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Modelling the effects of capital outflows on employment, poverty and inequality for Argentina

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1. Introduction

The present work intends to contribute to the current efforts to link CGE models to microsimulations in the study of the distributional consequences of macroeconomic shocks and policies, an area of great current interest (Davies 2009, p.49). It proceeds by developing a microsimulation model following the lines set by Francois Bourguignon, Anne-Sophie Robilliard and Sherman Robinson (2004) (BRR) and linking it to a real-financial macro CGE model[1], incorporating households and individuals' heterogeneity, and allowing to look into the macro and micro effects of a set of macro policies and shocks. While the model can be adapted to different middle-income countries and scenarios, I apply it to investigate the macro and distributional effects of the severe capital outflows suffered by the Argentinean economy at the end of its Currency Board.

As described by Bourguignon and Spadaro (2006, p.78), the seed of microsimulation as an instrument for economic analysis was planted by Orcutt (1957), and since the early 1980s the use of microsimulation models (MSMs) has been encouraged by the rise of large and detailed datasets on individual agents and the continuing increases in, and falling costs of, computing power. As explained by Carolina Diaz Bonilla (Diaz Bonilla 2005, p. 87-89), early microsimulation studies were mainly focused on wage distributions: Almeida dos Reis and Paes de Barros (1991) considered the effect of education on wage distribution in Brazil; Juhn et al. (1993) looked at wage differentials in the US from 1963 to 1989 and Blau and Khan (1996) sought to explain why US wage differentials systematically exceeded those of other OECD countries during the 1980s. The next stage of microsimulations was focused on broadening their application beyond wage distributions – as did Bourguignon and Ferreira (2003), who analysed the impact of different taxes on income distribution at household level. In the third (present) stage,

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[1] A full explanation of the CGE model can be found at http://www.mendeley.com/profiles/Dario-Debowicz/, 'Thesis Dario Debowicz UoS', Chapter 3 (final model).

household data is combined with data at a higher level (sector, market, or economy-wide) allowing, among other things, to simulate the effects of policies and other shocks on a sample of economic agents (individuals, households, firms) at the individual level, thereby permitting the evaluation of the full distributional impact of these shocks.

At present, efforts to link CGE models to microsimulations to study the distributional consequences of macroeconomic shocks and policies are an area of great interest (Davies 2009, p.49). The link can be made either by fully integrating them – as in Cogneau and Robilliard (2006) and Cockburn (2006), where information on sampled agents is integrated into the CGE model – or by "layering" the two models in what is called the "top-down" approach, whereby the CGE model (a level above actual individuals and households) is allowed to inform the microsimulation model. As Davies suggests, while the integrated approach is theoretically more transparent, the layered approach is also interesting and promising, and has a relative advantage when the concern is with short-term distributional impacts in a setting where realism is at a premium and theoretical niceties are less important (Davies 2009, p.53 and 56). Besides, the layered approach allows us to by-pass the problem of identifying the heterogeneity of factor endowments and preferences at the level of single households or individuals (Bourguignon, Robilliard et al. 2004, p.3).

As explained in BRR, layered microsimulation models can be subdivided into arithmetic and behavioral. Arithmetic ones assume that the distribution of income within (RHG) groups is exogenous and constant, and ignore behavioral responses. Behavioral microsimulations account for the changes in both between- and within- (RHG) groups' inequality and consider behavioral responses (typically, consumption demand and labor supply). The usefulness of the latter in the analysis of public policies and shocks mainly involves their ability to fully take into account the heterogeneity of the economic agents observed in micro-datasets. They allow us to investigate the effects on individuals and households with existing combinations of characteristics that cannot be apprehended through typical cases. They help to identify with precision who are likely to be winners

and losers following a reform or shock, thus providing crucial information on welfare effects.

In this layered behavioral approach, Ganuza, Paes de Barros and Vos (2001) build a micro-simulation model that selects at random the individuals who change labor status and/or sector. In contrast, BRR build a micro-simulation model that econometrically (and not fully randomly) model the way rationing occurs in the labor market – that is, as a function of the observed and unobserved characteristics of the individuals supplying labor. In BRR, then, the main purpose of the MSM is to select individuals who are barred from (or let into) jobs, thus allowing selection to depend on individuals' heterogeneity.

As in BRR, the microsimulation model developed in the present work consists of a household income generation model that follows the specification of the mentioned CGE model. The macro-level CGE results for a given shock provide updates for the levels of employment in each labor market segment, average wages in these segments, relative prices, and capital incomes[2]. The macro-level results are transferred down to the micro-level household income generation model, providing new individual employment status, wages and capital incomes, which in turn inform distributional indicators and figures that can be evaluated. As in BRR, the selection of the individuals who are fired (or hired) when there is a change in labor demand is based on econometric analysis.

Carolina Diaz Bonilla (2005) models the sector allocation of individuals in ways that depart from the BRR model. This chapter follows BRR in that it compares the microsimulated distributional results by applying different techniques (behavioral and arithmetic microsimulations, as BRR do). However, it departs from BRR's methodology due to two extensions: capital incomes, which are exogenous and fixed in BRR MSMs, are endogeneised here, and the transmission channels communicated from the CGE

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[2] Differently than in Diaz Bonilla (2005), I have chosen to endogenise capital income even though these incomes are perceived to be underestimated in the Argentine Permanent Household Survey. Letting capital income be exogenous would have led us to ignore a channel which, in this case, is relevant from a distributional point of view.

model to the microsimulation module (joint in BRR) are separated into 1) employment, 2) wages and prices and 3) capital income effects.

To illustrate the approach, I look at the distributional effects of the capital outflow suffered by Argentina in the period surrounding the end of the Convertibility Plan. Specifically, I capture the distributional effects of the drop in non-residents' deposits at domestic banks, amounting to 35.0 per cent in the period December 2000 – December 2001, from 32.9 billion dollars to 21.4 billion dollars, and separate the transmission channels involved. This shock is especially interesting given that the large and sustained capital outflows led the Argentinean government to abandon the Convertibility Plan – first by devaluing the exchange rate (December 2001) and then by letting the local currency float (February 2002) – and led to an economic crisis that included a short-run worsening of social indicators, including unemployment rates and the poverty and inequality indices (Frenkel and Rapetti 2006).

When implementing the model, and departing from the work of BRR[3], I improve the process of determining the unobservables affecting the selection of who is fired (or hired) when labor demand changes occur; I take account of sample selection bias in the wage equations by adapting the two-step Heckman procedure for consistency with the logit function used to explain employment; I improve the Newton algorithm process used to adjust the household income model after a macro shock, by allowing it to get closer to the macro target without sacrificing speed and, for the evaluation of poverty and distributional changes, I extend the set of indicators and graphs used. Specifically, I use international and national methodologies for setting the poverty line, include Lorenz Curves at household level, and graphically consider the changes in household per-capita income by classifying the households not only in percentiles but also in ventiles, and by comparing their results.

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[3] I especially thank Anne-Sophie Robilliard for providing me with the Stata code developed by her and Vivi Alatas for the microsimulations module of the mentioned paper on Indonesia.

In the microsimulations, the following steps are followed: 1) a household income model is specified consistent with the CGE model; 2) the specified model is estimated; 3) specific CGE macro outcomes are generated and communicated to the model; 4) these CGE outcomes are attributed at the micro level using behavioral and arithmetical microsimulations, which generates new distributions of employment status, wages, capital incomes and, in turn, household incomes; 5) distributional indicators and graphs are prepared and evaluated, throwing light on the magnitude of the channels illuminated by the behavioral (as opposed to the traditional arithmetical) approach, and the distributional effects of capital outflows in Argentina.

