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WHAT HAPPENS TO POOR HOUSEHOLDS: ARE THEY LEAVING, STAYING OR FALLING? EVIDENCE FROM INDONESIA'S UNIFIED DATABASE (UDB)

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What Happens to Poor Households: Are they leaving, staying or falling? Evidence from Indonesia's Unified Database (UDB)*

Abstract

Understanding why some households can move out of poverty while others fail is crucial for any effort to reduce poverty. A large number of studies using survey-based data have documented and examined the possible factors that contribute to household movement in-out of poverty. To carry out this project, we constructed a household-level panel data set of approximately 20 million households in Indonesia between 2011 and 2015. We proceed using two approaches, observe the correlation using the existing welfare measure, generated by different PMT models, and observe the same correlation who use a new welfare measure resulted from the same PMT model. We found that, in general, results are lower in magnitude than the existing model, however, trends are consistent across models and groups. On the household human capital characteristic, we find that the more education that each household member earned, the more likely they help their households to move out of poverty. While we see no clear pattern on the correlation between sets of demographic variables and the household welfare change, the correlation between physical assets with changes in welfare rank seems to be consistent across different approaches.

Keywords: *UDB, PMT model, poverty reduction.*

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Abbreviations and Acronyms

BPS	*Badan Pusat Statistik* (Statistics Indonesia)
GRDP	Gross Regional Domestic Product
NTB	Nusa Tenggara Barat (West Nusa Tenggara)
NTT	Nusa Tenggara Timur (East Nusa Tenggara)
PAD	*Pendapatan Asli Daerah* (Regional [Government] Own Revenues)
TKPK	*Tim Koordinasi Penanggulangan Kemiskinan* (Coordinating Team for Poverty Reduction)
TNP2K	*Tim Nasional Percepatan Penanggulangan Kemiskinan* (National Team for the Acceleration of Poverty Reduction)
UDB	Unified Database

Section One:

Introduction

Understanding why some households can move out of poverty while others fail is crucial for any effort to reduce poverty. A large number of studies using survey-based data have documented and examined the possible factors that contribute to household movement in-out of poverty. Less is understood regarding the factors or correlates that drive household movements in or out of poverty using an actual data used to deliver social programs. This additional qualifier becomes important since any change in the factors that affect poverty movement would likely to have real-welfare implication. Household is removed from the social registry data if the change deems to have positive impact on their welfare, vice versa.

In this paper, we investigate the correlates of households ranking of Indonesia's poor in the Unified Database (UDB). UDB keeps records of social, economic and demographic indicators of the Indonesian households that lie in the bottom 40 percent of the Indonesian population and is used by various government agencies, both central and local, to target their social protection programs. We evaluate four sets of correlates that determine a household's economic performance compared to their peers: (i) human capital; (ii) demographics; (iii) owned assets; and (iv) labour market performance–by controlling whether they receive and/or participate in social protection schemes. Our main outcome variable is a household's rank in the UDB, represented by their per capita expenditure percentile.

UDB data is constructed following the PPLS (Pendataan Program Perlindungan Sosial) 2011 and its follow-up, the BDT (*Basis Data Terpadu*) 2015. We utilize all information available, both at individual and household-level, at the UDB to shed ligt the relationship between observed factors and welfare ranking. The main novelty of our study is our examination using the actual administrative data used to target the social protection program, controlling for social protection program participation and other rich characteristics. To our knowledge, our study is the first that uses the actual administrative data for examining the correlates of welfare change among the poor population. In addition, the welfare metric in our data is relatively new, since it is model-generated rather than survey-collected. We do everything within our power to consider the different methods used to derive the welfare measure.

While our investigation can proceed with other household-level surveys that collected welfare measure and the respective characteristics, both directly or indirectly, such as the National Socioeconomic Survey (Susenas) or Indonesian Family Life Surveys (IFLS), the use of the UDB has several advantages. First, UDB is a large longitudinal data collected at household, and its respective individual information, level while Susenas and IFLS are a repeated cross-section and a longitudinal data undertaken at a relatively small-scale panel household level, respectively. An analysis using UDB will, therefore, result in greater statistical power relative to these datasets. Second, administratively, households in the UDB are the candidates for receiving social programs from the central government. Any factors that could lead to a change in welfare of these households would raise the interest of policy makers. While the first argument warrants the use of UDB rather than survey-based data, the last one is the main advantage of using UDB since we can evaluate which of the socioeconomic variables/indicators correlate with household welfare. Further understanding of these two relationships will help the government in (re)shaping their poverty reduction program. If socioeconomic indicators statistically correlate with welfare improvement of the poor then government should design its social program accordingly - incentivize the poor to change their socioeconomic structures and not only giving an in-kind contribution.

A significant challenge of this project is to discern whether changes in households’ welfare rank between 2011 and 2015 censuses are driven by changes in those correlates alone, and not driven by the different Proxy Means Test (PMT) methodologies used to generate the ranks or the change in a district-level poor households’ quota. The PMT for the PPLS 2011 rank was estimated using the National Susenas 2010 and 2011 while the PMT for the BDT 2015 rank was estimated using the Susenas 2011, 2012, 2013, and 2014. To isolate the effect of the different PMT models and the different estimates of the poor quota, we construct our own district-level PMT models based on the same set of universe explanatory variables pooled from the Susenas data 2010, 2011, 2012, 2013 and 2014 used to generate the two PMTs and adopt the existing poor households’ quota, estimated separately during the PPLS and the BDT process. Further on, we compares the empirical estimate of the correlation between household characteristics and the original rank in terms of percentiles with estimates that use the percentiles we generated. In doing so, we could reveal how much our results is due to the change in methodologies.

To carry out this project, we constructed a household-level panel data set of approximately 20 million households in Indonesia between 2011 and 2015. This data set contains information on the households’ housing characteristics, asset ownership, participation in the social protection program, and the socioeconomic characteristics of household members. Importantly, the data also contains households’ welfare ranking, shown by their associated per capita expenditure percentile. To our knowledge, our study has one of the largest longitudinal data sets–in terms of the number of households and individual units–ever used to document pattern of household movement in and out of poverty in a developing country, let alone the world, and their correlates.

We run a basic regression strategy that provides a benchmark estimate of the correlation between a set of household-level variables and welfare metric. In addition, we compare the correlation across poverty mobility status and districts to check whether the implied relations are sensitive to different poverty-dynamic of households. We also add time fixed effects that control for any changes over time that affect all panel households uniformly. To control for district-specific effect we include district fixed effects to capture any cross-sectional unobserved determinants of the change in household welfare mobility.

The first set of results show that, over the course of four years, we see slight mobility. About 2.2 million UDB households were classified as poor in 2011 and 2015, 2.9 million households moved out from their poor status, 3.2 million households fell into poor, while the last 12 million were never considered as poor in either period. We have a net loss of 0.3 million, more people becoming poor than those leaving poor. This finding raises an important point on whether, in the course of four years, the UDB households only experience sluggish change in their socioeconomic characteristics, which later affects their welfare mobility.

On human capital, we find that the more educated the household members, the more likely that they help their households to move out of poverty. While this finding reiterates the importance of education in helping people to move out of poverty, the exact interpretation is really hard to fathom due to the fact that education is seen to be endogenous to welfare changes. While we see no clear pattern on the correlation between other demographic variables and household welfare change, the correlation between physical assets and changes in welfare rank seems to be consistent across different specifications. Interestingly, we find that households who own a motorcycle and refrigerator are more likely to escape poverty. High-quality jobs are expected to help people move out of poverty in a more profound way. It is, therefore, not out of the realm of the two variables that we choose to include to represent labor market outcomes, that the number of adults working in the formal sector is seen to have a stronger/strong positive correlation with the households' welfare change.

This paper builds on a large volume of literature in poverty dynamics that stresses the role of household characteristics on their welfare outcomes. This includes research by Duncan & Hill (1985), Jalan and Ravallion (1998), Dercon et al. (2007), Widyanti et al. (2009), and Woolard & Klasen (2005). It also relates to poverty dynamics in the Indonesian context (Hernandez & Hadiwidjaja (2018), Sumner et al. (2014), Dartanto and Nurkholis (2013), and Miranti (2010)), as well as the determinants of relative poverty (Sumner et al. (2014) and Filmer and Pritchett (2001)). Our study also contributes to the literature in development economics on the use of national registry in evaluating poor people welfare (Bah et. al 2019).

The remainder of the paper is organized as follows: Section Two provides the literature review, Section Three describes our data and measurement, Section Four discusses results, while Section Five concludes with some policy implications.

Section Two:

Literature Review

Our study is related to a growing volume of literature in economics on the correlation between demographic variables and poverty status. Among others, Duncan & Hill (1985), Jalan and Ravallion (1998), and Woolard and Klasen (2005) provide evidence that demographic status affects poverty. These studies had the luxury of examining a relatively consistent measurement of the poverty status.

Measuring poverty may not always be straightforward–Madden (2000) emphasised that when measuring poverty, there are two issues to be addressed: identification and aggregation. Identification deals with choosing the poverty line, whether absolute, relative, or hybrid–which is the combination of both absolute and relative. Aggregation deals with the choice of aggregator–for example, the numbers of people below the poverty line–or a more complex approach that considers the distribution of income amongst the poor. In this study, the identification issue is more intriguing as there is a wide spectrum of the poor in Indonesia.

Is the absolute approach more preferable to the relative approach in identification of the poverty line? Foster (1998) states that the difference between the absolute and relative approaches is that the former is a fixed cutoff level that is applied to all potential resource distributions, while the latter uses standard of living for a certain distribution–for example, when the mean, median, or quintile income or consumption is used and the cutoff is defined as some percentage of this standard. The difference between the absolute and relative approaches is, therefore, in how the values change as the distribution changes, not the specific values obtained at a given date.

The use of different approaches yields different results, such as the case observed by Madden (2000). Using the Irish Household Budget Survey of 1987 and 1994, he found that, when the absolute approach is used, there is a significant fall in poverty, whereas it increased slightly when the relative approach was used. The use of an absolute poverty measure was further conducted by Martinez Jr (2016) to observe persistent and transient poverty dynamics in the Philippines during 2003-09. Comparing the spells and components approach, he concludes that poverty dynamics are sensitive to the poverty line or the poverty measure used. Foster (1998) notes that, for comparisons that involve long periods of time or different standards of living, the absolute line is a more important issue. The advantage of using a relative poverty measure, however, is that it is independent of income change. The proportion of the poor would be the same after there is a rise or fall of income levels, because the number of poor people would depend on the relative position of others in the society.

An example of a relative poverty measure approach was conducted by Sumner et al. (2014) using Indonesian cross-sectional data and the Demographic and Health Surveys (DHS) wealth index quintiles to measure education and health poverty. The DHS wealth index was generated by observing easy-to-collect information, for example ownership of bicycles, motorcycles, cars, sanitation facilities, and water access. They further constructed measures of education in each household by calculating the percentage of youth aged 15-24 years who have not completed primary school, and health was measured by the proportion of children who died below the age of five. They found that there was a rise in the proportion of both education and health poverty in the poorest quintile, and that the composition of education poverty remained constant during 1991-2007.

Filmer & Pritchett (2001) generated an asset index that includes 21 asset ownership indicators and 12 housing characteristics indicators. As with the DHS wealth index, their asset index is used to predict wealth, replacing average household per capita income or expenditure data. Using principal components analysis, they found that asset index is robust even when different sets of variables are used. Furthermore, it is consistent with expenditure–for example, two-thirds of those classified into the poorest 40 percent by expenditure are also classified into the poorest 40 percent by assets. Moreover, they estimated the effects of wealth–using the asset index–on children's school enrolment and found consistent results when compared to using expenditures as wealth. To further understand the difference between the absolute and relative poverty lines, Table 1 compares the two concepts.

Once the identification issue is solved, poverty can then be measured by addressing certain groups of characteristics. There is numerous literature on the correlation between demographic characteristics and poverty status. Poverty status is measured by observing whether households live below a certain income or consumption level. Observations during multiple periods will reveal how poverty dynamics take place in a region. For example, households that were poor in one period may no longer be poor in the next period. This movement in and out of poverty is driven by some characteristics related to households or its members and is valuable in assessing poverty alleviation programs. The most widely used characteristics in the literature include education attainment, asset ownership, labour market outcomes, and government assistance programs.

A household head's education attainment in much of the literature is found to be significant in lowering the probability of a household being poor. For example, Sumner et al. (2014), using six different poverty lines and panel data from the IFLS, found that the most robust determinant of the probability of being poor and remaining poor is education. Households are 20 percent less likely to be poor in the current and following period if their household heads have obtained a higher schooling.

Results are similar in other developing countries such as Bangladesh and Vietnam. Using a sample survey in Bangladesh during 2008-09, Rahman (2013) found that poverty in Bangladesh is mainly found in households with heads who are poorly educated. Illiterate household heads are 82 percent more likely to be poor than those who are literate. Moreover, the risk of being poor is 96 percent higher for households with illiterate heads, compared to heads who obtained primary schooling. Other variables used in this study are a household head's occupational status and age, household characteristics such as whether it is male or female headed, household size, and dependency ratio. Of all these variables, Rahman (2013) concludes that poverty is high in households with young household heads, low education level, female heads, large households, and with a high dependency ratio.

