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AN EMPIRICAL ANALYSIS OF WOMEN'S WORKING TIME, AND AN ESTIMATION OF FEMALE LABOUR SUPPLY IN ITALY

M.G. Campolo, A. Di Pino

1. INTRODUCTION

Estimating the labour supply function and wage-elasticity of women is a topic of great interest, especially in Italy, where women work less than elsewhere in Europe (see Del Boca, 2002; Del Boca and Vuri, 2007). Unfortunately, there are several methodological difficulties in estimating labour supply and wage-elasticity, and results may vary greatly depending on the procedure[1].

Several studies and review articles have used economic and statistical arguments to explain variations in estimation results across studies (cf., *inter alia*, Mroz, 1987; and Newey *et al.*, 1990), and have tried to test explicitly for the consequences of various economic and statistical misspecifications. However, questions relating to the consequences on the robustness of error distribution estimates, omitted regressors, sample selection bias and endogeneity remain open and, in any case, unanswered.

Taking into account that the female paid-work equation may be characterized by potentially endogenous regressors (e.g., individual wage) and censoring of the dependent variable (e.g. the weekly hours of work, which are observed on employed women only), analysts generally avoid Ordinary Least Square (OLS) as an estimator, and adopt parametric or semiparametric procedures that use instrumental variables (IV) in place of endogenous regressors and correction methods for selectivity (Smith and Blundell, 1986; Newey *et al.*, 1990; Blundell and Smith, 1994). However, procedures using IV often fail to provide significant results in terms of the efficiency and robustness of estimates, because of the difficulty of finding valid instruments that explain, at a first stage, instrumental variables.

In this paper, we suggest a possible solution for both the problems of misspecification of married women paid-work equation and the sensitivity of estimates. We also suggest a new criterion to improve model specification, which is based on the opportunity cost principle that assumes estimated hourly wage as a

[1] A detailed survey of the most important studies on the wage-elasticity of female labour supply estimation can be found in Killingsworth and Heckman (1986); Blundell and Macurdy (1999) and, more recently, De Mooij *et al.* (2008).

"shadow price" to evaluate the time devoted to unpaid domestic work as an indirect cost (see, *inter alia*, Gronau, 1986; Bonke, 1992). Following this line, we specify the married (or cohabiting) women's paid-work equation in a structural form, introducing the indirect cost of informal childcare and of domestic work as explanatory variables.

However, considering the economic costs of unpaid activities as potentially endogenous regressors, we use an IV procedure adopting reduced-form estimates of unpaid-work indirect costs as instrumental variables. As a consequence, a simultaneous equation model is here specified to estimate simultaneously the female paid-work equation and the reduced-form equations explaining instrumental variables.

At the same time, we verify the robustness of this approach comparing estimation results obtained by applying a parametric procedure (assuming normality of error term distribution) introduced by Amemiya (1979) and Newey (1987), and a semiparametric procedure (unconstrained by error distribution) introduced by Lee (1994). Both estimators are based on a Generalized Least Squares (GLS) approach to correct estimates for the influence of omitted variables given by household consumption and by a gender-rule influence on working time allocation between the partners.

For this study we use cross sectional micro-data selected from the 2002-2003 ISTAT (Italian National Institute of Statistics) Survey on Time Use in Italy[2]. Unfortunately, this survey contains no information on income, which forced us to resort to a matching procedure in order to "import" income data from another source: the Bank of Italy 2004 Survey on Household Income and Wealth data collected in the year 2002. Our test of sensitivity indicates that the matching procedure adopted here gives satisfactory results for the imputation of individual labour income (yearly labour income), but not for the imputation of household income and consumption data. This does not allow us to introduce taxation effects in the model of labour supply.

Moreover, so as to reduce the potential endogeneity in our estimates, we decided not to employ individual hourly wage as a regressor in paid-work estimation[3].

In this study, parametric and semiparametric estimation results indicate that female "uncompensated" wage-elasticity given by the wage-elasticity coefficient is about 0.7. Empirical results of wage-elasticity show that the sensitivity of estimates with respect to the estimation method is low. We can also measure the (negative) impact of the cost of domestic work and childcare on female paid-

[2] For the estimation of the labour supply equation utilizing datasets on the use of time use dataset, see, e.g., Klevmarken (2005); Bloemen *et al.* (2010); Kalenkowski *et al.* (2009).

[3] In our model, paid-work supply is empirically quantified in terms of weekly hours of work. With our data, we have specific information on the daily time devoted to work (with reference to a day that the respondent herself declares as "normal"), and on the number of working days in a week. But we ignore how many weeks the respondent works in a year. On the other hand, the logarithmic transformation of both the dependent variable (weekly working time) and the regressor (yearly wage) adopted here corrects the potential bias of the different scale due to the different time reference (year vs. week).

work supply. We interpret these results as indications that a higher level of potential or "expected" wage influences married women's labour supply directly and positively, but at the same time the opportunity cost of time devoted to domestic activity and child care may increase. These indirect costs affect negatively paid-work supply and discourage married women from working.

In the next section, we introduce a brief conceptual framework of the methodological problems (censoring and instrumental variables, in particular) affecting the labour supply equation estimation. In addition, the theoretical and methodological aspects of the economic evaluation of women's unpaid-work used as instrumental variables will be discussed. In section 3, we illustrate the model specification. In section 4, we show the characteristics of the dataset and the results of the matching procedure with related sensitivity test. In section 5, we discuss the estimation results. Finally, section 6 presents our final observations and remarks.

2. METHODOLOGICAL FRAMEWORK

In this section we discuss briefly a few methodological problems that hamper the estimation of women's labour supply models. In particular, these aspects concern: 1) the choice of the estimator; 2) the specification of the relationship between working time of the woman and of her partner; 3) the economic evaluation of unpaid domestic activities, here utilized as instrumental variables. For all these problems we suggest specific and partially original solutions.

2.1. *The choice of the estimator*

As discussed in the previous section, estimating the paid-work equation with potentially endogenous regressors and censoring in the dependent variable forces the researcher to adopt a simultaneous equation approach with IV. However, in a simultaneous equation model explaining labour supply of the household members, a further potential bias may be produced by omitted variables in the regressor set specification[4]. This bias effect may be corrected using estimated cross-covariances of the residuals, and implementing an iterative GLS algorithm. For this reason, we here adopt parametric and semiparametric estimation methods that allow us to implement a GLS procedure.

Under the assumption that error terms are normally distributed, an efficient parametric estimator of a limited dependent variable equation with endogenous regressors has been adopted (Amemiya, 1979; Newey, 1987). The Amemiya-Newey procedure utilizes, at a first stage, a Tobit reduced-form estimation for the equation of interest and Tobit and OLS reduced-form-estimation for instrumental variables replacing endogenous regressors. At a second stage, the structural

[4] Consider, for instance, the unobservable "gender effect" (cf. Alvarez and Miles, 2003; Di Pino, 2004). We have a "gender" effect on working time allocation if an unequal division of both market and domestic work between the partners does not depend on their own different productivity but is mainly due to the traditional gender-role.

form of the equation of interest is estimated using a GLS approach[5]. In this analysis the Amemiya-Newey Two-Stage estimator is labelled IV-Tobit.