2. Specification of the household income model

The household income model defines the total nominal income of each household as a non-linear function of the observed and unobserved characteristics of the household and its members. The model is composed of a household income identity, which separates out labor and non-labor income; an indicator function that determines the labor status of the individuals supplying labor; an equation that determines wages for the individuals at work; and an equation that sums up the non-labor income components. Next, I will discuss the specification of these equations, explaining its consistency with the modelling of the factor markets in the CGE model to which it is linked.

2.1. Household income identity

Nominal household income is simply the sum of nominal labor and non-labor income of the individuals in the household.

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

where:

YH_h: nominal income of household h

IW_i: dummy variable identifying labor status (1 for employed, 0 otherwise) of individual i in household h

W_i: nominal wage of working individual i in household h

Y_{0i}: non-labor income of individual i in household h

2.2. Employment status of individuals supplying labor

For the MSM to be consistent with the modelling of the labor market in the stylised macro CGE model to which it is conected, the characteristics of the latter need to be consistently translated into the former. This task is undertaken as described in the following table:

Table 1 Consistency between the macro and micro models

Macro model	Micro model
The labor market is segmented into formal skilled, formal unskilled and informal unskilled components, with no mobility among them in the short run.	Individuals supplying labor are assigned to one of these segments and once assigned remain there.
The labor supplies are exogenous and fixed in the short-run period under analysis.	Individuals supplying labor in the base simulation are those supplying labor after the simulations.
In the informal segment there is full employment.	All individuals informally employed remain so.
In the formal segments there is some unemployment.	The unskilled unemployed individuals are located into the formal segment. Individuals supplying labor in the formal segments need to be assigned among employed and unemployed alternatives in each simulation.

For individuals supplying labor in the formal labor segments, the assignment in terms of employed vs. unemployed is done according to some criterion the value of which is specific to the individual (CV_i^W). As in BRR, a view of the labor market as rationed suggests we refrain from calling this criterion value "utility", since employment and unemployment are not outcomes depending on a free decision taken by the individuals supplying labor, but an outcome of the job rationing in the labor market. For a given individual, his/her criterion value of being employed must exceed that of being unemployed in order to become employed. As there, the criterion value follows the additive random utility model (ARUM): it has a deterministic (observed by the analyst) and a random component, both being completely known by the individuals[4]:

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

where: (Amemiya and Shimono 1989, p.14)

IW_i: dummy variable identifying labor status (1 for employed, 0 otherwise)

Z_i: observed characteristics of labor suppliers affecting employment status

α^s: intercept affecting the criterion value of being employed in segment s

β^s: slopes in effect of observed characteristics on criterion value of being employed in segment s

u_i: unobserved determinants of employment status[5]

CV_i^W: criterion value for the employment alternative of individual i

$\overline{CV}^U$: criterion value for the unemployment alternative

2.3. Wage determination

Wages of employed individuals (strictly, their logs) are explained as a function of personal and household characteristics, with a residual capturing unobserved earning determinants and, probably, measurement errors. The coefficients of the equations are allowed to differ by labor segment, allowing observable characteristics to affect wages in different magnitudes across segments.

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[4] In Amemiya and Shimono, where the focus is on the labour supply decision, "utility is completely known to the individual but is a random variable for the econometrician" (Amemiya and Shimono, 1989, p.14). Here, as in RBR, "utility" is replaced by a "criterion value", as the focus is on whether the individual gets a job given his/her labour supply.

[5] Assuming absence of measurement errors.

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

where:

W_i: nominal wage of working individual i

X_i: characteristics of working individual i and his/her household

a^s: intercepts in log-wage earning equation in segment s

b^s: slopes in log-wage earning equation in segment s

v_i: unobserved determinants of log-wage of individual i[6]

2.4. Non-labor income

Non-labor income is the sum of dividend earnings, the net interest flow earned, and a residual element ($\overline{OTHY_i}$) that captures all other sources of income, all in nominal terms. With $\overline{OTHY_i}$ being exogenous and fixed in the CGE, it is kept as such in the micro model.

$$Y_{0i} = DIVD_i + FINT_i + \overline{OTHY_i} \qquad (4)$$

where:

Y_{0i}: non-labor income of individual i

$DIVD_i$: dividend earnings of individual i

$FINT_i$: net interest flow earned by individual i

$\overline{OTHY_i}$: other incomes of individual i

This completes the specification of the household income model consistently with the modelling of the factor market in the CGE model for Argentina.

3. Estimation of the model

Every element in the household income model must be determined, which implies 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 $\overline{OTHY_i}$), 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 ($u_i, CV_i^W, \overline{CV}^U$ and v_i).

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[6] Assuming absence of measurement errors.

3.1. Observation of variables in the household survey

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

The survey classifies individuals into employed, unemployed or inactive (i.e. neither working nor actively searching for a job). It thus allows for the identification of individuals at work and individuals supplying labor (including the employed and the unemployed). The survey has also information on gender, education (completed level and years of education), age, marital status[7], regional dummies, a household head indicator and number of children (individuals with age not exceeding 14 years old), which potentially affect the employability of the individuals and so are useful to provide covariates for the employment status equation (Z_i). Z_i includes work experience of the individual, which is proxied by the age minus the years of education minus the obligatory age of start of education. X_i is given by Z_i once the household head indicator and the number of children have been excluded, variables which are perceived as affecting the employability of labor suppliers but not having an effect on the wages of the individuals at work, and provide reasonable instruments for testing the presence of sample selection

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[7] Marital status is reported to affect performance and wages by Korenman (1991, p.282) when analyzing 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, F, 1997, p. 482).

bias due to incidental truncation, as explained in next section[8]. The survey allows for the categorisation of individuals into skilled and unskilled, the former being those who have completed high school. Formal workers are identified as those contributing to social security, with work risk insurance and/or compensation if they are fired. Finally, each sampled household is categorised into one of the representative household groups (RHG): households whose capital income exceeds labor income are classified as capitalist (C). Non-capitalist households whose household head finished secondary school are categorised as skilled[9](S). The rest of the households are categorised as unskilled (U). (Korenman and Neumark 1991; Gray 1997)

3.2. Econometric estimation of the parameters in the model

To estimate the effect of the mentioned covariates (Z_i and X_i) on employment status and (log) wages, respectively, econometric estimations are conducted, determining the values of the (α^s, β^s, a^s and b^s) parameters in the model.

Parameters in the employment equation. Parameters α^s and β^s in equation (2) are estimated using segment-specific binomial logit functions in the formal labor market, i.e. assuming that, in each of these segments, the unobservables are identically and independently distributed (IID) and come from a logistic pdf. 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 macro level more direct. Unemployment is taken as the base category for conducting the binomial logit estimation.

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 skilled and 6,858 formal unskilled workers, the reduction in observations by and large due to missing data on years of education. In both segments, the overall significance of the model is not rejected and completed

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[8] Finding a perfect instrument is virtually impossible given that observed variables tend to affect labor demand both in relation to whether an individual is hired and how much he or she is eventually paid.
[9] 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.

education level, experience, marital status, household head and number of children in the household are significant determinants of the employment status at the 1% level. Their effects are positive, except for number of children in the household, which has a negative effect. The positive effect of experience is reduced with each increase in its value.

