

# The Distributional Impacts of Indonesia's Financial Crisis on Household Welfare: A "Rapid Response" Methodology

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Analyzing the distributional impacts of economic crises is an ever more pressing need. If policymakers are to intervene to help those most adversely affected, they need to identify those who have been hurt most and estimate the magnitude of the harm they have suffered. They must also respond in a timely manner. This article develops a simple methodology for measuring these effects and applies it to analyze the impact of the Indonesian economic crisis on household welfare. Using only pre-crisis household information, it estimates the compensating variation for Indonesian households following the 1997 Asian currency crisis and then explores the results with flexible nonparametric methods. It finds that virtually every household was severely affected, although the urban poor fared the worst. The ability of poor rural households to produce food mitigated the worst consequences of the high inflation. The distributional consequences are the same whether or not households are permitted to substitute toward relatively cheaper goods. The geographic location of the household matters even within urban or rural areas and household income categories. Households with young children may have suffered disproportionately large adverse effects.

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The collapse of the Indonesian rupiah during the 1997 Asian currency crisis precipitated a 12 percent decline in Indonesia's gross domestic product the following year as well as rampant inflation. In an 18-month span, food prices nearly tripled, and prices for other goods also rose substantially. The degree to which Indonesian households were vulnerable to these changes depended on a mix of factors, including the types of goods the household consumed, which goods' prices rose fastest, and the degree to which changes in income were able to buffer households from the brunt of the price shocks.

In this article we focus on the first two factors—household consumption choices and goods price changes—to explore how the price changes affected households

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across income levels and regions of Indonesia. We develop and apply a simple methodology that requires only the sort of data that are often readily available immediately after an economic crisis. Although we focus on the Indonesian experience, our methodology is intended to be applicable to a wide range of situations and countries. We hope to present a meaningful and straightforward methodology that can be adopted to analyze the distributional consequences of financial crises and inflation anywhere in the world.

A careful and definitive investigation of the impacts of the Indonesian currency crisis and potential differential impacts across levels of living ideally requires detailed income and expenditure information for a large nationally representative sample of households, both before and after the crisis. These data do not exist. Some sources of data, in particular the Indonesian Family Life Survey (IFLS), approach this ideal. Waves 2 and 2+ of the IFLS gathered pre- and postcrisis information on a panel of 2,500 households. Studies using these data have investigated the impacts of the crisis on consumption, employment, and education (see Frankenberg, Thomas, and Beegle 1999, Smith and others 2002, Thomas and others 2001). Although these data present an impressive depth of information for households and communities, they are limited to a relatively small sample of households in a minority of provinces and thus cannot speak to the breadth of the crisis across the sweep of Indonesian geography or income distribution. About a year and a half after the release of the initial IFLS-based reports (and three years after the onset of the crisis), studies employing nationally representative postcrisis (nonpanel) household information have begun to appear, an example of which is Suryahadi and others (2000).

Our approach is distinct from these studies in that we use only household data collected before the onset of the crisis. We then match these consumption data with information on commodity price changes brought on by the crisis to calculate simple measures of compensating variation—the amount of money sufficient to compensate households following price changes and enable a return to pre-crisis levels of utility. We calculate this compensating variation with a variety of methods and compare and contrast the strengths and weaknesses of each approach. Our analysis employs data with sufficient degrees of freedom to allow an exploration of differences in compensating variation across the spectrum of household income and location.

Because the analysis presented here requires only pre-crisis household consumption information and price change data, our approach is applicable to other national and subnational settings. Many countries now conduct periodic household consumption surveys, and even more collect more or less current price data used for computing price indices. An important benefit of these methods is the immediacy of the findings. Postcrisis household surveys can yield valuable and even definitive information, but these data are available only after the substantial lag needed for data collection and processing. In the face of rapid economic change and social disruption, the information needs of policymakers are immediate. We propose a rapid response method that can be implemented at the onset

of a financial crisis, well before postcrisis household data can be collected and disseminated.

## I. THE DATA

We match household-level data on consumption with province-level information on commodity price changes. The consumption data come from the consumption module of the 1996 National Socio-Economic Survey, known by the Indonesian acronym SUSENAS. Indonesia conducts this extensive household consumption survey every three years; the 1996 wave, which surveyed 61,965 households, was the most recent survey before the onset of the crisis. These surveys tend to be large, but they are not panels, that is, there is no systematic effort to track the same households over time. They do cover the entire geographic range of the country and contain very detailed consumption data on 306 food and nonfood goods. SUSENAS also records whether food goods were purchased in the market or produced by the household. If food is self-produced, SUSENAS imputes a value at prevailing local prices. SUSENAS also imputes a rental value for owned housing.

SUSENAS does not contain information on prices. Rather, the data enable the computation of unit values, defined as the expenditure for a particular good divided by the quantity consumed. These unit values may differ across households that face identical prices due to differences in the choice of consumption quality. For example, though all households in a village may face the same prices for high-quality and low-quality rice, the unit values recorded for a household that bought mostly high-quality rice will be higher than the unit values recorded for the household that bought mostly low-quality rice. These higher unit values reflect the higher mean quality of total rice purchases. Demand systems can be estimated with unit values in lieu of actual prices by exploiting the spatial variation in the data using methods developed by Deaton (1988, 1990, 1997). The unit value data and demand system estimation technique are used in subsequent sections.

We also have recent price data supplied by the Indonesian Central Statistical Office (the Biro Pusat Statistik, or BPS). These data contain monthly price observations for 44 cities throughout the country from January 1997 to October 1998. This period, which begins before the advent of the crisis, spans the steep devaluation of the rupiah and subsequent (and temporary) stabilization at the new higher rate. We employ a single price change measure, the percentage change in price from January 1997 to October 1998. By adopting such a long time period from before the onset of rapid inflation until after the inflation had largely abated, we hope to capture a robust measure of the price changes associated with the crisis.

The price data provide information on both aggregate goods, such as food and housing, and individual goods, such as cassava and petrol. There are about 700 goods with observed prices in the data. However, the types of goods ob-

served vary by city, perhaps reflecting taste and consumption heterogeneity throughout the country. On average, a city has price information on about 350 goods. Jakarta has as many as 440 goods listed, whereas some small cities have price information for only 300 goods.

Each of the 27 Indonesian provinces is represented by at least one city in the price data. To match households from the SUSENAS data to as local a price change as possible, we calculate province-specific price changes from the city-level data. For provinces with only one provincial city in the price data, we take those price changes as representative of the entire province. For provinces with more than one city in the price data, we calculate an average provincial price change using city-specific 1996 population weights.

The accuracy of this extrapolation of city price data to an entire province will surely vary with the size and characteristics of the province considered. For example, Jakarta, the national capital, is its own province, and the observed price changes will fairly accurately represent the price changes faced by residents throughout the province. In contrast, the price changes for Irian Jaya, a vast mountainous province, are based on price changes observed in the provincial capital, Jayapura. Those price changes may not be a completely accurate proxy for price changes in remote rural areas. Indeed, Frankenberg, Thomas, and Beegle (1999) suggest that postcrisis inflation in rural areas may have been 5 percent higher than in urban areas. We frequently report separate results for rural and urban households; the fact that price data were collected in cities should be kept in mind as those results are reviewed.<sup>1</sup>

We match the price change data with the consumption data to calculate the measures of compensating variation, detailed in the next section. There are 219 products and product aggregates that appear in both the SUSENAS and our price data. We attempt to match goods across the two data sets at the lowest level of aggregation possible. For the case of food (both raw and prepared) we were able to match 155 individual goods between the two data sets. In the case of nonfood items we matched 64 different goods, both individual goods, such as firewood and kerosene, and aggregate goods, such as toiletries and men's clothing.

1. We explored how unit values in urban and rural areas have changed across different SUSENAS survey years (1984, 1987, 1990, 1993, and 1996) to investigate potential differences in the time trend of urban and rural prices. We accomplished this by fixing a specific food bundle and then pricing this bundle separately for both urban and rural areas in each survey year. Instead of actual prices, however, we used the mean national urban or rural unit values as our price measure. In essence, we generated separate series of price indices for urban and rural areas. The time trends of these indices are virtually identical. For example, the urban index increased 187 percent over the 1984–96 period, and the rural index increased 182 percent. Each three-year change in urban unit values is even closer in magnitude to its rural counterpart. This pre-crisis comovement of urban and rural unit values suggests that urban and rural prices may behave in a similar manner following the crisis and thus our extension of urban price changes to rural areas may not introduce significant bias.