Alternatively, assuming the error term distribution of the paid-work equation as non-normal, we adopt the semiparametric Symmetrically Censoring Least Squares (SCLS) estimator introduced by Powell (1986), and later extended by Lee (1994 and 1998) to estimate a limited-dependent variable equation with endogenous regressors in a Two-Stage version (2S-SCLS).

Lee's semiparametric estimator is characterized by a GLS procedure similar to the parametric approach of Amemiya-Newey. This approach consists in estimating semiparametrically, at a first stage, the instrumental variables that replace the endogenous regressors in the equation of interest. At a second stage, a SCLS semiparametric regression of the structural form of the equation of interest is applied.

The SCLS regression generally implies the use of a "trimming" procedure. Regarding the paid-work equation model, the trimming is based on the estimated probability of participating in the labour market, that allows us to select the observations to be used for the estimation of the equation of interest. In this study, to provide an adequate estimated probability distribution of the censoring indicator, we adopt a semiparametric estimator of the selection function (participation equation)[6]. In this way, observations included in the distribution quantile with a low probability of being uncensored are "trimmed" and taken out from the sample together with the observations included in the upper symmetrical quantile of the probability distribution.

For the selection function estimation (participation function), we use Khan's Nonlinear Least Square "Sieve" (Sieve-NLLS) estimator (Khan, 2005; Blevins and Khan, 2009) that allows us to circumvent the computational problem of high dimensionality ("curse" of dimensionality) due to the inclusion of several regressors in the selection equation. A Sieve-NLLS estimator is obtained by the minimization of the following function:

$$Q_n = \frac{1}{n}\sum_{i=1}^{n}[\,y_i - \Phi(x'_i\,\beta^* \exp(l(x_i)))]^2 \tag{1}$$

where y_i is a binary response variable (0; 1), Φ () is the normal standard cumulative function, β^* is a normalized vector (1, β) of parameters, and $\exp(l(x_i))$ is a "sieve" function[7]. Khan (2005) shows that a Sieve-NLLS model and a distribu-

[5] Newey (1987) shows how the properties of this GLS procedure are the same as a minimum-distance estimator.

[6] In this model the selection function is given by a participation equation, in which the dependent variable is a binary dummy equal to zero, if the woman does not work and equal to one, if the woman works.

[7] The method of sieves allows us to solve the problem of the computational complexity of several estimation procedures (especially nonparametric or seminonparametric) by optimizing an alternative criterion function over a sequence of significantly less complex parameter spaces called sieves (see, *inter alia*, Chen, 2007). For instance, a nonparametric model with two regressors, x_1 and x_2, may be estimated by optimizing equation (1), where the "Sieve" function $\exp(l(x_i))$ may be given by the following polynomial terms: $exp(l_0 + l_1 * x_1 + l_2 * x_2 + l_3 * x_1 * x_1 + l_4 * x_2 * x_2 + l_5 * x_1 * x_2)$.

tion free model under a conditional median restriction (Manski, 1985; Horowitz, 1992) are equivalent. At a second stage, the "trimmed" paid-work equation is estimated by GLS using the residuals of the reduced-form estimates of the instrumental variables[8].

Comparing the results of the application of both the parametric (IV-Tobit) and semiparametric (2S-SCLS) procedures, we can evaluate empirically the sensitivity of paid-work equation estimates with IV, in response to the adoption of both estimators.

2.2. *Specifying the allocation of working time between women and their partners*

The lack of empirical information about household income forced us not to distinguish, in model specification, the case in which it makes no difference who receives earned income in the family from the case in which the bargaining strength of the partners may depend on their earning power. As a consequence, we cannot interpret the partners' decisions about the allocation of working time either as an application of Becker's "unitary paradigm" (Becker, 1981) or of the "collective" bargaining-based approach (Chiappori, 1988; Lundberg and Pollak, 1993; *inter alia*).

However, what all these approaches have in common is that they specify a simultaneous equation model in which the time devoted by both partners to working activities (paid or unpaid) does not appear on the right side of the labour supply equation.

In this study, estimating a static model of married women's labour supply, we adopt a similar general specification criterion, whereby variables characterized by potentially strong endogeneity are not included on the right side of the model equations or are replaced by reduced-form estimated instrumental variables[9]. However, there are generally few strictly exogenous variables that can be used as "instruments" in such a model. As a consequence, to specify the reduced-form equations and, contextually, to ensure the identification of the model with a reasonable number of exclusion restrictions, we are forced to include some "weakly exogenous" explanatory variables as regressors. On the other hand, the validity of these regressors as "instruments"[10] is here verified using Sargan test statistics (cf. table 7 in section 5).

2.3. *The economic evaluation of indirect costs of unpaid activities*

As previously discussed in the first section, another problem in specifying female paid-work structural-form equation regards the introduction, in the regres-

[8] Lee (1994) studied the relative efficiency of the GLS version of the 2S-SCLS estimator that takes into account the complicated covariance structures of disturbances when instrumental variables are utilized.

[9] When running preliminary estimation proofs, women's labour supply is found to be irresponsive to the partner's wage. Therefore, we decided to exclude the latter from the regressors set.

[10] Instruments: regressors included in the reduced-form equations to specify instrumental variables. Instruments may be considered as "valid" if they enable us to directly explain instrumental variables, and "indirectly" the dependent variable of the equation of interest.

sors set, of variables measuring the indirect costs of unpaid-working activities. In particular, a preliminary difficulty arises: how valuable are non-market working activities? A tentative answer comes from measuring the time devoted to unpaid-work and "pricing" it. To this end, two criteria have been proposed in the literature: i) the "market price" criterion and ii) the "opportunity cost" criterion. With the former, the market price is the average market hourly wage of an outside collaborator recruited from the labour market. With the latter, the opportunity cost is given by the potential hourly wage of the subject assumed as a unit of evaluation (shadow price) for the time spent on his/her household duties (Gronau, 1986). There are several studies on the consequences for economic and statistical analysis that derive from the adoption of both evaluation methods[11]. In this analysis, we adopt a solution which partly represents a synthesis of the two[12]. In practice, the evaluation here attributed to domestic activity and childcare corresponds to the higher of the two hourly costs given, respectively, by the average price of the outside service and by the potential (estimated) wage of the subject: $\max(p_d T_h; \hat{w} T_h)$, where T_h are the hours of domestic work, p_d the average hourly price of the outside service for domestic activities, $\hat{w}$ the potential predicted hourly wage of the subject. This solution for the computation of the shadow price of home production is based on the consideration that if the subject (the woman, in this case) entrusts all household duties (including childcare) to outside collaborators, she will pay the service at an hourly price equal to p_d, and will not sustain any opportunity cost. Vice versa, if she prefers to personally attend to household duties, foregoing alternative payment $\hat{w}$ of her own time, she evidently considers direct involvement in household activity and childcare not qualitatively replaceable by outside services. In this case, $\hat{w}$ can be assumed as a proxy of the measurement of the home production opportunity cost.

Following this line, we propose to include on the right side of the labour supply equation, as explanatory variables, both the computed economic values of the time devoted by the woman, respectively, to domestic work and child-care. However, these variables are potentially endogenous regressors in paid-work equation, and for this reason we replace them with the corresponding reduced-form estimates as instrumental variables[13].

3. MODEL SPECIFICATION AND ESTIMATION PROCEDURE

The adoption of an IV approach to estimate the female labour supply equation forces us to impose several exclusion restrictions on this model, and as a conse-

[11] See, *inter alia*, Bonke (1992); De Santis (2004).