As a by-product of the estimation of this equation for the household income model, impact and marginal effects are estimated, with benchmarks being married males heading households in Great Buenos Aires who have not completed the educational level achievable inside their skill categories[10] and have mean experience (17.7 years for the skilled, 25.9 years for the unskilled). The probability of being employed is 90.2 per cent for the skilled benchmark and 55.5 per cent for the unskilled one. Providing both individuals in the benchmark with covariates with positive effects on their employment status reduces the gap between their employment probabilities. For example, *ceteris paribus*, completing education level (primary school for the unskilled, university for the skilled) increases the probability of being employed by 17.6 p.p. for the unskilled and 5.8 p.p. for the skilled, closing the probability gap by 11.8 p.p. An additional year of experience increases the probability of having a job by 2.5 p.p. (unskilled) and 0.8 p.p. (skilled). Heading a household increases the probability of being employed by 14.6 p.p. (unskilled) and 2.7 p.p. (skilled). Being married increases it by 15.7 p.p. (unskilled) and 4.3 p.p. (skilled). Belonging to a larger household is associated with a lower probability of being employed (1.1 p.p., unskilled and 0.5 p.p., skilled)[11]. There are regional differences in both labor segments: for skilled individuals, the probability of being employed is smaller in La Pampa and Great Buenos Aires; for unskilled individuals, the employment prospect is (20.7 p.p.) better in Patagonia than in Great Buenos Aires. Being male significantly increases the likelihood of being employed only for the unskilled (5.8 p.p.).

Parameters in the wage equation.   Separate regressions are run to estimate the parameters of the wage equation for each labor market segment. In the labor segments where

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[10] This level is primary for unskilled and university for skilled.
[11] This is consistent with the World Bank 1999 Poverty Assessment on Argentina finding that poor households tend to be larger.

unemployment is allowed (the formal ones), the wage equation is potentially subject to the presence of sample selection bias, by which the unobservables in the OLS estimation of the wage equation are correlated with those in the employment status equation, hence biasing the OLS estimates of the wage equation. This form of sample selection bias is known as "incidental truncation" (Wooldridge 2003,p560-2), by which we observe log-wages only for those at work i.e. the truncation of observed wages is incidental in the sense that it depends on another variable: employment status.

Table 1 Explanation of employment status in formal labor market segments

Binomial Logit CDF: $P(IW_i = 1|Z_i) = \frac{e^{\alpha^S + Z_i \beta^S}}{1 + e^{\alpha^S + Z_i \beta^S}}$

Variable	Formal skilled		Formal unskilled	
	Coef	dy/dx^M	Coef	dy/dx^M
Male^D	0.0393	0.0035	0.2333	0.0581
	(0.0560)	(0.0050)	(0.0651) ***	(0.0162)
Married^D	0.4145	0.0431	0.6360	0.1573
	(0.0643)***	(0.0071)	(0.0586) ***	(0.0142)
Household Head^D	0.2747	0.0270	0.5901	0.1462
	(0.0691)***	(0.0071)	(0.0666) ***	(0.0161)
Completed Education Level^D	0.9702	0.0583	0.7799	0.1762
	(0.0705)***	(0.0054)	(0.0825) ***	(0.0204)
Experience	0.0900	0.0079	0.0997	0.0246
	(0.0072)***	(0.0008)	(0.0083) ***	(0.0020)
Experience squared	-0.0013	-0.0001	-0.0014	-0.0003
	(0.0001)***	(0.00001)	(0.0001) ***	(0.00003)
Number of children	-0.0613	-0.0054	-0.0483	-0.0119
	(0.0133)***	(0.0012)	(0.0116) ***	(0.0028)
Region Northwest^D	0.1752	0.0144	0.1277	0.0313
	(0.0830)*	(0.0069)	(0.0884)	(0.0216)
Region Northeast^D	0.3896	0.0293	0.0793	0.0195
	(0.1037)***	(0.0077)	(0.1052)	(0.0258)
Region Cuyo^D	0.3618	0.0275	0.1742	0.0425
	(0.1060)***	(0.0079)	(0.1057)	(0.0257)
Region Pampa^D	0.0674	0.0057	-0.0770	-0.0190
	(0.0749)	(0.0065)	(0.0800)	(0.0198)
Region Patagonia^D	0.6654	0.0449	0.9434	0.2071
	(0.1056)***	(0.0072)	(0.1000) ***	(0.0220)
Constant	0.5730		-2.5913	
	(0.0996)***		(0.1637) ***	
N	14,574		6,858	
McFadden-R^2	0.0952		0.1252	
Prob > χ^2	0.0000		0.0000	

Base category: unemployed. Standard errors between parenthesis.

*: significant at 10% level. **: significant at 5% level. ***: significant at 1% level.

[D]: dummy variables
[M]: marginal and impact effects reported by segment for a married male heading a household in Great Buenos Aires who has not completed education level corresponding to his skill category (primary for unskilled, university for skilled) and has mean experience (25.9 years for unskilled, 17.7 years for skilled).

In the case of employment status being explained by a probit model, the standard OLS regression $log\ W_i = a^s + X_i b^s + v_i$, $E(v_i|X_i) = 0$ becomes $log\ W_i = a^s + X_i b^s + \lambda(\theta_i)\rho + v_i$, where $\lambda(\theta_i)$ is the inverse Mills ratio coming from the probit model i.e. minus the ratio of the standard normal pdf and cdf valued at the index function for each individual ($\theta_i = \alpha^s + Z_i \beta^s$), and where ρ is its associated coefficient in the log-wage equation. To detect and eventually correct for the selection bias, the widely used two-step Heckman procedure 1) computes $\lambda(\theta_i)$ using probit and 2) includes it as a regressor in the OLS equation to test the significance of the sample selection bias. If the null of lack of significance of sample selection bias ($H_0: \rho = 0$) is rejected, the additional regressor $\lambda(\theta_i)$ is included in the OLS regression to avoid the mentioned bias in the OLS estimates.

In this case, the 2-step Heckman procedure is adapted since the logistic distribution function (rather than the normal distribution) was used to estimate the employment status equation. The inverse Mills ratio is substituted by minus the ratio between the logistic pdf and cdf. Its cdf is given by $\frac{e^{\theta_i}}{1+e^{\theta_i}}$. Its pdf is the derivative of the cdf respect to θ_i.

Hence, $pdf = \left(\frac{e^{\theta_i}}{1+e^{\theta_i}}\right)' = \frac{(e^{\theta_i})'(1+e^{\theta_i})-e^{\theta_i}(1+e^{\theta_i})'}{(1+e^{\theta_i})^2} = \frac{e^{\theta_i}(1+e^{\theta_i})}{(1+e^{\theta_i})^2} - \frac{(e^{\theta_i})^2}{(1+e^{\theta_i})^2} = cdf_i - cdf_i^2 = cdf_i(1-cdf_i)$. Then the analogous to the inverse Mills ratio becomes $\lambda^{LOGIT}(\theta_i) = -\frac{cdf_i(1-cdf_i)}{cdf_i} = -(1 - cdf_i) = -pr_{0,i}$ with $pr_{0,i}$ being the predicted probability of the base outcome (unemployment) for each individual.

From the original 13,226 skilled, 3,732 formal skilled, and 10,559 informal unskilled employed individuals, the model is run on 10,627 skilled, 3,386 formal unskilled and 8,636 informal unskilled, again the reduction in observations by and large due to lack of

data on years of education. In all segments the overall significance of the model is not rejected. Sample selection bias in the wage equation of the formal segments could not be rejected and thus was corrected for by the adoption of the two-step procedure[12]. There are significant regional differences in wages. For example, a skilled individual working in La Pampa would expect to earn 3.38 per cent less than someone with the same observable characteristics working in Great Buenos Aires. In every labor segment, *ceteris paribus*, males earn more than women, and those who have completed education level enjoy higher wages than the rest, with the differences being statistically significant though quite tiny. For example, 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, which decrease on it, with the maximum being around 35 years of experience for the skilled and 41 years of experience for the informal unskilled[13]. There is a significant marital status premium in the skilled and informal unskilled segments.

3.3. Attribution of unobservables.

The unobservables in the employment equation and the wage equation $(u_i, CV_i^W, \overline{CV}^U$ and $v_i)$ need to be attributed in order to complete the determination of the elements in the household income model.

