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What's behind pro-poor growth?

The role of shocks and measurement error

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Abstract: Standard growth incidence curves describe how growth episodes impact on the overall income distribution. However, measuring the pro-poorness of the growth process is complex due to (i) measurement errors and (ii) effect shocks that may hit the percentiles of the income distribution in different ways. Therefore, standard growth incidence curves may misrepresent the true growth process and its distributive impact. Relying on a non-anonymous axiom, we compare actual growth episodes at each percentile of the initial personalized distribution with counterfactual mobility profiles which rule out the presence of shocks. We consider Indonesia in 2000–07 and 2007–14—two growth spells in which there was substantial, significant upward mobility among the initially poorer, a sizeable part of which cannot be explained by unobserved individual endowments or standard socioeconomic attributes. The difference between actual and expected growth can largely be attributed to individual recovery from previous negative losses, rather than resulting from purely exogenous positive shocks.

Key words: measurement error, shocks, pro-poorness, mobility

JEL classification: D31, I3, O12

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1 Introduction

In the context of the Sustainable Development Goals (SDGs), to promote countries' development and to raise the living standard of people at the bottom of the income distribution, the World Bank Group renewed its strategy by defining twin goals: (i) ending the share of people living in extreme and chronic poverty by 2030; and (ii) promoting shared prosperity (Basu 2013). The first goal deals with the reduction to less than 3 per cent of the share of people living below the World Bank's poverty line of US$1.25 per day. Empirical evidence has documented that economic growth represents the main tool to achieve absolute poverty reduction (Dollar and Kraay 2002; Dollar et al. 2016). However, Basu (2013) has argued that the observed growth rates are not enough to eradicate poverty and a more equal distribution of growth benefits is desirable. This is the spirit of the 'shared prosperity' goal, which calls for greater income growth of the poorest 40 per cent of people. With the definition of these twin goals, the World Bank Group recognizes that growth not only should be good for the poor but also has to be 'pro-poor'. Therefore, analysing the effects of income growth on poverty reduction and assessing the pro-poorness of growth are not only exercises for academic researchers but also crucial challenges for policymakers.

Prior to this, indeed, there has been an intense debate among researchers on the definition and measurement of the pro-poorness of growth, with two alternative definitions emerging: absolute versus relative. The former defines growth as pro-poor when either the absolute income gain of the poor is larger than the average income gain (strong absolute pro-poor growth) or the poor experience a positive growth rate (weak absolute pro-poor growth). The relative definition instead calls for the growth rate of the bottom part of the distribution to be larger than the average growth rate. Klasen (2008), in his review, highlights merits and weaknesses of each definition, arguing that the absolute (weak) definition is useful to measure the 'rate' of pro-poorness, while the relative definition is particularly suitable in assessing the 'state' of pro-poorness.[1]

This consideration seems consistent with the work of Ravallion and Chen (2003), who introduced the growth incidence curve (GIC). The GIC plots the percentile-specific income growth rate between two points in time. By comparing the average growth rate experienced by the individuals ranked in the bottom percentiles with the average growth rate of the overall distribution, a growth process can be defined as pro-poor in absolute (relative) terms if the former is positive (larger than the latter). In this regard, the facts documented by Dollar et al. (2016) suggest pro-poor growth only in absolute terms, since the poorest 40 per cent have experienced a positive income growth rate without increasing their income share.

However, Ravallion and Chen (2003) and subsequent literature (see among others Duclos 2009; Essama-Nssah 2005; Kraay 2006; Son 2004) measure the degree of pro-poorness of growth in an anonymous way, by focusing only on the income change experienced by each percentile of the distribution without considering the identity of individuals located on each percentile.

Therefore, two alternative growth processes generating the same income distribution as the previous period are considered equivalent, irrespective of whether individuals' positions within the income distributions are unchanged or completely reshuffled. This counterintuitive result makes

[1] See Essama-Nssah and Lambert (2009) for a review of the literature developing indices of pro-poorness of growth. See also Duclos (2009) for a formal characterization of absolute and relative pro-poorness.

the anonymous approach unsatisfactory when inter-temporal evaluation of the growth processes aims at assessing the mobility experienced by individuals.

By removing the anonymity assumption, Grimm (2007) and Bourguignon (2011) propose the 'non-anonymous' version of the GIC (na-GIC), which is obtained by keeping constant individuals' position in the initial income distribution. Thus, the na-GIC plots the income growth rate of all individuals as a function of their quantile in the initial distribution. A growing strand of recent literature adopts this non-anonymous approach to evaluating pro-poor growth (see among others Jenkins and Van Kerm 2016; Lo Bue and Palmisano 2020; Palmisano 2018; Palmisano and Peragine 2015).[2]

The individual income growth rate is also used by another relevant strand of literature aimed at measuring income mobility. The concept of mobility is multidimensional (Fields and Ok 1999; Klasen et al. 2018), as it embodies four different aspects, which are described by Jantti and Jenkins (2015): re-ranking within the income distribution, income growth, inequality reduction, and uncertainty (Barcena and Cantò 2018). The income mobility profiles proposed by Van Kerm (2009) represent an alternative formalization of the na-GIC. However, while the analysis of mobility is quite developed (see among others Fields 2008; Fields and Ok 1999), the investigation of the effect of mobility on the pro-poorness of growth is still limited.[3]

Both the na-GIC and mobility profiles may offer only a partial representation of the individual income growth process; this could be the result of either shocks or measurement errors. This issue has been raised, in the context of the anonymous GIC, by Ferreira (2012), who, referring to the literature on counterfactual distributions (see among others Dinardo et al. 1996; Juhn et al. 1993), proposes an alternative interpretation of the GIC. Ferreira (2012) shows that the individual income growth rate can be rewritten as the sum of different components, each of them measuring the impact of a specific determinant, such as changes in either worker characteristics or the return of these characteristics. This approach has been recently applied by Ferreira et al. (2018), who estimate a counterfactual GIC to relate the distributional impact of economic growth to changes to the structure of the economy.

