Has Indonesia's Growth Between 2007-2014 Been Pro-Poor? Evidence from the Indonesia Family Life Survey

Ariza Atifan Gusti
Advisor: Dr. Paul Glewwe

University of Minnesota, Department of Economics

Abstract— **A country's economic growth is said to help the poor and eradicate poverty if it is pro-poor, in that its impacts are broad-based, and benefit the poor in absolute terms. This research seeks to explore whether Indonesia's sustained growth between 2007-2014 were pro-poor by examining a panel data of household survey results given by the Indonesian Family Life Survey. Furthermore, since measurement errors are plentiful especially in household survey datasets, appropriate measures will be taken to minimize the possible bias.**

I. Introduction

There is no denying that the growth of an economy can lead to reductions in poverty, especially in developing nations. The Department for International Development of the UK strongly advocates economic growth for developing countries, stating that it is the most potent tool in reducing poverty and enhancing the quality of life in those countries (DFID, 2008). However, the extent to which economic growth can help the poor and eradicate poverty depends on how broad-based the growth is. One recent notion to describe growth that boosts the poor's income and possible outcomes, is pro-poor growth. An economy's growth is said to be pro-poor if and only if there are benefits reaped by the poor in absolute terms, as indicated by an appropriate measure of poverty (Ravallion and Chen, 2003).

How pro-poor a country's economic growth has been is an increasingly popular topic for economists and other academics alike. This study will contribute to the literature surrounding pro-poor growth by investigating whether Indonesia's recent economic growth has been pro-poor. Over the last 15 years, Indonesia has experienced sustained economic growth. The average annual GDP per capita growth rate is 5.4%, leading to its inclusion as the only South-East Asian country in the G20 (World Bank, 2016). However, this rapid growth has not been enjoyed by households at all levels of income. Inequality in Indonesia has been rising rapidly, as indicated by an increase in the Gini coefficient from 0.31 points in 2000 to 0.43 in 2013 (ADB, 2015). Consumption is also very unevenly distributed, with the richest 10% now consuming as much as the poorest 54% (World Bank, 2016).

This study tries to capture the extent to which this economic growth is pro-poor by drawing upon Glewwe and Dang (2011), who analyzed Vietnam's economic growth in the 1990s. Following their approach, this study employs two methods to examine whether Indonesia's growth has been pro-poor. The first method is a cross-sectional analysis of household consumption that compares the mean of per capita expenditures of a given quintile of the population in two different years. The second method compares, for a given quintile, the same households' mean per capita expenditures both in the first and second year, regardless of the quintiles those households are placed in the second year.

This article utilizes two of the most recent iterations of the Indonesia Family Life Survey (IFLS): the IFLS4, which was conducted in 2007 and the IFLS5, which was conducted in 2014. Since household surveys datasets are utilized, the main concern with the analysis is the presence of substantial measurement error in household survey datasets, which would cause serious bias in the results. Thus, a large part of this study involves trying to correct for measurement error to minimize the resulting bias. This is achieved by using instrumental variables and simulating the joint distribution of expenditure levels at two points in time.

This paper proceeds as follow. Section 2 presents a literature review of current theories of pro-poor growth. Section 3 reviews the quantitative methodology underpinning this study, with a strong focus on how to correct for measurement error. Section 4 presents the results of the analyses conducted. Section 5 concludes.

II. Literature Review

The notion of economic growth reducing poverty was first developed in the 1950s and 1960s, with the introduction of the trickle-down development concept. The trickle-down effect revolved around the idea that the benefits of economic growth vertically flow from rich to poor (Kakwani and Pernia, 2000). However, by turn of the century, this idea was widely contested as growth that consistently favors the rich which would instead result in a persistent increase in inequality between rich and poor (ADB 1999,6).

As a result, the concept of pro-poor growth has since gained in popularity among economists. However, although pro-poor growth has been an increasingly popular topic of discussion, there is not yet a widely-accepted definition of pro-poor growth nor a framework to determine whether an economy's growth is pro-poor. Ravallion and Chen (2003) deem pro-poor growth to be when the poor reap benefits of growth in absolute terms. This absolute benefit results in an absolute decrease in the level of poverty. However, many view this definition as too loose since it pertains solely to the poverty rate and ignores the socioeconomic gap between income groups.

Considering the distribution of growth between the poor and non-poor, Kakwani and Pernia (2000) define pro-poor growth as inclusive economic growth that provides, proportionally, more benefit to the poor than to the rich. They also argue that pro-poor growth is achieved by intentionally favoring the poor over the rich. Similarly, Grosse et al. (2008) state that growth is said to be pro-poor in the strongest sense when the poor's income growth rates are strictly higher than the non-poor's, which results in a decrease in inequality.