To impute the unobservables u_i and CV_i^W, u_i values need to be drawn randomly from the inverse of a logistic pdf and be consistent with the observed employment status: the u_i for every employed individual should be such that his/her criterion value for employment exceeds that for unemployment $(CV_i^W = \hat{\alpha}^s + Z_i\hat{\beta}^s + u_i > \overline{CV}^U)$ and for every unemployed individual his/her criterion values of employment does not exceed that limit, $(CV_i^W = \hat{\alpha}^s + Z_i\hat{\beta}^s + u_i \leq \overline{CV}^U)$. In BRR Stata code, the u_i are drawn randomly from the mentioned pdf, but the consistency with the observed employment status is not assured in practice. To assure consistency, I extended the code following Fields and

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[12] The same result showed up when checking using the traditional 2-step Heckman procedure.

[13] This comes from maximising log $W = a.EXP + b.EXP^2 + C$ 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.

Soares (2004,p249-250) explanation in their application to Malaysia: for individuals whose criterion value implied by the randomly generated residual is inconsistent with the observed employment status, their unobservables u_i are generated again, and the process is repeated until all individuals have criterion values consistent with their observed labor status[14].

Table 3 Explanation of log wages by labor market segment

$$logW_i = a^s + X_i b^s + \lambda(\alpha^s + Z_i \beta^s)\rho + v_i \qquad (3)$$

Variable	Formal skilled	Formal unskilled	Informal unskilled
Male	0.3538	0.1800	0.4347
	(0.0140)***	(0.0241) ***	(0.0164) ***
Completed Education Level	0.3692	0.1027	0.2563
	(0.0229)***	(0.0365)***	(0.0223 ***
Experience	0.0209	0.0033	0.0406
	(0.0031) ***	(0.0045)	(0.0021) ***
Experience squared	-0.0003	-0.00001	-0.0005
	(0.0005) ***	(0.00006)	(0.00003)***
Married	0.0594	-0.0386	0.1753
	(0.0166) ***	(0.0251)	(0.0175) ***
Region Northwest	-0.5441	-0.2794	-0.3334
	(0.0226) ***	(0.0273) ***	(0.0273) ***
Region Northeast	-0.6392	-0.3000	-0.4162
	(0.0273) ***	(0.0324) ***	(0.0308) ***
Region Cuyo	-0.5720	-0.2731	-0.3440
	(0.0283) ***	(0.0333) ***	(0.0319) ***
Region Pampa	-3.3764	-0.1500	-0.1115
	(0.0214) ***	(0.0253) ***	(0.0261) ***
Region Patagonia	-0.0891	0.0713	0.2595
	(0.0277) ***	(0.0374) *	(0.0320) ***
Inverse Mills Ratio	2.3143	0.8279	
	(0.1990) ***	(0.1296) ***	
Constant	6.2963	6.2981	4.4198
	(0.0705) ***	(0.1614) ***	(0.0420) ***
N	10,627	3,386	8,636
R^2	0.3182	0.2240	0.2109
Prob>F	0.0000	0.0000	0.0000

*: significant at 10% level. **: significant at 5% level. ***: significant at 1% level.

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[14] The randomness at stake does have an impact on the distributional result of the microsimulation. The impact proved to be rather small, what is consistent with the variability of the criterion values tending to be dominated by that of its deterministic component, as coming from comparing the standard deviations of CV_i^W (1.93) and u_i (1.60).

Standard errors between parentheses.

The criterion value associated with unemployment can be set arbitrarily: while BRR and Fields and Soares (2004) set the criterion value for the "unemployed" alternative at zero ($\overline{CV}^U = 0$), I set it for convenience at the mean of the index function of the employed alternative ($\overline{CV}^U = E(\hat{\alpha}^s + Z_i\hat{\beta}^s)$). This meant that instead of waiting for hours without Stata getting a set of consistent criterion values, the process was successfully completed with less than 100 iterations.

Unobservables v_i affecting the log wage are needed to impute potential wages for all the active individuals, and were imputed strictly following BRR. For individuals at work with a positive reported wage, it is imputed as the residual of the OLS regression (once sample selection bias was accounted for). For those unemployed or at work with a reported null wage, it is randomly attributed from a normal distribution with mean zero and a standard deviation which is 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 macro information from the macro CGE model. I turn now the attention to the CGE model. Given the focus of the present paper, I will explain briefly how the macro shock is simulated, the main transmission channels at stake and how the communication from the CGE model to the household income model is made[15].
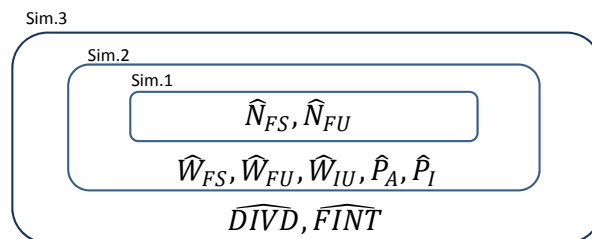
The macro CGE model explicitly models financial mechanisms and accounts for short-run wage rigidities. It is calibrated for the year 2001. The capital outflow is then simulated, the main transmission channels at stake highlighted and estimates of changes in relevant macro variables presented for subsequent communication to the micro model. Deposits of non-residents at domestic banks fell approaching the end of the Currency Board regime by 35.0 per cent, from 32.9 billion dollars (December 2000) to 21.4 billion dollars (December 2001). The transmission channels are shown in the diagram below.

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[15] A full explanation of the CGE model can be found at http://www.mendeley.com/profiles/Dario-Debowicz/, 'Thesis Dario Debowicz UoS', Chapter 3 (final model).

The shock essentially leads to a contraction of the economy, with falls in the use of formal skilled and unskilled labor ($\widehat{N}_{FS} = -6.17\%, \widehat{N}_{FU} = -6.54\%$), falls in labor nominal wages for formal skilled, formal unskilled and, especially, for informal unskilled ($\widehat{W}_{FS} = -0.39\%, \widehat{W}_{FU} = -0.05\%, \widehat{W}_{IU} = -7.21\%$), and falls in the price of primary and industrial goods ($\widehat{P}_A = -4.01\%, \widehat{P}_I = -2.32\%$), tiny falls in dividends earned by residents ($\widehat{DIVD} = -0.07\%$) and net interest earned by domestic households ($\widehat{FINT} = -0.04\%$). All the RHGs (skilled, unskilled and capitalist) suffer nominal incomes losses: ($\widehat{YH}_S = -5.77\%, \widehat{YH}_U = -4.56\%, \widehat{YH}_C = -8.89\%$)[16].

To decompose the behavioral microsimulation effects in order to understand the cumulative effects of the macro changes in the employment level, relative prices and capital incomes and then to compare the results against traditional arithmetic microsimulations, the CGE model is allowed to increasingly inform the microsimulation model in different simulations as shown in the following figure: it communicates macro changes in 1) the employment levels in the formal segments, 2) nominal wages and prices and 3) capital incomes. The CGE also informs RHGs incomes changes ($\widehat{YH}_S, \widehat{YH}_U, \widehat{YH}_C$), thus allowing to conduct traditional arithmetic microsimulations (Sim.4, RHG) which provide a comparison point for the behavioral microsimulations.

Figure 1 Behavioral microsimulations

Sim.3
Sim.2
Sim.1
$\widehat{N}_{FS}, \widehat{N}_{FU}$
$\widehat{W}_{FS}, \widehat{W}_{FU}, \widehat{W}_{IU}, \widehat{P}_A, \widehat{P}_I$
$\widehat{DIVD}, \widehat{FINT}$

---

[16] The relatively large fall in the income of the capitalist RHG is an unintended result of the model described in a previous chapter. The capital outflow reduces the money base and, for the banks' reserve ratio to remain constant, the deposits of the capitalist households turn negative. This makes the interest flowing from the banks to them on their deposits become negative, and their total income fall significantly. The behavioural microsimulations conducted here allow us to avoid this problem with the generation of household income counterfactuals.