Even Fields et al. (2015), in their analysis of earnings mobility in Argentina, Mexico, and Venezuela, recognize the confounding role of measurement errors and transitory earning shocks to which individuals may be subjected in the short run. Therefore, they propose a framework in which individuals' earnings are decomposed as the sum of two components, one associated with observable and permanent individual characteristics and another related to transitory earning components.[4]

By applying the na-GIC framework, in this paper we compare actual growth episodes at each percentile of the initial personalized distribution with a counterfactual pattern of predicted income

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[2] More specifically, Jenkins and Van Kerm (2016) and Palmisano and Peragine (2015), by focusing on individual-specific instead of quintile-specific growth rate, propose a welfare analysis of the distributive impact of growth. Palmisano (2018) suggests that the identification of individuals may be based on the ranking in the final distribution, and therefore pro-poorness is evaluated by focusing on the income trajectories of individuals who become poor. Lo Bue and Palmisano (2020) propose a non-anonymous version of GIC to evaluate the patterns of mobility experienced by the chronic and transitory poor, where identification is based either on the initial or the final distribution.

[3] Exceptions are the contributions by Bresson et al. (2018) and Barcena and Cantò (2018).

[4] By adopting a two-stage least squares procedure, Fields et al. (2015) first estimate the part of individuals' earnings associated with permanent characteristics. Then, the predicted values, which represent a proxy of the initial income of individuals, are used in a second regression as the explanatory variable of the individuals' income changes.

dynamics. To rule out the presence of shocks, the counterfactual distribution is derived under the assumption of time-constant marginal returns of individual endowments. Comparison between the observed and the counterfactual na-GIC allows an understanding of the extent to which growth-shaped individual income trajectories have resulted from unexpected changes in the marginal return of individual socioeconomic characteristics which substantially changed individual rankings in the income distribution. Using longitudinal survey data from Indonesia, we show that growth has been generally pro-poor over the period 2000–14, with the incidence of growth in the initial poorest quintile being larger than expected. We apply a double selectivity model of state-dependency to better understand the nature of these unpredicted percentile-specific gains. We find that most of the difference between actual and expected growth results from individuals' ability to recover from previous negative losses, rather than from purely exogenous positive shocks.

The remainder of the paper is structured as follows. In Section 2 we characterize the counterfactual individual growth incidence curve (CIGIC), introduce the concept of pro-poor shock within the individual growth incidence curve (IGIC) framework, and present the statistical inference procedures applied. An empirical illustration is presented in Section 3, based on data from Indonesia for 2000–14. Section 4 concludes.

2 Setting

2.1 The counterfactual individual growth incidence curve

Let $F(y_{t-1})$ denote the cumulative distribution function (*cdf*) of the income observed in time $t-1$ of a population with bounded support $(0, y^{max})$ and finite mean $\mu(F) = \int_0^{y^{max}} y\, dF(y)$. The left inverse continuous distribution function or quantile function, showing the income of an individual occupying position $p_{t-1} \in (0,1)$ in the distribution of incomes ranked in increasing order, is defined as $F^{-1}(p_{t-1}) \coloneqq \inf\{y_{t-1}: F(y_{t-1}) \geq p_{t-1}\}$.

To simplify the exposition, in the remainder of the paper we equivalently denote the quantile function with $y_{t-1}(p_{t-1})$. Likewise, $F(y_t)$ denotes the *cdf* of income observed in period t, while $y_t(p_{t-1})$ denotes the income experienced in time t by the individual ranked p_{t-1} in period $t-1$.

We rely on the non-anonymous version of the growth incidence curve (also denoted as *individual* GIC, IGIC), where the identity of each individual is formalized by their rank in the initial income distribution. Following Grimm (2007), in such a setting, the income growth rate experienced by the individuals located at the pth percentile in period $t-1$ can be formalized as:

$$g_t(p_{t-1}) = \frac{y_t(p_{t-1})}{y_{t-1}(p_{t-1})} - 1 \quad (1)$$

And, by integrating the area below the IGIC up to the initial headcount index H_{t-1}, one obtains the individual rate of pro-poor growth (IRPPG)—that is:

$$IRPPG_t = \frac{1}{H_{t-1}} \int_0^{H_{t-1}} g_t(p_{t-1})\, dp_{t-1} \quad (2)$$

which defines as pro-poor a non-anonymous pattern of growth if it is positive (absolute definition), or if it is larger than the average growth rate measured over the entire distribution (relative definition).

At the generic time t, the observed income y of each individual is defined as a function of a vector of the individual's characteristics C and a measurement error, ε, which represents the individual's propensity to misreport their income.[5] That is, the observed income can be formalized as

$$y_t = f_t(C_t, \varepsilon_t) \tag{3}$$

Given the income function shown in Equation 3, the non-anonymous income growth rate of the individual located at the generic pth percentile in period $t-1$, defined in Equation 1, can be rewritten as:

$$g_t(p_{t-1}) = \frac{f_t(C_t, \varepsilon_t)}{f_{t-1}(C_{t-1}, \varepsilon_{t-1})} - 1 \tag{4}$$

Looking at Equation 4, one may note that the initial percentile-specific income growth rate can be associated with either changes in the function f or variations in its arguments, i.e. the set of individual characteristics C (such as education, employment status, age, and household demographic characteristics) and measurement error ε. More specifically, for a given set of individual characteristics, changes in the function f can be interpreted as variations of the marginal returns associated with such characteristics. As to the argument of the function f, while characteristics may change over time, we assume that individuals' propensity to under-/over-report their income is constant over time, i.e. $\varepsilon_t = \varepsilon_{t-1} = \varepsilon$.

To investigate to what extent these percentile-specific income dynamics are driven by changes in individual characteristics or by shocks in the economy that modify the marginal returns of characteristics, we derive a CIGIC showing the income that the individual located at the generic pth percentile would experience in period t if their current characteristics exhibit the same marginal returns as in period $t-1$, i.e. $f_{t-1} = f_t$.

Let $\hat{y}_t^j(p_{t-1})$ denote the income of the individual ranked in the pth position in time $t-1$, which is predicted according to that individual's attributes at the beginning of period t (including income of the previous period); then, the CIGIC can be formalized as:

$$\hat{g}_t^j(p_{t-1}) = \frac{\hat{y}_t^j(p_{t-1})}{y_{t-1}(p_{t-1})} - 1 = \frac{f_{t-1}(C_t, \varepsilon)}{f_{t-1}(C_{t-1}, \varepsilon)} - 1 \tag{5}$$

where the subscript j indicates that the predicted income of each individual results from two alternative regression models. Specifically, when $j = QR$ we extract the predicted values ($\hat{y}_t^{QR}$) from a quantile regression that models the conditional quantiles p of the joint distribution of income and its predictors as:

$$Q_p log(y)_{i,t} = \beta_0(p) + \beta_1(p)C_{i,t} + \beta_2(p)log(y)_{i,t-1} + \vartheta_d + u_{i,t} \tag{6a}$$

