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Does the microsimulation approach used in macro-micro modelling matter? An application to the distributional effects of capital outflows during Argentina's Currency Board.

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Key words

Economic modelling, macro-micro modelling, CGE, microsimulations, income distribution, Argentina

Classification codes

O1,O54

Abstract

We provide a novel comparison between the behavioural and the non-parametric microsimulation approach. Coupled with a CGE model, we consider the distributional effects of the significant capital outflows faced by the Argentinean economy at the end of its Currency Board, in a context with significant macroeconomic similarities to the present crisis in Greece. Both the relatively straightforward 'non-parametric' approach and the more complex behavioural approach lead to distributional results that are consistent with the data, suggesting that both are viable alternatives. Looking forward, it would be desirable for researchers to look for additional evidence regarding the distributional effects that these microsimulation models can illuminate for given macroeconomic shocks.

Abbreviations

ARUM: additive random utility model

CDF: cumulative distribution function

CES: constant elasticity of substitution

CGE: computable general equilibrium

IFPRI: International Food Policy Research Institute

INDEC: *Instituto Nacional de Estadística y Censos* (National Institute of Statistics and Census) of Argentina

MS: microsimulation

OLS: ordinary least squares

PDF: probability density function

PHS: Permanent Household Survey

p.p.: percentage points

PPP: purchasing power parity

RHG: representative household group

1 INTRODUCTION

Capital outflows in Argentina during its Currency Board Regime (1991-2001) had significant economic and social consequences. National authorities in Argentina during this period ceded their power to modify the exchange rate due to a Currency Board and an array of foreign-currency-denominated contracts, were unable to print hard currency[1] and, with the economy suffering current and fiscal account deficits and increasing public and private foreign debts, were forced to impose capital controls and freeze bank deposits. This scenario provides a relevant case study with strong similarities to the current situation in Greece[2]. Non-residents' deposits at banks in Argentina dropped from US$32.9 billion to US$21.4 billion, from December 2000 to December 2001, by 35.0 per cent. Understanding the way in which this shock affected income distribution in the Argentinean economy is of special interest, given that it led to an economic crisis that included a significant short-run worsening of social indicators and, ultimately, a significant change in economic policy. Official unemployment rates increased from 14.7% (second semester of 2000) to 18.3% (second semester of 2001). The official moderated poverty rate, initially at 31.2 percent, increased by 6.5 p.p., and the Gini index of inequality, already at 48.9 percent initially, increased by more than 1 p.p. during this period. The associated manifestations of social discontent ultimately led the Argentinean government to abandon the Convertibility Plan, first by devaluing the exchange rate (December 2001), and then by letting the domestic currency float (February 2002).

In order to understand how a macroeconomic shock such as the severe capital outflows in the present work affects the different parts of an economy and its income distribution at the level of observed units (individuals or households) as it moves into a new general equilibrium, researchers have extensively used macro-micro economic modelling. This is an area to which this journal has dedicated significant attention (Harrigan et al (1991), Verikios and Zhang (2013), Breisinger and

[1] For a definition, please see Arestis et al (2005).
[2] In the case of Greece, the national authorities have also ceded the power to modify the exchange rate, but via participating in a monetary union.

Ecker (2014), Verikios and Zhang (2015)). However, while the macro-micro economic modelling literature has been and continues to be prolific[3], researchers do not always clearly define and justify the ways in which CGE models and MS models are integrated in their analysis of distributional results (Boccanfuso et al 2008). Focusing on this concern, the present work contributes to our understanding of the distributional consequences of macroeconomic shocks by providing a novel model comparison, applied to the effects of capital outflows in Argentina.

CGE and MS models have been combined in different ways, allowing for the taxonomy presented in Figure 1. The models have been fully integrated into a single one by increasing the number of elements in the set of households in the CGE model, allowing it to reflect relevant attributes of observed households in a disaggregated way. The link was also made by 'layering' the CGE and the MS models as distinct entities, and allowing some communication between them. In this layered approach, the MS model can be behavioural or not, with only the former modelling individuals' behaviour (typically, consumption demand or labour supply) by specifying an associated functional form and econometrically estimating its parameters[4]. Non-behavioural models have been applied in various ways: Agénor et al. (2003) communicate the percentage change in the welfare indicator (income or consumption) of each representative household group (RHG) in the CGE to that of the observed households classified under that representative household; Vos and Sanchez (2010) adapt a method used by Almeida dos Reis and Paes de Barros (1991) that they call the 'non-parametric'. This method changes the labour status of randomly selected individuals to match employment aggregates informed by the CGE model without explaining the underlying individuals' behaviour, and transmit percentage changes in the labour wages from the CGE model to workers in the MS model; Buddelmeyer et al (2008) alters the sample weights of labour

[3] For a recent and comprehensive review on macro-micro modelling, please see Cockburn et al (2014).
[4] The behavioural approach has been applied in a 'top-down' and, more recently, a 'top-down/bottom-up' fashion. While in the former the macro model (a level above actual individuals and households) is allowed to inform the MS model without allowing feedback to the macro model, in the latter approach the communication is bilateral and iterative.

suppliers in the microdata to match the simulated employment targets generated by the CGE model, minimizing a measure of the changes in weights subject to relevant totals (employment level, population size, etc), in what they call the 'reweighting approach'.

