Reading List

Concepts


This is a great book that deserves a full reading. However, the bits of most relevance for us are Chapters 3.3 and 5.

Surveys


Price Effects


Labour Markets


Examining the Social Impact of the Indonesian Financial Crisis using a Micro-Macro Model

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Abstract
In this paper, a novel approach is implemented to quantify the effects on poverty and inequality of the financial crisis that hit Indonesia in 1997. It relies on the combination of a micro-simulation model and a standard CGE model. These two models are used in a sequential fashion. The CGE model captures structural features of the economy, including binding macro constraints, and incorporates general equilibrium effects. The micro-simulation model is based on a detailed representation of the real income generation mechanism at the household level. It is based on a sub-sample of 9,800 households from the 1996 SUSENAS survey. This framework allows us to capture important channels through which macro shocks affect household incomes and to decompose the effects of the financial crisis.

JEL classification: D58; I32; O12.
Keywords: Micro-simulation; Poverty analysis; Financial crisis; Indonesia.

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1. Introduction

Figuring out the social cost of a macro-economic crisis like the one that hit Indonesia in 1997 is uneasy. One year after the crisis, the World Bank (1998) argued that if real GDP declined by 12 per cent in 1998 then the incidence of poverty could be up to 14.1 per cent of the population in 1999 from a level of 10.1 per cent in mid-1997. Other estimates released at the same time were much more pessimistic. CBS(1998) - the Indonesian Board of Statistics - predicted a four fold increase of the poverty head-count, from 11.3 per cent in 1996 up to 39.9 per cent by mid-1999, whereas ILO (1998) predicted a six fold increase to 66.3 per cent by the end of 1999. Ex-post estimates were much below these dramatic predictions. In a study based on data collected in the National Labor Force Surveys (SAKERNAS) from August 1997 through 1998, Manning (2000) found that the “traditional” features of the Indonesia labor markets contributed to cushion the economic shock of the crisis. Finally, recent estimates published by the World Bank (Suryahadi et al., 2000), based on a comparison of the poverty level between two SUSENAS surveys, show that the poverty head-count rose from 9.7 to 16.3 per cent between 1996 and 1999.

These various estimates illustrate the basic methodological ambiguity in either predicting what will happen to the poor just after a crisis struck or deciphering what happened ex-post in actual data. In both cases, an explicit counterfactual scenario is needed. In the first case it must show departures from the pre-crisis evolution of the economy. In the second case, it must permit figuring out what would have happened without the crisis and to disentangle the effects of the crisis from other exogenous shocks that are present in the data – e.g. El Nino in the case of Indonesia. This counterfactual scenario may be simple. For instance, it is natural to assume that the fall in household income or consumption depends on the economic activity of the social
groups being considered. A scenario would thus consist of a set of predictions about the rate of
growth of the various sectors of the economy or that of the aggregate income of the various
factors of production. The early rough estimates of the effect of the Indonesian crisis on poverty
were based on this type of approach. But the divergence between them suggests that establishing
even a simple counterfactual scenario of this type is not so easy and requires more than a rough
model of the economy.

The use of more rigorous multi-sector models would probably permit reaching more
consensual predictions at the level of the whole economy and for the various sectors and factors
of production. It is not clear, however, that this will also permit reaching satisfactory predictions
for the distribution of income and poverty. Associating household incomes with sector activity or
factor remuneration rates is in effect equivalent with defining “representative household groups”
which derive income from a pre-determined combination of factors. Models that incorporate both
several sectors and several representative household groups, with some exogenous distribution
within those groups, have now been used for some time (see for instance Dervis et al., 1982 and
the survey by Adelman and Robinson, 1989). Whether these models are used for analyzing
structural reforms like trade regimes or short-run macro-economic issues – like in Bourguignon
et al. (1992) - this approach has problems too, however. In particular, by ignoring changes in the
distribution of income within representative household groups, they may ignore major sources of
changes in the distribution of economic welfare and poverty. In most studies of changes in
inequality over time it was indeed found that changes in the relative income and weight of a few
groups of households with identical selected characteristics left a sizable unexplained residual.
Focusing on the inequality between representative groups as multi-sector multi-household models
presently do may thus lead to a biased view at the impact of macro or structural policies on the
distribution of income.

A simple example may help understand the nature of the problem. A majority of
households in Indonesia generate income from various sources: salaried employment of some
members in the formal sector, wage work in the informal sector of others and self-employment of
still another group. If representative household groups are defined, as usually done, by the sector
of activity and employment status of the head – e.g. small farmers, urban unskilled workers in the
formal sector, etc. - , it may not be too much of a problem to take into account this multiplicity of
income sources. Thus the change in the inequality between the group of small farmers and that of
urban unskilled workers in the formal sector may take into account the fact that both groups have
different secondary sources of income due to differences in household composition, labor supply
behavior, and the occupation of secondary members. Two difficulties arise, though. First, say that
a macro-economic crisis or a trade reform modifies the number of unskilled urban workers
employed in the formal sector. What should be done with the number of households whose head
is in that occupation? Should it be modified? If so, from which groups new households in that
representative household group must be taken or to which groups should they be allocated? May
this operation be done under the assumption that the distribution of income within all
representative household groups remains the same? Second, assuming that changes in occupation
affect only secondary members and not household heads, so that representative household groups
are unchanged, is it reasonable to assume that all households in a group are affected in the same
way by this change in the activity of some of their members? That a secondary member moves
out of the formal sector back in family self-employment may happen only in a sub-group of
households belonging to a given representative group. Yet, it may seriously affect the distribution
within this group. It is this kind of phenomena that may be behind the change in the “within” component in inequality decomposition exercises. But they are ignored in multi-sector multi-household group models.

In this paper, we introduce a new approach to quantify the effects of macro-economic shocks on poverty and inequality which tries to overcome the preceding difficulty. It combines a micro-simulation model with a standard multi-sector Computable General Equilibrium (CGE) model. The two models are used in a sequential fashion in order to simulate the full distributional impact of the financial crisis and generate meaningful counterfactual scenarios. The CGE model is based on a standard Social Accounting Matrix and is meant to capture structural features of the economy as well as the general equilibrium effects of the macro constraints arising from macro-shocks. The micro-simulation model is based on a sub-sample of the SUSENAS survey for the year 1996 and simulates income generation mechanisms for approximately 10,000 households. The two models are treated separately. The “macro” or CGE model communicates with the micro-simulation model by generating a vector of prices, wages, and aggregate employment variables corresponding to a given shock or policy. Then the micro-simulation model is used to generate changes in individual wages, self-employment incomes and employment status in a way that is consistent with the set of macro variables fed by the macro model. When this is done, the full distribution of real household income corresponding to the simulated shock or policy may be evaluated. This framework is designed to capture important channels through which a crisis of the type that hit Indonesia in 1997 may affect household incomes. Although its main focus is the structure and the functioning of labor markets, it also captures part of the expenditure side story by taking into account the increase in the relative price of food.
The paper is organized as follows. Section 2 shows the structure of the micro-simulation module and how it is linked to the CGE part of the model. Section 3 describes the general features of the CGE model. Scenarios and simulation results are presented in Section 4. Section 5 concludes.

2. The Micro-simulation Model

This section briefly describes the specification of the household income generation model used for micro-simulation and then focuses on the way consistency between micro-simulation and the predictions of the CGE model is achieved. A more detailed discussion of the specification and econometric estimates of the various equations of the household income generation model and simulation methodology may be found in Alatas and Bourguignon (2000).\textsuperscript{5}

With the notations used in the rest of this paper, the household income generation model for household $m$ with $k_m$ working age members consists of the following set of equations:

\begin{align}
\text{Log } w_{mi} &= \alpha_{g(mi)} + x_{mi} \beta_{g(mi)} + \nu_{mi} \\
\text{Log } y_m &= \gamma_{f(m)} + Z_m \delta_{f(m)} + \lambda_{f(n)} N_m + \eta_m \\
Y_m &= \frac{1}{P_m} \left( \sum_{i=1}^{k_m} w_{mi} IW_{mi} + y_m Ind\left(N_m > 0\right) + y_{0m} \right) \\
P_m &= \sum_{k=1}^{K} s_{mk} p_k \\
IW_{mi} &= Ind\left[\alpha_{\theta(mi)} + z_{mi} h_{\theta(mi)} + u_{mi} > Sup\left(0, \alpha_{\theta(mi)} + z_{mi} h_{\theta(mi)} + u_{mi}\right)\right]
\end{align}
The first equation expresses the (log) earnings of member $i$ of household $m$ as a function of his/her personal characteristics, $x$. The latter essentially include age, schooling level, and region. The residual term, $v_{mi}$, describes the effects of unobserved earning determinants. This earning function is defined separately on various “segments” of the labor market defined by gender, skill (less than secondary or more than primary), and area (urban/rural). Thus $g(mi)$ is an index function that indicates the labor market segment which member $i$ in household $m$ belongs to.

The second equation is the (net) income function associated with self-employment, or small entrepreneurial activity, which includes both the opportunity cost of household labor and profit. This function is defined at the household level. It depends on the number $N_m$ of household members actually involved in that activity and on some household characteristics, $Z_m$. These include area of residence, the age and schooling of the household head, and land size for farmers. The residual term, $\eta_m$, summarizes the effects of unobserved determinants of self-employment income. A different function is used depending on whether the household is involved in farm or non-farm activity. This is exogenous and defined by whether the household has access to land or not, as represented by the index function $f(m)$.

The third equation is an accounting identity that defines total household real income, $Y_m$, as the sum of wage income of its members, profit from self-employment, and (exogenous) non-labor income, $y_{0m}$. In this equation, the notation $W_{mi}$ stands for a dummy variable that is equal to unity if member $i$ is a wage worker and zero otherwise. Thus wages are summed over only those members actually engaged in wage work. Likewise, income from self-employment has to be
taken into account only if there is at least one member of the household engaged in self-
employment activity \( (N_m > 0) \). Total income is then deflated by a household specific consumer
price index, \( P_m \), which is derived from the observed budget shares, \( s_{mk} \), of household \( m \) and the
price, \( p_k \), of the various consumption goods, \( k \), in the model (equation 4).

The last two equations represent the occupational choice made by household members.
This choice is discrete. Each individual has to choose from three alternatives: being inactive,
being a wage worker, or being self-employed. This choice is represented within a discrete utility-
maximizing framework. The utility associated with the first alternative (inactivity) is arbitrarily
set to zero, whereas the utility of being a wage worker or a self-employed are linear functions of
a set of individual and household characteristics, \( z_{mi} \). The intercept of these functions has a
component, \( a^w \) or \( a^s \), that is common to all individuals and an idiosyncratic term, \( u_{mi} \), which
stands for unobserved determinants of occupational choices. The coefficients of individual
characteristics \( z_{mi} \), \( b^w \), or \( b^s \), are common to all individuals. However, they may differ across
demographic groups indexed by \( h(mi) \). For instance, occupational choice behavior, as described
by coefficients \( a^w \), \( a^s \), \( b^w \) and \( b^s \) may be different for household heads, spouses, male or female
children. The constants may also be demography specific.

Given this specification, an individual will prefer wage work if the utility associated with
that activity is higher than that associated with the two other activities. This is the meaning of
equation (5). Likewise, the number of self-employed workers in a household is the number of
individuals for whom the utility of self-employment is higher than that of the two alternatives, as
represented in equation (6).\(^6\)

The model is now complete. Overall, it defines the total real income of a household as a
non-linear function of the observed characteristics of household members \( (x_{mi} \text{ and } z_{mi}) \), some
characteristics of the household \((Z_m)\), its budget shares \((s_m)\), and unobserved characteristics \((v_{mi}, \eta_m, u^w_{mi}, \text{and } u^s_{mi})\). This function depends on five sets of parameters. The parameters in the earning functions \((\alpha^g \text{ and } \beta^g)\), for each labor market segment, \(g\); the parameters of the self-employment income functions \((\gamma^f, \delta^f, \text{and } \lambda^f)\) for the farm or non-farm sector, \(f\); the parameters in the utility of the alternative occupational choices \((a^w_{kh}, b^w_{kh}, a^s_{kh} \text{ and } b^s_{kh})\), for the various demographic groups \(h\); and the vector of prices \((p)\). We shall see below that it is through several of these parameters that the results of the CGE part of the model may be transmitted to the micro-simulation module.