[5] As recently investigated by Angel et al. (2019), measurement error in reported income occurs, for example, because of the presence of a social desirability bias in survey response or specific sociodemographic characteristics of the respondents. When per capita consumption expenditure is used as a proxy for individual wealth (as in the empirical application of this paper), its misreporting is mostly related to sociodemographic characteristics of the respondents, the recall bias, and the survey design.

with the terms ϑ_d and $\xi_{i,t}$ denoting the location (e.g. province or district) fixed effects and the error term respectively, with $p = .20, .40, .60, .80$. When $j = FE$ instead, the fitted values are extracted from the following panel two-way regression model:

$$log(y)_{i,t} = \beta_0 + \beta_1 C_{i,t} + \beta_2 log(y)_{i,t-1} + \tau_t + \mu_i + \vartheta_d + u_{i,t} \tag{6b}$$

where the term τ_t denotes the year dummies, the parameters μ_i and ϑ_d are the individual and the location fixed effects respectively, and $u_{i,t}$ represents the residual term. The fitted values obtained from both models capture the idea that the individual marginal returns are constant over time. By relaxing the common regression slope assumption, the model produced by Equation 6a also captures the idea that the effect of the income predictors changes according to the individual's rank in the income distribution.

According to the model produced by Equation 6b, the returns are instead fixed over time and along the distribution. By adding the prediction of the individual fixed effects to the standard fitted values, $\hat{y}_t^{FE}$ captures the effects of changes in observed individual characteristics and of unobserved time-invariant characteristics.

We define a shock as an unexpected increase or decrease in the marginal returns of the individual characteristics. To gauge the impact of such shocks on the upward and downward mobility patterns, we need to compare the IGIC in Equation 4 with the CIGIC in Equation 5. The differential between these two curves is defined as

$$\Delta g_t = g_t(p_{t-1}) - \hat{g}_t^j(p_{t-1}) = \frac{f_t(C_{t,}\varepsilon) - f_{t-1}(C_{t,}\varepsilon)}{f_{t-1}(C_{t-1,}\varepsilon)} \tag{7}$$

This residual can be interpreted as an upper bound of the impact of the shock. That is, the differential defined in Equation 7 corresponds to a broad measure of the impact of the shock on the percentile-specific income growth rates, as it includes both the effect of changes in marginal returns of individual characteristics (i.e. changes in the function f) and variations of unobserved characteristics and their associated returns that influence individual incomes.

By using Equation 7, we define a shock as pro-poor in *absolute* terms if the average of the Δg_t up to the poverty line is positive, i.e. if the positive differences between the IGIC and the CIGIC more than compensate the negative ones for all percentiles up to the poverty line. That is, an absolute index of pro-poorness of shocks can be formalized as

$$PPS_t = \frac{1}{H_{t-1}} \int_0^{H_{t-1}} \Delta g_t(p_{t-1})\, dp_{t-1} \tag{8}$$

A *relative* definition of pro-poor shock requires that the differential defined in Equation 7 is on average larger for the poor than for the rich. That is, let γ_t denote the average difference between the IGIC and the CIGIC over the entire distribution; then, a shock is pro-poor in relative terms if $PPS_t > \gamma_t$.

2.2 State-dependency, sample retention, and recovery from past negative shocks

When examining the role that shocks have on the mobility patterns over subsequent spells of growth, a complementary exercise is to assess the nature of the shocks themselves. For example, one could ask whether the positive shock implied in the setting characterized by $IRPPG > 0$ and $PPS > 0$ is the outcome of a genuine positive shock experienced by the initially poorer, or if it is a consequence of a recovery from past negative shocks. In order to answer this question, we need to assess, from an inter-temporal perspective, whether there is some form of state-dependence or current positive shocks are exogenous to past negative shocks.

Given the definitions in Equations 5, 6a, and 7, an individual positive shock ($ps_{i,t}$) can be defined as a binary indicator equal to 1 if $y_t - \hat{y}_t^{QR} > 0$, and equal to 0 otherwise.

Let's start by assuming that each individual has a latent propensity to experience a positive shock in time t, and let's set the hypothesis that this is a function of a vector, $\mathrm{X}_{i,t-1}$, of individual and place-of-residence characteristics and of the individual's propensity to have experienced a negative shock in the past ($ns_{i,t-1}^{*}$) and to have been retained[6] in the sample ($r_{i,t}^{*}$):

$$ps_{i,t}^{*} = f(ns_{i,t-1}^{*}, r_{i,t}^{*}, \mathrm{X}_{i,t-1}) \tag{9}$$

Following the approach proposed by Cappellari and Jenkins (2004, 2008), $ns_{i,t-1}^{*}$ can be defined as:

$$ns_{i,t-1}^{*} = \eta Z_{i,t-1} + \epsilon_i \tag{10a}$$

where Z is a vector of socioeconomic variables, including parental socioeconomic background. If this propensity exceeds some unobserved value (which can be set equal to 0), a negative shock is observed:

$$ns_{i,t-1} = 1\left[\, ns_{i,t-1}^{*} > 0\right] \tag{10b}$$

with $ns_{i,t-1}$ being the observable binary indicator, equal to 1 if $y_{t-1} - \hat{y}_{t-1}^{QR} \leq 0$ and to 0 otherwise.

The individual's chances of remaining in the sample are captured by $r_{i,t}^{*}$, the individual's latent propensity to be retained—which is a function of a vector W of individual and household characteristics, including the variables in Z and additional covariates on the quality of the interview:

$$r_{i,t}^{*} = \zeta W_{i,t-1} + \varepsilon_i \tag{11a}$$

whose observed counterpart is:

$$r_{i,t} = 1\,[\, r_{i,t-1}^{*} > 0] \tag{11b}$$

Following the procedures recommended and adopted in Sarkar et al. (2019), Tunali (1986), and Vella (1998), we focus on the *recovery* case (i.e. $ns_{i,t-1} = 1$ and $r_{i,t} = 1$), estimate Equations 10a and 11a simultaneously with a bivariate probit selection model, and extract the following two selection correction terms:

[6] Attrition is an issue that in our setting can arise from either sample attrition or missing per capita expenditure (in years $t-2$, $t-1$, and t) and/or in all the other variables used to obtain predicted per capita expenditure. If sample dropouts are not random and individuals with less favourable characteristics are also less likely to stay in the sample, our estimated transition probability of a positive shock experience in time t will be biased.

$$\lambda'_{i,t-1} = \phi(\eta Z_{i,t-1}) \frac{\Phi\left(\frac{\zeta W_{i,t-1} - \rho\eta Z_{i,t-1}}{\sqrt{1-\rho^2}}\right)}{\Phi_2(\eta Z_{i,t-1}, \zeta W_{i,t-1}; \rho)} \tag{12a}$$

and

$$\lambda''_{i,t-1} = \phi(\zeta W_{i,t-1}) \frac{\Phi\left(\frac{\eta Z_{i,t-1} - \rho\zeta W_{i,t-1}}{\sqrt{1-\rho^2}}\right)}{\Phi_2(\eta Z_{i,t-1}, \zeta W_{i,t-1}; \rho)} \tag{12b}$$

where $\Phi_2(.)$ is the bivariate standard normal distribution function, $\phi(.)$ and $\Phi(.)$ are the standard normal density and cumulative distribution functions, and $\rho = corr(\epsilon_i, \varepsilon_i)$.