For certain groups of goods, the price data are more disaggregated than the consumption data reported in SUSENAS. In these cases, we take the simple average of the underlying price changes and apply it to the larger consumption aggregate. In other cases we also aggregate commodity expenditure categories in SUSENAS to match a larger product category in the price data. The match between the price data and the consumption data is good but not perfect; we have detailed price data for most (but not all) of the goods that make up a household's total expenditure. On average, expenditures on the matched goods account for 79 percent of a household's total expenditure; this proportion is slightly greater for poor households and slightly less for wealthy ones.

For use in subsequent analysis, we calculate the budget shares of each of the 219 products and product aggregates based on the reported monthly expenditures for each item. For durable goods and other nonfood items, we use the monthly average of annual expenditure, and not the expenditures in the month preceding the survey, to more accurately measure monthly expenditures for durables that are infrequently purchased. Table 1 gives an overview of the consumption data by reporting budget shares for selected composite goods. These goods are not chosen from among the 219 items but rather are composite aggregates constructed only for the expositional purposes of table 1. Even the rice good in the first row of table 1 is an aggregate of three different varieties. To highlight the heterogeneity in consumption patterns, we report mean budget shares for the entire sample as well as for the top and bottom decile of household expenditures. Clearly, rice is the single most important commodity, as measured by the budget share, for the majority of Indonesians. Households in the bottom expenditure decile devote more than a quarter of all outlays to rice, whereas for the mean household a still substantial 16 percent of total expenditures goes toward rice. The next most important aggregate consumption category encompasses housing and utilities, especially so for the top expenditure decile, where 22 percent of spending goes toward those ends.

Alongside the budget shares, table 1 also reports the average price increase for each product aggregate. This is accomplished by calculating the household-specific price increase of the composite goods using household expenditure shares to weight the price increases of each constituent individual good. We then average these household-specific price increases over all households.

By any measure, the inflationary impacts of the crisis were large. The all-important rice price increased an average of almost 200 percent, and the prices for many foodstuffs increased more than 100 percent. Nonfood prices did not rise nearly as rapidly, with the housing and utilities price increasing least (only 24 percent on average). Listed next to the mean price increases are the standard deviations of the price increases for the aggregate goods. Due to the constructed nature of the reported price changes, variations in price change will arise due to both geographic variation in price changes and household variation in consumption of individual goods. For rice, a relatively homogenous good, all of the varia-

TABLE 1. Budget Shares and Price Changes for Selected Aggregate Goods

Product aggregate	Mean budget shares			Price changes	
	Bottom decile	All households	Top decile	Mean price increase (percent)	Standard deviation
Rice	0.269	0.164	0.048	195.2	29.2
Other cereals and tubers	0.030	0.010	0.003	137.5	101.8
Fish	0.033	0.040	0.032	89.1	67.4
Meat	0.008	0.025	0.040	97.0	49.3
Dairy and eggs	0.015	0.027	0.031	117.1	31.9
Vegetables	0.034	0.032	0.020	200.3	129.5
Pulses, tofu, & tempeh	0.025	0.023	0.012	95.2	76.0
Fruit	0.016	0.021	0.027	103.7	61.3
Oils	0.040	0.030	0.015	122.0	74.8
Sugar, coffee, & tea	0.041	0.034	0.019	142.9	28.3
Prepared food & beverages	0.025	0.047	0.058	81.4	51.7
Alcohol, tobacco, & betel	0.039	0.049	0.031	93.9	43.8
Housing, fuel, lighting, & water	0.146	0.162	0.223	23.8	10.9
Health	0.010	0.014	0.021	50.7	32.9
Education	0.013	0.021	0.037	55.3	31.9
Clothing	0.044	0.045	0.041	84.4	25.2
Durable goods	0.013	0.034	0.075	114.3	34.3

*Note:* Price increases are from January 1997 through October 1998. Mean price increases are computed as the average across all households reporting positive consumption for a given good. Mean budget shares are reported for the entire sample, as well as separately for the top and bottom expenditure decile.

*Source:* Authors' calculations from 1996 SUSENAS and BPS Price Data.

tion in the price increase is geographical, and a standard deviation of 30 percent shows how varied the price increases actually were.<sup>2</sup> If the price changes for rice were distributed in a roughly normal fashion, fully one-third of households experienced an increase in the rice price outside the interval (165 percent, 225 percent). Other reported price changes combine variation in household consumption choice with regional variation in price changes; the standard deviations of these price changes tend to be larger.

Given the wide dispersion of price changes both within and across product aggregates, what a household consumes and where a household lives will go a long way toward determining the particular impacts of the crisis. The next section discusses how we measure these household-specific consequences.

## II. METHODOLOGY

To consider the impacts of the price increases on household welfare, we look at changes in consumer surplus brought about by the change in prices.<sup>3</sup> We start

2. Although there are three rice varieties from the SUSENAS consumption data, the BPS price data provide only one price change for all rice varieties.

3. Ravallion and van de Walle (1991) adopt a conceptually similar approach in their investigation of the impact of food price policy reforms on poor Indonesian households

with a minimum expenditure function,  $C(u, p)$ , which, given existing prices  $p$ , relates the minimum cost needed to attain utility level  $u$ . (See Deaton and Muellbauer 1980, pp. 25–59, for a discussion of the general properties of cost functions.) A first-order Taylor expansion of the minimum expenditure function with respect to price will yield an approximation of the income required to compensate the household after a price change and to restore that household to the prechange utility level. Thus this expression will approximate the compensating variation. Noting that the partial derivative of the minimum expenditure function with respect to price yields quantities consumed, we derive this simple expression:

$$(1) \quad \Delta C \approx q \Delta p$$

where  $q$  is a  $1 \times n$  vector of consumption goods quantities,  $\Delta p$  a  $1 \times n$  vector of price changes, and  $n$  the number of consumption goods in the total demand system. We note that this first approximation of compensating variation requires information only on pre-crisis consumption quantities and on price changes; neither price levels nor, more important, postcrisis consumption choices are needed.

It is straightforward to reformulate expression (1) in terms of budget shares,  $w$ , and proportionate price changes with the following expression:

$$(2) \quad \Delta \ln C^h \approx \sum_{i=1}^n w_i^h \Delta \ln p_i^h$$

where  $i$  refers to individual goods in the commodity system and  $h$  refers to the household. The budget share  $w$  is simply the household cost of good  $i$  divided by pre-crisis total household expenditures. Made clear by expression (2) is the fact that any differential distributional impact of the price changes must derive both from the presence of large relative price changes and large differences in the budget shares across households. Table 1 shows that this combination of factors existed in Indonesia following the crisis.

In general, the costs of attaining pre-crisis utility levels will increase less rapidly than expression (2) may suggest, because households can substitute away from goods whose prices have risen disproportionately. Thus expression (2) provides a maximum bound on the impact of the crisis because it does not take into account the substitution toward relatively less costly products that will take place. Given the large relative price changes following the crisis, this substitution surely occurred to some extent. Expression (2) may therefore not be an entirely accurate approximation. Returning to the minimum expenditure function, a second-order Taylor expansion of the minimum expenditure function does allow for substitution behavior:

$$(3) \quad \Delta C \approx q \Delta p + \frac{1}{2} \Delta p^T s \Delta p.$$

In expression (3)  $q$  and  $\Delta p$  are quantity and price change vectors as before and  $s$  is the  $n \times n$  matrix of compensated derivatives of demand. As we did in expres-



sion (2), we can reformulate expression (3) in terms of budget shares and proportional price changes as:

$$(4) \quad \Delta \ln C^b \approx \sum_{i=1}^n w_i^b \Delta \ln p_i^b + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n c_{ij} \Delta \ln p_i^b \Delta \ln p_j^b$$

where the expression  $c_{ij}$  contains the Slutsky derivatives  $s_{ij}$  and is defined by the expression

$$c_{ij} = p_i s_{ij} p_j / C^b.$$

With some simple algebraic manipulation we can show the  $c_{ij}$  term to be equivalent to  $w_i \varepsilon_{ij}$ ,

$$c_{ij} = \frac{p_i s_{ij} p_j}{C^b}$$

where  $\varepsilon_{ij}$  is defined as the compensated price elasticity of good  $i$  with respect to price change  $j$ . Thus we can restate expression (4) as:

$$(5) \quad \Delta \ln C^b \approx \sum_{i=1}^n w_i^b \Delta \ln p_i^b + \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n w_i^b \varepsilon_{ij} \Delta \ln p_i^b \Delta \ln p_j^b.$$

We will use the two formulations of compensating variation given in expressions (2) and (5) to explore the possible differential impacts of the Indonesian currency crisis. The only additional pieces of information required in expression (5) and not found in expression (2) are the  $\varepsilon_{ij}$  terms. Thus an approximation to the compensating variation that also wishes to account for potential household substitution behavior requires estimates of a complete set of price elasticities in addition to the pre-crisis consumption quantities and postcrisis price changes.

