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The Measurement of Poverty Dynamics When Mortality is Correlated with Income - Theory, Concept and Empirical Implementation

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The Measurement of Poverty Dynamics
when Demographics are correlated with Income
Theory, Concept and empirical Implementation

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Abstract

The purpose of our paper is to derive instructive analytics on how to account for differentials in demographic variables, and in particular mortality, when performing welfare comparisons over time. The idea is to 'correct' in various ways estimated income distribution measures for 'sample selection' due to differential mortality. We implement our approach empirically using three waves (1993, 1997 and 2000) of the Indonesian Family Life Surveys (IFLS). We distinguish the direct effect of mortality, i.e. individuals who die are withdrawn from the population and do not longer contribute to monetary welfare, from the indirect effect, i.e. survivors pertaining to the same household of dead individuals may experience a decrease or an increase in monetary welfare given that the previous income contribution of the dead individual being withdrawn from household income, that the number of equivalent consumption units being modified, and that various labor supply or household composition adjustments occur. For the case of Indonesia, we show that the direct and indirect effects of mortality on the income distribution have opposite signs, but show roughly the same order of magnitude. We also show that the effect of other demographic changes, like changes in the structure of fertility, migration, and educational attainment, dominate the effects of mortality changes, whether direct or indirect. However, we find that none of these demographic developments are large enough to explain a significant part of the change in income distribution, whether the pre-crisis period (1993-1997) or the post-crisis period (1997-2000) is considered.

***JEL* Classification:** D10, D63, J17.

Key words: Differentials in Demographic Behavior, Multidimensional Poverty, Poverty Measurement, Welfare Comparisons over Time.

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1 Introduction

Demographic behavior may significantly affect the income distribution, whenever it is correlated with the used income measure. Poor people who are more likely to die than rich people, poor people who have more children than rich people or poor people who are more likely to migrate than rich people, are all channels which can have significant and may be substantial effects on income distribution dynamics. When analyzing the causes of distributional change, it seems worthwhile to isolate these effects from changes in labor supply behavior or changes in the returns on the labor market which in turn can also have a strong impact on the income distribution, but which are rather driven by structural and institutional change. Of course, the cited transmission channels can be interdependent and therefore hard to disentangle. For instance, the death of one household member can alter labor supply, educational investment, and consumption behavior of other household members.

The purpose of our paper is to derive instructive analytics on how to account for differentials in demographic variables, and in particular mortality, when performing welfare comparisons over time. The idea is to 'correct' in various ways estimated poverty indicators for 'sample selection' due to differential mortality. A central issue is then to derive reliable estimates for mortality rates as a function of income and age. Once the conditional density of mortality with respect to income is known, one can compute a reweighted poverty index giving the poverty variation attributable to individual deaths. Further complications arise when the household and not the individual is the unit of analysis. The key estimation problem becomes then to construct a counterfactual density that would have prevailed if the survivors would still live with their former household members and would decide jointly on labor supply and consumption expenditure. The semiparametric procedure we suggest to address these issues is very much in the spirit of the decompositions performed by DiNardo, Fortin and Lemieux (1996).

We proceed as follows. In the next section, we discuss the welfare implications of differentials in demographic variables and in particular differential mortality and provide a quick review of the related literature. In Section 3, we present our methodology able to account for differential mortality in poverty comparisons over time. In Section 4 we implement our approach empirically using three waves (1993, 1997 and 2000) of the Indonesian Family Life Surveys (IFLS). In Section 5, we summarize our main results and conclude.

2 Welfare implications of differential demographics

A well known problem of welfare comparisons over space and time are variations in population size. This problem was raised, for instance, by Dasgupta, Sen and Starrett (1973) in their note on Atkinson's seminal paper on the measurement of inequality (Atkinson, 1970). It appears also in the literature on the general form of social welfare functions. Two aspects are of importance here. First, which dimensions of personal well-being we allow to enter the individual welfare function, i.e. should the length of life matter. Second, should a social welfare function take into account the number of members in the society at a given point in time.

The pure Welfaristic approach[1] neglects non-materialistic sources of personal well-being; interpersonal utility comparisons would not be affected by the fact that two individuals have to expect a different length of life. In other words, two persons having the same wealth and the same individual utility function, but facing a different expected length of life, would be regarded as having the same utility at a given moment in time. In contrast to the pure Welfaristic approach, Sen's capability approach (Sen 1985, 2003) could be defined in a way, that *functionings* which allow a more or less long length of life are taken into account. Health or length of life can be produced in a complementary way through commodities q and personal characteristics and societal and environmental circumstances z. Therefore if q and z are favorable for health they will map into longer life and by this channel enlarge the capability set.

Turning now to the second point; the classical utilitarian (or *Benthamite*) social welfare function is given by the sum of individual utilities $W = \sum_{i=1}^{N} u_i(x_i)$, where N is the total number of individuals, x_i are commodities and u_i is the

[1] For details, see e.g. Sen (1970).

utility drawn by individual i from x_i. So, clearly, here the number of individuals in the society N can be seen as a source of social welfare. But of course, in most cases we think of a constant population when invoking such an utility function or simply use it in per capita terms (W/N) and sidestep this issue. The implicit ethical judgement, then, is that we are 'neutral' toward population. At the same time, the focus on per capita welfare means that we are indifferent to the unborn and are even biased toward keeping population growth down if it affects per capita welfare adversely. If we retain a more general form of a social welfare function, e.g. the Bergson-Samuelson form, which is $W(x) = F(u_1(x_i), u_2(x_i), ..., u_n(x_i))$, we can also take into account N, but many other specifications where N does not intervene are obviously possible.

Empirical studies on the dynamics of inequality and poverty generally do not really address this issue by supposing implicitly a constant population. They provide usually a kind of 'snapshot-measure' of economic well-being. In other words, we consider indicators such as GDP per capita, the Human Development Index, the poverty rate or the Gini coefficient at two different points in time without asking if the population size has changed during the relevant time period.

When considering a single country, variations in population size over time are driven by three demographic forces: fertility, mortality and migrations. If these forces are correlated with the used welfare measure, welfare comparisons may become complex and sometimes ambiguous. For instance, if mortality is negatively correlated with income which seems indeed to be the case in developing as well as in developed countries,[2] standard poverty measures as the headcount-index of the FGT-family (Foster, Greer, and Thorbecke, 1984), for instance, may show an improvement over time if individuals under the poverty line die. Or, put differently, higher mortality among the poor is 'good'

[2]For empirical evidence see e.g., Kitagawa and Hauser (1973), Deaton and Paxson (1999), Lantz *et al.* (1998), Kaplan *et al.* (1996), Menchik (1993). Valkonen (2002) provides a survey of the empirical evidence concerning social inequalities in mortality. He finds that social inequality was observed in almost all studies using different populations and using different indicators of socio-economic position, such as social or occupational class, socio-economic status, educational attainment, income and housing characteristics.

for poverty reduction. The current AIDS epidemic in developing countries, the 1918 influenza epidemic or the black plague centuries ago might thus have reduced poverty, not only by increasing the capital-labor ratio, but also simply by killing the poor if they are more than others affected by these phenomena.[3] Most people will agree that this is not compatible with the axiomatic on which poverty concepts are normally based. This point was recently raised by Kanbur and Mukherjee (2003).

The problem is alike if we consider fertility. Higher fertility among the poor may increase poverty simply due to differential growth rates over the income distribution. One might conclude that minimizing fertility among the poor is a mean to reach poverty reduction.[4] Again, this seems neither economically nor ethically reasonable or acceptable. Finally, migration from rural to urban migration might reduce rural and increase urban poverty, without having changed anything in the situation of those who stayed at their initial place.

The phenomenon appears also if one considers age-wealth or age-income profiles. Attanasio and Hoynes (1996), for instance, show that accounting for differential mortality produces wealth profiles with significantly more dissaving among the elderly. This has of course important implications for the assessment of the redistributive effects of social security over the life course (see Menchik, 1993)

Kanbur and Mukherjee (2003) proposed to compute FGT-poverty measures based on the lifetime income profile of an individual. They define a normative measure for the length of life to account for premature mortality among the poor which affect the poverty measure positively. There are however two crucial issues in their procedure. First, the choice of the normative length of life, which can influence on the poverty ranking of different populations. Second, the hypothetical income which has to be imputed for the years between the actual age of death and the normative age of death. This issue

[3] Brainerd and Siegler (2003) found empirical evidence that the 1918 influenza epidemic had a robust positive effect on per capita income growth across US states during the 1920s.

[4] See on this issue the analytics and discussions in Lam (1986), Chu and Koo (1990) and Lam (1997).

is handled by supposing constant income levels over time, no mobility across income levels, and that each individual at income level Y_i lives for l_i periods, after which time her or she is replaced by exactly one individual.

The critical assumption concerning the hypothetical income that should be imputed, raises the general question of which 'value' we might want to attribute to a forgone life. Even if we exclude here issues of personal pain and loss, the pure materialistic loss can only arbitrarily be computed.

Lewbel (2002), for instance, argues that calculating simply net income as the decendent's income minus personal expenses is not adequate given the existence of joint or shared consumption goods. According to Lewbel, net income can be interpreted as the money required for survivors to attain the same standard of living as before. Equivalence scales traditionally used for this type of calculation are according to Lewbel flawed. He proposes a new method for calculating net income based on a collective household model. His idea is that the issue does not require to compare the standard of living of two different households, but rather the comparison of the standard of living of the same individuals (survivors) in two different settings, namely by themselves and with the descendent ('situation comparison vs. welfare comparison').

Considering uncertain life-time in life cycle models of consumption and savings, Bommier (2001, 2003a, 2003b) analyses how a person might *herself* evaluate *her* length of life. A crucial point is here the treatment of the degree of risk aversion. In a similar spirit, Aldy (2003) develops a life-cycle model in which workers choose both consumption level and job fatality risks. After formulating an expression for the value of statistical life he develops an age-dependent measure of fatality risk and injury risk to be used in a hedonic labor market analysis. His empirical estimates suggest that the value of statistical life rises and then falls over the life cycle, with a peak in the 30s. Similar results have been found by Kniesner, Viscusi and Ziliak (2004).

In what follows we suggest some general methods to account for differential mortality in poverty comparisons over time. We first consider only what we call the 'direct effect' or 'pure demographic effect' and then develop successively measures which take into account the effect that a deaths might have changed household income (not only household income per capita), first because the person who died does not anymore contribute to the household income and, second, because the death might have changed labor supply behavior of the other household members. However, we do not address the issue of giving a value to a lost life.