Inside the layered CGE-MS framework, we develop an MS model using the behavioural approach. Following the lines set by Bourguignon et al. (2004), we rely on an econometric explanation of key behavioural relationships, in a household income model that fully accounts for the heterogeneity of the observed characteristics of individuals affecting their labour status. We also improve its implementation, as explained below. We link the MS model to a real-financial macro CGE model[5], and apply the combined model to investigate the distributional effects of the capital outflows suffered by the Argentinean economy at the end of its Currency Board regime. We compare the results to those achieved with straightforward RHG and 'non-parametric' approaches - which we also conduct -, adding to the results obtained by Herault (2010), who compared the results of the behavioural approach against the reweighting approach in a trade liberalization scenario in South Africa.

In this economic modelling comparison, the following steps – presented in associated sections below - are followed: (i) a household income model is specified consistent with a stylized CGE model; (ii) the specified model is estimated; (iii) CGE macro outcomes are generated and communicated to the household income model; (iv) CGE simulation outcomes are attributed at the micro level using behavioural and non-behavioural MS approaches, generating new distributions of employment status, wages, capital incomes and, in turn, household incomes; and (v) distributional indicators and graphs are evaluated, showing the magnitude of the channels illuminated by the behavioural approach in comparison to RHG and non-parametric layered approaches. From these results, we derive a set of conclusions concerning the domain of applicability of the various MS

[5] A full description of the model can be found at http://www.mendeley.com/profiles/Dario-Debowicz/, Thesis: Modelling trade and financial liberalisation effects for Argentina, Chapter 3 (final model).

approaches to the distributional impacts of macroeconomic shocks, and consider the direction that future research in this area can fruitfully follow.

2 SPECIFICATION OF THE HOUSEHOLD INCOME MODEL

The household income model defines the total income of each household as a function of the observed and unobserved characteristics of the household and its members. The model is composed of four elements: i) a household income identity, which separates labour from non-labour income; ii) an individual labour status (employed vs. unemployed) indicator function for labour suppliers; iii) a wage equation for individuals at work; and iv) a non-wage income equation. We explain in the following how these equations are specified.

2.1 Household income identity

Household income is simply the sum of labour and non-labour income of the individuals in the household.

$$YH_h = \sum_{i \in h} (W_i IW_i + Y_{0i}) \tag{1}$$

where YH_h is the income of household *h*, IW_i is a dummy variable identifying the labour status (1 for employed, 0 otherwise) of individual *i* in household *h*, W_i is the wage of the working individual, and Y_{0i} is the non-labour income of the individual.

2.2 Employment status of individuals supplying labour

Not all the labour suppliers can get a job. In order for her to be actually employed, the characteristics of the labour supplier must be such that her criterion value[6] of being employed exceeds her criterion value of being unemployed. This criterion value follows the additive random

[6] A view of the labour market as a rationed one suggests that we refrain from calling this criterion value ‘utility’, since employment and unemployment are not outcomes depending on free decisions taken by the individuals supplying labour, but rather an outcome of the job rationing in the labour market.

utility model (ARUM), with a deterministic (observed by the analyst) and a random component, both completely known by the individual[7]. More precisely,

$$IW_i = Ind\left(CV_i^W > \overline{CV}^U\right) = Ind\left(\alpha^s + Z_i\beta^s + u_i > \overline{CV}^U\right) \quad (2)$$

where IW_i is the dummy variable identifying labour status (1 for employed, 0 otherwise), CV_i^W and $\overline{CV}^U$ are the criterion values for the employment and the unemployment alternatives of individual i, Z_i are the observed characteristics of labour suppliers affecting their employment status, α^s is the intercept affecting the criterion value of being employed in labour segment s, β^s is the vector of slopes in the effect of the observed characteristics on the criterion value of being employed in segment s, and u_i captures the unobserved determinants of employment status[8].