Whether a household head completed primary schooling or not also determines poverty status. Using a multinomial logit model observing data from the Vietnam Household Living Standards Survey, Baulch and Dat (2010) found that households whose heads have completed primary school increase the probability that the household is never poor by one-sixth. The more highly educated the household head the more likely to never be poor, respectively. As with other studies, Baulch and Dat (2010) use demographic characteristics such as household size, ethnic status, education level and age of household head, access to clean water, and dependency ratio. In addition, they also use a household’s geographical location to observe different levels of poverty in each region. They found that households from an ethnic minority, with little or no education, and those living in the Northern Uplands or Central Highlands have a high probability of being chronically poor.

Although the literature finds education to be strongly significant in measuring poverty dynamics, Dercon et al. (2007) argue that it is endogenous to long-term wealth as it may not be observable whether education helps people escape poverty, or whether those who can afford education can offer other opportunities to their children. They further suggest that, instead of household panel data, one should use individual panel data to observe individual poverty dynamics and obtain a better understanding of the causality between education and poverty status. That would, however, involve higher costs in conducting surveys and may not be feasible with a large number of observations unless using methodological innovations.

Another important element in measuring poverty dynamics is asset ownership–the literature, for example, shows that endowments such as land and livestock contribute to the movement in and out of poverty. Dercon et al. (2007) used a linear regression to estimate a panel survey of Ethiopian households during 1989 and 1994 and found that households that own land and livestock can rely on them to help move out of poverty. They emphasized, however, that this may be due to economic liberalization that occurred during those periods and is likely to increase returns to these endowments. Dercon et al. (2007) use various characteristics apart from demographic, to obtain the result–such as the value of livestock and land area, export crops, amount of fertilizers used, crop prices, location, and shocks such as illness or low and high rainfall. Although they conclude that it is hard to generalize which factor is most important due to different contexts, they see a pattern that education greatly affects poverty dynamics.

In the case of Indonesia, Dartanto and Nurkholis (2013), using data from Susenas, found that physical assets such as land and house ownership play a role in determining poverty dynamics. Using a probit model, they found that a one-hectare increase in land size would increase the probability of being non-poor by 1.7 percent in Java and Bali, 1.3 percent outside Java and Bali and 1.7 percent nationally. Ownership of a larger house is also associated with a lower probability of being poor. Dartanto and Nurkholis (2013) further suggest that land and house certification may help alleviate poverty by allowing households to use them for collateral to gain credits/loans from financial institutions. Moreover, households that are able to accumulate assets are less likely to be poor in the future because they are able to deal with adverse shocks at the same consumption level (Bah 2013).

Labour outcomes, especially a household head’s employment or employment sector, also play a role in household poverty dynamics. Sumner et al. (2014) found that the household head’s sector of employment is not a robust determinant of staying out of poverty unless they are employed in wholesale, retail, restaurants, and hotels. Households in these sectors are seen to have higher consumption per capita and a lower probability of being poor. Meanwhile, those working in the agricultural sector have a higher likelihood of being poor due to very low productivity and low wages. Dartanto and Nurkholis (2013) confirmed that households in Java-Bali often experience crop loss, job loss, and falling prices and have a greater tendency to be poor and transient poor. Those outside Java-Bali, however, experience more negative shocks but it is insignificant to their poverty status due to their owning larger areas of land and being more able to reduce agricultural risks by diversification.

Not only does a household head's employment affect their poverty status, but their gender also plays a role because it may correlate with their expected wage. Rahman (2013) found that, in Bangladesh, households with female heads are often found to be more vulnerable to poverty than households with male heads due to their low wages in the labour market, and less years of education compared to male heads. Child to female ratio is also seen as a factor that constraints females from entering the labour force (Rahman 2013), the more children a family has, the less likely the mother would enter the labor force. Furthermore, looking closely at the case of Central Sulawesi, Indonesia using a multinomial logit model, Van Edig and Schwarze (2011) found that the probability of female-headed households to become chronically poor increases only in the case of those who were chronically poor in the US$1.00/day poverty line scenario, but not in the case of those chronically poor in the US$2.00/day scenario.

Receiving government assistance–such as health care insurance subsidies, microcredit, and in-kind transfers–may help households stay out of poverty since they act as buffers during economic shocks. Dartanto and Nurkholis (2013) confirmed that microcredit helps to alleviate poverty, particularly in Java-Bali where 5 percent of households have access to it. The probability of households being poor also decreases when cheap rice was distributed after an economic shock. Government assistance such as these, however, is most beneficial if problems relate to transient poverty instead of chronic poverty, therefore, helping them to return to their previous non-poor state. There are several studies using Indonesia's context that answer the determinant of poverty dynamics using panel data setting. Table 2 presents a summary complied from several studies that focus on Indonesia poverty dynamics.

Section Three:

Data & Measurement

3.1 Data

We use Indonesia's Unified Database (UDB) for Social Protection Programs to shed light on the relationship between household characteristics and welfare status. Established in 2011 and updated in 2015, the UDB is designed to register the poorest 40 percent of the Indonesian population and later use to deliver various social programs. The first set of data, PPLS 2011, covered around 25.2 million households across Indonesia. Using the pre-list from PPLS 2011, BDT 2015 re-interviewed approximately 80 percent of those households. Reaching 100 percent is not possible due to various factors: some households may no longer be registered due to death, emigration, the area where they live has been re-used for other purposes, or some no longer fit into the BDT criteria for a poor household–for example, by being enrolled in civil service jobs where they have a fixed income and can no longer be categorised as poor. The BDT 2015 found 5.4 million 'new households', equating to 18.1 million individuals, which were found in PPLS 2011, but were now living in different households in 2015. Despite these various types of attrition problems, the UDB includes 20.4 million households, making it the largest targeting registry with panel data households in the world (Bah et al. 2018). Furthermore, due to its innovative targeting approach, the UDB has been found to successfully reduce leakage of social assistance programs to non-poor households.

The UDB was constructed following two steps: data collection (enumeration) and PMT modeling (ranking). The data collection stage involved pre-identifying all potentially eligible households that should be surveyed. It was intended to cover a greater number of households and to avoid relying exclusively on subjective nominations from community leaders. A 'pre-list' of households to be surveyed was generated through a poverty mapping for PPLS 2011 while pre-list households for BDT 2015 were sourced from PPLS 2011 and various social protection programs.

3.2 Measurement

3.2.1 Poverty

Comprehending who are the poor very much depends on how poverty and its characteristics are measured. BPS (*Badan Pusat Statistik* - Statistics Indonesia) uses the basic needs approach, the amount of money needed to purchase the food consisting of minimum amount of calories (2,100 kcal per day) plus basic non-food necessities. This amount is then used to set the poverty line. People who spend above the poverty line are classified as not poor, while those spending below the line are classified as poor. In March 2018, BPS determined that about 9.81 percent of Indonesia's population was poor, which is approximately equivalent to the first decile or the 10^{th} percentile.

Our study observes 20 million panel households, taken from PPLS 2011 and BDT 2015 to compare how individual and household characteristics correlate with household welfare ranking**.** Embedded in the UDB data are the predicted per capita expenditures, also known as the *yhat*, and the associated household's ranking, known as the percentiles. To generate the predicted *yhat*, PMT models are employed–each with their specific estimating approach. With the percentile information, we further construct ranking information in terms of decile. If a household is always in the lowest deciles in the two years then we define it as always poor. At the other extreme, if a household was not classified in the lowest decile in either survey, we define it as never poor. In between are those households in transient poverty–that is those that were poor in 2011 but not in 2015. These are defined as moving-out households, while those households that were classified in a higher decile in 2011 but the lowest decile in 2015 are defined as falling into poverty.

3.2.2 Education

The first set of variables is human capital where we expect to see a strong correlation with a household's welfare ranking. We opt for four variables to represent human capital stock: (i) average years of education of all household members; (ii) dummy variable whether head of household has completed at least primary education; (iii) dummy variable whether head of household has completed at least a junior secondary education; and (iv) another dummy for whether the household head has completed at least a senior secondary education. One variable acts at the household level while the other three variables proxy human capital by using information on the head of household. All four variables are calculated using all educational variables that were asked in the PPLS 2011 and the BDT 2015 surveys.

3.2.3 Demographics

The second set of variables is the households' demographic structure. We calculate how many adults live in each household and whether they have an expectant mother to represent the demographics of households. With more adults, households should ideally have more resources that they can utilise to improve their welfare, assuming they are productive. If the adults in the household are not productive, then more adults translate into a drop in their welfare ranking. Unlike the number of adults, the presence of an expectant mother should correlate negatively with a household's welfare ranking. As with the set of education variables, we also calculate these two from the PPLS 2011 and the BDT 2015 data sets.

3.2.4 Assets

The next set of variables is assets which represent the ownership of capital. There are seven types of assets that were surveyed in PPLS 2011 and BDT 2015: (i) bicycle, (ii) motorcycle, (iii) fishing boat, (iv) refrigerator, (v) car, (vi) telephone, and (vii) flat-bottom wooden boat. We only consider bicycle, motorcycle, and refrigerator since economically meaningful patterns can only be found on these three while the other show no economic and statistical significance.

3.2.5 Labour Market

The most important driver of moving out of poverty is a high-quality job. While PPLS 2011 and BDT 2015 were not designed as a census for job-related information, the two have several basic questions on household members' participation in the labour market. The censuses ask whether a household member worked in the past week, in which sector each member worked, and the job status of their primary occupation. Using these three questions, we calculate how adult members in the household work and the number who work in the formal sector. The first represents how access to jobs may explain the welfare movement while the latter represents how a good-quality job, in this case participation in the formal sector, explains the welfare transition. It is expected that participation in the formal sector should drive the welfare movement better for poor households.

3.2.6 Social Protection

According to the literature, social protection has three major functions: (i) to protect those people who are near or below the poverty standard (by supporting their consumption level through the aid process); (ii) to facilitate those in persistent poor condition (by helping them to invest in the human capital development process); and (iii) to develop a systematic attempt to break the poverty cycle (Barrientos and Hulme 2005). Our model, therefore, controls for social protection participation as it may directly affect welfare ranking.

3.3 Descriptive Statistics

We perform three regression approaches; pooled OLS, panel fixed effect, and first difference. In addition to the overall regression analysis, we also try to consider the different poverty status of each household by showing how characteristics in each transition group correlate with the welfare ranking and the summary statistics when estimating the model for each district separately.

Before proceeding to regression analysis, the common approach to examining the correlates of poverty usually start with a descriptive profile of poverty mobility. Between 2011 and 2015, official poverty decreased from 12.49 percent to 11.22 percent.[4] Among the panel UDB households, we see slight mobility: 11 percent of UDB households were considered poor in both periods, 14 percent of UDB households moved out of poverty, and 16 percent of UDB households fell into poverty. Policy makers and researchers need to take these numbers with a grain of salt for they can often obscure important poverty mobility that occurred due to a significant proportion of the UDB households surveyed in 2011 that could not be identified during the 2015 census. Moreover, we only have two rounds of the poor census–with more rounds we could expect some households to be classified as 'sometime' poor (see Baulch and Hoddinott 2000).[5]

[4] The official poverty rate is calculated using the basic needs approach. In this paper we use the percentile/decile grouping to define poverty status.

[5] Of the 25.2 million households found in PPLS 2011, only 20.4 million were identified during the 2015 census. We have an approximately 19 percent attrition rate: households moved to other areas, died, cannot be identified, job status, and enumerator decision to remove them from the 2015 census. Despite 'losing' 4.8 million households, the 2015 census added roughly 5.4 million 'new' households into the database.

[6] See Dercon and Shapiro. (2007) for a survey on mobility studies.

We show four sets of household characteristics that the literature argues have some correlation with poverty mobility: (i) asset ownership; (ii) household demographics; (iii) education; and (iv) labour market outcomes.[6] We contrast three different timelines for these: start of the census, end of the census, and the average value between the two. In addition, we also compare four different groups: (i) those always poor; (ii) those who fell into poverty; (iii) those who moved out of poverty; and (iv) the never-poor households.

Household characteristic profiles of those who fell into poverty and moved out of poverty are different to those of the other two groups–the always-poor and the non-poor. Table 3 highlights the summary statistics of these selected characteristics, evaluated at the means, for all these groups. In terms of descriptive statistics, the difference between these four groups for some characteristics are statistically significant. For example, compared to those who are always poor, those who moved out of poverty had significantly more assets, more human capital (in terms of household members' years of education), and participated more in the formal labour market.

Compared to those who fell into poverty, those who moved out of poverty had a somewhat better performance in the labour market in terms of working in the formal sector. Furthermore, there is no significant difference in terms of employment. As expected, the non-poor have the 'best' characteristics–more assets, more education, and engage in the formal labour sector. In sum, this information illustrates a more general finding: those who moved out of poverty tend to be able to rely on their assets, education, and the formal labour market. One should bear in mind that this information was sourced during a period of changing social protection programs and dynamic technological advancement in Indonesia that might potentially contribute to how assets, social protection expansion coverage, education and labour market participation interact with each other.

Furthermore, both data reveals households poverty dynamics as seen in figure 1. The proportion of households living in decile 1 decreases. Out of those living in decile 1 in 2011, 43 percent of them still lives in decile 1 in 2015, while the rest moved up the ladder. In contrast, out of those living above decile 4 in 2011, just about 12 percent of them fell back into decile 1 in 2015. However, when we zoom into the bottom 10 percent as in figure 2, the proportions of households living in the first percentile are relatively stagnant throughout the years. This finding highlights that it is harder for those chronic poor people to move up the ladder.