5. The attribution of the changes at micro level

Changes are first attributed for employment and wage changes (Simulations 1 and 2), then also for capital income changes (Simulation 3), and finally for household income changes (Simulation 4).

5.1. Simulations 1 and 2

The household income model is used to generate micro changes consistent with the set of macro changes communicated from the CGE model. Households' and individuals' observed and unobserved characteristics need to remain unchanged. However, the parameters in the household income model need to change in order to generate micro results consistent with the equilibrium of aggregate markets in the CGE model in terms of employment levels and average wages (Simulations 1 and 2). Following the methodology designed by BRR, the changes in the parameters are made assuming "neutrality" with respect to individual characteristics i.e. changing the intercepts of the equations (2) and (3) of the household income model. The neutrality holds in the following sense: changing the intercepts a of the log wage equations generates a proportional change of all wages in each labor-market segment, and changing the intercepts α of the logit model implies that, for each individual, the relative change in his/her ex-ante probability of being employed depends only on his/her initial ex-ante probability rather than on his/her individual characteristics.

Figure 2 Transmission channels for a 60 per cent fall in the domestic deposits held by non-residents
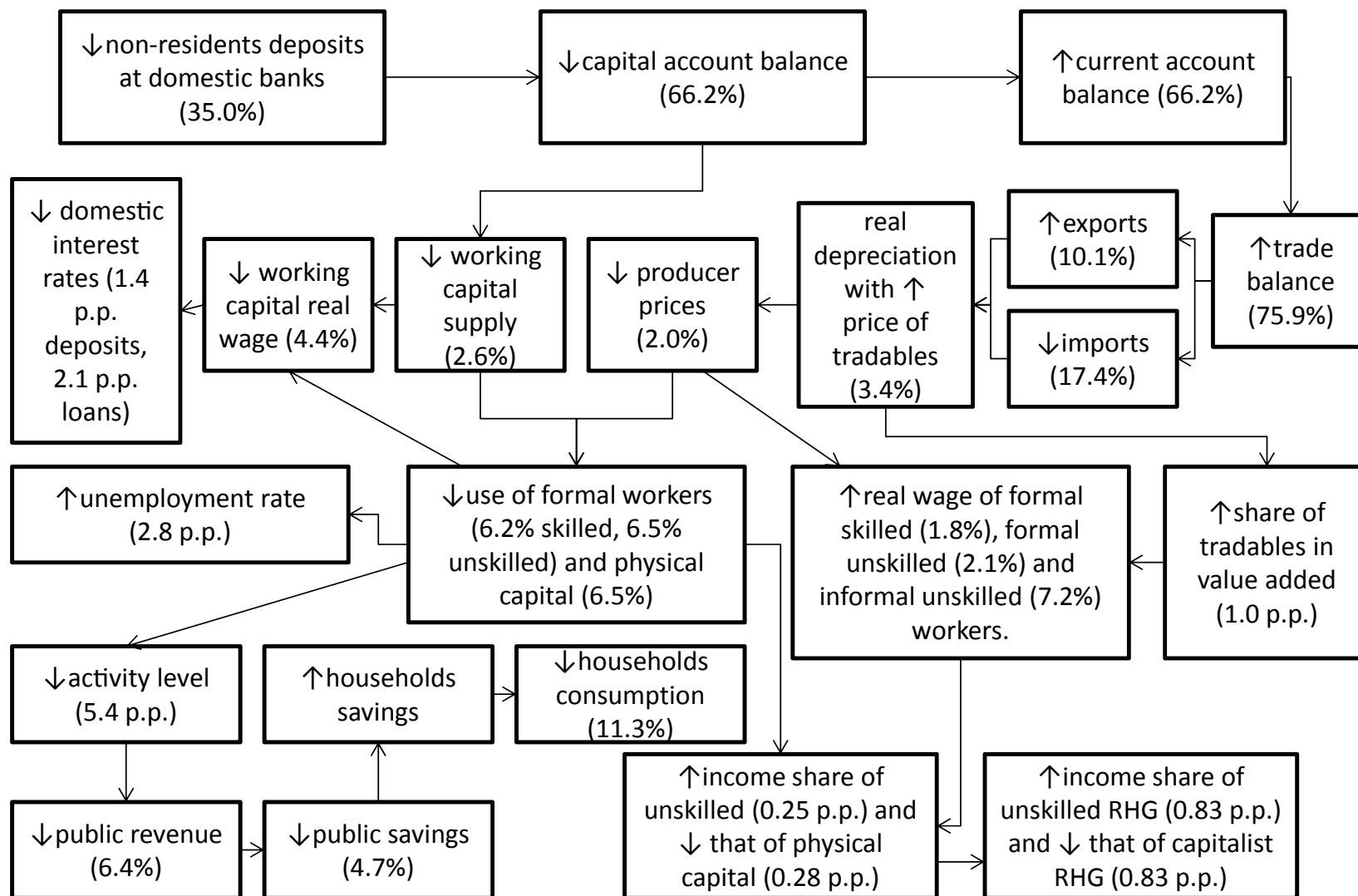
To implement the needed changes in the equation intercepts, let us call the set of intercepts row vector $x = (\alpha_{FS}\ a_{FS}\ \alpha_{FU}\ a_{FU}\ a_{IU})$, the original macro figures $f(x) = (N_{FS,0}, N_{FU,0}W_{FS,0}, W_{FU,0}W_{IU,0})$, the macro targets column vector $f^*(x) = (N^*_{FS}, N^*_{FU}W^*_{FS}, W^*_{FU}W^*_{IU})'$, with its elements given by $N^*_f = N_{f,0}.(1 + \widehat{N}_f)$ and $W^*_f = W_{f,0}.(1 + \widehat{W}_f)$, $N_{f,0}$ and $W_{f,0}$ being the employment rate[17] and the average nominal wage for each labor market segment in the sample once sample weights have been accounted for, and $\widehat{N}_f$ and $\widehat{W}_f$ the associated percentage changes coming from the CGE model.

The problem is to find an x vector consistent with the $f^*(x)$ macro target vector. This leads to a system of non-linear equations with as many equations as unknowns (5). The solution can be searched using the Newton's (also known as Newton-Raphson's) method, which works by finding successively better approximations to the root of a real-valued function or system of equations that is continuous and differentiable in the interval going from the initial guess to the root (Iserles 1996,p95-6). For a real-valued function with only one argument, as illustrated in the following graph, one starts with an initial guess (x_n) which should be reasonably close to the true root (x). The value of the function and its derivative are evaluated there ($f(x_n)$ and $f'(x_n)$) and used to get a new guess x_{n+1} given by the x-intercept of the tangent to the function evaluated at x_n. Algebraically, the new guess is given by $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$. The process is iterated until convergence to the root is reached.

Figure 3 Newton's method

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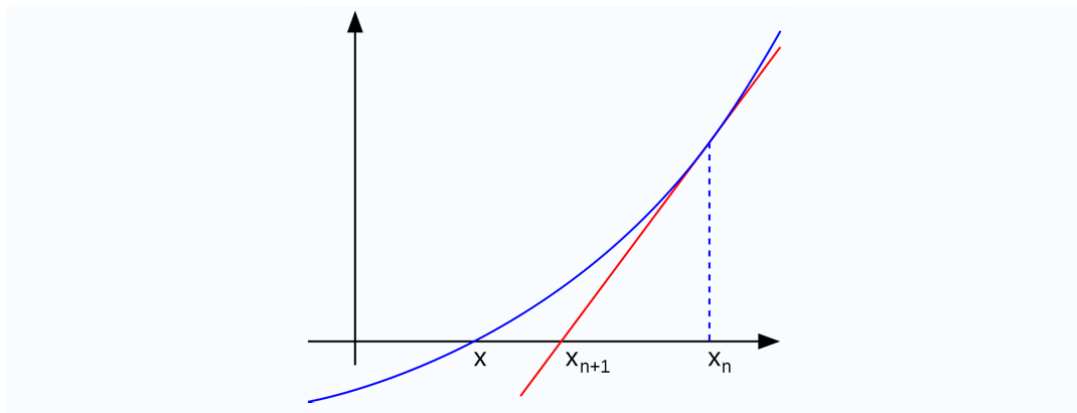
[17] Defined as the ratio between employed individuals and individuals supplying labor in the segment.

