence intervals for the ACME are reported in brackets below the point estimates.

Using instead youth unemployment as the mediator variable, the effect of good times on inequality which is explained by the youth unemployment channel is 38.3 percent for developing countries (Table 6). Youth unemployment explains a lower percentage of the effect of bad times on inequality (27 percent). For emerging market economies, 47.1 percent of the effect of good times on inequality is transmitted through the youth employment channel.

Table 6. Youth Unemployment as Mediator

Variables	Mediator (1)	GINI coefficient (2)	ACME (3)	ρ at wich ACME = 0 (4)	Absolute Percentage mediated (5)
	Labor market effects (71 developing countries)				
Good time (lag 1yr.)	**-2.027***** **(0.654)**	0.154 (0.516)	-0.264	0.191	38.264%
Unemployment youth		**0.130**** **(0.063)**	[-0.613, -0.013]		
Bad time (lag 1yr.)	**1.130**** **(0.541)**	-0.323 (0.426)	0.146	0.193	26.957%
Unemployment youth		**0.131**** **(0.063)**	[-0.011, 0.403]		
	Labor market effects (28 emerging countries)				
Good time (lag 1yr.)	**-1.910**** **(0.892)**	0.925 (0.644)	-0.365	0.252	47.068%
Unemployment youth		**0.190*** **(0.104)**	[-1.026, 0.037]		
Bad time (lag 1yr.)	0.778 (0.722)	-0.336 (0.479)	0.142	0.249	22.783%
Unemployment youth		**0.188*** **(0.104)**	[-0.151, 0.577]		

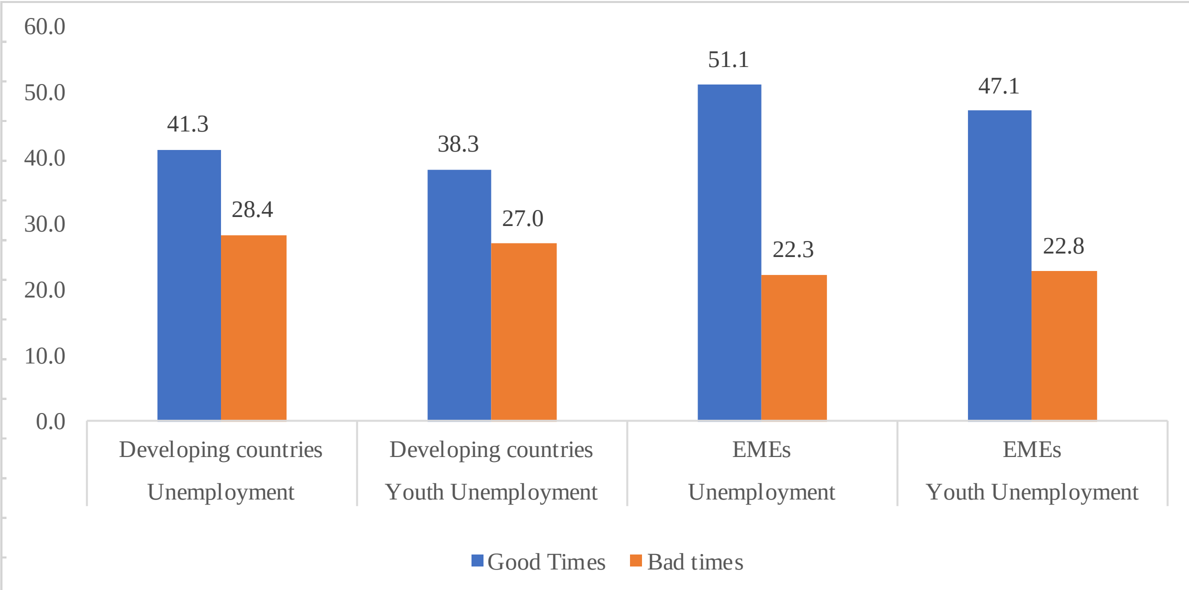
Notes: Unweighted GINI coefficient from PovcalNet data. Standard errors in parenthesis are clustered at the country level. The full vector of covariates, inequality characteristics, country and year fixed effects are introduced. *** p<0.01, ** p<0.05, * p<0.1.
The ACME is calculated as the product of the estimated effect of the exogenous regressor (good/bad times) on the mediator (unemployment) in column (1) and the estimated effect of the mediator on the outcome (in column 2). For example, the ACME of -0.264 is obtained by multiplying -2.027 by 0.130.
The absolute percentage mediated by unemployment is the ACME divided by the total effect of good/bad times on inequality.
Confidence intervals for the ACME are reported in brackets below the point estimates.