Section Four:

Results & Discussions

4.1 General Specification

Multivariate analysis that we are presenting in the following subsections aims to improve the rigorousness by revealing the quantitative contribution of each factor to the observed changes in welfare criteria, as well as establishing the marginal contribution of each factor to potential changes in the welfare metric. In this study we are not making any causal claims about the relationship between the aforementioned characteristics on relative welfare ranking since we cannot settle all the identification issues–that is, the correlations that might result from the unobserved factors.

Our proposed general model of the correlation between four sets of household characteristics and welfare status is as follows:

$$P^{h}_{r,t} = c + f_r + f_r + \mathbf{A}^h.\gamma + \mathbf{D}^h.\beta + \mathbf{E}^h.\alpha + \mathbf{S}^h.\delta + \mathbf{L}^h.\theta + \mathbf{C}^h.\theta_1 + \varepsilon_{i.r.t} \qquad (1)$$

where $P^{h}_{r,t}$ is the *assigned-percentile* of household *h* living in district *r* in year *t*, *c* denotes a constant, f_r is district fixed effect, f_t is a time fixed effect, $\mathbf{A}^h$ is vector of household assets for household *h*, $\mathbf{D}^h$ is vector of household demographic related variables of household *h*, $\mathbf{E}^h$ is vector of educational outcomes of household *h*, $\mathbf{L}^h$ is vector of labour market outcomes of household *h*, $\mathbf{C}^h$ is a vector of household specific variables, and $\varepsilon_{i,r,t}$ denotes the error. Our parameters of interest are *γ, β, α, δ* and *θ*.

As stated earlier, these characteristics and poverty ranking are likely to be endogenous. We aim to minimize this issue in the following manner. First, we include the actual *yhat* score that was used to generate the percentile in each wave of UDB. The actual *yhat* scores are generated using a proxy means test approach that exploits rich characteristics of individual, household and even geographical conditions. In doing this, we aim to control the possible correlation between the proposed characteristics and the characteristics used to generate the *yhat.* Second, we control for the possible uniform time effects and district fixed effects. In this step we aim to control for the possible correlation our proposed characteristics with the time varying factor constant across districts and the unique characteristics in each district that is constant across time. Third, to further ameliorate the omitted variable problem, we estimate the correlation by utilising the panel setting and employ several standard methods on them such as simple pool OLS, fixed effects, and first difference models. Four, to account for possible heterogeneity at district level, we estimate the models for each district separately and then present the summary statistics of each parameter in all the districts. Lastly, we estimate all the specifications for each possible transition matrix: always poor, falling into poverty, moving out of poverty, and never poor.

4.2 Unstandardised Result

4.2.1 Results from Simple Pooled Data

We now start with the most restrictive specification of model (1) by estimating it in pooled data setting. The simple difference of the summary statistics between the two periods are shown in Table 4. Most variables show positive change, the biggest change is seen in motorcycle ownership which means that, on average, there are more households owning motorcycles but fewer are owning bicycles. Table 5 presents estimates of specification (1) for two UDBs using the simple Pooled OLS method. Column 1 presents the estimated results control for the actual *yhat* score and time fixed effects. In Column (2) we try to correct the standard error while in Column (3) we estimate the model by including district fixed effects. Table 6 puts estimates of specification (1) by poverty transition while Table 7 summarises the estimates of each coefficient of interest when we split the estimation to each district separately.

Education

Households with higher average years of education among its members display a higher welfare ranking. The coefficients for the indicator variable of years of education, as seen in table 5, are positive and statistically significant. The suggested correlation is that every extra one year of education increased a household's ranking by a 1.03 to 1.04 percentile. We also include three additional binary variables at the head of household level as a proxy for human capital: whether they completed at least a primary, junior secondary, or senior secondary school education. As expected, the correlations between human capital and percentile, as proxied by the head of household's level of education, are positive and significant for an education level greater than primary.

When we split the households' panel into their respective poverty transition, we infer the same conclusion– that more education has a positive correlation with welfare ranking. We estimate the correlation using simple pool data with correction in standard errors. The coefficient correlation of average years of education for households that are always poor is lowest compared to households that fell into poverty, let alone households that are never poor. The coefficient correlation is almost one-tenth of those ranked as never poor. From the same table, we also find that households whose head completed at least a senior secondary education have, on average, a better welfare ranking by about five percentage points, when we compare all the three categories (always poor, fell into poverty and moved out) with the never poor.

Our last attempt to picture the correlation between household's human capital and household's percentile is to estimate the specification for each district independently. This approach aims to answer heterogeneity concerns that might arise, since the percentiles from both PPLS 2011 and BDT 2015 are generated at district level. The results for this approach are summarized in Table 7. First, we estimate model (1) for each district. Second, we compare the parameters of interest in each district. Third, we calculate the summary statistics of those variables as presented in Table 7. How should we interpret the results from this exercise? The average coefficient correlations between heads who completed at least senior secondary and household percentile is around 0.2 with a standard deviation of 2.34. The findings on the positive correlation between education and moving out to a better welfare position are aligned with what is known about the effect of human capital on welfare.

Demographics

The number of adults in a household and the presence of expectant mothers are important characteristics that could determine a household's financial position. Clearly, when grouped into different poverty status, they show visible characteristics. The number of adults in a household seems to correlate negatively with household rankings. The coefficient shows that an extra adult lowers the rank down by three percentiles (Table 5). The presence of expectant mothers, on the other hand, correlates positively when district fixed effect is not controlled–when a household has a pregnant woman, the rank increases by 0.034 percentile. The negative correlation when district fixed effect is controlled shows that, at the district level, there are unobserved characteristics captured which caused the rank to be lower.

The number of adults is seen to be positively correlated amongst households that moved out of poverty–indicating that these households benefited most by having more adults compared to the other groups. The never-poor household, in contrast, would be much lower in rankings if they had more adults in their households. In other words, amongst the never-poor, an extra adult decreases their percentile by 2.3 percentage points compared to the never-poor households that do not have extra adults (Table 6). This confirms the OLS findings that the more adults, the lower the rank. Moreover, the expectant mothers' correlation seems to be less across all groups except those who fell into poverty. Amongst households who fell into poverty, therefore, expectant mothers seem to have a 0.7 points correlation to the rankings, almost oppositely mirroring those categorised as never poor.

The summary statistics from estimating the district-specific show that the number of adults in a household, on average, correlates negatively with household rankings, more than the coefficient of the presence of expectant mothers. The average coefficient correlation is −0.342 for the former and −0.058 for the latter (Table 7).

Assets

Assets are often seen to be highly correlated with welfare. Asset ownership is estimated using physical assets as a proxy. Physical assets–such as bicycle, motorcycle, and refrigerator–that can potentially help households to improve their welfare rank are included in the set of variables.

We see that bicycle ownership lowers ranking by 1.83 percentiles, however, using district fixed effect could increase the estimate, making it 0.815 (Table 5). Motorcycle and refrigerator ownership, in contrast, show a highly positive correlation across the estimation methods–11.7 higher percentiles for those owning motorcycles, and 12.08 percentiles for refrigerator ownership.

The poverty transition further shows that all asset ownership is positive across transition groups, as seen in table 6. Within the never-poor households, asset ownership helps increase rankings more than the rest. For example, bicycle ownership helps the never-poor increase in rank by 0.45, while it only helps the always-poor by 0.047. The same can be said about motorcycle and refrigerator ownership. In this case, the never-poor benefit more by having assets.

The average coefficient correlation to household ranking is only positive for motorcycle ownership–that is 1.79 with a standard deviation of around 3.37 (Table 7). The bicycle and refrigerator ownership correlation, on average, is −0.058 and −1.633 respectively.

Labour Market Outcomes

The number of working adults and the number of adults working in a formal job within a household are chosen to represent participation in the labour market. These factors correlate with household ranking because both are related to a household's income. Regression analysis shows the correlation is negative for the former, and positive for the latter.

There is a persistent pattern on the negative correlation between the number of working adults and household ranking (Table 6). Never-poor households apparently have the lowest coefficient correlation, which means that, within the never-poor, more adults working may decrease their ranking. This could be due to the type of work–this is unexplained by the data but it may relate to low-quality jobs. Formal sector employment is, therefore, relevant for measurement and is seen in the next row. The number of adults working in the formal sector is positive across transition groups and highest under the never-poor households. In other words, formal-sector jobs help the never-poor most in terms of increasing their welfare rank.

4.2.2 Results from Panel Data

Results from the above pool OLS may still suffer from the omitted variables bias problem. One way to minimise this is by estimating model (1) in utilising the panel setting of the UDB data. Table 8 summarizes our findings from panel setting. One should bear in mind that non-random attrition of households between PPLS 2011 and BDT 2015 may bias our estimates of the correlates.

Education

The average years of education in the panel result in table 8 is relatively still consistent with OLS. An extra year of education can increase a household's ranking around 0.95 to 1.04 percentile. Completing at least a junior secondary education also has a positive correlation with the ranking.

Looking closely at each transition level, there is a strong correlation between years of education and household rank amongst the never-poor. It helps increase their rank by 0.954 percentage points, while it only helps the always poor by 0.04 percentage points (Table 9) . Even compared to the transient poor, the always-poor have the lowest correlation coefficient.

Demographics

The number of adults in a household seems to correlate negatively with the ranking, by a magnitude of around 2.8 to 3 percentiles (Table 8). The presence of expectant mothers increase rankings by 2.48, higher than the OLS result, while using district fixed effect results in a statistically insignificant coefficient.

When compared between transitions, the number of adults correlates negatively with household rankings. An extra adult in a household would move their ranking down by 0.19 to 2.54 percentage points (Table 9). In contrast, the presence of expectant mothers is positively correlated by 0.09 to 2.68 across the various types of household.

Asset

Asset ownership is seen to be positively correlated across household types. Owning a motorcycle and refrigerator still seems to have a relatively high coefficient correlation, compared to bicycle ownership, however, all assets seem statistically insignificant under the district fixed effect (Table 8). In the second column, if district fixed effect is not controlled, the magnitude is around 5.379 for refrigerator. Compared to OLS, the results are more statistically significant, even if magnitudes are lower.

When split into the different types of transition groups, all assets are statistically significant. The coefficient correlation of refrigerator ownership is highest in magnitude compared to all other assets for the never-poor and those who moved out of poverty (Table 9). Compared to other groups, asset ownership seems to help the never-poor more than others in terms of welfare.

Labour Market Outcomes

The number of working adults still correlates negatively with household ranking when standard error is not clustered (Table 8). Similar to OLS results, the magnitude is up to −3.4 and is statistically significant without clustered standard error and district fixed effect. When standard error is clustered, it increases rankings up to 0.9 percentile. The number of adults working in the formal sector is positively correlated and still only statistically significant if district level fixed effect is not added.

The poverty transition table also shows a negative correlation across groups within the always-poor and those that fell into poverty and is lowest within those that fell into poverty (Table 9). The number of adults working in the formal sector is positive across groups. Within the never-poor households, an extra adult working in the formal sector could increase their ranking by up to 1.19 percentage points. The magnitude is only 0.16 for the always-poor.

4.2.3 Results from First Difference

As with the panel regression, first difference estimation aims to control for time-invariant heterogeneity amongst districts. Coefficients should be similar to fixed effect estimation in the previous section when there are only two periods. Here, column (1) in table 10 performs a first difference without district fixed effect, while column (2) uses fixed effect.

Education

The average years of education is similar in columns (1) and (2) –an extra year of education would increase household ranking by 0.953 to 0.967 percentile. Household heads who have completed junior and senior secondary school also looks important for the ranking–most importantly for heads who have completed at least senior secondary because it could increase rankings by 3.5 percentile.

The poverty transitions picture shows that education mostly helps the never-poor to increase their rankings. Within the never-poor households, average years of education correlates strongly, around 1 percentage point, to the household rankings, while, within the always-poor, the average years of education only correlates by 0.021 percentage points (Table 11). Similarly, heads that completed senior high school have a 3.4 percentage points correlation within the never-poor. It means that completing senior secondary school helps the never-poor to move up the rank compared to the never-poor that did not complete senior secondary school.

Demographics

Within the scope of demographics, the number of adults in a household correlates negatively towards rankings**.** An extra adult in a household could decrease their ranking by 2.9 percentile (Table 10). In contrast, the presence of expectant mothers correlate positively by 2.36 to 2.48 and is statistically significant in both estimations.

Diving into poverty transitions, the number of adults correlates more positively to households that fell into poverty. Within households that fell into poverty, the coefficient correlation is 0.428, strongest compared to the rest of the groups (Table 11). The coefficient is lowest within the never-poor households which means that, within this group, those with more adults are 2.887 percentile lower than those never-poor households without extra adults.

The presence of expectant mothers seems to be correlated positively across all groups except the ones that fell into poverty. The never-poor households, however, have the highest coefficient correlation of around 2.6, much higher than the panel regression outcome. Expectant mothers, therefore, better correlates with rankings within this transition group. This may capture the possibility that having a pregnant woman in a household is an indication that the never-poor household is more financially sound, compared to their counterpart.

Asset

Asset ownership is positively correlated across all asset types. The coefficient for bicycle ownership is again lowest compared to the other two assets. It increases rankings by only about 0.5 percentile, while motorcycle and refrigerator ownership could increase ranking by 12.26 and 6.59 percentile, respectively (Table 10).

Spread into different transition groups, within the always-poor households owning a motorcycle seems to have the highest coefficient correlation towards rankings, that is 0.387, almost similar to the coefficient of owning a refrigerator **(**Table 11**).** Amongst the transient poor, owning a motorcycle again positively correlates with rankings, more so for the ones who moved out of poverty.