Exactly how these elasticities are estimated depends on the types of data used in the analysis. Our task appears difficult because we have neither information on household consumption changes over time nor information on price levels at the time of the household consumption survey. Instead of prices we have unit value data. In a series of articles, Deaton (1988, 1990, 1997) presents an approach to elasticity estimation using unit values as price proxies and only a single cross-section of household information. Crucial to this approach is the recognition that prices for equivalent goods can vary greatly across space in a developing economy setting and that household survey information is often gathered in clusters to reduce survey costs. Given these insights as well as certain assumptions on how households choose the quality of goods they purchase, the clustered nature of these data can be exploited to purge the unit value data of quality components. The cross-spatial variation in these purged unit values can then be used to identify own-price or cross-price elasticities. This is the method adapted here to estimate the  $\varepsilon_{ij}$  terms.

We now summarize this method in a bit more detail before moving on. Deaton suggests adopting the following econometric specifications for the log quantity ( $\ln q$ ) and log unit value ( $\ln v$ ) of a particular good:



$$\begin{aligned}\ln q_{hc} &= \alpha^0 + \beta^0 \ln x_{hc} + \gamma^0 z_{hc} + \varepsilon_p \ln \pi_c + f_c + u_{hc}^0 \\ \ln v_{hc} &= \alpha^1 + \beta^1 \ln x_{hc} + \gamma^1 z_{hc} + \psi \ln \pi_c + u_{hc}^1\end{aligned}$$

where  $h$  and  $c$  index household and cluster,  $x$  represents total household expenditures,  $z$  household demographic characteristics, and  $\pi$  the (unobserved) price of the good. The quantity equation also contains a cluster fixed effect,  $f_c$ , and the coefficient of interest is  $\varepsilon_p$ , the price elasticity. The simplified process to be described here concerns only the estimation of own-price elasticities; cross-price terms can be added through a relatively straightforward extension. The final estimate of  $\varepsilon_p$  derives from two main steps. In the first step, the within-cluster variation of household income and other characteristics is used to estimate  $\beta$  and  $\gamma$  (because prices are constant within clusters, these parameters can be consistently estimated). The estimated coefficients are then employed to generate two variables:

$$\begin{aligned}\hat{y}_{hc}^0 &= \ln q_{hc} - \hat{\beta}^0 \ln x_{hc} - \hat{\gamma}^0 z_{hc} \\ \hat{y}_{hc}^1 &= \ln v_{hc} - \hat{\beta}^1 \ln x_{hc} - \hat{\gamma}^1 z_{hc}.\end{aligned}$$

The next step is to calculate the cluster-level averages of  $y^0$  and  $y^1$ . Then a “regression” of the cluster averaged  $y^0$  on the cluster averaged  $y^1$  will yield an estimate of the ratio of  $\varepsilon_p$  to  $\psi$ :

$$\frac{\varepsilon_p}{\Psi} = \frac{\text{cov}(\hat{y}_c^0, \hat{y}_c^1)}{\text{var}(\hat{y}_c^1)}.$$

Combining this expression with an estimate of  $\psi$ —identified from previously estimated coefficients in an expression (not shown) determined by the model of household quality choice—enables the researcher to calculate the price elasticity estimate.<sup>4</sup>

If one wishes to estimate a demand system of our dimensions, some product aggregation is necessary. There are simply not enough degrees of freedom in the SUSENAS data to estimate a demand system for 219 products complete with the all-important cross-price elasticities. The types of goods for which we can estimate price elasticities are also limited by the fact that SUSENAS reports unit values solely for food goods. Hence we reduce the dimensions of the problem through aggregation and estimate elasticities for 22 composite goods—21 aggregate food goods and a residual nonfood consumption category. A subsequent table in the next section lists each of these aggregate goods.

Another issue concerns the services provided by owner-occupied housing and self-produced agriculture. Many households, especially in rural areas, own their own home. Although the price of housing has increased, these households are not any better or worse off in an absolute sense (they are still living in the same house). However, these households are better off relative to those who do not

4. This brief discussion ignores the identification of  $\psi$  as well as the important role of corrections for measurement error found in the original series of articles. We refer readers to those works for more extensive presentation and discussion.

own their own homes. We choose to account for these services provided by owner-occupied housing by treating the imputed rental value for these homes as a negative expenditure.

Many households, mostly rural, also produce some of their own food. Households that consume self-produced foodstuffs are also potential net exporters of agricultural products. As the price of food rose, the value of their production also increased. Clearly, if the household were a net exporter of food, the household would benefit from the price increase. To the extent that a household produced some of its own food, such production would mute the impact of price increases relative to a household that purchased food in the market. We account for self-produced agricultural products by treating the imputed value of self-produced food as a negative expenditure.<sup>5</sup>

Once the budget share and price change data have been matched and the price elasticities estimated, we calculate our two measures of compensating variation for each household. So that we can explore in a flexible manner how expressions (2) and (5) vary across levels of living, our principal approach is nonparametric. Specifically, we use locally weighted least squares to estimate the compensating variation at each point in the income distribution (see Fan 1992 for an introduction of this method). Local observations were weighted with a biweight kernel. After experimentation, we choose to adopt a bandwidth of 0.4 units of the independent variable (log per capita monthly household expenditures).

We use two measures to assess a household's level of living. The first is per capita household expenditure; the second is a binary poor/nonpoor measure dependent on whether the household's per capita expenditure exceeds or falls below a predetermined poverty line.

Perhaps the most standard approach to measuring the level-of-living in a developing economy setting is to use some estimate of household expenditures. In this view, the level of household consumption constitutes the lion's share of total household utility, and total consumption is most easily proxied by the household's actual expenditures. Expenditure levels are generally viewed as a better measure of welfare than income because the ability to smooth consumption in the presence of income shocks suggests that expenditures (rather than income) more closely track actual welfare.<sup>6</sup>

5. This approach will understate the effects of food price increases to the extent that we do not observe or adjust for price increases of intermediate inputs used in agricultural production. There is a long-standing debate over whether shadow prices in rural households engaged in agricultural production equate market prices for agricultural inputs such as labor or land. To the extent that these shadow prices diverge from market prices, the "valuation" for self-produced food, based on market prices, will not be entirely accurate. Benjamin (1992) presents evidence from rural Java that household shadow prices for agricultural inputs such as labor are not significantly different from market prices.

6. Chaudhuri and Ravallion (1994) investigate the competing merits of using these two welfare indicators and find little difference when the goal is to distinguish poor from nonpoor households. This article remains within the standard literature and uses household expenditures as a main measure of household welfare.

In addition to this continuous measure of level of living, an alternative binary poverty measure is adopted. A household is deemed poor if its per capita expenditure lies below a fixed poverty line. The poverty lines used here are calculated from the 1996 SUSENAS using a cost of basic needs approach to poverty determination, as set forth in Bidani and Ravallion (1993), Ravallion (1994), and Ravallion and Bidani (1994); the details of the particular method used here are presented in Friedman (forthcoming). The general approach is summarized as follows. A nutritionally adequate food bundle (with nutritional guidelines stipulated by WHO/FAO/UNU 1985) that reflects the actual consumption choices of Indonesian households is determined and then priced. The total cost of this bundle is scaled upward by an econometrically estimated factor that represents the cost of essential nonfood goods. This final value, which we take as the poverty line, proxies the total cost of essential food and nonfood consumption needs. Due to important differences in relative prices between urban and rural areas, poverty lines are computed separately for each area. For the 1996 SUSENAS, this method translates into a poverty line of 36,956 rupiahs per person per month in urban areas and 32,521 rupiahs in rural areas. These values yield poverty headcounts of 9.3 percent in urban areas and 24.9 percent in rural areas.