Our results are robust to alternative definitions of ‘good’ and ‘bad’ times.[19] Further, a quick analysis of the results of the mediation analysis (Figure 6) shows that the bulk of the effect of growth conditions on inequality through the unemployment channel actually comes from youth unemployment. This confirms the greater sensitivity of younger workers to economic conditions. It also brings into focus the issue of changes in intergenerational equity due to short-term growth fluctuations. Data limitations preclude a more in-depth analysis for developing countries, but recent work on European Union countries (Chen et al., 2018)

[19]In a test of robustness of results, we define ‘good’ and ‘bad’ times using absolute deviation of the growth rate of GDP per capita from the mean rather than in terms of the number of standard deviations from the mean. We find our results to be robust. The results of these regressions are available upon request.

shows that significant increases in poverty and income inequality across generations have occurred, especially after the recent crisis, despite broadly unchanged overall inequality.

Figure 6. Percentage Effect of Growth conditions on Inequality Mediated by Unemployment and Youth Unemployment



Source: Authors' calculations.

Note: the coefficient on the unemployment variables during bad times for EMEs is not statistically significant.

Robustness: Sensitivity of the mediation effect

As discussed in Section III.A on the methodology, the average causal mediation effect (ACME) is identified under the assumption of 'sequential ignorability'. Notably, sequential ignorability rules out the existence of an omitted covariate which can affect: (i) the variable of interest and the dependent variable; and/or (ii) the dependent variable and the mediator.

A violation of the sequential ignorability assumption implies non-zero correlation, denoted ρ, between the error term for the mediation equation and the error term for the outcome equation. The true value of ρ is unknown, but it is possible to calculate values of ρ for which the confidence interval of the ACME contains 0.

These values are shown in column (4) in Tables 5 and 6. They suggest that violations of the sequential ignorability assumption would have to be strong to reverse the analytical conclusions about the average causal mediation effects of unemployment and youth unemployment.[20]

VI. Concluding Remarks

In this paper, we investigate the effects of growth conditions to inequality in a broad sample of 71 developing countries. To do so, we define a polytomous variable and identify for each country whether any given year corresponded to 'good' ('bad') times depending on whether the growth rate of real GDP per capita was exceptionally high (low) or average. The results of our empirical analysis, based on data on inequality from the World Bank's PovcalNet database for the period 1981-2014, suggest that 'good' times result in lower inequality, as measured by the Gini index, while bad times tend to result in higher inequality. The decline in inequality is also apparent in a higher income (consumption) share of the bottom 50 percent of households with a simultaneous decline in the income (consumption) share of the top 10 percent. By contrast during 'bad' times, the income (consumption) share of the bottom 50 percent falls while that of the top 10 percent increases. Overall, reductions in inequality during 'good times' are largely undone in 'bad times'.

Using a novel estimation technique called mediation analysis, we are able to identify a causal effect from 'good' and 'bad' times on inequality through the channel of unemployment, and youth unemployment in particular. This channel is quantitatively important, especially for good times. It explains 41.3 percent of the effect of 'good' times in the full sample of developing countries and 51.1 percent of the effect of 'good' times in a sub-sample of 28 emerging market economies. In comparison, the percentage effect of bad times on inequality which is transmitted through the unemployment channel is slightly lower, at around 28.4

[20] For example, in Table 5, the estimates for the sample of developing countries suggest that if ρ=0.206, the average causal effect of unemployment in good times would be zero. A sensitivity analysis of the ACME to variations in the parameter ρ, reported in Appendix V, also confirms that the estimated mediated effects are robust.

percent in developing countries. A robust statistical causal relationship from ‘bad’ times to inequality, through the unemployment channel, cannot similarly be established for the sub-sample of emerging market economies.

In addition to contributing to the literature on short-term growth and inequality, our work adds two elements to the policy debate. First, it suggests that the quality of jobs created, and labor market policies would be important levers to reduce inequality in developing countries. As such, structural reforms may be needed to address the features of labor markets which tend to exacerbate disparities in the distribution of income. These features include the relatively high importance of informal or self-employment; the lack of established social safety nets relating to employment protection or unemployment benefits; and limited labor mobility. Second, it shows that the bulk of the effect of growth conditions on inequality through the unemployment channel comes from youth unemployment. Thus, policies targeted to increase the employability of younger workers and reduce their vulnerability to economic downturns would be important.

Further work with more granular data is needed to inform policy design, but our results can provide a useful starting point.

REFERENCES

Acemoglu, D. and Robinson, J.A., 2002. The political economy of the Kuznets curve. *Review of development economics*, *6*(2), pp.183-203.

Aguiar, M. and Gopinath, G., 2007. Emerging market business cycles: The cycle is the trend. *Journal of political Economy*, *115*(1), pp.69-102.

Alesina, A. and Rodrik, D., 1994. Distributive politics and economic growth. *The quarterly journal of economics*, *109*(2), pp.465-490.