[12] See Di Pino (2004).

[13] The economic value of the partner's domestic activity should also be introduced as an instrumental variable. But preliminary estimates show that the relationship between female paid-work supply and the partner's non-market working activity displays low significativity. For this reason (and to simplify the model) we decided to leave out this variable from the female labour supply equation.

quence the women paid-work equation becomes overidentified. Fertility, participation, domestic activity and childcare costs, and individual wage are the reduced-form estimated instrumental variables utilized in the model. Also, partner working activities equation has to be estimated to correct the influence of omitted variables by applying an iterative GLS procedure.

Therefore, a stochastic specification of the model is here provided, distinguishing endogenous and exogenous variables, and taking into account the overidentification restrictions in the women's paid-work equation. The model consists of nine equations, and the women paid-work equation is equation 9. We here report in table 1 extensively the nine simultaneous equations of the model, with the description of the nine dependent variables. The latter are included in brackets [..] if utilized as regressors.

The estimator adopted for each equation is also reported in table 1. The twenty-two exogenous variables utilized in the model are described in table 2.

Considering that the female paid-work equation estimation is the purpose of this study, we start to describe the specification of female paid-work equation (equation 9), in which the coefficient $a_{9.6,}$ measures the uncompensated wage-elasticity of women's labour supply. The coefficients $a_{9.7}$, and $a_{9.8}$, measure, respectively, the elasticity of women's labour supply depending on childcare and domestic work costs. Wage, childcare costs and domestic work costs are endogenous variables explained, respectively, by equations 6, 7 and 8 specified in a reduced-form. To avoid collinearity effects on the estimation results of equation 9, we decide not to introduce as regressors several variables utilized as instruments in other equations such as, for instance, day of interview (*dday*), and *ch* (number of children ever born), although these variables may be theoretically correlated with the time devoted to paid-work.

Equation 1 explains the number of children in the family ever born (*ch*) as a cumulative fertility estimation equation. Explanatory variables in equation 1 may be considered as determinants of the individual "expected" fertility, such as a regional fixed effect measuring cumulative fertility (*fert*), the influence of the age of woman at a first birth (*first*)[14], and the difference between the age of woman and her partner's (*dage*). The variable *age* (age of woman) is not included as an explanatory variable because it is collinear with the other regressors. The term ch_{random} is a latent component of the error term given by an unexpected random component of individual fertility. In equation 1 this latent variable is specified as an additive term of the disturbance reported in brackets (...). This random component may be identified empirically by the residuals of the reduced-form Poisson regression of equation 1 (cf. De Santis and Di Pino, 2009). Estimated unexpected fertility given by the residuals of equation 1 serves to correct for endogeneity bias the estimated equations of the model in which the number of children (*ch*) is introduced as a regressor (equations 2, 3, 4, 5, 7, 8).

[14] The variable "*first*" is obtained by measuring the age of woman at a first birth, for women who had children. For childless women younger than 50, the value of this variable is constant and equal to 50, while it is equal to the age of woman for childless women over 50.

TABLE 1

Simultaneous equation model specification

(1)	$ch = a_{1.0} + a_{1.1}fert + a_{1.2}dage + a_{1.3}first + (ch_{random} + u_1)$	Married Women Cumulative Fertility Equation. Dependent Variable: *ch* = No. of children ever born. Estimator: Reduced-Form Poisson Regression.
(2)	$L^* = a_{2.0} + a_{2.1}age + a_{2.2}edu_{father} + a_{2.3}dday + $ $+ a_{2.4}[ch] + a_{2.5}ch_{random} + a_{2.6}darea + u_2$ $\begin{cases} L = 1 & if\ L^* > 0 \\ L = 0 & otherwise \end{cases}$	Married Women Participation Equation. Dependent Variable: L^*: latent individual propensity to participate in the labour market. The corresponding observed dummy variable L is equal to one if the subject works), and equal to zero if the subject does not work. Estimator: SIEVE-NLLS
(3)	$chcare_{par} = a_{3.0} + a_{3.1}age_{par} + a_{3.2}age^2_{par} + a_{3.3}edu_{par} +$ $+ a_{3.4}darea + a_{3.5}[ch] + a_{3.6}ch_{random} + a_{3.7}colf +$ $+ a_{3.8}dday + a_{3.9}fulltime_{par} + a_{3.10}partime_{par} + u_3$	Partner Informal Childcare Equation. Dependent Variable: $chcare_{par}$= Log of time spent for childcare by the partner in a week. Estimators: OLS (parametric procedure), and LAD (semiparametric procedure).
(4)	$dom_{par} = a_{4.0} + a_{4.1}age_{par} + a_{4.2}age^2_{par} + a_{4.3}edu_{par} +$ $+ a_{4.4}darea + a_{4.5}[ch] + a_{4.6}ch_{random} + a_{4.7}colf +$ $+ a_{4.8}dday + a_{4.9}fulltime_{par} + a_{4.10}partime_{par} + u_4$	Partner Domestic Activity Equation. Dependent Variable: dom_{par}= Log of time spent for domestic activity (childcare not included) by the partner in a week. Estimators: OLS (parametric procedure), and LAD (semiparametric procedure).
(5)	$work_{par} = a_{5.0} + a_{5.1}age_{par} + a_{5.2}age^2_{par} + a_{5.3}edu_{par} +$ $+ a_{5.4}darea + a_{5.5}[ch] + a_{5.6}ch_{random} + +a_{5.7}dday +$ $+ a_{5.8}fulltime_{par} + a_{5.9}partime_{par} + u_5$	Partner Paid-work Equation. Dependent Variable: $work_{par}$= Log of Time weekly dedicated to external work by the partner (censoring for unemployed subjects). Estimators: Tobit (parametric procedure), and CLAD (semiparametric procedure).
(6)	$W = a_{6.0} + a_{6.1}eduage + a_{6.2}fulltime + a_{6.3}darea +$ $+ a_{6.4}GNP_{reg} + \mathrm{u}_6$	Married Women Wage Equation. Dependent Variable: *W* = Log of yearly wage (censoring for unemployed subjects). Estimators: Tobit (parametric procedure), and SCLS (semiparametric procedure, using estimation results of equation(2) to "trim" the sample).
(7)	$cost_{ch} = a_{7.0} + a_{7.1}age + a_{7.2}edu_{father} + a_{7.3}[ch] +$ $+ a_{7.4}ch_{random} + a_{7.5}sitting + a_{7.6}sitting^2 + a_{7.7}dday + u_7$	Childcare of Married Women Opportunity Cost Equation. Dependent Variable: $cost_{ch} = \ln\{[chcare] * \max\{[W/(work)]; p_d\}\}$ where *chcare* = time spent by the woman for childcare in a week, and p_d = average market hourly price of the outside service for domestic activities and child-caring. Estimators: OLS (parametric procedure), and LAD (semiparametric procedure).
(8)	$cost_{dom} = a_{8.0} + a_{8.1}age + a_{8.2}age^2 + a_{8.3}darea + a_{8.4}dday +$ $+ a_{8.5}colf + a_{8.6}[ch] + a_{8.7}ch_{random} + u_8$	Domestic Activity of Married Women Opportunity Cost Equation. Dependent Variable: $cost_{dom} = \ln\{[dom] * \max\{[W/(work)]; p_d\}\}$ where *dom* is referring to the time spent by the woman for domestic activity (childcare not included) in a week, and p_d is the average market hourly price of the outside service for domestic activities and child-caring. Estimators: OLS (parametric procedure), and LAD (semiparametric procedure).
(9)	$work = a_{9.0} + a_{9.1}age + a_{9.2}age^2 + a_{9.3}edu + a_{9.4}edu_{par} +$ $+ a_{9.5}darea + \mathrm{a}_{9.6}[\mathrm{W}] + +a_{9.7}[cost_{ch}] + a_{73}[cost_{dom}] + \mathrm{u}_9$	Married Women Paid-work Equation. Dependent Variable: *work* = Log of Time weekly dedicated to external work by the woman (censoring for unemployed subjects). Estimators: IV-Tobit (parametric procedure), and SCLS (semiparametric procedure, using estimation results of equation(2) to "trim" the sample).