III. Methodology

As mentioned above, this study follows the approach of Glewwe and Dang (2011) to analyze whether Indonesia's growth has been pro-poor. This approach incorporates two independent analytical frameworks. The first involves a cross-sectional analysis of the mean per capita expenditure of each quintile in the first year with the mean per capita expenditure of households in that same quintile in the second year. In contrast, the second takes advantage of the availability of panel data, and compares the mean per capita expenditure of the same households in each quintile over time regardless of which quintile the households are in for the second year. In both frameworks, sample households were divided into five quintiles in the first year according to their real per capita expenditure. Therefore, the first quintile represents the poorest 20% of the population while the fifth quintile represents the richest 20% of the population. If we assume that there is income mobility in that some households move to different quintiles between the two periods, then we expect the second method to generally produce results with higher growth rates for the poorest quintile than the first method.

Both methods produce useful interpretations of pro-poor growth. The first method is beneficial in that it shows the distribution of income in a country across quintiles and reflects the changes in inequality over time. On the other hand, the second approach reveals the degree of mobility for the poor to move into higher quintiles and therefore reflects the extent to which the growth of an economy can reduce inequality and eradicate poverty.

A. Data and Estimation Issues

The data utilized in this study were obtained from the Indonesia Family Life Survey, an ongoing longitudinal socioeconomic and health survey of a sample of households representative of about 83% of the Indonesian population. Dating back to the first version in 1993, four more iterations of the IFLS have been implemented, with the most recent completed in 2014. This study uses IFLS 4 and IFLS 5, conducted in 2007 and 2014, respectively. Every wave of the survey targets the original households/respondents initially interviewed in IFLS 1, along with their split-offs. Split-off members are those family members who have moved from the original household, as identified in the previous waves of survey, and are therefore counted in a new household. As a result, the number of households interviewed grew from 7,224 households in 1993 to 16,204 households in 2014.

The IFLS provides information on individuals, their families, households, communities, and health and educational facilities. In assessing whether economic growth has a substantial impact on household welfare, the two most important variables to analyze are income and consumption. In this study, I have decided to use consumption/expenditure as the main variable of interest since data on consumption are likely to be more accurate than income data. A possible reason for the inaccuracies of income data is that respondents, hoping for additional financial support from the government, tend to report lower incomes. Furthermore, with tendencies to smooth consumption over time, expenditure data are also likely to be less volatile than income and therefore possess a stronger link with households' overall welfare (Deaton, 1997). This study employs a pre-existing consumption variable constructed by the IFLS, which aggregates all food consumption (including self-produced food), and almost all kinds of non-food consumption, including utilities, education, and rent.

One issue with longitudinal household survey data is that it is difficult to keep constant the unit of observation (household) across time since household members are likely to move out or new members could move in. However, the fact that the IFLS keeps track of the split-offs of the original households allows one to keep the households as similar as possible across time. This is done by adding the split-off household members in 2014 back to their original households in 2007. To check for robustness of the overall results, this study will conduct two separate analyses, one that doesn't add the split-off members back and one that does (See Appendix).

A larger problem with household surveys is that they are very likely to measure income and expenditure with error, which can result in serious biases, especially for panel data analysis. Unlike the resulting bias caused by measurement error in the cross-sectional analysis, which is likely to be small, bias arising in the panel data analysis is likely to be very large and can significantly affect results (Glewwe, 2007). The reason for this is that measurement error tends to put households in the wrong quintiles, and since households are followed over time, this skews the analysis. For example, in the first year a household might report expenditure lower than the true value and is therefore included in a lower quintile than what it should have been. If the household reports a value closer to its true value in the second year and is included in the higher quintile, the analysis would suggest upward mobility for the household. However, this is a misleading since the household has always been in that higher quintile and there has been no upward mobility. As a result, it is vital to account for measurement error to produce results with minimal bias. The next section discusses how this study minimizes such bias.

B. Correcting for Measurement Error

Correcting for measurement error bias is extremely difficult. To attain an unbiased result free of measurement error, an ideal scenario would be to have the joint distribution of the true expenditure values in both years whereas the only data available are the joint distribution of the observed values, which are reported with error. Given this situation, this paper attempts to account for measurement error by making inferences on the density, mean and variances of the true values and simulating a joint distribution of the true values of per capita expenditures in 2007 and 2014. Using this simulated distribution, it then calculates quintile-specific growth rates and compares them with the actual growth rates obtained from the observed data.