To test for the true exogeneity of positive shocks, we include the correction terms $\lambda'_{i,t-1}$ and $\lambda''_{i,t-1}$ in a linear probability model[7] of 'recovery' which estimates the probability of experiencing a positive shock in time t, conditional on negative shock experience in the past and sample retention:

$$Prob\ (ps_{i,t} = 1 \mid ns_{i,t-1} = 1, r_{i,t} = 1) = \alpha X_{i,t-1} + \beta\lambda'_{i,t-1} + \gamma\lambda''_{i,t-1} + u_{i,t} \tag{13}$$

If $\beta = \gamma = 0$, we can conclude that if a positive shock experienced at time t is observed this cannot be identified as a recovery from negative shock in the past, nor can it be due to sample retention.

3 Empirical application

This section presents the empirical application of the approach proposed in the previous section. By using the IGICs and the corresponding CIGICs, we first illustrate the income growth process experienced in Indonesia over the period 2000–14. We distinguish two subperiods, 2000–07 and 2007–14. The pattern of IGICs and CIGICs and the differences among them at any percentile are informative of the impact of mobility on the pro-poorness of growth and on the role of shocks in shaping the observed mobility patterns. Second, to test the significance and heterogeneity of the growth processes we apply the Kolmogorov-Smirnov (KS) and Cramér-von Mises (CVM) tests. Third, we assess the nature of the shocks by implementing the procedure described in Section 2.2.

3.1 Data

The empirical analysis relies on data from the Indonesia Family Life Survey (IFLS), one of the largest longitudinal developing-country survey data sets. We use three waves (2000, 2007, and 2014[8]), and mobility patterns are evaluated in terms of changes in household per capita consumption expenditure, which is a suitable proxy for household wellbeing in developing countries. Heterogeneities in prices across time and space are taken into account by using temporal

[7] The application of a linear probability model in this context facilitates the inclusion of the correction terms and the interpretation of their coefficients.

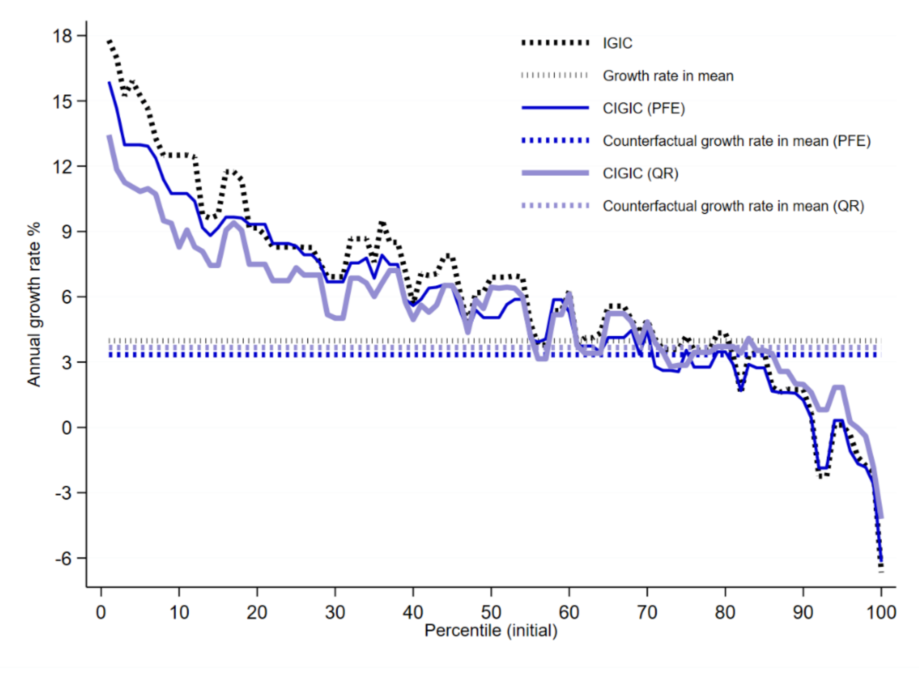
[8] For 2000 (IFLS3), see Strauss et al. (2004); for 2007 (IFLS4), see Strauss et al. (2009); for 2014, (IFLS4), see Strauss et al. (2016).

and spatial deflators with reference to Jakarta prices in 2002.[9] To construct a counterfactual GIC we use observed per capita expenditure in year $t-1$ and predicted per capita expenditure in year t, which is estimated using information on per capita expenditure in the previous wave, household sociodemographic characteristics (residence and composition by age group), and household head characteristics (gender, age, education, and employment status). For the second part of our analysis (i.e. the procedure illustrated in Section 2.2) we also use IFLS2 from 1997 (Frankenberg and Thomas 2000)) to retrieve the variables that are necessary to estimate $\hat{y}_{t-1}^{QR}$ and all the explanatory variables used in columns 1 and 2 of Table 5.

3.2 Results

Figures 1 and 2 illustrate the growth process experienced in Indonesia over the periods 2000–07 and 2007–14 respectively, while Table 1 reports some summary statistics about these processes. The black dashed curve corresponds to the IGIC, which describes the observed percentile-specific mobility patterns, while the two continuous curves are associated with the CIGICs, showing the counterfactual scenario under the hypothesis of no changes in the marginal return of individual characteristics. In both subperiods the actual impact of mobility on growth was pro-poor, with individuals ranked below the 70th percentile experiencing an income growth rate larger than average.