3 Some general methods to account for differential mortality in poverty comparisons over time

For each period t, the 'advantage' or outcome variable y (e.g. income or income per capita) is defined over a population of individuals. The outcome variable y is a continuous variable which may vary between 0 and $\max(y)$, with a c.d.f. $F_t(y)$ and a d.f. $f_t(y) = dF_t(y)$. In the utilitarian tradition, a monetary welfare index is then defined as

$$W(F_t) = \int_0^{y\max} w(y)dF_t(y)dy \tag{1}$$

w being a non-decreasing function of income. In the same sense, a large class of monetary poverty indexes corresponds to

$$P(F_t) = \int_0^z p(y)dF_t(y)dy \tag{2}$$

where z is the poverty line and p a non-decreasing non-negative function of income defined over $[0; z]$.

Expressed in its most general form, our problem is to design counterfactual distributions of y, $F^*_{t+1}(y)$ under alternative mortality processes (taking place between t and $t+1$), and then to compute

$$W(F^*_{t+1}) = \int_0^{y\max} w(y)dF^*_{t+1}(y)dy, \tag{3}$$

or

$$P(F^*_{t+1}) = \int_0^z p(y)dF^*_{t+1}(y)dy \tag{4}$$

More precisely, let us assume that we have some knowledge about the mortality process taking place between t and $t+1$. The occurrence of individual deaths should theoretically have at least three kinds of effects on the distribution of income:

1. a direct 'arithmetical' individual effect: people who die are withdrawn from the population and do not longer contribute to monetary welfare or to poverty;

2. an indirect micro-economic impact on household income: survivors pertaining to the same household of dead people may experience a decrease or an increase in y, with the previous income contribution of the dead being withdrawn from household income, with the number of equivalent consumption units being modified, and with various labor supply or household composition adjustments occurring;

3. a 'general equilibrium' or 'external' macroeconomic impact on the overall income distribution.

In the following, we shall not consider the third, general equilibrium, effect. Hence, the construction of a counterfactual distribution of income requires to deal with, first, the individual effect, and, second, the survivors' household effect.

However, what is meant by 'counterfactual' should first be clarified for both cases. Intuitively speaking, we seek to reconstruct what would be the distribution of income in $t+1$ if the observed deaths between t and $t+1$ had not occurred. This definition of a counterfactual raises no particular difficulty when the mortality process can be assumed exogenous from the distribution of income itself. Think at a sudden epidemics coming from outside the country or at a natural catastrophe like an earthquake or a flood. Of course the exogeneity of mortality does not preclude that it can be correlated with income. Things are more intricate when the probability of dying is causally determined by the contemporary individual income, by the distribution of income within some reference group, or by the overall distribution of income (see Deaton and Paxson, 1999). For instance, people whose income has fallen under a subsistence level (extreme poverty line) may have been exposed to death with a probability close to one. Giving these people a 'counterfactual income' under the subsistence level would have no meaning at all if nobody can survive in this situation. It seems to us that a meaningful counterfactual distribution of income should always include those deaths that are income determined, or, put in another way, should only try to discount the distribution of deaths that is exogenous to the final income distribution. In the remainder, we shall always make the assumption that mortality is exogenous to contemporary income.

Finally another important aspect regarding the construction of counterfactuals has to be emphasized. Assessing the impact of mortality between two dates does not mean the same than assessing the impact of changes in mortality. In the first case we need to subtract the impact of all deaths during the period, while in the second case we need to subtract the impact of the difference between the ex-post and ex-ante pattern of occurred deaths. We focus on the first case in the following section and examine the second case in the section after.

3.1 The direct arithmetical impact of individual mortality

Let us first assume that individual deaths have no external effects, whether on other individuals like household survivors, on neighbors or on the whole population. We therefore seek to design a counterfactual for a pure arithmetical individual effect. Assume second that mortality patterns between t and $t+1$ are totally described by observable individual attributes x which are either constant over time like sex, education of adults and even initial wealth, or varying with time like age, health, household composition. This makes the survival rate $s_{x,t}(x)$ independent from the distribution of attributes, i.e. the survival rate is independent from the population structure. Assume third that the income pattern belonging to each attribute (conditional density of income with respect to attributes) does not depend on the distribution of attributes but instead only on some 'income schedule' that changes over time through redistribution policies and other changes in the returns to attributes (in the spirit of the Oaxaca (1973) or Di Nardo *et al.* (1996) decompositions). This means that we again assume that mortality has neither external effects nor 'general equilibrium' effects. This also means that we exclude the possibility of non-random selection of deaths by contemporary unobservable determinants of income (y_{t+1}), i.e. income causation of mortality.

The econometrician observes $f(y|t_y = t)$ that is the actual density of income for each t. Hence, we can write

$$f(y, x|t_y = t+1) = f(y|x, t_y = t+1)dF(x|t_x = t+1) =$$

$$f(y|x, t_y = t+1)\frac{s_{x,t}(x)}{\Psi_{x,t}(x)}dF(x|t_x = t), \tag{5}$$

where $\Psi_{x,t}(x)$ characterises the changes which are not due to mortality (but instead due to births, migrations, household composition etc.) having occurred over $[t\ ;\ t+1]$. We may then compute two kinds of counterfactuals, by simply reweighing observations with $s_{x,t}(x)$ or its inverse.

$$f_t^*(y) = \int_{x\in\Omega_x} s_{x,t}(x) f(y|x, t_y = t)dF(x|t_x = t) \tag{6}$$

is the counterfactual distribution of income due to deaths related to initial attributes and

$$f_{t+1}^*(y) = \int_{x\in\Omega_x} f(y|x, t_y = t+1)\frac{dF(x|t_x = t+1)}{s_{x,t}(x)} \tag{7}$$

is the counterfactual distribution of income due to deaths related to final attributes.

Under the assumption of a non-zero survival rate and without any change in both income schedules and in the distribution of attributes, f_t^* and f_{t+1}^* should coincide. Differences within the two counterfactuals will then correspond, either to income schedule changes or to distribution of attributes changes, but also to the deaths linked to these latter changes. Concerning the distribution of attributes, other demo-economic changes like new births, migrations or educational expansion may modify the mortality pattern as observed in $t+1$ when compared with t, and therefore modify the counterfactual impacts of mortality when computed upon the $t+1$ income distribution rather than on the t distribution.

Semiparametric decompositions as proposed by Di Nardo et al. (1996) allow to go a little further by isolating the impact of changes in the distribution of all attributes. Hence, we can compute the following counterfactual

$$g_{t+1}^*(y) = \int_{x\in\Omega_x} f(y|x, t_y = t+1)dF(x|t_x = t) \tag{8}$$

using Di Nardo et al. (1996) and using the reweighing technique based on Bayes' rule:

$$\frac{\Psi_{x,t}(x)}{s_{x,t}(x)} = \frac{dF(x|t_x = t)}{dF(x|t_x = t+1)} = \frac{\Pr(t_x = t|x)}{\Pr(t_x = t+1|x)} \cdot \frac{\Pr(t_x = t+1)}{\Pr(t_x = t)},$$

where $\Pr(t_x = t|x)$ can be estimated with a probit model.[5] We then obtain, for instance:

$$g^*_{t+1}(y) = \int_{x\in\Omega_x} \frac{\Psi_{x,t}(x)}{s_{x,t}(x)} f(y|x, t_y = t+1) dF(x|t_x = t+1). \qquad (9)$$

Up to now, we have considered the counterfactual impact of the level of individual mortality. Computing the impact of *changes* in mortality patterns (based on individual observables) just calls for an additional preliminary reweighing of the $t+1$ income distribution by past survival rates:

$$f^{**}_{t+1}(y) = \int_{x\in\Omega_x} \frac{s_{x,t-1}(x)}{s_{x,t}(x)} f(y|x, t_y = t+1) dF(x|t_x = t+1) \qquad (10)$$

We shall come back to this latter decomposition when taking into consideration the indirect impact of the changes in the distribution of household survivors.

3.2 The indirect micro-impact of mortality on survivors income distribution

When the income concept that is used is household income or consumption expenditures per head or per adult equivalent unit, mortality has an obvious indirect impact on the distribution of income among household survivors (see above). For this indirect impact, the building of counterfactual income distributions raises different problems. Here the survivors's income is observed so that computing a counterfactual for the impact of overall mortality requires

[5] We may also compute: $g^{**}_{t+1}(y) = \int_{x\in\Omega_x} f(y|x, t_y = t+1) s_{x,t}(x) dF(x|t_x = t)$. The difference between $g^*_{t+1}(y)$ and $g^{**}_{t+1}(y)$ should indicate the impact of mortality on a distribution of income characterized by the final income schedules $f(y|x, t_y = t+1)$ and the initial distributions of attributes $dF(x|t_x = t)$. Then, the difference between $[g^{**}_{t+1}(y) - g^*_{t+1}(y)]$ and $[f^*_{t+1}(y) - f_{t+1}(y)]$ gives the mortality impact linked to the change in the distribution of attributes from $dF(x|t_x = t)$ to $dF(x|t_x = t+1)$, while double difference between $[g^{**}_{t+1/t}(y) - g^*_{t+1/t}(y)]$ and $[f^*_t(y) - f_t(y)]$ gives the mortality impact linked to the change in income schedule from $f(y|x, t_y = t)$ to $f(y|x, t_y = t+1)$. Note that given path dependence of decompositions, another one of that kind may be computed in reverse order, g^*_t and g^{**}_t, which would explain again the same difference (between $f^*_{t+1}(y) - f_{t+1}(y)$ and $f^*_t(y) - f_t(y)$).

computing a counterfactual income pattern. Let $z \in \{0,1\}$ be a variable indicating whether somebody has experienced a death in his/her household between t and $t+1$. The observed density of income is a weighted sum of conditional densities on z

$$f_{t+1}(y) = \Pr(z=0|t_z=t+1)f(y|z=0,t_y=t+1)+$$

$$\Pr(z=1|t_z=t+1)f(y|z=1,t_y=t+1). \tag{11}$$

We would like to design a counterfactual which can be written as

$$f^{\#}_{t+1}(y) = \Pr(z=0)f(y|z=0,t_y=t+1)+$$

$$\Pr(z=1)f_{z=0}(y|z=1,t_y=t+1). \tag{12}$$

It requires the estimation of the counterfactual density for survivors $f_{z=0}(y|z=1,t_y=t+1)$. Computing such a counterfactual is with no doubt very difficult. Quantile treatment IV estimators could be used (Abadie, Angrist, Imbens, 1998) if some instrument was available for the occurence of a death within the household (some knowledge about death causes could prove useful in this respect). Under the assumption of conditional independence on a set of attributes x,[6] quantile treatment effects may also be computed in line with the spirit of matching estimators (Firpo, 2004).