### III. RESULTS

The impacts of the crisis were probably not uniform. Instead, household consumption choices, sources of income, and location mattered greatly in determining the specific impact. The diversity of impacts was due both to wide geographical variation in price changes and wide variation in household structure and consumption. An earlier article (Levinsohn and others forthcoming) explores this heterogeneity in detail. Our focus here is solely on the relative differences in the compensating variation measures across the income distribution. This relative difference is exhibited clearly in table 2, which reports summary mean values of expression (2) by decile of household expenditure as well as poor/nonpoor status. When looking at all households, we see that the compensating variation has an inverted U-shape, with the lowest decile having an average compensating variation of 73 percent of initial household expenditures, rising to a 85 percent of household expenditures for those in the sixth, seventh, and eighth deciles and falling back to 77 percent for households in the top decile. From this perspective, it was the Indonesian households in the middle of the distribution that were most adversely affected by the price changes. Indeed, poor households needed to earn less income (as a proportion of initial expenditures) than nonpoor households—77 percent versus 82 percent—to return to original consumption levels.

However, we see in the next two columns that this story obscures important differences between households in rural and urban areas. For urban areas, households in the lower deciles needed the greatest relative amount of new income to return to pre-crisis consumption levels, and indeed this amount declined monotonically as household expenditures increase. For rural areas, lower-income

TABLE 2. Compensating Variation by Expenditure Decile and Poor/Nonpoor Status

Expenditure decile	All households	Urban	Rural
1	0.73	1.08	0.67
2	0.79	1.03	0.73
3	0.82	1.00	0.74
4	0.83	0.96	0.77
5	0.84	0.93	0.77
6	0.85	0.92	0.78
7	0.85	0.89	0.78
8	0.85	0.84	0.79
9	0.84	0.81	0.79
1	0.77	0.70	0.81
Poor	0.77	1.09	0.70
Nonpoor	0.82	0.90	0.78
All households	0.82	0.91	0.76

*Note:* Compensating variation measured as a proportion of 1996 household expenditures.

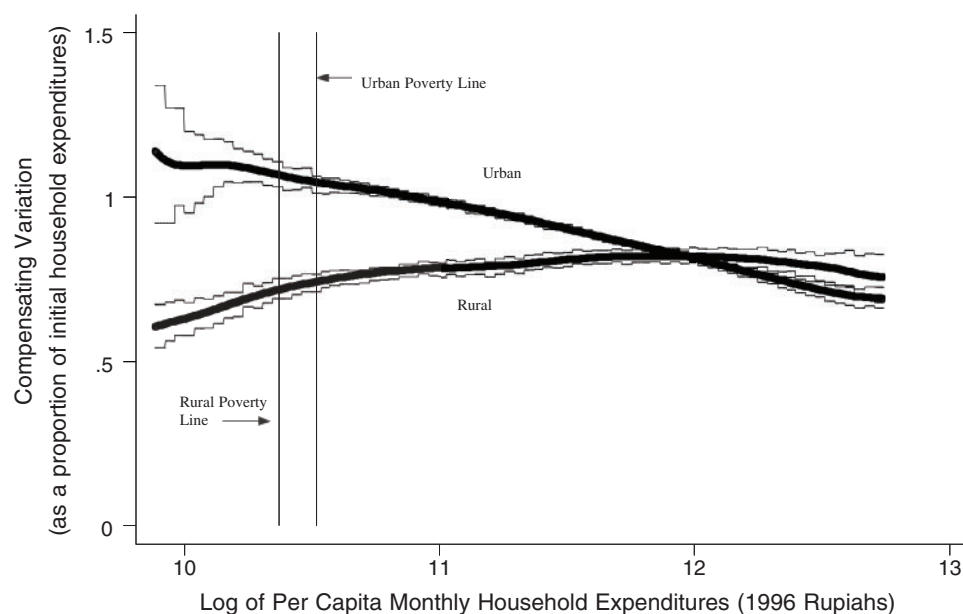
*Source:* Authors' calculations from 1996 SUSENAS and BPS Price Data.

households needed the least relative compensation, and this amount increases monotonically with expenditures. Table 2 suggests that it is the urban poor who were the most adversely affected by the crisis needing, on average, 109 percent of their pre-crisis income to reach pre-crisis utility levels. In contrast, the rural poor required only 70 percent of their pre-crisis income. In general, urban households, composed mainly of households that do not grow their own food, fared the worst under the price changes.

The same story is captured in figure 1, which depicts the entire distribution of the compensating variation measure as estimated by locally weighted least squares. The figure also includes the urban and rural poverty lines for reference, as well as bootstrapped 95 percent confidence intervals for each regression line.<sup>7</sup> The urban regression line declines almost entirely monotonically from its peak at the bottom of the income distribution to its trough at the high end of the distribution. In contrast, the rural regression line rises from its low at the bottom of the distribution and then flattens out for households beyond the top third of the distribution. After this point in the expenditure distribution there are virtually no differences in the compensating variation measure and no statistically significant difference between urban and rural households. However, the large differences between poor urban and poor rural households are indeed significant at conventional levels. As figure 1 shows clearly, the urban poor were the most adversely affected, and the rural poor were perhaps the least affected.

7. The bootstrapped standard errors were estimated with 50 draws (with replacement) from the total sample and took into account the clustered nature of the underlying survey data.

FIGURE 1. Compensating Variation, with 95 Percent Confidence Intervals



The results in table 2 and figure 1 derive from expression (2) and likely overstate the true compensating variation because expression (2) does not allow for the substitution behavior that surely occurred to some degree. As already discussed, the addition of the second-order terms in expression (5) may give a better approximation to the true compensating variation because it includes substitution terms. These elasticities were identified by the spatial variation of consumption choices and unit values in the 1996 SUSENAS using the methods discussed earlier. Before moving on to estimates of expression (5), table 3 presents these estimated price elasticities for the 22 composite good demand system (21 food goods and the residual nonfood category). The own-price elasticities for each composite good are located on the diagonals in the price matrix, and they are negative for almost every good. The own-price elasticity of rice is estimated to be  $-0.48$ , exactly equal to that found by Case (1991) using earlier SUSENAS data and different methods of estimation. The three goods (preserved meat, prepared beverages, and alcohol) that are estimated to have positive own-price elasticities are goods that have substantially fewer positive consumption values than the other goods. In other words, these goods are not widely consumed; as such their elasticities are not likely to be precisely estimated. The cross-price elasticities are generally smaller in magnitude than the own-price elasticities and, of course, vary in sign depending on whether the data suggest a particular pair of goods to be either substitutes or complements.

With this matrix of own- and cross-price elasticities we reestimate the compensating variation using expression (5) and then contrast the results with those

TABLE 3. Estimated Price Elasticities for Aggregate Food Goods and Residual Consumption

Product	Rice	Other cereals	Tubers	Fresh Fish	Preserved Fish	Fresh meat	Preserved meat	Eggs	Dairy	Green vegetables
Rice	-0.479	0.082	-0.032	-0.029	-0.038	0.098	-0.016	-0.008	-0.009	-0.018
Other cereals	2.762	-5.046	-0.413	-0.074	0.387	-0.200	-0.134	-0.300	-0.014	0.048
Tubers	2.521	-0.127	-0.590	0.233	0.205	-0.672	0.087	-0.531	-0.167	-0.919
Fresh fish	-0.383	0.027	0.217	-0.996	0.026	0.169	0.219	-0.087	-0.012	0.026
Preserved fish	-0.533	-0.295	-0.059	0.373	-0.686	0.013	-0.015	-0.022	0.138	-0.103
Fresh meat	0.042	0.073	-0.046	0.056	0.118	-0.616	-0.004	-0.134	0.109	-0.135
Preserved meat	-0.224	0.318	0.127	0.256	0.254	-0.418	0.955	-0.281	-0.260	-0.215
Eggs	-0.458	0.128	0.013	-0.006	-0.080	0.084	-0.080	-0.985	-0.028	0.113
Dairy	-0.194	0.121	0.097	-0.072	-0.083	-0.216	0.548	0.040	-0.133	0.077
Green vegetables	-0.384	0.097	0.189	-0.202	-0.041	-0.067	0.136	0.014	-0.023	-0.789
Other vegetables	-0.465	-0.005	-0.042	0.125	0.017	-0.115	0.074	0.034	-0.004	0.002
Pulses	-0.406	0.367	-0.001	-0.153	-0.064	0.266	-0.271	-0.248	-0.474	-0.014
Tofu & tempeh	-0.104	0.077	0.010	0.102	-0.033	-0.111	-0.159	0.160	-0.025	0.017
Fruit	-0.181	-0.144	-0.141	0.098	-0.006	-0.253	0.044	-0.147	-0.110	-0.021
Oils	-0.238	-0.012	0.027	-0.143	-0.003	-0.136	-0.019	-0.004	0.007	-0.009
Beverage additives	-0.173	0.059	0.044	-0.167	0.013	0.001	-0.111	-0.047	-0.106	0.064
Spices	-0.210	-0.018	0.104	-0.072	-0.007	0.000	-0.034	-0.057	-0.107	0.032
Other food	0.140	-0.056	0.069	-0.027	0.004	-0.238	0.098	0.112	0.013	0.029
Prepared food	0.020	0.243	0.055	0.092	-0.006	-0.037	-0.037	0.060	-0.093	0.042
Prepared beverages	-0.429	0.026	-0.083	0.246	0.005	0.034	0.259	-0.191	-0.203	0.146
Alcohol	-2.806	-0.681	0.161	0.859	0.265	-2.175	2.039	0.506	-0.012	-0.770
Tobacco & betel	-0.441	0.053	0.001	-0.104	-0.037	0.151	-0.182	0.001	-0.025	0.033
Other consumption	0.010	0.017	0.008	-0.010	-0.003	0.019	-0.003	-0.013	-0.008	-0.002