In general, adopting an instrumental variables approach to estimate equation 9 in a structural form, the equations from equation 1 to equation 8 are utilized to obtain valid instrumental variables for equation 9. We try to obtain this result using both a parametric and a semiparametric estimator, with different assumptions about error terms distribution. The related steps of both procedures are here reported in detail:

TABLE 2

Exogenous variables

1	*intercept*	12	*-edu$_{par}$* = Partner education level (years of schooling);
2	*-age*= Age;	13	*-eduage* = Education level /age ratio;
3	*-age^2* = Square of age;	14	*-edu$_{father}$* = Father's education level (years of schooling);
4	*-age$^2_{par}$*= Square of age of the partner;	15	*-fert* (geographical fixed effect) = Regional cumulated fertility rate at the age of woman (provided by ISTAT - Italian National Institute of Statistics);
5	*-age$_{par}$*= Age of the partner;	16	*-first* = age of the woman at the birth of first child and correction values for childless women (cfr note n° 12);
6	*-ch$_{random}$* (latent error component) = Unexpected fertility of woman;	17	*-fulltime* = (dummy)=1 if the woman does work full time;
7	*-colf* = Home help service time (minutes in a week);	18	*-fulltime$_{par}$* = (dummy)=1 if the partner does work full time;
8	*-dage* = Age of woman – age of partner (man);	19	*-GNP$_{reg}$* (regional fixed effect) = per capita GNP of administrative regions
9	*-darea* = Regional area (Dummy: North-Centre=0; South=1);	20	*-partime$_{par}$* = (dummy)=1 if the partner does work part time;
10	*-dday*= Reference day activities of the diary (Dummy: weekend = 0; Mon.-Fri.=1);	21	*-sitting* = Baby sitter time (minutes in a week);
11	*-edu* = Education level (years of schooling);	22	*-sitting^2* = Square of baby sitter time;

1) 2S-SCLS semiparametric procedure

A preliminary stage of this procedure consists in estimating a reduced-form labour force participation equation (equation 2) adopting a semiparametric Sieve-NLLS procedure. The purpose is to select the observations to "trim". Predicted wage and predicted cost of unpaid-work, estimated semiparametrically from equation 6 and equations 7 and 8[15], are utilized as instrumental variables to estimate the structural equation of female labour supply (equation 9) by means of a 2S-SCLS procedure.

2) IV Tobit parametric procedure

This procedure uses predicted wage (from equation 6), estimated by Tobit, and predicted cost of unpaid-work (from equations 7 and 8 by OLS estimates) as instrumental variables to estimate the structural equation of female labour supply (equation 9) by using the Two-Stage Amemiya-Newey procedure previously discussed (denominated IV-Tobit). Residuals of the reduced-form estimates are utilized as an iterative GLS procedure in the final estimation of equation 9.

Regarding the stochastic specification of the model, the disturbance terms of the model equations are assumed i.i.d. distributed with zero mean. But, as discussed in section 2, the cross-covariances of the error terms of the equation 9 (paid-work equation) and the other equations are assumed to differ from zero, because of omitted variables and endogeneity. As a consequence, we have a covariance matrix, Ω, of the errors specified as follows (Srivastava and Giles, 1987):

[15] We utilized, respectively, a SCLS estimator for equation 6 and a Censoring Least Absolute Deviation (CLAD) regression (Powell, 1984) for equations 7 and 8.

$$\Omega = \overset{9\times 9}{\Sigma} \otimes \overset{n\times n}{\mathbf{I}} = \begin{bmatrix} \sigma_1^2 \overset{9\times 9}{\mathbf{I}} & 0 & .. & \sigma_{19} \overset{9\times 9}{\mathbf{I}} \\ & \sigma_2^2 \overset{9\times 9}{\mathbf{I}} & .. & \sigma_{29} \overset{9\times 9}{\mathbf{I}} \\ & & .. & .. \\ & & & \sigma_9^2 \overset{9\times 9}{\mathbf{I}} \end{bmatrix} \tag{2}$$

with:

$$\overset{sxs}{\Sigma} = \begin{bmatrix} \sigma_1^2 & 0 & .. & \sigma_{19} \\ & \sigma_2^2 & .. & \sigma_{29} \\ & & .. & .. \\ & & & \sigma_9^2 \end{bmatrix} \tag{3}$$

where **I** is a n-dimension identity matrix (n is the sample size). Note that only the variances in the diagonal and the covariances in the last column of the covariance matrix (3) are assumed to be different from zero.

The order condition for identification of equation 9 (paid-work equation) is satisfied, that is the number of exogenous variables, g=16, excluded from the equation (equalling the number of instruments), is higher than the k=3 endogenous regressors less one. In total, considering the classical simultaneous equation parametric approach, we have $g - k + 1 = 13$ overidentification restrictions.

The identification of equation 9 is ensured even if we adopt a semiparametric approach, even if the identification condition of a semiparametric model is stronger than the identification condition for the classical simultaneous equation model[16].

Furthermore, considering the semiparametric approach, identification of the selection equation (equation 2 or participation equation) with respect to the labour supply equation (equation 9) is ensured by including the years of education of the father (edu_{father}) in the participation equation regressors set. The father's education is here assumed to influence the participation decision of the subject, but not how much time the subject has to spend working in the market.

Considering overidentification restrictions imposed on the paid-work equation estimation (number of instruments not included in equation 9), we test the null hypothesis of overidentification and of validity of instruments (Sargan Test) using the IV-Tobit estimation results. The result of the overidentification test, provided in the next section 5 (table 7) confirms the validity of the instruments excluded from equation 9 (age_{par}, $age^2{}_{par}$, ch_{random}, *colf*, *eduage*, edu_{father}, *first, fert, sitting*, *sitting*^{2}, *full-time*, $fulltime_{par}$, $partime_{par}$, *eduage*, GNP_{reg}).

[16] In practice, we should take into account that, utilizing a semiparametric procedure, the introduction (or the utilization) of a selection bias term of unknown form to correct the structural equation adds the exogenous variables identifying the selection term to the exogenous variables of the structural equation.

In the next section, the Italian Time Use sample characteristics and the matching procedure adopted to draw data on wage from Bank of Italy SHIW survey will be discussed.

