United Nations University

WIDER

World Institute for Development Economics Research

Discussion Paper No. 2003/57

# How Responsive is Poverty to Growth?

## A Regional Analysis of Poverty, Inequality, and Growth in Indonesia, 1984-99

Jed Friedman*

August 2003

**Abstract**

This paper uses six nationally representative household consumption surveys to develop successive poverty profiles for Indonesia over a fifteen-year period of sustained high growth followed by rapid contraction. Adopting a 'cost-of-basic-needs' approach to poverty determination (an approach particularly suited to measures of absolute poverty), this paper develops price indices and calculates poverty lines from unit value data, an oft neglected source of information. The summary findings confirm that Indonesia has witnessed broadbased gains in poverty reduction over the period 1984-96 and then a dramatic reversal during the recent financial crisis. These summary findings, however, mask substantial diversity in growth, inequality, and poverty change across Indonesian regions and so subsequent analysis focuses on the links between growth, inequality, and changes in poverty at the regional level. As opposed to previous studies of poverty change that have used short panels of cross-national data to identify the relationship between growth and poverty, this study employs a longer panel for a single country.../...

Keywords: poverty, growth, inequality, Indonesia.
JEL classification: I32, O12, O53, R11

---



*Development Research Group, The World Bank Group.

This study has been prepared within the UNU/WIDER project on Spatial Disparities in Human Development, directed by Ravi Kanbur and Tony Venables.

UNU/WIDER gratefully acknowledges the financial contribution to the project by the Government of Sweden (Swedish International Development Cooperation Agency—Sida).

in order to investigate how poverty change at the provincial level varies with province growth rates and province changes in inequality (while controlling for time invariant province characteristics). The results indicate that poverty change is highly responsive to overall growth. However closer analysis reveals that regional differences in poverty levels persist even after controlling for the effects of provincial income levels, particularly for rural areas. These findings suggest that local factors play an important role in poverty determination and may interact with growth to impact poverty reduction in differing ways across Indonesia. Future investigations will need to take a more careful look at these local determinants of poverty change and attempt to identify the types of growth toward which poverty measures are particularly responsive.

**Acknowledgements**

Many thanks are due James Levinsohn, David Lam, and Jan Svejnar for their invaluable advice and assistance. An anonymous referee supplied very useful direction. Culpability for all remaining errors accrues solely to the author



UNU World Institute for Development Economics Research (UNU/WIDER)
Katajanokanlaituri 6 B, 00160 Helsinki, Finland

Camera-ready typescript prepared by Lorraine Telfer-Taivainen at UNU/WIDER
Printed at UNU/WIDER, Helsinki



ISSN 1609-5774
ISBN 92-9190-500-3 (printed publication)
ISBN 92-9190-501-1 (internet publication)

## 1 Introduction

Events such as the 1997 Asian currency crisis have focused much popular attention on increasing global integration and its consequences for the world's poor. Both sides of the debate, the pro- and anti-globalizers, promote their development strategies as pro-poor and look to recent history to support their views. This uncertainty surrounding the potential impacts of globalization on the world's poorest households has motivated several recent studies to re-examine the relationship between global integration and economic growth on the one hand and economic growth and poverty reduction on the other.[1] This paper will offer further evidence on the second question by documenting changes in poverty in Indonesia over the period 1984-99 and then relating the observed changes to income growth and changes in inequality.

Most studies that explore the poverty reduction–growth relationship have utilized a short panel of country-level data to estimate a mean response of a particular poverty measure to population wide gains in income. These studies have indeed typically shown that national poverty change is fairly responsive to national economic growth. For example Dollar and Kraay (forthcoming) find that, on average, a 1 per cent gain in mean income is associated with a 1 per cent gain in income among households in the bottom quintile. If accepted at face value, the summary estimates of poverty responses to growth convey a sense of how much growth is needed to reduce poverty to low levels. Additionally, if poverty change is largely determined by growth, then the question concerning the effects of globalization on the *poor* largely becomes a question concerning the effects of globalization on *growth*. However just as there may very well be no single 'effect' of global integration on economic growth—growth in turn may impact the poor in different ways. These impacts can vary on a national and regional basis as well as across time due to such factors as differing initial economic conditions or differing government policy choices. The use of summary national measures necessarily ignores the potential heterogeneity in the growth–poverty relationship that may exist across countries and also exist even within a country, especially a large country with imperfectly integrated regional economies such as Indonesia.

This paper will revisit the poverty–growth relationship but this time with a long panel of information (six repeated cross sections over the period 1984-99) for one country and investigate how poverty change at the provincial level varies with province growth rates and province changes in inequality (while importantly controlling for time invariant provincial

---

[1] See for example Ben-David (1993), Sachs and Warner (1995), Edwards (1998), and Rodriguez and Rodrik (1999) that explore the former question and Bruno et al. (1998), Dollar and Kraay (2000), and Ravallion (2001) that explore the latter.

characteristics). A necessary first step in this process involves the generation of successive regional poverty profiles with which to document, as carefully as possible, long-run changes in poverty. This is the first aim of this paper. The definition of poverty adopted for analysis here follows a 'cost-of-basic-needs' approach and as such is particularly suited to measures of absolute poverty and deprivation. Typical studies of this kind need information on the prices of basic consumption commodities in order to determine a poverty line. When price information is lacking, researchers must often turn towards other definitions of poverty. Although the consumption data used here does not contain price information, it does enable computations of a price proxy, the unit value, which is simply the household's total expenditure on a given good divided by the total quantity consumed. Utilizing a simple structural model of consumer choice, this paper argues that unit values can indeed serve as good proxies for prices.

The main body of the paper presents a regional analysis of poverty responses to overall economic growth. This regional focus avoids three difficulties associated with the aforementioned national-level studies. The first difficulty concerns data comparability. Typically cross-national studies employ secondary datasets that by necessity are comprised of measures derived from underlying primary data of differing design and quality. For example, poverty measures for a particular country can be estimated from either income or consumption surveys, depending on the type of data available. Atkinson and Brandolini (1999) explore various shortcomings with secondary data and identify several measurement concerns when utilizing national-level data collected from heterogeneous sources. By using the repeated cross-sections of a household consumption survey as a uniform data source, this study avoids the pitfalls of measurement heterogeneity often found in secondary data.

The cross-national studies are able to control for time invariant country-level characteristics that may influence the poverty–growth relation. However, the potential existence of time-varying national-level variables that affect poverty and also are related to economic growth presents a second difficulty. One example of such a time-varying national-level variable is a national pro-poor welfare policy enabled by high growth. The failure to control for these unobserved variables may bias estimates of the poverty–growth relationship. By looking within a country, this study de facto controls for such national-level factors.

The final difficulty with these studies derives from the simple observation that the poor do not constitute a homogenous group but rather differ substantially along dimensions such as region and urban/rural location. The national scope of previous studies obscures important heterogeneity *among* the poor and the failure to account for such heterogeneity may limit the applicability of the results. Friedman and Levinsohn (2002) find that the consumption impacts of the Indonesian crisis for poor households were dramatically different depending on whether the poor lived in cities or in the country as well as which particular region of the country. By looking at poverty variations within a single country, this study will more carefully account for such heterogeneity.

From a policy perspective, however, the conclusion that growth is good for the poor (or a particular group among the poor) is not especially illuminating. Most economists would expect some benefits of overall growth to accrue to the poor. A more useful question from the policy perspective might instead be posed as: which *types* of growth are better for the poor? This is a more difficult question to answer. However for this question, it is possible to push the data a little harder and look at how poverty responds to growth in different regions across Indonesia. A priori, it is quite possible that poverty differentially responds to the differing sources and structures of growth that can exist across provinces.[2] This paper finds some evidence to support this view. Regional differences in poverty persist even after controlling for the effects of provincial income and inequality levels. Given these findings, future studies need to take a more careful look at these local determinants of poverty and attempt to identify the sources and structures of growth towards which poverty measures are particularly responsive.

The remainder of the paper is structured as follows: the next section describes the data used in the study, summarizes the methods of poverty determination, and presents the estimated poverty trends in Indonesia over the period 1984-99 at both the national and regional level. Section 3 documents the degree of regional variation in growth and inequality change present in the data, examines the relation between poverty reduction and economic growth in a regression context, and explores regional heterogeneity in this relationship. Section 4 concludes. An appendix then explains the methods of poverty line determination adopted herein.

## 2 Data and methods

The poverty measurements used in this study are derived from Indonesian household consumption and demographic data. This information is provided by six successive waves of the Indonesian National Socioeconomic Survey—known by its Indonesian acronym SUSENAS—which is is an annual survey that includes a detailed consumption component every three years. This study utilizes the 1984, 1987, 1990, 1993, 1996, and 1999 consumption components. Every SUSENAS surveys thousands of households from each of Indonesia's 27 provinces (for a total sample size of 50,000 to 60,000 households, depending on the survey

[2] In the case of India, Ravallion and Datt (2002) find that the degree of poverty reduction associated with gains in non-farm output varies across provinces.

year).[3] Population weights enable representative analysis at the provincial level and, unless otherwise noted, are used in the analysis to follow.[4]

SUSENAS gathers household consumption data at a fairly detailed level, especially for food items. For example, the 1996 SUSENAS records the total weekly consumption and expenditure for 217 individual foods such as tomatoes or rice (actually four different varieties of rice are included in the survey). The consumption component contains a large core of important individual consumption items that are recorded in every survey year, thus enabling a consistent comparison of consumption across time. SUSENAS is also fielded in January or February of each year to ensure that intertemporal comparisons are not confounded by seasonal variation in household income and consumption. For self-produced food items, SUSENAS interviewers are trained to impute the value of such consumption based on prevailing local prices. The survey itself does not report direct price observations. However a price proxy, the unit value, can be computed by dividing total household expenditures on a particular food by total quantity consumed. These unit values play an important role in determining the poverty lines used later in the analysis.[5]

Table 1 gives an overview of the six SUSENAS surveys as well as some simple summary statistics. The general trend in urbanization in Indonesia is quite apparent. The percentage of rural households in the total sample declines from 78 per cent to 61 per cent over the 15-year period. Table 1 also reports mean per capita household expenditures in 1984 rupiahs. It is important to note that the deflators used in this study are not the standard deflators derived from official price data but rather a food-only price deflator derived from the household consumption information in SUSENAS.[6] This deflator is a welfare consistent measure in that it represents the cost of a predetermined, culturally appropriate, and adequately nutritious basket of food goods. These issues will be explored further when we discuss poverty line determination methods but we note here that the cost of this basket is one of the poverty lines adopted by this study.

---

3 Due to the unclear sampling frame of the data from the contested province of East Timor (urban areas were not surveyed) this province is dropped from subsequent analysis.

4 From 1993 on, the SUSENAS sampling frame was modified to enable representative analysis at the Regency (Kabupaten) level, one administrative level lower than province. To remain consistent with the pre-1993 period, this study will use the province as the sole geographic unit.

5 SUSENAS also collects expenditure information for approximately 100 non-food goods and aggregate goods such as electricity or male apparel. Also included are expenditures on festivities and ceremonies as well as taxes and insurance. Due to the aggregate nature of most of these non-food categories, SUSENAS does not record the quantities of the goods consumed. As such, and unlike food goods, researchers are unable to impute unit values for these goods.

6 This price deflator is a 'democratic' deflator in the spirit of Prais (1959) in that it gives greater weight (indeed total weight) to the most basic necessities, in this case food.

Table 1: Summary characteristics of the SUSENAS survey, 1984-99

| Characteristics | Year | Total | Urban | Rural |
|---|---|---|---|---|
| Proportion rural households | 1984 | 0.779 | -- | -- |
| | 1987 | 0.742 | -- | -- |
| | 1990 | 0.712 | -- | -- |
| | 1993 | 0.696 | -- | -- |
| | 1996 | 0.644 | -- | -- |
| | 1999 | 0.608 | -- | -- |
| Per capita monthly expenditures (1984 Rupiahs)* | 1984 | 17307 | 27427 | 14436 |
| | 1987 | 20555 | 31213 | 16852 |
| | 1990 | 20619 | 30025 | 16819 |
| | 1993 | 24248 | 35963 | 19130 |
| | 1996 | 26262 | 37861 | 19856 |
| | 1999 | 19021 | 25276 | 14984 |
| Food share of total expenditures | 1984 | 0.675 | 0.590 | 0.699 |
| | 1987 | 0.662 | 0.574 | 0.693 |
| | 1990 | 0.658 | 0.572 | 0.692 |
| | 1993 | 0.625 | 0.554 | 0.656 |
| | 1996 | 0.622 | 0.552 | 0.661 |
| | 1999 | 0.681 | 0.616 | 0.722 |
| Unweighted # of households | 1984 | 50296 | 15893 | 34403 |
| | 1987 | 51257 | 15651 | 35606 |
| | 1990 | 46026 | 11646 | 34380 |
| | 1993 | 58100 | 22725 | 35375 |
| | 1996 | 61965 | 24472 | 37493 |
| | 1999 | 62210 | 25626 | 36584 |
| Unweighted # of individuals | 1984 | 244347 | 80567 | 163780 |
| | 1987 | 245416 | 79141 | 166275 |
| | 1990 | 212860 | 56924 | 155936 |
| | 1993 | 260368 | 105581 | 154787 |
| | 1996 | 269869 | 110180 | 159689 |
| | 1999 | 258211 | 107926 | 150285 |

Note: *As determined from a food price deflator estimated from SUSENAS.

Source: Author's calculations from SUSENAS surveys, various rounds.

Over the period 1984-96, changes in Indonesian food prices tracked quite closely with overall inflation and so the food deflator here yields real income changes consistent with other studies of income change (Biro Pusat Statistik 1997). Household welfare, as measured by either the mean real per capita monthly household expenditure or by the average share of food expenditures, shows clear gains over the 1984-96 period of sustained national growth. Real mean per capita household expenditure (in 1984 rupiahs) increases from 17,300 rupiahs/person/month in 1984 to 26,300 in 1996. Gains of similar magnitude are found in both urban and rural areas.

As a result of the financial crisis and the lifting of price controls in late 1997, Indonesia experienced a prolonged period of high inflation where food prices rose even more rapidly than non-food prices. Because of this, the food deflator over the 1996-9 period will overstate overall inflation and the decline in real per capital expenditure when compared with the deflators used in most other studies of the post-crisis impacts. Table 1 reveals a 28 per cent decline in mean per capita expenditure—from 26,260 to 19,020 1984 rupiahs per person per month. This decline stands in comparison to a 17 per cent decline over the same period when consumption change is measured with a general price index (Suryahadi et al. 2000). We will not adjust our deflators so that they correspond with more commonly used ones since we are primarily concerned with the poverty–growth relationship and the approach should not lead to biases in the multivariate analysis to come once appropriate period controls are included. We also hope to exhibit in this study the types of analysis possible with only repeated consumption surveys (a point made clear in the appendix). However we do note that our approach will overstate the real expenditure declines as a result of the 1997 financial crisis.

Despite the use of a food price deflator, our summary findings are qualitatively similar to other studies documenting the impacts of the crisis. We observe a greater decline in consumption in urban areas as opposed to rural (33 per cent versus 26 per cent). Frankenberg et al. (1999) find a similar sectoral difference with a measured 34 per cent decline in per capita expenditure in urban areas and 18 per cent in rural over the single year period 1997-8. The detrimental impacts of the crisis are also apparent in the proportion of household expenditures devoted to food, another common welfare measure. The food share declines over the 1984-96 period from 68 per cent to 62 per cent of total household expenditures. This decline is partly due to the decreasing mean food shares within urban and rural areas as well as the increasing proportion of the population living in cities. However, given the rise in relative food prices and fall in real income as a result of the crisis, the national food share returns to 68 per cent in 1999. The proportional rise in the food share is greater for urban households, from 55 per cent to 62 per cent. Unlike real expenditures, the magnitude of change in this welfare measure is not dependent on the particular choice of price deflator.

Although Table 1 reports changes in summary measures of mean household welfare, we are mainly concerned with the welfare of households towards the bottom of the distribution, particularly households deemed ‘poor’. The poverty determination methods adopted here define poor households as those households unable to afford a basic consumption bundle which, while also reflecting prevailing notions of taste, ensures adequate nutrition as well as a necessary amount of non-food expenditures. This approach is generally termed the ‘cost-of-basic-needs’ approach and the relative merits of this approach are discussed in Ravallion and Bidani (1994). The method used here is, in many ways, a refinement and adaptation of work developed by Ravallion (1994) and Bidani and Ravallion (1993). The approach involves the estimation of the total cost for a bundle of ‘basic food goods’ as well as ‘basic non-food goods' typically utilizing direct observations of price. The method adopted here enables poverty computations without direct information on prices but instead uses a simple model of consumer choice to impute prices from unit values.

A household is deemed poor if its per capita expenditure lies below a fixed poverty line. As a check on the robustness of any results, three different poverty lines representing different levels of welfare are in fact determined and used in the analysis. The poverty line methodology is explained in detail in the appendix but the general approach is summarized as follows: a nutritionally adequate food bundle (with nutritional guidelines stipulated by WHO et al. 1985) that reflects the actual consumption choices of Indonesian households is determined and then priced. To ensure time consistent welfare comparisons the food bundle is fixed and applied to each survey year. The total cost of this bundle represents one poverty line termed the food poverty line. The food poverty line can then be scaled upwards by an econometrically estimated factor that represents the cost of essential non-food goods. Two such scale factors are utilized, one more generous than the other. Thus these final values, which we term the lower and upper poverty lines, proxy the total cost of essential food and non-food consumption needs.