In the case we have information on survivors at period t, that is people having experienced a death within the household between $t-1$ and t, a counterfactual for the impact of *changes* in mortality patterns can prove easier to construct. Indeed, when survivor status z is known for both periods, we may apply the DiNardo *et al.* (1996) reweighing technique to isolate the effects of changes in the 'survivor's rate'. We write

$$f^{indir}_{t+1}(y) = \int\int f(y|x,z,t_y=t+1)dF(z|x,t_{z|x}=t)dF(x|t_x=t+1) =$$

$$\int\int \Psi_{z|x}(z,x)f(y|x,z,t_y=t+1)dF(z|x,t_{z|x}=t+1)dF(x|t_x=t+1), \tag{13}$$

where

$$\Psi_{z|x}(z,x) = dF(z|x,t_x=t)/dF(z|x,t_x=t+1) =$$

[6] $\Pr(z=1|y_{z=0},y_{z=1},x) = \Pr(z=1|x)$.

$$z\frac{\Pr(z=1|x,t_{z|x}=t)}{\Pr(z=1|x,t_{z|x}=t+1)}+[1-z]\frac{\Pr(z=0|x,t_{z|x}=t)}{\Pr(z=0|x,t_{z|x}=t+1)}$$

can be estimated using a standard probit model such as

$$\Pr(z=1|x,t_{z|x}=t)=1-\Phi(-\beta_t' H(x)).$$

We may then design a triple decomposition for the impact of changes in mortality patterns between t and $t+1$. First, we compute a counterfactual for the $t+1$ distribution of income discounting the direct arithmetic impact of *changes* in individual mortality patterns based on observable attributes:

$$f_{t+1}^{**}(y)=\int_{x\in\Omega_x}\frac{s_{x,t-1}(x)}{s_{x,t}(x)}f(y|x,t_y=t+1)dF(x|t_x=t+1). \tag{14}$$

Second, we compute a counterfactual for the $t+1$ distribution of income discounting both the direct and the indirect impact of changes in mortality patterns based on observable attributes:

$$f_{t+1}^{\Delta}(y)=\int\int\Psi_{z|x}(z,x)\frac{s_{x,t-1}(x)}{s_{x,t}(x)}$$

$$\cdot f(y|x,z,t_y=t+1)dF(z|x,t_{z|x}=t+1)dF(x|t_x=t+1). \tag{15}$$

Third, we compute a counterfactual for the $t+1$ distribution of income discounting the effect of all changes in the distribution of observable attributes:

$$g_{t+1}^{\Delta}(y)=\int\int\frac{\Psi_{x,t}(x)}{\Psi_{x,t-1}(x)}\Psi_{z|x}(z,x)\frac{s_{x,t-1}(x)}{s_{x,t}(x)}$$

$$\cdot f(y|x,z,t_y=t+1)dF(z|x,t_{z|x}=t+1)dF(x|t_x=t+1). \tag{16}$$

In this paper, as far as the indirect impact of mortality is concerned, we shall then only analyze the impact of changes in mortality patterns based on observable attributes like age, education and initial wealth.

4 An empirical implementation for the case of Indonesia

4.1 Data

To illustrate the methods proposed in section 3, we use the the three waves of the Indonesian Family Life Survey ('IFLS' hereafter) conducted by RAND, UCLA and the Demographic Institute of the University of Indonesia. The IFLS is a continuing longitudinal socioeconomic and health survey. It is representative for 83% of the Indonesian population living in 13 of the nation's 26 provinces. The first wave (IFLS1) was carried out in 1993 and covers 33,083 individuals living in 7,224 households. IFLS2 sought to reinterview the same respondents in 1997. Movers were tracked to their new location and if possible interviewed there. Finally a full 94.4% of IFLS1 households were relocated and reinterviewed, in the sense that at least one person from the IFLS1 household was interviewed. This procedure added a total of 878 *split-off* households to the *origin* households. The whole cross-section of IFLS2 includes 33,945 individuals living in 7,619 households. The third wave, IFLS3, was conducted in 2000. It covered 6,800 IFLS1 households plus 3,774 split-off households, in total comprising 43,649 individuals. In IFLS3 the re-contact rate was 95.3% of IFLS1 households. Hence, nearly 91% of IFLS1 households are complete panel households. These re-contact rates can be considered as high as or higher than most longitudinal surveys in the United States and Europe.[7] Table 1 presents some descriptive statistics of the complete samples in 1993, 1997 and 2003. The sample of 1997 and 2003 are cross-sections in the sense that they include besides the panel-individuals also the individuals who were born after 1993 or joined a household of the initial sample or a *split-off* household by another reason.

Using IFLS1, IFLS2 and IFLS3 we constructed two longitudinal samples: 1993 to 1997 and 1997 to 2000. Table 2 provides detailed information for these two samples. We included in each those individuals who were reinterviewed at the end of the respective period or for whom a death or another reason for an 'out-migration' was declared. Out-migration means here that these individuals left their households for other reasons and moved to provinces not covered by the survey.[8] The survey informs about the exact date of the interviews and the month of death, such that a relatively detailed survival analysis can be performed. Between 1993 and 1997 we counted 743 deaths and between 1997

[7] For details see Frankenberg and Karoly (1995) and Frankenberg and Thomas (1997) and Strauss, Beegle and Sikoki *et al.* 2004.

[8] Or they migrated to provinces covered by the survey but have not been relocated.

Table 1
Description of cross-section samples

	1993	1997	2000
Male	49.61	49.6	49.82
Age (years)			
0 to 14	31.6	28.84	29.45
15-39	44.08	45.46	42
40–59	17.15	18.1	20.06
60–	7.17	7.61	8.48
Urban	35.35	40.32	44.33
Education (persons 15 years and older)			
None	18.93	14.51	11.84
Element.	48.15	44.66	42.5
Jun.-High.	13.14	15.21	15.80
Sen.-High.	15.89	19.71	22.05
Coll./Univ.	3.89	5.91	7.81
HH-Size (mean)	4.55	4.41	4.21
Sample Size	33,083	33,945	43,649

Source: IFSL1, IFLS2 and IFSL3; computations by the authors.

Table 2
Description of longitudinal samples

	1993—1997			1997—2000		
	Survivors	Death	Other exit	Survivors	Death	Other exit
Total share	87.02	2.36	10.61	94.05	2.14	3.81
Number of persons	27,376	743	3,338	24,481	558	991
Survival time (months)	48.58	24.22	27.13	34.15	16.58	19.59
Male	49.2	56.26	52.73	48.46	48.02	53.66
Age (years)						
0 to 14	34.53	9.14	16.28	24.61	2.61	11.47
15-39	39.92	17.04	81.22	47.08	14.52	82.98
40–59	18.98	24.46	1.8	20	24.42	4.44
60–	6.58	49.37	0.7	8.31	58.45	1.11
Urban	34.16	32.21	36.82	36.84	34.09	37.54
Education (persons 15 years and older)						
None	20.02	47.1	5.53	15.83	42.57	5.04
Element.	50.14	41.1	39.5	46.62	43.76	33.77
Jun.-High.	12.22	6.67	20.64	14.69	5.7	22.25
Sen.-High.	14	3.35	29.9	18.01	6.24	31.6
Coll./Univ.	3.61	1.78	4.43	4.85	1.73	7.34
Current health status (persons 15 years and older)						
Very healthy	17.96	7.9	26.22	10.35	4.73	14.15
Somewhat healthy	72.19	55.12	66.29	79.68	56.2	79.46
Unhealthy	9.75	36.99	7.49	9.94	39.08	6.4
HH-Size (mean)	4.61	4.5	4.34	4.38	4.23	3.69

Source: IFSL1, IFLS2 and IFSL3; computations by the authors.

and 2000 558 deaths.

The IFLS contains detailed information on household expenditure. In contrast, household incomes and especially individual incomes are not completely observed, therefore we use in what follows real household expenditure per capita as welfare or income measure.

4.2 Some illustrative simulations

In what follows we give on order of magnitude of the potential effects of differential mortality on standard income distribution indicators. We use a fictitious sample of 10,000 individuals i where the only observed heterogeneity stems from income y_i. To this sample we apply a crude death rate of d. In the baseline scenario, deaths are drawn randomly, i.e. independent of income. Then we analyze various scenarios where the selection of death events is driven by income, but perturbed by some unobserved heterogeneity γ_i. The relative risk r_i of death is assumed to be given by the relationship:

$$\ln r_i = \lambda \ln y_i + \gamma_i \tag{17}$$

The term for unobserved heterogeneity is drawn from a normal distribution $N(\mu_\gamma, \sigma_\gamma^2)$. Therefore the correlation coefficient between r_i and income y_i, $\varphi(r_i, y_i)$, depends, for a given distribution of y_i, on λ, μ_γ and σ_γ^2. Persons who die are selected by ranking in a descending order the sample according to r_i and simulating a death for the d times 10,000-persons for whom r_i is the highest. Therefore, we can write the individual probability of death, P_i, as follows:

$$\begin{aligned} P_i = P(d_i = 1) = P(r_i \geq \tilde{r}) = P(\lambda \ln y_i + \gamma_i \geq \ln \tilde{r}) = \\ P\left[\frac{\gamma_i - \mu_\gamma}{\sigma_\gamma} \geq \frac{\ln \tilde{r} - \mu_\gamma - \lambda \ln y_i}{\sigma_\gamma}\right] \end{aligned} \tag{18}$$

and the corresponding c.d. as:

$$P_i = 1 - \Phi\left(\frac{\ln \tilde{r} - \mu_\gamma - \lambda \ln y_i}{\sigma_\gamma}\right) \tag{19}$$

In total we examine four different simulations, which we compare with the baseline scenario. The different sets of parameters assumed figure in Table 3.

The incomes y_i are drawn from a log-normal distribution where the mean and the variance correspond to those observed in our sample drawn from the IFLS (1993). As income distribution indicators we consider the Gini-coefficient and the poverty headcount-index, i.e. the percentage of persons below the

Table 3
The effects of differential mortality
on standard income distribution indicators
(some illustrative simulations)

	$d = 0.03$	$d = 0.06$
$\mu_\gamma = \overline{\ln(y_i)}$ $\sigma_\gamma = \sigma_{\ln(y_i)}$ $-1 \leq \lambda \leq 1$	Sim. 1	Sim. 2
$\mu_\gamma = 0.5\overline{\ln(y_i)}$ $\sigma_\gamma = 0.5\sigma_{\ln(y_i)}$ $-1 \leq \lambda \leq 1$	Sim. 3	Sim. 4

Notes: For $\lambda = -1$, the constellation of the noted parameters yields the following correlation coefficients, $\varphi(r_i, y_i)$, between the risk factor r_i and income y_i: Simulation 1 and 2: $\varphi(r_i, y_i|\lambda = -1)$= -0.333; Simulation 3 and 4: $\varphi(r_i, y_i|\lambda = -1)$= -0.441.

poverty line. We chose two alternative poverty lines. A first which considers the 10% and a second which considers the 50% at the bottom of the income distribution in the base year as poor. The corresponding simulation results are presented in Figure 1.