Figure 1: IGIC and CIGICs, Indonesia 2000–07

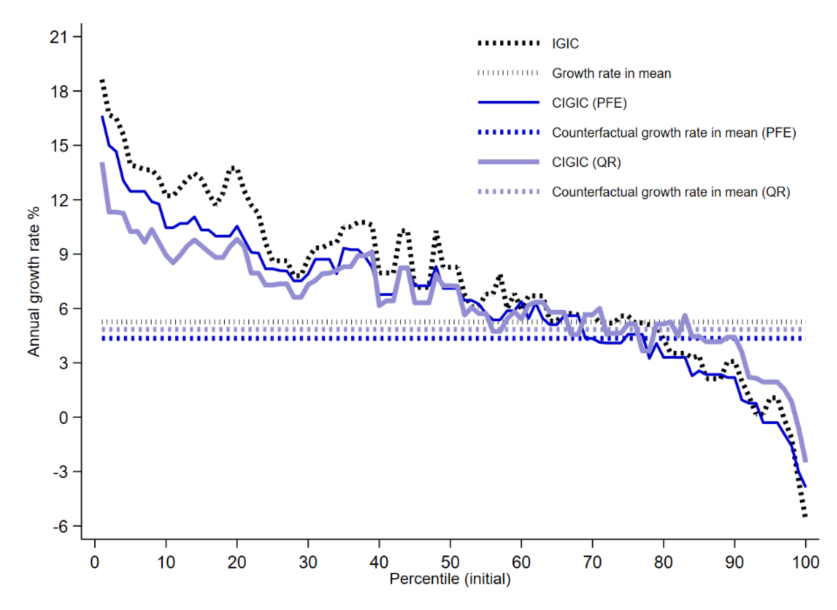


Notes: PFE = panel fixed effects regression; QR = quintile regression.

Source: authors' illustration based on IFLS data.

[9] Data on both the consumer price index (CPI) and regional poverty lines (urban and rural) come from Indonesia's central statistics agency, Badan Pusat Statistik (BPS 2020a, 2020b).

Figure 1: IGIC and CIGICs, Indonesia 2007–14



Source: authors' illustration based on IFLS data.

The two CIGICs exhibit the same pattern as the IGIC. The counterfactual based on the panel fixed effect regression (CIGIC-PFE) tends to lie at no point above the IGIC, with almost no differences between IGIC and CIGIC at the bottom 30 percentiles and at the 70th to 100th percentiles. The CIGIC obtained using quintile regression (CIGIC-QR) instead is located below the CIGIC-PFE and below the IGIC up to the 40th percentile, while for the top 20 percentiles the rank between the actual and counterfactual curves is reversed, with the CIGIC-QR placed above the actual one. The three curves tend to coincide at the 40th percentile and along the 60th to 80th percentiles.

It can be noted, moreover, that the difference between the two CIGICs, which can be attributed to unobserved time-invariant individual characteristics that are not accounted for in the CIGIC-QR, is largest along the first to tenth percentiles and again from the 20th to 30th percentiles. In the second period the distance between the two counterfactual curves is instead larger for the bottom and top 20 per cent of the initial distribution.

Overall, the ranking between the actual and the two counterfactual curves suggests that in both periods the income growth rates experienced by the individuals initially located at the bottom part of the distribution were larger than expected.[10] Assuming that individuals' propensity to under-/over-report their income is constant over time, this can be interpreted as an upper bound of the impact of a positive shock on the income growth rates of the initially poor. Given the definitions

[10] The ranking between the actual IGIC and each of the two CIGIC is reflected in the difference between the actual and predicted annual growth rates in mean reported in Table 1. We observe substantial differences when the actual growth rate in mean is compared with the predicted rate based on the panel fixed effects regressions. Recall that the expectation that the actual and predicted growth rates in mean should be the same would be fulfilled if the negative differences between actual and predicted growth for some individuals are compensated by positive actual–predicted differences for other individuals (due, for example, to different types of shocks at different parts of the distribution and, taking into account measurement error, systematic under- and over-reporting of income at the top and bottom of the distribution). We observe that the CGIC-PFE tends to lie below the IGIC at the bottom of the distribution, and then to basically overlap with it. So the observed difference between the actual and predicted growth rates in mean reflects the fact that the 'positive shocks' (or—as we will show in the second part of the analysis—the dissipation of previous negative shocks) take place only in one part of the distribution.

provided in Section 2.1, this positive shock is the gross effect of changes in marginal returns of individual characteristics (e.g. changes in the broader structure of the economy that favoured the income growth of the poor), and of variations in individual unobserved characteristics (e.g. improvements in education and occupation levels) and associated returns that influence individual incomes. The proposed measure of the shock pro-poorness, i.e. the index PPS, is indeed positive and decreasing over the income distribution (see Table 1), with the largest values associated with the period 2007–14.

Table 1: Summary statistics on pro-poorness of growth and shocks

PANEL A: Predicted values from panel fixed effects regressions	Actual	2000–07 Predicted	Actual	2007–14 Predicted
Annual growth in mean	3.98	3.34	5.26	4.35
IRPPG 10	14.47	12.71	14.90	13.10
IRPPG 25	11.77	10.56	13.19	11.21
IRPPG 50	9.59	8.56	11.16	9.62
PPS 25		1.17		2.03
PPS 50		0.99		1.54
PPS 75–100		0.30		0.47
PANEL B: Predicted values from quintile regressions	Actual	2000–07 Predicted	Actual	2007–14 Predicted
Annual growth in mean	3.98	3.67	5.26	4.85
IRPPG 10	14.47	10.71	14.90	10.75
IRPPG 25	11.77	8.92	13.19	9.62
IRPPG 50	9.59	7.50	11.16	8.56
PPS 25		2.82		3.63
PPS 50		2.07		2.58
PPS 75–100		−0.87		−1.26

Source: authors' estimations based on IFLS data.

The observed negative slope of our IGICs and CIGICs might, however, simply result from 'convergence' of incomes or 'regression towards the mean'. This is indeed a *leitmotif* of the na-GICs that have been estimated so far in the literature for different countries, including Indonesia (Grimm 2007; Lo Bue and Palmisano 2020). In order to understand to what extent the observed pattern is a pure Galtonian process, we need to first test if the actual expenditure dynamics simply result from non-classical measurement error, generating a spurious relation between the base-year reported income and the associated income change.

Second, our results for both the actual and counterfactual mobility patterns have to be validated against the constant distribution and the distribution-neutral growth hypotheses. This inference procedure, based on the KS and CVM tests and recently applied by Ferreira et al. (2018) in the context of anonymous GICs, checks whether (i) the actual and predicted income dynamics that we observe for any initial percentile are statistically different from zero, and (ii) these dynamics are not significantly different along the initial distribution, i.e. IGIC and CIGIC are equal to the average growth rate for all percentiles.