In the present case, the Newton's method is used to solve not one equation but a system of equations, which amounts to finding the zeroes of continuously differentiable functions $f(x): R^5 \rightarrow R^5$. Instead of a simple derivative, one needs to get a Jacobian matrix J with all the possible combinations of partial derivatives of the elements of $f(x)$ respect to the elements of x:

$$J = \begin{bmatrix} \dfrac{\partial N_{FS}}{\partial \alpha_{FS}} & \dfrac{\partial N_{FS}}{\partial a_{FS}} & \dfrac{\partial N_{FS}}{\partial \alpha_{FU}} & \dfrac{\partial N_{FS}}{\partial a_{FU}} & \dfrac{\partial N_{FS}}{\partial a_{IU}} \\ \dfrac{\partial W_{FS}}{\partial \alpha_{FS}} & \dfrac{\partial W_{FS}}{\partial a_{FS}} & \dfrac{\partial W_{FS}}{\partial \alpha_{FU}} & \dfrac{\partial W_{FS}}{\partial a_{FU}} & \dfrac{\partial W_{FS}}{\partial a_{IU}} \\ \dfrac{\partial N_{FU}}{\partial \alpha_{FS}} & \dfrac{\partial N_{FU}}{\partial a_{FS}} & \dfrac{\partial N_{FU}}{\partial \alpha_{FU}} & \dfrac{\partial N_{FU}}{\partial a_{FU}} & \dfrac{\partial N_{FU}}{\partial a_{IU}} \\ \dfrac{\partial W_{FU}}{\partial \alpha_{FS}} & \dfrac{\partial W_{FU}}{\partial a_{FS}} & \dfrac{\partial W_{FU}}{\partial \alpha_{FU}} & \dfrac{\partial W_{FU}}{\partial a_{FU}} & \dfrac{\partial W_{FU}}{\partial a_{IU}} \\ \dfrac{\partial W_{IU}}{\partial \alpha_{FS}} & \dfrac{\partial W_{IU}}{\partial a_{FS}} & \dfrac{\partial W_{IU}}{\partial \alpha_{FU}} & \dfrac{\partial W_{IU}}{\partial a_{FU}} & \dfrac{\partial W_{IU}}{\partial a_{IU}} \end{bmatrix}$$

The departure point for the implementation of the Newton algorithm was given by the code used in BRR. A direct adaptation of the code led to a problem in the case at stake: once the macro target was relatively close (but the distance to it exceeded the tolerance), the intercepts started to move up and down without reducing with each simulation the distance to the target. To avoid this problem, I adjusted the algorithm so that it is able to approach the target at a relatively high speed but when the target is passed the speed changes: when the macro figure is below (above) the target before the step, but above (below) it after the step, the algorithm reduces the step by which the intercept in the equation is adjusted.

In more detail, the Newton algorithm was conducted in the following way:

1. The maximum number of iterations for the algorithm $imax$ was set, as well as the tolerance Euclidean distance tol between the final $f(x)$ and the target $f^*(x)$ macro figure, and a $dump$ diagonal matrix which regulates the size of the steps given when changing the different intercepts in each iteration.
2. $f(x)$ was computed for the original intercepts x.
3. $f^*(x)$ target was assigned using the CGE outcomes.
4. A vector $diff = f(x) - f^*(x)$ was computed, as well as its Euclidean distance to the origin: $dist = \sqrt{diff' * diff}$.

5. If *dist* exceeds *tol* and while number of iterations is below or equal to *imax*:

   a. Compute the Jacobian matrix J and its inverse JI

   b. Compute vector $jdif = dump * JI * diff$

   c. Decrease x by $jdif$

   d. Compute $f(x)$

   e. Calculate $diff$ and $dist$

   f. If *dist* changes sign (i.e. if the target was "missed"), half the *dump* diagonal matrix element

6. The outcome intercepts x and the Euclidean distance of macro values to target *dist* are reported, as well as the labor income of each individual (zero for those unemployed).

As pointed out by Iserles (1996,p95-6), the computation of a Jacobian matrix and the solution of a linear system in each iteration makes the Newtonian technique costly. However, for small systems of equations as the one at stake, the solution is reached relatively fast. With the commented adaptation in the algorithm, a maximum of 100 iterations allowed, an original dump factor of 0.5, and a tiny target distance $(1*10^{-6})$, the algorithm hits the iteration limit (100 iterations) in less than 5 minutes per simulation, arriving at simulated intercepts that allow the percentage variations in employment rates and average wages to be replicated at two decimal points of precision. As expected, α_{FS} and α_{FU} fall to allow employment levels to shrink. However, a_{FS}, a_{FU} and a_{IU} do not fall systematically, which reflects that some individuals with wages exceeding the average wage in the associated labor segments are fired, making the average wage fall, *ceteris paribus*, and calling for wage increases for those still employed in order for the average wages not to fall more than is indicated by the macro target.

Table 4 Estimated and simulated intercepts of labor and wage equations

tercept	egression	imulation 1	imulations 2 & 3
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

The adjustment of individual capital incomes (Simulation 3) and household incomes (Simulation 4) is pretty straightforward, as it is performed arithmetically. The capital incomes are adjusted in simulation 3 using the percentage changes $\widehat{DIVD}, \widehat{FINT}$ coming from the CGE model. For simulation 4, the income of each sampled household is adjusted using the income change of the RHG associated to that household ($\widehat{YH_S}, \widehat{YH_U}$ or $\widehat{YH_C}$).

6. Income distribution, poverty and welfare effects at household level

For microsimulations regarding individual incomes (SIM1-SIM3), simulated incomes at the individual level are translated at the household level making use of the household income identity (1) and -before- of the non-labor income equation (4). Then, to evaluate the income distribution, poverty and welfare effects of the capital outflow using household level data, I use the following set of tools: an average income indicator, inequality indicators (Gini and General Entropy), poverty indicators (Foster-Greer-Thorbecke using different poverty lines) and graphs looking at the percentage changes in income by ventiles and percentiles of household per capita income, taking account of sample weights[18].

Four different poverty lines are used to calculate the FGT indicators: the dollar-a-day and 2-dollar-a-day poverty lines, and those used by the National Statistics Office in Argentina (INDEC): extreme and moderated poverty lines. In the base scenario, where the dollar and the Argentinean peso are traded in a one-to-one relation, household specific dollar-a-day and 2-dollar-a-day poverty lines are computed as 30 times the household size, given that the recollection period is one month.

INDEC's methodology to define the poverty line is based on adult equivalents in the households and estimated consumption needs. The number of adult equivalents in each household is calculated by summing the adult equivalent of each individual in the household, which is in turn a function of the gender and age of the individuals (an "Adult Equivalent" table provided by INDEC was used). The household-specific INDEC poverty lines are then generated reflecting constant economies of scale in consumption (as INDEC methodology

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[18] Original frequency weights are proportionately adjusted upwards keeping the total sum of weigths constant given that some households are dropped from the sample, as explained below.

states), by simply multiplying the number of adult equivalents in the household times the value of the poverty lines per adult equivalent as informed by INDEC for October 2001 (A$ 61.02 for the extreme one and A$ 150.11 for the moderated one).