To make inferences on the density of the true values requires some derivations, which are explained in detail this section. Assume that the relationship between the true values of expenditure in 2007 and the observed values of expenditure in 2007 is given by the following equation:

$$y_1 = y_1^* \epsilon_{y_1} \Rightarrow \ln(y_1) = \ln(y_1^*) + \ln(e_{y_1}) \tag{1}$$

In the above equation, y_1^* indicates the true values of expenditure in 2007, y1indicates the observed values of expenditure in 2007 while e_{y_1} is the random measurement error. With the assumption that $\ln(e_{y_1})$ is symmetrically distributed and has a mean of 0, we can infer that the medians of $\ln(e_{y_1})$ is also zero and median of e_{y_1} is one. As can be observed from the model above, a multiplicative random measurement error framework is used instead of an additive one. The reason for this is that an additive measurement error could potentially generate unreasonable negative values of expenditure when there is a large negative measurement error. Furthermore, an additive measurement error also suggests that error is unrelated to household expenditure whereas a multiplicative measurement error implies that error is proportional to expenditure values, which is found to be more likely.

One can also form a similar equation, presented in equation (2) that shows the relationship between true values of expenditure in 2014 and the observed values of expenditure in 2014. The analogous equation is as follows:

$$y_2 = y_2^* \epsilon_{y_2} \Rightarrow \ln(y_2) = \ln(y_2^*) + \ln(e_{y_2}) \tag{2}$$

In equation (2), y_2 denotes the observed expenditure values in 2014, y_2^* denotes the true expenditure values in 2014 while e_{y_2} denotes the random measurement error in the model. Like in equation (1), $\ln(e_{y_2})$ is also assumed to be symmetrically distributed with a mean of 0. Thus, $\ln(e_{y_2})$ has a median of zero and e_{y_2} has a median of 1. A key assumption is that the random measurement errors, e_{y_1} and e_{y_2}, are both classic random measurement error. This means not only that they are uncorrelated with each other, but they are also uncorrelated with y_1^* and y_2^*.

With the assumptions of how measurement error relates to the observed and true values firmly established, one can now proceed to the framework to simulate the joint distributions. Assume that the relationship between the true values of expenditure in 2014 and 2007 is determined by the following equation:

$$\ln(y_2^*) = \alpha_2^* + \beta_2^* \ln(y_1^*) + u_2 \tag{3}$$

In this equation, α_2^* and β_2^* indicate a simple linear relationship between the true values of expenditure in 2014 and 2007, while u_2 is a residual with a mean of zero. If one observed the true values of expenditures in 2007, Ordinary Least Squares (OLS) regression can be used to obtain unbiased estimates of both α_2^* and β_2^* However, since y_1^* is measured with error, its observed value is correlated (endogenous) with the residual term, u_2, and thus OLS estimates of α_2^* and β_2^* will be biased and inconsistent. To rectify this, one can use instrumental variables to run a 2SLS regression, which provides us with consistent estimates of α_2^* and β_2^*. The difficulty is in finding suitable instrumental variables which, by definition, are variables that are correlated with the independent variable, in this case y_1^*, and uncorrelated with u_2. A similar equation to equation (3) could also be formed by switching the independent and dependent variables, as shown in equation (4):

$$\ln(y_1^*) = \alpha_1^* + \beta_1^* \ln(y_2^*) + u_1 \tag{4}$$

As with equation (3), this equation displays the relationship, indicated by α_1^* and β_1^*, between the true values of expenditure in 2007 and 2014. In the equation above, u1 denotes the residual term, has a mean of zero, and is uncorrelated with y_2^*. Since the true value of expenditure in 2014 is not observed, one can once again run a 2SLS regression and make use of instrumental variables to obtain consistent estimates of α_1^* and β_1^*.

As previously mentioned, this study attempts to correct for measurement error by simulating a joint distribution of the true expenditure values in 2007 and 2014. The simulation of the joint distribution will be done using either equation (3) or equation (4). Which equation we choose to adopt depends on which equation exhibits a more linear relationship. To check for linearity, one can regress both equations using their observed values while adding a squared term of the independent variable as an additional exogenous variable. To check for the linearity of equation (3), one can add $\ln(y_1^*)^2$ to the regression equation. The relationship is said to be linear if the squared term of the regression produces an insignificant coefficient. Therefore, this study adopts the equation that produces a more insignificant quadratic term. After running both regressions, we find equation (3) better approximated by a linear regression when analyzing the panel data without adding back the split-offs. We find equation (10) is more appropriate when analyzing the panel data with adding back the split-offs.