Alvaredo, F. and Gasparini, L., 2015. Recent trends in inequality and poverty in developing countries. In *Handbook of income distribution* (Vol. 2, pp. 697-805). Elsevier.

Atkinson, A.B. and Morelli, S., 2011. Economic crises and inequality. *UNDP-HDRO Occasional Papers* No. 2011/6.

Atkinson, A.B., 2015. *Inequality*. Harvard University Press.

Atkinson, A.B. and Bourguignon, F., 2015. Introduction: Income distribution today.

Banerjee, A.V. and Duflo, E., 2003. Inequality and growth: What can the data say? *Journal of economic growth*, *8*(3), pp.267-299.

Baron, R.M. and Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, *51*(6), p.1173.

Barro, R.J., 2000. Inequality and Growth in a Panel of Countries. *Journal of economic growth*, *5*(1), pp.5-32.

Berg, A.G. and Ostry, J.D., 2017. Inequality and Unsustainable Growth: Two Sides of the Same Coin? *IMF Economic Review*, *65*(4), pp.792-815.

Berg, A., Ostry, J.D. and Zettelmeyer, J., 2012. What makes growth sustained? *Journal of Development Economics*, *98*(2), pp.149-166.

Calderón, C. and Yeyati, E.L., 2009. Zooming in: From aggregate volatility to income distribution. The World Bank.

Chen, S. and Ravallion, M., 2010. The developing world is poorer than we thought, but no less successful in the fight against poverty. *The Quarterly Journal of Economics*, *125*(4), pp.1577-1625.

Chen, T., Hallaert, M.J.J., Pitt, M.A., Qu, M.H., Queyranne, M.M., Rhee, A., Shabunina, M.A., Vandenbussche, J. and Yackovlev, I., 2018. *Inequality and Poverty across Generations in the European Union*. International Monetary Fund.

Conger, R.D., Elder Jr, G.H., Lorenz, F.O., Conger, K.J., Simons, R.L., Whitbeck, L.B., Huck, S. and Melby, J.N., 1990. Linking economic hardship to marital quality and instability. *Journal of Marriage and the Family*, pp.643-656.

Dabla-Norris, M.E., Kochhar, M.K., Suphaphiphat, M.N., Ricka, M.F. and Tsounta, E., 2015. *Causes and consequences of income inequality: A global perspective*. International Monetary Fund, SDN/15/13.

Desbureaux, S., and A. Rodella, 2017, Shocks in the cities: the economic impact of water shocks in Latin American metropolitan areas, The World Bank.

Dippel, C., Gold, R. and Heblich, S., 2015. *Globalization and its (dis-) content: Trade shocks and voting behavior* (No. w21812). National Bureau of Economic Research.

Ferreira, F.H., Lustig, N. and Teles, D., 2015. Appraising cross-national income inequality databases: An introduction. *World Bank Policy Research Working Paper*

Forbes, K.J., 2000. A Reassessment of the Relationship between Inequality and Growth. *American economic review*, *90*(4), pp.869-887.

Förster, M. F. and Tóth, I. G., 2015, Cross-Country Evidence of the Multiple Causes of Inequality Change in the OECD Area, *Handbook of Income Distribution*, Volume 2B, Elsevier, B.V.

Furceri, D., Jaumotte, F. and Loungani, P., 2013. The distributional consequences of capital account liberalization. *IMF Washington, DC*.

Furceri, D. and Loungani, P., 2014. Who let the Gini out? Searching for sources of inequality.

Goldin, C. and Katz, L.F., 1999. *The returns to skill in the United States across the twentieth century* (No. w7126). National bureau of economic research.

Hamilton, J.D., 2017. Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics*, (0).

Heathcote, J., Perri, F. and Violante, G.L., 2010a. Unequal we stand: An empirical analysis of economic inequality in the United States, 1967–2006. *Review of Economic dynamics*, *13*(1), pp.15-51.

Heathcote, J., Perri, F. and Violante, G.L., 2010b. Inequality in times of crisis: Lessons from the past and a first look at the current recession. *manuscript, University of Minnesota*.

Huber, M., 2016. Disentangling policy effects into causal channels. *IZA World of Labor*.

Imai, K., Keele, L. and Yamamoto, T., 2010. Identification, inference and sensitivity analysis for causal mediation effects. *Statistical science*, pp.51-71.

Imai, K., Keele, L., Tingley, D. and Yamamoto, T., 2011. Unpacking the black box of causality: Learning about causal mechanisms from experimental and observational studies. *American Political Science Review*, *105*(4), pp.765-789.

International Monetary Fund, 2017, *Tackling Inequality*, October 2017 Fiscal Monitor (Washington, D.C). Available at:

http://www.imf.org/en/publications/fm/issues/2017/10/05/fiscal-monitor-october-2017

Kenny, D.A., Kashy, D.A. and Bolger, N., 1998. Data analysis in social psychology (In D. Gilbert, S. Fiske, & G. Lindzey (Eds.). *The handbook of social psychology* (Vol. 1, pp. 233–265).