The poverty lines are adjusted in simulations 2 to 4 in the light of changes in commodity prices $\hat{P}_A, \hat{P}_I$, which affect the value of the INDEC poverty lines, weighting the price changes following the official poverty line methodology (27.5 per cent for A and 72.5 per cent for I)[19].

The indicators and graphs are then prepared for the income distribution vector in the benchmark and the simulations, adjusting for sample frequency weights. By analysing the simulated incomes based on the 21.795 of the 22.991 households that were originally in the database[20], and using their associated sample weights, it is found that household per capita income falls more than 3 per cent mainly due to the fall in employment levels (SIM1) and not as much (only around 1 per cent) due to the fall in wages (SIM2), a result in turn coming from the wage rigidity captured in the CGE model. Changes in capital income (SIM3) are tiny (as informed from the CGE output). Overall, household per capita income falls 4.4 per cent in the behavioral microsimulations (SIM3), below the 5.4 per cent in the arithmetic ones based on representative household groups (RHG), the difference capturing the different weights that factor incomes have in household incomes in the CGE model and in the micro database.

The cumulative effects of employment, wages and capital income changes (Simulation 3) consistently lead to increases in every inequality and poverty indicator for every poverty line. The Gini coefficient increases from 48.9 to 49.8. However, with the average income falling from A$ 309.1 to A$ 295.5, the average expected difference between two individuals randomly taken falls around 2 per cent (from A$ 302.3 to A$ 294.3)[21]. The increases in the Gini are due to the loss of jobs and to a lesser extent to the reduction of labor wages. The Entropy Index shows a similar behavior, but starts at a higher level than the Gini and increases by more than it given that the Entropy Index gives a higher weight to the upper tail of the income distribution, and that the households in the upper tail of the distribution have an

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[19] The official moderated poverty line comes from multiplying the extreme poverty line (the price of a Basic Food Basket) by the inverse of the Engel coefficient, which is kept fixed.

[20] Households with one or more individuals not reporting wage covariates were dropped, and frequency weights for the remaining households were proportionately adjusted.

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

income which significantly differs from the rest[22] and do not suffer the significant income fall affecting the rest of the households. Arithmethic microsimulations, unable to capture the effect of the loss of jobs on individual incomes, lose a large part of the action, and lead to conclude that inequality goes down, independently of the inequality indicator used (the Gini falls from 48.9 to 48.7 and the Entropy Index from 63.9 to 63.2). Independent of the microsimulation at stake, the changes in inequality are too small to be visualised in a Lorenz curve (Figure 4).

In the behavioral microsimulations, as per capita income falls and inequality increases, the poverty headcounts, the poverty gaps and the poverty severity indices rise for the different poverty lines, reflecting increases in the share of the households below the poverty line, the average difference between the income of the poor households and the poverty line, and income inequality among the poor households. For all these indicators and with all the poverty lines at stake, the increase is mainly due to the employment fall, though there are some slight increases due to the wage fall, and there is no change at all due to the capital income changes.

For the middle and upper percentiles of household per capita income, the employment effect on income proves to be larger than the wage effect, both effects being negative. However, for the first 30 centiles, the wage effect is larger than the employment effect. As clearly shown in Figure 5 and Figure 9, it is the distribution of lost jobs the one basically shaping the income changes after a threshold given by the 30th centile. Though, as shown in the same figures for those at the bottom of the distribution the wage effect is typically larger than the employment effect, reflecting that jobs lost affect their income less severely than wage falls. The analysis of income changes in terms of percentiles allow to see a higher degree of heterogeneity than the analysis in terms of ventiles.

Capital income changes are insignificant[23], which is hardly surprising given the tiny changes in capital income communicated from the macro model. Finally, Figures 7 and 11 give a clear indication of the power of behavioral microsimulations to capture the heterogeneity of income changes in different parts of the income distribution due to a macro shock, as opposed to arithmetic microsimulations, which would give us the impression that the shock has a pretty homogenous effect and that its slight heterogeneity leads to a more progressive income distribution.

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[22] Not tabulated.
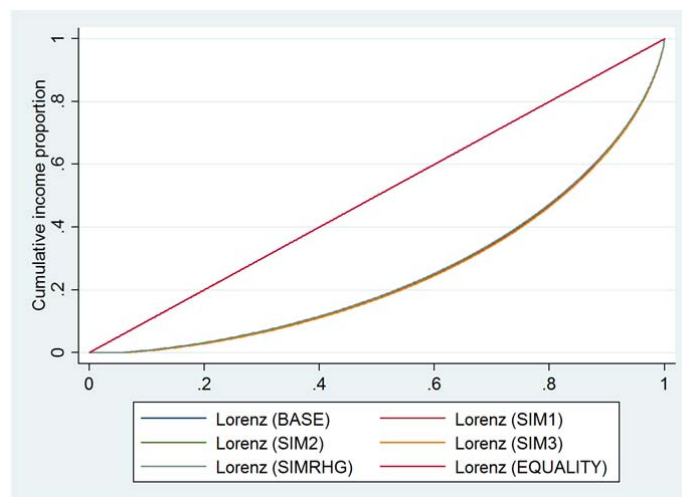[23] This is the reason why in Figures 6 and 10 only a single line can be seen.

Figure 4 Lorenz curves

Table 5 Per capita income, inequality and poverty by simulation

Indicator	BASE	SIM1	SIM2	SIM3	SIMRHG
Per capita income	309.1	298.6	295.5	295.5	292.4
Inequality					
Entropy Index ($\alpha=2$)[24]	63.9	66.7	67.8	67.8	63.2
Gini Index	48.9	49.5	49.8	49.8	48.7
Poverty					
Official Extreme Poverty Line					
Head-Count Index (P_0)	11.5	12.8	12.9	12.9	11.8
Poverty Gap Index (P_1)	6.7	7.9	8.0	8.0	6.8
Poverty Severity Index (P_2)	5.4	6.6	6.6	6.6	5.5
Official Moderated Poverty Line					
Head-Count Index (P_0)	31.1	32.9	32.8	32.8	31.9
Poverty Gap Index (P_1)	15.2	16.6	16.7	16.7	15.5
Poverty Severity Index (P_2)	10.4	11.7	11.7	11.7	10.6
US$ 1-a-day Poverty Line					
Head-Count Index (P_0)	7.3	8.6	8.9	8.9	7.7
Poverty Gap Index (P_1)	5.2	6.4	6.5	6.5	5.3
Poverty Severity Index (P_2)	4.6	5.8	5.8	5.8	4.7
US$ 2-a-day Poverty Line					
Head-Count Index (P_0)	14.1	15.6	16.1	16.1	15.1
Poverty Gap Index (P_1)	8.0	9.2	9.5	9.5	8.3
Poverty Severity Index (P_2)	6.1	7.3	7.5	7.5	6.3

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[24] $\alpha=2$ such that zero income cases can be captured in the index

7. Conclusions

Linking the CGE model to a behavioral microsimulation model in a layered way is useful to evaluate the short-run effects of macro policies and shocks on the full income household distribution, allowing us to take full account of the observed households' and individuals' heterogeneity and capturing the presence of job rationing. Departing from the state-of-the-art work by BRR, in this work I take account of the presence of sample selection bias in the wage equation consistently with the functional form assumed for the employment status equation, endogeneised the capital income in the household income model, improved the algorithm used to adjust the individual labor status and wages of the individuals, and extended the set of distributional and poverty indicators and graphs used.

The conclusion of BRR, by which the selectivity of labor market rationing is the channel through which economy-wide phenomena have the most distributional impact (Bourguignon and Spadaro 2006, p.95), was confirmed here for most of the household groups (ventiles or percentiles). However, for the first groups, it was found that the wage changes affect them more than employment changes. Backing up these points, the relative importance of the employment channel was quantified and shown graphically, filling an existing gap in the literature. As in BRR, it was found that the distributional effects coming from behavioral microsimulations are larger than those found conducting the traditional RHG approach.