Due to important differences in relative prices between urban and rural areas, poverty lines are computed separately for each area. Poverty lines can also be determined with national mean prices or with more local provincial prices. We have estimated poverty lines from both types of price data as a check on the robustness of our findings. Since the results from the subsequent analysis do not appreciably differ if local or national prices are used, we only present the results with poverty estimates based on local prices since they will more accurately reflect local conditions. After the determination of a particular poverty line we then use the class of Foster-Greer-Thorbecke poverty measures to assess poverty. In particular we will use the headcount index, the poverty gap, and the squared gap measure. These measures are also described in the appendix. To give some sense of the precision of the poverty estimates, bootstrapped standard errors will be reported alongside some of the poverty measures in the analysis to follow.[7]

Table 2 and Figure 1 present national trends in the overall poverty measures. As is readily apparent, Indonesia has indeed experienced broad gains in poverty reduction over the 12-year period 1984-96. Table 2 contains the values of all three poverty measures (the headcount, poverty gap, and squared gap measures) calculated at each poverty line (the food line, the lower, and the upper) for each of the six survey years. The national poverty headcount, as

[7] Since SUSENAS has a clustered survey design, the bootstrapped standard errors are calculated by drawing random samples of clusters with replacement. For each cluster selected, all households are used in the error calculation. As noted in Deaton and Paxson (1998), failure to recognize the clustered design of the survey data will result in an understatement of sampling variability.

measured by the upper poverty line, declined 61 per cent from 1984 to 1996, while the lower poverty line national head count posted even greater declines of 71 per cent. While Indonesia made significant gains in reducing the proportion of population living in poverty, it made even greater gains in reducing the severity of poverty, with the squared gap measure declining by more than 80 per cent over the period. To give some sense of the precision of these estimates, Table 2 also lists the estimated standard errors for the upper poverty line headcount measure. As is quite apparent by the relatively small standard errors, the headcount measures are all precisely estimated and the year-on-year changes in poverty are statistically significant at standard significance levels.

Table 2: Summary national poverty measures, 1984-99

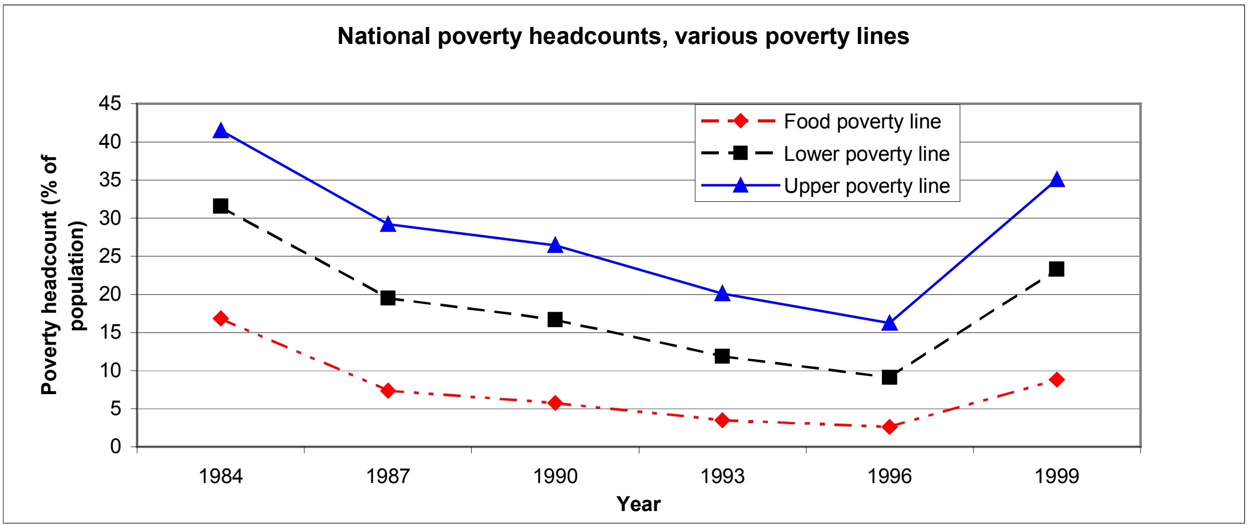
| Poverty Line | Poverty Measure | 1984 Total | 1984 Urban | 1984 Rural | 1987 Total | 1987 Urban | 1987 Rural | 1990 Total | 1990 Urban | 1990 Rural |
|---|---|---|---|---|---|---|---|---|---|---|
| Upper Poverty Line | Headcount | 0.4151 | 0.1972 | 0.4819 | 0.2920 | 0.1282 | 0.3508 | 0.2647 | 0.1464 | 0.3160 |
| | Standard error | 0.0065 | 0.0068 | 0.0070 | 0.0053 | 0.0075 | 0.0071 | 0.0037 | 0.0081 | 0.0062 |
| | Poverty gap | 0.1165 | 0.0461 | 0.1381 | 0.0632 | 0.0244 | 0.0771 | 0.0537 | 0.0274 | 0.0651 |
| | Squared gap | 0.0459 | 0.0166 | 0.0549 | 0.0199 | 0.0071 | 0.0245 | 0.0162 | 0.0078 | 0.0198 |
| Lower Poverty Line | Headcount | 0.3157 | 0.1155 | 0.3771 | 0.1951 | 0.0648 | 0.2418 | 0.1671 | 0.0723 | 0.2083 |
| | Poverty gap | 0.0806 | 0.0250 | 0.0977 | 0.0371 | 0.0106 | 0.0466 | 0.0299 | 0.0115 | 0.0379 |
| | Squared gap | 0.0298 | 0.0085 | 0.0363 | 0.0107 | 0.0028 | 0.0135 | 0.0082 | 0.0029 | 0.0105 |
| Food Poverty Line | Headcount | 0.1684 | 0.0461 | 0.2056 | 0.0737 | 0.0150 | 0.0948 | 0.0578 | 0.0192 | 0.0745 |
| | Poverty gap | 0.0362 | 0.0091 | 0.0445 | 0.0114 | 0.0024 | 0.0146 | 0.0083 | 0.0024 | 0.0109 |
| | Squared gap | 0.0120 | 0.0029 | 0.0148 | 0.0028 | 0.0006 | 0.0036 | 0.0020 | 0.0005 | 0.0026 |

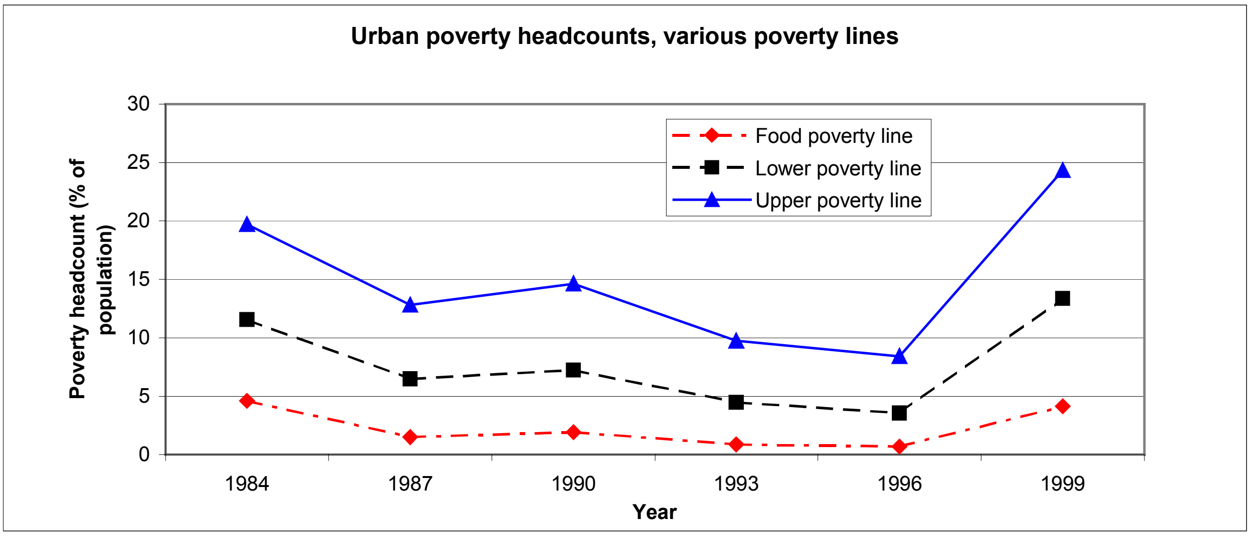
| Poverty Line | Poverty Measure | 1993 Total | 1993 Urban | 1993 Rural | 1996 Total | 1996 Urban | 1996 Rural | 1999 Total | 1999 Urban | 1999 Rural |
|---|---|---|---|---|---|---|---|---|---|---|
| Upper Poverty Line | Headcount | 0.2013 | 0.0973 | 0.2520 | 0.1625 | 0.0843 | 0.2083 | 0.3508 | 0.2433 | 0.4223 |
| | Standard error | 0.0048 | 0.0056 | 0.0073 | 0.0034 | 0.0036 | 0.0045 | 0.0046 | 0.0070 | 0.0054 |
| | Poverty gap | 0.0370 | 0.0169 | 0.0468 | 0.0286 | 0.0136 | 0.0373 | 0.0775 | 0.0502 | 0.0957 |
| | Squared gap | 0.0103 | 0.0043 | 0.0132 | 0.0077 | 0.0035 | 0.0102 | 0.0248 | 0.0153 | 0.0312 |
| Lower Poverty Line | Headcount | 0.1190 | 0.0447 | 0.1552 | 0.0913 | 0.0355 | 0.1239 | 0.2329 | 0.1338 | 0.2989 |
| | Poverty gap | 0.0191 | 0.0063 | 0.0254 | 0.0143 | 0.0050 | 0.0198 | 0.0449 | 0.0234 | 0.0592 |
| | Squared gap | 0.0048 | 0.0013 | 0.0065 | 0.0035 | 0.0011 | 0.0049 | 0.0130 | 0.0062 | 0.0175 |
| Food Poverty Line | Headcount | 0.0349 | 0.0088 | 0.0477 | 0.0261 | 0.0070 | 0.0373 | 0.0884 | 0.0413 | 0.1197 |
| | Poverty gap | 0.0045 | 0.0008 | 0.0063 | 0.0032 | 0.0008 | 0.0046 | 0.0135 | 0.0052 | 0.0191 |
| | Squared gap | 0.0009 | 0.0001 | 0.0014 | 0.0007 | 0.0002 | 0.0009 | 0.0034 | 0.0011 | 0.0049 |

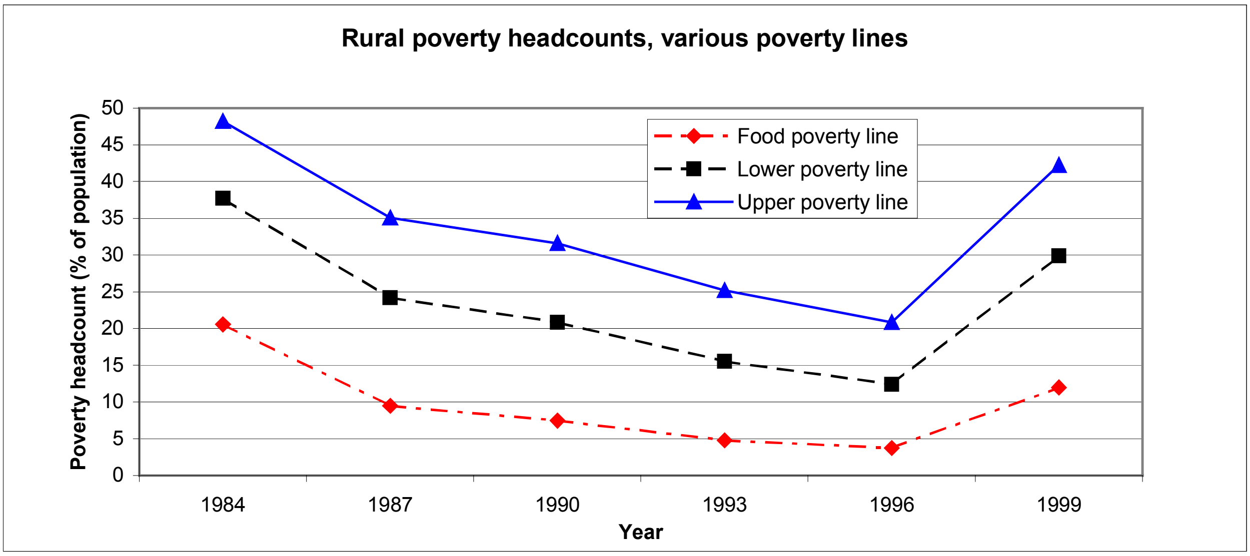
Source: Author's calculations from SUSENAS surveys, various rounds.

Broadbased gains in poverty reduction were found in both rural and urban areas. The greatest poverty reductions were witnessed in rural areas with the headcount measure based on the

Figure 1: Overall poverty trends in Indonesia, various poverty lines



upper poverty line declining by 57 per cent and the squared gap measure falling by 81 per cent. Similar to the national figures, not only did rural Indonesia experience large declines in the incidence of poverty, but the severity of poverty, as conveyed by the squared gap measure, fell by an even greater amount. The story is slightly different in urban areas as poverty does not decline monotonically over time. Indeed most urban poverty measures post a slight increase over the 1987 to 1990 period.[8]

In terms of the timing of poverty reduction, the greatest gains were reported over the 1984-7 period. There is some fear that SUSENAS underreports consumption (van de Walle 1988), and this may be especially true for the 1984 wave. Inspecting the underlying consumption baskets across the years, it is clear that the reported consumption of one of the rice varieties is substantially less in 1984 than in all subsequent periods. If the 1984 SUSENAS does indeed underreport consumption then the 1984 poverty measures may be overestimated. It is not immediately clear what can be done to correct for such possible consumption underestimation without further information on survey implementation or consumption patterns. As such, we report the numbers without correction. However subsequent multivariate analysis will include a vector of time period dummy variables that should absorb any year-to-year variation in poverty measures due to idiosyncrasies in survey implementation.

After the gains in poverty reduction from 1984-96, the increase in poverty as a result of financial crisis is severe and abrupt. We estimate increases in poverty headcounts on the order of 116 per cent when using the upper poverty line, 155 per cent with the lower poverty line, and 239 per cent with the food poverty line (albeit the food poverty line increase starts from a low base). The gap and squared gap measures, more sensitive to distributions among the poor, show even greater increases thus indicating an increased mass of households at the very tail end of the expenditure distribution. As previously discussed, the measured magnitude of these poverty changes depends on our choice of an all-food price deflator. Since food prices rose more rapidly than non-food prices, and even the poorest of households consume some non-food items, these poverty change measures surely overstate the actual change in poverty at

---

8 Even though each poverty measure determined at each poverty line records the same general decline (or increase) in poverty, we look into whether another arbitrary poverty line or poverty measure might convey a different result by estimating the successive cumulative distribution functions for household consumption (results not shown). These results confirm that there will be no reversals in estimated poverty change if any arbitrary poverty line is adopted. We find that the 1996 consumption CDF stochastically dominates the 1993 CDF, as 1993 dominates 1990, and so on, at any point the CDF for 1996 lies below that for 1993, as 1993 lies below 1990. That is, a combination of any arbitrary poverty line and measure will record the same general decline in poverty for 1984-96; see Foster and Shorrocks (1988) for a discussion of stochastic dominance and poverty measures. Of course these gains are reversed by the financial crisis where the CDF for 1999 almost coincides with the CDF from the earliest period, 1984. Again, a deflator with a non-food component would not have yielded quite this extreme a change in consumption even though the drop in consumption would still be severe. Similar analysis conducted separately for urban and rural areas confirms that the higher poverty rates observed in urban areas in 1990 than 1987 would have been found with any poverty line or measure.

least to some extent. As a point of comparison, Suryahadi et al. (2000) calculate the increase in national poverty headcounts to be on the order of 57 per cent to 129 per cent depending on the exact type of deflator used.

Regardless of the exact magnitude of the poverty increase, it is clear that the impacts of the crisis do not fall equally across urban and rural areas. For example the headcount measure based on the upper poverty line increases 189 per cent for urban households and 103 per cent for rural households. The difference in the increase in the squared gap measure is even greater. These differential changes are consistent with other studies. Friedman and Levinsohn (forthcoming) predict that the urban poor would be especially affected by the crisis and Frankenberg et al. (1999) have indeed found this to be the case. Clearly there are important distinctions to be made among the urban and rural poor. Even within urban or rural areas, there is significant variation in the incidence of poverty across the different Indonesian regions. Table 3 presents the regional poverty profiles for the survey years 1987 and 1993, two years in the middle of a period of sustained high national growth. Reported in this table are both the upper poverty line headcounts for each provincial rural/urban cell, as well as the Gini coefficient, in order to give a sense of the extent of variation in regional poverty and regional inequality.

Within urban and rural areas, poverty levels are quite varied. The capital Jakarta has the lowest poverty headcount in both years whereas cities in both West and East Nusa Tenggara (a collection of islands east of Bali) tend to have the highest poverty incidence. Poverty levels overall are higher in rural areas but still varied across Indonesia. Some of the lowest rural poverty in both years is found in the Sumatran province of Jambi and some of the highest in the remote island of Irian Jaya as well as the islands of Nusa Tenggara. A cursory inspection across the two years will also confirm a good deal of heterogeneity in the change of poverty incidence. In most regions poverty decreases, with the rural areas of Java and Bali experiencing the largest reduction in poverty. Nevertheless, a handful of regions, such as rural South Sumatra actually post an increase in poverty incidence.

In regards to inequality, the regional Gini coefficient is generally lower in rural areas. Since real income is also lower in rural areas, the combination of low mean income and low inequality necessarily implies higher poverty levels in rural regions. Nevertheless there is also a good deal of regional variation in inequality—Gini coefficients in 1987 range from .25 to .35 in urban areas and from .21 to .31 in rural areas. Temporal trends in regional inequality are harder to discern from this table, although inequality does appear to be increasing for most urban areas and decreasing for rural ones. These trends will be explored in a more comprehensive fashion in the next section.