Krueger, D., Perri, F., Pistaferri, L. and Violante, G.L., 2010. Cross-sectional facts for macroeconomists. *Review of Economic dynamics*, *13*(1), pp.1-14.

Mackinnon, D. P., 2008, *Introduction to Statistical Mediation Analysis.* Taylor & Francis, New York.

MacKinnon, D.P., Fairchild, A.J. and Fritz, M.S., 2007. Mediation analysis. *Annu. Rev. Psychol.*, 58, pp.593-614.

Milanovic, B., 2015. All the Ginis dataset. *The World Bank.*

Ostry, M.J.D., Berg, M.A. and Tsangarides, M.C.G., 2014. Redistribution, inequality, and growth. International Monetary Fund.

Parker, J.A. and Vissing-Jorgensen, A., 2009. Who bears aggregate fluctuations and how? *American Economic Review*, *99*(2), pp.399-405.

Piketty, T., 2015. About capital in the twenty-first century. *American Economic Review*, *105*(5), pp.48-53.

Solt, F., 2009. Standardizing the world income inequality database. *Social Science Quarterly*, *90*(2), pp.231-242.

Stiglitz, J.E., 2012. Macroeconomic fluctuations, inequality, and human development. *Journal of Human Development and Capabilities*, *13*(1), pp.31-58.

Williamson, J.G. and Lindert, P.H., 1980. Long-term trends in American wealth inequality. In *Modeling the distribution and intergenerational transmission of wealth* (pp. 9-94). University of Chicago Press.

World Bank, *PovcalNet*, available at:

http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx

APPENDIX I. SUMMARY STATISTICS FOR MAIN VARIABLES

	Name	Description	Source(s)	Observations	Mean	S.D.	Min	Max
Inequality								
	Gini coefficient	Index ranging from 0 (perfect equality) to 100 (perfect inequality). It is based on either consumption or income data from household surveys	PovcalNet (July 2017)	1,167	39.1	10.1	16.2	64.8
	Bottom50	Share of income (or consumption) going to the bottom 50 percent of households for a country in any given survey year	PovcalNet (July 2017)	1,167	24.3	6.0	9.6	39.0
	Top10	Share of income (or consumption) going to the top 10 percent of households for a country in any given survey year	PovcalNet (July 2017)	1,167	30.7	7.6	17.0	54.3
Growth conditions								
	Real per capita GDP growth rate	Gross domestic product, constant prices in national currency divided by population	WEO (July, 2017) and Authors' construction based on population data from WDI	3,460	2.1	4.7	-45.0	33.0
Covariates								
	ln(GDPpc)	Log of GDP per capita	PWT9.1	1,145	9.1	1.0	6.0	11.4
	ln(GDPpc2)	Log of the squared value of GDP per capita	PWT9.1	1,145	84.1	18.3	36.3	130.4
	ln(pop)	Log of total population	WDI (July 2017)	1,167	16.4	1.5	12.2	21.0
	Pop structure	Share of Population ages 15-64 (% of total)	WDI (July 2017)	1,159	63.8	5.6	47.0	74.4
	Unemployment	Unemployment, total (% of total labor force)	WDI (July 2017)	1,052	8.8	7.7	0.2	37.3
	Unemployment, youth	Unemployment, youth total (% of total labor force ages 15-24)	WDI (July 2017)	1,052	18.3	16.6	0.3	71.8

APPENDIX II. CROSS-COUNTRY INEQUALITY DATABASES: AN OVERVIEW

The availability of cross-country inequality databases has increased rapidly over the last decades, contributing to the development of a rich empirical literature. Förster and Tóth (2015) and a special edition of the *Journal of Economic Inequality* in 2015 provide detailed reviews on the strengths and limitations of each. For developing countries, Atkinson and Bourguignon (2015) note the dearth of benchmarking exercises comparing results from different databases. The consensus from these reviews is that the choice of the database will depend on the question at hand. In the following, we provide an overview of the most widely-used databases and discuss briefly the PovcalNet data which was employed for the empirical analysis in this paper.

Cross-country inequality databases can be classified in two categories, namely: primary and secondary databases (Atkinson and Morelli, 2011). Most of the databases measure inequality using either income or consumption data.[21]

Primary databases are built with micro data from household surveys, standardized as much as possible, to make them comparable across countries and time periods. Popular primary databases include Luxembourg Income Study (LIS), the OECD income distribution database, Socio Economic Database for Latin America and the Caribbean (SEDLAC) and the World Bank's PovcalNet and WYD. Building on earlier work by Atkinson and Morelli (2011), the chartbook of economic inequality website also provides a database, covering 25 countries.