4. SAMPLE SELECTION AND MATCHING RESULTS

For this study we use cross-sectional microdata selected from the 2002-2003 ISTAT Survey on Time Use in Italy, in which individual decisions on time allocation and on the use of time are surveyed with the diary method, i.e. with a high level of detail. The subjects interviewed in the ISTAT Time Use Italian Survey provide detailed information on their own daily time allocation through the compilation of a diary in which they register all of their daily activities. These can be classified into four categories: i) paid-work or market working time; ii) domestic work or unpaid-work; iii) child-care; iv) non-working time[17]. The selected sample is composed of 5698 women, aged 18-60, living with their partners, and equitably distributed by area of residence and employment status[18]. The descriptive analysis (table 3) shows that in the surveyed households men generally work more for the market than women.

TABLE 3

Partner characteristics on selected variables

	Men		Women	
	Mean	S.E.	Mean	S.E.
Domestic work (*)	1.0	1.5	5.7	3.0
Child-care (*)	0.4	0.9	1.2	1.7
Paid-work (*)	8.4	3.6	3.4	4.0
Age	44	8.9	41	8.6
Yearly Wage (Euros)	13,088	132	12,363	125

Day of interview: Monday-Friday; (*) daily hours computed in the "diary"

Conversely, women spend more time in domestic work and child-care than men. Furthermore, with more children in the family, women spend more hours working indoors, but fewer in paid-work (table 4).

TABLE 4

Women's time allocation by number of children in the family

No of Children 0-13	Domestic work		Child-care		Paid-work	
	Mean	S.E.	Mean	S.E.	Mean	S.E.
0	5.93	3.00	–	–	2.40	3.77
1	5.51	2.76	1.55	1.63	2.16	3.52
2	5.59	2.56	2.22	1.82	1.66	3.13
3	6.43	2.47	2.89	2.11	1.08	2.51
4	6.36	2.41	3.24	2.19	0.66	1.95

Day of interview: Monday-Friday; daily hours computed in the "diary"

[17] The variable "non working time" is the result of the sum of the time dedicated to leisure-activities and the time spent in physiological and personal activities.

[18] The self-employed are included in the sample.

The ISTAT Time Use dataset contains no information on income, which forced us to resort to a matching procedure in order to "import" income data from the Bank of Italy Survey on Household Income and Wealth (SHIW) in the year 2002. We drew from the Bank of Italy dataset the labour income data of 3637 employed people[19]. The variables, common to both datasets, chosen to condition the probability of assignment are: age, sex, education of the father, number of children in the family (aged 0-5 and 6+ years), father's working status when the subject was fourteen, regional fixed effects of economic activity, status of the subject within his/her family, geographical area of residence and type of work (part-time or full-time).

The conditional probability of assignment is estimated by utilizing a Probit regression, where the dependent variable is a binary dummy equalling one if the observation belongs to the ISTAT Use of Time dataset (treated cases), and equalling zero if the observation belongs to the SHIW survey (untreated cases or control sample). Table 5 shows the Propensity Score estimation results. Statistics on covariate balancing, not reported here (but available on request), demonstrate that the matching procedure here adopted (applying a "Caliper" algorithm to the estimated propensity score intervals) increases the similarity between the treated sample (Time-Use dataset observations) and the control sample (SHIW dataset observations).

TABLE 5

Matching procedure: Conditional propensity score estimation

Dependent variable: Dummy 0 = SHIW; 1 = ISTAT Time Use Estimator: Probit	Cat.	Coeff.	S.E.	p-value
intercept		-1.021	0.226	*
sex		0.200	0.039	*
father's working status		0.425	0.033	*
age		0.000	0.002	#
area5 (categorical)	NW	-0.064	0.023	*
Reference Category: Islands	NE	-0.151	0.027	*
	C	-0.272	0.047	*
	S	0.128	0.028	*
edu_{father}		0.023	0.003	*
dummy position of the subject in the family		-0.285	0.038	*
$WAGE_{reg}$ (regional fixed effect)		0.041	0.005	*
GNP_{reg} (regional fixed effect)		0.000	0.001	#
child 0-5 years		0.035	0.023	#
child >5 years		-0.022	0.013	#
dummy partfull		-0.117	0.040	*
Total observations: 16603; Time Use Survey: 12366; SHIW: 3637				
Percentage correctly predicted L=1 (Use of Time): 99.95%				
Percentage correctly predicted L=0 (SHIW): 1.62%				
Likelihood ratio (Chi^2. 15 dof): 125.99				
p-value: * < 1%; ** < 5%; # >=5%				

In order to avoid the risk of importing data characterized by self-selection, we adopt a sensitivity test to verify if latent factors affect assignment to the treatment. Specifically, if we assume that assignment to the treatment is influenced by latent omitted variables (see, *inter alia*, Rosenbaum, 2002 and 2005), the odds of assignment to the treatment of a subject, Γ, may be considered generally higher

[19] Wages are matched on working people only.

than one as the effect of the hidden bias involved by the latent factors. Consequently, matching results can be considered sensitive to the latent variables effect if the assignment changes when Γ registers a small increase. On the contrary, matching results can be considered insensitive if the assignment changes only for a very large value of Γ. A Mantel-Haenszel statistic may be computed to test the sensitivity of matching with respect to the increasing value of Γ. Two different *p*-values are obtained testing each value Γ>1 under both the hypothesis of overstating and of understating the effect of omitted factors on the treatment. In this way for each value of Γ>1 a corresponding interval of *p*-values reflecting uncertainty due to hidden bias can be computed. The value of Γ>1 at which the *p*-value interval becomes uninformative is a measure of sensitivity of matching to the hidden bias. As reported in table 6, we can consider as uninformative the interval (> 5%) corresponding to a high level of Γ (Γ = 6.2). Consequently, matching results can be reasonably considered as less sensitive to latent "confounding" factors.

TABLE 6

Sensitivity analysis: p-value bounds of the Mantel-Haenszel test

Γ	Q_mh +	Q_mh -	p-value_mh +	p-value_mh -	p-value_mh interval
1	7.316	7.316	0.000	0.000	0.000
3	3.492	13.395	0.000	0.000	0.000
5	2.136	17.478	0.016	0.000	0.016
5.8	1.771	18.866	0.038	0.000	0.038
6.2	1.611	19.522	0.054	0.000	0.054
7	1.323	20.774	0.093	0.000	0.093

5. ESTIMATION RESULTS

We report in table 7 the estimation results of the "structural-form" married women paid-work equation (equation 9)[20]. We can observe that very negligible differences exist in the estimated wage-elasticity coefficient, close to 0.7 if we use a parametric IV-Tobit estimator or semiparametric 2S-SCLS procedure. The estimated coefficients of the regressors $cost_{ch}$ and $cost_{dom}$ represent, respectively, the elasticity of the indirect cost of children and of domestic work with respect to labour supply. Both parametric and semiparametric estimates give negative values for estimated coefficients of unpaid-work cost elasticity.

Table 7 also reports the results of an overidentification test that allows us not to reject the null hypothesis of validity of the instruments not included in the equation, but utilized to estimate instrumental variables in a reduced form.

The contextual estimated positive value of wage-elasticity and negative value of unpaid-work elasticity implies that individual wage influences paid-work supply in two different ways: i) directly and positively by wage-elasticity impact, ii) indirectly and with opposite sign via the indirect cost of domestic work and childcare activity. In fact, individual wage is also utilized to compute the indirect cost of unpaid-work, and consequently both the indirect costs of childcare and domestic work increase when the woman's wage arises.