[insert Figure 1]

The first line (Simulation 1) of Figure 1 shows that for a death rate of 3% and relatively important unobserved heterogeneity the Gini-coefficient decreases by roughly one percentage point if we decrease λ from zero to -1. A value for -1 for λ implies that the an increase of y by one percent decreases the risk factor of death by also one percent. If λ is zero, i.e. there is no differential mortality, the Gini-coefficient corresponds of course to that of the baseline. If mortality was positively correlated with income, i.e. λ between zero and one, inequality tends also to decrease. In both cases, negative and positive correlation between mortality and income, inequality decreases, because in each case we 'eliminate' persons at the (lower or upper) end of the income distribution. In contrast, a scenario, where in particular individuals of the middle class faced higher mortality could lead to an increase of inequality. If we increase the death rate to 0.06 (Simulation 2) or decrease the importance of the error term (Simulation 3) or both (Simulation 4), we can state, as one can expect, that variations in inequality become correspondingly stronger. As one can see, the effects on inequality are not symmetric for negative and positive values of λ. This is due to the fact that the initial distribution is skewed to the left, i.e. is normal in $\ln(y)$, not in y.

The second and third row in Figure 1 show, that the poverty rate reacts also strongly to the degree of differential mortality. Assuming a death rate of 0.03 (Simulation 1 and 3) and strong negative differential mortality, results in a decrease of the poverty headcount-index by roughly 2 percentage points, which corresponds in the case of the low poverty line to roughly 20%. Again, the effect is stronger if the death rate increases (Simulation 2), the error term becomes less important (Simulation 3), or both (Simulation 4). For instance in Simulation 4, the headcount-index for the 10% poverty line decrease by roughly 50%. For positive values of λ and the low poverty line the headcount-index is of course less affected than with the higher poverty line.

These simple simulations illustrate the potential and pure demographic effects of differential mortality on income distribution. In the next section, we try to isolate this effect from the total change in inequality observed for the IFLS data between 1993 and 1997. The empirical application poses of course a lot of additional problems, such as the fact that individuals are grouped in households taking joint decisions on labor supply and expenditure. The empirical estimation of the slope of the gradient between income and mortality, will yield a parameter, which can be compared to the ratio λ/σ_γ. This will show at which point in Figure 1 Indonesia is approximately situated.

4.3 Results for Indonesia for the period 1993 to 2000

4.3.1 Estimates of the direct arithmetical impact of mortality

We here construct 'without individual deaths' counterfactuals of the Indonesian distribution of the logarithm of consumption expenditures per capita for 1997 and 2000, drawing on the methodological discussion in Section 3.

We begin with the estimation of the $s_{x,t}(x)$ and $\Psi_{x,t}(x)$ weights, for $t =$ 1993 and $t = 1997$. For each sex, we first estimate a (weighted by cross-section sample weights) probit model of surviving between 1993 and 1997 (resp. 1997 and 2000), depending on a set of individual attributes: a third degree polynomial of age in the initial year, the size of the household, dummies for the education level of the individual and of the household head, sex of the household head, a third degree polynomial for the age of the household head, and a dummy for urban areas. We add to this list the logarithm of household expenditures per capita in 1993 (resp. 1997) and the same variable interacted with the age of the individual in the initial year. It is important to stress that the effect of these two latter variables is not meant to reflect a causal effect of variations of income on mortality, but rather to capture wealth or permanent income effects that are not captured by other observables. In that respect, initial expenditures are treated as just another individual attribute x which may be observed both in 1993 and in 1997 (resp. in 1997 and in 2000). We also checked that the exclusion of this variable did not modify our main conclusions. Table A1 (Appendix) gives the probit estimates of the $s_{x,t}(x)$ function, for both sexes and for both periods. It is interesting to see that mortality differentials linked to income are only significant in the case of women between 1993 and 1997. Differentials linked to education, whether of the individual or of the household head, are significant for both sexes and both periods except for males between 1993 and 1997. We also estimated probit models for 'being present in 1997' and for 'being present in 2000', in order to compute the $\Psi_{x,t}(x)$ weights (results not presented). From these estimations, we can see that these probabilities are non-linearly linked to age (whether of the individual or of the household head), to education, to living in urban areas and finally to initial income interacted with age (in the 1993-97 period only for this latter variable). These probabilities reflect overall demographic changes including migration and the educational expansion having occurred during both periods. They may also reflect some sampling bias linked to the panel structure of the IFLS surveys (attrition).

We then first compute density estimates (gaussian kernels with bandwidth=0.2) of f_{93}, f_{97} and f_{00}, for the actual distributions of (log.) income (Figure 2). Figures 2a and 2b reveal that the income distribution has strongly improved between 1993 and 1997, with a large reduction in poverty and inequality.[9] The vertical line corresponds to a poverty line.[10] In 2000, that is after the macro-economic crisis of 1997/98, the income distribution came only back to its 1997 features, in line with the results already found by Strauss et alii. (2002). Figure 2b confirms this diagnosis. The 1997-1993 density difference shows a large decrease in the weight of poor individuals, while the 2000-1997 difference is pretty flat.

[insert Figures 2a and 2b]

We next compute (weighted by cross-section sample weights) kernel estimates of f^*_{93}, f^*_{97}, and f^*_{00} for the 'direct mortality impact' counterfactual distributions. We also compute a $f^{(0)}_{93}$ (resp. $f^{(0)}_{97}$) density estimated on the 1993 (resp. 1997) population from which (future) dead individuals between 1993 and 1997 (resp. 1997 and 2000) have been removed (Figures 3a and 3b).[11] Figure 3a compares the three counterfactual density impacts of individual deaths: $f^{(0)}_{93} - f_{93}$ (without dead individuals), $f^*_{93} - f_{93}$ (1993 reweighted), and $f_{97} - f^*_{97}$ (1997 reweighted). Again, the vertical line corresponds to the poverty line. Figure 3b does the same for the 1997-2000 period. The two figures show rather similar features: mortality more often kills poorer individuals whether because poorer households have a larger size, whether because individuals die more often when they live in a (initially) poorer household or they earn a lower income because of a lack of personal education. In particular, reweighing the 1993 (resp. 1997) density by survival probabilities or reweighing the 1997 (resp. 2000) density by their inverse makes no substantive difference. The 'without dead individuals' impacts also take into account individual mortality differentials linked to unobservable factors. The absence of large differences between these latter counterfactuals and the two others gives confidence in our choice to compute mortality impacts through reweighing techniques based on observables.[12] In all cases, individual mortality directly contributes to a

[9]The Gini index goes down from 0.463 in 1993 to 0.442 in 1997, while the P0 poverty headcount goes down from 13.3% to 4.2%. Between 1997 and 2000, the Gini again looses

[10]The poverty line was determined such that we matched exactly the official headcount index of 1993 (taken from Lanjouw *et al.*, 2001), i.e. 20,107 Rupiahs per month. We then held constant this poverty line through 1997 and 2000.

[11]Whenever we compute density differential impacts we smooth them again by a gaussian kernel of bandwidth 0.2.

[12]Figure 3b however mitigates this latter diagnosis, as it can be seen that the $f^{(0)}_{97} - f_{97}$

decrease in poverty, as argued by Kanbur and Mukherjee (2003). However, as can be seen from the scale of the vertical axis in Figure 2b, the magnitude of all these counterfactual impacts is very small when compared to the magnitude of observed changes in the distribution between 1993 and 1997.

[insert Figures 3a and 3b]

We last compute kernel estimates of g_{97}^{*} and g_{00}^{*} for the 'constant distribution of attributes' DiNardo *el al.* (1996) counterfactual distributions. Remember that these 'all observable attributes' counterfactuals also include the impact of individual mortality on the distribution of observable attributes in the population. In Figure 4, we then present the relevant differences $f_{97} - g_{97}^{*}$ and $f_{00} - g_{00}^{*}$ and compare them to $f_{97} - f_{97}^{*}$ (1997 reweighted), and to $f_{00} - f_{00}^{*}$ (2000 reweighted). The comparison shows that individual mortality plays only a minor role in the distributional changes that can be imputed to demographic changes. The mortality impacts are ten (in the case of 1993-97) to twenty times (1997-2000) lower in magnitude than overall demographic and educational impacts. Interestingly enough, however, we can see that overall changes in the distribution of observable attributes go in the same direction than individual mortality, in that they are unambiguously poverty decreasing.

[insert Figure 4]

Finally, Figures 5a and 5b summarize the results by sequentially discounting from the $f_{97} - f_{93}$ (resp. $f_{00} - f_{97}$) density difference, first the impact of mortality, and second the impact of all changes in the distribution of attributes (including mortality). Obviously, mortality and population structure changes do not contribute to the explanation of the change in income per capita density between 1993 and 1997. As for the 1997-2000 period, the distributional impact of demographic changes other than mortality has the same order of

counterfactual impact is more pronounced than $f_{97}^{*} - f_{97}$(based on 1997-2000 mortality) and even more than the $f_{00} - f_{00}^{*}$ reweighted impact. It should however be reminded that the 'without dead individuals' counterfactuals do not take into account the influence of changes in the distribution of the population; strictly speaking, they should only be compared to the reweighted counterfactuals when computed on the initial year (that is the impact 'in 93' in Figure 3a, and the impact 'in 97' in Figure 3b).

magnitude than the observed distributional changes. Reweighing indicates that demographic changes induce a shift towards the right of the distribution of (log.) income; without such changes the poverty rate would have been worse than those observed in 2000. In a way, demographic changes have contributed to the observed recovery from the 1997/98 crisis, but do not explain much of the changes in inequality. However, it should be reminded that we are commenting upon very small changes, the reliability of which remains to be ascertained.

All the above conclusions are maintained when initial log consumption expenditures are excluded from the set of observable attributes.

[insert Figures 5a and 5b]

4.3.2 Estimates of the direct and indirect impact of changes in mortality patterns

We now integrate in our analysis the indirect impact of mortality on the income of household survivors, in line with the methodology described above. We therefore add to our individual survival probabilities estimates an estimation of the conditional (on household observables) individual probability of having experienced a death in the household of origin between 1993 and 1997 or between 1997 and 2000, that is of $\Pr(z = 1|x, t_{z|x} = 1993)$ and $\Pr(z = 1|x, t_{z|x} = 1997)$. This estimation is performed using a (by cross-section sampling weights weighted) probit model for both sexes and both periods, whose results are given in Table A2. All estimates show that households finally headed by a woman have more often experienced a death event, which can be easily understood. In three cases, with the exception of males in 1993 to 1997, initial log consumption expenditures per capita decrease the probability of a death event. Education differentials also play some role in explaining the probability of death events, like in the case of individual survival probabilities.