Table 3: Headcount poverty estimates at the upper poverty line and Gini coefficients, by province

| Province | Urban | | | | Rural | | | |
|---|---|---|---|---|---|---|---|---|
| | 1987 | | 1993 | | 1987 | | 1993 | |
| | Poverty count | Gini coefficient | Poverty count | Gini coefficient | Poverty count | Gini coefficient | Poverty count | Gini coefficient |
| Aceh | 0.096 | 0.291 | 0.083 | 0.319 | 0.272 | 0.243 | 0.160 | 0.248 |
| N. Sumatra | 0.104 | 0.278 | 0.108 | 0.307 | 0.340 | 0.253 | 0.221 | 0.228 |
| W. Sumatra | 0.094 | 0.272 | 0.080 | 0.333 | 0.221 | 0.248 | 0.196 | 0.258 |
| Riau | 0.096 | 0.251 | 0.039 | 0.245 | 0.275 | 0.209 | 0.151 | 0.242 |
| Jambi | 0.082 | 0.211 | 0.089 | 0.242 | 0.219 | 0.234 | 0.130 | 0.227 |
| S. Sumatra | 0.128 | 0.295 | 0.064 | 0.296 | 0.231 | 0.250 | 0.291 | 0.238 |
| Bengkulu | 0.133 | 0.266 | 0.058 | 0.274 | 0.297 | 0.212 | 0.250 | 0.210 |
| Lampung | 0.136 | 0.281 | 0.156 | 0.282 | 0.366 | 0.270 | 0.310 | 0.251 |
| Jakarta | 0.015 | 0.305 | 0.012 | 0.356 | -- | -- | -- | -- |
| W. Java | 0.158 | 0.322 | 0.108 | 0.305 | 0.273 | 0.278 | 0.134 | 0.271 |
| C. Java | 0.203 | 0.290 | 0.166 | 0.307 | 0.409 | 0.256 | 0.307 | 0.269 |
| Yogyakarta | 0.180 | 0.320 | 0.068 | 0.339 | 0.275 | 0.287 | 0.107 | 0.270 |
| E. Java | 0.132 | 0.332 | 0.120 | 0.361 | 0.394 | 0.280 | 0.265 | 0.237 |
| Bali | 0.135 | 0.322 | 0.100 | 0.327 | 0.300 | 0.313 | 0.177 | 0.283 |
| W. Nusa Tenggara | 0.390 | 0.331 | 0.192 | 0.328 | 0.504 | 0.281 | 0.395 | 0.246 |
| E. Nusa Tenggara | 0.217 | 0.347 | 0.221 | 0.328 | 0.593 | 0.253 | 0.485 | 0.208 |
| W. Kalimantan | 0.155 | 0.273 | 0.114 | 0.300 | 0.529 | 0.218 | 0.463 | 0.253 |
| C. Kalimantan | 0.110 | 0.247 | 0.077 | 0.291 | 0.335 | 0.220 | 0.257 | 0.214 |
| S. Kalimantan | 0.071 | 0.284 | 0.036 | 0.275 | 0.293 | 0.249 | 0.176 | 0.262 |
| E. Kalimantan | 0.083 | 0.314 | 0.026 | 0.303 | 0.248 | 0.277 | 0.118 | 0.251 |
| N. Sulawesi | 0.125 | 0.309 | 0.076 | 0.291 | 0.295 | 0.280 | 0.264 | 0.257 |
| C. Sulawesi | 0.037 | 0.257 | 0.104 | 0.292 | 0.363 | 0.265 | 0.225 | 0.262 |
| S. Sulawesi | 0.159 | 0.291 | 0.104 | 0.259 | 0.414 | 0.238 | 0.205 | 0.258 |
| SE. Sulawesi | 0.141 | 0.281 | 0.141 | 0.272 | 0.533 | 0.256 | 0.312 | 0.251 |
| Maluku | 0.064 | 0.251 | 0.050 | 0.246 | 0.488 | 0.280 | 0.426 | 0.263 |
| Irian Jaya | 0.171 | 0.311 | 0.126 | 0.290 | 0.669 | 0.310 | 0.515 | 0.360 |

Source: SUSENAS 1987 and 1993


12

## 3 Poverty change and economic growth

Having documented Indonesia's gains in poverty reduction over 1984-96 and its reversal from 1996-9 we now turn to how these poverty changes covary with income growth. Several previous studies cited in the introduction have found a significant positive association between poverty reduction and growth in cross-national studies and, thus, they conclude that overall growth benefits even the very poor. This section of the paper explores the same topic. However instead of using national variation in poverty and income growth to trace out any association between poverty change and growth, this section will look within one country and utilize regional variation to identify the association between poverty change and income growth at the local level.

For a given poverty line and initial poverty level, the growth and poverty relationship will be determined by how changes in inequality and gains in overall income levels covary over time. These time paths of inequality and income can be quite different across the different regions of Indonesia, given the diversity in sectoral composition of economic activity and in initial provincial conditions. To explore in a descriptive and flexible manner how the growth-poverty relation may vary across regions, we plot kernel density estimates of the log of household per capita expenditure (PCE) in each survey year separately for each provincial urban/rural cell. The resulting cell groupings of density estimates were quite varied. For expositional purposes we present the density estimates for two such cells: rural Bali and urban Central Kalimantan.

Figure 2 presents the per capita expenditure densities for rural Bali. Each year of observation is plotted and three years are labeled: 1984, 1996, and 1999. For rural Bali, the results of high growth from 1984-96 are apparent in the rightward shift of the density plots over time. The fact that the expenditure density maintains its rough shape as it shifts to the right indicates that expenditure distributions in Bali have been fairly consistent over time. The general distributional shape is also maintained after the crisis, indicating that inequality has been left relatively unchanged by the crisis. The exact magnitude of the leftward shift of the 1999 density depends of course on the choice of deflator (which is here again a food price deflator).

The story revealed in Figure 3, for urban Central Kalimantan, is quite different. In this cell, growth appears to occur simultaneously with an increase in inequality as the density plots shift rightward over time from 1984 to 1996 but also flatten out, thus increasing the density in both tails. The growth that occurred in this cell has very different distributional implications than the type of growth observed in rural Bali. Furthermore the financial crisis not only results in a leftward shift of the density but also a contraction of the right tail. The distribution in 1999 appears very similar to that for 1984 and so another consequence of the crisis, besides the income decline, is a decline in inequality.

Figure 2: Density plots of per capita household consumption—rural Bali, 1984-99

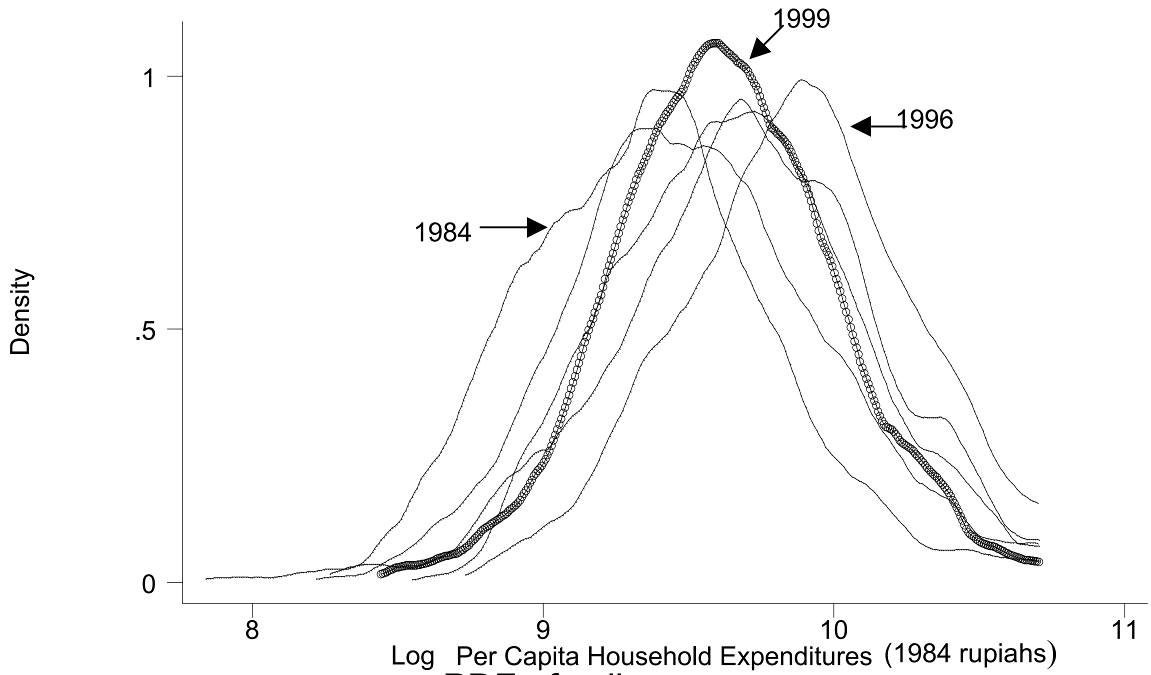
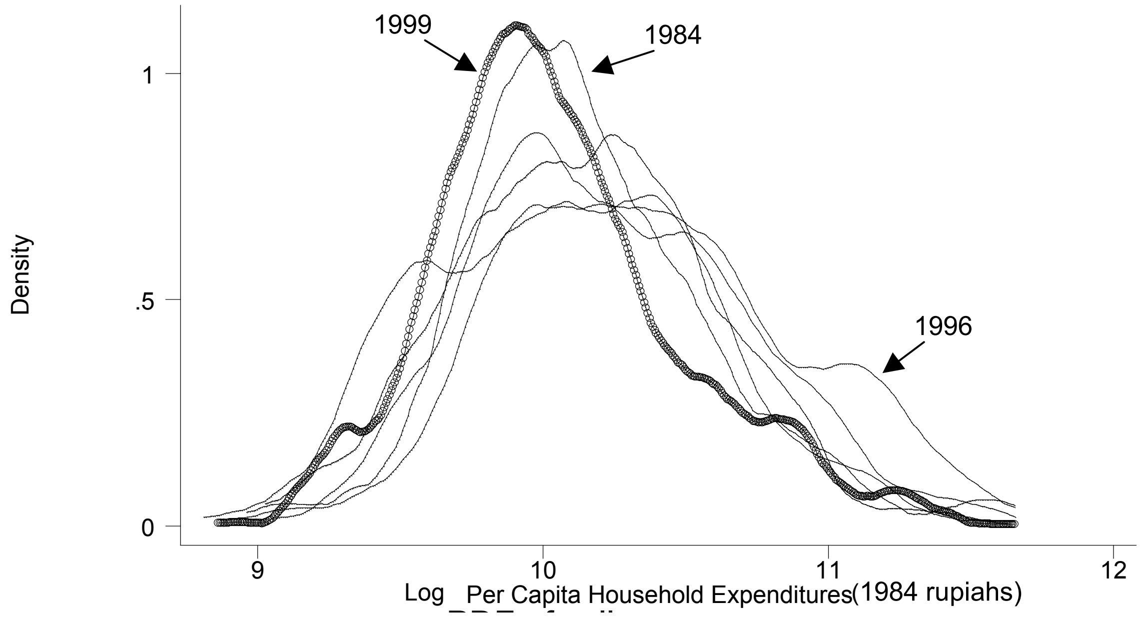



Figure 3: Density plots of per capita household consumption—urban central Kalimantan, 1984-99



The heterogeneity in regional growth and inequality change suggested by the province specific density plots is summarized in Figures 4 and 5, which portray the magnitude of growth and inequality change for each province in the data. Figure 4 depicts the proportional change in mean regional PCE over two periods—the growth period of 1984-96, and the contractionary period 1996-99—for each provincial urban/rural cell. For expositional ease, provinces are ordered from west to east and the major island groups to which they belong are indicated on the horizontal axis. The regional diversity in the provincial growth experience, in either period, is very apparent. Most provincial rural-urban areas gained in mean PCE from 1984-96, especially rural areas in Java and Lampung (the southernmost Sumatran province close to Java). However even in this period of national growth, the restive eastern most and western most provinces of Aceh and Irian Jaya actually experienced drops in mean PCE. The severe consequences of the financial crisis suggested by the density plots are also apparent in Figure 4 where every region experiences a drop in mean PCE, often of a magnitude at least as great as the gains in PCE over the preceding 12 years. Again, the magnitude of this loss is far from uniform. Urban areas generally experienced greater declines in mean PCE than their rural counterparts although the reverse is the case for the eastern most provinces of Irian Jaya, Maluku, and Southeast Sulawesi where rural areas appear to have suffered a greater proportional decline in income.

Given the diversity of change in regional inequality (measured as the proportional change in the Gini coefficient) apparent in Figure 5, fewer generalizations can be made for either the growth or contractionary periods. In the earlier period, a greater number of urban regions witnessed rising inequality than rural regions, with the greatest increase in inequality experienced by the capital Jakarta. Other regions, such as the rest of urban Java, saw little change in inequality in either direction. Over the crisis period, the vast majority of regions in both rural and urban areas experienced a decline in inequality with the magnitude of this change in certain regions greater than 20 per cent. Thus not only did the crisis negatively impact overall income, but this decline was not distributionally neutral for most regions the crisis disproportionately affected the better off households consequently reducing inequality as well as income. In terms of income and inequality comovements, changes in regional income and inequality are positively correlated in both periods, especially over the 1984-96 period (a correlation coefficient of .40 compared with a coefficient of .14 for the 1996-99 period). As we have seen, however, these summary measures mask a great deal of underlying regional heterogeneity.

Having described how regional income and inequality vary (and covary), we turn now to parameterized estimates of the poverty–growth relationship as we look at regressions of changes in poverty on changes in various income measures. We will return to the regional heterogeneity suggested in Figures 3-6 soon after. We first estimate a simple econometric specification relating poverty change to income change with the following expression:

$$\Delta \ln P_{\alpha,i}^{t+1,t} = \gamma_0 + \gamma_1 \Delta \ln \mu_i^{t+1,t} + f_p + e_i^{t+1,t}$$

where $\Delta \ln P_\alpha$ is the change in the natural log poverty measure $\alpha$ for region $i$, $\Delta \ln \mu_i$ is the change in mean real income for region $i$ (here nominal income is once again deflated by the food poverty line as in the previous section), and $f_p$ a vector of time period dummies.

These difference regressions are estimated separately for rural and urban areas as well as jointly on the pooled sample. The coefficient $\gamma_1$ yields what we can term the gross effect of income growth on poverty change since there is no control for changes in regional inequality. It simply conveys the association between poverty change and mean income change net of period intercept effects. A second specification specifically controlling for changes in regional inequality is given by the following:

$$\Delta \ln P_{\alpha,i}^{t+1,t} = \gamma_0^{'} + \gamma_1^{'} \Delta \ln \mu_i^{t+1,t} + \gamma_2^{'} \Delta \ln G_i^{t+1,t} + f_p + e_i^{t+1,t}$$

where $\ln G_i$ is the natural log of some inequality measure, here taken to be the standard Gini coefficient used in the earlier figures and tables.[9] In this specification $\gamma_1$' yields what we will term the net effect of income growth on poverty change since it can be interpreted as the estimated association between distributionally neutral growth and poverty measures, i.e. the effect of income growth net of changes in inequality. $\gamma_2$' yields the impact of inequality change on poverty while holding income constant.

We also estimate a third specification that includes the initial levels of regional inequality and regional mean income. Since the poverty–growth elasticity is determined by the magnitude of changes in mean income and the shape of the income distribution, as well as the location of the poverty line, the poverty–growth response may vary over time, or across regions, partly due to the initial conditions of the region. Unless each regional cell has the same average income and distributional shape, and the kernel density plots have shown this not to be the case, then even distributionally neutral growth will yield poverty–growth elasticities that vary across regions. Put another way, the density of the distribution around the poverty line at the start of a period may be a significant factor influencing the poverty growth elasticity. Therefore we also adopt a third specification that includes the initial period mean income $\mu_i$

[9] An alternative inequality measure, the variance of log income, was also used in this analysis with little impact on the overall results. For brevity's sake, only results with the Gini coefficient will be reported.

and inequality $G_i$ of the distribution in order to investigate whether regional initial conditions impact the poverty–growth elasticity:

$$\Delta \ln P_{\alpha,i}^{t+1,t} = \gamma_0^{''} + \gamma_1^{''} \Delta \ln \mu_i^{t+1,t} + \gamma_2^{''} \Delta \ln G_i^{t+1,t} + \gamma_3^{''} \ln \mu_i^{t} + \gamma_4^{''} \ln G_i^{t} + f_p + e_i^{t+1,t}$$

Figure 4: Proportional change in real mean per capita household expenditures, by province 1984-96 and 1996-99

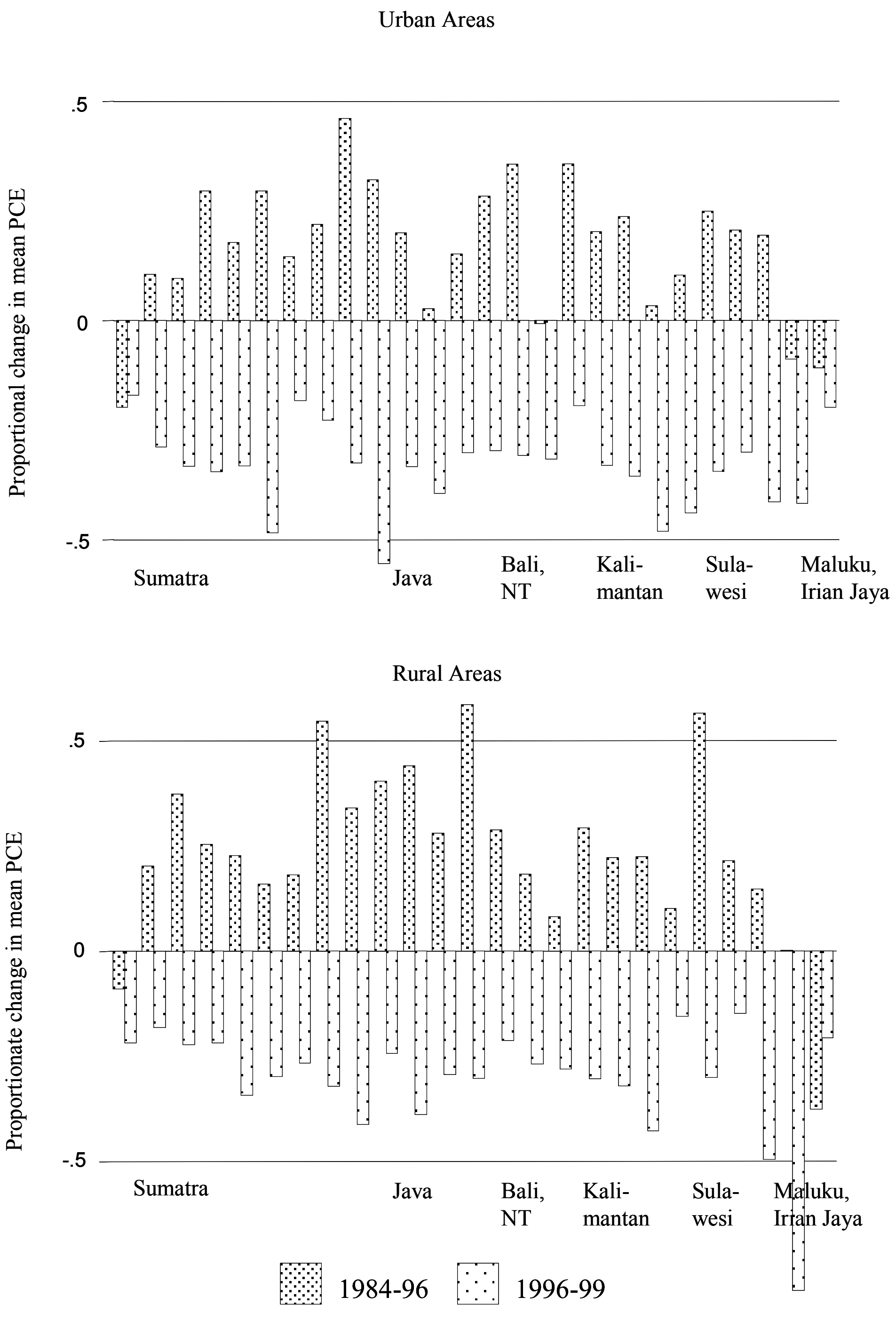


Figure 5: Proportional change in inequality (Gini coefficient), by province 1984-96 and 1996