To simulate the joint distribution using either equation, it is necessary to obtain estimates of the relevant components in each equation. So, if one were to simulate using equation (3), estimates of α_2^*, β_2^*, $Var(u_2)$ and $Var[\ln(y_1^*)]$ are required. Furthermore, in addition to the assumption of a linear relationship between true expenditure values in both years, several other assumptions must be made. Two key assumptions that pertain to the classical linear model are exogeneity, i.e. $E[u_2|y_1^*] = 0$, and homoscedasticity of errors, i.e. $E[u_2^2|y_1^*]$ is constant. Another necessary assumption is that expenditure in both years follows a log-normal distribution. This implies that $\ln(y_1^*)$, $\ln(y_2^*)$ and u_2 are normally distributed. To test this assumption, one can plot a kernel density of the observed expenditures in both years and compare it to a normal distribution with the same mean and variance. Figures 1 and 2 displays the density plots for observed expenditure in 2007 and 2014 respectively. Although they do not perfectly follow a normal distribution, this fit is still close. Therefore, it is not unreasonable to claim that the expenditures follow a log-normal distribution.

Figure 1: Density Plot of log expenditure in 2007

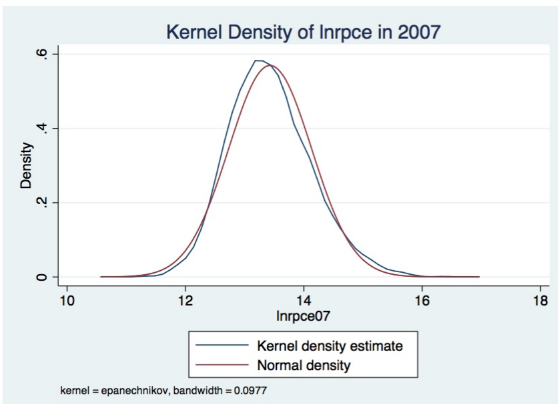
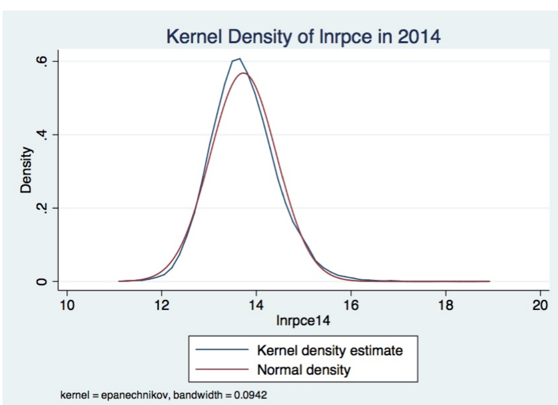


Figure 2: Density Plot of log expenditure in 2014



As previously shown, β_1^* and β_2^* can be obtained by running a 2SLS regression using instrumental variables. In this study, BMI (body mass index), constructed from the surveys height and weight variables, is used as instrumental variable. It is not unreasonable to choose BMI as an instrument because it satisfies the two criterions of instruments. First, BMI is likely to be correlated with current expenditure levels since people who consume more food are likely to be heavier therefore households with heavier members are likely to have higher expenditure values. On the other hand, an individuals current BMI is unlikely to be correlated with the level of income in the other time period after conditioning on current income.

The constants of the regressions, α_1^* and α_2^*, can be estimated using the equations (4) and (3) respectively, by using properties of expectations. Using equation (4) to solve for α_1^* and taking expectation of equation (4) yields

$$\alpha_1^* = E[\ln(y_1^*)] - \beta_1^* E[\ln(y_2^*)] - E(u_1) \tag{5}$$

$$\alpha_1^* = E[\ln(y_1^*)] - \beta_1^* E[\ln(y_2^*)] \tag{6}$$

Equation (6) makes use of the fact that $E[\ln(\epsilon y_1)] = 0$ and $E(u_1) = 0$. As a result, an unbiased estimate of α_1^* can be obtained using equation (6), where β_1^* is estimated using 2SLS regression. The same procedure is used to acquire an estimate of α_2^*. Another component that needs to be estimated is $Var(u_2)$, which could be obtained by taking the variance of equation (3). Taking the variance of equation (3) yields us the following equation.

$$Var(u_2) = Var[\ln(y_2^*)] - (\beta_2^*)^2 Var[\ln(y_1^*)] \tag{7}$$

Observing equation (7), it is clear that one needs to find estimates of $Var[\ln(y_1^*)]$ and $Var[\ln(y_2^*)]$. This can be done by the following equation, which is a standard equation for the OLS estimates if a regression is run for equation (3) using the observed values.