Between 1993-1997 and 1997-2000, overall individual mortality rates decrease (see Table A2); the mortality gradients also change, as can be seen in Table A1. Likewise, the occurrence of household death events decrease between the two periods; there are also some changes in the probability functions of being a household survivor, as can be seen in Table A2. With the ratio of survival probability estimates, we compute kernel estimates of the direct effect of changes in mortality patterns on the evolution on income distribution ($f_{00} - f_{00}^{**}$). With the ratio of the household survivors probability functions, we compute the indirect effect of changes in mortality ($f_{00} - f_{00}^{indir}$). The impact of such such changes in mortality levels and gradients are assessed in Figure 6, which presents the impact on the 2000 distribution of income of mortality functions being kept at their 1993 to 1997 estimations between 1997 and 2000.

[insert Figure 6]

The direct effect of the change in mortality patterns ($f_{00} - f_{00}^{**}$) is unambiguously poverty increasing, although (again) with a very small order of magnitude. All happens as if the mortality decrease between 1993-1993 and 1997-2000 had not modified the correlation between the distribution of income and the distribution of death events (income inequalities in front of death). Put differently, poor individuals have not benefited more than others from mortality improvements. *The direct effect of the mortality decrease is to increase monetary poverty.*

Conversely, the indirect effect of the change in mortality patterns ($f_{00} - f_{00}^{indir}$) is unambiguously poverty decreasing, although (still) with a very small order of magnitude. In contrast with the direct impact, the indirect impact of mortality changes ($f_{00} - f_{00}^{indir}$) indeed contributes to a decrease in the weight of the poorest. All happens as if households of 'survivors' were (with other observables equal) poorer than their 'unaffected' counterparts; so that a decrease in mortality rather make the poorest households richer and improves the distribution of income. *The indirect effect of the mortality decrease is to decrease monetary poverty.*

Hence, when the direct and indirect impact of changes in mortality patterns are summed together ($f_{00} - f_{00}^{\triangle}$), the result is more ambiguous. The overall changes in mortality patterns seem to have contributed to a slight increase in the inequality of the income distribution rather than to poverty evolution. *The overall effect of the mortality decrease on monetary poverty is ambiguous.*

Finally, we compute the impact of overall changes in the population structure, including survivor's status (that is, $f_{00} - g_{00}^{\Delta}$). Figure 7 shows that the mortality effects, whether direct or indirect, are completely dominated by other demographic effects. Here again, demographic changes influence the distribution of income in the same direction than the direct arithmetic effect of mortality, but at a higher level of magnitude. The changes in the evolution of the population structure in terms of age, education and place of residence (urban/rural) have again a poverty increasing effect. If the speed of demographic changes had remained the same in 1997-2000 than in 1993-1997, then the resulting distribution of income in the year 2000 would have shown less poverty and less inequality. Instead, some deceleration of positive demographic changes has occurred, having emphasized the impact of the 1997/98 macro-economic crisis.

[insert Figure 7]

However, Figure 8 shows that the overall impact of these overall demographic evolutions is rather small. The absence of such a demographic 'deceleration' would not have very significantly changed the observed evolution between 1997-2000.

[insert Figure 8]

5 Conclusion

We have presented a general methodology designed to study the counterfactual impact of mortality and changes in mortality on income distribution. This methodology is inspired by the work of Di Nardo *et al.* (1996). It relies on the non-parametric reweighing of income distributions by functions of individual observable attributes (like sex, age, education, place of residence etc.). We believe that this methodology offers a stronger theoretical and empirical foundation than the methodology recently proposed by Kanbur and Mukherjee (2003) to 'correct' poverty measures for the effect of differential mortality. Like Kanbur and Mukherjee, we are able to deal with the direct arithmetic effect of individual deaths on poverty changes, which is most important when individual deaths are unevenly distributed across the income distribution. But we are also able to correct for the indirect effect of an individual death on the income of survivors pertaining to the same household, which might be as much important. If the mortality risk is negatively correlated with income, then, when mortality increases (resp. decreases) over time, the direct effect is usually poverty decreasing (resp. increasing). Conversely, if mortality is negatively correlated with income and if a death in a household decreases household income, then, when mortality increases over time (resp. decreases), the indirect effect should be poverty increasing (resp. decreasing). We apply our methodology using the Indonesian Family Life Survey panel data-set, which covers the periods 1993-1997 and 1997-2000. For a mortality decrease, we show that the direct and indirect effects of mortality on the income distribution have indeed opposite signs and show the same order of magnitude, so that they almost cancel out each other. We also show that the effect of other demographic changes, like changes in the structure of fertility, migration, and educational attainment, dominate the effects of mortality changes, whether direct or indirect. We however find that none of these demographic developments are large enough to explain a significant part of the changes in income distribution, whether the pre-crisis period (1993-1997) or the post-crisis period (1997-2000) is considered.

Appendix

Table A1
Survival probability $s_x(x)$ estimates
Probit Model for the probability of surviving
100 $\times$marginal probabilities computed at sample mean

	1993-1997		1997-2000	
	Coeff.	Std. Err.	Coeff.	Std. Err.
MEN				
log. consumption exp. per head	-0.161	(0.325)	0.035	(0.241)
log. cons. exp. per head $\times$ age	0.004	(0.006)	0.003	(0.005)
log. household size	-0.248	(0.289)	0.299	(0.182)
Age (in initial year)	0.064	(0.077)	0.015	(0.064)
Age squared	-0.004*	(0.001)	-0.002*	(9.9e-4)
Age cubed	1.68e-5	(1.07e-5)	1.03e-5	(7.3e-6)
Still at school or no education	(ref.)	(ref.)	(ref.)	(ref.)
Primary education & can read	-0.216	(0.460)	0.676*	(0.211)
Junior highschool & can read	-1.077	(1.395)	0.433	(0.313)
Senior highschool or higher	0.546	(0.520)	0.411	(0.291)
Male household head	-0.537	(0.520)	0.302	(0.413)
Head age	1.244	(2.100)	0.007	(0.112)
Head age squared	-0.003	(0.004)	-6.4e-5	(0.002)
Head age cubed	2.25e-5	(2.49e-5)	8.89e-6	1.4e-5
Head No education	(ref.)	(ref.)	(ref.)	(ref.)
Head Primary education	0.141	(0.442)	-0.108	(0.275)
Head Junior highschool	0.915	(0.531)	-0.063	(0.417)
Head Senior highschool or higher	0.507	(0.485)	-0.761	(0.529)
Urban area	-0.346	(0.025)	0.205	(0.171)
No. of obs.	13,507		14,371	
Pseudo-R^2	0.196		0.200	
WOMEN				
log. consumption exp. per head	0.680*	(0.269)	0.073	(0.186)
log. cons. exp. per head $\times$ age	-0.011*	(0.005)	-0.002	(0.003)
log. household size	-0.643*	(0.193)	-0.444*	(0.156)
Age (in initial year)	0.177*	(0.057)	0.128*	(0.043)
Age squared	-0.003*	(8.8e-4)	-0.003*	(6.8e-4)
Age cubed	1.3e-5*	(6.3e-6)	1.3e-5*	(4.5e-6)
Still at school or no education	(ref.)	(ref.)	(ref.)	(ref.)
Primary education & can read	0.641*	(0.204)	-0.233	(0.230)
Junior highschool & can read	0.545	(0.294)	0.245	(0.265)
Senior highschool or higher	0.705	(0.304)	0.653*	(0.198)
Male household head	-0.019	(0.279)	-0.307	(0.153)
Head age	0.136	(0.140)	-0.014	(0.108)
Head age squared	-0.002	(0.003)	-3.1e-4	(0.002)
Head age cubed	1.13e-5	(1.63e-5)	4.7e-6	(1.3e-5)
Head No education	(ref.)	(ref.)	(ref.)	(ref.)
Head Primary education	-0.446	(0.247)	-0.087	(0.168)
Head Junior highschool	-0.020	(0.397)	0.143	(0.240)
Head Senior highschool or higher	0.281	(0.328)	0.088	(0.239)
Urban area	0.084	(0.196)	0.266*	(0.135)
No. of obs.	14,411		15,474	
Pseudo-R^2	0.210		0.246	

Notes: * coefficient significant at the 5% level.

Source: IFLS1, IFLS2 and IFLS3 longitudinal samples; estimations by the authors.

Table A2
Probability of having experienced a death in the household of origin
Probit Model
100 ×marginal probabilities computed at sample mean

	1993-1997		1997-2000	
	Coeff.	Std. Err.	Coeff.	Std. Err.
MEN				
log. consumption exp. per head	-0.664	(0.630)	-2.403*	(1.054)
log. cons. exp. per head × age	-0.009	(0.018)	0.016	(0.015)
log. household size	0.968	(0.710)	-0.447	(0.544)
Age (in initial year)	0.059	(0.212)	-0.269	(0.159)
Age squared	0.001	(0.003)	0.002	(0.001)
Age cubed	-1.0e-5	(2.5e-5)	-5.6e-6	(1.5e-5)
Still at school or no education	(ref.)	(ref.)	(ref.)	(ref.)
Primary education & can read	-0.084	(0.899)	0.031	(0.686)
Junior highschool & can read	-1.363	(0.998)	0.293	(0.796)
Senior highschool or higher	0.084	(0.981)	1.551*	(0.874)
Male household head	-15.20*	(1.331)	-10.46*	(3.494)
Head age	-0.409	(0.282)	0.040	(0.106)
Head age squared	9.4e-4	(0.006)	-4.9e-4	(0.001)
Head age cubed	3.7e-5	(3.9e-5)	4.5e-7	1.0e-6
Head No education	(ref.)	(ref.)	(ref.)	(ref.)
Head Primary education	-1.435*	(0.690)	0.612	(0.594)
Head Junior highschool	-0.247	(0.998)	1.929*	(1.188)
Head Senior highschool or higher	0.555	(0.992)	0.999	(0.891)
Urban area	0.128	(0.561)	-0.326	(0.425)
No. of obs.	16,178		18,772	
Pseudo-R^2	0.030		0.026	
WOMEN				
log. consumption exp. per head	-2.285*	(0.648)	-1.580*	(0.512)
log. cons. exp. per head × age	0.046*	(0.016)	-0.005	(0.014)
log. household size	3.252*	(0.640)	-0.828	(0.496)
Age (in initial year)	-0.319	(0.198)	0.102	(0.156)
Age squared	-0.003	(0.003)	-5.2e-4	(6.3e-4)
Age cubed	9.3e-6	(2.4e-5)	4.4e-7	(5.8e-7)
Still at school or no education	(ref.)	(ref.)	(ref.)	(ref.)
Primary education & can read	-1.340	(0.725)	-0.026	(0.627)
Junior highschool & can read	-1.394	(0.936)	0.560	(0.819)
Senior highschool or higher	-2.195*	(0.830)	1.355	(0.773)
Male household head	-13.65*	(0.982)	-9.43*	(0.790)
Head age	-0.468	(0.261)	0.096	(0.109)
Head age squared	0.002	(0.005)	-9.3e-4	(0.001)
Head age cubed	3.2e-5	(3.5e-5)	8.4e-7	(1.1e-6)
Head No education	(ref.)	(ref.)	(ref.)	(ref.)
Head Primary education	-1.129	(0.625)	0.508	(0.535)
Head Junior highschool	0.579	(0.978)	1.732*	(0.848)
Head Senior highschool or higher	1.210	(0.930)	-0.151	(0.707)
Urban area	0.409	(0.550)	-0.346	(0.438)
No. of obs.	17,331		19,776	
Pseudo-R^2	0.036		0.029	

Notes: * coefficient significant at the 5% level.