The analysis which was conducted (and especially its visual inputs, Figures 7 and 11) give a clear indication of the power of behavioral microsimulations to capture the heterogeneity of income changes in different parts of the income distribution due to a macro shock, clearly having an advantage for this purpose in comparison to arithmetic microsimulations. Arithmetic microsimulations seem to miss a large part of the action in this case, as they ignore the effect of the employment level fall on the income of the individuals who lose their jobs, a link which proves to be key in the distributional effects of the illustrated macro shock.

The macro-micro analysis that was conducted indicates that the severe capital outflows suffered by Argentina in the end of its Currency Board led the economy to lose more than 226 thousand jobs. This, in turn, shifted 77 thousand households in the country into poverty - a result robust to different poverty lines – and made the income inequality indicators shift up, with an increase in the Gini coefficient of almost 1 percentage point.

The macro-micro framework built here, which integrates a real-financial CGE model with a household income model, was applied in this work to investigate the distributional effects of capital outflows in Argentina, but it could be usefully applied to look into the effects of feared or observed capital flows in other middle-income countries including those recently affecting Greece and Turkey.

Figures. Percentage changes in household per capita income and employment by income ventile
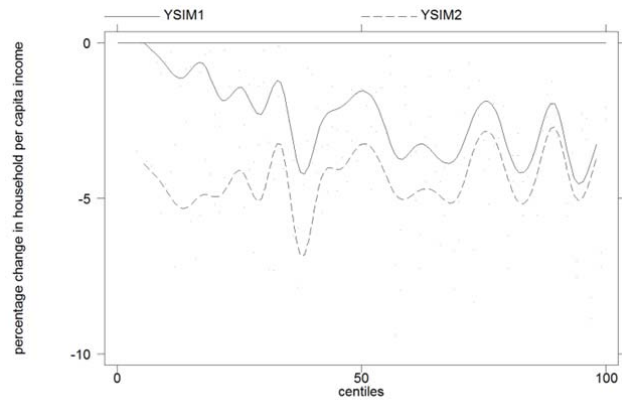
Figure 5 Income simulations 1 and 2 by ventiles
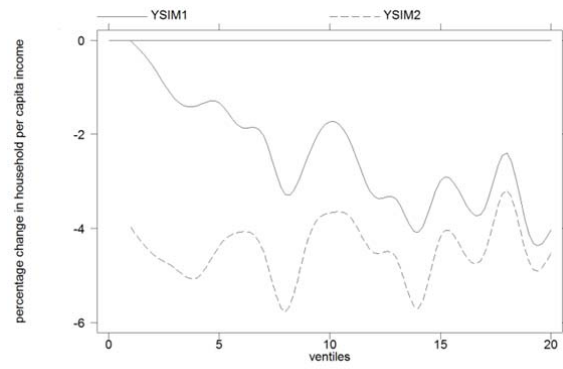
Figure 6 Income simulations 2 and 3 by ventiles
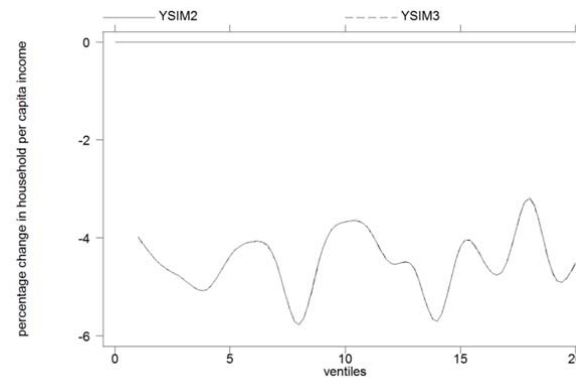
Figure 7 Income simulations 3 and RHG by ventiles
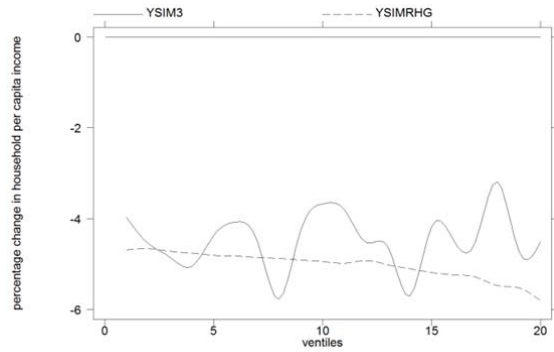
Figure 8 Income and employment simulation 3 by ventiles
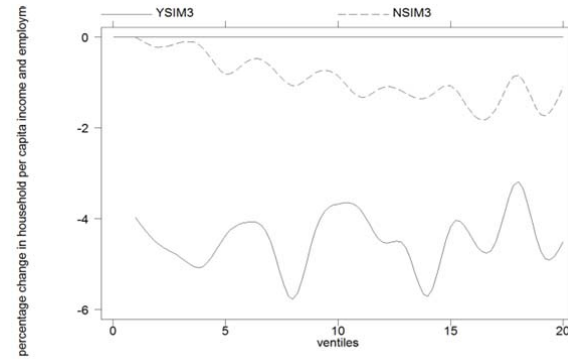
Figures. Percentage changes in household per capita income and employment by income percentile

Figure 9 Income simulations 1 and 2 by percentiles

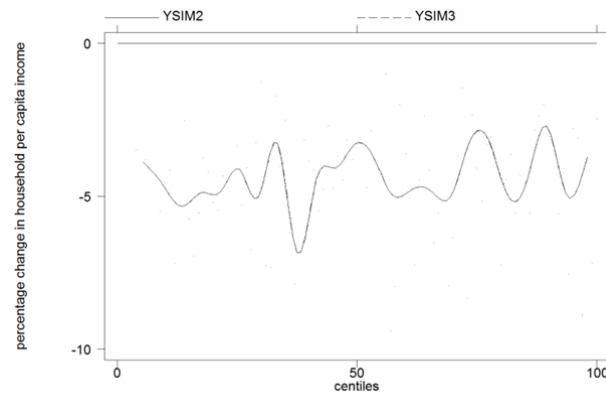Figure 10   Income simulations 2 and 3 by percentiles

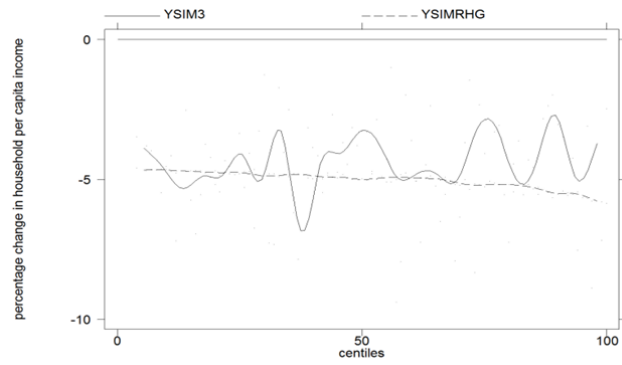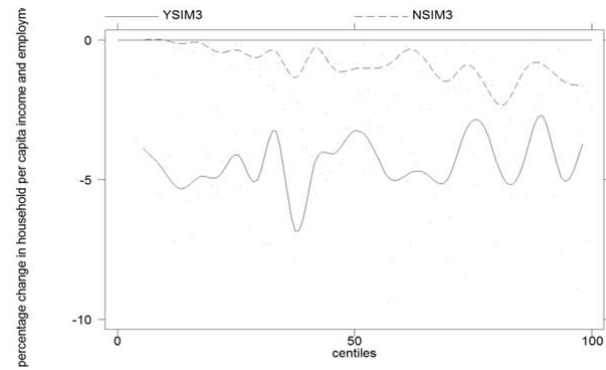Figure 11 Income simulations 3 and RHG by percentiles

Figure 12 Income and employment simulation 3 by percentiles

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