[20] Estimation results of the reduced form equations are available in Appendix.

TABLE 7

Females paid-work "structural-form" equation estimation

(Equation 9 – Women only)				
Dependent variable: *work*	2S-SCLS		IV TOBIT	
regressors:	Coeff.	S.E.	Coeff.	S.E.
intercept	-2.497	1.019	1.180	0.371
age	-0.024	0.026	0.076	0.001
age^2	0.001	0.000	-0.001	0.000
darea	0.744	0.063	0.960	0.029
edu	0.019	0.008	-0.055	0.003
edu_{par}	0.018	0.008	-0.005	0.003
W	0.718	0.074	0.691	0.017
$cost_{ch}$	-0.052	0.013	-0.008	0.001
$cost_{dom}$	-0.123	0.147	-0.483	0.162
Cases	5698 (selected by trimming: 2977)		5698 (3091 uncensored)	
Adj R^2 =	0.84		0.97	

IV Tobit - Wu-Hausman *F* test of exogeneity of IV: 207.04, *F*(6, 5680) P-value = 0.0000 (H0: regressors are exogeneous)

IV Tobit - Sargan Test of overidentifying restrictions *(Chi*^2 Statistics): 6.156 dof(10) P-value = 0.802 (H0: validity of instruments)

These considerations are useful to introduce the discussion about the estimation results of paid-work equation on different subsamples related to the geographical area of residence (table 8) or to the education level and presence of small children in the family (tables 9 and 10). Regarding the distinction between areas, 2S-SCLS and IV-Tobit provide different results for evaluating wage-elasticity. Using a semiparametric procedure, wage-elasticity is found to be markedly higher in the Southern regions (0.937) with respect to the North-Centre (0.696). An opposite result is obtained using a parametric approach. Estimating the influence of unpaid-work on labour supply, the unpaid-work cost coefficient is found to be higher when utilizing a semiparametric approach in the North-Centre.

When estimating the paid-work equation for different education levels, wage-elasticity turns out to be higher for the more educated women, especially graduates. It is interesting to note that, by adopting the semiparametric procedure, the indirect cost of domestic work and childcare influences more graduated women's labour supply (table 9). Moreover, estimating by means of IV-Tobit, the impact of childcare cost on labour supply rises if the number of small children (aged 0-5) increases, while an opposite result is obtained using the 2S-SCLS estimator (table 10).

TABLE 8

The female paid-work equation estimation for geographical area

Area:	North-Centre				South			
Dependent variable: *work*	2S-SCLS		IV TOBIT		2S-SCLS		IV TOBIT	
regressors:	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
intercept	-1.892	1.345	0.833	0.364	-3.933	1.67	1.911	0.389
age	-0.042	0.031	0.046	0.013	-0.023	0.047	0.089	0.011
age^2	0.001	0.000	-0.001	0.000	0.001	0.001	-0.001	0.000
edu	0.0313	0.009	-0.041	0.003	0.004	0.015	-0.075	0.003
edu_{par}	0.014	0.009	-0.002	0.003	0.011	0.014	0.003	0.003
W	0.696	0.072	0.774	0.019	0.937	0.026	0.619	0.014
$cost_{ch}$	-0.070	0.015	-0.014	0.011	-0.026	0.023	0.036	0.011
$cost_{dom}$	-0.477	0.468	-0.420	0.156	-0.395	0.509	-0.499	0.165

TABLE 9

Wage-elasticity and unpaid-work elasticity estimated coefficients in the female paid-work equation for different education level

Estimator: 2S-SCLS						
Dependent variable: *work*	Compulsory School		High School		Degree	
regressors:	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
W	0.708	0.099	0.742	0.014	0.797	0.029
$cost_{ch}$	-0.052	0.022	-0.045	0.021	-0.087	0.038
$cost_{dom}$	-0.772	0.901	-0.123	0.478	-0.685	0.651
Estimator: IV-TOBIT						
Dependent variable: *work*	Compulsory School		High School		Degree	
regressors:	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
W	0.671	0.019	0.723	0.030	0.784	0.088
$cost_{ch}$	0.004	0.030	-0.019	0.018	-0.029	0.025
$cost_{dom}$	-0.378	0.440	-0.242	0.268	-0.158	0.234

TABLE 10

Wage-elasticity and unpaid-work elasticity estimated coefficients in the female paid-work equation for number of children aged 0-5 who live in the family

Estimator: 2S-SCLS - Dependent variable: *work*						
No. of children 0-5	0		1		>1	
regressors:	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
W	0.739	0.026	0.702	0.017	0.675	0.030
$cost_{ch}$	–	–	-0.116	0.034	-0.152	0.085
$cost_{dom}$	-0.335	0.621	0.604	0.897	0.618	1.24
Estimator: IV-TOBIT - Dependent variable: *work*						
No. of children 0-5	0		1		>1	
regressors:	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
W	0.708	0.047	0.717	0.034	0.737	0.080
$cost_{ch}$	–	–	0.054	0.028	0.031	0.067
$cost_{dom}$	-0.083	0.317	-0.569	0.340	0.281	0.789

6. FINAL OBSERVATIONS AND REMARKS

The inclusion of the costs of unpaid-work as instrumental variables in the married women's labour supply estimation allows us to obtain an apparently robust estimate of the female paid-work equation adopting either parametric or semiparametric methods. Both estimation methods yield small differences in the level of wage-elasticity coefficient that, in both cases, seems to be highly significant. Estimation performance using both the parametric and semiparametric method shows that the sensitivity of our estimates may be considered low with respect to the parametric assumptions in the model. These results suggest that the IV method here proposed may improve both the Mroz (1987) and Newey *et al.* (1990) methodological approach to the female labour supply estimation.

The use of instrumental variables forced us to impose several overidentification restrictions in the model specification. For this reason, a test of validity of instruments has been provided to support the conclusion that our estimation is sufficiently robust, irrespective of the details of model specification (see table 7).

On the other hand, the results of both estimation methods show a negative influence of the indirect costs of unpaid-working activities on women's labour supply. If we consider that the indirect cost of both childcare and domestic activity is here computed by multiplying the time employed by the individual in these activities by individual "potential" hourly wage, an increase or a reduction in wage level impacts strongly on the indirect cost level. Irrespective of previous empirical studies on the static model of female labour supply, we found that wage impacts directly and positively on paid-work supply, but contextually influences labour supply with the opposite sign through the indirect costs of domestic activity and childcare.

The latter costs may be reduced if the time devoted by women to non-market activities diminishes. Therefore, in order to reduce the influence of indirect non-market activity costs on married women's labour supply, it may be particularly useful to support families in their informal childcare (or eldercare) activity with the availability of external services, and by promoting a more intensive commitment of the partner in domestic duties with the extension of part-time opportunities (cf. Del Boca, 2002).

Kalenkosky *et al.* (2009), using time use survey data in the United Kingdom, found that partner commitment in domestic work increases if woman's wage rises. In this study, preliminary statistics not reported here show that the allocation of working time of men is generally irresponsive to partner's wage. On the other hand, this relationship is very difficult to estimate here, because of the lack of information about household income, which would be necessary to model a pooling effect of labour income on working activities.