The first validation exercise is conducted following the approach proposed by Fields et al. (2003) and applied in the context of na-GICs by Grimm (2007). The test considers the ratio of the minimum amount of variance of stochastic measurement error relative to variance of true income that would be required to overturn the observed pattern of convergence. If this ratio is large enough to exceed a critical threshold, the downward pattern of our estimated IGICs can be evaluated as robust against the hypothesis of regression to the mean.

The test, which is conducted for different combinations of the serial correlation coefficient and of the correlation between base-year expenditure and measurement error, is shown in Table 2. Results suggest that the estimated negative slope of the IGIC is strongly robust against measurement error in the first period, with the ratios largely exceeding the value 0.9, and moderately robust in the second, where the ratios are in the range 0.3 to 1.08.[11]

Table 2: Ratio of measurement error variance to true expenditure variance, implying zero correlation between true initial expenditure and true change in expenditure.

Correlation between base-year expenditure and measurement error	Serial correlation coefficient	2000–07 $\beta = -0.711$	2007–14 $\beta = -0.457$
0	0	2.463	0.841
0	0.1	3.768	1.031
0	0.2	8.015	1.331
−0.1	0	1.995	0.681
−0.1	0.1	3.052	0.835
−0.1	0.2	6.492	1.078
−0.2	0	1.577	0.538
−0.2	0.1	2.412	0.660
−0.2	0.2	5.129	0.852
−0.4	0	0.887	0.303
−0.4	0.1	1.357	0.371
−0.4	0.2	2.885	0.479

Source: authors' estimations based on IFLS data.

The results for the second validation exercise are reported in Table 3. As the figures suggest, the observed dynamics described by the actual and counterfactual curves are found to be statistically significant by the inference tests for the significance and uniformity of the growth process. The KS and the CVM tests reject the null hypothesis that the observed growth process is static and distribution-neutral over the period considered, i.e. the IGIC is strongly significantly different from zero and from the average growth for any percentile in both subperiods.

Moreover, the two tests reject the null hypothesis that in both periods our counterfactual income distributions did not change at all.

When we test the distribution neutrality of the growth process, conditional on the joint distribution of covariates, both the KS and the CVM tests reject the null hypothesis that the CICIGs are equal to the average growth rate at any percentile, which is consistent with the heterogeneous patterns illustrated in Figure 1 and Figure 2.

[11] By relying on two validation studies based on US data, Fields et al. (2003) assume that a credible range for the minimum critical threshold of this ratio is equal to about 0.1 to 0.3.

Table 3: Kolmogorov-Smirnov (KS) and Cramér-von Mises (CVM) tests

Null hypothesis		2000–07 KS	*Critical values 1%*	*5%*	*10%*	2007–14 KS	*Critical values 1%*	*5%*	*10%*
IGIC	$g(p) = 0$	0.178	0.109	0.094	0.089	0.186	0.116	0.104	0.100
	$g(p) = \bar{g}$	0.130	0.109	0.094	0.089	0.133	0.117	0.106	0.101
CIGIC (FE)	$\hat{g}^{FE}(p) = 0$	0.159	0.082	0.075	0.071	0.166	0.077	0.073	0.069
	$\hat{g}^{FE}(p) = \bar{g}^{FE}$	0.117	0.082	0.076	0.072	0.104	0.078	0.072	0.069
CIGIC (QR)	$\hat{g}^{QR}(p) = 0$	0.134	0.094	0.084	0.079	0.141	0.096	0.084	0.079
	$\hat{g}^{QR}(p) = \bar{g}^{QR}$	0.096	0.095	0.085	0.079	0.089	0.097	0.083	0.079

Null hypothesis		2000–07 CVM	*Critical values 1%*	*5%*	*10%*	2007–14 CVM	*Critical values 1%*	*5%*	*10%*
IGIC	$g(p) = 0$	6.637	2.712	2.551	2.462	7.864	2.727	2.615	2.534
	$g(p) = \bar{g}$	3.475	2.676	2.513	2.438	3.629	2.714	2.605	2.519
CIGIC (FE)	$\hat{g}^{FE}(p) = 0$	5.863	2.005	1.891	1.849	6.748	1.968	1.857	1.812
	$\hat{g}^{FE}(p) = \bar{g}^{FE}$	3.161	1.977	1.883	1.839	3.116	1.918	1.827	1.775
CIGIC (QR)	$\hat{g}^{QR}(p) = 0$	5.505	2.283	2.161	2.096	6.518	2.305	2.124	2.073
	$\hat{g}^{QR}(p) = \bar{g}^{QR}$	2.393	2.271	2.148	2.081	2.244	2.284	2.115	2.057

Source: authors' estimations based on IFLS data.

As implied in our results so far, in both periods expenditure growth was generally progressive (pro-poor). The negatively sloped IGIC matches with expectations about what the relative gains at each percentile should be, given individual socioeconomic attributes and the returns associated with them. However, we observe that a sizeable part of this observed progressive pattern cannot be entirely explained by this, as the growth rates of the poor are significantly larger than expected.

We need, therefore, to understand if this unexpected positive growth for the poor resulted from events that do not relate to individual exposure to negative shocks in the past (e.g. changes in the labour market that increased the returns to education), or if the unpredicted income dynamics simply reflect individuals' recovery from past negative shocks, due for example to improvements in their ability to cope with negative shocks in the past or simply the dissipation of a past negative shock.

In order to shed light on this question, we consider for each of the two growth spells (2000–07 and 2007–14) the proportion of individuals who at the end of each period experienced a positive shock ($y_t - \hat{y}_t^{QR} > 0$), conditional on retention and on observing, at the beginning of the period, a negative income shock ($y_{t-1} - \hat{y}_{t-1}^{QR} \leq 0$). These individuals amount to about 24 per cent of the observations retained in the panel and about 13 per cent of the entire sample (see Table 4).

Attrition at t arises from either sample attrition or missing per capita expenditure and/or in all the other variables used to obtain predicted per capita expenditure.

Because individual shock experience is measured based on the household-level expenditure variable, the covariates used in the double selectivity regression model are also measured at the household level. More specifically, the covariates refer to the household head and his/her spouse (age, sex, employment status, education), and to the household itself (several variables summarizing household composition and parental socioeconomic background). The standard errors are bootstrapped and estimated to be robust to heteroscedasticity and arbitrary serial correlation among observations in the same province.