Labour Market Outcomes

Both variables in this category are positively correlated with rankings, and also statistically significant. An extra working adult could increase rankings by 0.93 percentile. Meanwhile, an extra adult working in a formal sector job increases rankings by 1.5 percentile (Table 10).

Within the group that is always poor, the number of working adults in a household correlates negatively with rankings. The coefficient correlations are positive in other groups and strongest amongst the never-poor, which means that more adults working contributes to better welfare for the household except for the never-poor. Amongst the transient poor, the coefficient is higher within the households who moved out of poverty. The number of adults working in formal sector jobs has the highest correlation amongst the never-poor, and lowest amongst those who fell into poverty.

4.3 Standardised Result

In this section, we want to determine whether the correlation between observed characteristics and their welfare rank is sensitive to the PMT specifications used to generate the predicted per capita expenditure**.** We use two different scenarios for this purpose. The first scenario (Scenario A) uses the existing *yhat* obtained from PPLS 2011 and BDT 2015 (the actual *yhat*). As noted in the appendix, both have different variable sets to estimate PMT. Because we try to find out what would happen if we standardise the variables, we create the second scenario (Scenario B) that unifies the characteristics used in both data sets and generate our own *yhat* using the same specification as equation (1). We then rank them using the existing quota. To do this, we do the following steps:

1. We synchronize the Susenas data set between 2010-2014. PPLS 2011 relies on Susenas 2010
2. and 2011 to estimate their PMT model, while BDT 2015 uses Susenas 2011 to 2014.
3. Both PPLS 2011 and BDT 2015, estimate their PMT models at the district level. We design our PMT model for 50 selected districts (list of districts are available upon request). Further, we perform a similar, as carried out by the PPLS and the BDT, stepwise approach to find the optimal PMT model
4. We use the coefficients obtained from step (2) to estimate households' *yhat* for both panel households of PPLS 2011 and BDT 2015.

5. We then combine this *yhat* with the existing 40 percent household quota for the 50 districts directly adopted from PPLS 2011 and BDT 2015 quota.
6. Lastly, the outcome is associated with the percentile ranks.

Out of the 10 percentiles used in the regression, we grouped them into four categories: the always-poor; transient poor; and the never-poor. The first category consists of the lowest decile, that is the group that is always poor (poor in both periods), while the second and third categories are the transient poor, those who move out and fall back into poverty. They live close to the poverty line, therefore, easily entering and exiting poverty, depending on the circumstances. The fourth decile and above are grouped into the never-poor, they were neither poor in 2011 nor in 2015. Table 12 highlights the summary statistics of these selected characteristics, evaluated at the means, for all these groups. Similarly, we further perform ordinary least square, panel, and first difference regression. In each regression table we try to compare the magnitude between the two different scenarios. This may be due to the different PMT models used to generate the *yhat* or driven by the correlates. The difference in correlates between 2011 and 2015 (Table 13) confirms that, regardless of the model, changes are apparent. By isolating the effect of the models, Scenario B provides evidence of the correlates between each variable and household rank, controlling for the same methods to generate *yhat.*

Similar to the previous section, we first observe the poverty dynamics of our data set. This time, we present two scenarios. Figure 3 and 4 represent scenario A, while figure 5 and 6 represent scenario B. In scenario A the proportion of households living in decile 1 decreases. Out of those living in decile 1 in 2011, almost 50 percent of them still lives in decile 1 in 2015, while the rest moved up the ladder. In contrast, out of those living above decile 4 in 2011, just about 10 percent of them fell back into decile 1 in 2015. Similarly, when divided into percentiles, the proportions of households living in the first percentile are relatively stagnant throughout the years.

4.3.1 Results from Simple Pool Data

We first run a simple pooled OLS regression model, with and without district cluster, controlling for *yhat* score and year dummy (Table 14). We then provide a detailed poverty transition using both percentiles as dependent variables. Table 15 shows household characteristics by poverty transitions using Scenario A, and Table 16 uses Scenario B. Table 17 shows summary statistics between districts.

Education

Table 14 shows that there is a relatively wide difference between both scenarios for education. A one year increase in education attainment increased household rankings by 1.17 percentiles in Scenario A, whereas only 0.108 in Scenario B. Household heads who completed at least senior secondary schooling are also seen to be able to move up the rank. Although the magnitude differs, it displays a positive sign.

Breaking down the poverty transition clustered by district using Scenario A, those who moved out of poverty and the never-poor have higher average years of education correlation compared to the always-poor or those who fell into poverty (Table 15). Moreover, completing at least senior secondary school is also seen to be highly correlated with better status within these groups. Scenario B (Table 16) shows that the most statistically significant correlate is household head's senior secondary school completion. It correlates positively within households that fell into poverty and the never-poor.

The average coefficients of correlation differs slightly between districts for the two scenarios (Table 17). Furthermore, the correlation between primary and junior secondary completion is negative on the household percentile level. In other words, on average, those households with heads who have completed schooling up to junior secondary level are associated with lower ranks. When they complete senior secondary school, however, the average coefficient correlation to the rank becomes positive, and are both more than 1. Completing senior high school, therefore, correlates highly with household percentile rank.

Demographics

Under the OLS result, there appears to be a negative correlation between the number of adults and household rank. All other things being constant, comparing the two households with the same characteristics, an extra adult in a household would decrease rankings up to 6 percentiles in Scenario B (Table 14). In other words, the more adults, the less likely they escape poverty because there is a higher burden compared to households with fewer adults. The coefficient of the presence of expectant mothers is positive in Scenario B, but negative in Scenario A. Isolating the effect of PMT models might, therefore, contribute to this difference.

The correlation between the number of adults to household ranking is positive within the always-poor and households that moved out of poverty (Table 15). In contrast, the presence of expectant mothers are not seen to have a statistically significant correlation, at least in Scenario A. In Scenario B, however, the correlates are positive and statistically significant within several groups (Table 16). Furthermore, the number of adults in a household is negative across all transition groups and lowest within the never-poor.

The summary statistics table shows that, between districts, the average coefficient correlation between the number of adults and household rank differs in magnitude between the two scenarios, but both correlate negatively (Table 17). Thus, in poor households, the more adults, the less they are able to help themselves. This might be counter-intuitive and can only be explained by examining their employment status, quality of work or the level of wage they receive. The average coefficient of the presence of expectant mothers differs quite a lot between the two scenarios.

Asset

Bicycle ownership negatively correlates with household rank in both scenarios (Table 14). When a household owns a bicycle, they could be 1.39 to 2.3 percentiles lower than households that do not own a bicycle. On the other hand, the coefficients are highly positive for motorcycle and refrigerator ownership.

Looking at the poverty transitions, motorcycle ownership seems to correlate highly positively amongst those who moved out of poverty and the never-poor, while refrigerator ownership only correlates positively within the never-poor (Table 15). Under Scenario B (Table 16), motorcycle and refrigerator ownership is better correlated across groups. Refrigerator ownership, in particular, greatly affects ranking within the never-poor, by up to 7 percentage points, but only around 3 percentage points for the transient poor. Summary statistics (Table 17) between districts makes clear that the average coefficient correlation between having assets and household rankings are positive, particularly under Scenario B.

Labour Market Outcomes

Employment and working status may correlate with household ranks–as previously stated, the quality of work and wage contributes to whether or not a household can escape poverty. The number of working adults correlates negatively to their household percentile ranks (Table 14). For example, under Scenario A, an extra working adult is associated with a 5.7 lower percentile, and even lower under Scenario B. This is in line with the previous result on demographics that the more adults in a household, the less likely they are able to escape poverty. The type of job may contribute to the reasons why this is the case. Looking at the next row, the number of adults working in the formal sector may still correlate negatively to the ranks, but it contributes more towards moving up the ranks than the number of working adults.

When broken down into transition groups, the number of working adults amongst households that are never poor correlates negatively by about 3.7 percentage points (Table 15). Formal job sector also do not appear to have positive correlation. Scenario B shows consistent trend for both variables (Table 16). On average, working in the formal sector positively correlates with household rankings between districts in both scenarios (Table 17), however, the number of working adults still appears to be correlated negatively–more so under Scenario B. Therefore, the number of working adults may not be as important in moving them up the ranks as working in the formal sector.

4.3.2 Results from Panel Data

As with results in the previous section, here we perform a panel regression analysis to take attrition into account. Furthermore, we also complement the estimation using fixed effect to control for time-invariant unobserved heterogeneity. The same set of characteristics are estimated following the same households in the second survey period. We discuss how each set of categories differs between the two percentile scenarios. Table 18 shows the general panel regression result, indicating the two scenarios and whether or not fixed effect is used. Tables 19 and 20 show the breakdown of transition levels using Scenarios A and B while controlling for fixed effect.

Education

The results for the trend in education coefficients are similar to the OLS result. In Scenario A, more years of schooling increase the household percentile level to about 1.16 when panel fixed effect is controlled. In line with previous findings, heads who completed lower than senior secondary schooling do not correlate much with moving up the household welfare ranks. A smaller magnitude is seen when PMT effect is controlled. Nevertheless, both scenarios are persistent in showing positive and statistically significant findings for these two particular characteristics under the education category. Poor households have the least correlates towards education endowment, both in terms of years of education, and the level of schooling, even when PMT effect is controlled, because the same pattern can be seen in Tables 19 and 20.

Demographics

There is an interesting change in demographics under Scenario A where the sign and magnitude differs significantly with OLS for the presence of an expectant mother (Table 18). Furthermore, Scenario B displays a higher magnitude. When a pregnant woman lives in a certain household, that household is likely to be 4.2 percentile higher in ranking than those without pregnant women.

The number of adults living in a household has a persistently negative correlation to the rankings–this finding is also consistent with the OLS result. Splitting into poverty transitions, we see that in both scenarios, the richer a household is, the more negative they correlate with the number of adults. On the other hand, the richer a household is, the more positive they correlate with the presence of an expectant mother.

Asset

Asset characteristics are also somewhat consistent with OLS findings–bicycle ownership is associated with lower household rankings, while motorcycle and refrigerator ownership are associated with higher rankings. Magnitudes, in general, are biggest compared to other categories, showing how much their ability to buy or afford certain things links to their poverty status. Clearer evidence is shown under different poverty transition groups. Motorcycles, and refrigerator ownership especially, correlates highly positively with those who moved out of poverty and the never-poor but not so much for the poor.

Labour Market Outcomes

Several modest differences are seen when comparing with the previous OLS result (Table 18). The number of working adults still displays a negative correlation, except under Scenario A with fixed effect, although this is quite small. Interestingly, the number of adults working in the formal sector becomes positive in both scenarios when fixed effect is controlled, which means that the type of job may actually matter to raising the welfare rank, not just whether or not they work.

The number of working adults is only negative within the always-poor (Table 19), however, in Scenario B it becomes negative across all groups (Table 20) so the effect of PMT modelling might be strong here. Moreover, working in a formal job is seen to be correlated negatively under Scenario A but positively under Scenario B, except for those who fell into poverty. Only those who fell into poverty seem to not be having strong correlates with labour market outcomes.

4.3.3 Results from First Difference

First difference estimation is used to control characteristics that do not change over time, similar to fixed effect. When there are two periods, as in our case, fixed effect and first difference estimation would yield the same results, however, it is more efficient than fixed effect when the change in the error term is uncorrelated (Wooldridge, 2010). Table 21 displays the general first difference result for both scenarios. Table 22 shows the poverty transitions using Scenario A, and lastly Table 23 uses Scenario B.

Education

When compared between OLS, panel regression, and first difference, we see consistent results. There is a positive correlation between average years of schooling and household head completing at least senior secondary and household ranking. Scenario B in table 21 have smaller magnitude than Scenario A, although signs are both positive. Furthermore, the never-poor are seen to benefit more than the rest on these two characteristics in Scenario A, but not as much under Scenario B (Tables 22 and 23).

Demographics

Demographics also show a consistent trend between the three estimations. The number of adults persistently correlates negatively with household rank. The magnitude does not differ much across estimations. The coefficient of the presence of expectant mother is higher in first difference and fixed effect model than OLS which may imply that there is unobserved heterogeneity captured in this case. Splitting into poverty transitions, it also appears that both scenarios have similar trends.

Asset

All three types of asset ownership show a positive correlation towards household ranking, with motorcycle ownership having the highest coefficient correlates (Table 21). When split into different transition groups, motorcycle ownership very much favours the never-poor. Their ranking could be about 10 percentage points higher than their counterparts who do not own motorcycles under Scenario B. The magnitude is only about 1 percentage point within the always-poor.

Labour Market Outcomes

Both coefficients show a consistent result with the fixed effect model. The number of working adults is only negative under Scenario B, and positive under Scenario A, while the formal sector coefficient is positive in both. Looking at the poverty transition tables, the number of working adults is mostly positive under Scenario A, but negative under Scenario B, while the number of adults working in the formal sector has a mostly positive correlation under Scenario B.

Section Five:

Conclusion

Using Indonesia's UDB, this paper analyses longitudinal patterns of relative poverty among the bottom 40 percent group of the Indonesian population. In doing so, this study aims to better understand why households move into and out of poverty.

The results from simple transition matrix show that, over the course of four years, we see slight mobility: 11 percent of UDB households were considered poor in both periods, 14 percent moved out of poverty, and 16 percent fell into poverty. There is a difference of 2 percent. Policy makers and researchers need to take these numbers with a grain of salt for they can often obscure the important poverty mobility due to attrition.