2.3 Wage determination

Wages of employed individuals (strictly, their logs) are explained by personal and household characteristics and unobserved earning determinants. The coefficients of the equations are specific to each labour segment, allowing observable characteristics to affect wages in different magnitudes across labour segments.

$$logW_i = a^s + X_i b^s + v_i \quad (3)$$

where W_i is the wage of working individual i, X_i is the characteristics of working individual i and his or her household, a^s is the intercepts in the log-wage earning equation in segment s, b^s are the slopes in the log-wage earning equation in segment s, and v_i captures the unobserved determinants of the log wage of individual i.[9] To correct for sample selection bias, the equation is estimated through a Heckman-type approach, as described in section 3.

The microsimulation model includes three labour market segments (formal skilled, formal unskilled, and informal) and abstracts from mobility of individuals among them. Adjustment takes

[7] In Amemiya and Shimono (1989, p. 14), where the focus is on the labour supply decision, 'utility is completely known to the individual but is a random variable for the econometrician'. Here, as in Bourguignon et al. (2004), 'utility' is replaced by a 'criterion value', as the focus is on whether the individual obtains a job given his or her labour supply.
[8] Assuming the absence of measurement errors which, either via mis-estimating the dependent or the independent observed variables, could also affect the estimated coefficients and the error term.
[9] Assuming the absence of measurement errors.

place via quantity and wage changes in the formal segments, and via wage changes in the (full employment) informal segment. All these changes are informed by the macro model.

2.4 Non-labour income

Non-labour income is the sum of dividend earnings ($DIVD_i$), the net interest flow earned ($FINT_i$), and an exogenous element ($\overline{OTHY_i}$) that captures all other sources of income.

$$Y_{0i} = DIVD_i + FINT_i + \overline{OTHY_i} \tag{4}$$

This completes the specification of the household income model.

3 ESTIMATION OF THE MODEL

Every element in the specified household income model must be identified, including the sequential observation of variables in the household survey ($YH_h, IW_i, W_i, Y_{0i}, Z_i, X_i,$ $DIVD_i, FINT_i$ and $\overline{OTHY_i}$, as defined above), econometric estimation of the parameters in the employment (α^s and β^s) and wage (a^s and b^s) equations, and attribution of unobservables in those equations ($\overline{CV}^U, u_i, CV_i^W$ and v_i).

3.1 Observation of variables in the household survey

The household survey used to gauge labour and non-labour incomes, employment status, and explanatory variables for the employment and wage equations is the October 2001 wave of the Permanent Household Survey (PHS) carried out by the National Institute of Statistics and Census (INDEC, *Instituto Nacional de Estadística y Censos*) in Argentina. It gathers information on individual socio-demographic characteristics, income sources, and labour indicators, and provides sample weights indicating the number of individuals or households represented by each observation, once corrected for missing data. This wave of the survey covers 29 urban areas (all the urban areas in the country with more than 100,000 inhabitants), and accounts for 87.2 per cent of the country's population.

The survey classifies individuals as employed, unemployed or inactive (that is, neither working nor actively searching for a job). It thus allows for the identification of individuals at work and individuals supplying labour (including the unemployed). The survey also includes information on gender, education (completed level and years of education), age and marital status; regional dummies; a household head indicator; and number of children (under 14 years old) – all factors which potentially affect the employability of the individuals and so are useful to provide covariates for the employment status equation (Z_i). These covariates include the work experience of the individual, which is proxied by the individual's age minus his or her years of education minus the obligatory age of start of education. The covariates of the wage equation (X_i) differ from Z_i only because the household head indicator and the number of children are excluded, variables which are perceived as affecting the employability of labour suppliers but not having an effect on the wages of the individuals at work. These covariates provide reasonable instruments for testing the presence of sample selection bias due to incidental truncation, as explained in the following section.[10] The survey allows for the categorisation of individuals into skilled and unskilled, with the former identified as those who have completed high school. Formal workers are identified as those either contributing to social security or with work-risk insurance and/or compensation if they are fired. Finally, each sampled household is categorised into one of the representative household groups: Households whose capital income exceeds labour income are classified as capitalist (C). Non-capitalist households whose household head finished secondary school are categorised as skilled[11] (S). The rest of the households are categorised as unskilled (U).

3.2 Econometric estimation of the parameters in the model

To estimate the effect of the covariates on employment status and (log) wages, econometric estimations are conducted, determining the values of the associated parameters in the model.

[10] Finding a perfect instrument is virtually impossible given that observed variables tend to affect labour demand in relation to both whether an individual is hired and how much he or she is eventually paid.

[11] In the case of missing information for the household head, the skill level of other members of the household was evaluated, starting with the partner of the household head.