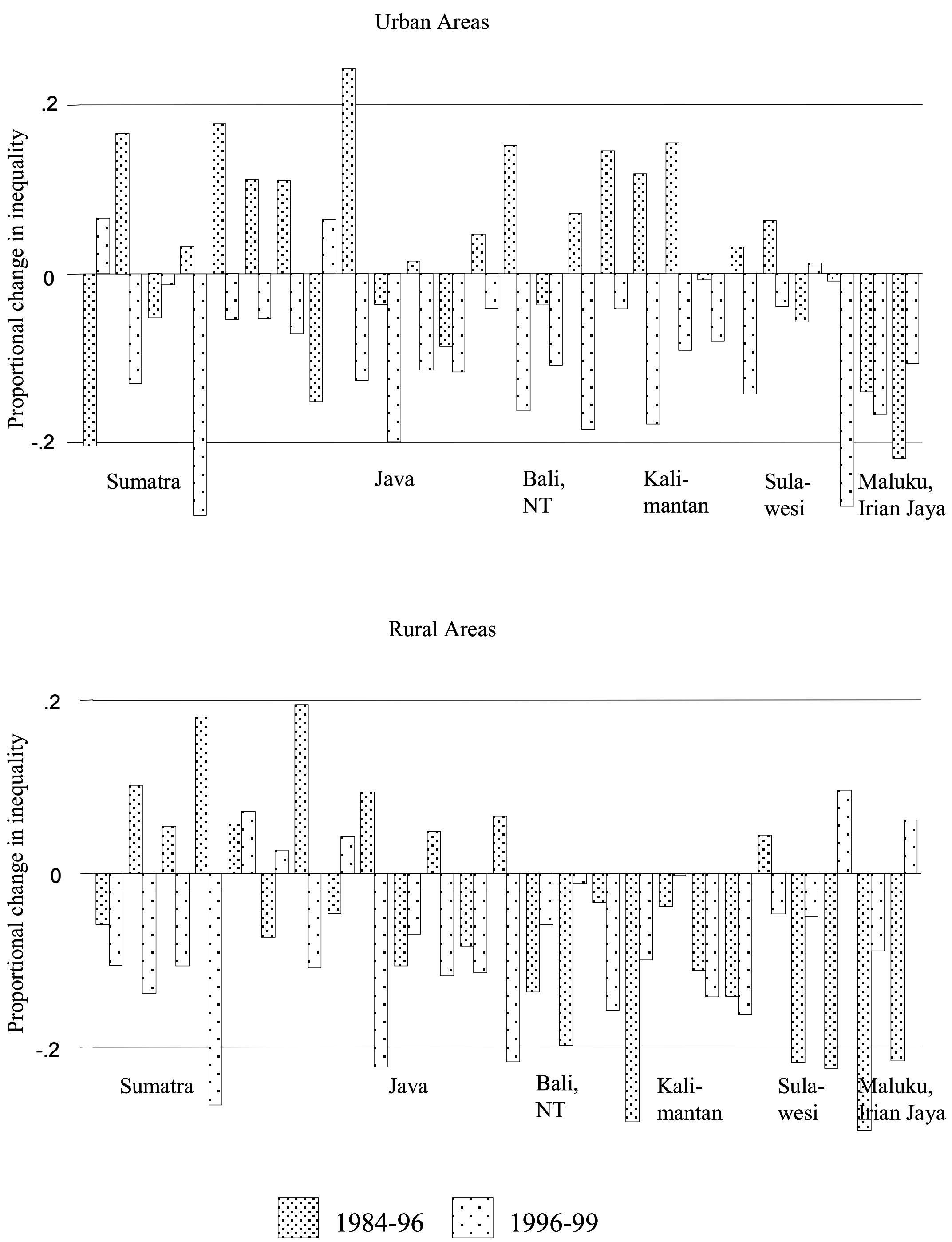


Table 4: Difference regressions, poverty change on mean income and inequality change, various specifications, local prices

| Poverty measure | Gross effect | | Net effect of growth | | | | Net effect of growth with initial conditions | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Growth | | Growth | | Inequality change | | Growth | | Inequality change | | Base income | | Base inequality | |
| *Total sample* | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Head count upper | -1.959 | 0.110 | -2.624 | 0.116 | 1.432 | 0.114 | -2.722 | 0.122 | 1.527 | 0.125 | -0.127 | 0.044 | 0.128 | 0.090 |
| Head count lower | -2.332 | 0.161 | -3.111 | 0.155 | 1.797 | 0.147 | -3.222 | 0.167 | 1.863 | 0.165 | -0.123 | 0.070 | 0.063 | 0.116 |
| Gap upper | -2.546 | 0.160 | -3.572 | 0.129 | 2.202 | 0.129 | -3.650 | 0.132 | 2.183 | 0.146 | -0.117 | 0.050 | -0.049 | 0.112 |
| Gap lower | -3.025 | 0.216 | -4.139 | 0.205 | 2.664 | 0.211 | -4.230 | 0.213 | 2.557 | 0.236 | -0.118 | 0.079 | -0.187 | 0.186 |
| Square gap upper | -3.150 | 0.209 | -4.117 | 0.171 | 2.666 | 0.183 | -4.183 | 0.178 | 2.559 | 0.205 | -0.099 | 0.067 | -0.226 | 0.159 |
| Square gap lower | -3.488 | 0.264 | -4.682 | 0.295 | 3.517 | 0.307 | -4.853 | 0.300 | 3.377 | 0.336 | -0.179 | 0.108 | -0.381 | 0.269 |
| | | | | | | | | | | | | | | |
| *Urban areas* | | | | | | | | | | | | | | |
| Head count upper | -1.782 | 0.225 | -2.890 | 0.213 | 2.223 | 0.232 | -2.947 | 0.206 | 2.041 | 0.262 | -0.164 | 0.081 | -0.084 | 0.174 |
| Head count lower | -2.142 | 0.369 | -3.665 | 0.363 | 3.179 | 0.351 | -3.759 | 0.393 | 3.261 | 0.410 | -0.129 | 0.197 | 0.133 | 0.343 |
| Gap upper | -2.324 | 0.329 | -3.916 | 0.278 | 3.175 | 0.282 | -4.000 | 0.297 | 3.097 | 0.324 | -0.113 | 0.142 | -0.112 | 0.240 |
| Gap lower | -3.040 | 0.457 | -4.691 | 0.488 | 4.325 | 0.496 | -4.666 | 0.520 | 4.104 | 0.554 | -0.025 | 0.260 | -0.294 | 0.328 |
| Square gap upper | -2.639 | 0.421 | -4.422 | 0.379 | 3.833 | 0.388 | -4.413 | 0.405 | 3.636 | 0.432 | -0.034 | 0.208 | -0.305 | 0.274 |
| Square gap lower | -2.284 | 0.618 | -5.082 | 0.747 | 5.698 | 0.717 | -5.047 | 0.791 | 5.316 | 0.810 | -0.033 | 0.398 | -0.551 | 0.541 |
| | | | | | | | | | | | | | | |
| *Rural areas* | | | | | | | | | | | | | | |
| Head count upper | -1.938 | 0.116 | -2.122 | 0.108 | 0.795 | 0.111 | -2.175 | 0.117 | 0.901 | 0.137 | -0.069 | 0.069 | 0.194 | 0.138 |
| Head count lower | -2.317 | 0.170 | -2.531 | 0.143 | 1.346 | 0.130 | -2.582 | 0.159 | 1.347 | 0.169 | -0.053 | 0.079 | 0.003 | 0.176 |
| Gap upper | -2.689 | 0.169 | -3.200 | 0.136 | 1.747 | 0.128 | -3.229 | 0.150 | 1.715 | 0.164 | -0.049 | 0.078 | -0.062 | 0.160 |
| Gap lower | -3.076 | 0.219 | -3.822 | 0.177 | 2.120 | 0.163 | -3.793 | 0.196 | 2.053 | 0.212 | -0.001 | 0.110 | -0.117 | 0.209 |
| Square gap upper | -3.369 | 0.221 | -3.964 | 0.175 | 2.132 | 0.173 | -3.914 | 0.194 | 1.990 | 0.220 | -0.022 | 0.110 | -0.250 | 0.214 |
| Square gap lower | -3.807 | 0.279 | -4.486 | 0.260 | 2.402 | 0.277 | -4.428 | 0.284 | 2.165 | 0.339 | -0.047 | 0.156 | -0.441 | 0.332 |

Note: Estimates from Feasible Generalized Least Squares. N=255 for total sample estimates, 130 for urban, and 125 for rural estimates

Source: Author's estimates from SUSENAS surveys, various rounds.

19

The gross growth elasticities, the net growth elasticities, and the net effects with initial conditions were estimated on the entire sample and then separately for rural and urban areas with Feasible Generalized Least Squares to account for heteroskedasticity across regions.[10] The coefficients and standard errors for all regressions are presented in Table 4 and some of the findings are also summarized graphically in Figure 5, which depicts the gross elasticity and the net elasticity with initial conditions of the upper poverty line measures to growth. Looking at the results we see that for any combination of poverty measure and poverty line, the gross effect of growth on poverty reduction is large and significant.[11, 12] For example, a 10 per cent increase in regional mean income is associated with an average reduction of 20 per cent in the upper line poverty headcount (and conversely, a 10 per cent decline in income is associated with a 20 per cent increase in poverty). The poverty headcount from the lower line is even more responsive to mean income growth. Alternative poverty measures that account for the depth or severity of poverty, the gap and squared gap measures, yield even larger estimated elasticities than the headcount measure. Not only is the incidence of poverty reduced by income growth, but also the poorest of the poor seem to gain relatively more than the poor closer to the poverty line as Indonesian regions grow.

Since increases in regional inequality are at least weakly positively correlated with gains in income, then we should expect the net response of poverty change to income growth to be

[10] This framework loosens the restrictions on the regression residuals and allows the within-region variance to vary by region. The point estimates from FGLS are virtually identical to the point estimates from OLS and the OLS Huber-White corrected standard errors still result in the precise estimation of each growth and inequality change coefficient. We report the FGLS results but obtain very similar results with OLS.

[11] The poverty measures and the growth measures estimated here derive from the same underlying consumption surveys. It is possible for errors in survey measurement to create a negative correlation between income measures such as the mean income and poverty measures. This spurious correlation can create an upward bias in the estimated poverty–growth elasticities. Ravallion (2001), working with a cross-national sample, explores this issue by instrumenting mean survey income with a national accounts income measure and indeed finds indications of such upward bias. In the case of Indonesia, the regional accounts data are only loosely correlated with the survey means of regional income (with a correlation coefficient near zero for many survey periods) and as such serve as weak instruments at best. Indeed the 2SLS estimates of the poverty–growth elasticities using regional per capita GDP growth as an instrument result in estimated elasticities larger in magnitude than the results in Table 4. This increase in the estimated elasticities more likely reflects the low correlation between survey measures and regional accounts data rather than the absence of survey measurement error.

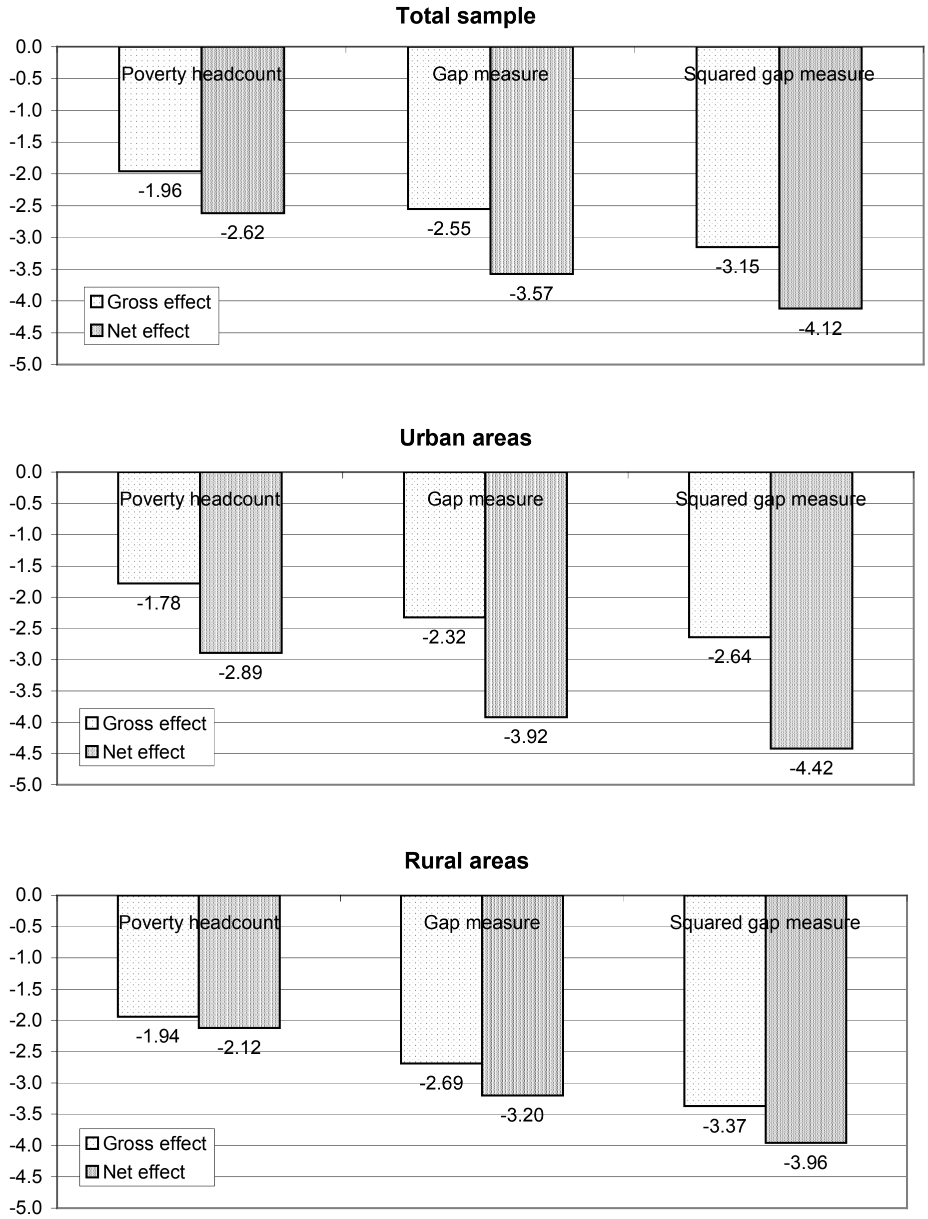
[12] One caveat for these results concerns population migration across provinces or between urban and rural areas and the possible impact of such migration on the consistency of parameter estimates. By aggregating the household data into provincial urban/rural cells and then comparing cell level measures across time, we have created a pseudo panel of information. McKenzie (2001) shows that if the underlying cohort composition does not retain the same mean properties over time then parameters estimated from a pseudo panel may be inconsistent. The concern in the context of this study is the potential presence of differential household or individual migration by income level and its implications for estimates of the poverty–growth elasticity. Surprisingly Frankenberg et al. (1999) find that household migration rates after the financial crisis do not vary across income quintiles. Nevertheless possible differential migration before the crisis can pose problems and will need to be explored further in future work. Given the relatively brief time interval of three years, however, it is unlikely that differential migration would substantially affect cohort composition in this data.

even greater once inequality changes are controlled for. This is indeed the case. The net elasticity of the upper headcount to mean income growth is -2.62. Elasticities for the gap and squared gap measures are still greater in magnitude. When looking within urban and rural areas, the increase in magnitude from the gross to the net growth elasticity is much greater in urban areas than in rural (-1.78 to -2.89 for the upper line urban poverty headcount as opposed to -1.94 to -2.12 for the rural count), indicating that the association between rising inequality and economic growth is much greater in urban areas than rural. Of course inequality change itself is significantly and positively correlated with poverty change. A mean income preserving 10 per cent reduction in the Gini coefficient would reduce the upper line head count measure by 14 per cent and the squared gap measure by 27 per cent. The inequality coefficients are far greater for urban areas, again attesting to the relatively inequitable growth in urban areas as opposed to rural.

When the base period conditions are included in the poverty growth regressions, the coefficients on mean income growth and inequality change are statistically indistinguishable from the net effects regressions without the initial regional conditions. This suggests that, for this data, the initial conditions of the regional expenditure distributions would add little to historical predictions of poverty change once information on the changes in those distributions are taken into account. The initial condition coefficients themselves are generally insignificant and small in magnitude. By already controlling for inequality change, base period inequality exerts no discernible influence whatsoever on poverty change. Regional mean income does exert some influence on poverty reduction, at least in the total sample estimates, where the greater the mean income, the more responsive the poverty headcounts are to overall growth. This is not the case, however, within urban or rural areas (except for the upper line poverty headcount in urban areas).