To observe how household characteristics correlate with welfare ranking, we proceed using two approaches, observe the correlation using the existing welfare measure, generated using two PMT models, and generating our own PMT model to create our own welfare measure which latter used to identify the correlation between the examined characteristics and the new welfare metric. We found that, in general, results are lower in magnitude than the existing model, however, trends are consistent across models and groups.

On the household human capital characteristic, we find that the more education that each household member earned, the more likely they help their households to move out of poverty. While this finding reiterates the importance of education in helping people to move out of poverty, the exact interpretation is hard to determine due to the fact that education is seen to be endogenous to long-term poverty changes.

While we see no clear pattern on the correlation between sets of demographic variables and the household welfare change, the correlation between physical assets with changes in welfare rank seems to be consistent across different specifications. Interestingly, we find that households who own a motorcycle and refrigerator are more likely to escape the poor condition. High-quality jobs are expected to help people move from poverty in a more profound way. It is, therefore, not out of the realm of the two variables that we choose to represent the labour market outcomes. Moreover, the number of adults working in the formal sector is seen to have a stronger positive correlation with the households' welfare chang

Appendix: PMT in the UDBs

One crucial issue when using welfare status in the UDBs is the different model that is being used to estimate it. The two UDBs, PPLS 2011 and BDT 2015, use the same PMT approach but the exact model to produce the welfare is different. Suppose the following general model is used to estimate real per capita expenditure in PMT 2011:

$$\boldsymbol{W}_{i,r,p,2011} = a_{2011} + \boldsymbol{X'}_{i,r,p,2011/2015} \cdot b_{2011} + \boldsymbol{S'}_{i,r,p,2011} \cdot c_{2011} + e_{i,r,p,2011} \quad \textbf{(2)}$$

where $\boldsymbol{X'}_{i,r,p,2011/2015}$ denotes vector of variables used in PMT 2011 and available in PMT 2015 and $\boldsymbol{S'}_{i,r,p,2011}$ represents vector of variables specific in PMT 2011.

Following the estimate of real per capita expenditure for the households in the UDB, the next step is constructing the *relative* ranking of households. In general household *i* relative ranking can be expressed as follows.

$$\boldsymbol{P}_{i,r,p,2011} = \boldsymbol{G}(\boldsymbol{w}_{Wi,r,p,2011,}\ \mathbf{W}_{-\,i,r,p,2011,}\ \mathbf{C}_{\mathbf{r},p,2011}) \quad \textbf{(3)}$$

where $\mathbf{P}_{i,r,p,2011}$ denotes percentile of household i live in region r province p at year 2011. Thus household *i* percentile ranking is a function of its estimated real per capita expenditure, other households in the same region estimated real per capita expenditure, and vector of regional characteristics.

While to estimate the real per capita expenditure in PMT 2015, the following model is used:

$$\boldsymbol{W}_{i,r,p,2015} = a_{2015} + \boldsymbol{X'}_{,r,p,2015} \cdot b_{2015} + \boldsymbol{Z'}_{i,r,p,2015} \cdot c_{2015} + e_{i,r,p,2015} \quad \textbf{(4)}$$

where $\boldsymbol{X'}_{i,r,p,2011/2015}$ denotes vector of variables used in PMT 2011 and available in PMT 2015 and $\boldsymbol{S'}_{i,r,p,2015}$ represents vector of variables specific in PMT 2015.

Subtracting (4) from (2) we get:

$$\begin{aligned}\boldsymbol{W}_{i,r,p,2015} - \boldsymbol{W}_{i,r,p,2011} = {} & a_{2015} - a_{2011} + \boldsymbol{X'}_{i,r,p,2015} \cdot b_{2015} - \boldsymbol{X'}_{i,r,p,2011} \cdot b_{2011} \\ & + \boldsymbol{Z'}_{,r,p,2015} \cdot c_{2015} - \boldsymbol{S}_{ti,r,p,2011} \cdot c_{2011} + e_{i,r,p,2015} - e_{i,r,p,2011} \quad \textbf{(5)}\end{aligned}$$

The change in welfare status is, therefore, induced by change in the intercept, change in vector of variables used both in PMT 2011 and PMT 2015, change in the slopes of $\boldsymbol{X'}_{2011/2015}$, change in the specific variables, $\boldsymbol{Z'}$ and $\boldsymbol{S'}$, and change in the slopes of those specific variables.

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Table 1. Absolute and Relative Poverty Line

Absolute Poverty Line	Relative Poverty Line
Aims to have the same purchasing power, irrespective of the country and time.	Set at a constant proportion of the current mean or median income.
When incomes grow at the same proportionate rate, the absolute poverty line fails because measures should be homogenous of degree 0 between the mean and the poverty line.	People may attach value to their income relative to the mean in their country of residence, thus relative income is a source of utility.
Aggregate poverty increases when poverty increases in any subgroup and does not change for any other group.	Social inclusion should be considered and that the cost of social inclusion is proportional to the mean income.
Moving a person between groups with no absolute loss to own consumption, cannot increase aggregate poverty.	

Ravallion and Chen (2011)

Table 2. Literature Review

Author	Sample	Method	Findings
Sumner et al. (2014)	IFLS 2000 & 2007 and Susenas 2000 - 2013	IFLS 2000 & 2007 and Susenas 2000 - 2013	Their findings show that: 1. Determinants of the probability of a household staying poor are education and asset ownership. 2. In the case of transient poverty, when one defines security from poverty as a 10 percent chance of being poor in the future, at poverty lines of US$2.00, US$4.00 and US$5.00 PPP/day, one has to double the poverty line to get to a security line of US$4.00, US$8.00 or US$13.00 respectively. 3. When the 'national poverty line' is used, large numbers of people have a low probability of remaining poor.
Dartanto & Nurkholis (2013)	Susenas 2005 & 2007	'Spell' approach to identify poverty and ordered probit model to examine the determinants of poverty dynamics.	Their findings show that: 1. The determinants of poverty dynamics in Indonesia are educational attainment, the number of household members, physical assets, employment status, health shocks, the microcredit program, access to electricity, and changes in employment sector, employment status, and the number of household members. 2. 28 percent of poor households are classified as chronically poor (remaining poor in two periods), and 7 percent of non-poor households are vulnerable to being transient poor. 3. Households in Java–Bali are more vulnerable to negative shocks than those outside Java–Bali.

Author	Sample	Method	Findings
Sumner (2012)	Demographic and Health Surveys 1991, 1994, 1997, 2002/3 & 2007	Correlations between education/ health poverty and residence, wealth quintile, and education of household head.	Findings show that: 1. Education poverty has a positive correlation with place of residence and a negative correlation with wealth quintile and education of household head. 2. Health poverty has weaker correlations to place of residence, wealth quintile and household head.
Van Edig & Schwarze (2011)	Randomly selected households in 2005 & 2007 at Lore Lindu National Park.	Multinomial Logit Model	They found that: 1. Higher education increases transitory poverty; non-agricultural employment increases the probability of staying out of poverty, household size is another determinant of poverty. 2. Using two different poverty lines (namely, the US$1.00/day and US$2.00/day) yields the same result, that poverty increased.
Miranti (2010)	Panel Susenas 1984-2002	Fixed Effects	Findings show that: 1. A 10 percent increase in consumption per capita reduces poverty by 24.3 percent. 2. Growth Elasticity of Poverty (GEP) was stable during the three episodes (policy liberalisation, slower liberalisation, and recovery period of the Asian financial crisis) at around -2.37 to -2.49. 3. Inequality elasticity of poverty ranged between 0.78 to 1.30 across the three episodes.

Author	Sample	Method	Findings
Kim et al. (2009)	IFLS 1993 & 1997	Propensity Score Matching	They found that: 1. Equivalence scale greatly affects how having a new-born child highly affects household's welfare. 2. When the equivalence scale used is that food share indicates the inverse of the level of household welfare, then households experience 20-65 percent reduction in consumption of that obtained when per-capita consumption is used as a measure of household consumption. 3. Households with a new-born child between 1993 & 1997 experience about a 20 percent reduction in consumption when per-capita consumption is used as a measure of household consumption.
Widyanti et al. (2009)	IFLS 1993, 1997 & 2000	Foster-Greer-Thorbecke (FGT) to calculate poverty indicators, ordered probit to examine the relationship between household composition and poverty status.	Results show that: 1. The larger the household size, the higher the probability of a household being chronically poor. 2. There is no evidence that households change their compositions (such as sending their children to live with relatives) to cope with poverty and unemployment.

Table 3. Household Correlates by Poverty Transition

Category	**Correlates**	**Always poor**	**Fell into Poverty (nonpoor in 2011, poor in 2015)**	**Moved out of poverty (Poor in 2011, nonpoor in 2015)**	**Always nonpoor**	**Overall mean**
Asset	HH has bicycle	0.233	0.235	0.264	0.432	0.241
	HH has motorcycle	0.215	0.288	0.340	0.293	0.352
	HH has refrigerator	0.036	0.060	0.092	0.070	0.109
Demographics	# Adults in household	3.140	2.888	3.041	2.669	2.778
	Presence of expectant mother	0.030	0.032	0.026	0.024	0.026
Education	Years of education of all members	4.388	4.488	5.122	5.289	5.080
	Mean years of education of adults	4.809	4.867	5.661	5.717	5.521
	Mean years of education of male adults	4.783	5.087	5.711	6.259	5.827
	Head completed primary education	0.731	0.766	0.754	0.784	0.772
	Head completed junior secondary education	0.252	0.288	0.344	0.380	0.355
	Head completed senior secondary education	0.175	0.200	0.215	0.257	0.236
Labour market outcome	# Adults working	0.860	0.830	0.819	0.792	0.780
	# Adults work in formal sector	0.148	0.159	0.152	0.168	0.161

Table 4. Summary Statistics: Difference Between 2011 and 2015

Correlates	Difference	Std. Deviation	Min	Max
HH has bicycle	-0.019	0.432	-1	1
HH has motorcycle	0.214	0.536	-1	1
HH has refrigerator	0.115	0.371	-1	1
# Adults in household	-0.0458	1.198	-19	18
Presence of expectant mother	-0.001	0.225	-5	6
Average years of education	0.139	3.667	-23	23
Head completed at least primary education	0.014	0.518	-1	1
Head completed at least junior secondary education	0.024	0.507	-1	1
Head completed at least senior secondary education	0.010	0.454	-1	1
# Adults working	-0.027	0.468	-1	1
# Adult working in formal sector	-0.004	0.454	-1	1

Table 5. Correlates of Households Ranking: Pooled OLS

Correlates	Dependent Variable: Percentile in UDB		
	(1)	(2)	(3)
Education			
Average years of education	1.042 (0.001)	1.042 (0.047)	1.035 (0.001)
HH head completed at least primary education	-5.972 (0.012)	-5.972 (0.276)	-5.536 (0.011)
HH head completed at least junior secondary education	1.185 (0.012)	1.185 (0.250)	1.237 (0.012)
HH head completed at least senior secondary education	5.673 (0.014)	5.673 (0.279)	5.805 (0.014)
Demographics			
# Adults in household	-2.759 (0.002)	-2.759 (0.172)	-3.022 (0.002)
Presence of expectant mother	0.034 (0.022)	0.034 (0.194)	-0.967 (0.021)
Assets			
Household owns bicycle	-1.838 (0.009)	-1.838 (0.404)	0.815 (0.009)
Household owns motorcycle	10.541 (0.008)	10.54 (0.331)	11.679 (0.008)
Household owns refrigerator	11.213 (0.012)	11.213 (0.450)	12.085 (0.012)
Labour Market Outcome			
# Adults working	-3.892 (0.009)	-3.892 (0.344)	-4.588 (0.009)
# Adults working in formal sector	0.111 (0.010)	0.111 (0.338)	1.091 (0.010)
Other Controls			
Social protection coverage	Yes	Yes	Yes
Actual yhat score	Yes	Yes	Yes
District fixed effect	No	No	Yes
Time fixed effect	Yes	Yes	Yes
Clustered Standard Error	No	Yes	No
Number of observations	40,529,166	40,529,166	40,529,166

Table 6. Correlates of Household Welfare Ranking by Poverty Transition

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.022 (45.95)**	0.079 (32.76)**	0.348 (274.97)**	0.959 (571.27)**
HH head completed at least primary education	-0.205 (59.84)**	-0.290 (14.97)**	-2.197 (202.84)**	-5.141 (320.51)**
HH head completed at least junior secondary education	0.117 (32.86)**	0.089 (4.37)**	1.042 (96.86)**	0.641 (40.19)**
HH head completed at least senior secondary education	0.050 (10.13)**	0.278 (10.82)**	1.623 (127.07)**	4.804 (279.93)**
# Adults in household	-0.085 (120.38)**	-0.160 (34.20)**	0.008 (3.23)**	-2.335 (546.14)**
Presence of expectant mother	-0.047 (9.55)**	0.700 (23.74)**	-0.363 (18.42)**	-0.717 (23.19)**
Household owns bicycle	0.047 (20.39)**	0.062 (4.42)**	0.321 (37.96)**	0.450 (34.51)**
Household owns motorcycle	0.500 (219.15)**	2.209 (174.54)	2.218 (271.57)**	9.984 (865.86)**
Household owns refrigerator	0.630 (130.62)**	1.453 (60.35)**	5.461 (451.37)**	10.459 (672.93)**
# Adults working	-0.159 (61.61)**	-0.359 (24.15)**	-1.089 (123.04)**	-3.623 (288.18)**
# Adults working in formal sector	0.086 (34.18)**	0.270 (17.72)**	0.275 (29.56)**	1.070 (77.88)**
Number of observations	4,421,400	6,400,208	5,766,064	23,941,494
R^2	0.50	0.66	0.60	0.19