Secondary databases put together indicators of income distribution from published databases. Examples of secondary databases include the World Income Inequality Database (WIID) and the "All the Ginis" by Branko Milanovic. A related database, the Standardized World Income Inequality Database (SWIID) by Solt (2009) seeks to broaden coverage over time and across countries of the WIID through imputations of missing values using a data algorithm.

[21] The WID which has been developed by the World Income Inequality Lab (2017) is an important exception. It builds on the former World Top Incomes Database (WTID) and also reports data on wealth inequality, mostly for advanced economies.

(continued…)

Most empirical analyses of inequality for developing countries employ either the World Bank's PovcalNet or SWIID given their broad coverage.[22] In this paper we opted to use the PovcalNet database. This choice was motivated by two main considerations. In the first instance, we sought to minimize the trade-off between coverage and comparability. PovcalNet is based household survey data, harmonized to some extent, and measures inequality using household income or consumption for over 110 countries (advanced and developing).

The database is used to generate the World Bank's global estimates of "dollar-a-day" poverty (Chen and Ravallion, 2010). It also provides Gini coefficients of inequality and others measures of income inequality such as the share of income (or consumption) held by the top 10 percent and the bottom 50 percent of households. For most developing countries, PovcalNet estimates are based on household consumption data. Exceptions include Latin American and Caribbean countries where household income data is used. In a few country cases, there is a switch between income and consumption to measure of inequality used. These seem to reflect methodological changes. In the regression analyses, we control for these differences across countries in the measure used to compute inequality as well as breaks in the methodology for the same country through the inclusion of dummy variables.

The second consideration in the choice of database was the research question itself. Since the analysis focuses on the dynamics of inequality over the short term, SWIID was ruled out as results could be sensitive to imputed observations.

[22] See Alvareddo and Gasparini (2013) for empirical applications of the PovcalNet data. Applications of the SWIID include Furceri, Jaumotte and Loungani (2013); Furceri and Loungani (2014); Ostry and others (2014); and the October 2015 Regional Economic Outlook for Sub-Saharan Africa.

APPENDIX III. COVERAGE OF THE POVCALNET DATABASE 1980-2014

Country	Data type	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Albania	C																																			
Argentina	I																																			
Armenia	C																																			
Australia	I																																			
Austria	I																																			
Azerbaijan	C																																			
Bangladesh	C																																			
Belarus	C																																			
Belgium	I																																			
Belize	C (1995), I																																			
Bolivia	I																																			
Bosnia and Herzegovi	C																																			
Botswana	C																																			
Brazil	I																																			
Bulgaria	C (1989,1994-95,1997,2001,2003)																																			
Burkina Faso	C																																			
Cambodia	C																																			
Cameroon	C																																			
Canada	I																																			
Chile	I																																			
China-Urban	C																																			
China-Rural	C, I (1981,1984,1987)																																			
Colombia	I																																			
Costa Rica	I																																			
Cote d'Ivoire	C																																			
Croatia	C, I (1988,2011-12)																																			
Cyprus	I																																			
Czech Republic	I																																			
Denmark	I																																			
Dominican Republic	I																																			
Ecuador	I																																			
El Salvador	I																																			
Estonia	C (1995,1998,2000-02), I																																			
Ethiopia	C																																			
Finland	I																																			
France	I																																			
Georgia	C																																			
Germany	I																																			

Source: World Bank PovcalNet

Notes:

Unless otherwise stated, the GINI coefficient data are based on national household surveys.

Inequality can refer to inequality in household consumption (C) or income (I). In a few cases, there is a switch between consumption and income for calculating the GINI index. This in indicated in the second column for the measure which is used less frequently.

Country	Data type	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Ghana	C																																			
Greece	I																																			
Guatemala	I																																			
Guinea	C																																			
Guinea-Bissau	C																																			
Honduras	I																																			
Hungary	C (1998-2003), I																																			
Iceland	I																																			
India-Urban	C																																			
India-Rural	C																																			
Indonesia-Urban	C																																			
Indonesia-Rural	C																																			
Iran	C																																			
Ireland	I																																			
Israel	I																																			
Italy	I																																			
Jamaica	C																																			
Kazakhstan	C, I (1988 1993)																																			
Kenya	C																																			
Kosovo	C																																			
Kyrgyzstan	C, I (1988)																																			
Lao	C																																			
Latvia	C (1997-98,2002-03), I																																			
Lesotho	C																																			
Lithuania	C (1996,1998-99,2000-03),I																																			
Luxembourg	I																																			
Macedonia	C																																			
Madagascar	C																																			
Malaysia	I																																			
Mali	C																																			
Mauritania	C																																			
Mexico	C (1984), I																																			
Moldova	C, I (1988,1992)																																			
Mongolia	C																																			
Montenegro	C																																			
Morocco	C																																			
Nepal	C, I (1984)																																			
Netherlands	I																																			
Nicaragua	I																																			

Source: World Bank PovcalNet

Notes:

Unless otherwise stated, the GINI coefficient data are based on national household surveys.