The micro-simulation model gives a rather complete description of household income generation mechanisms by focusing on both earning and occupational choice determinants. However, a number of assumptions about the functioning of the labor market are incorporated in this specification. The fact that labor supply is considered as a discrete choice between inactivity and full time work for wages or for self-employment income within the household calls for two sets of remarks. First, the assumption that individuals either are inactive or work full time is justified essentially by the fact that no information on working time is available in the micro data source used to estimate the benchmark set of the model's coefficients. Practically, this implies that estimated individual earning functions (1) and profit functions (2) may incorporate some labor supply dimension. Second, distinguishing between wage work and self-employment is implicitly equivalent to assuming that the Indonesian labor market is imperfectly competitive. If this were not the case, then returns to labor would be the same in both types of occupation and self-employment income would be different from outside wage income only because it would incorporate the returns to non-labor assets being used. The specification that has been selected is partly justified by the fact that assets used in self-employment are not observed, so that one cannot distinguish between self-employment income derived from labor and that derived from
other assets. But it is also justified by the fact that the labor market may be segmented in the
sense that labor returns are not equalized across wage work and self-employment. There may be
various reasons for this. On the one hand, there may be rationing in the wage labor market.
People unable to find a job as wage workers move into self-employment, which is a kind of
shelter. On the other hand, there may be externalities that make working within and outside the
household imperfect substitutes. All these interpretations are fully consistent with the way in
which the labor-market is represented in the CGE part of the model.7

We now describe how the link is made with the CGE part of the model and how the
effects of macro-economic shocks and policies are simulated on each household in the data base.
The principle of these simulations is extremely simple. It consists of associating macro-economic
shocks and policies simulated in the CGE part of the model to changes in the set of coefficients
of the household income generation model (1)-(6). With a new set of coefficients \((\alpha^g, \beta^g, \gamma^f, \delta^f, \\
\lambda^f, a^w_h, b^w_h, a^s_h, b^s_h)\) and the observed and unobserved individual and household characteristics
\((x_{mi}, z_{mi}, Z_m, s_m, v_{mi}, \eta_m, u^w_{mi}, u^s_{mi})\), these equations permit to compute the occupational status of
all household members, their earnings, the self-employment income and finally the total real
income of the household. But this association has to be done in a consistent way. Consistency
with the equilibrium of aggregate markets in the CGE model requires that: (1) changes in average
earnings with respect to the benchmark in the micro-simulation must be equal to changes in wage
rates in the CGE model for each segment of the market for wage labor; (2) changes in self-
employment income in the micro-simulation must be equal to changes in informal sector income
per worker in the CGE model; (3) changes in the number of wage workers and self-employed by
labor-market segment in the micro-simulation model must match those same changes in the CGE
model, (4) and changes in the consumption price vector, $p$, must be consistent with the CGE model.

The linkage between the CGE part of the model and the micro-simulation part is obtained through the resolution of the following system of equations:

$$
\sum_m \sum_{i,g(m_i)=G} \text{Ind}(a_{h(m_i)}^w + z_{m_i} \hat{b}_{h(m_i)}^w + \hat{u}_{m_i}^w > \text{Sup}(0, a_{h(m_i)}^w + z_{m_i} \hat{b}_{h(m_i)}^w + \hat{u}_{m_i}^w)) = E_G^*
$$

$$
\sum_m \sum_{i,g(m_i)=G} \text{Ind}(a_{h(m_i)}^* + z_{m_i} \hat{b}_{h(m_i)}^* + \hat{u}_{m_i}^w > \text{Sup}(0, a_{h(m_i)}^* + z_{m_i} \hat{b}_{h(m_i)}^* + \hat{u}_{m_i}^w)) = S_G^*
$$

$$
\sum_m \sum_{i,g(m_i)=G} \text{Exp}(\alpha_s^* + x_m \hat{\beta}_G + \hat{\gamma}_{m_i}) \text{Ind}(a_{h(m_i)}^w + z_{m_i} \hat{b}_{h(m_i)}^w + \hat{u}_{m_i}^w > \text{Sup}(0, a_{h(m_i)}^w + z_{m_i} \hat{b}_{h(m_i)}^w + \hat{u}_{m_i}^w)) = w_G^*
$$

$$
\sum_m \sum_{i,f(m_i)=F} \text{Exp}(\gamma_f^* + Z_m \hat{\delta}_F + \hat{\lambda}_f \hat{N}_m + \hat{\eta}_m) \text{Ind}(N_m > 0) = I_F^*
$$

with

$$\hat{N}_m = \sum_i \text{Ind}(a_{h(m_i)}^w + z_{m_i} \hat{b}_{h(m_i)}^w + \hat{u}_{m_i}^w > \text{Sup}(0, a_{h(m_i)}^w + z_{m_i} \hat{b}_{h(m_i)}^w + \hat{u}_{m_i}^w))$$

where the unknowns are $\alpha^*_s$, $\gamma^*_f$, $a_{h}^w$ and $\alpha^*_h$. This system of equations has as many equations as unknowns, and has a unique solution which can be obtained through standard Gauss-Newton techniques. Once the solution is obtained, it is a simple matter to compute the new income of each household in the sample, according to model (1)-(6), with the new set of coefficients $\alpha^*_s$, $\gamma^*_f$, $a_{h}^w$ and $\alpha^*_h$ and then to analyze the modification that this implies for the overall distribution of income.

The justification for using the intercepts rather is that it implies a "neutrality" of the changes being made with respect to individual or household characteristics. For example, changing the intercepts of the log earning equations generates a proportional change of all earnings in a labor-market segment, irrespectively of individual characteristics—outside those
that define the labor-market segments, that is skill, gender, and area. The same is true of the change in the intercept of the log self-employment income functions. It turns out that a similar argument applies to the criteria associated with the various occupational choices. Indeed, it is easily shown that changing the intercepts of the multi-logit model implies the following neutrality property. The relative change in the *ex-ante* probability that an individual has some occupation depends only on the initial ex-ante probabilities of the various occupational choices, rather than on individual characteristics.

In the Indonesian case, the number of variables that allow the micro and the macro parts of the overall model to communicate, that is the vector \((E^*_G, S^*_G, w^*_G, I^*_F, q^*)\), is equal to 26 plus the number of consumption goods used in defining the household specific CPI deflator. There are 8 segments in the labor market. The employment requirements for each segment in the formal (wage work) and the informal (self-employment) sectors \((E^*_G, S^*_G)\) lead to 16 restrictions. In addition there are 8 wage rates in the formal sector \((w^*_G)\) and 2 levels of self-employment income \((I^*_F)\) in the formal and the informal sector. Thus, simulated changes in the distribution of income implied by the CGE part of the model are obtained through a procedure that comprises a rather sizable number of degrees of freedom.

Two last points must be kept in mind in order to evaluate the actual scope of the micro-simulation model. First, the household-specific price index, \(P_m\), is based on the disaggregation of expenditure into only two goods, food and non-food. It turns out that this disaggregation is indeed the most relevant one for the analysis of the consequences of the Indonesian crisis. Second, other incomes, \(y_{0m}\), are considered as exogenous (in real terms) in all simulations. They include housing and land rents, dividends, royalties, imputed rents from self-occupied housing,
and transfers from other households and institutions. It could have been possible to endogenize some of these items in the CGE model, but this was not done.

3. The CGE Model

The CGE model is based on a Social Accounting Matrix (SAM) for the year 1995. The SAM has been disaggregated using cross-entropy estimation methods (Robinson, Cattaneo, and El-Said, 2000) in order to include 38 sectors, 14 goods, 14 factors of production (8 labor categories and 6 types of capital), and 10 households types, as well as the usual accounts for aggregate agents (firms, government, rest of the world, savings-investment). The CGE model starts from the standard neoclassical specification in Dervis et al. (1982), but it also incorporates the disaggregation of production sectors into formal and informal activities and associated labor-market imperfections.

Markets for goods, factors, and foreign exchange are assumed to respond to changing demand and supply conditions, which in turn are affected by government policies, the external environment, and other exogenous influences. The model is Walrasian in that it determines only relative prices, and other endogenous real variables in the economy. Financial mechanisms are modeled implicitly and only their real effect is taken into account in a simplified way. Sectoral product prices, factor prices, and the real exchange rate are defined relatively to the producer price index of goods for domestic use, which serves as the numéraire. The exchange rate represents the relative price of tradable goods vis-a-vis nontraded goods (in units of domestic currency per unit of foreign currency).
Activities and Commodities

Indonesia’s economy is dualistic, which the model captures by distinguishing between formal and informal “activities” in each sector. Both sub-sectors differ in the type of factors they use. This distinction allows treating formal and informal factor markets differently. Informal and formal sectors are further differentiated by the fact that formal sectors are assumed to rely on foreign credit to operate whereas informal sectors do not.

For all activities, the production technology is represented by a set of nested CES (constant-elasticity-of-substitution) value-added functions and fixed (Leontief) intermediate input coefficients. On the demand side, imperfect substitutability is assumed between formal and informal products. Thus, consumers demand an aggregate of the formal and informal products. Domestic prices of commodities are flexible, varying to clear markets in a competitive setting where individual suppliers and demanders are price-takers.

Following Armington (1969), the model assumes imperfect substitutability, for each good, between the domestic commodity – which results itself from a combination of formal and informal activities - and imports. What is demanded is a composite good, which is a CES aggregation of imports and domestically produced goods. For export commodities, the allocation of domestic output between exports and domestic sales is determined on the assumption that domestic producers maximize profits subject to imperfect transformability between these two alternatives. The composite production good is a CET (constant-elasticity-of-transformation) aggregation of sectoral exports and domestically consumed products.
These assumptions of imperfect substitutability and transformability grant the domestic price system some degree of autonomy from international prices and serve to dampen export and import responses to changes in the producer environment. Such treatment of exports and imports provides a continuum of tradability and allows two-way trade at the sector level—which reflects what is observed empirically at the level of aggregation of the model.

Factors of Production

There are eight labor categories in the Indonesia CGE model: Urban Male Unskilled, Urban Male Skilled, Urban Female Unskilled, Urban Female Skilled, Rural Male Unskilled, Rural Male Skilled, Rural Female Unskilled, and Rural Female Skilled. Male and female, as well as skilled and unskilled labor are assumed to be imperfect substitutes in the production activity of urban or rural sectors.

In addition, labor markets are assumed to be segmented between formal and informal sectors. In the formal-sector labor markets, imperfect competition mechanisms are assumed to result into some increasing wage-employment curve and real wages are defined by the intersection of that curve and competitive labor demand. Informal sector labor is equivalent with self-employment. Wages in that sector are set so as to absorb any labor not employed in the formal sectors. Wages adjust to clear all labor markets in the informal sectors, while employment adjusts in the formal sectors.

Land appears as a factor of production in the agricultural sectors. Only one type of land is considered in the model. It is competitively allocated among the different crop sectors so that marginal value-added is equalized across activities.
Capital markets are segmented into six categories: owner occupied housing, other unincorporated rural capital, other unincorporated urban capital, domestic private incorporated capital, public capital, and foreign capital. Given the short-term perspective of the model, it is assumed that capital is fixed in each activity.

The model also incorporates working capital requirements by all sectors. Sectors demand domestic working capital in proportion to their demands for domestically produced intermediate inputs. They also demand working capital denominated in foreign exchange in proportion to their demands for imported intermediate inputs. Informal sectors are assumed not to require any imported intermediate inputs.