Parameters in the employment equation. These parameters are estimated using segment-specific (skilled vs. unskilled) binomial logit functions $P(IW_i = 1|Z_i) = \frac{e^{\alpha^S + Z_i\beta^S}}{1+e^{\alpha^S + Z_i\beta^S}}$ in the formal labour market, that is, assuming that in each of these segments the unobservables are identically and independently distributed and come from a logistic probability density function. [12]

From the original 15,221 formal skilled and 7,238 formal unskilled workers present in the micro database, the model is run on 14,574 formal skilled and 6,858 formal unskilled workers, the reduction in observations mainly due to missing data on years of education. In both labour segments, the overall significance of the labour status model is not rejected. Completed education level, experience (and its square), marital and household head status, and number of children in the household are significant determinants of the employment status at a one percent level of significance. All these variables add to the probability of labour suppliers being employed, except for number of children in the household, and the square of experience – which have a negative effect -, suggesting that the positive effect of experience is reduced with each increase in its value.

Parameters in the wage equation. We run separate regressions to estimate the parameters of the wage equation for each labour market segment. In the formal labour segments, where unemployment is allowed, the wage equation is potentially subject to the presence of sample selection bias, by which the unobservables in the ordinary least squares (OLS) estimation of the wage equation are correlated with those in the employment status equation, hence biasing the OLS estimates of the wage equation (Wooldridge 2003,p560-2). To detect and subsequently correct for sample selection bias, we use the two-step Heckman procedure, adapted to take into account that the behavioural approach – following Bourguignon et al (2004) - uses the logistic (rather than the normal) distribution function to estimate the employment status equation. Specifically, we substitute the inverse Mills ratio in the Heckman procedure by the ratio between the logistic (rather than probit)

[12] Logit is preferred to probit given the property satisfied only by the former, by which the average in-sample predicted probability equals the sample frequency, which makes the link between the coefficients in the segment-specific logit functions and employment rates at the macro level more direct. Unemployment is taken as the base category for conducting the binomial logit estimation.

PDF and CDF. From the original 13,226 skilled, 3,732 formal unskilled and 10,559 informal unskilled employed individuals, the regression is conducted on 10,627 skilled, 3,386 formal unskilled and 8,636 informal unskilled individuals, with the reduction in observations again due primarily to lack of data on years of education. In each segment, the overall significance of the wage model is not rejected. Sample selection bias in the wage equation of the formal segments could not be rejected and thus was corrected for.[13] In every labour segment, ceteris paribus, men were found to earn more than women, and those with completed education levels were found to earn higher wages than the rest, with the differences being statistically significant. For a skilled individual, keeping other characteristics constant, being male increases the predicted wage by 0.35 per cent on average. Experience has a premium only in the formal skilled and informal unskilled segments. The marginal premium decreases as experience goes up, with the maximum premium being around 35 years of experience for the skilled and 41 years of experience for the informal unskilled.[14] There is a significant marital status premium in the skilled and informal unskilled segments.[15]

3.3 Attribution of unobservables

The unobservables in the employment equation and the wage equation ($\overline{CV}^U, u_i, CV_i^W,$ and v_i) need to be attributed in order to complete the determination of the elements in the household income model. Following Bourguignon et al. (2004), $\overline{CV}^U$ is arbitrarily assigned, but for convenience at the mean of the deterministic component of CV_i^W rather than at null; the unobservable values u_i are drawn randomly from the inverse of a logistic PDF and consistently with the observed employment status; in particular, the process is repeated iteratively until all the individuals have stochastically generated unobservables consistent with their employment status. This meant, in the particular

[13] The same result was obtained when checked using the traditional two-step Heckman procedure.
[14] This comes from maximising log $W = a.EXP + b.EXP^2 + C$ with respect to EXP, with W being wage, EXP being experience, a and b being the estimated coefficients of experience and its square for each labour segment, and C being all other log-wage determinants.
[15] Marital status is reported by Korenman and Neumark (1991, p. 282) to affect performance and wages when analysing evidence on white males. One of the most robust findings in human capital wage equations has been that married men earn more than men who never marry (Gray 1997, p. 482).

database we analysed, around 100 iterations.[16] CV_i^W is generated using equation (2). Unobservables v_i affecting the log wage are imputed using the OLS residuals (accounting for sample selection bias) when possible and randomly attributed from a normal distribution with zero mean and standard deviation given by the estimated residuals of the OLS regression.

4 COMMUNICATION OF CGE MACRO OUTCOMES

At this stage, the household income model is ready to receive information from the macro CGE model. Given our focus on the integration of the microsimulation model, we only briefly explain how the macro shock is simulated and what the main transmission channels operating in the CGE model are.