Table 4: State-dependence and initial shock experience, with and without non-retained sample

Panel (a) 2000–07	Status at time *t* − 1	Status at time *t*		
		$y_t > \hat{y}_t^{QR}$	$y_t \leq \hat{y}_t^{QR}$	*Not retained*
	Sample retained			
	$y_{t-1} > \hat{y}_{t-1}^{QR}$	28.41	24.26	
	$y_{t-1} \leq \hat{y}_{t-1}^{QR}$	24.56	22.77	
	All	52.97	47.03	
	All individuals			
	$y_{t-1} > \hat{y}_{t-1}^{QR}$	15.99	13.65	22.75
	$y_{t-1} \leq \hat{y}_{t-1}^{QR}$	13.82	12.81	20.98
	All	29.81	26.46	43.73
Panel (b) 2007–14		$y_t > \hat{y}_t^{QR}$	$y_t \leq \hat{y}_t^{QR}$	*Not retained*
	Sample retained			
	$y_{t-1} > \hat{y}_{t-1}^{QR}$	28.10	24.87	
	$y_{t-1} \leq \hat{y}_{t-1}^{QR}$	24.33	22.70	
	All	52.43	47.57	
	All individuals			
	$y_{t-1} > \hat{y}_{t-1}^{QR}$	14.91	13.20	24.35
	$y_{t-1} \leq \hat{y}_{t-1}^{QR}$	12.91	12.05	22.58
	All	27.83	25.25	46.93

Note: pooled transitions from IFLS, waves 2–5. Sample size (retained) = 15,960. Retained individuals are followed in 1997–2000–2007–2014 and with non-missing variables on per capita expenditure and its predictors in each year. Total sample size in Panel (a): 28,364. Total sample size in Panel (b): 30,073. Panel (a) includes individuals retained plus individuals with non-missing per capita expenditure in 1997 and 2000 and complete information on the predictors of per capita expenditure. Panel (b) includes individuals retained plus individuals with non-missing per capita expenditure in 2000 and 2007 and complete information on the predictors of per capita expenditure.

Source: authors' estimations based on IFLS data.

As implied by the estimated correlation term between negative shock experience at the baseline and retention (Table 5), those retained in the sample are less likely to experience a negative shock at the beginning of the first period. However, for the next period we do not find statistically significant evidence of initial-conditions selectivity of sample attrition.

We also observe that in both periods, individuals with a lower socioeconomic background are more likely to be retained in the sample. These are individuals from households in which the household head's spouse is an unpaid worker and has low education levels, with lower socioeconomic background associated with their family of origin. However, we see also that—apart from this common trend—the household demographic drivers of sample retention change substantially from one period to the other. Specifically, smaller households and households with family members above the age of 16 are more likely to drop out of the sample in the first period but more likely to be retained in the second period.

Table 5: Probability of retention and initial negative shock experience; marginal effects of explanatory variables

	(1)	(2)	(3)	(4)
	Retention	*Initial status:* $ns_{i,2000} = 1$	*Retention*	*Initial status:* $ns_{i,2007} = 1$
Age (years) of HH head	0.008***	0.009***	0.008***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Age squared of HH head	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Female-headed HH (dummy)	−0.016	−0.046***	−0.000	0.010
	(0.012)	(0.017)	(0.011)	(0.013)
Years of schooling HH head	−0.000	0.010***	−0.002*	0.028***
	(0.001)	(0.001)	(0.001)	(0.002)
Years of schooling HH spouse	−0.003*	−0.003	−0.007***	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
HH size	0.009	−0.098***	0.015*	−0.081***
	(0.009)	(0.012)	(0.008)	(0.013)
HH size squared	−0.001	0.005***	−0.001**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Ratio of family members aged 19+	−0.166***	0.263***	0.088**	0.314***
	(0.058)	(0.065)	(0.041)	(0.038)
Ratio of family members aged 16–18	−0.166***	0.225***	0.235***	0.336***
	(0.044)	(0.065)	(0.047)	(0.055)
Ratio of family members aged 13–15	−0.018	0.175***	0.275***	0.265***
	(0.069)	(0.066)	(0.052)	(0.036)
Ratio of family members aged 6–12	−0.069	0.050	−0.298***	0.083**
	(0.072)	(0.055)	(0.045)	(0.036)
HH head is government worker (dummy)	0.005	0.158***	-0.040	0.127
	(0.017)	(0.018)	(0.069)	(0.083)
HH head is private worker (dummy)	0.039***	−0.049***	0.012	−0.023
	(0.012)	(0.017)	(0.038)	(0.060)
HH head is unpaid worker (dummy)	0.000	0.024	0.131	−0.152
	(0.029)	(0.054)	(0.155)	(0.173)
HH spouse is government worker (dummy)	−0.017	0.151***	−0.317**	1.762***
	(0.029)	(0.036)	(0.129)	(0.055)
HH spouse is private worker (dummy)	0.035**	−0.104***	0.156	−0.019
	(0.014)	(0.027)	(0.136)	(0.261)
HH spouse is unpaid worker (dummy)	0.048***	−0.065***	0.174***	0.268**
	(0.014)	(0.018)	(0.068)	(0.105)
Parental SES: Mother’s education	−0.008***	0.001	−0.006***	−0.004**
	(0.002)	(0.001)	(0.001)	(0.002)
Parental SES: Father’s education	0.004**	−0.006***	−0.002	−0.003**
	(0.002)	(0.002)	(0.002)	(0.001)
Parental SES: Mother is retired (dummy)	−0.018	−0.002	0.016	−0.001
	(0.013)	(0.014)	(0.011)	(0.014)
Parental SES: Father is retired (dummy)	0.005	−0.010	−0.013	−0.016
	(0.013)	(0.011)	(0.010)	(0.010)

Parental SES: Mother is unemployed (dummy)	−0.046***	−0.004	0.003	−0.004
	(0.010)	(0.009)	(0.010)	(0.010)
Parental SES: Father is unemployed (dummy)	0.003	−0.005	−0.010	−0.008
	(0.013)	(0.010)	(0.010)	(0.010)
Accuracy of the interview (dummy)	0.047		0.121	
	(0.030)		(0.103)	
Rating of the interview missing (dummy)	0.018		−0.108***	
	(0.051)		(0.028)	
Seriousness of the interview (dummy)	0.070*		0.029	
	(0.038)		(0.091)	
Observations	28,345	28,345	30,026	30,026
Correlation between unobservable factors affecting r_{it} and ns_{it-1}		0.034**		−0.156
Province fixed effects	Yes	Yes	Yes	Yes

Notes: HH = household; SES = socioeconomic status. Robust standard errors clustered at the province level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. For each sample, estimates are obtained from a bivariate probit model that jointly estimates the probability of initial status and retention, following the double selectivity model. Omitted category for the employment of HH head and HH head's spouse is self-employment.