Working capital is treated as a factor input which is strictly complementary to physical capital. The model incorporates a nested production function in all sectors, with aggregate “capital” consisting of an aggregation of physical capital, domestic working capital, and foreign working capital (foreign exchange). Both types of working capital are assumed to be required in fixed proportions to physical capital. When the supplies of aggregate domestic and foreign working capital are reduced, as an effect of the financial crisis, they are assumed to be competitively allocated across sectors, so that their marginal revenue product is the same everywhere. As physical capital is fixed, this causes capacity under-utilization in some sectors.

The effect of this treatment is to make aggregate output sensitive to any reduction in the supply of working capital. With cuts in working capital, the utilization of physical capital will also decline. The sector impact depends on sectors' dependence on intermediate inputs, both domestic and imported.
Households

The disaggregation of households in the CGE model is not central for our purpose since changes in factor prices are passed on directly to the micro-simulation model, without use of the representative household groups (RHG) used in the original SAM. Consumption demand by households at the CGE level is determined by the linear expenditure system (LES), in which the marginal budget share is fixed and each commodity has a minimum consumption (subsistence) level.

Macro Closure Rules

Equilibrium in a CGE model is defined by a set of constraints that need to be satisfied by the economic system but are not considered directly in the decisions of micro agents (Robinson, 1989, pp. 907-908). Aside from the supply-demand balances in product and factor markets, three macroeconomic balances are specified in the Indonesia CGE model: (i) the fiscal balance, with government savings equal to the difference between government revenue and spending; (ii) the external trade balance (in goods and non-factor services), which implicitly equates the supply and demand for foreign exchange - flows, not stocks since the model has no assets or asset markets; and (iii) savings-investment balance. Practically, a “balanced” macro closure is used whereby aggregate investment and government spending are assumed to be in a fixed proportion of total absorption. Any shock affecting total absorption is thus assumed to be shared proportionately among government spending, aggregate investment, and aggregate private consumption. While simple, this closure effectively assumes a «successful» structural adjustment program whereby a
macro shock is assumed not to cause particular actors - government, consumers, and industry - to bear an disproportionate share of the adjustment burden.

4. Scenarios and Simulations

As mentioned above, both parts of the model are handled separately, with the macro level communicating with the micro part through a vector of “linkage variables” that consists of prices, wages, and aggregate employment variables. The overall structure is “top down” in that there is no feedback from the micro-simulation model back to the macro CGE model. This top-down sequential structure allows running various kinds of experiments. In the first set of experiments - labeled “historical simulation” - historical changes in the “linkage variables” are derived from price statistics and labor market surveys taken during and after the crisis, and fed directly into the micro-simulation model, without any use of the macro CGE model. Thus, this historical simulation is essentially meant to test the capacity of the micro-simulation model to generate income distribution predictions on the basis of a few observed macro indicators. In the second set of simulations - labeled “policy simulations” - the value of linkage variables is taken from runs with the CGE model. These simulations are used to decompose the historical shock into various elementary components.

Time Horizon

The question of the time horizon calls for some comments. The financial crisis hit Indonesia during Summer 1997 and the turmoil spanned approximately 20 months until March 1999 when the first signs of output recovery where recorded (Azis and Thorbecke, 2001). Given
the equilibrium nature of the macro framework and of the linkage variables between the macro and the micro models, we chose not to try to track the crisis month by month, but instead to analyze the impact of the shock using comparative statics. The deviations from base values used as historical references are thus computed for a period extending from July-August 1997 to September-October 1998. The latest date corresponds to the peak of the crisis with respect to macroeconomic indicators (Azis and Thorbecke, 2001) as well as poverty indicators (Suryahadi et al., 2000).

The analysis of this short-term shock in a CGE framework is made possible by imposing a number of rigidities in the specification of factor markets – as seen above. The base year for the macro model is the Social Accounting Matrix for the year 1995, with consumption structure derived from SUSENAS 1996 and factor disaggregation based on SUSENAS 1996. The sample used for the micro-simulation is a sub sample of SUSENAS 1996. Some inconsistency could arise between the macro and the micro parts of the model because they do not refer to the same year. The sequential nature of the framework used in this paper permits to dispense with full consistency between the macro and the micro sides of the model, however. Indeed all the analysis may be performed in terms of deviations from benchmarks which may not fit perfectly well to each other.  

10

Historical Changes in Poverty

As pointed out earlier, different estimates of the impact of the financial crisis on poverty and income distribution based on before-after comparison have been published. The results reported by Suryahadi et al. (2000) are used as a reference for analyzing the historical change in
poverty and income distribution. These authors used various household surveys to compute changes in real income over the period 1996 to 1999. Although poverty rates derived from SUSENAS would be consistent with the household sample used in the model, changes derived from the Indonesia Family Life Survey (IFLS), adjusted to achieve consistency with other estimates (Suryahadi et al., 2000), were used as a general benchmark. This choice is justified on the one hand by the fact that, being three years apart, SUSENAS surveys do not permit isolating the crisis period, and on the other hand by the fact that the second wave of the IFLS survey was specifically designed to understand how the crisis affected welfare (Frankenberg, Thomas, and Beegle, 1999). Based on IFLS estimates adjusted by Suryahadi et al. (2000), poverty incidence increased by 164 per cent between September 1997 and October 98.11

Since IFLS results reported by Suryahadi et al. do not permit distinguishing the urban and the rural sectors, we report in Table 1 estimates based on SUSENAS 1996 and 1999 surveys to show how urban and rural households fared over the period. The overall increase in poverty appears to be much smaller than the one, just quoted, obtained using IFLS data. This is consistent with the difference in the time coverage of both sources since poverty decreased with the recovery after October 1998. Figures in Table 1 also show that poverty increased more in the urban sector than in the rural sector. Poverty remains nevertheless higher in the rural sector because of the initial disadvantage of that sector. The strong increases in the poverty gap indicator (P1) and the poverty severity index (P2) also show that the situation has deteriorated more over the 1996-99 period for the poorest of the poor.
Historical experiment

The first experiment, called “historical”, uses historical vectors of the linkage variables (prices, wages, and aggregate employment changes) to feed into the micro-simulation model. Changes in the last two sets of variables are shown in Table 2. They are derived from the comparison of two SAKERNAS surveys for 1997 and 1998. Consumer price changes – not reported - are taken from reports by BPS. SAKERNAS surveys do not permit observing the changes in self-employment incomes. We assume that they are equal to changes in wages. This assumption is probably unsatisfactory in the case of rural self employment incomes because of the effect of the increase in relative output prices. The comparison of the 1997 and 1998 employment surveys shows a dramatic fall in real wages and an important shift out of wage work and into self employment activities over the period. It also suggests that overall inactivity did not increase significantly. The picture differs slightly however across labor types. The movement out of wage work and into self employment activities is observed for all but two categories, urban and rural unskilled females. Concerning the employment rate, although stable overall, it decreases for all skilled categories while it increases for all unskilled categories.\textsuperscript{12}

Results in terms of poverty and inequality from the micro-simulation model under the preceding assumptions are presented in Table 3. They show a 238.6 per cent increase in poverty, higher than the historical change of 164 per cent reported by Suryahadi et al. (2000) based on the comparison of IFLS 1997 and 1998. This over estimation can be explained by the simulation ignoring the fact that self employment incomes decreased less than real wages. The poverty increase appears to be fuelled by the dramatic income shock - a 40.4 per cent drop in mean per capita income. Results also show an increase in inequality driven by the increase of \textit{within-sector} inequality: although rural and urban mean per capita income “converge” as the fall in per capita
income in the urban sector is bigger than in the rural sector -44.8 and -26.5 per cent respectively – the decrease in between-sector inequality does not compensate the increases within the urban and rural sectors. In terms of the rural-urban divide, the results appear consistent with the historical record shown in Table 1, although it refers to a distinct period. The poverty increase in the urban sector is much higher than in the rural sector, but poverty remains higher in the rural sector.

These different results show the capacity of the micro-simulation framework to generate plausible income distribution predictions on the basis of a few observed macro indicators.

**CGE experiments**

In the following experiments, the vector of linkage variables fed into the micro-simulation is derived from the results of the CGE model. The set of experiments presented attempts to reproduce and decompose the effect of the crisis within the framework of the CGE model.

The base CGE scenario seeks to reproduce the evolution of the Indonesian economy between 1997 and 1998 in terms of changes in employment, wages, and macroeconomic aggregates. The most important external shocks during that period are the financial crisis and the extended El Nino drought. The drought is simulated through a negative 5 per cent shock on the total productivity factor in agricultural sectors. It is also assumed that there was a 25 per cent increase in the marketing cost of food. This reflects the fact that traders, more than producers, are expected to benefit from the food price increase. The financial crisis is simulated through a combination of different shocks. First, it is assumed that the need to adjust the current account led to a real devaluation which is simulated through a 30 per cent decrease in the exogenous
foreign saving flows to the economy (SIMDEV scenario). As a result of the devaluation, all sectors experienced a “credit crunch”, simulated through a cut in the supply of working capital. As seen above, two types of working capital are considered. In a first stage the impact of a 25 per cent cut in the availability of foreign working capital is examined in combination with the real devaluation described above (the DEVCCF scenario). In a second stage, the impact of a 20 per cent cut in the availability of domestic credit crunch (FINCRI scenario) is considered. The domestic credit crunch shock is viewed as stemming from the foreign credit crunch. As a result, it is simulated in combination with the two previous components of the financial crisis. The resulting simulation can then be analyzed as mimicking a “pure” financial crisis shock, without any other historical shock. The effect of El Nino drought is first simulated alone (SIMELN scenario) and then in combination with the financial crisis, thus yielding something that should be close to the what actually happened in Indonesia between 1997 ad 1998 (the SIMALL scenario).

Table 4 shows the contribution of the different elements of the crisis to the total negative real GDP shock. The historical simulation captures the main changes observed over the period: a 14.4 per cent drop in GDP, a fall in imports and a surge of exports, an increase in the relative price of food commodities, and a drop in real wages. The combination of the different shocks show that the “credit crunch” is the major force explaining the collapse of GDP, while the drought combined with the increase in the marketing cost of food appears to be the main driving force behind the increase in the relative price of food commodities.

In terms of the impact of the macro shocks on poverty and income distribution, results in Table 5 show that the modeling exercise yields a 143.4 per cent increase in the poverty headcount ratio when all components of the crisis are taken into account (SIMALL). This surge in poverty
appears to be fuelled both by the drop in the average income per capita and by an important increase in inequality indicators. Both the financial crisis and El Nino drought contribute to the negative income impact and the increase in inequality.

In terms of the rural-urban divide, the CGE experiments are able to capture to some extent the differences in per capita income changes simulated in the historical simulation. This divide is apparent in terms of poverty changes, since urban poverty increases by 301.4 per cent, while rural poverty increases by 112.2 per cent. This can be explained by the differential income shocks in the urban and in the rural sector. Results also show that inequality indicators increase in both sectors.

5. Summary and Conclusion

The new micro-macro framework introduced in this paper generates income changes in a sample of households drawn from a household survey which are consistent, once they have been aggregated, with the predictions of a multi-sector CGE-like macro model. It was shown in this paper that this framework could capture important channels through which the financial crisis affected household incomes. This result is obtained through an explicit representation of the actual combination of different income sources within households, and the way in which this combination may change through desired or undesired modifications of occupational status of household members.

Compared to standard CGE or before-after analysis, the framework developed in this paper allows for an original analysis of the distributional effects of a financial crisis like the one that hit Indonesia in 1997. At the macro-level, the analysis showed that the credit crunch was an
important driving force behind the collapse of GDP in Indonesia, while the devaluation combined with the increase in the marketing costs of food appear to be the main driving force behind the increase in the relative price of food with respect to non-food commodities. At the micro-level, heterogeneity of households with respect to factor endowments, consumption behavior and occupational choices, whether free or forced, proved to be important in explaining the poverty and distribution effect of the crisis.