4.1 The CGE model and the drop in non-residents' deposits

Deposits by non-residents at domestic banks fell by 35.0 per cent toward the end of Argentina's Currency Board regime, from US$32.9 billion (December 2000) to US$21.4 billion (December 2001). The macro CGE model, which is calibrated for the year 2001, is a stylized extension of the IFPRI (International Food Policy Research Institute) Standard Model that explicitly models financial mechanisms and accounts for short-run wage rigidities. In terms of the model's macro closures, savings drive investments, the public deficit is endogenous and the nominal exchange rate is fixed, reflecting the Currency Board regime. With the price of imported goods in foreign currency also fixed (small-country assumption), the domestic currency price of imported goods becomes locked and the numéraire of the model is provided by the bundle of imported goods. The sector-specific value-added production functions are neoclassical, with positive and decreasing marginal productivity of each factor and constant economies of scale. As illustrated in Figure 2, sector-specific value added, which is combined with intermediates via a Leontief function to generate gross value added, is a nested constant elasticity of substitution (CES) function of labour, physical capital and working capital, following the 'money in the production function' tradition

[16] The randomness at stake proved to impact the distributional result of the microsimulation. The impact proved to be rather small, with the variability of the criterion values tending to be dominated by the variability of the deterministic component, as seen from comparing the standard deviations of CV_i^W (1.93) and u_i (1.60).

begun by Friedman (1969). Workers are mobile across production sectors. While in the formal segments of the labour market (skilled and unskilled) there is some wage rigidity captured with a wage curve and hence involuntary unemployment, the informal segment clears entirely through wage adjustment (no unemployment). Physical capital is characterized by the existence of different capital vintages, with the capacity utilization rate falling as soon as the sector-specific remuneration of capital reaches a lower threshold. Working capital is provided by the banks to the companies in the formal segments of the economy, with its remuneration clearing for the domestic interest rate.

The banks' supply of working capital is financed by deposits in domestic banks and is particularly hit by the significant drop in non-residents' deposits in the scenario under analysis. The shock initially leads to a fall in the supply and use of working capital. This fall in turn lowers the productivity and the demand for all the other factors, leading to significant decreases in the employment level of formal skilled and unskilled workers and decreases in the wages of formal skilled, formal unskilled and, especially, informal unskilled workers, as well as in the returns to physical and working capital. This leads to some decreases in dividends earned by residents and net interest earnings of domestic households, as shown in Figure 3 and Table 1. Besides marginal decreases in the returns to utilized capital, as non-residents withdraw their deposits, the capitalist household group – the ultimate owner of the domestic commercial banks – suffers a significant income loss due to the reduction of financial activity. Subsequently, the decrease in factor use leads to decreases in the activity level of the economy and in the incomes of the representative household groups.

The CGE model is allowed to increasingly inform the MS model in three different simulations, as shown in Figure 4: it communicates in a cumulative way the macro changes in the employment levels in the formal segments (Sim. 1), relative wages and prices (Sim. 2), and capital incomes

(Sim. 3)[17], allowing us to consider the extent to which the changes in the employment levels explain the overall distributional changes generated by the capital outflows.

The cumulative effect generated with the behavioural MS model is compared against non-behavioural ones, that is, the 'non-parametric' approach of Vos and Sanchez (2010) and the traditional RHG approach. The adjustments of household incomes with the RHG approach (Sim. H) are fairly straightforward, as they are performed arithmetically. Specifically, the income of sampled households is adjusted in this simulation using the macro model income changes for the RHG associated with each sampled household (namely, skilled, unskilled, and capitalist, as defined in section 3.1). Finally, in the non-parametric approach (Sim. F), changes in labour status are randomly assigned such that they are consistent with macro changes in the segment-specific employment levels and proportional changes in wages and capital incomes are communicated arithmetically[18].

4.2 The attribution of the changes at the micro level

4.2.1 Changes in employment and relative wages and prices in behavioural simulations

The household income model is used to generate micro changes in employment status (Sim. 1) and relative wages (Sim. 2) consistent with the set of macro changes communicated from the CGE model. Following Bourguignon et al. (2004), the changes in the parameters are made assuming 'neutrality' with respect to individual characteristics. The neutrality holds in the sense that only changes in the intercepts of equations (2) and (3) of the household income model are allowed, that is, wages in each labour market segment change by the same proportion and, for each individual, the relative change in her ex ante probability of being employed depends only on her initial probability rather than on her individual characteristics.

[17] In other words, Simulation 2 includes Simulation 1, but also wage and price changes, while Simulation 3 includes Simulation 2 and also capital income changes.

[18] The process is iterated 100 times, consistently with the number of iterations in the behavioural approach we follow.

The new intercepts are determined using a Newton's algorithm. The departure point for the implementation of the Newton algorithm was provided by the code used in Bourguignon et al (2004). A direct adaptation of the code led to a problem in the case at hand: once the macro target was relatively close, the intercepts (and hence the employment levels and average wages) started to move up and down without reducing the distance to the targets. To avoid this problem, we adjusted the algorithm so that it is able to approach the target at a relatively high speed, but the speed goes down every time the target is passed. As expected, in Sim. 1, α_{FS} and α_{FU} fall to allow employment levels to shrink, while all the intercepts fall in Sim. 2 and 3, allowing falls both in the employment and average wages (Table 2).