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 7. Summary Statistics of Estimated Parameters

Correlates	Mean	Standard Deviation	Minimum	Maximum
Education				
Average years of education	0.016	0.365	-1.261	2.198
HH head completed at least primary education	0.085	2.017	-12.589	6.662
HH head completed at least junior secondary education	-0.002	1.739	-5.826	12.514
HH head completed at least senior secondary education	0.213	2.342	-14.234	11.404
Demographics				
# Adults in household	-0.342	1.105	-7.118	2.096
Presence of expectant mother	-0.058	1.227	-11.645	4.168
Asset				
Household owns bicycle	-0.058	2.013	-13.735	10.378
Household owns motorcycle	1.790	3.371	-11.371	22.887
Household owns refrigerator	-1.633	5.967	-21.050	22.377
Labour Market Outcome				
# Adults working	-0.376	2.289	-12.237	12.348
# Adults working in formal sector	0.444	2.414	-18.978	18.268

Table 8. Correlates of Households Ranking: Panel Results

Correlates	Dependent Variable: Percentile in UDB		
	(1)	(2)	(3)
Education			
Average years of education	1.040 (780.85)**	0.953 (382.00)**	1.035 (0.001)
HH head completed at least primary education	-5.764 (478.95)**	-3.487 (186.47)**	-5.536 (0.011)
HH head completed at least junior secondary education	1.215 (96.87)**	1.314 (68.20)**	1.237 (0.012)
HH head completed at least senior secondary education	5.589 (393.32)**	3.417 (148.89)**	5.805 (0.014)
Demographics			
# Adults in household	-2.816 (927.98)**	-2.938 (538.57)**	-3.022 (0.002)
Presence of expectant mother	0.386 (17.55)**	2.486 (87.54)**	-0.967 (0.021)
Assets			
Household owns bicycle	-1.734 (198.42)**	0.549 (37.04)**	0.815 (0.009)
Household owns motorcycle	10.791 (1,290.65)**	11.901 (975.74)**	11.679 (0.008)
Household owns refrigerator	10.690 (868.42)**	5.379 (307.71)	12.085 (0.012)
Labour Market Outcome			
# Adults working	-3.415 (357.40)**	0.934 (66.09)**	-4.588 (0.009)
# Adults working in formal job	0.278 (27.46)**	1.132 (79.31)**	1.09 (0.010)
Other Controls			
Social protection coverage	Yes	Yes	Yes
Actual yhat score	Yes	Yes	Yes
District fixed effect	No	No	Yes
Time fixed effect	Yes	Yes	Yes
Clustered Standard Error	No	Yes	No
Number of observations	40,529,166	40,529,166	40,529,166
R^2	0.13	0.18	

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 9. Correlates of Household Welfare Ranking by Poverty Transition

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.040 (40.94)**	0.223 (44.61)**	0.463(181.09)**	0.954 (281.92)**
HH head completed at least primary education	-0.228 (35.16)**	-0.941 (26.37)**	-2.525 (134.79)**	-3.706 (141.39)**
HH head completed at least junior secondary education	0.102 (15.17)**	0.167 (4.51)**	0.824 (43.03)**	1.218 (45.86)**
HH head completed at least senior secondary education	0.011 (1.19)	0.997 (20.64)**	2.098 (89.39)**	3.171 (104.54)**
# Adults in household	-0.199 (128.73)**	-0.788 (77.22)**	-0.649 (133.85)**	-2.544 (309.21)**
Presence of expectant mother	0.097 (12.66)**	1.162(25.46)**	0.407 (13.96)**	2.681 (63.58)**
Household owns bicycle	-0.017 (3.95)**	0.109 (4.14)**	0.318 (21.47)**	0.578 (27.43)**
Household owns motorcycle	0.702 (183.49)**	3.782 (171.77)**	2.408 (191.64)**	11.580 (661.45)**
Household owns refrigerator	0.879 (113.62)**	2.437 (60.36)**	5.526 (306.63)**	5.115 (224.97)**
# Adults working	-0.02 4(5.49)**	-0.057 (2.22)*	0.162 (11.05)**	0.723 (36.91)**
# Adults working in formal sector job	0.164 (39.04)**	0.430 (17.15)**	0.308 (20.87)**	1.196 (59.15)**
R^2	0.39	0.69	0.72	0.21
Number of observations	4,421,400	6,400,208	5,766,064	23,941,494

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 10. Correlates of Households Ranking: First Difference Result

Correlates	Dependent Variable: Percentile in UDB	
	(1)	(2)
Education		
Average years of education	0.953 (382.00)**	0.967 (408.62)**
HH head completed at least primary education	-3.487 (186.47)**	-3.707 (208.74)**
HH head completed at least junior secondary education	1.314 (68.20)**	1.227 (67.19)**
HH head completed at least senior secondary education	3.417 (148.89)	3.506 (161.22)**
Demographics		
# Adults in household	-2.938 (538.57)**	-2.975 (574.30)**
Presence of expectant mother	2.486 (87.54)**	2.361 (87.69)
Asset		
Household owns bicycle	0.549 (37.04)**	0.565 (40.06)**
Household owns motorcycle	11.901 (975.74)**	12.262 (1,053.78)**
Household owns refrigerator	5.379 (307.71)**	6.595 (391.73)
Labour Market Outcome		
# Adults working	0.934 (66.09)**	0.755 (56.25)**
# Adults working in formal job	1.132 (79.31)**	1.519 (111.82)**
Other controls		
Social protection coverage	Yes	Yes
Actual yhat score	Yes	Yes
District fixed effect	No	Yes
R2	0.11	0.20
Number of observations	20,178,760	20,178,760

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 11. Correlates of Household Welfare Ranking by Poverty Transition

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.021 (27.18)**	-0.006 (1.48)	0.493 (209.39)**	1.004 (314.89)**
HH head completed at least primary education	-0.181 (35.91)**	0.115(4.20)**	-2.604 (150.85)**	-4.130 (167.22)**
HH head completed at least junior secondary education	0.060 (11.66)**	-0.057 (2.02)*	0.984 (56.02)**	1.225 (49.02)**
HH head completed at least senior secondary education	0.103 (14.03)**	-0.059 (1.59)	2.121 (98.50)**	3.397 (119.02)**
# Adults in household	-0.123 (100.65)**	0.428 (53.62)**	-0.932 (204.42)**	-2.887 (371.48)**
Presence of expectant mother	0.116 (19.72)**	-0.074 (2.13)*	0.541 (20.24)**	2.675(67.40)**
Household owns bicycle	-0.010 (2.84)**	-0.027 (1.33)	0.333 (24.42)**	0.579 (29.10)**
Household owns motorcycle	0.387 (127.39)**	0.446 (25.87)**	3.131 (264.38)**	12.443 (749.53)**
Household owns refrigerator	0.375 (60.26)**	-1.760 (56.24)**	6.170 (359.23)**	6.780 (311.92)**
# Adults working	-0.019 (5.44)**	0.067 (3.40)**	0.115 (8.47)**	0.561 (30.36)**
# Adults working in formal sector job	0.05 1(15.79)**	-0.041 (2.15)*	0.490(36.00)**	1.617 (84.65)**
R^2	0.58	0.66	0.22	0.20
Number of observations	2,191,511	3,185,494	2,862,612	11,939,143

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 12. Household Correlates by Poverty Transition

Category	Correlates	Always Poor	Fell into Poverty (non-poor in 2011, poor in 2015)	Moved out of Poverty (poor in 2011, nonpoor in 2015)	Always Nonpoor	Overall Mean
Asset	Household has bicycle	0.219	0.205	0.239	0.201	0.209
	Household has motorcycle	0.262	0.317	0.358	0.389	0.359
	Household has refrigerator	0.070	0.099	0.143	0.184	0.153
Demographics	# Adults in household	3.458	2.961	3.372	2.605	2.861
	Presence of expectant mother	0.030	0.037	0.025	0.024	0.027
Education	Average years of education	4.580	4.999	4.790	5.237	5.064
	Head completed at least primary education	0.726	0.760	0.746	0.779	0.75
	Head completed at least junior secondary education	0.308	0.350	0.344	0.399	0.374
	Head completed at least senior secondary education	0.183	0.210	0.218	0.262	0.239
Labour Market Outcomes	# Adults working	0.879	0.847	0.810	0.748	0.786
	# Adults working in formal sector	0.196	0.197	0.196	0.198	0.197

Table 13. Summary Statistics: Difference Between 2011 and 2015

Correlates	Difference	Standard Deviation	Minimum	Maximum
Household owns bicycle	-0.014	0.431	-1	1
Household owns motorcycle	0.229	0.545	-1	1
Household owns refrigerator	0.147	0.421	-1	1
# Adults in household	-0.043	1.243	-15	18
Presence of expectant mother	-0.002	0.230	-4	4
Average years of education	0.156	3.741	-23	18
HH head completed at least primary education	0.013	0.517	-1	1
HH head completed at least junior secondary education	0.02	0.499	-1	1
HH head completed at least senior secondary education	0.008	0.448	-1	1
# Adults working	-0.032	0.475	-1	1
# Adults working in formal sector	0.004	0.490	-1	1
Household owns refrigerator	-1.633	5.967	-21.050	22.377
Labour Market Outcome				
# Adults working	-0.376	2.289	-12.237	12.348
# Adults working in formal sector	0.444	2.414	-18.978	18.268

Table 14. Comparison of Correlates on 50 Districts for Two Sets of Percentiles: Pooled Least Square

Correlates	Scenario A		Scenario B	
	(1)	**(2)**	**(3)**	**(4)**
Education				
Average years of education	1.176 (0.003)***	1.176 (0.125)***	0.108 (0.004)***	0.108 (0.124)
HH head completed at least primary education	-5.805 (0.034)***	-5.805 (0.719)***	0.0328 (0.0366)	0.0328 (0.661)
HH head completed at least junior secondary education	0.648 (0.034)***	0.648 (0.613)	-1.68 (0.037) ***	-1.685 (0.766)**
HH head completed at least senior secondary education	7.101 (0.036)***	7.101 (0.915)***	2.673 (0.039)***	2.673 (0.651)***
Demographics				
# Adults in household	-2.199 (0.008)***	-2.199 (0.616)***	-6.275 (0.008)***	-6.275 (0.361)***
Presence of expectant mother	-0.228 (0.0633)***	-0.228 (0.752)	2.215 (0.068)***	2.215 (0.849)
Assets				
Household owns bicycle	-1.391 (0.026)***	-1.391 (1.157)	-2.314 (0.027)***	-2.314 (1.182)*
Household owns motorcycle	10.27 (0.024)***	10.27 (1.201)***	5.668 (0.025)***	5.668 (0.780)***
Household owns refrigerator	10.79 (0.031)***	10.79 (0.943)***	7.219 (0.034)***	7.219 (1.357)***
Labour Market Outcomes				
# Adults working	-5.723 (0.027)***	-5.723 (1.141)***	-6.398 (0.029)***	-6.398 (1.761)**
# Adults working in formal sector	-0.847 (0.027)***	-0.847 (0.927)	-1.054 (0.029)***	-1.054 (1.181)
Other controls				
Social protection coverage	Yes	Yes	Yes	Yes
Yhat score	Yes	Yes	Yes	Yes
District cluster	No	Yes	No	Yes
R^2	0.178	0.178	0.295	0.295
Number of observations	5,485,773	5,485,773	5,485,773	5,485,773

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 15. Correlates of Household Welfare Ranking by Poverty Transition (Scenario A with District Cluster)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.056 (0.98)	-0.164 (2.07)*	0.491 (3.26)**	1.184 (10.03)**
HH head completed at least primary education	-0.695 (1.82	0.941 (1.64)	-3.015 (4.12)**	-6.326 (9.27)**
HH head completed at least junior secondary education	-0.557 (2.01)*	-1.115 (2.75)**	0.473 (1.00)	0.943 (1.23)
HH head completed at least senior secondary education	1.196 (2.36)*	1.220 (1.91)	3.225 (3.59)**	7.094 (7.58)**
# Adults in household	0.423 (3.59)**	-0.448 (1.03)	0.512 (1.59)	-1.410 (2.01)*
Presence of expectant mother	0.154 (1.67)	0.93 (1.66)	0.174(0.54)	-0.046 (0.06)
Household owns bicycle	-0.538 (1.23)	-0.687 (0.46)	-0.749 (1.66)	-1.552 (1.16)
Household owns motorcycle	0.173 (0.49)	1.848 (2.00)	2.737 (4.06)**	9.212 (7.49)**
Household owns refrigerator	-1.134 (2.18)*	-2.394(1.91)	1.94 2(1.86)	9.526 (9.46)**
# Adults working	-0.738 (3.00)**	0.126 (0.22)	-1.333 (1.79)	-3.778 (3.08)**
# Adults working in formal sector job	-0.844 (2.72)**	-2.620 (2.33)*	-0.859 (2.40)*	-1.297 (1.30)
R^2	0.62	0.63	0.34	0.17
Number of observations	687,446	768,126	707,903	3,322,298