Source: IFLS1, IFLS2 and IFLS3 longitudinal samples; estimations by the authors.

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References

Abadie A., J. D. Angrist, G. W. Imbens (1998), *Instrumental Variables Estimation of Quantile Treatment Effects*, NBER Working Paper t0229, Cambridge.

Aldy J.E. (2003), Age variations in workers' value of statistical Life. NBER Working Paper 10199, Cambridge.

Atkinson A.B. (1970), On the Measurement of Inequality. *Journal of Economic Theory*, 2: 244-263.

Attanasio O.P. and H.W. Hoynes (1996), Differential Mortality and Wealth Accumulation. Institute for Research on Poverty Discussion Paper 1079-96, University of Bologna.

Bommier A. (2001), Uncertain lifetime and intertemporal choice: risk aversion as a rationale for time discounting. Working Paper LEA-INRA 01-07, INRA Jourdan, Paris.

Bommier A. (2003a), Mortality and life cycle models. Mimeo, Université de Toulouse (GREMAQ) and INRA Jourdan, Paris.

Bommier A. (2003b), Valuing Life under the Shadow of Death: on Stationary Lifetime Preferences. Working Paper LEA-INRA 03-01, INRA Jourdan, Paris.

Brainerd E. and M.V. Siegler (2003), The economic effects of the 1918 influenza epidemic. CEPR Discussion Paper No. 3791, CEPR, London.

Chu C.Y.C. and H. Koo (1990), Intergenerational income-group mobility and differential fertility. *American Economic Review*, 80: 1125-1138.

Dasgupta P., A. Sen and D. Starrett (1973), Notes on the Measurement of Inequality. *Journal of Economic Theory*, 6: 180-187.

Deaton A. and C. Paxson (1999), Mortality, education, income and inequality among American cohorts. Mimeo, Princeton, Princeton University.

DiNardo J., N.M. Fortin and T. Lemieux (1996), Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica*, 64 (5): 1001-1044.

Firpo S. (2004), *Efficient Semiparametric Estimation of Quantile Treatment Effects*, University of British Colombia, Vancouver, Discussion Paper 04-01.

Foster J., J. Greer and E. Thorbecke (1984), A Class of Decomposable Poverty Measures. *Econometrica*, 52: 761-776.

Frankenberg E. and L. Karoly (1995), The 1993 Indonesian Family Life Survey: Overview and Field Report, RAND, DRU-1195/1-NICHD/AID.

Frankenberg E. and D. Thomas (2000), The Indonesian Family Life Survey: Study Design and Results from Waves 1 and 2, RAND, DRU-2238/1-NIA/NICHD.

Kanbur R. and D. Mukherjee (2003), Premature Mortality and Poverty Measurement. ISER Working Papers 2003-6, ISER, University of Essex.

Kaplan G., E.R. Pamuk, J.M. Lynch, R.D. Cohen and J.L. Balfour (1996), Inequality in income and mortality in the United States: analysis of mortality and potential pathways. *Britisch Medical Journal*, 312: 999-1003.

Kitagawa E.M. and P.M. Hauser (1973), *Differential Mortality in the United States: A Study in Socioeconomic Epidemiology.* Cambridge: Harvard University Press.

Kniesner T.J., W.K. Viscusi and J.P. Ziliak (2004), Life-Cycle Consumption and the Age-Adjusted Value of Life. NBER Working Paper No. W10266, NBER, Cambridge.

Lam D. (1986), The dynamics of population growth, differential fertility and inequality. *American Economic Review*, 76: 1103-1116.

Lam D. (1997), Demographic variables and income inequality. In M.R. Rosenzweig and O. Stark (eds.), *Handbook of Population and Family Economics* (pp. 1015-1059), Amsterdam: North-Holland.

Lanjouw P., M. Pradhan, F. Saadah, H. Sayed and R. Sparrow (2001), Poverty, Education and Health in Indonesia: Who benefits from Public Spending. Mimeo, World Bank, Washington D.C.

Lantz P.M., J.S. House, J.M. Lepkowski, D.R. Williams, R.P. Mero and J. Chen (1998), Socioeconomic factors, health behaviors, and mortality. *Journal of the American Economic Medical Association*, 279: 1703-1708.

Lewbel A. (2002), Calculating Compensation in Cases of Wrongful Death. Mimeo, Boston College.

Menchik P.L. (1993), Economic Status as a Determinant of Mortality Among Black and White Older Men: Does Poverty Kill? *Population Studies*, 47 (3): 427-436.

Oaxaca R. (1973), Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review*, 14: 693-709.

Sen A.K. (1970), *Collective Choice and Social Welfare*, Amsterdam: North-Holland.

Sen A.K. (1985), *Commodities and Capabilities.* Amsterdam: North-Holland.

Sen A.K. (2003), Development as capability expansion. In Sakiko Fukuda-Parr and A.K. Shiva Kumar (eds.), *Readings in Human Development. Concepts, Measures and Policies for a Development Paradigm* (pp. 3-16), Oxford: Oxford University Press.

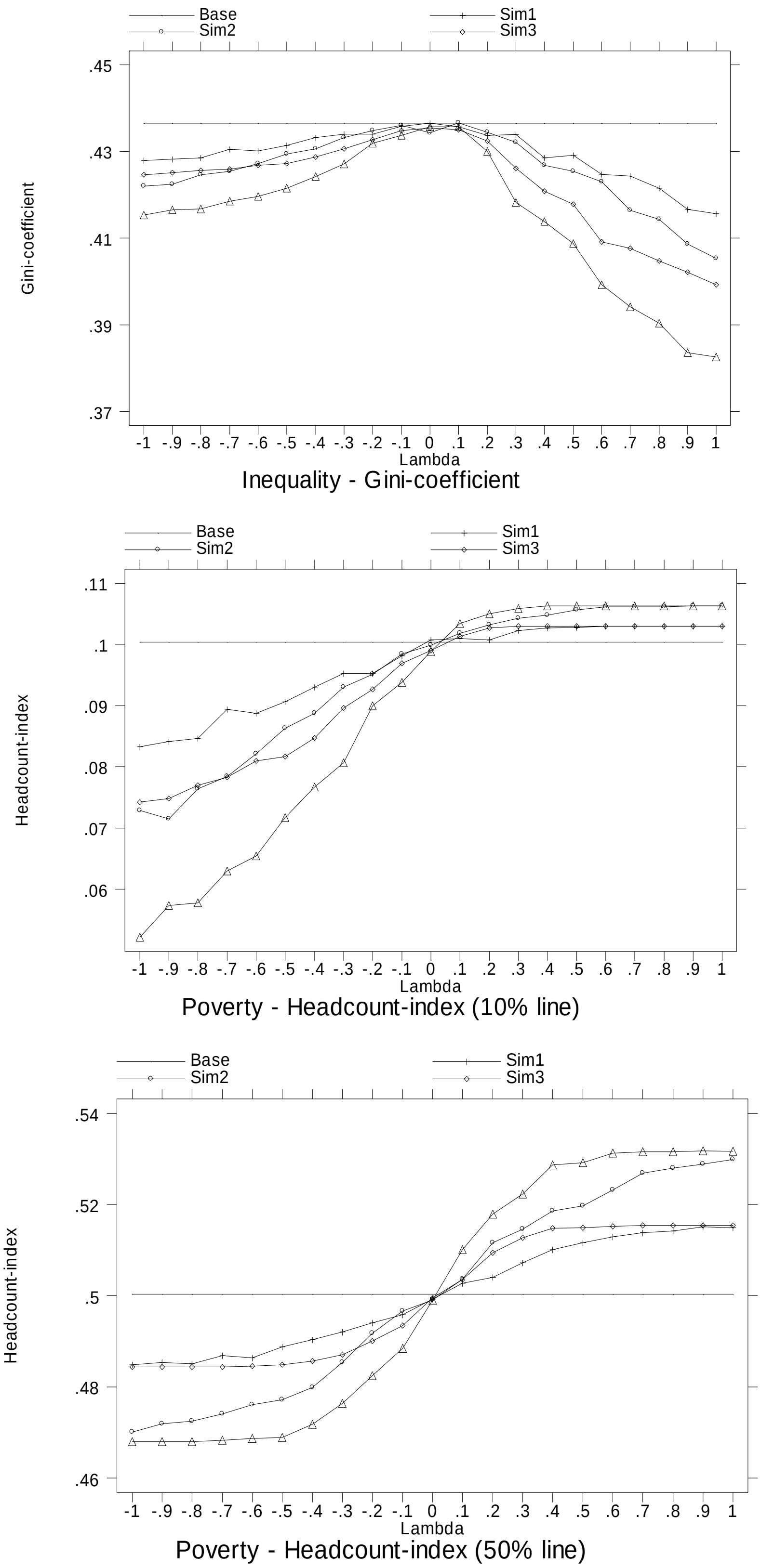
Strauss J., K. Beegle, A. Dwiyanto, Y. Herawati, D. Pattinasarany, E. Satriawan, B. Sikoki, B. Sukamdi and F. Witoelar (2002), Indonesian living standards three years after the crisis: evidence from the Indonesia Family Life Survey, Executive Summary, unpublished, Michigan State University, World Bank, Centre for Population and Policy Studies (University of Gadjah Mada, Yogyakarta), RAND Corporation.

Strauss J., K. Beegle, B. Sikoki, A. Dwiyanto, Y. Herwati and F. Witoelar (2004), The Third Wave of the Indonesia Family Life Survey (IFLS3): Overview and Field Report. WR-144/1-NIA/NCHID, RAND Corporation.