4.2.2 Changes in capital incomes and in non-behavioural simulations

The adjustments of individual capital incomes cumulated in the behavioural microsimulations (Sim. 3) and of household incomes in the RHG approach are fairly straightforward, as they are performed arithmetically. The capital incomes are adjusted in Sim. 3 using the percentage changes in dividends and interest flows coming from the CGE model, following their weights in the income of the sampled households. Household incomes are adjusted in Sim. H using the macro model income changes for the RHG associated with each sampled household. Finally, following Vos and Sanchez (2010), the proportional changes in wages and capital incomes are communicated arithmetically and changes in labour status are randomly assigned such that they are consistent with macro changes in the segment-specific employment levels (Sim. F). For all the microsimulations conducted (except Sim. H, which delivers household incomes directly), simulated incomes at the individual level are translated at the household level, making use of the household and non-labour income identities.

5 INCOME DISTRIBUTION, POVERTY AND WELFARE EFFECTS AT THE HOUSEHOLD LEVEL

As shown in Table 3, we find that with behavioural microsimulations, household per capita income falls more than 3 per cent due to the drop in employment levels (Sim. 1) and only around an additional 1 per cent due to the drop in wages for those who remain employed (Sim. 2), reflecting a high degree of wage rigidity in the formal labour markets, as captured in the macro model. Overall, household per capita income falls 4.4 per cent applying behavioural microsimulations (Sim. 3, total cumulated effect), 0.5 percentage points less than in the non-parametric microsimulations (4,9 p.p.) and 1.0 less than in the ones linked by the RHGs to the macro model (Sim. H, 5,4 p.p.). The smaller decrease in income that the behavioural approach predicts presumably reflects the fact that only in this approach workers with the highest estimated probability of being jobless are fired, and these workers have wages that are, on average, relatively low.

In the behavioural approach the cumulative effects of changes in employment (Sim. 1), relative wages (Sim. 2) and capital income (Sim. 3) consistently lead to increases in every inequality and poverty indicator for every poverty line. The Gini coefficient increases almost 1 percentage point, from 48.9 to 49.8. However, as the average income falls from A$309.2 to A$296.1, the average expected difference between two randomly chosen individuals falls around 2 per cent (from A$302.4 to A$294.9).[19] The increases in the Gini coefficient are due both to the loss of jobs and to changes in labour wages. The entropy index shows similar behaviour but starts at a higher level and increases more than the Gini coefficient.

Non-parametric microsimulations (Sim. F) also lead to increases in every inequality and poverty indicator that we considered, in each of the transmission channels analysed (the final effect is presented in Table 3, as well as its comparison to the final effect in the behavioural approach). The increases in inequality are smaller. Given that the wage falls are the same than in the behavioural

[19] The expected difference between two individuals randomly chosen is given by twice the Gini coefficient times the average income (Ray 1998).

approach, this is presumably due to the workers with the lower wages not being especially prone to being fired in this approach. Traditional RHG-based microsimulations (Sim. H), unable to capture the effect of the loss of jobs on individual incomes, miss a large part of the action and lead to the conclusion that inequality goes slightly down, independently of the inequality indicator used.

In the behavioural microsimulation, as per capita income falls and inequality increases, the poverty head counts, poverty gaps and poverty severity indices rise for all the poverty lines considered: the 1.25- and 2-dollar-a-day 2005 PPP (purchasing power parity) poverty lines – the former being the new international poverty line and the latter the median poverty line across the full sample of poor countries as categorized by the World Bank (Ravallion et al 2009) – and the extreme and moderated poverty lines used by the INDEC[20]. The increase in poverty indicators reflects increases in the share of households below the poverty line, in the average difference between the income of poor households and the poverty line, and in income inequality among poor households. For all these indicators and with all the reference poverty lines, the drop in employment (Sim. 1) is sufficient to explain most of the change, though there are some slight increases due to the decrease in wages (Sim. 2); and there is no change at all due to the capital income changes (Sim. 3), reflecting the lack of capital income among the poor. The household-linked microsimulations suggest that the shock does not significantly affect poverty, while the non-parametric approach shows strikingly similar effects on poverty to the behavioural one.