$$\beta_2 = \frac{Cov[\ln(y_1), \ln(y_2)]}{Var[\ln(y_1)]} = \frac{Cov[\ln(y_1^*), \ln(y_2^*)]}{Var[\ln(y_1)]} \tag{8}$$

Equation (8) follows from the fact that adding uncorrelated random measurement errors to each variable does not change the covariance between the two variables. Furthermore, if one were to run an OLS regression using the true values, one would get the following equation

$$\beta_2^* = \frac{Cov[\ln(y_1^*), \ln(y_2^*)]}{Var[\ln(y_1)]} \tag{9}$$

Taking the ratio of equation (8) and equation (9), provides an estimate of the variance of $ln(y_1^*)$.

$$\frac{\beta_2^*}{\beta_2} = \frac{Var[\ln(y_1)]}{Var[\ln(y_1^*)]} \tag{10}$$

$$Var[\ln(y_1^*)] = \frac{\beta_2}{\beta_2^*} Var[\ln(y_1)] \tag{11}$$

To obtain an estimate of $Var[\ln(y_2^*)]$, assume proportional measurement error, whereby the contribution of measurement error to $Var[\ln(y_1)]$ is proportionally the same as the contribution of measurement error to $Var[\ln(y_2)]$. Using this assumption provides following derivations.

$$\frac{Var[\ln(y_2)]}{Var[\ln(y_2^*)]} = \frac{Var[\ln(y_1)]}{Var[\ln(y_1^*)]} = \frac{\beta_2^*}{\beta_2} \tag{12}$$

$$Var[\ln(y_2^*)] = \frac{\beta_2}{\beta_2^*} Var[\ln(y_2)] \tag{13}$$

With all of the necessary components derived, these components can then be plugged into either equation (3) or (4) to simulate the joint distribution between the true expenditure values in 2007 and 2014. The following table summarizes how to obtain estimates for the necessary components of equation (3).

Table 1: A Summary of How to Obtain the Estimates of the Components to Simulate Equation (3)

Estimate	Equation
α_2^*	$= E[\ln(y_2^*)] - \beta_2^* E[\ln(y_1^*)]$
β_2^*	2SLS Regression using IV
$E[\ln(y_1^*)]$	$E[\ln(y_1)]$
$Var(u_2)$	$Var[\ln(y_2^*)] - (\beta_2^*)^2 Var[\ln(y_1^*)]$
$Var[\ln(y_1^*)]$	$\frac{\beta_2}{\beta_2^*} Var[\ln(y_1)]$
$Var[\ln(y_2^*)]$	$\frac{\beta_2}{\beta_2^*} Var[\ln(y_2)]$

IV. Results

To determine whether Indonesia's economic growth between 2007 and 2014 has been pro-poor, this section applies the two analytical approaches discussed above to the Indonesia Family Life Survey. The results shown first are for the cross-sectional analysis. Then, results are presented for the panel data analysis. The panel data results first show growth rates from an analysis that does not include the split-off household members. A similar analysis that includes the split-off household members is included in the Appendix. Lastly, we present growth rate results from a simulation of the joint distribution of true expenditure values.

A. Cross-Sectional Analysis

Table 2 shows the growth rates in expenditure between 2007 and 2014 by quintiles using the cross-sectional method discussed in Section 3. In this analysis, the unit of observation is the household and the consumption expenditure values are expressed in real terms according to 2014 price levels. The fourth column in Table 2 contains the overall growth rate over seven years while the last column is the average annual growth rate.

From the last row of Table 2, we see that the average real per capita expenditure increased from Rp. 735,276 in 2007 to Rp. 1,009,687 in 2014, which amounts to a 4.63% average growth rate per annum. This is in line with Indonesia's overall real GDP growth rate reported by the National Accounts, which was estimated to be around 5%. Looking at the results by quintiles, the first quintile experienced the lowest overall growth rate over seven years, with mean per capita expenditure rising from Rp. 247,689 in 2007 to Rp. 335,571 in 2014. This amounts to an annual growth rate of 4.43%. Compared with the other 4 quintiles, one can see that the poorest 20% experienced the lowest growth rate. The third quintile has the highest growth rate, with mean per capita expenditure rising from Rp. 542,975 in 2007 to Rp. 756,134 in 2014, which equals an overall growth rate of 39.26% or 4.84% annually.