It remains that these are pure simulations meant to be consistent with what was observed in aggregate terms in Indonesia but which cannot be compared with actual data at the micro-economic level. Under these conditions, it is difficult to say that a simulation or a methodology is “better” than the other one. The appeal of the framework developed in this paper is to account for realistic shocks on household economic conditions and in particular on the occupational status of their members. That it does so in a way that is selective across households is also appealing as suggested by casual observation of household conditions in crisis periods. The main problem, however, is that this selectivity is introduced essentially by translating observed cross-sectional differences in household income generation behavior into the time dimension. In other words, the simulation methodology in this paper relies on the standard assumption in economics that a household who will face some specific conditions on the labor market tomorrow in a period of crisis will behave like a household which is observed in the same conditions today. Checking whether this is justified could be done only with panel data. This is left for future work.
References


Table 1: Evolution of Poverty in Indonesia, 1996-1999

<table>
<thead>
<tr>
<th></th>
<th>All Households</th>
<th>Urban Households</th>
<th>Rural Households</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1996 1999 % change</td>
<td>1996 1999 % change</td>
<td>1996 1999 % change</td>
</tr>
<tr>
<td>Head-Count Index (P0)</td>
<td>9.75 16.27 66.8%</td>
<td>3.82 9.63 152.3%</td>
<td>13.10 20.56 56.9%</td>
</tr>
<tr>
<td>Poverty Gap Index (P1)</td>
<td>1.55 2.79 80.2%</td>
<td>0.53 1.51 183.0%</td>
<td>2.12 3.61 70.5%</td>
</tr>
<tr>
<td>Poverty Severity Index (P2)</td>
<td>0.39 0.75 91.9%</td>
<td>0.12 0.37 201.6%</td>
<td>0.54 0.99 83.6%</td>
</tr>
</tbody>
</table>


Table 2: Evolution of occupational choices and wages by segment 1997-1998

<table>
<thead>
<tr>
<th>Segment</th>
<th>Inactive</th>
<th>Wage Worker</th>
<th>Self Employed</th>
<th>Nominal Wage</th>
<th>Real Wage*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban Male Unskilled</td>
<td>-0.9</td>
<td>-6.5</td>
<td>5.7</td>
<td>8.2</td>
<td>-40.8</td>
</tr>
<tr>
<td>Urban Male Skilled</td>
<td>11.9</td>
<td>-12.7</td>
<td>9.9</td>
<td>5.3</td>
<td>-42.3</td>
</tr>
<tr>
<td>Urban Female Unskilled</td>
<td>-2.6</td>
<td>5.1</td>
<td>5.9</td>
<td>21.8</td>
<td>-33.4</td>
</tr>
<tr>
<td>Urban Female Skilled</td>
<td>5.9</td>
<td>-15.5</td>
<td>2.3</td>
<td>10.3</td>
<td>-39.6</td>
</tr>
<tr>
<td>Rural Male Unskilled</td>
<td>-1.8</td>
<td>-13.6</td>
<td>5.1</td>
<td>27.9</td>
<td>-30.0</td>
</tr>
<tr>
<td>Rural Male Skilled</td>
<td>2.5</td>
<td>-13.3</td>
<td>9.3</td>
<td>16.8</td>
<td>-36.1</td>
</tr>
<tr>
<td>Rural Female Unskilled</td>
<td>-5.5</td>
<td>0.0</td>
<td>7.5</td>
<td>47.3</td>
<td>-19.4</td>
</tr>
<tr>
<td>Rural Female Skilled</td>
<td>2.7</td>
<td>-14.3</td>
<td>3.4</td>
<td>12.2</td>
<td>-38.6</td>
</tr>
<tr>
<td>All</td>
<td>-0.3</td>
<td>-10.2</td>
<td>5.8</td>
<td>11.7</td>
<td>-38.9</td>
</tr>
</tbody>
</table>

Notes: 1. Numbers for 3 first columns are percent changes in proportions.
2. Real wage is equal to nominal wage deflated by CPI base year 1996 = 100.

Table 3: Historical Simulation Results

<table>
<thead>
<tr>
<th>Income and relative price changes</th>
<th>All Households</th>
<th>Urban Households</th>
<th>Rural Households</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per Capita Income (Rp. thousands)</td>
<td>121.1 -40.4</td>
<td>171.0 -44.3</td>
<td>90.6 -35.9</td>
</tr>
<tr>
<td>Entropy Index 0 (x 100)</td>
<td>35.5 2.7</td>
<td>38.7 10.2</td>
<td>25.6 9.0</td>
</tr>
<tr>
<td>Entropy Index 1 (x 100)</td>
<td>49.3 0.9</td>
<td>53.9 8.7</td>
<td>33.1 4.9</td>
</tr>
<tr>
<td>Gini Index (%)</td>
<td>45.6 0.2</td>
<td>47.5 3.9</td>
<td>38.7 2.9</td>
</tr>
<tr>
<td>Head-Count Index (P0)</td>
<td>9.2 238.6</td>
<td>4.0 432.9</td>
<td>12.4 200.4</td>
</tr>
<tr>
<td>Poverty Gap Index (P1)</td>
<td>2.2 340.5</td>
<td>1.0 528.8</td>
<td>2.9 299.0</td>
</tr>
<tr>
<td>Poverty Severity Index (P2)</td>
<td>0.9 408.8</td>
<td>0.4 648.5</td>
<td>1.2 355.9</td>
</tr>
</tbody>
</table>

Source: Results from micro-simulation module using historical changes in prices, wages and occupational choices by segment (see Table 2). Self employment income is assumed to be cut by the same magnitude as male unskilled wage, that is -40% in the urban sector and -30% in the rural sector.
Notes: 1. Base values for BASE column and percent change for other simulations.
2. Per capita income is total monthly income.
Table 4: Simulation Results: Macro Aggregates

<table>
<thead>
<tr>
<th></th>
<th>BASE</th>
<th>SIMELN</th>
<th>SIMDEV</th>
<th>DEVCCF</th>
<th>FINCRI</th>
<th>SIMALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP at Factor Costs (Rp. thousands of billions)</td>
<td>535.6</td>
<td>-0.5</td>
<td>-0.9</td>
<td>-10.7</td>
<td>-14.1</td>
<td>-14.4</td>
</tr>
<tr>
<td>Exports (Rp. thousands of billions)</td>
<td>122.7</td>
<td>-0.4</td>
<td>28.8</td>
<td>19.4</td>
<td>15.4</td>
<td>13.1</td>
</tr>
<tr>
<td>Imports (Rp. thousands of billions)</td>
<td>126.8</td>
<td>-0.3</td>
<td>-19.2</td>
<td>-28.4</td>
<td>-32.2</td>
<td>-34.4</td>
</tr>
<tr>
<td>Exchange Rate</td>
<td>1.0</td>
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<td>31.8</td>
<td>27.3</td>
<td>27.2</td>
<td>24.3</td>
</tr>
<tr>
<td>Food/Non Food Terms of Trade</td>
<td>1.0</td>
<td>27.3</td>
<td>15.4</td>
<td>-4.2</td>
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<td>21.0</td>
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<tr>
<td>Incorporated Capital Income</td>
<td>1.0</td>
<td>-13.2</td>
<td>7.8</td>
<td>43.0</td>
<td>32.2</td>
<td>19.7</td>
</tr>
<tr>
<td>Agricultural Self Employment Income</td>
<td>1.6</td>
<td>-5.9</td>
<td>8.2</td>
<td>-8.0</td>
<td>-18.5</td>
<td>-23.4</td>
</tr>
<tr>
<td>Skilled Labor Wage</td>
<td>4.9</td>
<td>-17.5</td>
<td>-12.8</td>
<td>-37.5</td>
<td>-42.2</td>
<td>-50.9</td>
</tr>
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<td>Unskilled Labor Wage</td>
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<td>-12.6</td>
<td>-32.3</td>
<td>-35.5</td>
<td>-43.0</td>
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Notes: 1. Base values for BASE column and percent change for other simulations.
2. Incorporated Capital Income includes private, public, and foreign capital income.
3. Self employment and wage incomes are equal to value-added divided by quantity of labor units in the Social Accounting Matrix.
4. SIMELN = El Nino Drought; SIMDEV = Real Devaluation; DEVCCF = Real devaluation + Foreign Credit Crunch; FINCRI = Real devaluation + Foreign Credit Crunch + Domestic Credit Crunch; SIMALL = Real devaluation + Foreign Credit Crunch + Domestic Credit Crunch + El Nino Drought.

Table 5: Simulation Results: Per capita income, inequality, and poverty indicators

<table>
<thead>
<tr>
<th></th>
<th>ALL BASE</th>
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<th>DEVCCF</th>
<th>FINCRI</th>
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<tr>
<td>Per Capita Income (Rp. thousands)</td>
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<td>-3.0</td>
<td>1.3</td>
<td>5.2</td>
</tr>
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<td>1.7</td>
<td>-2.9</td>
<td>1.0</td>
<td>6.7</td>
</tr>
<tr>
<td>Gini Index (%)</td>
<td>45.5</td>
<td>1.3</td>
<td>0.3</td>
<td>-1.8</td>
<td>0.2</td>
<td>2.2</td>
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<tr>
<td>Head-Count Index (P0)</td>
<td>9.2</td>
<td>49.7</td>
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<tr>
<td>Poverty Severity Index (P2)</td>
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<table>
<thead>
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<td>Entropy Index 0 (x100)</td>
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<td>5.4</td>
<td>4.5</td>
<td>8.0</td>
<td>15.0</td>
</tr>
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<td>4.5</td>
<td>6.8</td>
<td>15.1</td>
</tr>
<tr>
<td>Gini Index (%)</td>
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<td>2.4</td>
<td>2.1</td>
<td>3.5</td>
<td>6.9</td>
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<td>167.1</td>
<td>301.4</td>
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<td>135.1</td>
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<table>
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<th>RURAL BASE</th>
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<th>SIMDEV</th>
<th>DEVCCF</th>
<th>FINCRI</th>
<th>SIMALL</th>
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</thead>
<tbody>
<tr>
<td>Per Capita Income (Rp. thousands)</td>
<td>90.6</td>
<td>-10.5</td>
<td>-2.0</td>
<td>-7.7</td>
<td>-12.8</td>
<td>-21.5</td>
</tr>
<tr>
<td>Entropy Index 0 (x100)</td>
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<td>3.7</td>
<td>5.1</td>
<td>8.8</td>
<td>12.0</td>
</tr>
<tr>
<td>Entropy Index 1 (x100)</td>
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<td>3.6</td>
<td>5.5</td>
<td>9.8</td>
<td>14.6</td>
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<tr>
<td>Gini Index (%)</td>
<td>38.7</td>
<td>1.8</td>
<td>1.3</td>
<td>1.9</td>
<td>3.7</td>
<td>5.1</td>
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<tr>
<td>Head-Count Index (P0)</td>
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<td>36.0</td>
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<td>50.8</td>
<td>88.5</td>
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Note: 1. Base values for BASE column and percent change for other simulations.
2. Per capita income is total monthly income.
3. SIMELN = El Nino Drought; SIMDEV = Real Devaluation; DEVCCF = Real devaluation + Foreign Credit Crunch; FINCRI = Real devaluation + Foreign Credit Crunch + Domestic Credit Crunch; SIMALL = Real devaluation + Foreign Credit Crunch + Domestic Credit Crunch + El Nino Drought.
1 Results from ILO and CBS reports are taken from Booth (1998).

2 Starting with Mukherjee and Shorroks' (1982) study of UK.

3 A detailed comparison of the approach used in this paper with the representative household group approach mentioned earlier is offered in a companion paper (Bourguignon et al, 2002).

4 A tighter integration of the micro and macro models has been attempted within a simpler framework by Cogneau (2001) and Cogneau and Robilliard (2001) and applied to Madagascar. For a general discussion of the link between CGE modeling and micro-unit household data see Plumb (2001).