Valkonen T. (2002), Social inequalities in mortality. In G.Caselli, J. Vallin and G. Wunsch (eds.), *Demography: Analysis and Synthesis*, (pp. 51-67).

Figures

Figure 1
The effects of differential mortality on standard income distribution indicators
(some illustrative simulations)



Source: Simulations by the authors.

Figure 2a
(Log.) income (per capita) kernel densities in 1993, 1997 and 2000

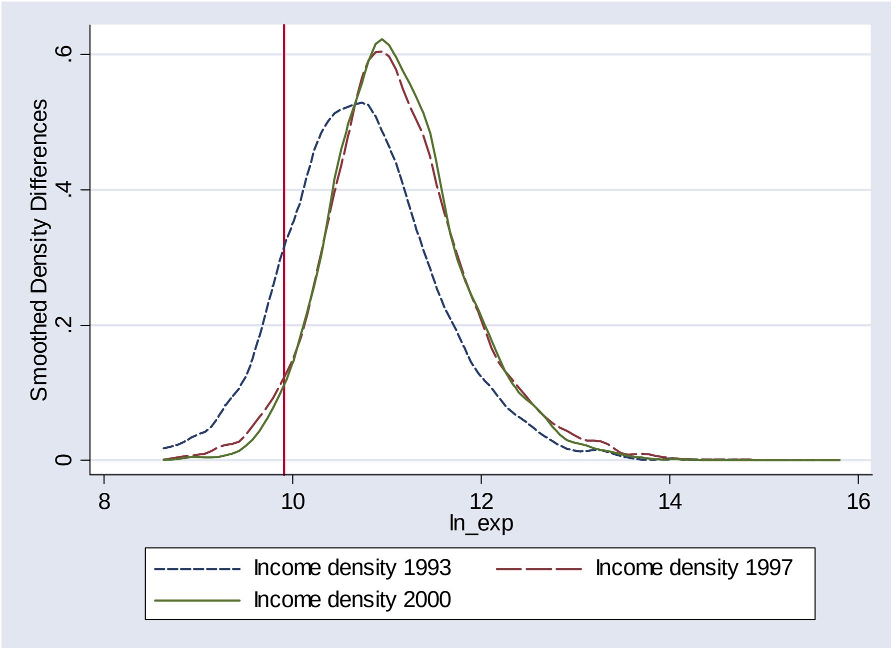
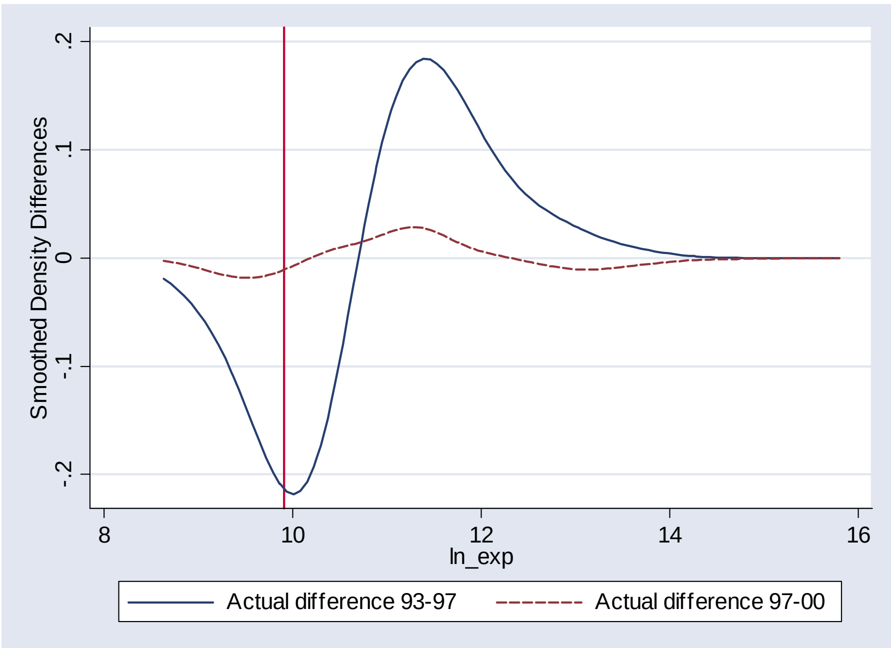


Figure 2b
Changes in (log.) income (per capita) distribution 1993-97 and 1997-2000



Notes: Vertical line corresponds to poverty line.
Source: IFLS1, IFLS2 and IFLS3; estimations by the authors.

Figure 3a
Smoothed impact of individual deaths 1993-97

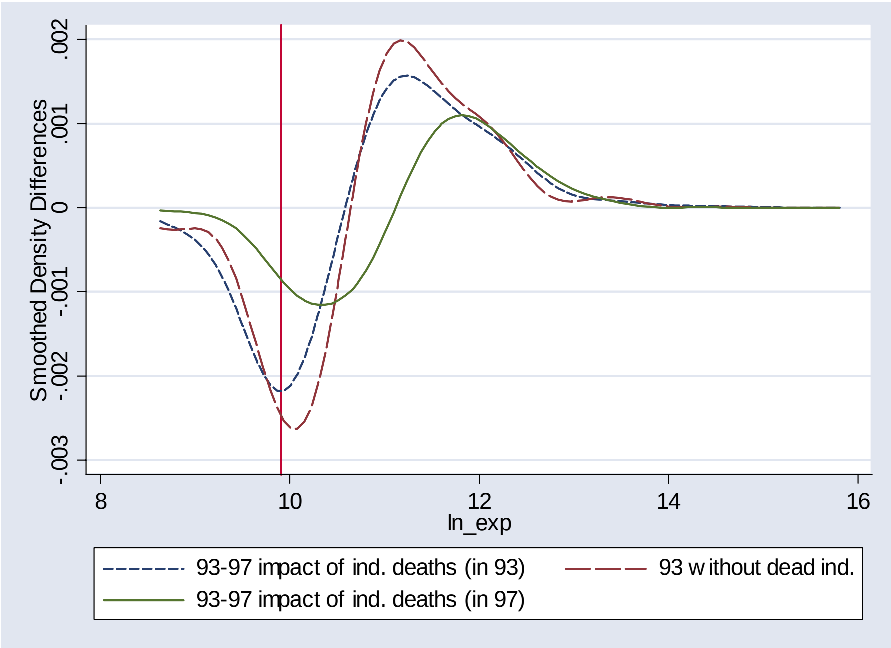
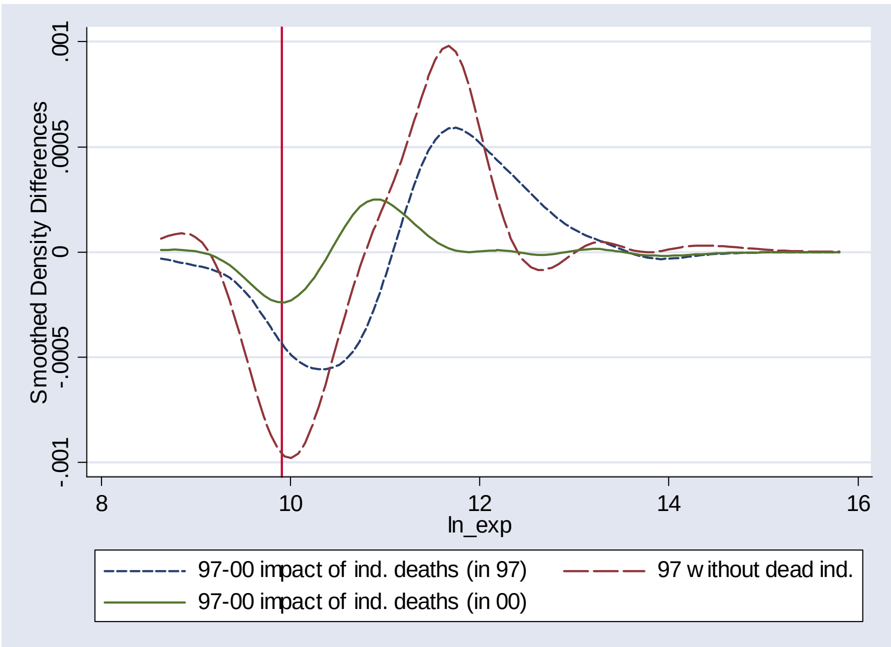
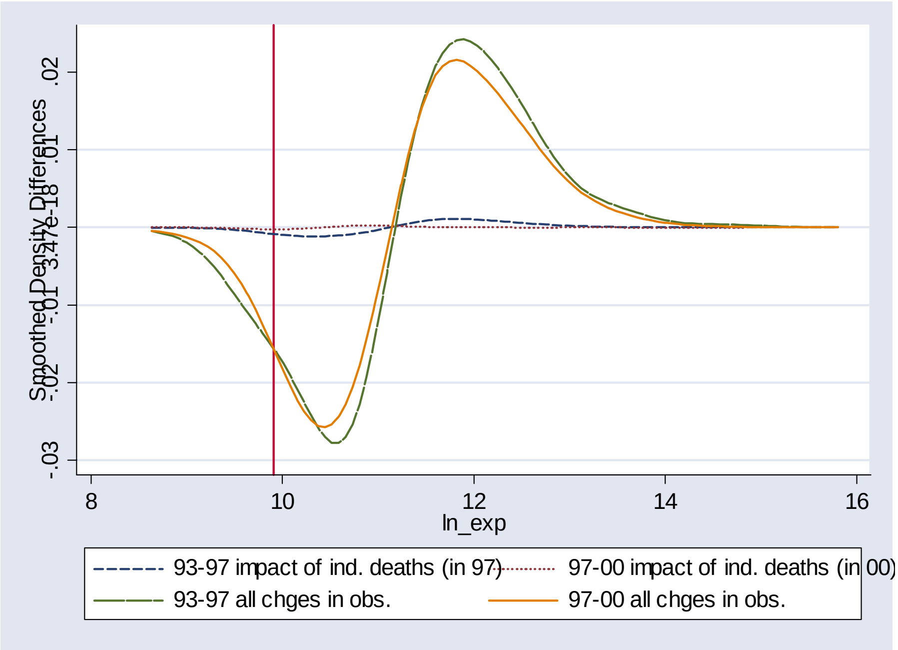


Figure 3b
Smoothed impact of individual deaths 1997-2000



Notes: Vertical line corresponds to poverty line.
Source: IFLS1, IFLS2 and IFLS3; estimations by the authors.

Figure 4
Smoothed impacts of individual mortality
compared to impacts of changes in all observable attributes



Notes: Vertical line corresponds to poverty line.
Source: IFLS1, IFLS2 and IFLS3; estimations by the authors.