Inequality can refer to inequality in household consumption (C) or income (I). In a few cases, there is a switch between consumption and income for calculating the GINI index. This in indicated in the second column for the measure which is used less frequently.

Appendix IV. Countries Samples used in Empirical Analysis

All countries (101) *		Developing countries (71)		Emerging countries (28)
Albania	Latvia	Albania	Moldova	Argentina
Argentina	Lithuania	Argentina	Mongolia	Belarus
Armenia	Luxembourg	Armenia	Montenegro	Brazil
Australia	Macedonia	Azerbaijan	Morocco	Chile
Austria	Madagascar	Bangladesh	Nicaragua	China
Azerbaijan	Malaysia	Belarus	Niger	Colombia
Bangladesh	Mauritania	Belize	Nigeria	Croatia
Belarus	Mexico	Bolivia	Pakistan	Dominican Republic
Belgium	Moldova	Brazil	Panama	Ecuador
Belize	Mongolia	Bulgaria	Paraguay	Hungary
Bolivia	Montenegro	Burkina Faso	Peru	India
Brazil	Morocco	Cambodia	Philippines	Indonesia
Bulgaria	Netherlands	Chile	Poland	Malaysia
Burkina Faso	Nicaragua	China	Romania	Mexico
Cambodia	Niger	Colombia	Russia	Morocco
Canada	Nigeria	Costa Rica	Rwanda	Pakistan
Chile	Norway	Cote d'Ivoire	Senegal	Peru
China	Pakistan	Croatia	Serbia	Philippines
Colombia	Panama	Dominican Republic	South Africa	Poland
Costa Rica	Paraguay	Ecuador	Sri Lanka	Romania
Cote d'Ivoire	Peru	El Salvador	Tajikistan	Russia
Croatia	Philippines	Georgia	Thailand	South Africa
Cyprus	Poland	Ghana	Tunisia	Sri Lanka
Czech Republic	Portugal	Guatemala	Turkey	Thailand
Denmark	Romania	Guinea	Uganda	Turkey
Dominican Republic	Russia	Honduras	Ukraine	Ukraine
Ecuador	Rwanda	Hungary	Uruguay	Uruguay
El Salvador	Senegal	India	Uzbekistan	Venezuela
Estonia	Serbia	Indonesia	Venezuela	
Finland	Slovak Republic	Iran	Vietnam	
France	Slovenia	Jamaica	West Bank and Gaza	
Georgia	South Africa	Kazakhstan	Zambia	
Germany	Spain	Kyrgyzstan		
Ghana	Sri Lanka	Lao		
Greece	Sweden	Macedonia		
Guatemala	Switzerland	Madagascar		
Guinea	Tajikistan	Malaysia		
Honduras	Thailand	Mauritania		
Hungary	Tunisia	Mexico		
Iceland	Turkey			
India	Uganda			
Indonesia	Ukraine			
Iran	United Kingdom			
Ireland	United States			
Israel	Uruguay			
Italy	Uzbekistan			
Jamaica	Venezuela			
Kazakhstan	Vietnam			
Kosovo	West Bank and Gaza			
Kyrgyzstan	Zambia			
Lao				

Sources: World Bank List of Economies June 2017 and IMF, Fiscal Monitor databases

Note: The "All countries" sample only includes countries with at least 5 rounds of survey data.

APPENDIX V. ROBUSTNESS CHECKS

Table 1. Developing Countries: Relationship between the Income (Consumption) Share of the Bottom 50 percent and Growth Conditions

Dependent Variable: Share of Bottom 50 percent	(1)	(2)	(3)	(4)	(5)	(6)
Good times (lag 1 year)	0.398**		0.334*		0.366*	
	(0.183)		(0.186)		(0.190)	
Bad times (lag 1 year)		-0.406***		-0.227		-0.246
		(0.149)		(0.158)		(0.159)
Log of GDP per capita	-1.921	-1.687	5.929*	5.980*	5.100	5.146
	(3.217)	(3.223)	(3.113)	(3.129)	(3.118)	(3.138)
Log of GDP per capita squared	0.086	0.072	-0.409**	-0.409**	-0.358*	-0.357*
	(0.192)	(0.192)	(0.196)	(0.196)	(0.196)	(0.196)
Log of population	3.894***	4.049***	0.254	0.466	0.293	0.528
	(1.330)	(1.304)	(1.557)	(1.536)	(1.559)	(1.544)
Population structure	0.124**	0.129**	0.056	0.057	0.047	0.047
	(0.057)	(0.057)	(0.060)	(0.060)	(0.059)	(0.060)
Unemployment			-0.136***	-0.137***		
			(0.036)	(0.036)		
Youth Unemployment					-0.052***	-0.052***
					(0.019)	(0.020)
Constant	-9.352	-12.121	11.996	9.299	14.602	11.646
	(16.893)	(16.888)	(18.301)	(18.370)	(18.383)	(18.505)
Observations	854	854	771	771	771	771
Adjusted R-squared	0.898	0.899	0.914	0.914	0.913	0.913
rmse	1.906	1.899	1.716	1.717	1.725	1.726