Considering some methodological aspects developed in this paper, we should observe that, by adopting the 2S-SCLS estimator, a contingent of selected women homogeneous in terms of probability of working is selected by trimming the sample. This circumstance leads us to consider estimates obtained by 2S-SCLS presumably more robust and coherent than the parametric IV-Tobit results.

Surprising conclusions occur from the interpretation of the semiparametric estimation results. For instance, the different estimated wage-elasticity between North-Centre and South leads to the conclusion that a woman who lives and works in the less developed Italian Southern Regions could spend more working time in the market with respect to a woman of the more developed North-Centre, as a response to a higher retribution (cf. table 8).

Furthermore, a semiparametric estimation results show that the positive wage-elasticity slowly decreases if small children (aged 0-5) live in the family (cf. table 10). Conversely, the negative childcare cost elasticity increases especially if more than one small children lives in the family.

Comparing these results with past and more recent studies on the labour supply of Italian women, we can observe that the wage-elasticity estimated here is higher (by 0.2 to 0.3 p.ts) than that obtained by Colombino and Del Boca (1990) and by Aaberge *et al.* (1999). However, the approach used in the previous studies to estimate wage-elasticity is generally based on the simulation of the response of labour supply to an average increase of 1% in empirical wage level. Instead our procedure provides the estimation of a specific elasticity coefficient. Therefore, divergence in the estimated wage-elasticity level across studies on female labour supply may be the consequence of a different model specification and/or the adoption of a different criterion to compute elasticity.

Finally, we should observe how the unavailability of data about both household consumption and income limits our analysis to the estimation of uncompensated elasticity. If we had this information, we could include a utility function equation in the model, and wage-compensated elasticity could be computed for any given "predicted" level of utility.

Department of Economics, Statistics,
Mathematics and Sociology (DESMaS) "V. Pareto"
University of Messina

MARIA GABRIELLA CAMPOLO
ANTONINO DI PINO

APPENDIX: REDUCED FORM ESTIMATION RESULTS

TABLE A1

Reduced form estimation of fertility and of participation function

Dependent Variable:	*ch*		*L*	
	Equation 1		Equation 2	
Estimator:	POISSON		SIEVE-NLLS	
	Coeff.	p-value	Coeff.	p-value
intercept	0.197	*	1.000	*
fert	0.339	*		
dage	-0.014	*		
first	-0.042	*		
age			0.000	#
edu_{father}			0.095	*
dday			0.069	#
ch			-0.104	#
ch_{random}			-0.552	*
darea			-1.178	*
No. of Observations:	5698		5698	
pseudo R^2	21%		59%	
p-value: * < 1%; ** <5%; # > 5%				

TABLE A2

Parametric estimation of partner working activities (paid-work, domestic work and childcare)

Dependent Variable:	$chcare_{par}$		dom_{par}		$work_{par}$	
Estimator:	Equation 3 OLS		Equation 4 OLS		Equation 5 TOBIT	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
intercept	1.515	#	1.228	#	3.736	*
age_{par}	-0.130	*	0.120	**	-0.018	#
$age^2{}_{par}$	0.001	#	-0.001	**	0.000	#
edu_{par}	0.122	*	0.087	*	0.000	#
ch	2.203	*	-0.246	*	0.024	#
ch_{random}	-1.022	*	0.132	#	0.069	#
$fulltime_{par}$	-0.381	#	-2.100	*	4.341	*
$partime_{par}$	-0.200	#	-1.802	*		
colf	0.000	#	-0.002	#	0.000	#
Dummy Variables:						
darea	-0.474	*	-0.960	*	-0.074	*
dday	0.049	#	-1.328	*	0.027	#
No. of Observations:	5698		5698		5698 (5540 uncensored)	
R^2	32%		5%		pseudo R^2 22%	
p-value: * < 1%; ** <5%; # > 5%						

TABLE A3

Reduced form parametric estimation of log wage equation and cost of unpaid activities equations

Dependent Variable:	W		$cost_{ch}$		$cost_{dom}$	
	Equation 6		Equation 7		Equation 8	
Estimator:	TOBIT		OLS		OLS	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
intercept	-21.185	*	1.050	*	2.086	*
age			-0.048	*	0.049	*
age²					0.000	*
edu_{father}			0.022	*		
ch			1.868	*	0.106	*
ch_{random}			-0.660	*	-0.010	#
sitting			0.008	*		
sitting²			0.000	*		
eduage	6.747	*				
GNP_{reg}	4.752	*				
fulltime	10.301	*				
colf					-0.001	*
Dummy Variables:						
darea	-1.004	**			0.138	*
dday			0.463	*	0.034	#
No. of Observations:	5698(3091 uncensored)		5698		5698	
	pseudo R^2	18%	R^2	55%	R^2	5%
p-value: * < 1%; ** <5%; # > 5%						

TABLE A4

Semiparametric estimation of partner working activities (paid and unpaid-work)

Dependent Variable:	$chcare_{par}$		dom_{par}		$work_{par}$	
	Equation 3		Equation 4		Equation 5	
Estimator:	LAD		LAD		CLAD	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
intercept	-4.000	*	3.175	*	7.272	*
age_{par}	5.66E-10	#	0.104	**	2.22E-10	#
age^2_{par}	-1.04E-11	#	-0.001	**	-3.39E-12	#
edu_{par}	1.29E-10	#	0.044	*	-4.69E-10	*
ch	3.151	*	-0.205	*	1.68E-10	#
ch_{random}	-1.7E-08	#	0.020	#	-3.64E-11	#
$fulltime_{par}$	-2.3E-09	#	-1.313	*	0.511	*
$part\text{-}time_{par}$	-1.6E-09	#	-0.928	**		
colf	1.1E-11	#	-0.002	**	4.13E-04	*
Dummy Variables:						
darea	-1.03E-09	#	-0.822	*	8.40E-11	#
dday	3.0E-10	#	-1.140	*	6.56E-10	#
No. of Observations:	5698		5698		5540	
Pseudo R^2	15%		3%		3%	
p-value: * < 1%; ** <5%; # > 5%						

TABLE A5

Reduced form semiparametric estimation of log-wage equation and cost of unpaid activities equations

Dependent Variable:	W		$cost_{ch}$		$cost_{dom}$	
	Equation 6		Equation 7		Equation 8	
Estimator:	SCLS		LAD		LAD	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
intercept	-3.228	#	-2.303	*	2.610	*
age			-4.80E-10	*	0.042	*
age²					0.000	*
edu_{father}			2.53E-10	#		
ch			2.585	*	0.037	**
ch_{random}			-2.84E-08	*	-0.003	#
sitting			0.010	*		
sitting²			-7.84E-06	*		
eduage	0.029	#				
GNP_{reg}	1.335	#				
fulltime	6.504	*				
colf					-0.002	*
Dummy Variables:						
darea	2.085	*			0.087	*
dday			3.41E-10	#	0.033	#
No. of Observations:	2918		5698		5698	
	R^2	59%	Pseudo R^2	51%	Pseudo R^2	2%

p-value: * < 1%; ** <5%; # > 5%

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REFERENCES

R. AABERGE, U. COLOMBINO, S. STROM, (1999), *Labour supply in Italy: an empirical analysis of joint household decisions, with taxes and quantity constraints*, "Journal of Applied Econometrics", 14, part 4, pp. 403-422.

B. ALVAREZ, D. MILES, (2003), *Gender effect on housework allocation: evidence from spanish two-earner couples*, "Journal of Population Economics", 16, part 2, pp. 227-242.