Figure 5a
Counterfactual impacts of individual mortality and of changes in all observable attributes on the 1993-1997 change in (log.) income (per capita) distribution

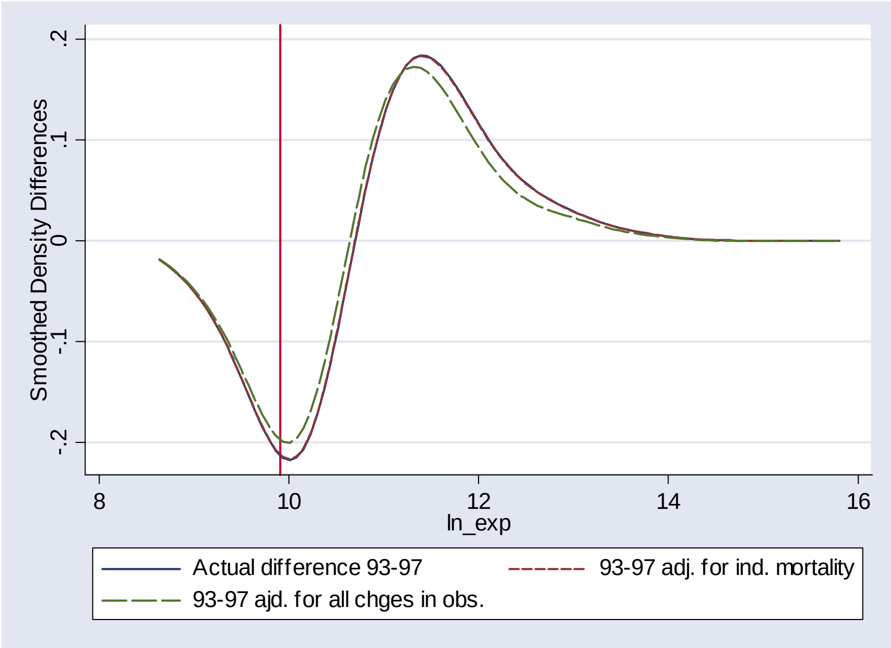
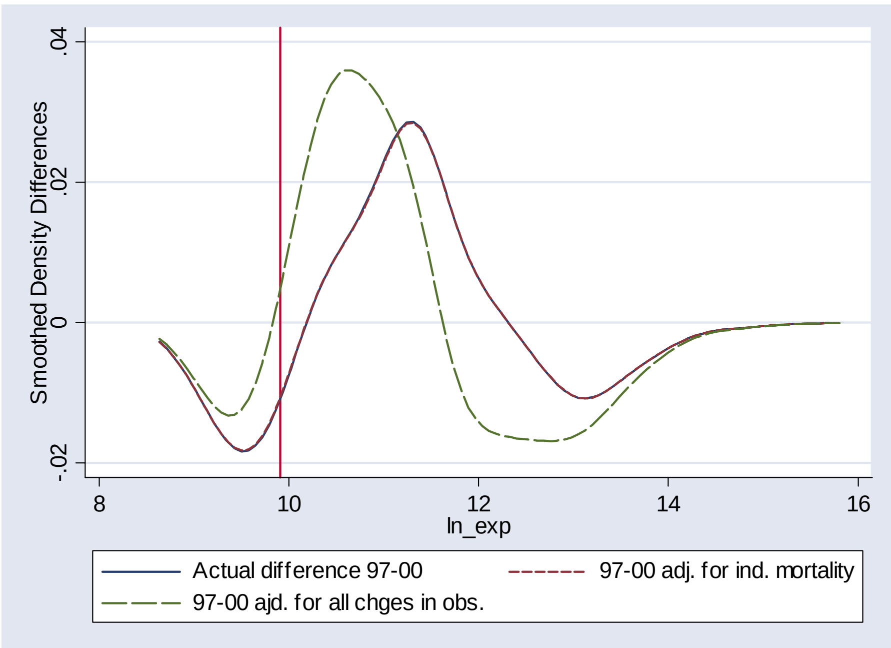
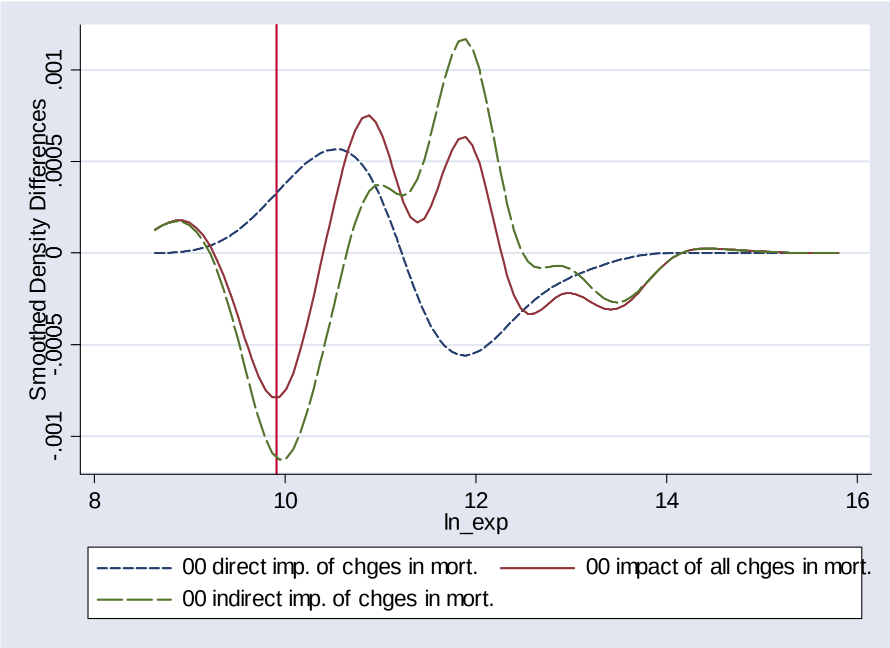


Figure 5 b
Counterfactual impacts of individual mortality and of changes in all observable attributes on the 1997-2000 change in (log.) income (per capita) distribution



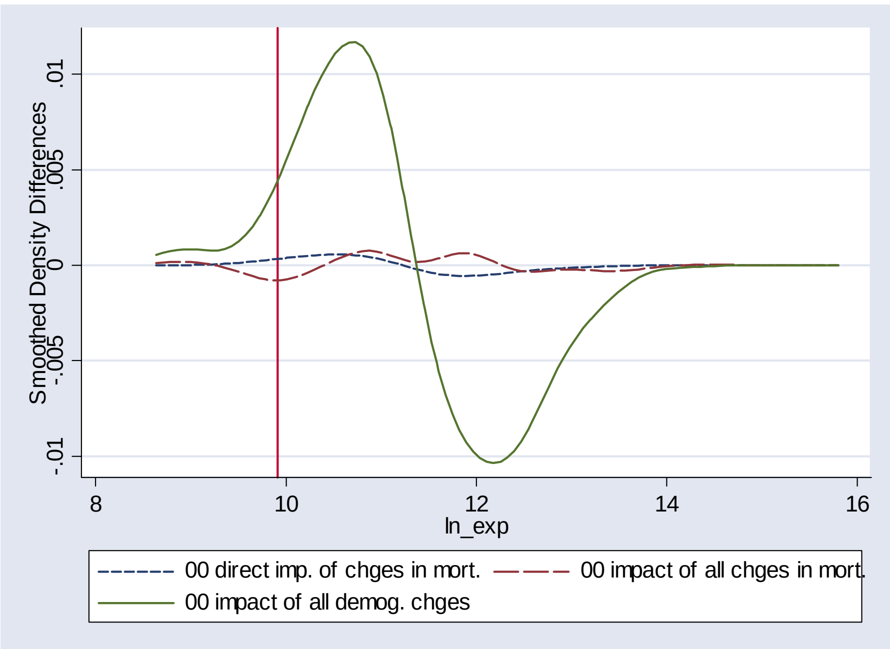
Notes: Vertical line corresponds to poverty line.
Source: IFLS1, IFLS2 and IFLS3; estimations by the authors.

Figure 6
Smoothed impact of changes in mortality patterns between 1993-1997 and 1997-2000
on the 2000 density of (log.) income (per capita)



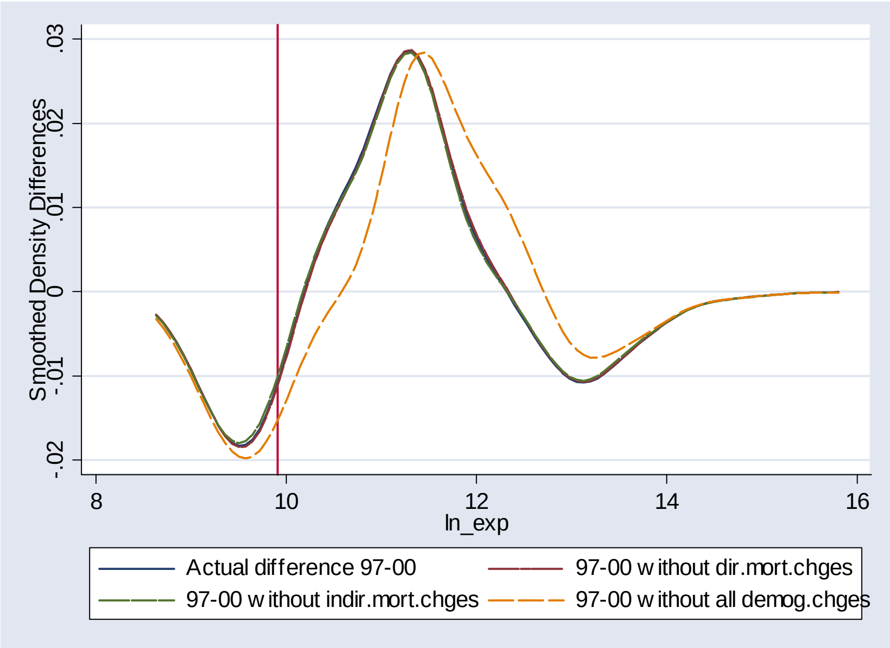
Notes: Vertical line corresponds to poverty line.
Source: IFLS1, IFLS2 and IFLS3; estimations by the authors.

Figure 7
Smoothed impacts on the 2000 density of (log.) income (per capita) -
Changes in mortality patterns between 1993-1997 and 1997-2000
compared to other changes in population evolution



Notes: Vertical line corresponds to poverty line.
Source: IFLS1, IFLS2 and IFLS3; estimations by the authors.

Figure 8
Counterfactual impacts of changes in mortality patterns and other observables on the 1997-2000 change in (log.) income (per capita) distribution



Notes: Vertical line corresponds to poverty line.
Source: IFLS1, IFLS2 and IFLS3; estimations by the authors.