Table 4 and Figure 6 present the association between growth in provincial mean income and poverty reduction and found that poverty responds strongly to gains in mean income. Mean income growth is, of course, only one potential measure of growth and the data enable further investigations into the elasticity of poverty to changes in other points in the income distribution in addition to this summary mean measure. Therefore we re-estimate the above specifications using the change in income at the 10th, 25th, 50th, 75th, and 90th expenditure percentiles as alternative growth measures. Figure 7 summarizes the estimated gross and net elasticities of the upper line poverty gap measure using these alternative income change measures in order to give some sense of the results without presenting a large table with numerous coefficients and standard errors. All poverty growth elasticities in the tables are precisely estimated. Not surprisingly, poverty reduction responds quite strongly to gains at low levels of income. For example the elasticity of the upper line poverty gap to an increase in the 10$^{th}$ income percentile is –3.6, indicating a greater poverty response to 10$^{th}$ percentile

Figure 6: Gross and net elasticities of upper line poverty measures to mean income growth




income growth than to mean income growth. Similar coefficients are found for the gross effect of increases in the 25th expenditure percentile. Growth in higher points in the income distribution is substantially less related to poverty reduction. A one per cent gain in the 90th income percentile translates into only a 1.5 per cent decline in the upper poverty gap. Indeed in urban areas, gains in the 90th income percentiles implies less than a 1 per cent decline in the gap. Clearly, growth in the upper tail of the income distribution is only weakly correlated with growth in the bottom tail, especially for urban areas. Controlling for inequality, however, the net effects of gains in income at any percentile are now much more similar. The upper line gap elasticities for the entire sample now range from -2.7 with respect to the 90th income percentile to -3.6 with respect to the 10th percentile. The narrowing of differences across percentiles is not surprising, of course, since by netting out the effects of inequality change we force the entire income distribution to increase in lock step with the particular income measure.

Table 5: Net effects of growth distinguished by periods of expansion and contraction

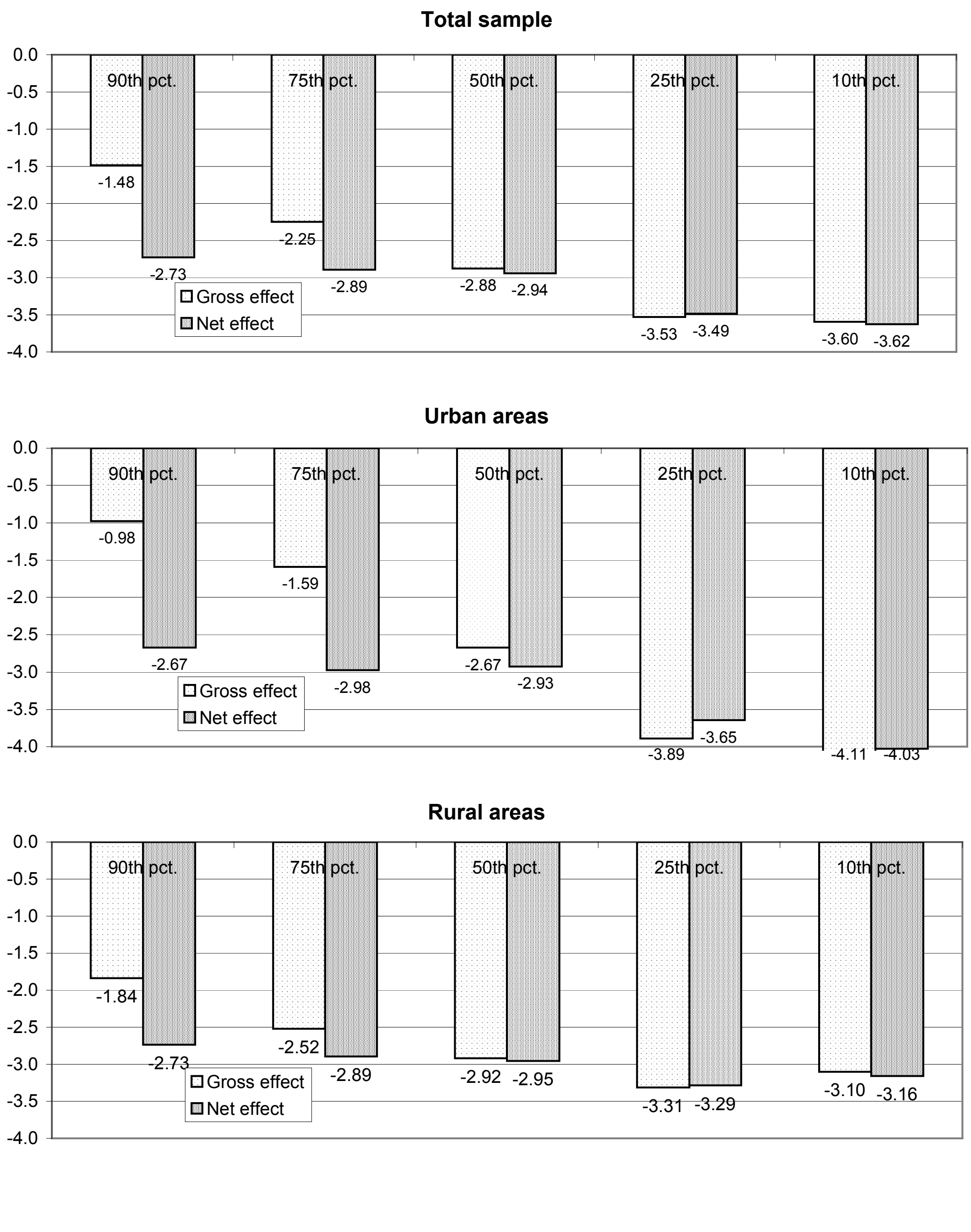
| Poverty measure | Periods of positive growth | | | | Periods of negative growth | | | |
|---|---|---|---|---|---|---|---|---|
| | Net effect of growth | | Inequality change | | Net effect of growth | | Inequality change | |
| *Total sample* | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Head count upper | -3.181 | 0.185 | 1.832 | 0.147 | -2.007 | 0.241 | 1.265 | 0.159 |
| Head count lower | -3.756 | 0.168 | 2.479 | 0.139 | -2.461 | 0.302 | 1.582 | 0.145 |
| Gap upper | -3.640 | 0.144 | 2.325 | 0.196 | -3.075 | 0.259 | 1.950 | 0.195 |
| Gap lower | -3.959 | 0.326 | 2.772 | 0.362 | -3.777 | 0.379 | 2.743 | 0.261 |
| Square gap upper | -4.056 | 0.241 | 2.762 | 0.299 | -3.947 | 0.283 | 2.455 | 0.216 |
| Square gap lower | -4.816 | 0.457 | 3.783 | 0.467 | -4.892 | 0.460 | 3.793 | 0.478 |
| *Urban areas* | | | | | | | | |
| Head count upper | -3.094 | 0.387 | 2.128 | 0.368 | -2.961 | 0.379 | 2.764 | 0.286 |
| Head count lower | -2.685 | 0.430 | 3.355 | 0.357 | -4.718 | 0.648 | 3.428 | 0.380 |
| Gap upper | -3.081 | 0.202 | 2.942 | 0.291 | -3.827 | 0.537 | 3.161 | 0.354 |
| Gap lower | -2.625 | 0.728 | 3.692 | 0.657 | -4.530 | 0.945 | 4.453 | 0.547 |
| Square gap upper | -2.826 | 0.430 | 3.043 | 0.468 | -3.990 | 0.680 | 3.671 | 0.423 |
| Square gap lower | -3.626 | 1.126 | 4.235 | 1.081 | -5.182 | 1.399 | 7.005 | 0.843 |
| *Rural areas* | | | | | | | | |
| Head count upper | -3.212 | 0.216 | 1.532 | 0.158 | -1.328 | 0.232 | 0.897 | 0.132 |
| Head count lower | -4.011 | 0.307 | 2.064 | 0.214 | -1.987 | 0.293 | 1.058 | 0.247 |
| Gap upper | -4.076 | 0.274 | 1.939 | 0.219 | -2.899 | 0.247 | 1.279 | 0.209 |
| Gap lower | -4.917 | 0.403 | 2.420 | 0.316 | -3.388 | 0.318 | 1.568 | 0.298 |
| Square gap upper | -4.661 | 0.393 | 2.408 | 0.305 | -3.742 | 0.263 | 1.392 | 0.276 |
| Square gap lower | -5.029 | 0.565 | 2.768 | 0.435 | -4.684 | 0.297 | 1.414 | 0.403 |

Note: Estimates from Feasible Generalized Least Squares with N=139 for expansionary periods (67 in urban areas and 72 in rural areas) and 166 for contractionary periods (63 urban and 53 rural)
Initial inequality and income levels included in analysis but results not shown.

Source: Author's estimates from SUSENAS surveys, various rounds.

All regression results until now have been estimated on the entire sample and, thus, implicitly constrain the poverty growth elasticities to be the same during periods of expansion and of contraction. However the historical poverty responses to growth and contraction may very well be different given not only differences in initial conditions but also in the way expansions and contractions affect regional expenditure distributions. Remember that the contractions over the 1996-99 crisis period appear to have disproportionately affected the upper tail of the distribution. To explore these potential differences further, we estimate the net elasticity with initial conditions regressions separately for periods of growth and decline in mean regional expenditures and report the results in Table 5. Some differences in the poverty response during periods of expansion and contraction are readily apparent. The headcount measure from the upper and lower poverty lines exhibit a significantly greater response to gains in mean income than declines, yet this is not the case for the gap and squared gap measures. When looking within rural and urban areas, we see that these differences only arise in rural areas—the urban elasticities are the same for both expansions and contractions while the headcount elasticities in rural areas are substantially greater during periods of growth.

Figure 7: Gross and net elasticities of upper poverty line poverty gap to growth in various percentiles of income distribution



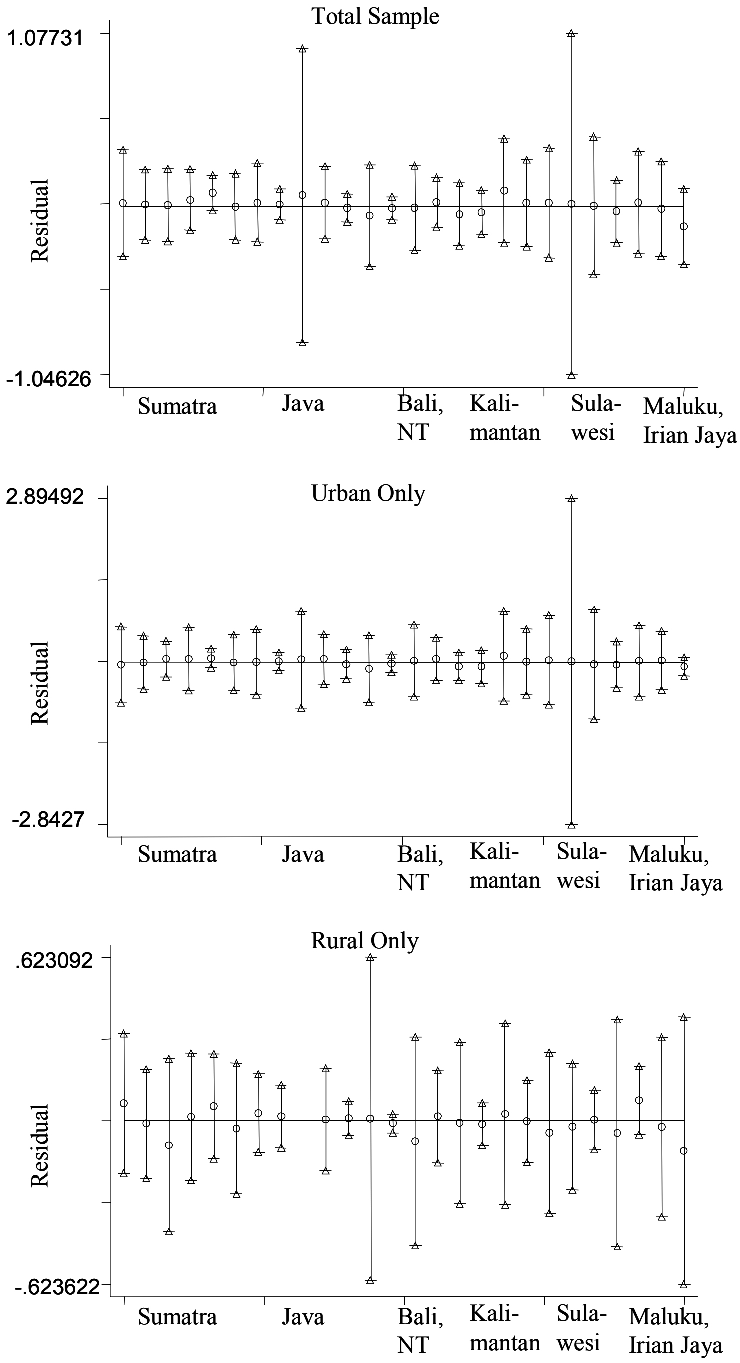
A clear link between income growth and poverty reduction has been established, it is fairly robust across income measure, and it is largely similar whether an Indonesian region experiences an expansion or contraction. None of the results have yet looked at potential geographic variation in poverty responses even though it is quite possible for poverty to respond to growth in a non-uniform way across different regions. This possibility is indeed suggested by the comparison of density estimates across the two provinces in Figures 3 and 4. Regional differences can arise for many reasons, for example if the sectoral composition of growth both varies across provinces and impacts on poverty in different ways. It is also possible that regional variations in the implementation of national policy lead to different poverty outcomes. Furthermore, simple geographic differences in market integration may cause poverty to respond differently to growth. To look further into these possibilities, we return to the net effects with initial conditions regressions in Table 4 and plot the mean residuals of these regressions by province in order to investigate whether there is any clear spatial pattern to their distribution.

These mean residual plots are presented in Figure 8. The first plot in Figure 8 relays the residual from the pooled urban and rural regression of the upper line poverty gap change on income growth. The 95 per cent confidence interval band around the mean is plotted as well. From this simple inspection, little systematic variation in the residual is apparent. Although there is evidence of heteroskedasticity across the various regions, none of the mean residuals are significantly different from zero. The point estimates for the mean residual are all very close to zero as well. The following two graphs in Figure 8 plot the mean residuals derived from the separate urban and rural regressions. An inspection of these plots draws the same conclusions. The poverty response to income change in any particular province does not appear to deviate from the nationally estimated mean response in a systematic geographic fashion.[13]

These preliminary investigations find no evidence of systematic variation across regions in the response of poverty to growth. One potential reason for the failure to find such variation, if it does indeed exist, is a problem common to all difference estimators measurement error. If the underlying dataset contains measurement error then differenced data will tend to exacerbate measurement error problems (see, for example, Card 1996) and there surely must be some error in the poverty and income measures. One approach to increase the signal to noise ratio is to return to the levels data and investigate how deviations from mean income and inequality covary with poverty rates within a time period.

[13] The conclusions are the same regardless of the poverty measure and also do not change if instead we investigate the residuals from the gross elasticity regressions.

Figure 8: Mean residual plots (and 95 per cent CI) from upper line poverty gap difference regressions, by province



Similar specifications to the difference regressions above were estimated on the pooled level data of provincial poverty measures and income. Specifically the poverty measure $P_\alpha$ was regressed on income according to the following gross and net specifications:

$$\ln P_{\alpha,i}^{t} = \gamma_0 + \gamma_1 \ln \mu_{it} + f_c + f_t + e_{it}$$
$$\ln P_{\alpha,i}^{t} = \gamma_0^{'} + \gamma_1^{'} \ln \mu_{it} + \gamma_2^{'} \ln G_{it} + f_c + f_t + e_{it}$$

where $f_c$ is a vector of cell dummies and $f_t$ is a vector of survey year dummies. The results from these fixed effect GLS estimates are given in Table 6.

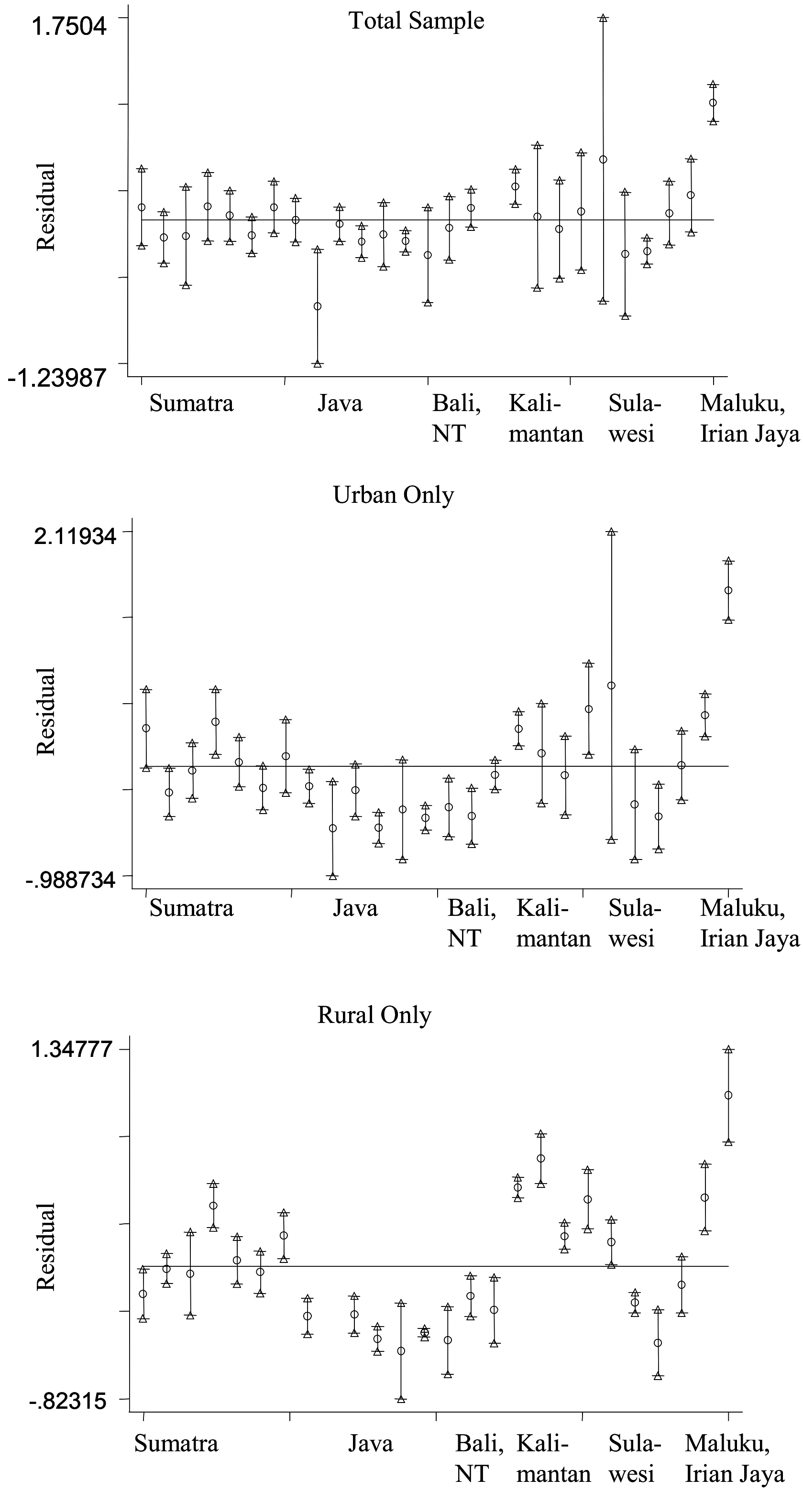
Table 6: Levels regressions, growth and inequality elasticities of poverty measures