Table 2. A Summary of Growth Rates According to Quintiles Using the Cross Section Method

Quintile	Mean Real Per Capita Expenditure 07	Mean Real Per Capita Expenditure 14	Growth	Annual Growth
1	247,689	335,571	35.48%	4.43%
2	389,618	540,038	38.61%	4.77%
3	542,975	756,134	39.26%	4.84%
4	777,958	1,073,418	37.98%	4.71%
5	1,718,484	2,383,717	38.71%	4.79%
Overall	735,276	1,009,687	37.32%	4.63%

Whether one would classify these growth rates as pro-poor depends on the definition one is willing to use. If pro-poor growth were defined using the definition of Ravallion and Chen (2003), Indonesia's growth would be classified as pro-poor since the poor (indicated by the first quintile) have fared better in absolute terms and thus poverty has declined. However, using the definition of pro-poor growth provided by Kakwani and Pernia (2000), the fact that the poorest quintile does not experience the highest growth among the five quintiles suggests that Indonesia's economic growth between 2007 and 2014 has not been pro-poor. This supports the proposition that inequality in Indonesia has risen over the seven years, evident in the noted increase in Gini coefficient.

B. Panel Data Analysis without Correcting for Measurement Error

Table 3 presents the growth rates in per capita expenditure between 2007 and 2014 across quintiles using the panel data method, which compares the same households over time. The data analyzed were constructed by using only the households who were found and interviewed in both years, and without adding back household members who have moved away from the original household (split-off members). Once again, the unit of observation is the household and per capita expenditure figures are expressed in real terms using 2014 prices.

Table 3 shows that the mean of per capita expenditure increases from Rp. 788,929 in 2007 to Rp. 1,091,589 in 2014, amounting to an average growth rate of 4.75% per year. This is slightly higher than the overall growth rate reported in Table 2, which was 4.63%.

The next section of Table 3 shows the growth rates of per capita expenditure when households are being followed based on their per capita expenditure in 2007. Clearly, growth rates of per capita expenditure when households are ranked based on 2007 per capita expenditure are dramatically different to the growth rates obtained from the cross-section analysis. Unlike the cross-sectional analysis, which suggests that the poor fared the worst among the other quintiles, the panel data analysis shows that the poor experienced the highest growth rate. The poorest quintile experienced an average growth rate of 11.85% per year, with expenditure increasing from Rp. 245,110 in 2007 to Rp. 536,909 in 2014. Furthermore, another major difference with the cross-sectional analysis is that growth rates of expenditure seem to be decreasing as one moves to higher quintiles. For example, the richest 20% experienced the lowest growth, and had a negative average annual growth rate of -0.08%. In terms of pro-poor growth classification, Table 3 suggests that Indonesia's growth between 2007 and 2014 has been pro-poor according to the requirements of both Ravallion and Chen (2003) and Kakwani and Pernia (2000). There are several reasons why Table 3's results, which were obtained from a panel data analysis is markedly different from Table 2's results, which were obtained from a cross-sectional analysis. The first reason is that the households included in the panel data analysis are not representative of the sample of the entire population, which was used in the cross-sectional analysis. This is possible since in the construction of the panel dataset for Table 3 used only those households that were found in both 2007 and 2014. However, the last 5 rows of Table 3, which present a cross-sectional version of panel data in which the mean of per capita expenditures of 2014 was defined according to 2014 quintiles, show results similar to those of Table 2. The similarity of these two analyses suggests that panel attrition does not explain the differences between the growth rates in Tables 2 and 3.

Table 3. A Summary of Growth Rates According to Quintiles Using the Panel Data Method Without Adding Back Splitoff Household Members

Quintile	Mean PCE07	Mean PCE14	Growth	AnnGrowth
Overall	788,929	1091589	38.36%	4.75%
By 2007 Quintile				
1	245,110	536,909	119.05%	11.85%
2	381,829	729,807	91.13%	9.70%
3	526,532	868,356	64.92%	7.41%
4	746,835	1,022,716	36.94%	4.59%
5	1,587,439	1,578,273	-0.58%	-0.08%
By 2014 Quintile				
1	245,110	326,353	33.15%	4.17%
2	381,829	531,520	39.20%	4.84%
3	526,532	7417,08	40.87%	5.02%
4	746,835	1,048,969	40.46%	4.97%
5	1,587,439	2,296,902	44.69%	5.42%

Furthermore, the result that poorer quintiles fare better than the richer quintiles is expected assuming that there is upward mobility. With upward mobility, some households that were found to be in the first quintile in 2007 may end up in the second quintile in 2014 and thus contribute to a larger growth rate. This differs from a cross-sectional analysis, where the first quintile for 2014 includes only households that are found in the first quintile in 2014. Furthermore, an increase in expenditure in absolute terms for households in the poorer quintile will contribute to a larger growth rate than an increase in expenditure in absolute terms of the same magnitude experienced by a richer quintile. Another possible reason that can explain this difference in growth rates in Table 3, and one that will be the subject of the next section, is measurement error. As explained in Section 3, household survey datasets often measure income and expenditure with error, and this is likely to cause bias in the analysis. This bias problem is particularly severe for panel data analysis that follows the same households over time, as we did above.