Robust standard errors in parentheses. Standard errors are robust to autocorrelation and heteroskedasticity.
*** p<0.01, ** p<0.05, * p<0.1

Table 2. Emerging Market Economies: Relationship between the Income (Consumption) Share of the Bottom 50 percent and Growth Conditions

Dependent Variable: Share of Bottom 50 percent	(1)	(2)	(3)	(4)	(5)	(6)
Good times (lag 1 year)	0.414*		0.349		0.363	
	(0.225)		(0.240)		(0.242)	
Bad times (lag 1 year)		-0.369**		-0.294*		-0.296*
		(0.154)		(0.157)		(0.156)
Log of GDP per capita	-29.285***	-28.908***	-15.453*	-15.904*	-16.507*	-16.960**
	(6.482)	(6.487)	(8.348)	(8.263)	(8.412)	(8.329)
Log of GDP per capita squared	1.458***	1.436***	0.646	0.673	0.703	0.730
	(0.364)	(0.363)	(0.468)	(0.461)	(0.472)	(0.464)
Log of population	5.061**	5.037**	-2.207	-1.966	-1.892	-1.633
	(2.474)	(2.425)	(3.233)	(3.114)	(3.238)	(3.116)
Population structure	0.194*	0.197*	0.198	0.196	0.173	0.172
	(0.108)	(0.110)	(0.141)	(0.139)	(0.140)	(0.139)
Unemployment			-0.114***	-0.113***		
			(0.042)	(0.042)		
Youth Unemployment					-0.050**	-0.049**
					(0.022)	(0.022)
Constant	51.537	50.732	124.850***	122.870***	125.116***	122.751**
	(38.287)	(38.208)	(47.537)	(47.150)	(47.938)	(47.577)
Observations	425	425	370	370	370	370
Adjusted R-squared	0.938	0.939	0.946	0.946	0.945	0.946
rmse	1.536	1.526	1.382	1.375	1.387	1.381

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Developing Countries: Relationship between the Income (Consumption) Share of the Top 10 percent and Growth Conditions

Dependent Variable: Share of top 10 percent	(1)	(2)	(3)	(4)	(5)	(6)
Good times (lag 1 year)	-0.557**		-0.458*		-0.495*	
	(0.256)		(0.258)		(0.260)	
Bad times (lag 1 year)		0.499***		0.303		0.326
		(0.188)		(0.204)		(0.202)
Log of GDP per capita	2.599	2.298	-7.669	-7.749	-6.726	-6.796
	(4.787)	(4.870)	(4.915)	(5.000)	(4.893)	(4.983)
Log of GDP per capita squared	-0.106	-0.089	0.550*	0.551*	0.492*	0.492*
	(0.276)	(0.280)	(0.289)	(0.292)	(0.288)	(0.292)
Log of population	-3.792**	-4.013**	-0.065	-0.350	-0.116	-0.429
	(1.717)	(1.695)	(2.117)	(2.103)	(2.132)	(2.124)
Population structure	-0.163**	-0.168**	-0.050	-0.051	-0.040	-0.040
	(0.079)	(0.080)	(0.084)	(0.085)	(0.084)	(0.085)
Unemployment			0.152***	0.154***		
			(0.048)	(0.049)		
Youth Unemployment					0.058**	0.058**
					(0.025)	(0.026)
Constant	59.564**	63.217**	42.087	45.731	39.226	43.164
	(24.750)	(25.124)	(28.720)	(29.183)	(28.817)	(29.345)
Observations	854	854	771	771	771	771
Adjusted R-squared	0.882	0.882	0.900	0.899	0.899	0.899
rmse	2.642	2.637	2.387	2.389	2.396	2.397