5 A more general discussion of the model may be found in Bourguignon, Ferreira and Lustig (1998) and Bourguignon, Fournier and Gurgand (2001). For a general discussion of the link between CGE modeling and micro-unit household data see Plumb (2001).

6 Actually, the model also considers the possibility that a person be involved simultaneously in wage work and self-employment. This is taken as an additional alternative in the discrete choice model (5). A dummy variable controls for this in the earning equation (1) and this person is assumed to count for half a worker in the definition of $N_m$. We do not insist on this aspect of the data, and of the model, in order to keep the presentation simple. See Alatas and Bourguignon (2000).

7 This rationing interpretation of the functioning of the labor market leads to reinterpreting the ‘utility’ function defined in (5)-(6) as combining both utility aspects and the way in which the rationing scheme depends on individual characteristics.

8 For the Jacobian used in that method to make sense in the present framework, it is necessary that the number of households and the dispersion of their characteristics be sufficiently high. If this were not the case then the discontinuity implicit in the Ind( ) functions would create problems.

9 This representation of the output effect of the crisis fits the analysis made by Stiglitz. See for instance Stiglitz and Furman (2000).

10 In particular, no attempt was made to reconcile the household survey data with the national accounts.

11 In order to be consistent with the latest estimates of the poverty headcount for 1996, the percent changes reported by Suryahadi et al. (2000) between 1996 and 1997 is applied to the base value computed by Pradhan et al. (2000). This generates an estimate of the poverty headcount of 9.7% in 1997. We then chose an income poverty line that generates the same headcount for our sample and use it as the reference value.

12 Since the SAKERNAS survey does not permit deriving the evolution of self-employment income for agricultural and non-agricultural activities, it was assumed in this historical simulation that self-employment incomes decreased in real terms by the same magnitude as unskilled male wages in the urban and the rural sectors.
Export-led-growth, pro-poor or not?
a case study of Madagascar’s textile and apparel industry∗

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Abstract
Fueled by the low labor costs and recent preferential agreements, such as the African Growth Opportunity Act, exports of textile products originating from Sub-Saharan countries have grown dramatically in the last decades. This paper analyzes the implications that the growth in the textile and apparel sector has for social welfare and poverty reduction in Madagascar. In quantifying the effects of sectoral growth on households, this paper adopts a methodology that combines the wage premium literature and the matching methods literature. The results indicate that the benefits of a sustained export-driven growth in the Malagasy textile and apparel sector are split almost equally between poor and non poor households having the consequence of reducing poverty but also increasing inequality. Welfare effects vary among the different typologies of workers, with skilled individuals gaining the most.

JEL Classification: F14, I32, J31, L67, R20
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1. Introduction

The question of the costs and benefits of the globalization process for developing countries has given rise to a lively debate. Those in favor of globalization argue that trade openness in developing countries increases economic growth and that the poor are fully participant of the benefit of growth. On the other hand, the sceptics note that the empirical evidence is inconclusive and mostly based on average results from which it is problematical to discern the effects on specific segments of the population. Furthermore, they argue that opening to international markets may have several drawbacks including increased volatility, anti-competitive practices by multinationals, reduced opportunities for learning, exploitation of labor, and above all, the possibility that the poor may be marginalized from benefits because they lack skills, have little bargaining power, or live in most remote areas.\(^1\)

So far, studies of the impact on poverty from comparative-advantage based growth have been mostly based on models relying on few representative households as in the CGE models.\(^2\) Those type of studies rely on a macroeconomic framework and rarely analyze the extent to which the benefits, or the costs, are distributed across different population groups.\(^3\) However, welfare effects of economic growth averaged by country, or by broad household groups, although informative, are clearly insufficient in the analysis of a microeconomic phenomenon such as poverty. Economy-wide models become more difficult to estimate in the case of developing countries where data availability and reliability is always an issue. Moreover, developing countries economies are often quite distorted and the behavior of agents and markets are more difficult to model. In such cases economy-wide models quickly become extremely complex as to require a large set of assumptions which may oversimplify the peculiarity of the economy, especially at the microeconomic level.\(^4\)

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1 McCulloh et al 2001 illustrates the linkages between trade liberalization growth and poverty.
2 Such as Löfgren, 2000, and Hertel et al., 2004.
3 The notable exception being Harrison and al, 2003 and Bourguignon et al 2002. However, a fundamental problem is that microeconomic data needs to be combined (and reconciled) with microeconomic data, a process which involves a degree of arbitrariness and assumptions and which increases with the number of representative households in the model.
4 The results of CGE models critically depends on assumed parameters and functions which can barely be tested one-by-one, let alone in combination.
Abstracting from macroeconomic models, a few studies have investigated the effect of globalization on welfare at a more detailed level. The results from those studies have found compelling evidence that integration into world markets, although beneficial for the poor, results in an unequal distribution of the benefit, with the poor gaining less than the non-poor\(^5\) (Bruno et al., 1996; Hanson, 1997; Lundberg and Squire, 1999; and Nicita 2004). From a policy standpoint, the issue on the distribution of the benefit of globalization is important since an increasing number of preferential treatments are also expected to help the poorest countries to grow out of poverty.\(^6\) In this regard, if the poor in developing countries fail to reap any benefit from the increase in trade flows, then the reliability of those preferential treatment aimed to curb poverty would be diminished.

To address the concern if poor benefit and in what extent, this paper introduces a new methodology suited to identify the beneficiaries of globalization and to quantify the benefits at the household level, so as to understand which segments of the population that benefit most and which, if any, are marginalized. The analysis focuses on the labor market which has been recognized as the main transmission between economic growth and poverty (Winters 2001, Hertel and Reimer, 2004).

Economic growth works through the labor market to reduce poverty by creating employment, raising real wages, and increasing participation rates. However, employment growth per se is not sufficient to guarantee poverty reduction. For example, if employment growth is limited to low paying sectors, or if the poor do not own skills sought by expanding sectors, economic growth will likely do little to reduce overall poverty. The extent to which growth is limited to low paid sectors and the extent to which poor own skills sought by expanding industries are precisely the issues examined in this paper.

An exhaustive analysis of the effects of growth on individual welfare would ideally draw on econometric estimates from household and firm surveys, along with macro information that would be embedded in an economy-wide simulation model. So far, in

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\(^5\) Also, a typical outcome is the increase in inequality between urban and rural areas and between skilled and unskilled workers.

\(^6\) AGOA and EBA are the two major examples.
spite of recent progress, this all-encompassing approach is still beyond reach, and there is still much to be learnt by firm or household-level analysis. This paper develops a simple partial equilibrium model that draws on the information available from household surveys providing a quantification of the effects of economic growth on the income and its distribution adjustments across households.

The methodology developed in this paper can be also used as the “second-step” in studies that combine general equilibrium models with post simulation analysis of household impacts. The purpose of the “second-step” would be to translate the growth rates (forecasted within economy-wide models in the “first-step”) into more precise welfare and poverty indicators.

As detailed below, the estimation methodology combines the matching methodology literature (to identify individuals most likely to move into the expanding sector) with the industry wage premium literature (to quantify the gains of the individuals that move into the expanding sector). This methodology has parsimonious data requirements (a household survey that identifies individuals and their sectors of employment) and is well-suited to analyze the consequences of the integration of least developed countries into the world economy.

The methodology is applied to analyze the impact on social welfare of export-led growth in the textile industry in Madagascar. Arguably, Madagascar is an excellent example of how sectoral growth can affect poverty because of its rapid export growth in the textile and apparel industry and the country’s widespread poverty. Because Madagascar shares many of the characteristics of least developed countries (high rates of poverty, low wages, and a large pool of ‘reserve labor’), results from this case study might apply to other low-income countries.

The results of the analysis suggest that the expansion of the textile industry will produce a substantial increase in social welfare. However, while the poor receive a

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7 Studies using a two-step approach are becoming more common in the trade and poverty literature because they took away part of the burden of including all the households in the CGE model, while still producing detailed distributional results, as in Bourguignon et al (2003).

8 The methodology is applied to study the effect of export-led growth in one sector of the economy, nevertheless it can be easily extended in a multi-sector context.
reasonable share of the increase in welfare, non-poor households gain more both in percentage and in absolute terms. With respect to poverty, in a five-year scenario under a plausible employment growth of 20% per year in the textile industry, about 120,000 individuals will be lifted out of poverty, decreasing national poverty by about 0.7 percentage point.

The paper is structured as follows: section 2 describes the methodology; section 3 describes the characteristics of the Malagasy textile sector; section 4 discusses the econometric results; section 5 presents and discusses the results from a micro simulation exercise; and finally, section 6 summarizes the main conclusions. An appendix discusses the data.

2. Identifying beneficiaries and benefits: a household-based approach

In an exercise seeking to identify beneficiaries of a development strategy, the standard neoclassical approach used by CGE models in which market wages adjust to clear labor markets for a few broad categories of workers discard too much useful information on the characteristics of individuals. Besides using information available in household surveys, an alternative approach whereby firms choose individuals with characteristics that closest match those of incumbents, assumed to be initially optimal, presents a more adequate view of firm behavior in reality. Furthermore, the neoclassical approach does not easily allow one to assign benefits to individuals, which misses critical aspects of quantifying the effect on a micro-economic phenomena such as poverty.

To spell out a full model on firm behavior with multiple types of labor is beyond the purpose of this paper, however the approach used here is fully compatible with the profit maximizing behavior of firms in a competitive setting as well as within a setting of monopsonystic labor demand. Wages paid by firms in each sector can be assumed to represent value marginal product of labor embedded in individual characteristics after controlling for exogenous factors (so that wages can increase with the price of output), or firms can be assumed to pay wages below the marginal product of labor.

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9 This reflect the historical growth rate of the textile and apparel industry in Madagascar between 1999
so that wages can increase with the decreasing of monopsony power as in the case when new firms enter the market). Furthermore, to capture the widely recognized dualistic structure of labor markets in low-income countries, I allow for the existence of sectoral wage differentials.

To estimate the impact on household welfare resulting from the growth in employment and increase in the wages, this paper combines the matching methodology literature (Heckman, Ichimura and Todd 1997) with the industry wage premium literature (Krueger and Summers, 1988; Helwege, 1992; Haisken-DeNew and Schmidt, 1997).

In summary, this methodology allows to identify the individuals that best match the characteristics sought by the expanding sector, the wage premium that the expanding sector offers relative to the former sector of employment, and the expected increase in the earnings of workers in the expanding sector. Finally, the predicted increase in income is distributed across household members to obtain estimates of poverty levels and social indicators.10 The methodology is applied to study the welfare effect of export-led growth in one sector (textile and apparel), but can be easily extended in a setting with multiple sectors.11

The labor force is divided into four sectors of employment: informal, services, textiles (the expanding industry), and other industries.12 The informal sector can be thought of as a reserve labor sector and is composed of agriculture, small commerce and other marginal sectors identified as informal in the data.13 The selection process is achieved by estimating propensity scores, i.e. the predicted probability that each individual has

and 2001, when employment has increased from about 136,000 to 190,000 individuals.

10 The paper adopts the assumption that the intra-household allocation of income is equal between the genders. This is the classical assumption that treats households as monolithic entities. Attempts to investigate the different patterns of intra-household allocation of income and consumption have been done, but the theoretical framework is still controversial and very constrained by the data requirement. For example see: Bourguignon and Chiappori (1992), Davies and Joshi (1994) and Deaton (1997).

11 In particular, the propensity score would need to be estimated via a multinomial logit, and propensity scores assigned to take into account individuals best matches across sectors.