C. Simulation Correcting for Measurement Error

Table 4 presents simulated growth rates that have been corrected for measurement error using equation (3) as discussed in Section 3. The annual growth rate for the overall population, 4.33%, is nearly equivalent to previously computed overall growth rates presented in Tables 2 and 3. This suggests, as predicted, that measurement error causes little or no bias when taking the mean of all households. Measurement error also does not cause substantial bias when taking the mean of households across quintiles (without following the same households over time) as corroborated in the last five rows of Table 4. The last five rows of Table 4 show a cross-sectional analysis using panel data in which one takes the mean of per capita expenditure in 2014 calculated according to 2014 quintiles. As one can see, the growth rates across quintiles is very similar to the growth rates presented in Table 2 and thus indicate that measurement error does not have a large effect on these cross-sectional analyses.

Table 4. A Summary of Simulated Growth Rates Using Equation (3)

Quintile	Mean PCE07	Mean PCE14	Growth	AnnGrowth
Overall	829,493	1,116,376	34.59%	4.33%
By 2007 Quintile				
1	295,697	601,421	103.39%	10.67%
2	490,940	836,443	70.38%	7.91%
3	684,420	1,041,268	52.14%	6.18%
4	957,208	1,285,482	34.29%	4.30%
5	1,719,200	1,817,266	5.70%	0.80%
By 2014 Quintile				
1	295,697	398,139	34.64%	4.34%
2	490,940	662,984	35.04%	4.39%
3	684,420	922,064	34.72%	4.35%
4	957,208	1,287,139	34.47%	4.32%
5	1,719,200	2,311,591	34.46%	4.32%

On the other hand, the top five rows of Table 4, which show the simulated growth rates of expenditure using panel data analysis, differ greatly from the corresponding results from Tables 2 and 3. This implies that measurement error causes serious bias when one computes growth rates by following the same households over time. Comparing Table 3 and 4, one can see that measurement error, which was not accounted for in Table 3, overestimates growth rates for all quintiles except the fifth quintile and results in a wider dispersion of growth rates in Table 3. According to Table 4, the poorest quintile experienced an annual growth rate of per capita expenditure of 10.67%, more than 1 percentage point lower than the growth rate reported in Table 3. Similar overestimations of growth rates also occur with the second, third and fourth quintiles which were overestimated by 1.8, 1.2 and 0.30 percentage points respectively. Another interesting observation from Table 4 is that the poorest 20% performed better than the other quintiles and in fact, experienced a growth rate of nearly 10 times higher than that of the top 20%. This suggests that Indonesia's growth between 2007 and 2014 has been pro-poor and contradicts the previous notion that inequality in Indonesia has been rising. However, it is unlikely that the poorest 20% did indeed perform 10 times better than the top 20%, suggesting that there is still measurement error that has not yet been corrected and that the methodology from Section 3 may only partially correct this persistent problem with panel data analysis.

V. Conclusion

This study was conducted with the intention to contribute to the pro-poor growth literature that has been gaining popularity recently. This study focuses on Indonesia's economic growth between 2007 and 2014, which has been impressively high but may have adverse effects by widening inequality between the poor and the rich. To fully grasp whether economic growth in Indonesia has been pro-poor, this study follows the approach of Glewwe and Dang (2011), who examined whether Vietnam's growth in the 1990s was pro-poor. This study uses two analytical approaches to determine whether Indonesia's growth has been pro-poor. The first, which is useful in giving a picture of the distribution of income, compares the mean of per capita expenditure per given quintile in both 2007 and 2014. The second method, which utilizes a panel data of households, follows the same households over time and compares their per capita expenditures over time. An important aspect of this research involves dealing with measurement error, which is plentiful in household surveys, and causes serious biases when analyzing panel data. To correct for measurement error, this paper simulates a joint distribution of the true expenditure values in 2007 and 2014 by making inferences on the joint density, mean and variances of the variables.