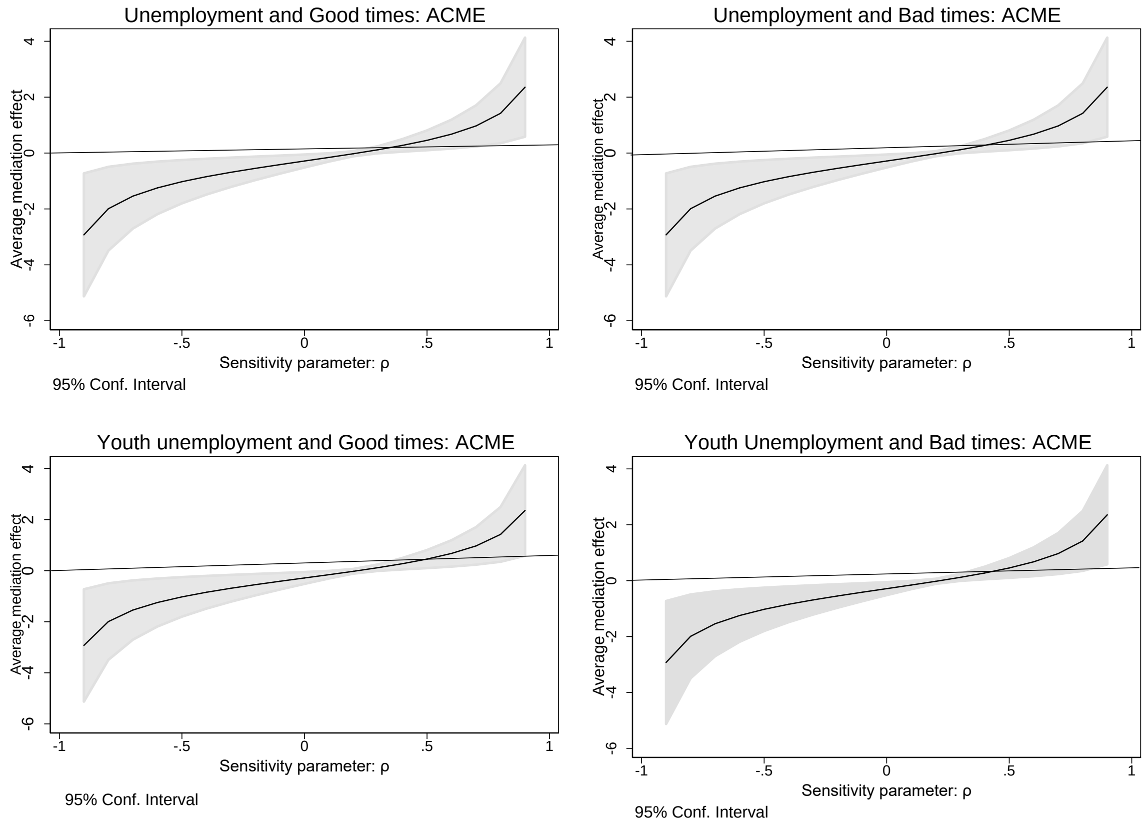
Robust standard errors in parentheses. Standard errors are robust to autocorrelation and heteroskedasticity.
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Emerging Market Economies: Relationship between the Income (Consumption) Share of the Top 10 percent and Growth Conditions

Dependent Variable: Share of top 10 percent	(1)	(2)	(3)	(4)	(5)	(6)
Good times (lag 1 year)	-0.658**		-0.576*		-0.591*	
	(0.321)		(0.348)		(0.349)	
Bad times (lag 1 year)		0.507**		0.443*		0.444*
		(0.221)		(0.228)		(0.226)
Log of GDP per capita	38.020***	37.474***	21.731**	22.331**	22.989**	23.606**
	(7.475)	(7.479)	(10.635)	(10.483)	(10.653)	(10.502)
Log of GDP per capita squared	-1.912***	-1.881***	-0.932	-0.969	-0.999	-1.037*
	(0.425)	(0.423)	(0.605)	(0.593)	(0.607)	(0.594)
Log of population	-8.399***	-8.404***	-1.319	-1.671	-1.683	-2.062
	(3.165)	(3.108)	(4.303)	(4.172)	(4.310)	(4.174)
Population structure	-0.170	-0.175	-0.131	-0.129	-0.100	-0.099
	(0.152)	(0.153)	(0.211)	(0.209)	(0.212)	(0.210)
Unemployment			0.139**	0.138**		
			(0.064)	(0.064)		
Youth Unemployment					0.062*	0.061*
					(0.034)	(0.034)
Constant	28.969	30.702	-33.858	-30.775	-34.484	-30.878
	(49.242)	(48.854)	(64.601)	(63.493)	(65.110)	(64.002)
Observations	425	425	370	370	370	370
Adjusted R-squared	0.926	0.926	0.929	0.930	0.929	0.929
rmse	2.190	2.182	2.077	2.070	2.082	2.075

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1. Sensitivity of the Average Causal Mediated Effect (ACME) to violations of the Sequential Ignorability Assumption



Notes: The figure shows the estimated ACME for different values of ρ for unemployment and youth unemployment during good and bad times, respectively. The solid black lines show the value of the ACME for different values of the parameter ρ, which measures potential violations of the sequential ignorability assumption, and the shaded grey areas correspond to the 95% confidence intervals for the estimates.