12 The lack of sufficient observation for several sectors does not allow a more disaggregate differentiation.

13 It also includes unemployed individuals. For these, the imputed wage (lower than the reservation wage) is assumed to be in line with the other workers of the informal sectors.
of being selected based on his observed characteristics. The propensity scores are obtained from the estimation of a logit model.

\[ L_i = \beta_0 + \beta_1 X_i + \beta_2 H_i + \varepsilon_i \]  

(1)

Where \( L_i \) is the logit of a dichotomous variable that takes the value 1 if the \( i \)th individual is employed in the textile sector and 0 otherwise, \( X_i \) is a vector of individual characteristics, and \( H_i \) is a vector of household characteristics. Expansion in the textile sector will then imply drawing resources, including labor, to this sector.

The core of the analysis is the impact on the labor market resulting from expansion in the textile sector. Each person has a probability becoming employed in the textile sector to seek higher pay. The probability of moving into the textile sector is a function of a series of demographic characteristics. These include gender, age, level of education, head of household status, marital status, urban/rural dummy, regional location, number of members in the household, and a dummy for the presence of other family members working in the textile sector. The individuals are then ranked according to the estimated probabilities and, for those with highest rank, the sector of employment is changed to textiles.

As will be shown in section 3, wages in the textile sectors are significantly higher than in the informal sectors. Because not all individuals report wages, one must first impute a predicted wage for all the individuals for which the actual wage is not

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14 The estimation ranks the individuals according to their propensity to be employed in the textile and apparel sector based on the characteristics of the individuals already employed in the same sector.

15 Therefore, if their reservation wage is higher than the ones expected in the textile sector, they will not change sector. Those individuals whose actual wages are not directly observed and whose expenditures are twice the poverty line are also not allowed to move. This tends to correct for unobserved workers’ characteristics that are in part manifested in their expenditures.

16 Gender is also interacted with age and with education.

17 Regional variables are justified by the fact that migration flows between regions are still very small and recruitment is likely to be done by "word of mouth" and mostly locally.

18 The reliability of those estimates can be checked analyzing the composition of the employees in the industry across time. Table 1 reports little change of workers characteristics between 1997 and 2001, therefore it is plausible that the industry draws new employment with characteristics and skills similar to existing employees.

19 The informal sector is defined to include non-commercial agriculture, small commerce and other sectors categorized as informal or marginal in the household survey.
observed. Then the estimation produces the expected wage that every individual is likely to receive if employed in the textile industry. The wage differential of every individual is therefore calculated as the difference between the observed (or predicted) wage across the four economic sectors. The estimation regresses the log of worker $i$’s wages ($\ln W_{ij}$) on a vector of worker $i$’s characteristics ($X_{ij}$) and a set of industry indicators ($I_{ij}$) and takes the Mincerian form:

$$\ln W_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_2 I_{ij} + \epsilon_{ij}$$  (2)

The Mincerian wage equation is a model linking individual’s characteristics with his or her wage. The underlying assumption of this model is that workers’ characteristics proxy for workers’ skills and that skills levels closely reflect productivity and wages. The specification follows Krueger and Lindahl, 2001.  

Workers’ characteristics include gender, age, education, head of household status, number of household members, marital status, and formality of employment. A dummy variable for the gender of the household’s head controls for women-headed households. A urban/rural dummy and one dummy per region control for wage differentials across space. The coefficient on the industry dummy captures the wage premium paid to each industry in comparison to the textile and garment industry (which is omitted).  

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20 This is done by estimating the wage equation (2) for each of the four sector of the economy. To impute reservation wages for workers which earnings are not observed (such as intra-household worker and formally unemployed) we assume that their wage can be equated to wages of workers of similar characteristics employed in the informal sector. 

21 A drawback assumption of the Mincerian model is that all years of education generate an equal rate of return to the student (i.e. linear relationship between the log of earnings and the number of years of education). Furthermore, there is no control for quality of education. Estimation follows standard OLS.

22 In other words the coefficient of the industry dummy represents the part of the variation in wages that cannot be explained by worker characteristics, but can be explained by the workers' industry affiliation.
Next, I need to estimate to what extent wages have grown for the different typologies of workers. In predicting wage growth for textile workers, I assume that future wage growth will be identical to the wage growth observed between 1999 and 2001 which can be assumed to be “typical” (see section 3). To see whether real wages have increased for some categories of workers more than for others, the estimates are obtained by pooling the cross-sectional data of 1999 and 2001 together. The estimation is constrained by the scarcity of a wider time series and by the difference in the construction of some of the variables between the two surveys. The estimation takes the simple form:

\[
\ln W_i = \beta_0 + \beta_1 X_{it} + \beta_2 T_i + \beta_3 X_{it} T_i + \epsilon_i \quad (3)
\]

Where \( \ln W_i \) is the log of the wage of the individual \( i \) in time \( t \), \( X_{it} \) is a vector of individual characteristics which include gender, skilled/unskilled and age. \( T_i \) is a time dummy that takes value 1 for 2001. Therefore, the coefficient on the time dummy captures the wage differential between 1999 and 2001 while the interaction terms, \( X_{it} T_i \), capture the time differential effects for gender, skilled/unskilled, and age. The estimation if performed only on the individuals for which wages are observed in the household surveys.

The results from the econometric estimates are then used in a simulation exercise. Having identified the individuals that are more likely to move into the textile industry and having estimated their specific wage differential, I calculate the impact on household income and social welfare.

In the simplest model, the indirect utility function of the households can be written as:

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23 The implicit assumption is that workers’ earnings grow at different paces as a function of labor demand and supply for particular skills.
24 Data on 1997 was left out because it is not completely comparable with the newer surveys.
25 An individual is considered skilled if he or she has completed more than 9 years of education, or has completed 6 years of education and is older than 35, or has completed 6 years of education and has had technical education in the textile sector.
26 Household income is simply the sum of the income of each of its members.
\[ u_h = V_h[y_h, P] \quad \text{where}: \quad y_h = w\ell_h \quad (4) \]

Household utility \( u_h \) is expressed as a function of a vector of prices \( P \) faced by the household and the household’s income \( y_h \), which in turn is a function of the amount of labor the household sells on the market \( \ell_h \) at the prevailing wage \( w \). Prices \( P \) are assumed to be fixed, while income varies with the change in sector of employment and the increase in real wages.

Further, assuming that households choose optimally the amount of labor to sell in the labor market, the effect of prices and wages on profits can be obtained by differentiating (4) and dividing by income of household \( h \) to obtain the percentage change in welfare:

\[
\frac{du_h}{y_h} = \theta_h' dw_h \quad (5)
\]

where \( \theta_h' = w\ell_h / y_h \) is the share of income obtained in the labor market by household \( h \).

For the sake of simplicity, the social welfare function is assumed Paretian, so that the increase in anybody’s income in the society is welfare augmenting. In this setup, the change in social welfare \( W \) can be written as the sum of the change in the welfare of each individual household:\textsuperscript{27}

\[
dW = \sum_h du_h = \sum_h \theta_h' dw_h y_h \quad (6)
\]

where the change in wage income \( dw_h \) of the household is calculated as follows:

\[
dw_h = \sum_i dw_i = \left[ (1 + zw_i)(1 + kw_i)' - 1 \right] R_i \quad (7)
\]
where \( zw_i \) is the wage differential for individual \( i \) estimated by equation (2), \( kw_i \) is the increase in the wage for the individual \( i \) in household \( h \) between 1999 and 2001 estimated by equation (3). Finally, \( R_i \) is a dichotomous variable taking the value one for the individuals employed in the textile sector or for the individuals with the best matching characteristics estimated according to equation (1), and zero otherwise.

3. Characteristics of the textile and apparel sector in Madagascar

Madagascar’s textile industry is one of the fastest growing in Sub-Saharan Africa. Given Madagascar’s low labor costs and a fairly productive labor force, the industry attracts investors from Mauritius, Hong Kong, Malaysia, Singapore and China as well as from middle eastern countries. Moreover, Madagascar enjoys a number of policy induced comparative advantages. In particular, Madagascar has quota and duty-free access to EU and to the US markets as a consequence of EBA, Cotonou and AGOA agreements. As an additional advantage, Madagascar’s textile and apparel industry is exempted from rules of origin embedded in the AGOA agreements.28 Because of all these issues, export of textile products has been soaring in Madagascar since the late 1990s. Figure 1 shows export growth in Madagascar’s textile and apparel between 1990 and 2001.

FIGURE 1 [ Exports of textiles and apparel products – 1990-2001]

Between 1990 and 2001 exports jumped from less than 50 million USD to more than 450 million. The growth in exports was driven first from a surge in exports to the European markets in the mid 1990s, and thereafter from a surge in exports to the US markets driven by the advantages provided in the AGOA agreement.

The growth of the textile and apparel industry revealed in the export performance is also observed in the data from the household surveys. Table 1 reports some key

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27 For the purpose of this paper, a different welfare function such as the one proposed by Atkinson, or Sen where social marginal utility is assumed to be inversely related to income rank, would just complicated the computation without adding much substance to the results.

28 The ability to source their intermediate inputs from anywhere in the world is applicable only until 2004. Also, quota free access will cease to be an advantage after 2004 as all quotas on textiles and apparel trading between WTO members are due to be eliminated.
characteristics of the labor force employed in the textile and apparel industry in Madagascar at three points in time.

Table 1 here [Characteristics of textile and apparel industry in Madagascar 1997-1999-2001]

During the late 1990s employment in the industry, as observed from the analysis of household surveys, has been growing at a very fast pace. In 1997, about 46,000 individuals reported employment in the textile sector.29 Employment was reported at about 135,000 individuals in 1999, and by 2001 total employment in the textile and apparel industry had risen to almost 200,000 individuals (or about 2 percent of the active workforce). The textile industry was in 2001 already the fourth most important sector of employment after agriculture (74%), commerce (6%) and public administration (2.5%).

About ¾ of the labor force are women, and about half of it is skilled.30 The labor force is fairly young (average age is in the early 30s) and fairly educated, as the average worker reported about 8 years of formal education. The industry is localized predominantly in the capital, with about 90% of its employees residing in the urban and rural areas in the province of Antananarivo. The industry relies on temporary workers for about 20 percent and pays average wages of about the equivalent of 50 USD per month. Skilled workers earn substantially more, about 76 USD per month compared to about 33 USD per month for unskilled employees. About 42 percent of the employees in the industry report expenditure below the poverty line.

During the period 1997-2001, the characteristics of textile and apparel workers did not change substantially. The fact that the percentage of skilled workers has been declining (especially between 1999 and 2001) together with a reduction of the average age of employees, suggests a possible shortage in the supply of skilled labor, or an

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29 This number may be underestimated as the Industriel Census 1995 (RI95) and Annual Inquiry in Industry 1996 (EAI96) reports similar numbers for 1995 with an expected growth rate in employment of 28.6% per year.

30 Following standard practice in the analysis of labor surveys, an individual is considered skilled if he or she has completed more than 9 years of education, or has completed 6 years of education and is older than 35, or has completed 6 years of education and has had technical education in the textile sector.
increase reliance upon “in-firm” training which is not observed in the data. The percentage of temporary workers has been declining as well, which could suggest a more mature industry not longer subjected to a high oscillation in orders. With the increase in employment, average wages paid to employees have also risen substantially in the late 1990s. Average wages rose from about 37 USD per month in 1997 to about 50 USD in 2001. However, real wages have increased at a very different pace for skilled and unskilled workers. While the real wage of skilled workers almost doubled between 1997 and 2001, the wage of unskilled workers rose only minimally in real terms.

4. Estimation results: Propensity Scores and Wages

To identify the determinants that make individuals more likely to find new employment in the expanding sector, table 2 reports the result of the estimation of the propensity scores as in equation (1). The columns show the estimated coefficients with the corresponding robust standard errors corrected for survey design (Binder, 1983).