| Poverty measure | Gross effect | | Net effect of growth | | | |
|---|---|---|---|---|---|---|
| | Growth | | Growth | | Inequality change | |
| *Total sample* | Coef. | S.E. | Coef. | S.E. | Coef. | S.E. |
| Head count upper | -2.072 | 0.103 | -2.592 | 0.105 | 1.317 | 0.112 |
| Head count lower | -2.444 | 0.146 | -3.129 | 0.131 | 1.857 | 0.144 |
| Gap upper | -2.639 | 0.134 | -3.491 | 0.118 | 2.152 | 0.130 |
| Gap lower | -3.038 | 0.171 | -4.056 | 0.178 | 2.654 | 0.211 |
| Square gap upper | -3.178 | 0.150 | -4.139 | 0.157 | 2.650 | 0.186 |
| Square gap lower | -3.472 | 0.199 | -4.678 | 0.247 | 3.431 | 0.296 |
| *Urban areas* | | | | | | |
| Head count upper | -1.960 | 0.225 | -3.244 | 0.209 | 2.518 | 0.216 |
| Head count lower | -2.318 | 0.334 | -3.946 | 0.311 | 3.467 | 0.333 |
| Gap upper | -2.520 | 0.287 | -4.071 | 0.256 | 3.343 | 0.278 |
| Gap lower | -3.300 | 0.347 | -4.996 | 0.432 | 4.663 | 0.465 |
| Square gap upper | -2.936 | 0.336 | -4.716 | 0.348 | 4.054 | 0.380 |
| Square gap lower | -2.883 | 0.484 | -5.794 | 0.620 | 6.300 | 0.644 |
| *Rural areas* | | | | | | |
| Head count upper | -1.957 | 0.106 | -2.185 | 0.106 | 0.739 | 0.122 |
| Head count lower | -2.383 | 0.156 | -2.612 | 0.143 | 1.348 | 0.139 |
| Gap upper | -2.721 | 0.151 | -3.244 | 0.123 | 1.756 | 0.120 |
| Gap lower | -3.079 | 0.194 | -3.831 | 0.155 | 2.220 | 0.158 |
| Square gap upper | -3.296 | 0.175 | -4.061 | 0.151 | 2.231 | 0.169 |
| Square gap lower | -3.762 | 0.207 | -4.660 | 0.209 | 2.552 | 0.264 |

Note: Estimates from Fixed Effect Generalized Least Squares with N=306 for total sample, 156 for urban, and 150 for rural areas

Source: Author's estimates from SUSENAS surveys, various rounds.

Figure 9: Mean residual plots (and 95 per cent CI) from upper line poverty gap levels regressions, by province



Similar to the findings with the difference regressions, deviations of provincial income from its mean are highly and significantly associated with reduced poverty. In addition, the gap and squared gap measures are even more responsive to income deviations as in the difference regressions. The estimated coefficients for both the gross and net effect of growth, as well as the coefficient on inequality, are all similar to the coefficients in the difference regressions and few deviate in any statistically significant manner. For example, the gross effect of mean income growth on the upper line headcount has an estimated elasticity of -2.07 from the fixed effect estimator and -1.96 from the difference estimator. The difference in these two estimates is not statistically significant. The response of poverty to growth and inequality change, already found to be quite robust over various specifications of difference regressions, is also robust across the use of differenced or level data.[14]

Turning to potential geographic variation in the relation between levels of poverty and income and inequality, we plot the mean residuals from the net effect levels regressions by province. The residual plots for the upper line gap measure, analogous to the Figure 8 plots, are given in Figure 9. Several differences from Figure 8 are readily apparent. The plots of the mean residual for the overall sample appear to follow systematic geographical regularities. Residuals from provinces in the island of Sumatra tend to all be centered on zero. Provinces from Java and Bali generally appear to have residuals falling below zero (although some of these mean residuals are not significantly different from zero). Thus a researcher would tend to overpredict the incidence of poverty in Java given the regression coefficients estimated on the national sample. Provinces from the east of Indonesia (Irian Jaya, Maluku) have residuals above the zero axis. Poverty in those regions would be systematically underpredicted given the nationally estimated relation between income, inequality, and growth.

Looking at the residuals from the split sample regressions within urban or rural areas, it is quite apparent that, while there is indeed spatial variation in urban area residuals and several residuals are significantly different from zero, it is the regional differences in rural areas that are most pronounced with numerous mean residuals significantly different from zero. This contrasts sharply with the mean residuals from the difference regressions where no clear regional pattern was observed. Based on the levels regressions, poverty levels in rural Java, Bali, and parts of Sulawesi would be systematically overestimated. Poverty in Irian Jaya, Maluku, Kalimantan, and some Sumatran provinces would be systematically underestimated. These residual plots make clear that regional factors have an important impact on poverty determination independent of the effects of within region income change.

[14] If the true poverty–growth relation is linear then the fixed effect and difference specifications are functionally equivalent. The fixed effect estimator is efficient when the $e_{it}$ are serially uncorrelated. Standard tests for serial correlation fail to reject the null of the absence of serial correlation.

While suggestive, it would be premature to conclude that the regional variation in the fixed effect GLS residuals is necessarily a result of regional specific differential responses to growth. Since we are now analyzing levels data, these residual patterns may be generated by differing regional poverty–growth elasticities. Alternatively, they may instead simply reflect the persistence of high poverty regions and low poverty regions overtime. The poverty reduction record of Indonesia casts some doubt on this second alternative since, for example, rural Java began the 1984-96 period with relatively high poverty and witnessed the greatest reduction in poverty by 1996. It is indeed rural Java that has significantly negative residuals in Figure 9.

We can try to distinguish between these two possibilities by returning to the difference data and this time adopting a random coefficients regression framework that allows the growth coefficient to vary by major island group. To control for the potentially confounding effects of base period inequality (a high level of inequality can stifle poverty reducing growth), instead of regressing poverty change on the rate of growth, we now regress it on the distribution corrected rate of growth in mean regional income. Following Ravallion (1997) we define the distribution corrected rate of growth as (1-$G_i$)($\Delta\ln\mu_i$) and estimate the following:

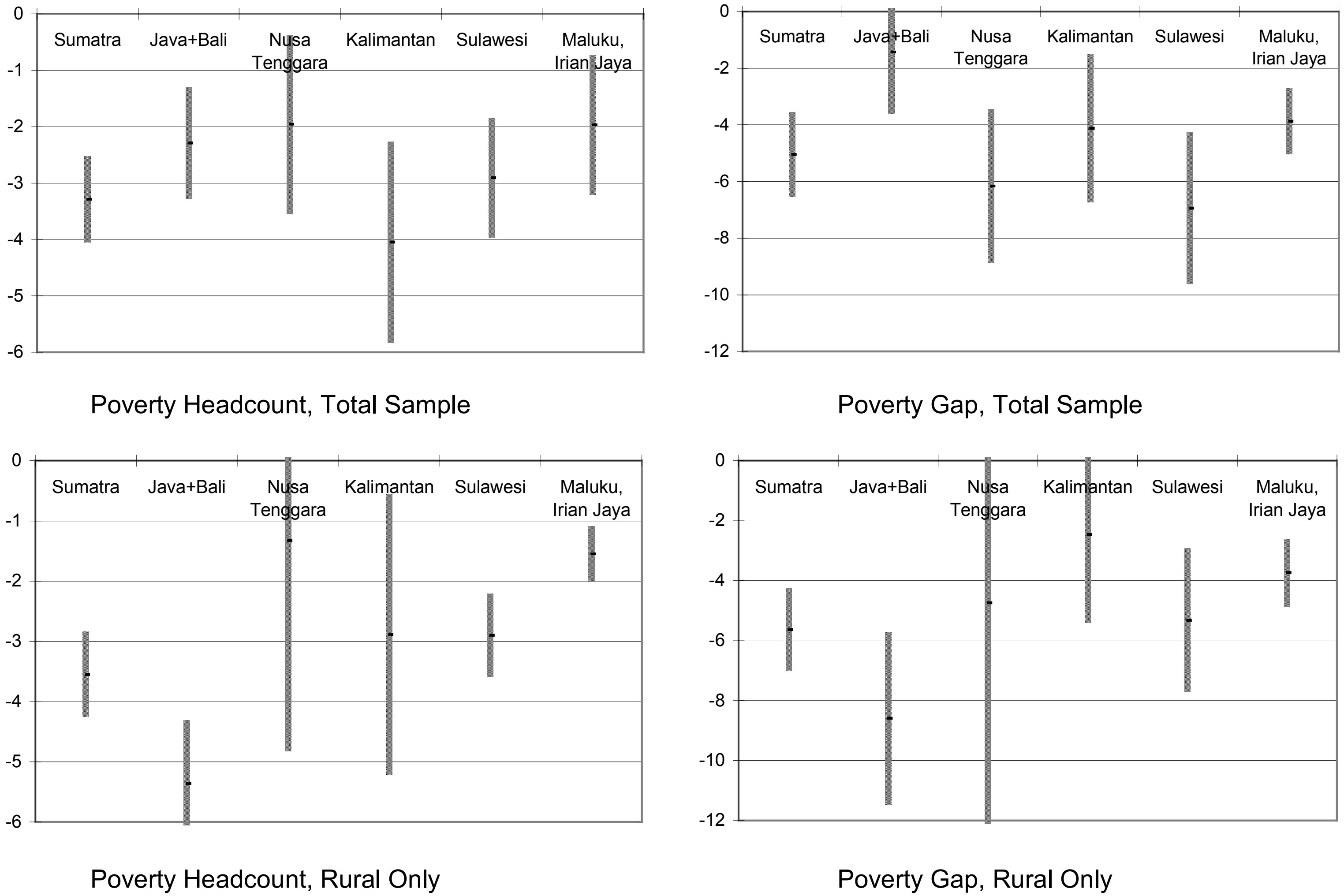
$$\Delta\ln P_{\alpha,i}^{t+1,t} = \gamma_0 + \gamma_{1j}(1-G_i^t)\Delta\ln\mu_i^{t+1,t} + f_p + e_i^{t+1,t}$$

Where j indexes six major island groups: Sumatra, Java and Bali, Nusa Tenggara, Kalimantan, Sulawesi, and Maluku and Irian Jaya. Figure 10 presents the results from the above specification with both the upper line headcount and gap poverty change measures. The set of $\gamma_{1j}$ is plotted for both the total sample and for only rural areas and the point estimates are bracketed by 95 per cent confidence bands. Since we are utilizing differenced data, measurement error is again a major concern, especially now as we are multiplying a noisy rate of growth measure with a Gini coefficient also measured with noise. Nevertheless, the results are suggestive, especially when considered in conjunction with the residual plots of Figure 9.

The island group specific point estimates for both the headcount and the gap measure suggest the presence of regional differences in the poverty response to distribution corrected growth for the total sample, however the large standard errors of the residuals rule out any statistically significant deviations. This is not the case in the rural estimates where poverty responses are statistically distinct across regions. The poverty responses for Java and Bali are greatest in magnitude and significantly different from Sumatra, Sulawesi, and Maluku and Irian Jaya for the headcount measure and different from Kalimantan and Maluku and Irian Jaya for the gap measure. The estimated poverty responses for Maluku and Irian Jaya, Nusa Tenggara, and Kalimantan (in the case of the gap measure) are relatively low in magnitude and some are

.

Figure 10: Estimated response of upper line poverty measures to growth in distribution corrected mean income, with 95% confidence band



significantly different from the more responsive regions of Java, Bali, and Sumatra. Nusa Tenggara in particular is estimated with a great deal of imprecision indicating a wide diversity of responses within that small region. Ignoring that island group, the plots in Figure 10 highlight the regional diversity of poverty responses and suggest a spatial pattern very similar to the residual patterns of Figure 9. We conclude from the analysis that there are indeed identifiable regional deviations from nationally estimated growth-poverty elasticities in Indonesia over the 1984-99 period. Although growth in every region has reduced poverty, growth in certain regions has reduced poverty at a significantly faster rate than in other regions.

## 4 Conclusions

Motivated by recent discussion concerning the impacts of globalization on the world's poor, this paper utilized successive waves of a large-scale household consumption survey to investigate poverty change in Indonesia. Any attempt to measure the impact of increased international integration on the poor would first require consistent estimates of poverty change over a relatively long period. The creation of such estimates was the first goal of this study.

This paper extends poverty measurement methods with a simple structural model of consumer choice in order to estimate the 'cost-of-basic-needs' method in the absence of price information. This method was used to generate repeated poverty profiles of Indonesia over the 1984-99 period. These profiles reveal first substantial reductions in poverty, in both urban and rural areas and as measured by numerous poverty lines and poverty measures, and then a dramatic reversal after the 1997 financial crisis. The second goal of this paper was to investigate how regional poverty measures covary with economic growth. For the case of Indonesia over the period studied, all poverty measures are found to be highly responsive to the growth or decline in mean income or other points of the income distribution. This is certainly true for the net results, but even when provincial changes in inequality are ignored (income growth and increasing inequality are positively related over this period), poverty is found to strongly respond to mean income growth.

The spatial distribution of poverty responses to growth was investigated and little regional variation in these responses was observed with the first differences estimator. However the increased detrimental effects of measurement error in differenced data may obscure any such variation. Looking into this further we found that levels regressions with fixed effects generated very similar elasticities of poverty reduction to income growth as found with the difference regressions. However the residuals from the level regressions do appear to vary systematically by region. This suggests the presence of persistent provincial level characteristics that affect poverty, even after controlling for income and inequality, especially in rural areas. These findings are further confirmed by a random coefficients framework that found significant differences in the poverty response to distribution corrected growth rate across rural regions.

Both the residual plots and the random coefficients framework indicate that poverty has been much more responsive to growth in rural Java and Bali than in the more remote areas of Kalimantan, Maluku and Irian Jaya with other regions such as Sumatra and Sulawesi falling somewhere in between these two extremes. Future work will need to explore why this is the case, and also why there appears to be relatively little variation in the urban poverty–growth elasticities across regions. Nevertheless we can speculate over the cause for these rural regional differences. Huppi and Ravallion (1991) analyse Indonesian household data from the 1980s and illustrate the importance of off-farm employment opportunities for poverty reduction in rural households, with members employed in rural industry significantly better off than otherwise observationally equivalent households. Opportunities for off-farm employment, especially in rural industry, are not randomly distributed across regions but tend to cluster in areas with well-developed transport networks and ease of access to large urban and export markets (Krugman 1991). These conditions apply to Java and Bali but not to the more remote areas and the ability for rural areas to take advantage of these conditions when present offers one potential explanation for the observed differences, but certainly not the only one.

Unlike Java, regions such as Kalimantan, Maluku, and Irian Jaya are more ethnically diverse and at points over the 1984-99 period suffered from ethnic conflict. If ethnic conflict limits the ability of a region to invest in public goods, as has been argued by Easterly and Levine (1997), this in turn may impact on the ability of the poor to benefit from overall growth processes, especially poor households facing social exclusion, and thus stands as another potential cause of regional differences.

The empirical findings in this paper point to the importance of future work, with additional data sources, to better understand why the poor in some regions appear to benefit from growth opportunities while the poor in other regions do not. First, causes of the observed persistent regional differences in poverty can be investigated with the inclusion of further provincial level information. This information can include, but is not limited to, provincial level data on sectoral economic activity, measures of market integration (such as population density or quality of transport networks), provincial level measures of social programme coverage and efficacy, and so on. In addition, household level information can be utilized to better explore the covariates of poverty change at the household level and investigate how these covariates, and the relation between them and poverty reduction, vary spatially across Indonesia.

## Appendix

### Generating poverty lines from SUSENAS data

This appendix summarizes the approach to poverty measurement used in the analysis, an approach derived from Ravallion (1994) and Bidani and Ravallion (1993).[15] The method begins with a look at household food consumption.

*Determining the food bundle*

Although human nutritional requirements form an important basis for determining basic food needs, food consumption choices are also determined by national (or local) cultural and dietary practices. Numerous different bundles of food goods can achieve the necessary caloric and other nutritional requirements for healthful living, but only certain bundles are actually consumed by the target population. It would be unfair to the locality studied to have the chosen food bundle simply be determined from calculations of the cheapest aggregate source of calories if this bundle is not a realistic consumption choice given local dietary practices. As such, the food bundle in this study is chosen to reflect the existing food choices of 'lower' income households in Indonesia. 'Lower' income households are here defined as the bottom quintile of per capita household expenditure. The mean food consumption levels of this quintile will constitute the initial food bundle under consideration (this initial bundle will be modified as described below).

Within a large and diverse country such as Indonesia, the possibility of wide variation in local food choices is quite high. A staple in one area may not be consumed at all in another. Ideally these regional differences should be incorporated in a national poverty study. However regional differences in income and living standards are often conflated with regional taste differences and it is difficult to determine food consumption differences that should be attributed to regional differences in income and consumption differences due to regional differences in taste. Hence the chosen food bundle in this study includes only relatively common food items that are universally or near universally consumed in every Indonesian province. In practice this translates into a basket only containing food goods that are consumed by at least 10 per cent of all households in at least 80 per cent of all Indonesian provinces. This selection rule results in a food basket of 34 main food

[15] It is important to mention, at least in passing, two factors in poverty analysis that this method is unable to address. The first factor concerns the intra-household allocation of resources. SUSENAS data contain no information on the within-household distribution of consumption. If a relatively well off household allocates resources in such an unequal fashion that certain members should be deemed 'poor', this method will fail to identify those individuals. Another factor concerns access to non-market goods such as clean water or non-market healthcare that may not be fully captured by an income or expenditure based measure of poverty. Clearly a low-income household located near a public health clinic or source of clean water is better off than an otherwise identical household lacking such access. This study will not be able to identify differential access to such goods across households, although biases due to this second factor may not be such a problem. Previous research with SUSENAS and other Indonesian data (Wiebe 1994) finds that lack of access to non-market health care, education, and clean water is highly correlated with poverty measures similar to those used in this study.

items.[16] Appendix Table 1 lists each of these 34 foods contained in the basic needs food basket. Note that this basket includes the two most important staples—rice (actually two varieties) and cassava—as well as a wide range of meat, fish, vegetables, and seasonings. Also included are packaged noodles, the only prepared food in this basket.