Source: Authors' calculations from 1996 SUSENAS.

TABLE 3. (continued)

Other vegetables	Pulses	Tofu and tempah	Fruit	Oils	Beverage Additives	Spices	Other food	Prepared food	Prepared beverages	Alcohol	Tobacco and betel	Other consumption
0.003	0.001	0.023	-0.053	0.058	0.032	-0.042	-0.037	-0.026	0.032	0.036	-0.138	0.274
-0.667	0.002	0.262	-0.195	0.289	-0.239	0.086	-0.210	-0.292	0.430	0.649	-0.276	2.684
-0.147	0.010	0.467	-0.142	-0.590	-0.387	-0.196	0.621	0.225	0.660	-0.292	0.052	-0.822
0.071	0.042	-0.038	0.165	-0.012	-0.104	0.135	-0.003	-0.025	0.185	0.128	0.304	-1.065
0.091	-0.186	0.524	-0.198	0.011	-0.014	-0.093	0.058	-0.043	-0.143	0.164	-0.603	1.066
-0.173	0.092	-0.091	-0.023	-0.182	0.052	0.065	0.113	0.163	-0.075	-0.047	-0.063	-1.091
-0.106	0.259	-0.212	-0.094	-0.276	0.325	0.007	0.372	0.269	1.018	0.330	0.540	-5.594
0.031	0.071	-0.052	0.027	0.019	-0.155	0.131	0.033	0.007	-0.019	-0.135	0.015	0.390
-0.002	0.122	-0.097	0.132	-0.150	0.216	0.283	-0.145	0.124	-0.296	-0.037	0.441	-2.696
0.057	0.060	-0.099	0.033	0.110	0.106	0.138	0.004	0.064	-0.023	0.257	-0.086	-0.088
-0.840	0.041	-0.001	-0.114	-0.134	0.031	0.061	-0.095	-0.028	0.156	0.242	-0.096	0.432
0.169	-0.772	-0.136	0.120	-0.135	-0.378	0.216	0.192	-0.048	-0.149	-0.281	0.038	0.936
0.052	-0.057	-0.965	0.035	0.032	0.059	0.292	-0.194	0.022	-0.056	-0.106	-0.069	0.606
0.003	0.115	-0.006	-0.831	-0.111	-0.094	0.074	0.005	0.030	-0.060	-0.069	0.016	0.478
0.022	0.008	0.058	-0.064	-1.003	-0.039	0.038	-0.017	-0.031	0.144	0.019	0.036	0.789
-0.036	0.056	-0.029	-0.082	0.109	-0.625	0.017	0.029	-0.013	0.132	0.101	0.019	0.055
0.023	0.049	-0.073	-0.016	0.032	-0.033	-0.305	0.027	-0.062	-0.005	-0.080	-0.114	0.248
-0.010	0.091	-0.059	0.027	0.019	0.039	0.177	-1.161	0.064	-0.008	0.114	0.139	-0.763
-0.033	-0.078	-0.090	0.209	-0.044	-0.060	0.062	0.089	-0.775	-0.339	-0.135	0.124	-0.401
-0.227	-0.040	-0.206	0.025	-0.162	0.720	0.137	-0.231	0.310	1.912	-0.517	-0.296	-3.857
0.447	0.143	0.204	-0.311	-0.545	-0.602	0.668	-0.569	1.183	1.501	6.106	1.226	-9.039
0.030	-0.070	0.061	-0.017	0.070	0.067	-0.025	0.026	-0.147	-0.260	0.023	-0.876	0.664
0.002	0.007	0.005	-0.001	0.002	0.013	0.029	-0.003	-0.002	-0.001	0.020	-0.011	-0.482



obtained using expression (2). The comparisons, estimated with locally weighted least squares, are separated by urban and rural household location (figure 2). As is readily apparent, the qualitative conclusions drawn with expression (2) also hold with results that now allow for substitution behavior. Across urban areas the compensating variation declines as household expenditures increase, again suggesting that poor urban households are affected the most severely by the price changes. Similarly, poor rural households appear to fare the best, with little difference between wealthier urban and rural households.<sup>8</sup>

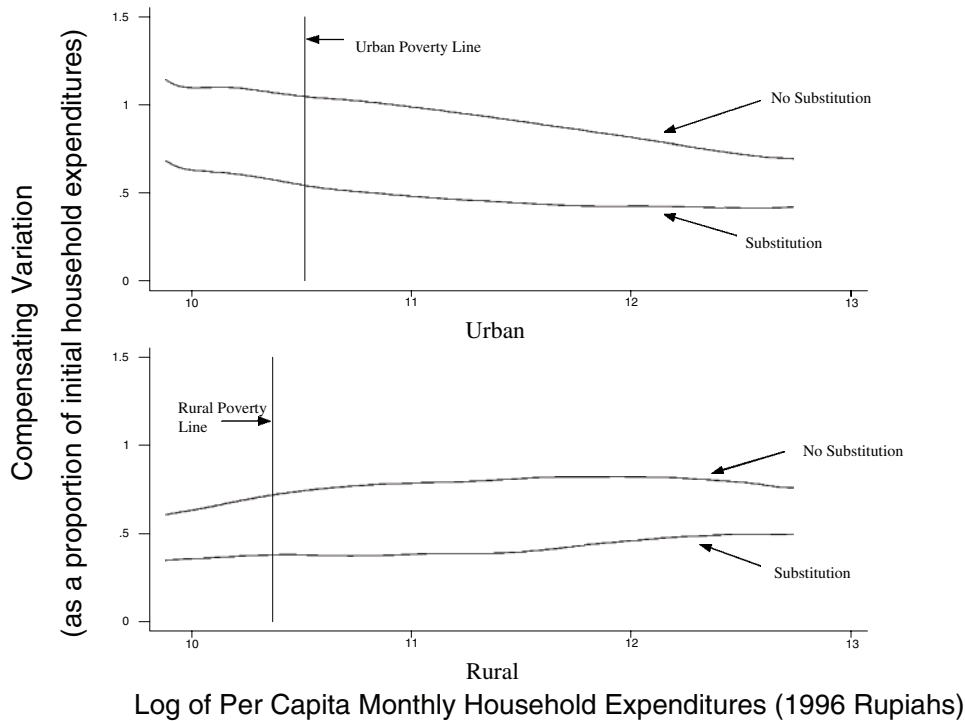
However, the differences in the levels estimated for expressions (2) and (5) are quite pronounced. The compensating variation measures that allow for substitution are substantially smaller than those that do not at all expenditure levels and for both urban and rural households. Indeed, as a rule of thumb, the estimates of expression (5) are roughly half the estimates of expression (2), with the difference greatest for lower-income urban households. Thus expression (5) suggests that the overall impacts of the crisis were not nearly as severe as suggested by expression (2).

Without further information it is difficult to know which of the results from expressions (2) and (5) are closer to the truth. We know that expression (2) surely overstates the impacts of the price changes, because it restricts households to consuming goods in the same proportions as they did before the large relative price changes of the crisis. However, we have reason to believe that expression (5) as currently estimated may dramatically understate the true compensating variation. If it does, the true compensating variation lies somewhere between the two regression lines for these expressions.