Table 2 here [Propensity score Estimation]

The coefficients measure the change in the log-odds in favor of being selected to fill the job in the textile industry as the dependent variable changes by a unit. For example, residing in urban areas increases the log-odd by 0.62 (taking the antilog will result in approximately an 86 percent increase in the odds of being selected). Similarly, it is possible to see that the odds of being selected peak for individuals with about 11 years of education, and at the age of 30. The most important determinant of being selected is the presence of another family member employed in the textile industry. Important determinants are also, gender (women are overwhelmingly favored) and household size (individuals in larger households have lower log-odds). The significance of coefficient on the interaction term gender*education suggests that education is more important for men as a determinant of being selected. Regional

31 The coefficient suggests an astonishing probability almost 5000% higher than similar individuals who don’t have any family member employed in the textile industry. This can result from the fact that
dummies are also significant, with the Antananarivo region having the highest log-odds.

The results on the propensity scores make it possible to compare the characteristics of the individuals selected with the ones already in the industry. Table 3 reports some of the characteristics of the 100,000 individuals with highest propensity score along with the characteristics of the employees in the textile and apparel industry in 2001.

Table 3 [Characteristics top 100,000 individuals from prop scores]

The best matching individuals appear to be generally similar to the employees in the textile and apparel sector. The only evident difference is that the latter seems to have slightly lower formal education. More importantly, the earnings of the textile workers are substantially higher than those of the best matching individuals suggesting that employment in the textile and apparel sector will result in substantial welfare impact for the new entrants.

To analyze the extent to which earnings are different across economic sectors, table 4 reports the coefficients from the estimation of the earning equation (2) along with their robust standard errors. Equation (2) is estimated three times, first for all sample, and then, to better capture eventual differences across skills (and assuming a segmented labor markets across broad skills), is estimated only for unskilled workers, and finally only for skilled workers.

Table 4 here [Wage equation estimation]

All the variables of interest are significant and have the expected sign. In particular, age, education, and gender have all positive signs and are significant at the 5% level or better. The coefficient on the education variable shows that each year of education is reflected in an increase of about 9 percent in earnings across all workers, while the coefficient on the gender dummy indicates that, ceteris paribus, men have a wage 25 percent higher than women. The coefficient on the industry dummies reports the wage that most of the recruitment is done through “word of mouth”, for which immediate family members
differential with respect to the textile industry. On average, employment in the textile industry has a premium of about 34 percent with respect to the informal sector. When the equation is estimated for skilled and unskilled workers, the premium resulted higher for unskilled workers (48 percent) than for skilled workers (31 percent).\footnote{In the computation of welfare indicators the results used are those from the skilled and unskilled regressions.} No significant differences are present between the wages of textile workers and workers in the manufacturing and services sector, with the exception of skilled workers in the service sector whose earnings were estimated to be about 17 percent higher relative to similar individuals in the textile and apparel industry.

Finally, to analyze the changes in wages occurring between 1999 and 2001 in the textile and apparel sector, table 5 presents the coefficient from the estimation of the pooled regression (equation 3) along with the robust standard errors. The estimation is performed with three different specifications to take into account different interaction effects.

Table 5 here [Pooled regression estimation]

Considering only the simple specification without interaction terms, and correcting for differences in skills, age and gender, the coefficient on the year dummy indicate an increase in the average wage of about 23 percent in two years. The inclusion of the interaction term year*skill suggests that while skilled wages have increased of approximately 37 percent, unskilled wages didn’t report any significant increase in real terms. Finally, the results from the third specification with the inclusion of two more interaction terms (year*gender and year*age) substantially mimic the results of the second specification.\footnote{In the computation of welfare indicators the results used are those from the skilled and unskilled regressions.}

5. Simulation Results

Having identified the individuals that best match the skills sought by the expanding industry, the wage differentials between economic sectors, and the trend in the wages in the expanding sectors of the economy, I can now measure the effect that the growth
of the textile and apparel industry has on its workers and on social welfare in general.
The micro simulation results reported here are for two five-year scenarios. The first
scenario (low-growth) assumes a rate of growth in employment of 10 percent per year
while the second scenario (high-growth) assumes a rate of growth of 20 percent per
year. Table 6 presents the average gains for several typologies of worker in the
textile and apparel sector in five-year scenarios of low and high economic growth.

TABLE 6 [average gains by worker]

In the low growth case, the average gains per worker correspond to an increase in real
wage of about 112 dollars per month. Skilled workers gain more than three times
relative to unskilled workers (165 USD per month vs. 47 USD per month). Moreover,
women gain substantially less than men (102 USD per month vs. 143 USD per
month). Gains per worker are similarly distributed in the case of the high growth
scenario. However, average gains per worker are lower in the high-growth scenario
relative to the low-growth scenario. The reason being that a high rate of growth will
likely hit a shortage in the supply of skilled labor and therefore draw a higher
percentage of less skilled workers for which, on average, gains are lower.

The change in social welfare is approximated by the sum of the changes in the
monetary income of each household (as in equation 7). Figure 2 illustrates the change
in social welfare (in real dollars, per month) for the two scenarios. To better illustrate
how much welfare is actually to the benefit of poor households, figure 2 also reports
the change in welfare for the poor (in real dollars) with a line to indicate the
percentage of social welfare that is to the direct benefit of the poor. The lines in figure
2 illustrate of the extent to which economic growth is pro-poor or marginalizes the
poor for the two growth scenarios. For example, very low percentages would imply
that most of the benefits are reaped by non-poor households, so that growth will do
little to affect poverty levels. On the contrary, high percentage values implies that the
poor as a whole are very participant of the benefits.

33 Specification two is used in the computation of welfare indicators.
34 Employment in the industry grew at a rate of about 25 percent per year from 1997 to 2001.
In a five year scenario of high employment growth, the change in social welfare is estimated to be about 45 million USD, while the welfare of poor households increases by about 20 million USD. Results are lower in the case of the low-growth scenario (respectively 35 million USD and 14 million USD for the poor). The results indicate that, in the fifth year of economic growth the poor reap about 45 percent of the change in welfare in the high growth scenario and about 39 percent in the low-growth scenario. The upward slope of the lines in figure 3 shows that the poor tend to benefit much less in the short term. This result is driven by the fact that the boom of the textile industry draws employment at an increasing rate from the poorer sector of the population (that is, the new employees added to the industry in the first year are more rich than the new employees added in the fifth year). In any case, given the fact that the poor as a whole represents about 70 percent of the population, but collect less than half of the benefits, a consequence of economic growth would be the increase in inequality, especially in the short term.

The gains in social welfare across the five years indicate that the percentage of gain collected by the poor increases with time. (30 percent of welfare will be to the benefit of the poor in the first year versus 45 percent in the fifth year). This is possibly driven by the fact that the textile and apparel industry draws at an increasing pace from the poor strata of the population to fuel its growth, suggesting that short period of growth will produce less significant changes in poverty rates.

Figure 3 presents national changes in the poverty rates (solid lines) as well as changes in urban poverty (dashed lines).

As a direct effect of five years of sustained employment growth in the textile and apparel industry, overall poverty is expected to fall about 0.7 percentage point (or about 120 thousand individuals). In the case of lower rate of growth, poverty is expected to decline approximately 0.4 percentage points. However, poverty reduction is almost exclusively confined to urban areas, where poverty is expected to decline.
about 1.5 percentage points in the case of high growth and of about 1 percentage point in the case of low rates of growth. In rural areas (not in figure), poverty is expected to fall only about 0.4 percentage points in the case of the high growth scenario.\textsuperscript{35} The size of those results are not surprising considering that the textile and apparel industry is quite small compared to on the overall economy and the fact that the overwhelming majority of poor lives in rural areas which are less likely to harbor employment growth.

\textbf{6. Concluding Remarks}

This study proposes a methodology which assesses the gains at the households levels from export led growth and quantifies the extent to which growth has been pro-poor. In this regard, this paper responds to the need for better informed analysis in the debate on the effect of globalization. The methodology is applied on the effects of the growth of the Malagasy textile industry which provides a significant example of the likely effects on poverty resulting from a given comparative-advantage based growth.

This study found that the textile and apparel industry in Madagascar gives viable means for a sizable mass of individuals and households to increase income and ultimately escape from poverty. The textile industry’s capability to improve households’ living conditions is due to two main factors: the creation of employment and the increase in wages. First, fueled by an increase in exports, employment in the textile and apparel industry grew at a rate of more than 20\% per year in the late 1990s. Second, the textile and apparel industry has an average earning premium of about 40\% over the average income of the workers in the informal sectors. Moreover, skilled wages in the textile and apparel sectors are rapidly increasing. However, upward pressure on unskilled wages is unlikely to occur as long as we see a large reserve unskilled labor force and continued high turnover in low-skilled textile jobs.

The results found that even if the bulk of the gains are collected by non-poor households both in absolute and relative terms, the poor still reap about 45 percent of the change in welfare. In this respect, a side-effect would be an increase in inequality.

\textsuperscript{35} And almost exclusively in rural Antananarivo.
between poor and non-poor, between urban and rural areas and between skilled and unskilled workers.

Finally, without taking into account inevitable positive spillovers to other sectors of the economy, the results indicate that in a five year period of sustained economic growth, poverty is expected to fall of about 0.7 percentage points or 120 thousand individuals. At the individual level, the growth in the textile sector will produce an average increase in the wages of each worker (former or new) of about 110 US dollars per month. Even if for many of them the gains are not sufficient to lift their family out of poverty, they surely represents a substantial improvement.
References


Figure 1 – Madagascar exports of textiles and apparel products, 1990 – 2001.

Table 1 – Characteristics of textile and apparel industry in Madagascar 1997-1999-2001

<table>
<thead>
<tr>
<th></th>
<th>1997</th>
<th>1999</th>
<th>2001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Employees</td>
<td>46,000</td>
<td>136,000</td>
<td>191,000</td>
</tr>
<tr>
<td>Skilled workers (%)</td>
<td>51%</td>
<td>54%</td>
<td>46%</td>
</tr>
<tr>
<td>Unskilled workers (%)</td>
<td>49%</td>
<td>46%</td>
<td>56%</td>
</tr>
<tr>
<td>Average years of education</td>
<td>8.5</td>
<td>9</td>
<td>7.9</td>
</tr>
<tr>
<td>Temporary employment (%)</td>
<td>34%</td>
<td>39%</td>
<td>20%</td>
</tr>
<tr>
<td>Workers below the poverty line (%)</td>
<td>50%</td>
<td>39%</td>
<td>42%</td>
</tr>
<tr>
<td>Average earnings</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>of skilled workers</td>
<td>$41</td>
<td>$52</td>
<td>$76</td>
</tr>
<tr>
<td>of unskilled workers</td>
<td>$32</td>
<td>$29</td>
<td>$33</td>
</tr>
<tr>
<td>Average age</td>
<td>36</td>
<td>34</td>
<td>32</td>
</tr>
<tr>
<td>Female laborforce (%)</td>
<td>76%</td>
<td>75%</td>
<td>80%</td>
</tr>
<tr>
<td>Workers' Localization by Region (%)</td>
<td>Urban Antananarivo</td>
<td>49%</td>
<td>58%</td>
</tr>
<tr>
<td></td>
<td>Rural Antananarivo</td>
<td>9%</td>
<td>32%</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>42%</td>
<td>10%</td>
</tr>
</tbody>
</table>
Table 2 – Propensity scores estimation
(dependent variable – dummy textile employment = 1)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coeff.</th>
<th>S.E</th>
<th>Observations</th>
<th>Adj R squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.287***</td>
<td>(3.49)</td>
<td>4396</td>
<td></td>
</tr>
<tr>
<td>Age squared</td>
<td>-0.005***</td>
<td>(2.95)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>1.180***</td>
<td>(6.99)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education squared</td>
<td>-0.056***</td>
<td>(6.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>-2.360*</td>
<td>(2.11)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender*Age</td>
<td>-0.017</td>
<td>(0.78)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender*Educ</td>
<td>0.169**</td>
<td>(2.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marital Status</td>
<td>-0.339</td>
<td>(1.25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region1 dummy</td>
<td>-12.220***</td>
<td>(9.17)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region2 dummy</td>
<td>-14.240***</td>
<td>(9.62)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region3 dummy</td>
<td>-15.110***</td>
<td>(10.53)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region4 dummy</td>
<td>-14.300***</td>
<td>(10.25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region5 dummy</td>
<td>-15.400***</td>
<td>(9.85)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region6 dummy</td>
<td>-14.180***</td>
<td>(10.17)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban/Rural</td>
<td>0.620***</td>
<td>(3.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH size</td>
<td>-0.119**</td>
<td>(2.26)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Textile work hh member</td>
<td>3.843***</td>
<td>(12.54)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Robust standard errors are shown in brackets. Significance level of 1%, 5% and 10% are indicated by *** , ** and * respectively.