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 16. Correlates of Household Welfare Ranking by Poverty Transition (Scenario B with District Cluster)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	-0.026 (1.95)	0.011(0.15)	0.025(0.40)	0.181 (1.31)
HH head completed at least primary education	0.151 (1.78)	0.594(1.43)	-0.299(0.96)	-0.294 (0.39)
HH head completed at least junior secondary education	-0.149 (2.67)*	-0.246(0.39	-0.649(2.02)*	-1.866 (2.52)*
HH head completed at least senior secondary education	0.001 (0.04)	1.256(2.76)**	0.615(1.78)	2.636 (3.79)**
# Adults in household	-0.165 (5.27)**	-2.467(8.05)**	-1.430(10.82)**	-6.958 (14.74)**
Presence of expectant mother	0.106 (2.69)**	1.823(2.23)*	0.185(0.67)	2.689 (3.05)**
Household owns bicycle	0.021 (0.15)	-0.955(1.30)	-0.611(1.13)	-2.956 (2.40)*
Household owns motorcycle	0.509 (5.32)**	2.524(4.45)**	0.277(0.64)	4.898 (5.36)**
Household owns refrigerator	0.156 (1.19)	3.844(5.73)**	3.143(3.11)**	7.151 (4.94)**
# Adults working	-0.203 (1.96)	-4.564(4.10)**	-2.278(3.59)**	-5.143 (3.10)**
# Adults working in formal sector job	-0.216 (1.54)	-0.856(1.37)	-1.075(2.22)*	-1.358 (1.07)
R^2	0.27	0.32	0.36	0.23
Number of observations	687,446	768,126	707,903	3,322,298

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 17. Summary Statistics of Estimated Parameters: OLS Between Districts

Correlates	Scenario A	Scenario B
Education		
Average years of education	0.098	0.141
HH head completed at least primary education	-0.302	-0.232
HH head completed at least junior secondary education	-0.181	-0.75
HH head completed at least senior secondary education	1.037	1.777
Demographics		
# Adults in household	-0.386	-5.425
Presence of expectant mother	-0.074	1.167
Asset		
Household owns bicycle	0.396	1.353
Household owns motorcycle	2.337	4.933
Household owns refrigerator	-0.178	6.863
Labour Market Outcome		
# Adults working	-1.119	-6.748
# Adults working in formal sector	1.027	1.277

Table 18. Correlates of Households Ranking: Panel Results

Correlates	Scenario A		Scenario B	
	(1)	**(2)**	**(3)**	**(4)**
Education				
Average years of education	1.182 (0.003)***	1.159 (0.007)***	0.126 (0.004)***	0.682 (0.007)***
HH head completed at least primary education	-5.709 (0.034)***	-4.253 (0.053)***	0.130 (0.037)***	-0.394 (0.058)***
HH head completed at least junior secondary education	0.692*** (0.035)	1.010*** (0.054)	-1.669 (0.037)***	-0.722 (0.059)***
HH head completed at least senior secondary education	7.022 (0.037)***	4.509 (0.062)***	2.565 (0.040)***	0.908 (0.067)***
Demographics				
# Adults in household	-2.249 (0.008)***	-2.419 (0.015)***	-6.437 (0.009)***	-8.372 (0.0168)***
Presence of expectant mother	0.0407 (0.063)	2.353 (0.082)***	2.388 (0.067)***	4.243 (0.089)***
Assets				
Household owns bicycle	-1.345 (0.026)***	0.667 (0.043)***	-2.144 (0.028)***	0.857 (0.047)***
Household owns motorcycle	10.45 (0.024)***	11.26 (0.035)***	6.020 (0.026)***	9.409 (0.038)***
Household owns refrigerator	10.37 (0.031)***	4.891 (0.045)***	7.348 (0.034)***	8.007 (0.049)***
Labour Market Outcomes				
# Adults working	-5.215 (0.027)***	0.826 (0.041)***	-6.167 (0.03)***	-3.027 (0.045)***
# Adults working in formal sector job	-0.705 (0.027)***	0.145 (0.039)***	-0.817 (0.029)***	1.424 (0.043)***
Other controls				
Social protection coverage	Yes	Yes	Yes	Yes
Yhat score	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effect	No	Yes	No	Yes
R^2		0.216		0.144
Number of observations	5,485,773	5,485,773	5,485,773	5,485,773
Number of panels	2,752,154	2,752,154	2,752,154	2,752,154

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 19. Correlates of Household Welfare Ranking by Poverty Transition (Scenario A with Panel Fixed Effect

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.162 (20.48)**	0.095 (7.23)**	0.595 (47.61)**	1.211 (126.18)**
HH head completed at least primary education	-1.123 (20.04)**	-0.442 (4.44)**	-2.976 (32.32)**	-4.505 (60.73)**
HH head completed at least junior secondary education	-0.334 (5.95)**	-0.385 (3.92)**	0.830 (8.78)**	1.251 (16.56)**
HH head completed at least senior secondary education	1.162 (16.76)**	0.587 (5.10)**	2.848 (25.84)**	4.564 (54.28)**
# Adults in household	0.505 (34.13)**	-0.438 (14.12)**	-0.109 (5.12)**	-2.192 (90.62)**
Presence of expectant mother	0.086 (1.14)	0.479 (3.70)**	0.589 (4.11)**	2.675 (22.10)**
Household owns bicycle	-0.127 (2.92)**	0.291 (3.55)**	-0.057 (0.81)	0.536 (8.71)**
Household owns motorcycle	0.312 (8.51)**	2.979 (44.88)**	3.580 (59.39)**	11.564 (230.05)**
Household owns refrigerator	-0.238 (4.08)**	0.271 (2.70)**	1.514 (20.10)**	4.804 (79.99)**
# Adults working	-0.210 (2.56)*	1.651 (20.93)**	0.824 (11.74)**	1.191 (21.48)**
# Adults working in formal sector job	-0.169 (4.43)**	-0.577 (8.17)**	-0.206 (3.14)**	-0.075(1.35)
R^2	0.61	0.68	0.32	0.24
Number of observations	687,446	768,126	707,903	3,322,298

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 20. Correlates of Household Welfare Ranking by Poverty Transition (Scenario B with Panel Fixed Effect)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.044 (20.44)**	0.147 (8.95)**	0.327 (26.10)**	0.835 (76.15)**
HH head completed at least primary education	-0.096 (6.27)**	0.626 (5.02)**	-1.243 (13.43)**	-0.415 (4.90)**
HH head completed at least junior secondary education	-0.044 (2.85)**	0.026 (0.21)	0.001 (0.01)	-0.939 (10.88)**
HH head completed at least senior secondary education	0.055 (2.92)**	0.179 (1.24)	0.966 (8.71)**	0.837 (8.71)**
# Adults in household	-0.368 (91.09)**	-4.665 (120.30)**	-3.750 (174.95)**	-10.124 (366.20)**
Presence of expectant mother	0.320 (15.55)**	2.991 (18.43)**	0.788 (5.46)**	4.981 (36.01)**
Household owns bicycle	0.249 (21.02)**	-0.435 (4.24)**	0.160 (2.25)*	0.776 (11.04)**
Household owns motorcycle	1.055 (106.86)**	4.322 (52.69)**	1.626 (26.94)**	10.173 (177.06)**
Household owns refrigerator	1.028 (64.63)**	2.982 (23.79)**	4.544 (60.09)**	8.736 (127.26)**
# Adults working	-0.126 (9.82)**	-2.107 (21.30)**	-0.760 (10.77)**	-3.237 (51.09)**
# Adults working in formal sector job	0.276 (26.54)**	-0.966 (10.90)**	0.361 (5.47)**	1.435 (22.68)**
R^2	0.18	0.48	0.51	0.14
Number of observations	687,446	768,126	707,903	3,322,298
Number of observations	687,446	768,126	707,903	3,322,298

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 21. Correlates of Households Ranking: First Difference Result

Correlates	Scenario A (1)	Scenario B (2)
Education		
Average years of education	1.159 (0.007)***	0.682 (0.007)***
HH head completed at least primary education	-4.253 (0.053)***	-0.394 (0.058)***
HH head completed at least junior secondary education	1.010 (0.054)***	-0.722 (0.059)***
HH head completed at least senior secondary education	4.509 (0.062)***	0.908 (0.067)***
Demographics		
# Adults in household	-2.419 (0.015)***	-8.372 (0.0168)***
Presence of expectant mother	2.353 (0.081)***	4.243 (0.089)***
Asset		
Household owns bicycle	0.667 (0.043)***	0.857 (0.047)***
Household owns motorcycle	11.26 (0.035)***	9.409 (0.038)***
Household owns refrigerator	4.891 (0.045)***	8.007 (0.049)***
Labour Market Outcome		
# Adults working	0.826 (0.041)***	-3.027 (0.0448)***
# Adults working in formal sector job	0.145 (0.039)***	1.424 (0.043)***
Other controls		
Social protection coverage	Yes	Yes
Yhat score	Yes	Yes
Year Dummy	Yes	Yes
Number of observations	2,733,619	2,733,619
R^2	0.111	0.115

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 22. Correlates of Household Welfare Ranking by Poverty Transition (Scenario A using First Difference)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.162 (20.48)**	0.095 (7.23)**	0.595 (47.61)**	1.211 (126.18)**
HH head completed at least primary education	-1.123 (20.04)**	-0.442 (4.44)**	-2.976 (32.32)**	-4.505 (60.73)**
HH head completed at least junior secondary education	-0.334 (5.95)**	-0.385 (3.92)**	0.830 (8.78)**	1.251 (16.56)**
HH head completed at least senior secondary education	1.162 (16.76)**	0.587 (5.10)**	2.848 (25.84)**	4.564 (54.28)**
# Adults in household	0.505 (34.13)**	-0.438 (14.12)**	-0.109 (5.12)**	-2.192 (90.62)**
Presence of expectant mother	0.086 (1.14)	0.479 (3.70)**	0.589 (4.11)**	2.675 (22.10)**
Household owns bicycle	-0.127 (2.92)**	0.291 (3.55)**	-0.057 (0.81)	0.536 (8.71)**
Household owns motorcycle	0.312 (8.51)**	2.979 (44.88)**	3.580 (59.39)**	11.564 (230.05)**
Household owns refrigerator	-0.238 (4.08)**	0.271 (2.70)**	1.514 (20.10)**	4.804 (79.99)**
# Adults working	-0.120 (2.56)*	1.651 (20.93)**	0.824 (11.74)**	1.191 (21.48)**
# Adults working in formal sector job	-0.169 (4.43)**	-0.577 (8.17)**	-0.206 (3.14)**	-0.075 (1.35)
R^2	0.58	0.54	0.28	0.11
Number of observations	343,497	383,795	350,426	1,655,901

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Table 23. Correlates of Household Welfare Ranking by Poverty Transition (Scenario B using First Difference)

Correlates	Always Poor	Fell into Poverty	Moved out of Poverty	Never Poor
Average years of education	0.044 (20.44)**	0.147 (8.95)**	0.327 (26.10)**	0.835 (76.15)**
HH head completed at least primary education	-0.096 (6.27)**	0.626 (5.02)**	-1.243 (13.43)**	-0.415 (4.90)**
HH head completed at least junior secondary education	-0.044 (2.85)**	0.026 (0.21)	0.001 (0.01)	-0.939 (10.88)**
HH head completed at least senior secondary education	0.055 (2.92)**	0.179 (1.24)	0.966 (8.71)**	0.837 (8.71)**
# Adults in household	-0.368 (91.09)**	-4.665 (120.30)**	-3.750 (174.95)**	-10.124 (366.20)**
Presence of expectant mother	0.320 (15.55)**	2.991 (18.43)**	0.788 (5.46)**	4.981 (36.01)**
Household owns bicycle	0.249 (21.02)**	-0.435 (4.24)**	0.160 (2.25)*	0.776 (11.04)**
Household owns motorcycle	1.055 (106.86)**	4.322 (52.69)**	1.626 (26.94)**	10.173 (177.06)**
Household owns refrigerator	1.028 (64.63)**	2.982 (23.79)**	4.544 (60.09)**	8.736 (127.26)**
# Adults working	-0.126 (9.82)**	-2.107 (21.30)**	-0.760 (10.77)**	-3.237 (51.09)**
# Adults working in formal sector job	0.276 (26.54)**	-0.966 (10.90)**	0.361 (5.47)**	1.435 (22.68)**
R^2	0.07	0.06	0.09	0.10
Number of observations	343,497	383,795	350,426	1,655,901

Note: Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

Figure 1. Welfare Dynamics of Indonesia's Bottom 40 Percent (2011 & 2015)

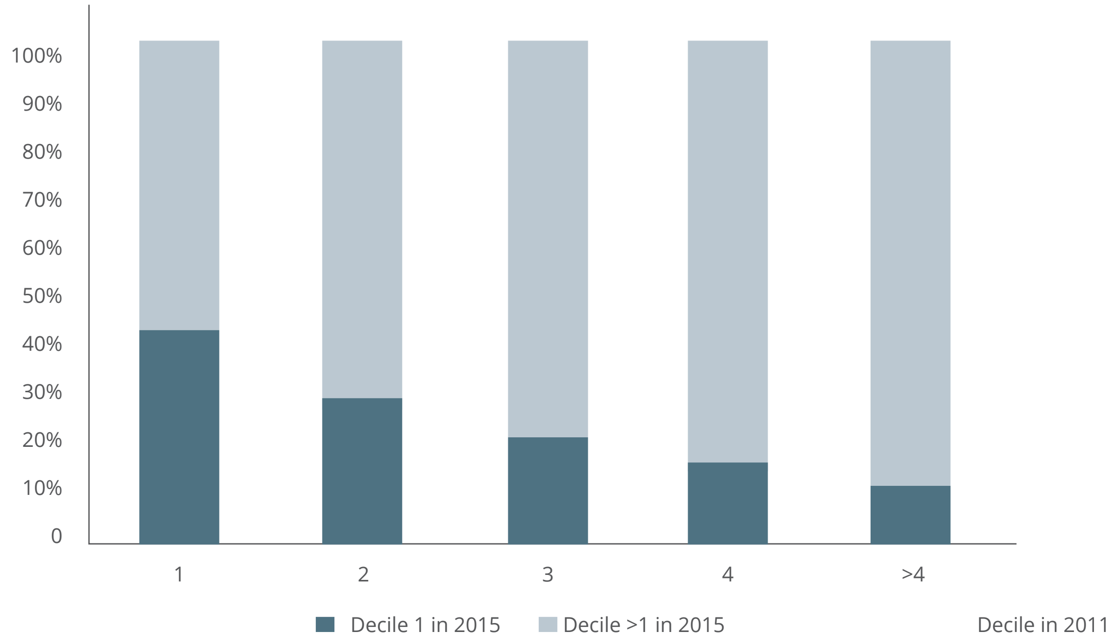


Figure 2. Welfare Dynamics of Indonesia's Bottom 10 Percent (2011 & 2015)