We believe the results for expression (5) may overstate the true degree of substitution because the reduction in food consumption implied by the  $\varepsilon$  matrix and the price changes results in very low caloric intakes—much lower than would actually be exhibited (and indeed has been suggested by measured changes in the body-mass index in Frankenberg, Thomas, and Beegle 1999). Essentially the problem lies with the estimated elasticities themselves. We believe these estimates may not be accurate for two important reasons. First and foremost is the fact that the estimated elasticities are essentially local approximations based on consumer behavior at the observed prices. Hence SUSENAS may give fairly good estimates of how households respond to a price change on the order of 5–10 percent. When the price changes are on the order of 100–300 percent, however, the answer is essentially dictated by choice of functional forms. This is troubling for

8. The functional forms used to estimate the elasticities are not flexible enough to allow the price responses to vary across the expenditure distribution. A more flexible approach may find that the poor substitute more than the wealthy because they are forced to economize on every price change. Alternatively, the wealthy may substitute more because their greater distance from subsistence gives them more opportunity to do so. If either of these possibilities is true, allowing the elasticities to vary by household expenditure level may yield different a distributional impact than that found with expression (5).

FIGURE 2. Compensating Variation, with and without Substitution Effects



most any parametric approach to the estimation of demand elasticities. In essence, we are forced to make out-of-sample predictions for every household; the farther the real price changes are from the range of prices (or unit values) in SUSENAS, the more important the choice of functional form becomes. A related problem is that our compensating variation calculations are averaged over all households in a per capita expenditure group, but our elasticity estimates include only those households with nonzero purchases of the various good aggregates. Ideally, we want an average price response over all households; excluding nonpurchasers from the elasticity estimates will overstate the offsetting effects of price substitution.

We still present results with the cross-price elasticities because, in principle, they are an important refinement over expression (2). Noting the difficulties of accurately accounting for substitution behavior given only one cross-section of households and price changes of the magnitude found in Indonesia in 1998, we do not claim that the true postcrisis compensating variations are those estimated from expression (5). We do find it reassuring that the distributional consequences implied by expression (5) are the same as those implied by expression (2) and present results from both specifications. The combined results from both expressions (2) and (5) may be of greater use to policymakers than either expression alone.

## IV. EXTENSIONS

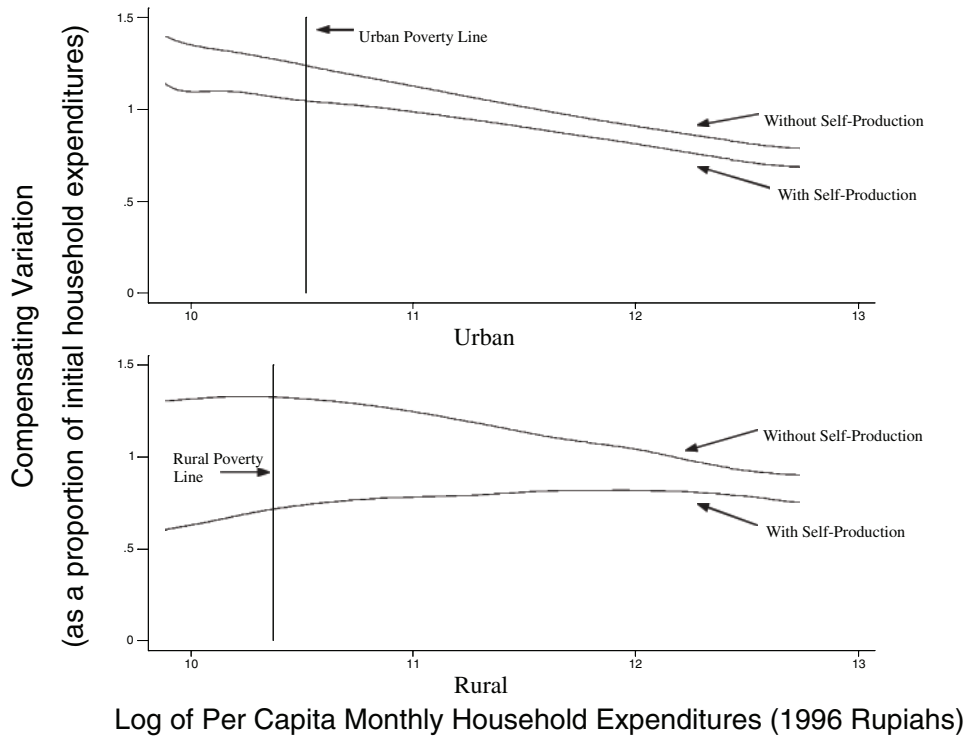
Having presented the basic results for expressions (2) and (5), we now turn to four extensions that explore the robustness of the findings. These extensions explore the effects of ignoring the services provided by owned housing and self-produced food, examine what happens if we use a smaller number of more highly aggregated goods instead of the 219 highly disaggregate goods, study the degree of spatial variation in the compensating variation measures, and look at how the compensating variation measures may be influenced by household size and demographic composition.

The first extension investigates differences in our findings if we do not account for the services provided by owned housing and self-produced food. Figure 3 presents this scenario, separately for urban and rural households, by depicting the nonparametric regression lines for the compensating variation given in expression (2) with and without valuing self-produced food and owned housing as negative expenditures. Ignoring household self-production dramatically changes the results, especially for rural households. For households in urban areas, where only a minority of households produce some of their own food, the qualitative results are the same whether or not we value self-production: poor urban households are affected substantially more than wealthy ones. However, without self-production and owned housing, the regression line is shifted upward in an almost parallel fashion, so that the levels of compensating variation are about 15 percent greater than before.

For rural areas, ignoring self-production results in attributing the greatest adverse consequences to the rural poor as opposed to the rural wealthy, a complete reversal of the findings in figure 1. The levels of compensating variation for the rural poor also increase dramatically, almost doubling to about 130 percent of initial expenditures from the 70 percent reported in table 3. The levels also rise for the rural wealthy but by a much smaller proportion. Clearly, the ability of rural households (especially lower-income rural households) to produce their own food buffered those households from the worst effects of the crisis. Urban households to a large degree could not share in this benefit.

We are also interested in exploring how the degree of aggregation or disaggregation affects the results. Remember that we attempted to match consumption and price changes at as low a level of aggregation as possible to allow more fully for heterogeneity in both consumption choices and price changes. The motivation, however, for looking at a more aggregate index stems from the fact that the disaggregated index accounts for only 79 percent of household expenditures on average. It is possible that we excluded important unmatched goods and that this exclusion can exacerbate or mitigate the measured welfare effects, depending on the relative price changes of those excluded goods. Concerned about this potential bias, we compute another compensating variation measure based on 19 aggregate commodities instead of the original 219. These aggregates include 15 food categories, such as cereals and meat, and 4 nonfood categories, such as housing

FIGURE 3. Compensating Variation, with and without Self-Production

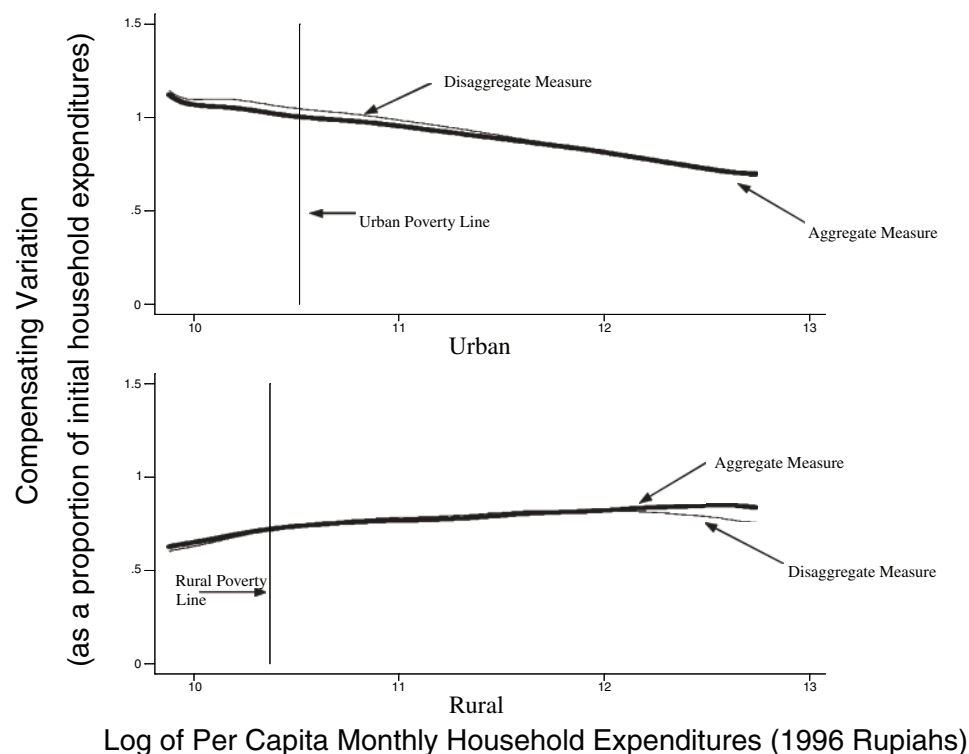


and clothing. A benefit of this aggregate measure is that it covers 97 percent of the average household's expenditures (this coverage is virtually the same for rural or urban households and across the income distribution).