Table 3 – Characteristics of the 100,000 best matching individuals to fit jobs in the textile and apparel industry.

<table>
<thead>
<tr>
<th></th>
<th>2001</th>
<th>Best Matching</th>
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</thead>
<tbody>
<tr>
<td>Number of Employees</td>
<td>191,000</td>
<td>100,000</td>
</tr>
<tr>
<td>Skilled workers (%)</td>
<td>46%</td>
<td>60%</td>
</tr>
<tr>
<td>Unskilled workers (%)</td>
<td>56%</td>
<td>40%</td>
</tr>
<tr>
<td>Average years of education</td>
<td>7.9</td>
<td>10.2</td>
</tr>
<tr>
<td>Temporary employment (%)</td>
<td>20%</td>
<td>13%</td>
</tr>
<tr>
<td>Workers below the poverty line (%)</td>
<td>42%</td>
<td>72%</td>
</tr>
<tr>
<td>Average earnings</td>
<td>$50</td>
<td>$28</td>
</tr>
<tr>
<td>of skilled workers</td>
<td>$76</td>
<td>$33</td>
</tr>
<tr>
<td>of unskilled workers</td>
<td>$33</td>
<td>$21</td>
</tr>
<tr>
<td>Average age</td>
<td>32</td>
<td>31</td>
</tr>
<tr>
<td>Female laborforce (%)</td>
<td>80%</td>
<td>76%</td>
</tr>
<tr>
<td>Workers' Localization by Region (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban Antananarivo</td>
<td>44%</td>
<td>39%</td>
</tr>
<tr>
<td>Rural Antananarivo</td>
<td>41%</td>
<td>51%</td>
</tr>
<tr>
<td>Other</td>
<td>25%</td>
<td>10%</td>
</tr>
</tbody>
</table>
Table 4 – Wage regression estimation
(dependent variable: log earnings)

<table>
<thead>
<tr>
<th>Variable</th>
<th>All Coefficient</th>
<th>All S.E.</th>
<th>Unskilled Coefficient</th>
<th>Unskilled S.E.</th>
<th>Skilled Coefficient</th>
<th>Skilled S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.014***</td>
<td>(6.57)</td>
<td>0.012***</td>
<td>(3.69)</td>
<td>0.016***</td>
<td>(7.16)</td>
</tr>
<tr>
<td>Urban/Rural</td>
<td>0.039</td>
<td>(1.01)</td>
<td>0.023</td>
<td>(0.38)</td>
<td>0.044</td>
<td>(0.96)</td>
</tr>
<tr>
<td>Marital Status dummy</td>
<td>0.060</td>
<td>(1.32)</td>
<td>0.150***</td>
<td>(2.46)</td>
<td>-0.015</td>
<td>(0.25)</td>
</tr>
<tr>
<td>Education</td>
<td>0.087***</td>
<td>(13.39)</td>
<td>0.096***</td>
<td>(5.46)</td>
<td>0.086***</td>
<td>(8.00)</td>
</tr>
<tr>
<td>Manufacturing dummy</td>
<td>0.069</td>
<td>(0.91)</td>
<td>0.008</td>
<td>(0.06)</td>
<td>0.089</td>
<td>(1.03)</td>
</tr>
<tr>
<td>Service dummy</td>
<td>0.061</td>
<td>(0.79)</td>
<td>-0.096</td>
<td>(0.68)</td>
<td>0.174**</td>
<td>(2.36)</td>
</tr>
<tr>
<td>Informal dummy</td>
<td>-0.343***</td>
<td>(4.01)</td>
<td>-0.476***</td>
<td>(3.44)</td>
<td>-0.319**</td>
<td>(2.37)</td>
</tr>
<tr>
<td>HH head dummy</td>
<td>0.035</td>
<td>(0.60)</td>
<td>0.069</td>
<td>(0.94)</td>
<td>0.021</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Temporary employment</td>
<td>-0.105***</td>
<td>(2.53)</td>
<td>-0.006</td>
<td>(0.08)</td>
<td>-0.179***</td>
<td>(4.42)</td>
</tr>
<tr>
<td>HH size</td>
<td>-0.023*</td>
<td>(1.65)</td>
<td>-0.023</td>
<td>(1.17)</td>
<td>-0.017</td>
<td>(1.17)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.250***</td>
<td>(4.15)</td>
<td>0.261***</td>
<td>(3.51)</td>
<td>0.244***</td>
<td>(2.91)</td>
</tr>
<tr>
<td>Region1 dummy</td>
<td>10.950***</td>
<td>(84.89)</td>
<td>11.000***</td>
<td>(54.74)</td>
<td>10.906***</td>
<td>(68.76)</td>
</tr>
<tr>
<td>Region2 dummy</td>
<td>10.821***</td>
<td>(75.32)</td>
<td>10.950***</td>
<td>(49.84)</td>
<td>10.750***</td>
<td>(53.97)</td>
</tr>
<tr>
<td>Region3 dummy</td>
<td>10.900***</td>
<td>(72.80)</td>
<td>11.040***</td>
<td>(44.29)</td>
<td>10.812***</td>
<td>(63.96)</td>
</tr>
<tr>
<td>Region4 dummy</td>
<td>11.012***</td>
<td>(76.40)</td>
<td>11.330***</td>
<td>(48.05)</td>
<td>10.820***</td>
<td>(65.01)</td>
</tr>
<tr>
<td>Region5 dummy</td>
<td>10.986***</td>
<td>(79.95)</td>
<td>11.210***</td>
<td>(48.61)</td>
<td>10.861***</td>
<td>(63.64)</td>
</tr>
<tr>
<td>Region6 dummy</td>
<td>11.154***</td>
<td>(80.92)</td>
<td>11.510***</td>
<td>(53.26)</td>
<td>10.900***</td>
<td>(63.37)</td>
</tr>
</tbody>
</table>

Observations: 2528
Adj R squared: 0.531

Note: Robust standard errors are shown in brackets. Significance level of 1%, 5% and 10% are indicated by ***, ** and * respectively.

Table 5 – Pooled regression estimation
(dependent variable: log earnings)

<table>
<thead>
<tr>
<th>Specification</th>
<th>Coeff.</th>
<th>S.E.</th>
<th>Coeff.</th>
<th>S.E.</th>
<th>Coeff.</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specification 1</td>
<td></td>
<td></td>
<td>Specification 2</td>
<td></td>
<td></td>
<td>Specification 3</td>
</tr>
<tr>
<td>constant</td>
<td>11.09***</td>
<td>(72.56)</td>
<td>11.13***</td>
<td>(49.18)</td>
<td>10.87***</td>
<td>(32.93)</td>
</tr>
<tr>
<td>Age</td>
<td>0.01***</td>
<td>(3.62)</td>
<td>0.02**</td>
<td>(2.75)</td>
<td>0.02**</td>
<td>(2.29)</td>
</tr>
<tr>
<td>Gender</td>
<td>0.40***</td>
<td>(4.87)</td>
<td>0.37***</td>
<td>(3.47)</td>
<td>0.55***</td>
<td>(3.76)</td>
</tr>
<tr>
<td>Year dummy</td>
<td>0.21***</td>
<td>(2.83)</td>
<td>-0.02</td>
<td>(0.16)</td>
<td>0.39</td>
<td>(1.13)</td>
</tr>
<tr>
<td>Skill Dummy</td>
<td>0.43***</td>
<td>(4.82)</td>
<td>0.33**</td>
<td>(2.54)</td>
<td>0.33**</td>
<td>(2.49)</td>
</tr>
<tr>
<td>Skill*Year</td>
<td>0.32**</td>
<td>(2.08)</td>
<td></td>
<td></td>
<td>0.31**</td>
<td>(2.01)</td>
</tr>
<tr>
<td>Gender*Year</td>
<td></td>
<td></td>
<td>-0.32</td>
<td>(1.56)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age*Year</td>
<td></td>
<td></td>
<td>-0.01</td>
<td>(0.93)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations: 464
Adj R squared: 0.121

Note: Robust standard errors are shown in brackets. Significance level of 1%, 5% and 10% are indicated by ***, ** and * respectively.
Table 6 – Average monetary gains per worker

<table>
<thead>
<tr>
<th></th>
<th>Low-Growth Scenario</th>
<th>High-Growth Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Gains per Worker (USD)</td>
<td># workers (thousand)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>112</td>
<td>310</td>
</tr>
<tr>
<td>Skilled</td>
<td>165</td>
<td>196</td>
</tr>
<tr>
<td>Unskilled</td>
<td>47</td>
<td>114</td>
</tr>
<tr>
<td>Men</td>
<td>143</td>
<td>72</td>
</tr>
<tr>
<td>Women</td>
<td>102</td>
<td>238</td>
</tr>
</tbody>
</table>

Figure 2 – Change in social welfare

![Figure 2 – Change in social welfare](image)

Figure 3 – Change in poverty Headcount index

![Figure 3 – Change in poverty Headcount index](image)
Data Appendix

The analysis relies primarily on data from the 2001 *Enquete Prioritaire Aupres des Menages* (EPM).\(^{36}\) The household-level data used for the analysis were collected by the Direction des Statistiques des Ménages (DSM) of the Institut National de la Statistique (INSTAT) in Madagascar. The surveys are stratified, multi-staged and clustered. The 2001 survey was collected from September to November 2001 and is representative of the entire population. The surveys are designed to be representative at the regional level (*faritany*) as well as the urban/rural level within each region. The surveys include income, consumption, the households’ characteristics and the individuals’ characteristics. Following the standard practice in the literature, the total expenditure is used as a proxy for income to calculate poverty indicators. Because the welfare measures are concerned with the well being of individuals, all expenditures were converted to a per capita basis.\(^{37}\)

One problem that often arises with the use of household surveys dataset is the presence of large deviations (outliers) that can distort estimates of regression coefficients. This is caused by the vast amount of information and the great likelihood of misreporting and typos in the collection of data. In large datasets, such as household surveys, it is impossible to check the consistency of each single observation and the commonly used solution consists of taking out the most offending observations from the regression. To correct for this issue, in addition to estimate robust standard errors\(^{38}\), in all regressions I exclude the 1 percent of the observations with the highest Cook’s distance.\(^{39}\)

\(^{36}\) The analysis also makes use of the 1999 EPM for the estimation of the increase in wage between 1999 and 2001. The construction of the 1999 survey is similar to that of 2001. Nevertheless, some comparability problems restricted the estimation to only variables that could be considered consistent between the two surveys.

\(^{37}\) To obtain per capita measures, this paper adopts the standard practice of dividing household income and expenditures by its residents, with children of age 14 or less counting as half of adults.

\(^{38}\) Robust standard errors are corrected for heteroskedasticity using the Huber-White estimates.

\(^{39}\) Cook’s distance is given by: 

\[
D_i = \frac{\sum (\hat{Y}_j - \hat{Y}_{i(j)})^2}{p \cdot MSE},
\]

where \(\hat{Y}_j\) is the predicted value of observation \(j\) and \(\hat{Y}_{i(j)}\) is the predicted value of observation \(j\) when taking observation \(i\) out of the estimation, \(p\) is the number of parameters in the model and \(MSE\) is the mean squared error. In words, Cook’s distance is a measure of the influence of the \(i\)-th observation on all the other observations.