The results of our two analyses produce two varying conclusions. Findings from the cross-sectional analysis show that growth rates across quintiles are very similar, with the poorest quintile experiencing a somewhat lower growth rate. This suggests not only that Indonesia's growth has not been pro-poor (using Kakwani and Pernia's (2000) definition), but also that the pattern of income distribution and inequality between 2007 and 2014 has not changed. This analysis did not correct for measurement error since studies have shown that the resulting bias of cross-sectional analysis is likely small.

On the other hand, findings from the panel data analysis show that Indonesia's growth between 2007 and 2014 has been pro-poor. In particular, analyses using both observed values and simulated growth rates indicate that the poorest 20% experienced a higher growth than the other four quintiles. This implies that Indonesia's growth is likely to be accompanied by upward mobility between quintiles. Furthermore, simulation of growth rates, which correct for measurement error, demonstrates how large the bias that measurement error can cause in panel data analyses. Findings from the simulated growth rates show that measurement error leads to overestimating of growth rates, and widens the dispersion of growth rates among quintiles.

Although useful in providing a picture of how pro-poor Indonesia's growth has been, the question of pro-poor growth in Indonesia can certainly not be answered by this paper alone. Further research must be conducted to better understand what pro-poor growth entails and how to measure whether an economy's growth has been pro-poor. Furthermore, since measurement errors are plentiful in household survey data, which are required to conduct the second methodology, more studies should also be dedicated in trying to better correct for measurement error.

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References

[1] Aji, P. (2015). Summary of Indonesias Poverty Analysis (ADB Papers on Indonesia No. 4). Manila, Philippines: Asian Development Bank.

[2] Deaton, A. (1997). The Analysis of Household Surveys: A Microeconometric Approach to Development Policy. Baltimore, MD: Johns Hopkins University Press.

[3] Department for International Development. (2008). Growth Building Jobs and Prosperity in Developing Countries.

[4] Glewwe, P. (2012). How Much of Observed Economic Mobility is Measurement Error? IV Methods to Reduce Measurement Error Bias, with an Application to Vietnam. The World Bank Economic Review, 26(2), 236264. https://doi.org/10.1093/wber/lhr040

[5] Glewwe, P., & Dang, H.-A. H. (2011). Was Vietnams economic growth in the 1990s pro-poor? An analysis of panel data from Vietnam. Economic Development and Cultural Change, 59(3), 583608.

[6] Grosse, M., Harttgen, K., & Klasen, S. (2008). Measuring Pro-Poor Growth in Non-Income Dimensions. World Development, 36(6), 10211047. https://doi.org/10.1016/j.worlddev.2007.10.009

[7] Kakwani, N., Pernia, E. M., & others. (2000). What is pro-poor growth? Asian Development Review, 18(1), 116.

[8] Ravallion, M., & Shaohua, C. (2003). Measuring Pro-Poor Growth. Economic Letters, (78), 9399.

[9] World Bank. (2016). Indonesias Rising Divide. Jakarta, Indonesia: The World Bank.

Table 5. A Summary of Growth Rates According to Quintiles Using the Panel Data Method Using Dataset in which Splitoff Members are Added Back

Quintile	Mean PCE07	Mean PCE14	Growth	Annual Growth
Overall	702,939	1,100,137	56.51%	6.61%
By 2007 Quintile				
1	244,777	644,811	163.43%	14.84%
2	381,974	817,831	114.11%	11.49%
3	528,742	984,143	86.13%	9.28%
4	751,168	1,161,296	54.60%	6.42%
5	1,608,581	1,867,504	16.10%	2.16%
By 2014 Quintile				
1	244,777	366,516	49.73%	5.94%
2	381,974	602,886	57.83%	6.74%
3	528,742	836,266	58.16%	6.77%
4	751,168	1,164,346	55.00%	6.46%
5	1,608,581	2,530,979	57.34%	6.69%

Table 6. A Summary of Simulated Growth Rates using Equation (3) Using Dataset in which Splitoff Members are Added Back to Original Household

Quintile	Mean PCE07	Mean PCE14	Growth	Annual Growth
Overall	811,286	1,110,605	36.89%	4.59%
By 2007 Quintile				
1	300,393	606,414	101.87%	10.56%
2	493,013	842,064	70.80%	7.95%
3	679,690	1,033,916	52.12%	6.18%
4	937,447	1,261,299	34.55%	4.33%
5	1,645,884	1,809,332	9.93%	1.36%
By 2014 Quintile				
1	300,393	422,151	40.53%	4.98%
2	493,013	685,245	38.99%	4.82%
3	679,690	937,826	37.98%	4.71%
4	937,447	1,285,641	37.14%	4.62%
5	1,645,884	2,222,163	35.01%	4.38%