The results suggest that little is changed if we base the compensating variation measures on the more aggregate consumption goods (figure 4). Indeed, the regression lines representing the aggregate and disaggregate measures are virtually identical for both urban and rural households. The analysis based on aggregated data is essentially unaffected by aggregation bias, at least in this case, where our disaggregate measures include many important consumption goods. We find this reassuring on two fronts. First, figure 4 implies that our main results are not biased by any "missing" consumption. Second, not every household survey records consumption at such a disaggregate level as SUSENAS. Figure 4 suggests that similar analysis conducted with other surveys may suffer little aggregation bias as long as the basic consumption categories are present in the data.

All of the preceding analysis has ignored cross-spatial variation in the compensating variation measures, except by distinguishing urban from rural households. However, Indonesia's population is spread out over 27 provinces on numerous islands. Many of the studies previously cited concerning postcrisis household changes have shown that different areas of the country were affected

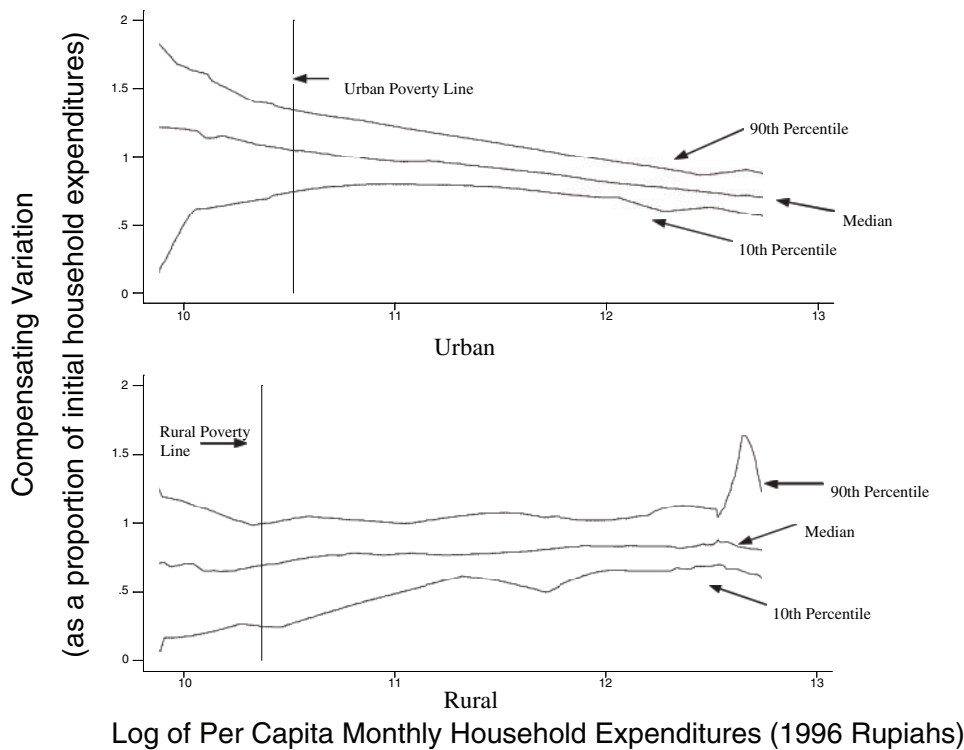
FIGURE 4. Compensating Variation, Aggregate and Disaggregate Measures



differently by the crisis due to geographic variation in both price changes and sources of income. Our findings are no different. When we calculate the mean province-level values of our main compensating variation measure, the geographical diversity is readily apparent. For example, households in urban East Nusa Tenggara, a collection of islands east of Bali, needed an additional 53 percent of pre-crisis expenditures to maintain consumption, whereas households in urban Southeast Sulawesi needed 124 percent. Although in every province rural households faced a smaller compensating variation than their urban counterparts, the regional variation among rural households is equally dramatic. In Bengkulu, a Sumatran province, the compensating variation for rural households averaged 105 percent, whereas the figure for Irian Jaya was only 30 percent.

To summarize the geographic results visually, we estimated the nonparametric regression lines separately for each province, ordered the estimated compensating variations at each point in the expenditure distribution, and plotted the 10th and 90th percentile of the province-specific compensating variations, along with the median. The resulting figure presents some measure of the geographic variance of the impacts while controlling for per capita household expenditures (figure 5). It is apparent that the effects of the crisis depended not only on the location of the household in the national expenditure distribution but also on

FIGURE 5. Dispersion of Compensating Variation across Provinces, 10th, 50th, and 90th Percentiles (with Self-Production)



the location of the household in space. For urban households the 90th percentile is roughly twice that of the 10th percentile, and this ratio is even greater for poorer households. Among rural households the spread between the 90th and 10th percentiles is even greater than that for urban households. Clearly, even within rural and urban areas, household location is an important determinant of the overall impact of the crisis.

Up to this point our principal measure of household welfare has been the household's per person expenditure level. Although a common measure, it imposes certain restrictions on how welfare may or may not vary across observable demographic information, such as household size or age and gender composition. Specifically, this measure does not recognize the possibility of scale economies at the household level or the fact that consumption needs of individual household members may vary across gender or the life cycle. Larger households, especially those with a larger number of working age adults, may be better off than smaller households at equivalent income levels because purchases of household public goods are shared among a greater number of household members. A consequence of this may be proportionally greater household expenditures for food (an important household private good), as public goods, such as housing, are more easily

afforded. In addition to household size, the demographic composition of the household is likely to affect household consumption choices to the extent that consumption needs vary across characteristics of household members. For example, households with children will almost surely spend more on education than otherwise equivalent households without children. Of course, differences in household consumption due to demographic influences will affect our compensating variation measures.

We explore these issues in our final extension with some simple ordinary least squares regressions of the main compensating variation measure on household size and demographic composition, as well as some relevant covariates, including per capita household expenditures (table 4). An earlier finding of this article is apparent in table 4 in the estimated coefficients for household expenditures: The positive coefficient for rural households indicates that the impact of the crisis increases with income levels in rural areas, whereas the opposite story is indicated by the urban household coefficient. Turning to the question of household size, larger households (especially in rural areas) are associated with higher compensating variations. The potential reasons for this result are numerous, but

TABLE 4. CV Regressions with Household Demographic Controls

Independent variables	Rural households		Urban households	
In(Household PCE)	0.0919	0.0948	-0.1709	-0.1720
	0.0144	0.0147	0.0075	0.0076
In(Household size)	0.1034	0.0722	0.0293	0.0013
	0.0105	0.0127	0.0067	0.0068
Proportion of household:				
male, 0–4 years old	—	0.1362	—	0.0817
		0.0401		0.0211
female, 0–4 years old	—	0.1224	—	0.0758
		0.0404		0.0235
male, 5–14 years old	—	0.0511	—	0.0289
		0.0300		0.0158
female, 5–14 years old	—	0.0186	—	-0.0106
		0.0307		0.0165
male, 15–59 years old	—	—	—	—
female, 15–59 years old	—	-0.0516	—	-0.0293
		0.0276		0.0139
male, 60 years or more	—	-0.0226	—	-0.0791
		0.0352		0.0303
female, 60 years or more	—	-0.1441	—	-0.1857
		0.1362		0.0276
$R^2$	0.1117	0.1131	0.2620	0.2677
Unweighted N	37493		24472	

*Note:* Ordinary least squares regressions include age, gender, and education of household head as well as provincial dummies. Standard errors, reported below the estimated coefficients, are corrected for observational dependence within survey clusters.