Figure 5 gives a clear indication of the power of behavioural microsimulations to capture the heterogeneity of income changes in different parts of the income distribution due to a macro shock, as opposed to microsimulations linked through households, which would give us the impression that the shock has a fairly homogenous effect and that its slight heterogeneity leads to a more progressive income distribution. Interestingly, the figure also suggests that the non-parametric approach can capture this heterogeneity to a large extent: even when it does not explain

[20] This occurs despite an endogenous fall in the official poverty lines. Reflecting the fall in the price of industrial goods (2.32%) and other commodities (4.01%) informed by the CGE model, and the weight of the industrial good in the Household Expenditure Survey of 1996-1997 of Argentina (72.5%), these simulated poverty lines fall by 2.78%. The dollar-denominated poverty lines are exogenous and fixed.

employment and wages econometrically, it does account for the effect of unemployment on income at the household level. As Figure 6 shows, the percentage changes in employment by centile are not too different in these two approaches. This suggests that, if a researcher has the single goal of understanding the distributional effects of the macro shock under analysis, the non-parametric approach may do a reasonably good job, avoiding the complexities of the behavioural approach.

The behavioural and non-parametric microsimulations also allow the magnitude of each of the (cumulative) transmission channels to be examined by centiles of household income. Following the behavioural approach, it can be seen that for the middle and upper centiles of household per capita income, the employment effect on income proves to be larger than the wage effect, with both effects being negative (Figure 7[21]). However, for the first 30 centiles, the wage effect is larger than the employment effect, reflecting their relatively high dependence on informal unskilled wages, which are fully flexible. In any case, it is clear that the distribution of lost jobs strongly shapes the change in income distribution across the entire income spectrum.

6. CONCLUSIONS

The significant distributional effects of capital outflows observed in Argentina are missed by the RHG microsimulation approach, but are captured by the behavioural and the non-parametric ones. Our analysis suggests that while the standard RHG approach is less time-consuming for the researcher, it does not capture individual heterogeneity in a meaningful way, or the effect of job losses on individual incomes, and as such it misses a large part of the action regarding distributional changes generated by macroeconomic events.

This observation calls for a careful definition and justification of the approach selected by researchers conducting macro-micro modelling. While the nuances embodied in the modelling design and implementation mean that only a researcher faced with a given set of issue, economy

[21] Note that the curve for Sim. 2 overlaps with the curve of Sim. 3 in this figure, given the insignificance of the endogenous changes in capital income in relation to the total income of the households.

and data and time availability can successfully make this selection, our analysis sheds light on the domain of applicability of the available approaches which can, in turn, inform this selection.

Linking the CGE and MS models through factor markets, as in the behavioural and non-parametric approach, is significantly more time-consuming than the traditional approach of linking the models through the incomes of the representative household groups: it requires analysing a wider set of variables in the household survey and linking household-level and individual-level data typically present in different database files. However, only by linking the models through the factor markets can researchers capture the individual-level income erosion generated by changes in individuals' labour status, which is frequently the most relevant transmission channel in the generation of the distributional effects of macroeconomic shocks (Bourguignon and Spadaro 2006, p.95).

To analyse an economy with significant presence of job rationing, a behavioural MS model like the one illustrated – and improved in terms of implementation – here allows identifying with precision how the selectivity of the labour market rationing (that is, the determination of who gets fired and who gets hired when the employment level changes) translates economy-wide phenomena to changes in individual labour status and economy-wide income distribution in the short run. This approach reflects the individual-level income erosion associated with job losses, accounts for the effect of changes in macroeconomic conditions on employment status and associated wages, and takes observed and unobserved individuals' determinants of employability into account. The importance of this employment channel also extends to other macroeconomic shocks that affect the total employment level and, in the presence of significant differences in the wages paid by different production sectors, to the reallocation of given workers. Furthermore, by fully accounting for the heterogeneity of the economic agents observed in micro-datasets and illuminated by the econometric explanation of the employment status, this approach can help in identifying complementary policies that affect the determinants of employability of the individuals - as captured in the regressors of the employment equation -, so that negative distributional consequences can be minimized or avoided.

However, surprisingly, the relatively straightforward non-parametric approach leads to distributional results in the analysed scenario that are not significantly different from those produced by the behavioural approach. This evidence adds to what Herault (2010) found: the reweighting approach has also delivered similar results to the behavioural approach. However, the results cannot be blindly generalized, as the mentioned similarities are not guaranteed for other cases. In other words, there is no way of fully knowing a priori how the individuals randomly fired or hired in each segment of the labour market by the non-parametric approach will relate to those fired or hired using the behavioural approach. Given this caveat, the present analysis does suggest the hypothesis that the two approaches lead to similar results. In the light of this finding, looking forward, researchers could fruitfully use the non-parametric approach when time or data limitations preclude them from using the behavioral approach. It would also be desirable for researchers to conduct model comparisons in other contexts, helping to accumulate empirical evidence regarding the distributional effects that different microsimulation models can illuminate.