Before discussing how the various goods in the food bundle are priced, problems with intertemporal comparisons of welfare need to be highlighted. Since this study attempts to measure poverty over repeated cross sectional surveys, the choice of the base year food bundle will impact the estimated poverty levels. If relative prices or expenditure patterns change over time then the results for years relatively far from the base period will not reflect the actual consumption patterns in those years. The choice of base period and resulting problems are well documented in discussions of Laspeyres (where the base time period is the initial period) and Paasche (base period is final period) price indices. Most importantly the two indices fail to account for demand substitutions due to changes in relative prices. This can be a concern with the SUSENAS consumption data. For example the per capita weekly consumption of local rice increased from 0.80 kg to 0.99 kg over the six-year period 1987-93, while the consumption of hybrid rice decline from 1.01 kg to 0.98 kg in the same period. The adoption of either the initial period or final period consumption levels as the base of comparison would not account for this potentially important substitution.

The Fisher Ideal Index, a hybrid index defined as the geometric mean of the quantities in the various periods studied, does account for the substitution patterns over time. The Fisher Ideal Index is a superlative index in that it is exactly equal to a true cost-of-living index if preferences are homothetic (Diewert 1976), and it can better account for the problems presented by intertemporal substitution effects. Changes in consumption patterns due to income effects are not accounted for as nicely in the Fisher Index (nor in the other indices as well), and of course if preferences are not homothetic then the level of living suggested by the Fisher Index is only an approximation of the true level of living. Nevertheless the Fisher Index is at least a marginal improvement over the Laspeyres and Paasche indices. As such, the food bundle used in this study is calculated from the geometric mean of the consumption quantities determined in each of the first five survey years studied.

To ensure that the consumption bundle achieves the necessary food-energy requirements, the quantities actually consumed by the lowest expenditure quintile are then scaled so that the total total bundle ensures 2,100 daily calories per person—the standard mean daily caloric requirement (see WHO et al. 1985). These scaled quantities are listed alongside the food items in Appendix Table 1. The total cost of this food bundle yields the first of the three poverty lines employed in this study; the food poverty line, $z^f$. This poverty line represents the cost of an adequately nutritious and nationally representative personal food bundle.

[16] These 34 food goods constituted 79 per cent of mean household food expenditures for the bottom expenditure quintile in 1993.

Higher poverty lines, to be discussed shortly, are based on $z^f$ but also make some allowance for non-food expenditures.

Table A1: Food consumption bundle and mean monthly per capita consumption levels for the lowest expenditure quintile (scaled to ensure adequate average calorie intake)

| Item | Item (Bahasa Indonesia) | Unit | Quantity |
|---|---|---|---|
| Local rice | Beras lokal | kg | 5.7236 |
| Hybrid rice | Beras kualitas unggul | kg | 7.1405 |
| Cassava | Ketela pohon | kg | 2.3595 |
| Mackerel | Ikan tonggol | kg | 0.0431 |
| Preserved anchovies | Ikan tering - Teri | ons | 0.7840 |
| Beef | Daging sapi | kg | 0.0067 |
| Chicken | Daging ayam | kg | 0.0340 |
| Chicken eggs | Telur ayam | kg | 0.1181 |
| Spinach | Bayam | kg | 0.6226 |
| Water lilies | Kangkung | kg | 0.5044 |
| String beans | Kacang panjang | kg | 0.5004 |
| Tomatoes | Tomat sayur | ons | 0.5192 |
| Eggplant | Terong | kg | 0.3334 |
| Red onions | Bawang merah | ons | 1.8232 |
| Garlic | Bawang putih | ons | 0.2728 |
| Red pepper | Cabe merah | ons | 0.5242 |
| Cayenne pepper | Cabe rawit | ons | 1.6607 |
| Peanuts | Kacang tanah | kg | 0.0403 |
| Soft soybean cake | Tahu | kg | 0.3383 |
| Dried soybean cake | Tempe | kg | 0.4785 |
| Other bananas | Pisang lainnya | kg | 0.7550 |
| Coconut oil | Minyak kelapa | liter | 0.3235 |
| Other cooking oil | Minyak goreng lainnya | liter | 0.2571 |
| Coconut | Kelapa | number | 1.9228 |
| Sugar | Gula pasir | ons | 6.4074 |
| Tea | Te-h | ons | 0.5610 |
| Ground coffee | Kopi bubuk | ons | 0.5094 |
| Salt | Garam | ons | 3.2254 |
| Coriander seeds | Ketumbar/Jinten | ons | 0.1218 |
| Red peppers | Merica/Lada | ons | 0.0695 |
| Tamarind | Asam | ons | 0.2814 |
| Fish paste | Terasi/Petis | ons | 0.5468 |
| Soy sauce | Kecap | 10ml | 1.0929 |
| Noodles (dried) | Mie | kg | 0.0337 |

Note: ons=100 gms

Source: SUSENAS, various rounds.

*Pricing the food bundle: unit values as proxies for price*

In pricing the food bundle derived in the previous subsection, there are two main conceptual issues to resolve. The first concerns regional variation in price and the question of which prices to adopt: national or local prices. The second issue concerns the absence of direct price observation in the data. Instead of prices, the survey data allows for the imputation of unit values, and this use of unit values instead of observed prices presents some important concerns.

With regards to regional price variation, many developing countries with only partially integrated markets exhibit significant price differences across regions. This is especially true for price difference between rural and urban areas. For this reason the food bundle costs for rural and urban areas are computed separately. Likewise there may be significant variation in rural or urban prices across different provinces or regions. This problem may be especially pertinent for Indonesia, which has approximately 200 million people spread out over a large archipelago. Indeed the impact of the 1997 currency crisis on price changes has exhibited a high degree of heterogeneity across Indonesian provinces—for further details see Levinsohn et al. (2003). Because SUSENAS is a large nationally representative sample the data enable the food bundle to be priced at both a national level and priced separately for each province. Since there are 26 Indonesian provinces (not including East Timor) this enables the computation of 52 separate food poverty lines (one rural and one urban food poverty line for each province). Subsequent analysis will contrast poverty measurements obtained with both national and regional prices.

Another conceptual problem arises due to the lack of information on actual market prices. In lieu of market prices, SUSENAS data records the weekly consumption quantity of various disaggregate food goods as well as the total weekly expenditure on each of those goods. Although the imputed unit values are related to the prices paid by the household, they are not identical because consumers not only choose the quantity but also the *quality* of the good consumed. Since we do not directly observe prices we must rely on the unit values to serve as proxies for prices.[17] This use of unit value data presents three estimation problems not encountered with the use of price data. Specifically, there are problems with commodity heterogeneity, quality choice, and measurement error. Each problem will be discussed in turn.

Even though the 200 or so food items included in the SUSENAS surveys record consumption at a fairly disaggregate level, it is possible that a food good may be composed of two or more distinctive food items (for example the commodity 'sugar' may combine both refined and unrefined types). If this were true then the unit values should exhibit multimodal distributions. Hence we inspect the histograms and kernel density estimates of the unit values for each food good in order to detect the presence of multiple modes or gross outliers. Any gross outliers discovered were discarded, and none of the 34 food goods exhibited multimodal distributions in any survey year.

Following the example of Deaton and Tarozzi (1999), an automatic method for outlier detection was also employed where any unit value whose logarithm lies more than 3.5

---

[17] Two other studies that employ unit value data in poverty analysis are Chen and Ravallion (1996) and Wodon (1997), however the methods adopted in these studies are different that those proposed here.

standard deviations beyond the mean was discarded. In addition, if unit values are actually good proxies for true prices and prices vary regionally, there should be a high degree of unit value homogeneity within districts and a high degree of variation in unit values between districts.[18] Analysis of variance tests were conducted and determined that a significant and substantial portion of variance in unit values can be attributed to intercluster variation for all 34 food goods. We conclude that the unit values used in this study exhibit relatively few problems with commodity heterogeneity and behave similarly to true prices.

Quality choice is another problem that can confound the naive adoption of unit values. Previous work by Deaton (1988, 1997) has focused on how unit values can be utilized to estimate genuine price elasticities of various commodities. His estimation methods exploit the structure of household surveys such as SUSENAS that, in order to reduce survey costs, household information should be collected from clusters of households located close to each other. Deaton's approach makes the key identifying assumption that there is no within-cluster price variation for goods of identical quality. This assumption enables Deaton to exploit the intercluster variation in prices in order to estimate various price elasticities. Similarly, we make the assumption that food goods of identical quality have identical within-cluster prices. This structural assumption will then enable the imputation of a price for each food good while controlling for the level of quality typically purchased by a low-income household. Formally $UV_{gic}$, the unit value of a particular food good $g$ consumed by household $i$ in cluster $c$, is a multiplicative function of the cluster price level $\lambda_{gc}$ for good $g$ and the intercluster price of quality chosen by household $i$, $p_{gi}$:

$$UV_{gic} = \lambda_{gc} p_{gi}$$

We assume that the quality price $p_g$ varies over a range $[p_{upper}, p_{lower}]$ and that this range of quality choice is available to all clusters. This structure forces the relative price, say, of high quality spinach to low quality spinach to be the same in every location. Since $p_{gi}$ is a choice variable—households choose the quality of goods consumed—simple mean unit values may not accurately serve as a proxy for prices. We further assume that food quality can be treated as a one-dimensional measure and that the choice of a particular point in the quality continuum is determined both by a household's demographic composition and its level-of-living. That is, the choice of $p_{gi}$ is a function of household expenditures $X_i$ and household demographic variables $Z_i$:

$$p_{gi} = e^{f_g(X_i, Z_i)}$$

Thus the reported unit value is modeled as a function of cluster price levels and household characteristics. In log form the unit value is expressed as:

[18] Note that the SUSENAS consumption surveys were executed in January or February of each survey year hence there should be little or no seasonal variation in the unit value data.

$$\ln UV_{gic} = \ln \lambda_{gc} + \ln p_{gi} = \ln \lambda_{gc} + f_g(X_i, Z_i)$$

These structural assumptions enable estimations of the elasticity between the quality of a particular food good and total household expenditure. These elasticities are exactly the same as the 'expenditure elasticities of quality' first studied in the seminal work by Prais and Houthakker (1955) on household consumption patterns. This estimated elasticity of quality is used to 'quality correct' the unit values in order to proxy the price of a food good at a quality level typically bought by an arbitrarily defined group of 'poor' households.

If indeed prices vary only across clusters, then a simple regression of unit values on household expenditures with cluster fixed effects and other controls will trace out the relation between the quality component of the unit value and the wealth level of the household. We estimate the following regression for each of the 34 food goods:[19]

$$\ln UV_{gic} = \alpha_g + \beta_g \ln X_i + \varphi_g Z_i + f_c + u_{gic}$$

The vector of household demographic variables $Z_i$ includes total household size, the proportion of household members in various age and gender categories, the number of adult workers in the household, and the age, gender, education, and marital status of the household head. The cluster fixed effect is denoted by $f_c$. In this specification the constant $\alpha_g$ is simply the intercluster log mean unit value for that good, i.e. the mean $\ln\lambda_{gc}$. Once these coefficients are estimated, we then compute the estimated price for a good at a quality level consumed by a household at the 20$^{th}$ percentile of household expenditure and with the mean demographic makeup of the bottom expenditure quintile. That is the price $P_g$* is determined to be:

$$\ln P_g * = \ln \overline{\lambda}_g + \hat{\beta}_g \ln X_{20th} + \hat{\varphi}_g \overline{Z}_{bottomquintile}$$

Appendix Table 2 lists the mean unit values for each good from the 1993 SUSENAS along with the 'corrected' unit values ($P_g$*) that will serve as the price proxy. As is readily apparent, the 'corrected' unit values for each good are less than the mean unit values, but quite close overall. If quality were a normal good, then we would expect the corrected price to be less than the mean unit value since at lower incomes households purchase lower quality goods. However the more homogenous a food good in terms of quality, the smaller the range of quality choice a household has and hence the closer the corrected price is to the mean unit value. The fact that the corrected price of red onions is, for example, much closer to the red onion mean unit value than is the corrected price of chicken to its unit value, suggests that red onions may not vary in quality as much as chicken. Goods that

[19] Various related functional forms were tried, with no noticeable improvement in fit.

have the largest quality expenditures of elasticity tend to be packaged goods like prepared noodles or tea. The quality corrected value for sugar is virtually identical to the mean unit value, perhaps reflecting strict price controls for sugar at that time. Although Appendix Table 2 presents the mean unit values and corrected prices for the national sample in the 1993 SUSENAS, separate prices for each provincial rural/urban area can be and are estimated in the same manner.[20]

Table A2: The mean unit values and estimated prices (rupiahs) for the food bundle

| Item | Unit | Mean Unit Value (UV) | Corrected Price (P*) | P*/UV |
|---|---|---|---|---|
| Local rice | kg | 6.220 | 6.040 | 0.971 |
| Hybrid rice | kg | 5.822 | 5.749 | 0.988 |
| Cassava | kg | 1.474 | 1.321 | 0.896 |
| Mackerel | kg | 20.966 | 18.003 | 0.859 |
| Preserved anchovies | ons | 3.317 | 2.887 | 0.870 |
| Beef | kg | 67.340 | 64.119 | 0.952 |
| Chicken | kg | 34.126 | 31.319 | 0.918 |
| Chicken eggs | kg | 21.959 | 21.030 | 0.958 |
| Spinach | kg | 4.739 | 3.900 | 0.823 |
| Water lilies | kg | 4.051 | 3.357 | 0.829 |
| String beans | kg | 5.560 | 4.942 | 0.889 |
| Tomatoes | ons | 0.892 | 0.854 | 0.957 |
| Eggplant | kg | 3.608 | 3.133 | 0.868 |
| Red onions | ons | 1.937 | 1.843 | 0.952 |
| Garlic | ons | 5.150 | 4.770 | 0.926 |
| Red pepper | ons | 2.934 | 2.641 | 0.900 |
| Cayenne pepper | ons | 2.819 | 2.541 | 0.901 |
| Peanuts | kg | 18.419 | 17.339 | 0.941 |
| Soft soybean cake | kg | 9.195 | 8.512 | 0.926 |
| Dried soybean cake | kg | 10.226 | 9.710 | 0.950 |
| Other bananas | kg | 4.327 | 3.590 | 0.830 |
| Coconut oil | liter | 12.639 | 12.333 | 0.976 |
| Other cooking oil | liter | 12.752 | 12.373 | 0.970 |
| Coconut | butir | 2.397 | 2.225 | 0.928 |
| Sugar | ons | 1.329 | 1.324 | 0.997 |
| Tea | ons | 4.218 | 3.504 | 0.831 |
| Ground coffee | ons | 5.038 | 4.330 | 0.859 |
| Salt | ons | 0.497 | 0.433 | 0.871 |
| Coriander seeds | ons | 3.365 | 3.043 | 0.904 |
| Red peppers | ons | 5.445 | 4.775 | 0.877 |
| Tamarind | ons | 1.448 | 1.326 | 0.916 |
| Fish paste | ons | 2.697 | 2.328 | 0.863 |
| Soy sauce | 10ml | 0.550 | 0.521 | 0.948 |
| Noodles (dried) | kg | 20.922 | 15.777 | 0.754 |
| Total cost of food bundle (Rps): | | 15349.927 | 14556.766 | 0.948 |

Source: SUSENAS 1993.

[20] For certain good and province pairs, it was not possible to estimate a local price due to a lack of observations. In these few cases the price of the closest neighboring province was adopted.

The third problem that prevents the naive adoption of unit values as a direct measure of price plagues all survey based analysis to varying degrees, measurement error. In the SUSENAS surveys, households must report the total quantity consumed in the past week of 200 or so food items as well as the total weekly expenditure of each item. Clearly this is an exacting task for any household and may well lead to reporting errors. It is also likely that any misreporting of expenditures will be positively correlated with misreporting of quantity. For example a household may inaccurately recall the quantity of a good consumed and then estimate expenditure based on some notion of price paid.

We adopt a simple model of consumption misreporting to investigate the potential consequences of measurement error in unit value data. Assume that the reported log quantity, ln$q$*, and log expenditure, ln$x$*, for a particular good (the subscript $g$ is dropped for ease of exposition) are additive functions of the true quantity and expenditure, ln$q$ and ln$x$, as well as mean zero error terms $u_q$ and $u_x$. Formally:

$$\ln q^* = \ln q + u_q$$
$$\ln x^* = \ln x + u_x$$

with $E(u_q) = E(u_x) = 0$. The assumption of mean zero error terms is obviously key. Differing approaches to modeling the error term can yield very different results. Assume that each right hand side variable has variance $\sigma_q$, $\sigma_x$, $\sigma_{uq}$, and $\sigma_{ux}$. Also assume that the reporting error terms may have a non-zero covariance $\sigma_{uqux}$. All other potential covariance terms are assumed to be zero for ease of exposition with no loss in generality. As mentioned above, there are strong reasons to suspect that $\sigma_{uqux} > 0$ however this covariance is free to take any value. The statistic of interest in this study is the mean unit value for any particular good (or rather the mean value adjusted for quality effects) with the standard formulation:

$$\overline{\ln UV} = \frac{1}{n}\left(\sum_n \ln\left(\frac{x}{q}\right)\right)$$

However instead of calculating the mean unit value with the true x and q we observe the error prone $x$* and $q$*. In order to explore the consequences of this measurement error for our poverty measurements, expressions for the expected mean and variance of the noisy unit values are solved in terms of the mean and variance of the true unit values.

$$E\overline{\ln UV^*} = E\left[\frac{1}{n}\sum_n \ln\left(\frac{x^*}{q^*}\right)\right] = \frac{1}{n}\left[\sum_n E(\ln x + \mu_x - \ln q - \mu_q)\right] = \frac{1}{n}\sum_n (\ln x - \ln q) = \overline{\ln UV}$$

$$V\overline{\ln UV^*} = V\left[\frac{1}{n}\sum_n \ln\left(\frac{x^*}{q^*}\right)\right] = \frac{1}{n^2}\left[\sum_n V(\ln x + \mu_x - \ln q - \mu_q)\right] = \frac{1}{n^2}\left[\sum_n (\sigma_x + \sigma_{\mu x} + \sigma_q + \sigma_{\mu q} - 2\sigma_{\mu x \mu q})\right] =$$
$$= \frac{1}{n}(\sigma_x + \sigma_{\mu x} + \sigma_q + \sigma_{\mu q} - 2\sigma_{\mu x \mu q}) = V\overline{\ln UV} + \frac{1}{n}(\sigma_{\mu x} + \sigma_{\mu q} - 2\sigma_{\mu x \mu q})$$

The above expressions make clear that, at least for large samples, the consequences of the measurement error are not especially severe. The mean of the noisy unit value measure is an unbiased estimate of the true mean and the variance of the noisy measure approaches the variance of the true measure as sample size increases. Hence we can conclude that:

$$p \lim \overline{\ln UV^*} = \overline{\ln UV}$$

Of course the mean estimate based on the observed finite sample unit values will have higher variance than a mean estimated without measurement error. Note, though, that if $\sigma_{uxuq} > 0$, as we suspect it is, then this mitigates the variance of the noisy measure. In fact if $\sigma_{uxuq}$ is relatively large in comparison with $\sigma_{ux}$ and $\sigma_{uq}$ then there are few negative consequences in the use of the noisy measure even for relatively small samples.