*Source:* Authors' calculations from 1996 SUSENAS and BPS price data.



surprisingly, higher food shares resulting from the larger household sizes is not one of these explanations. If anything, food shares are negatively related to household size (data not shown), especially in urban areas, once we control for per capita household expenditures. This finding may be somewhat surprising in light of the earlier discussion, but it is largely consistent with the multicountry results reported in Deaton and Paxson (1998). For whatever reasons, larger rural households tend to consume more of goods whose prices have disproportionately risen. The finding for urban households is the same, although not as pronounced. Indeed, once we control for household demographic composition the impact of household size on the compensating variation measure disappears for urban households.

The second columns in both the urban and rural panels of table 4 report the results from a regression of the compensating variation measure on the proportion of household members falling into eight age and gender categories: young (under age 5) boys and girls, children and adolescents (age 5–14), adult men and women, and male and female elders (age 60 and older). The excluded reference category is the proportion of adult men in the household. The results do indeed suggest that consumption patterns differ by age and, to a lesser extent, by the gender composition of the household members. Urban and particularly rural households with a large proportion of young children face a significantly higher compensating variation measure. Households with young children tend to spend more on food, especially rice; because the prices of these commodities rose the fastest, these households suffered disproportionately. Conversely, households with a higher proportion of adult women, especially elderly women (and elderly men in urban areas), tend to face lower compensating variations, in part reflecting the relatively low food needs of these groups. Thus in addition to urban/rural status, provincial location, and overall income, important factors that mediate the crisis impact at the household level include household size (in rural areas) and household composition.

## V. CONCLUSIONS AND DISCUSSION

Analyzing the distributional impacts of economic crises is important and, unfortunately, an ever more pressing need. If policymakers are to intervene to help those most adversely affected, they need to identify those who have been hurt most and measure the magnitude of the harm they have suffered. Furthermore, policy responses to economic crises typically must be timely. We developed a simple methodology to fill the order and applied our methodology to analyze the impact of the Indonesian economic crisis on household welfare there. In particular, we estimated the compensating variation for Indonesian households following the 1997 Asian currency crisis. We found that virtually every household was severely affected, although the urban poor fared the worst. The ability of poor rural households to produce food mitigated the worst consequences of the high inflation. We found that the distributional consequences were the same

whether we allowed households to substitute toward relatively cheaper goods or not. Furthermore, these findings were not biased by any missing consumption. We obtained very different results, however, if we ignored the relative benefits of self-production or owned housing. Finally, even within urban or rural areas, the geographic location of the household mattered greatly, and households with young children suffered disproportionately adverse effects.

Although our methodology is simple and uses more or less readily available data, it is not perfect. Two limitations in particular need to be kept in mind. First, it is easy to forget that the economic crisis was not the only change affecting Indonesia's economy over this period. Concurrent with the crisis, some areas of Indonesia were hard hit by forest fires and others by drought. These disasters affected prices, so that not all the price changes we observe in the data are due solely to the economic crisis. Put another way, prices would have changed some even without the crisis. Our analysis speaks to the net effect of the many concurrent economic changes Indonesian households faced. We do not make any attempt to decompose what portion of the price changes were due to the financial crisis.

Second, all of the analysis concerns nominal changes. We focus on compensating variation because consumption is an important component of household welfare and we have detailed information on household consumption as well as detailed information on price changes for consumption goods. Given these initial conditions we believe we can look at compensating variation measures in a careful and nuanced manner. SUSENAS contains much less detail on sources of household income, and the available information on changes in factor incomes is also much less detailed. Our inability to accurately forecast changes on the income side renders us mute in terms of the real impacts of the crisis. However, in future work it may be possible to match our compensating variation measures with estimates of changes in nominal income in order to obtain a forecast of the "real" impacts of the crisis.<sup>9</sup> Multiple methods of forecasting or identifying vulnerability, combined with a greater understanding of the behavioral responses to crisis, will likely yield improved tools for policymakers hoping to understand and alleviate the effects of economic crisis.

How well our nominal measures predict actual outcomes is another topic of future research. For now we are able to compare our predictions with results from studies that have analyzed postcrisis household data. Several such studies present summary results broadly consistent with our predictions. Our method predicts greater consumption impacts in urban than in rural areas, as Frankenberg, Thomas, and Beegle (1999) have documented. Although the exact magnitude of the estimated expenditure decline depends on the particular price deflator adopted, Frankenberg, Thomas, and Beegle consistently find that urban house-

9. Robilliard, Bourguignon, and Robinson (2002) present a novel approach for estimating changes on the income side by matching a microsimulation model based on household data with a computable general equilibrium model.

holds suffered greater declines than rural ones. For example, when applying the BPS deflators (derived from the same underlying price change data used here), they find that real per capita expenditures declined 34 percent in urban households and 13 percent in rural households. Exploiting the panel nature of the data, the authors also find that larger households are more likely to enter poverty than are smaller households, a result suggested by our table 4.

The crisis impacts at the bottom of the expenditure distribution were also more severe for urban households than rural ones. Suryahadi and others (2000) found that between 1996 and 1999 urban poverty headcounts increased 152 percent (from 3.8 percent to 9.6 percent), whereas rural poverty increased only 57 percent (from 13.1 percent to 20.6 percent). An alternative poverty measure more sensitive to distributions among the poor increased 202 percent in urban areas and 84 percent in rural areas. Thus changes in the severity as well as the incidence of poverty were greater in urban areas.<sup>10</sup>

These studies also highlight behavioral responses that households undertook to cushion the effects of the crisis. Our compensating variation measures do not take into account these behavioral possibilities. Households were able to smooth consumption through two main mechanisms. First, households were able to adjust their labor supply in response to the changing conditions. These labor responses include women drawn into unpaid family work in household enterprises, perhaps the most common response observed by Frankenberg, Thomas, and Beegle (1999). Second, households with relatively liquid assets were also able to smooth consumption in relation to asset-poor households. Although the compensating variation measures are not currently flexible enough to incorporate these behavioral mechanisms, they nevertheless appear to retain merit as predictors of post-crisis outcomes.

If our measures have predictive value, they can aid in the design and targeting of policy responses. After 1997 Indonesia implemented several major policy programs to alleviate the adverse effects of the crisis. Our results would suggest that special attention needs to be paid to urban areas. However except for some employment programs, most policy responses did not target urban areas.<sup>11</sup> Furthermore, most of the programs contained no geographic targets for regions most affected by the crisis (Sumarto, Suryahadi, and Widyanti 2001). Because the dis-

10. The dynamic effects of the crisis are also important to consider when assessing changes in household welfare. The estimated poverty rates increased dramatically from August 1997 to August 1998, but by August 1999 they had fallen more than halfway to the 1997 levels. Because the record shows that prices rose rapidly and wages were slower to respond, our method appears most applicable at the start of a crisis, before factor returns can fully respond to the increase in commodity prices.

11. The four most significant policy responses to the crisis were the following. Rice subsidies were originally targeted to the poor but were subsequently shared more broadly; monthly scholarships at the primary and secondary level targeted the poor but were not widely available; block grants were provided to community health centers, with no concomitant rise in overall government spending on health; work programs from a variety of government organizations were initially located in urban areas, but made no special efforts to target the most poor.

tributional impacts of the crisis appear to vary spatially, our methods could also potentially aid the geographic targeting of policy responses.<sup>12</sup>

In sum, these measures of compensating variation appear to have some predictive power when applied to the 1997 Indonesian currency crisis. Equally important, they are relatively simple to estimate and are available as soon as data on commodity price changes are collected. Any attempt to comprehensively measure the real costs to households requires time and energy intensive data collection; the results of these efforts may be available long after policymakers have responded to the crisis with new or modified social policies. Because informational needs are immediate, the simple measures presented here should prove useful. Exactly how these measures predict actual outcomes remains a topic of ongoing research.

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12. Although poverty changes have been more severe in urban areas, overall poverty levels are greater in rural areas. This, of course, begs the question of whether spending and relief programs should be targeted to the "poor" or to the "shocked." In that sense our methods are suited to the design of safety "ropes" as opposed to safety "nets" insofar as these methods identify households most affected by change, not necessarily those with the lowest overall welfare (see Sumarto, Suryahadi, and Pritchett 2000).

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