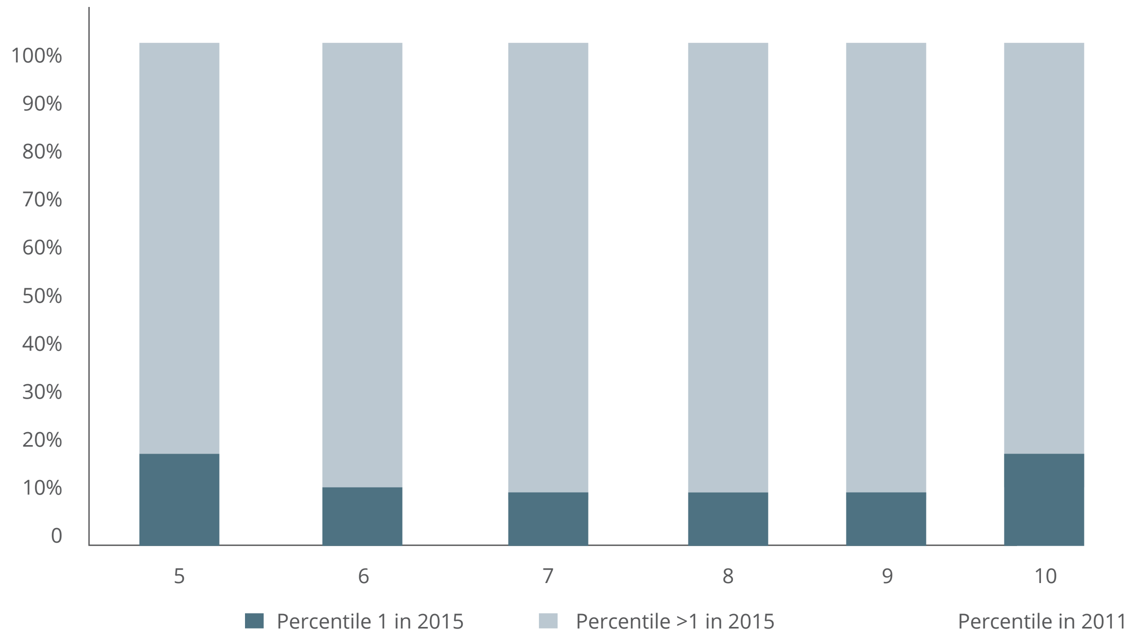


Figure 3. Scenario A: Welfare Dynamics of Indonesia's Bottom 40 Percent- 50 Districts (2011 & 2015)

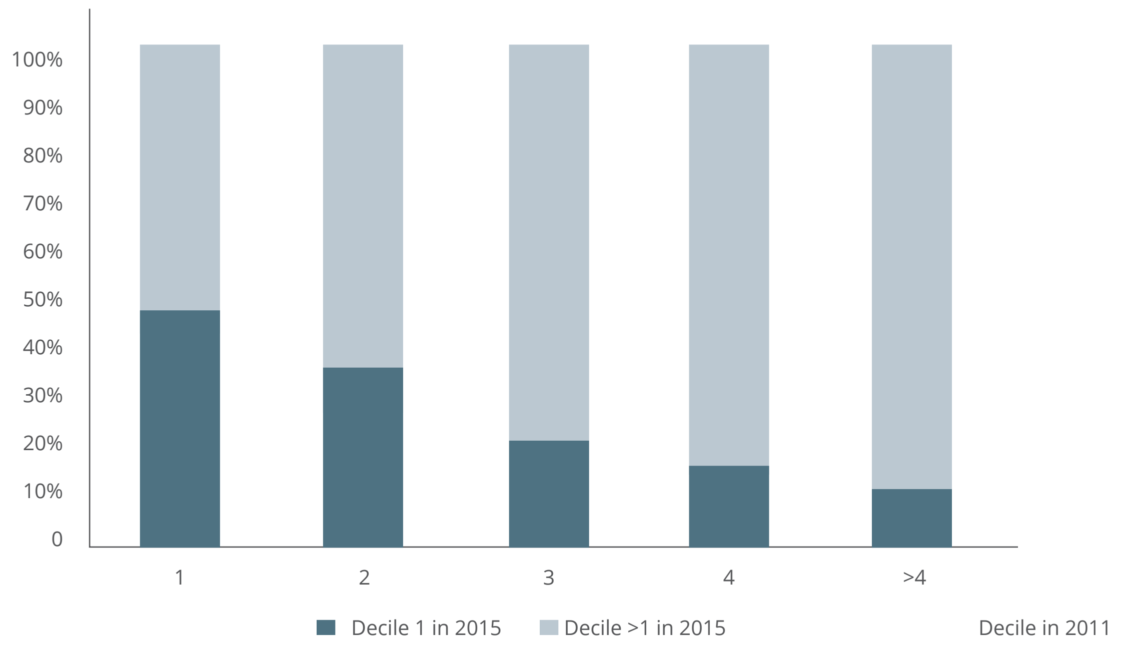


Figure 4. Scenario A: Welfare Dynamics of Indonesia's Bottom 10 Percent- 50 Districts (2011 & 2015)

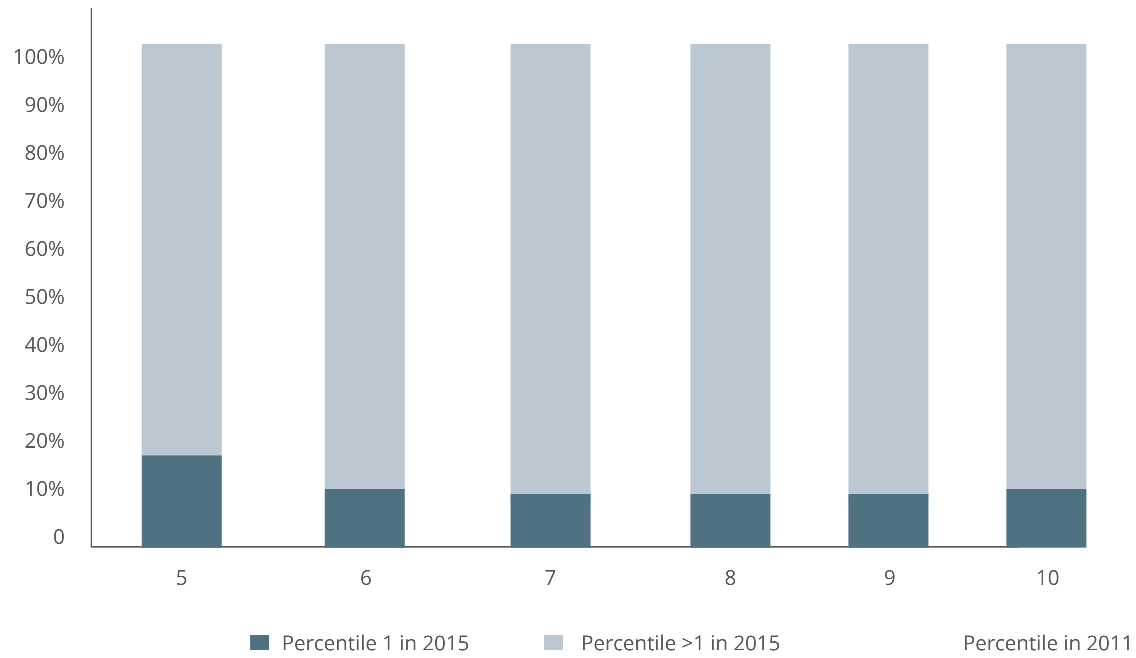


Figure 5. Scenario B: Welfare Dynamics of Indonesia's Bottom 40 Percent- 50 Districts (2011 & 2015)

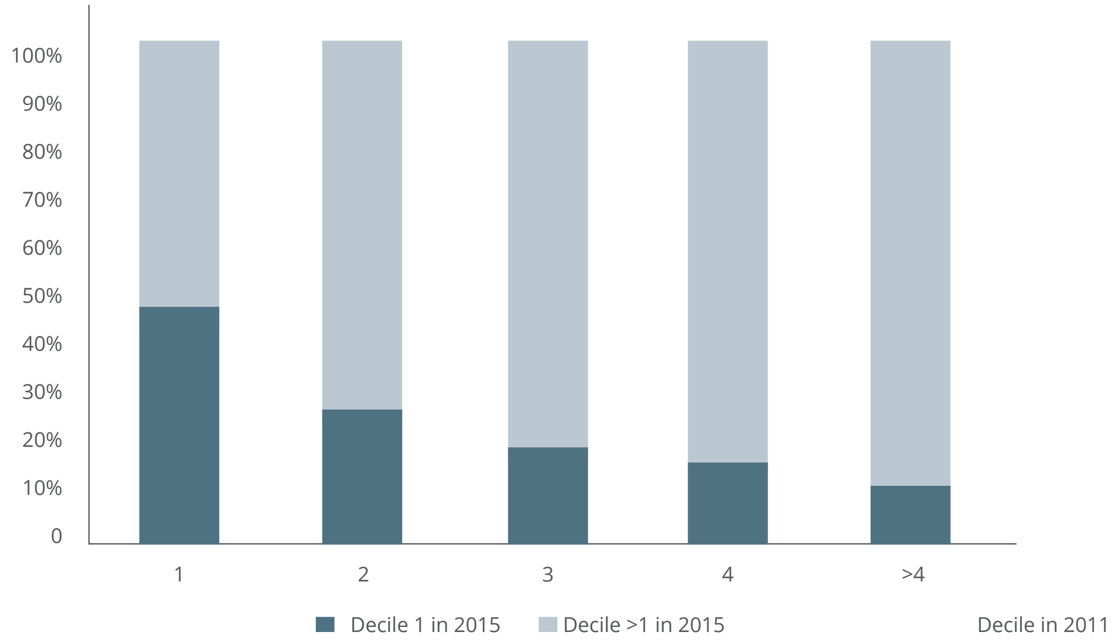
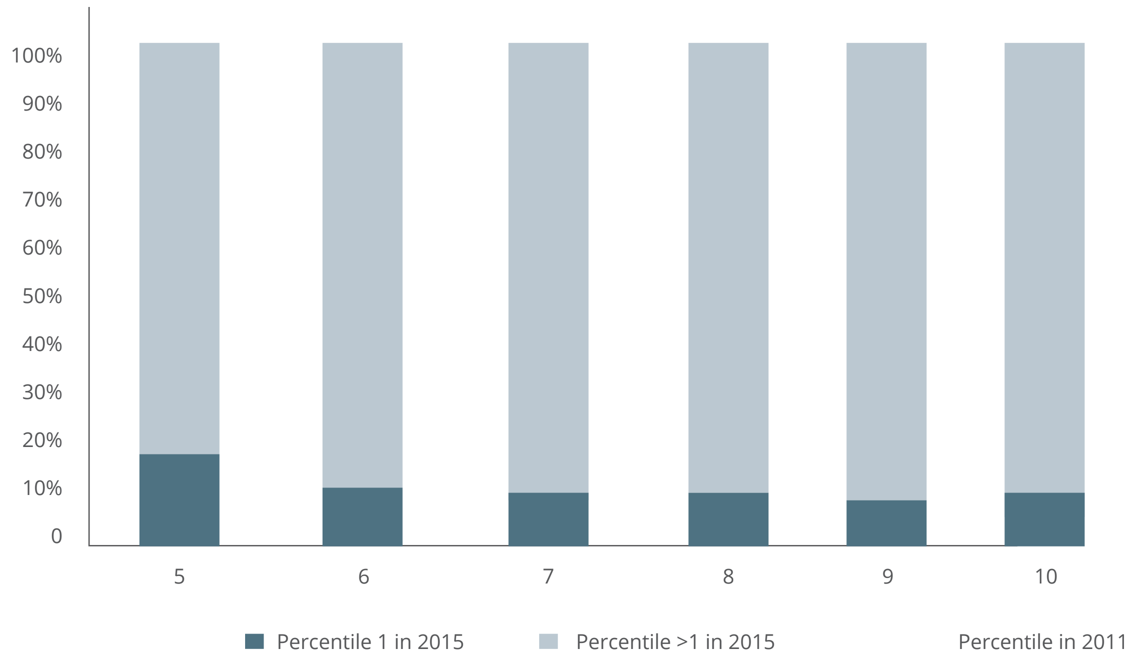


Figure 6. Scenario B: Welfare Dynamics of Indonesia's Bottom 10 Percent- 50 Districts (2011 & 2015)



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