If indeed the error terms are mean zero, the mean unit values derived from the national sample yield unbiased estimates of the true mean unit value and, since the sample is large, the loss in efficiency is probably slight. Other conclusions can possibly be reached with different assumptions regarding the behaviour of the error term. Since the true nature of misreporting error is unknown, this study makes no attempt to correct for measurement error in the unit values. Regardless of the specific form of misreporting error, the calculated mean unit values for the provincial and urban/rural cells (the local price estimates) will be relatively less accurate due to the smaller sample sizes. These higher variances of local price estimates resulting from the smaller sample sizes must be kept in mind when reviewing the results.

It is these modified unit values, essentially mean unit values corrected to reflect quality choices made by low income households, that are used to price the food bundle and yield the food poverty line $z^f$. However even the poorest household must also consume some amount of non-food goods and the next subsection discusses two approaches to measure the cost of basic non-food goods.

*Estimating non-food expenditures*

Household consumption data usually contains much less detailed information on non-food consumption, and the types of goods consumed are much more heterogeneous than the food goods listed in Appendix Table 1. SUSENAS data is no exception to this rule. These differences make the construction of a non-food bundle very difficult. An alternative approach to estimating non-food expenditures, as put forth by Ravallion (1994), is to define a 'basic non-food good' as a good for which people are willing to forego food in order to obtain. The goal, in other words, is to determine the non-food expenditure level that would displace some portion of basic food spending ($z^f$). This entails a look at the typical value of non-food expenditures by those households who can just afford basic nutritional requirements $z^f$ but choose not to do so. This level of non-food expenditure plus

$z^f$ yields the 'lower' poverty line, $z^l$. (An 'upper' poverty line will be defined below.) This level of non-food spending can be estimated with the simple food demand function:

$$s_i = \alpha + \beta_1 \log(X_i/z^f) + \beta_2[\log(X_i/z^f)]^2 + \varphi Z_i + D_{prov} + u_i$$

where $s_i$ is the food share of total expenditures for household $i$, $X$ measures household expenditures, $Z$ conveys household demographic makeup as before, and $D_{prov}$ is a vector of provincial dummy variables. The constant, $\alpha$, estimates the average food share for those households where $X$=$z^f$, net of demographic and regional effects. The lower poverty line would then be constituted by $z^f$ plus this estimated amount of non-food expenditure, $z^f$-$\alpha z^f$, or expressed more concisely as:

$$z^l = z^f(2-\alpha)$$

The parameter $\alpha$ is estimated separately for rural and urban households. In principle this method can also be used to estimate non-food spending for each provincial and rural/urban cell. However we encounter the same conceptual difficulties discussed earlier. That is, regional differences in income and living standards can be conflated with regional differences in taste for non-food goods or regional differences in availability of non-food goods. With respect to non-food goods the problem is exacerbated because little detailed information on non-food consumption is contained in the SUSENAS surveys. Because we cannot control for regional differences in the composition of non-food good consumption, separate food share equations for each local cell are not estimated. Instead only a national $\alpha$ is estimated and utilized, even if $z^f$ is determined separately for each province with local price estimates.

Yet another more generous poverty line can be calculated by considering the level of non-food spending exhibited by those households where the food share actually reaches $z^f$. This amount of non-food expenditures can be considered as an upper bound on the allowance for basic non-food needs if those households that reach their food requirements also satisfy their non-food requirements. This amount of non-food expenditure added to $z^f$ yields $z^u$, the upper poverty line.

To calculate $z^u$, we need to estimate $s$*, the expected value of the food share when food spending equals the food poverty line. Once $s$* is obtained, $z^u$ is simply given as $z^f/s$*. The value of $s$* can be implicitly defined by:

$$s^* = \alpha' + \beta_1 \ln(1/s^*)$$

Where $\alpha$' is the $\alpha$ of the previous regression net of provincial and demographic mean effects. If we approximate ln($s$*) by $s$*-1 (since $s$* is close to zero) we can then generate a first guess of $s^*$: $s^* = (\alpha+\beta)/(1+\beta)$. Using Newton's method we iterate until $s^*$ converges with the following expression:

$$s_{t+1}^* = s_t^* - ((s_t^* + \beta \ln(s_t^*) - \alpha))/(1 + \beta/s_t^*)$$

This algorithm usually converges rapidly. Similar to the discussion of $\alpha$ above, $s^*$ can be estimated separately for each province, however we refrain from doing so due to the inability to control for regional variation in the types of non-food goods consumed.[21]

Appendix Table 3 gives the estimated national values for $\alpha$ and $s^*$, as well as $z^f$, $z^l$, and $z^u$, for both the rural and urban sectors in each of the five surveys. These poverty lines are very close to the actual poverty lines used in the study. The next step in this poverty estimation process is to generate household-specific poverty lines based on $z^f$, $z^l$, and $z^u$ but adjusted by each household's specific caloric needs as determined by its demographic makeup.

*Determining the household specific poverty line*

For the final step in the poverty line determination methodology we modify the three poverty lines so that they more accurately reflect the actual caloric needs of each household as determined by its demographic makeup. Previously, the food quantities consumed were scaled to ensure a caloric content of 2,100 daily calories. The 2,100 calorie figure is the usual benchmark caloric need for an active adult. However caloric needs vary across individuals and these needs are in part determined by age, gender, and activity level.

A household with many young children or elderly would have a lower caloric need than an equivalent sized household of working adults. Hence using the 2,100 caloric benchmark may inadvertently identify that first household as poor, even though the caloric needs of that household are actually being met. In an attempt to correct this type of bias, we recalibrate the estimated poverty lines to reflect the particular demographic makeup of each household and thus create a poverty line specific to each household. We do this by first obtaining the mean caloric needs for 8 major demographic groups as calculated from WHO et al. (1985). The 8 groups include: (1) male children aged 0-4, (2) female children aged 0-4, (3) male children aged 5-14, (4) female children aged 5-14, (5) physically active adult men, aged 15-59, (6) physically active adult women aged 15-59, (7) partially sedentary elderly men, aged 60 and over, and (8) partially sedentary elderly women, aged 60 and over. The household proportions of each of these eight demographic groups partially constitute the Z vector of demographic variables used in earlier regressions. The particular caloric requirements of each group are listed in Appendix Table 3 alongside other summary information.

---

21 Similar problems plague the intertemporal comparison of basic non-food needs. Thus the final values of $\alpha$ and $s^*$ employed in the analysis are determined from the geometric means of the $\alpha$ and $s^*$ parameters estimated separately in each survey year.

Appendix Table 3: Estimated values of various parameters and national poverty lines

| | 1984 | | 1987 | | 1990 | |
|---|---|---|---|---|---|---|
| Measure | Urban | Rural | Urban | Rural | Urban | Rural |
| zf (Rupiahs/person/month) | 8184 | 7619 | 9436 | 8844 | 12566 | 11726 |
| alpha | 0.698 | 0.727 | 0.698 | 0.727 | 0.698 | 0.727 |
| zl (Rupiahs/person/month) | 10657 | 9701 | 12287 | 11260 | 16364 | 14930 |
| s* | 0.642 | 0.690 | 0.642 | 0.690 | 0.642 | 0.690 |
| zu (Rupiahs/person/month) | 12752 | 11041 | 14703 | 12815 | 19581 | 16992 |

| | 1993 | | 1996 | | 1999 | |
|---|---|---|---|---|---|---|
| Measure | Urban | Rural | Urban | Rural | Urban | Rural |
| zf (Rupiahs/person/month) | 15250 | 14022 | 23208 | 21262 | 62744 | 59807 |
| alpha | 0.698 | 0.727 | 0.698 | 0.727 | 0.698 | 0.727 |
| zl (Rupiahs/person/month) | 19859 | 17854 | 30222 | 27072 | 81704 | 76150 |
| s* | 0.642 | 0.690 | 0.642 | 0.690 | 0.642 | 0.690 |
| zu (Rupiahs/person/month) | 23763 | 20320 | 36163 | 30811 | 97768 | 86668 |

Daily Caloric Needs, by Age Group and Gender

| Gender and Age Group | Daily Calories (kcal) |
|---|---|
| Male, 0-4 years | 1456 |
| Female, 0-4 years | 1289 |
| Male, 5-14 years | 2545 |
| Female, 5-14 years | 2253 |
| Male, 15-59 years | 2432 |
| Female, 15-59 years | 1982 |
| Male, 60+ years | 2018 |
| Female, 60+ years | 1609 |

Source: Author's calculatios from SUSENAS various rounds; also WHO (1985).

Once the caloric needs of each demographic good are determined, any poverty line $z$ is simply scaled to reflect the demographic makeup of the specific household by the following expression:

$$z_i* = \left( \sum_D (\tau_D / 2100)(D_i / N) \right) \cdot z$$

where $\tau_D$ is the caloric requirement of demographic group $D$, $D_i$ is the number of household members in that group, and $N$ is the total family size. These modified poverty lines yield the particular expenditure levels employed to distinguish poor from non-poor households.

**Poverty measurements**

After the determination of a particular poverty line, the next choice is an appropriate poverty measure. In fact three poverty measures are employed. All three poverty measures are additively decomposable with the proper population weights and are discussed at length in Foster, Greer, and Thorbecke (1984). The general Foster-Greer-Thorbecke (FGT) poverty measure is given as:

$$P_\alpha(x;z) = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-x_i}{z}\right)^\alpha$$

where $q$ is the number of poor individuals (belonging to households where per capita income $x$ is no greater than $z$) and $n$ the total population. Differing values of the parameter α generate different poverty measures. The three particular poverty measures used in this paper are as follows:

(a) The poverty headcount index ($\alpha$=0). This standard poverty measure gives the proportion of the population residing in households where the per capita expenditure is less than the poverty line. While easy to interpret, this measure is insensitive to the degree of poverty or the distribution of poverty among the poor. For example, if an already poor household suffers an even further decline in income then overall poverty increases yet the headcount measure remains unchanged.
(b) The poverty gap index ($\alpha$=1). This index relates the per capita consumption deficit of aggregate poverty as a proportion of the poverty line. The poverty gap index is simply the mean of the poverty deficit, $(z-x)/z$, averaged over the entire population. Similarly, the ratio $P_1/P_0$ yields the mean of the poverty deficit averaged over all poor households and thus represents the average transfer (expressed as a proportion of the poverty line) every poor individual would need to receive in order to bring all poor up to the poverty line. Unlike the headcount ratio, the poverty gap index conveys some measure of the depth of poverty.
(c) The squared measure ($\alpha$=2), here also known as the squared-gap measure. Unlike the previous two measures, this measure is sensitive to income distributions among the poor and thus gives some indication of the severity of poverty. This measure is essentially a weighted average of the poverty gap index where the individual is weighted by the distance from the poverty line. Although this measure is the most difficult of the three measures to interpret, it will be an important measure in this study since it gives greater weight to the poorest of the poor.

## References


Atkinson, A. and A. Brandolini (1999) ‘Promise and Pitfalls in the Use of ‘Secondary’ Datasets: Income Inequality in OECD Countries’, unpublished manuscript, Nuffield College: Oxford.

Ben-David, D. (1993) ‘Equalizing Exchange: Trade Liberalization and Income Convergence’, *Quarterly Journal of Economics* 108(3):653-79.

Bidani, B. and M. Ravallion (1993) ‘A Regional Profile of Poverty in Indonesia’. *Bulletin of Indonesian Economic Studies* 29(3):37-68.

Biro Pusat Statistik (1997) *Statistical Yearbook of Indonesia*, Biro Pusat Statistik: Jakarta.

Bruno, M., M. Ravallion and L. Squire (1998) ‘Equity and Growth in Developing Countries: Old and New Perspectives on Policy Issues’, in V. Tanzi and K.-Y. Chu (eds) *Income Distribution and High Quality Growth*, MIT Press: Cambridge MA.

Card, D. (1996) ‘The Effect of Unions on the Structure of Wages: A Longitudinal Analysis’, *Econometrica* 64(4):957-80.

Chen, S. and M. Ravallion (1996) ‘Data in Transition: Assessing Rural Living Standards in Southern China’, *China Economic Review* 7(1):23-56.

Deaton, A. (1988) ‘Quality, Quantity, and Spatial Variation of Price’, *American Economic Review* 78(3):418-31.

Deaton, A. (1997) *The Analysis of Household Surveys*. Johns Hopkins University Press: Baltimore.

Deaton, A. and C. Paxson (1998) ‘Economies of Scale, Household Size, and the Demand for Food’, *Journal of Political Economy* 106(5):897-931.

Deaton, A. and A. Tarozzi (1999) ‘Prices and Poverty in India’, unpublished manuscript, Research Programme in Development Studies, Princeton University: New Jersey.

Diewert, E. (1976) ‘Exact and Superlative Index Numbers’, *Journal of Econometrics* 4(2):114-45.

Dollar, D. and A. Kraay (forthcoming) ‘Growth Is Good for the Poor’, in A.F. Shorrocks and R. van der Hoeven (eds) *Growth, Inequality and Poverty: Prospects for Pro-Poor Economic Development*, Oxford University Press: Oxford.

Easterly, W. and R. Levine (1997) ‘Africa’s Growth Tragedy: Policies and Ethnic Divisions’, *Quarterly Journal of Economics* 112(4):1203-50.

Edwards, S. (1998) ‘Openness, Productivity, and Growth: What Do We Really Know?’, *Economic Journal* 108(4):383-98.

Foster, J., J. Greer and E. Thorbecke (1984) ‘A Class of Decomposable Poverty Measures’, *Econometrica* 52(3):761-6.

Foster, J. and A. Shorrocks (1988) ‘Poverty Orderings’, *Econometrica* 56(1):173-7.

Frankenberg, E., D. Thomas and K. Beegle (1999) ‘The Real Costs of Indonesia’s Economic Crisis: Preliminary Findings from the Indonesia Family Life Surveys’, *RAND Working Papers* 99-04, RAND: Santa Monica.

Friedman, J. and J. Levinsohn (2002) ‘The Distributional Impacts of Indonesia’s Financial Crisis on Household Welfare: A Rapid Response Methodology’, *World Bank Economic Review* 16(3): 397-423.

Huppi, M. and M. Ravallion (1991) ‘The Sectoral Structure of Poverty During an Adjustment Period: Evidence for Indonesia in the Mid 1980s’, *World Development* 19(12):1653-78.

Krugman, P. (1991) ‘Increasing Returns and Economic Geography’, *Journal of Political Economy* 99(3):483-99.

Levinsohn, J., S. Berry and J. Friedman (2003) ‘Impacts of the Indonesian Economic Crisis: Price Changes and the Poor’, in M.P. Dooley and J.A. Frankel (eds) *Managing Currency Crises in Emerging Markets,* University of Chicago Press: Chicago.

McKenzie, D. (2001) ‘Asymptotic Theory for Heterogeneous Dynamic Pseudo-Panels’, mansucript, Stanford University: Stanford.

Prais, S. (1959) ‘Whose Cost of Living?’, *Review of Economic Studies* 26(2):126-34.

Prais, S. and H. Houthakker (1955) *The Analysis of Family Budgets,* Cambridge University Press: Cambridge.

Ravallion, M. (1994) ‘Poverty Comparisons’, *Fundamentals in Pure and Applied Economics* Vol. 56, Harwood Academic Press: Chur.

Ravallion, M. (1997) ‘Can High Inequality Developing Countries Escape Absolute Poverty?’ *Economics Letters* 56(1):51-7.

Ravallion, M. (2001) ‘Growth, Inequality, and Poverty. Looking Beyond Averages’, *World Development* 29(11):1803-15.

Ravallion, M. and B. Bidani (1994) ‘How Robust is a Poverty Profile?’, *World Bank Economic Review* 8(1):75-102.

Ravallion, M. and G. Datt (2002) ‘Why Has Economic Growth Been More Pro-Poor in Some States of India than Others?’, *Journal of Development Economics* 68(2):1453-73.

Rodriguez, F. and D. Rodrik (1999) ‘Trade Policy and Economic Growth: A Skeptic’s Guide to the Cross-National Evidence’, *NBER Working Papers* 7081, National Bureau of Economic Research: Cambridge MA.

Sachs, J. and A. Warner (1995) ‘Economic Reform and the Process of Global Integration’, *Brookings Papers on Economic Activity* 1:1-118.

Suryahadi, A., S. Sumarto, Y. Suharso and L. Pritchett (2000) 'The Evolution of Poverty during the Crisis in Indonesia, 1996 to 1999', *Policy Research Working Papers*. 2435, World Bank: Washington DC.

van de Walle, D. (1988) 'On the Use of the SUSENAS for Modeling Consumer Behaviour', *Bulletin of Indonesian Economic Studies* 24(2):107-22.

WHO/FAO/UNU Expert Panel (1985) 'Energy and Protein Requirements', *WHO Technical Reports* 724, WHO: Geneva.

Wiebe, F. (1994) 'Measuring Poverty in Indonesia: Identifying the Poor Under Heterogeneous Conditions', Ph.D. dissertation, Stanford University: Stanford.

Wodon, Q. (1997) 'Food Energy Intake and Cost of Basic Needs: Measuring Poverty in Bangladesh', *Journal of Development Studies* 34(2):66-101.