T. AMEMIYA, (1979), *The estimation of a simultaneous-equation Tobit model*, "International Economic Review", 20, part 1, pp. 169-181.

BANK OF ITALY, (2004), *Survey on Households Income and Wealth (SHIW) in Italy, in the Year 2002*.

G.S. BECKER, (1981), *Treatise on the Family*, Harvard University Press, Cambridge, MA.

J.R. BLEVINS, S. KHAN, (2009), *Distribution-Free estimation of heteroskedastic binary response models in Stata*, Duke University Working Paper.

H.G. BLOEMEN, S. PASQUA, E.G.F. STANCANELLI, (2010), *An empirical analysis of the time allocation of Italian couples: are they responsive?,* "Review of Economics of the Household", 8, pp. 345-369.

R.W. BLUNDELL, T. MACURDY, (1999), *Labor supply: a review of alternative approaches*, in O. ASHENFELTER, D. CARD (eds.) *Handbook of Labor Economics,* 3, part 1, Elsevier, pp. 1559-1695.

R.W. BLUNDELL, R.J. SMITH, (1994), *Coherency and estimation in simultaneous models with censored or qualitative dependent variables*, "Journal of Econometrics", 64, pp. 355-373.

J. BONKE, (1992), *Distribution of economic resources: implications of including household production*, "Review of Income and Wealth", 38, part 3, pp. 281-293.

X. CHEN, (2007), *Large sample Sieve estimation of semi-nonparametric models*, in J.J. HECKMAN and E.E. LEAMER (eds.), *Handbook of Econometrics*, 6, part 2, Elsevier, pp. 5549-5632.

P.A. CHIAPPORI, (1988), *Rational household labour supply*, "Econometrica", 56, pp. 63-90.

U. COLOMBINO, D. DEL BOCA, (1990), *The effect of taxes on labour supply in Italy*, "Journal of Human Resources", 25, pp. 390-414.

D. DEL BOCA, (2002), *The effect of childcare and part time opportunities on participation and fertility decisions in Italy*, "Journal of Population Economics, 15, pp. 549-573.

D. DEL BOCA, D. VURI, (2007), *The mismatch between employment and childcare in Italy: the impact of rationing*, "Journal of Population Economics", 20, part 4, pp. 805-832.

R. DE MOOIJ, M. EVERS, D. VAN VUUREN, (2008), *The wage-elasticity of labour supply: a synthesis of empirical estimates,* "De Economist", 156, pp. 25-43.

G. DE SANTIS, (2004), *The monetary cost of children. Theory and empirical estimates for Italy*, "GENUS", 61, pp. 161-183.

G. DE SANTIS, A. DI PINO, (2009), *Female labour participation with concurrent demographic processes: An estimation for Italy*, in H. ENGELHARDT, H.P. KOHLER and A. FÜRNKRANZ-PRSKAWETZ (eds.), *Causal Analysis in Population Studies. Concepts, Methods, Applications*, 23, Springer, pp. 149-165. doi: 10.1007/978-1-4020-9967-0_7.

A. DI PINO, (2004), *Economic estimation of the time devoted to household chores and childcare in Italy*, "GENUS", 61, pp. 139-159.

R. GRONAU, (1986), *Home production – A survey*, in O. ASCHENFELTER and R. LAYARD (eds.), *Handbook of Labor Economics*, 1, Elsevier, pp. 273-304.

J.L. HOROWITZ, (1992), *A smoothed maximum score estimator for the binary response model,* "Econometrica", 60, 505-531.

ISTAT - Italian National Institute of Statistics, (2007), *The Use of Time – Multi-Purpose Survey on Italian Families in 2002-2003*.

S. KHAN, (2005), *Distribution free estimation of heteroskedastic binary response models using Probit/Logit criterion functions*, University of Rochester Working Paper.

G.M. KALENKOSKY, D.C. RIBAR, L.S. STRATTON, (2009), *The influence of wages on parents' allocation of time to childcare and market work in the United Kingdom*, "Journal of Population Economics", 22, pp. 399-419.

M.R. KILLINGSWORTH, J.J. HECKMAN, (1986), *Female labor supply: a survey*, in O. ASCHENFELTER and R. LAYARD (eds.), *Handbook of Labor Economics*, Elsevier, pp. 103-204.

N.A. KLEVMARKEN, (2005), *Estimates of a labour supply function using alternative measures of hours of work*, "European Economic Review", 49, part 1, pp. 55-73.

L.F. LEE, (1994), *Semiparametric istrumental variable estimation of simultaneous equation sample selection models*, "Journal of Econometrics", 63, pp. 341-388.

L.F. LEE, (1998), *Semiparametric estimation of simultaneous-equation microeconometric models with index restrictions*. "Japanese Economic Review", 49, part 4, pp. 343-380.

S. LUNDBERG, R.A. POLLAK, (1993), *Separate spheres bargaining and the marriage market*, "Journal of Political Economy", 101, part 6, 988-1010.

C.F. MANSKI, (1985), *Semiparametric analysis of discrete response: asymptotic properties of Maximum Score estimation,* "Journal of Econometrics", 27, pp. 313-334.

T. MROZ, (1987), *The sensitivity of an empirical model of married women's hours of work to economic and statistical assumptions*, "Econometrica", 55, part 4, pp. 765-799.

W.K. NEWEY, (1987), *Efficient estimation of limited dependent variable models with endogenous explanatory variables*, "Journal of Econometrics", 36, pp. 231-250.

W.K. NEWEY, J.L. POWELL, J.R. WALKER, (1990), *Semiparametric estimation of selection models: some empirical results*, "American Economic Review", 80, part 2, pp. 324-328.
J.L. POWELL, (1984), *Least absolute deviations estimation for the censored regression model*, "Journal of Econometrics", 25, part 3, pp. 303-325.
J.L. POWELL, (1986), *Symmetrically trimmed least squares estimation for Tobit models*, "Econometrica", 54, pp. 1435-1460.
P.R. ROSENBAUM, (2002), *Observational Studies*, Springer, New York.
P.R. ROSENBAUM, (2005), *Sensitivity analysis in observational studies*, in B.S. EVERITT and D.C. HOWELL (eds.), *Encyclopedia of Statistics in Behavioral Sciences,* John Wiley & Sons, pp. 1809-1814.
R.J. SMITH, R.W. BLUNDELL, (1986), *An exogeneity test for a simultaneous equation Tobit model with an application to labour Supply*, "Econometrica", 54, pp. 679-685.
K.V. SRIVASTAVA, D. GILES, (1987), *Seemingly Unrelated Regression Equations Models*, New York, Basel, Marcel Dekker.

SUMMARY

An empirical analysis of women's working time, and an estimation of female labour supply in Italy

Empirical studies show that misspecification of the married (or cohabiting) women's labour supply equation may produce inefficient wage-elasticity estimates. In order to reduce the variability of these estimates, we suggest a new approach based on instrumental variables given by the economic value of the domestic unpaid-work of women. Using Italian micro-data on time use (ISTAT Survey on Time Use), and applying both a parametric and a semiparametric procedure, we estimate robust wage-elasticity coefficients of married women's labour supply. Our results suggest that women's labour supply is negatively influenced by the indirect cost of their informal activity of childcare and domestic work.