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Table 1 Main results from macroeconomic model

Variable	% change
Formal skilled employment level (N_{FS})	-6.17
Formal unskilled employment level (N_{FU})	-6.54
Formal skilled wage level (W_{FS})	-0.39
Formal unskilled wage level (W_{FU})	-0.05
Informal wage level (W_{FU})	-7.21
Price of industrial goods (P_I)	-2.32
Price of other goods (P_O)	-4.01
Dividends (DIVD)	-0.07
Interest flows paid to households (FINT)	-0.04
Skilled household income (YH_S)	-5.77
Unskilled household income (YH_U)	-4.56
Capitalist household income (YH_C)	-8.89

Source: author's elaboration based on CGE model.

Table 2 Estimated and simulated intercepts of labour and wage equations

Intercept	Base	Sim. 1	Sim. 2
α_{FS}	0.5730	0.4746	0.4746
a_{FS}	6.2963	6.2942	6.2903
α_{FU}	-2.5913	-2.6634	-2.6634
a_{FU}	6.2981	6.2941	6.2935
a_{IU}	4.4198	4.4198	4.3450

Source: Econometric results of employment equation and CGE-MS results of capital outflows

Table 3 Per capita income, inequality and poverty indicators by simulation[22]

Indicator	Base	Sim. 1	Sim. 2	Sim. F	Sim. H
Per capita income	309.2	299.2	296.1	293.9	292.5
		(76.3)	(100.0)	(116.8)	(127.5)
Inequality					
Entropy index (α=2)[23]	64.0	65.9	67.0	66.4	63.3
		(63.3)	(100.0)	(80.0)	(-23.3)
Gini coefficient	48.9	49.5	49.8	49.7	48.8
		(66.7)	(100.0)	(88.9)	(-11.1)
Poverty					
Official Extreme Poverty Line					
Head-Count Index (P_0)	11.5	12.9	13.0	13.0	11.8
		(93.3)	(100.0)	(100.0)	(20.0)
Poverty Gap Index (P_1)	6.8	8.0	8.0	8.1	6.9
		(100.0)	(100.0)	(108.3)	(8.3)
Poverty Severity Index (P_2)	5.5	6.6	6.7	6.8	5.5
		(91.7)	(100.0)	(108.3)	(0.0)
Official Moderated Poverty Line					
Head-Count Index (P_0)	31.2	32.7	32.6	32.7	32.0
		(107.1)	(100.0)	(107.1)	(57.1)
Poverty Gap Index (P_1)	15.2	16.6	16.6	16.7	15.6
		(100.0)	(100.0)	(107.1)	(28.6)
Poverty Severity Index (P_2)	10.4	11.7	11.8	11.8	10.6
		(92.9)	(100.0)	(100.0)	(14.3)
$ 1.25-a-Day Poverty Line					
Head-Count Index (P_0)	7.3	8.6	8.9	9.0	7.7
		(81.3)	(100.0)	(106.3)	(25.0)
Poverty Gap Index (P_1)	5.2	6.4	6.5	6.6	5.4
		(92.3)	(100.0)	(107.7)	(15.4)
Poverty Severity Index (P_2)	4.6	5.7	5.8	5.9	4.7
		(91.7)	(100.0)	(108.3)	(8.3)
$ 2-a-Day Poverty Line					
Head-Count Index (P_0)	14.1	15.7	16.2	16.2	15.2
		(76.2)	(100.0)	(100.0)	(52.4)
Poverty Gap Index (P_1)	8.0	9.3	9.5	9.6	8.3
		(86.7)	(100.0)	(106.7)	(20.0)
Poverty Severity Index (P_2)	6.2	7.4	7.5	7.6	6.4
		(92.3)	(100.0)	(107.7)	(15.4)

Source: Author calculation based on Permanent Household Survey (2001) of Argentina and CGE-MS results. Figures in brackets are the simulated changes, as percentage of the simulated change in the full behavioural simulation. The results for Simulation 3 are not presented separately given that they are equal to those for Simulation 2.

[22] Incomes in Argentinean pesos per month

[23] α=2 such that zero-income cases can be captured in the index

Figure 1 Types of microsimulation models combined with macro models

Source: Author elaboration based on literature review

Figure 2 The production function in the CGE model

Source: Debowicz (2010)

Figure 3 Main transmission channels in the CGE model

Source: author's elaboration

Figure 4 Behavioural microsimulations

Source: Debowicz (2010)

Figure 5 Percentage changes in household per capita income by centile – behavioural, traditional and 'non-parametric' approach

Source: CGE-MS results

Figure 6 Percentage changes in employment level by household per capita income centile – behavioural and 'non-parametric' approach

Source: CGE-MS results. The dots are resulting changes in simulated employment levels, used in the construction of the graphed lines

Figure 7 Percentage changes in household per capita income by centile – behavioural simulations

Source: CGE-MS results