Source: authors' estimations based on IFLS data.

When looking at the drivers of negative shock experience at the baseline, our results suggest that, overall, lower socioeconomic background (as proxied by years of education of the household head and his/her parents), as expected, increases the likelihood of a negative shock.[12]

Turning to the individual probability of recovery (i.e. positive shock experience, conditional on previous negative shock experience), we observe in Table 6 that this tends to be higher for individuals with a lower socioeconomic background. Moreover, the coefficients of the selection correction terms on initial negative shock experience and retention are individually and jointly significant in both periods.

We find strong statistical evidence of state-dependence in those 'unexpected gains' which shaped the mobility patterns of the individuals observed in 2000–07. The selection term is positive and significant at the 1 per cent level, implying that the unobserved factors that raised the probability of experiencing a negative shock at the baseline also increased the chances of recovering from the shock at the end of the period. This counteractive result should be interpreted in light of our definition of shocks, which simply takes into account the difference between actual and predicted expenditure. Therefore, for the first period it is more likely that the unobserved gains in mobility are related to systematic bias in reporting expenditure than to a genuine shock or recovery from a shock.

For the second period, we see instead (although this is associated with a weaker level of statistical significance) that the progressive pattern of the CIGIC can be explained by recovery from a negative shock experience at the baseline, especially among the initially poorer.

[12] However, a possibly counterintuitive result is given by the coefficient on the dummy for the household spouse being a government worker. Here we observe that individuals from such households are, with respect to the case where the household head's spouse is self-employed, more likely to experience a negative shock at the baseline. This result could be due to under-reporting of consumption expenditure by individuals belonging to the upper part of the distribution.

Table 6: Probability of experiencing a positive shock, conditional on past negative shock and retention

	(1)	(2)
	Recovery in 2007	*Recovery in 2014*
Age (years) of HH head	−0.002	−0.009***
	(0.002)	(0.002)
Age squared of HH head	0.000	0.000***
	(0.000)	(0.000)
Female-headed household (dummy)	−0.006	−0.015*
	(0.010)	(0.008)
Years of schooling HH head	−0.004***	−0.013***
	(0.001)	(0.003)
Years of schooling HH spouse	−0.003***	−0.002**
	(0.001)	(0.001)
HH size	0.030***	0.078***
	(0.011)	(0.009)
HH size squared	−0.002***	−0.004***
	(0.001)	(0.000)
Ratio of family members aged 19+	−0.069*	−0.247***
	(0.040)	(0.036)
Ratio of family members aged 16–18	−0.036	−0.274***
	(0.037)	(0.042)
Ratio of family members aged 13–15	−0.044	−0.147***
	(0.036)	(0.037)
Ratio of family members aged 6–12	−0.140***	−0.083***
	(0.029)	(0.027)
HH head is government worker (dummy)	−0.017	−0.081
	(0.018)	(0.051)
HH head is private worker (dummy)	−0.020**	0.047**
	(0.008)	(0.020)
HH head is unpaid worker (dummy)	−0.015	−0.111
	(0.020)	(0.123)
HH spouse is government worker (dummy)	0.018	−0.120
	(0.021)	(0.140)
HH spouse is private worker (dummy)	−0.025	0.030
	(0.016)	(0.118)
HH spouse is unpaid worker (dummy)	−0.023**	−0.034
	(0.011)	(0.059)
Selection—retention	0.259***	0.167***
	(0.031)	(0.011)
Selection—negative Shock at time $t - 1$	0.254***	−0.086*
	(0.062)	(0.051)
Constant	0.455***	0.987***
	(0.085)	(0.084)
Observations	19,891	21,579
R-squared	0.065	0.089
Province fixed effects	Yes	Yes

Notes: bootstrapped standard error in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Omitted category for employment of HH head and HH head's spouse is self-employment.

Source: authors' estimations based on IFLS data.

4 Concluding remarks

Growth incidence curves are the main tool proposed to assess the distributive impact of growth. However, this tool is unsatisfactory for a deeper investigation of the nature of the observed growth pattern, which can mask either measurement errors or the presence of shocks affecting percentiles in different ways.

This paper offers a guide to correctly interpreting the pro-poorness and mobility implications of growth processes within the context of the na-GIC framework. As a first step, we compare the actual growth episodes at each percentile of the initial personalized distribution with a counterfactual pattern of income growth predicted on the basis of individual attributes. As a second step, we examine the difference between actual and counterfactual individual growth rates. This allows us to understand whether unpredicted positive growth for the initially poor is the result of genuine positive shocks, favouring upward mobility, or whether it can be attributed to processes of state-dependence and so to individual ability to recover from previous negative shocks. The methodological framework is applied in the context of a sample of 15,960 individuals from Indonesia followed over two seven-year periods, 2000–07 and 2007–14. Our results document that there has been substantial and significant upward mobility among the initially poorer. However, a significant part of this progressive growth cannot be reconciled with either unobserved individual endowments or changes in certain socioeconomic attributes. The lion's share in explaining the difference between actual and expected growth rate is taken by recovery from previous negative shocks. That is, according to the framework proposed in this paper, we cannot reject the hypothesis of state-dependency, as the unexpected positive gains for the initially poorer were not exogenous to initial shock experience and sample retention. For Indonesia, the period considered in this paper has been one of rapid and sharp changes in the economy and in society. The year 2000 marked the transition from the autocratic rule of Suharto, the recovery from the Asian financial crisis, the beginning of a process of decentralization, and, subsequently, the commodity boom—four different economic, political, and social events that arguably had an impact on people's lives and so on their income trajectories. Several studies (Bresson et al. 2017; Grimm 2007; Lo Bue and Palmisano 2020), including the present one, have shown that there has been growth in this period, and that the incidence of growth has been larger among the initially poor. But why do the poor exhibit higher growth rates than those individuals initially belonging to richer percentiles? The findings of this study, which can be reconciled with the snapshot of rising inequality and falling poverty depicted by the World Bank (2016), suggest that what is observed is the product of the coexistence of high vulnerability and reactivity to shocks for the poor, and economic security for the middle and upper middle class, which continued to grow according to expectations. We do observe high mobility among the bottom 30 per cent, but this has to be interpreted simply as resilience and ability to escape chronic poverty, rather than as a signal of increased opportunities to climb the socioeconomic ladder.

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