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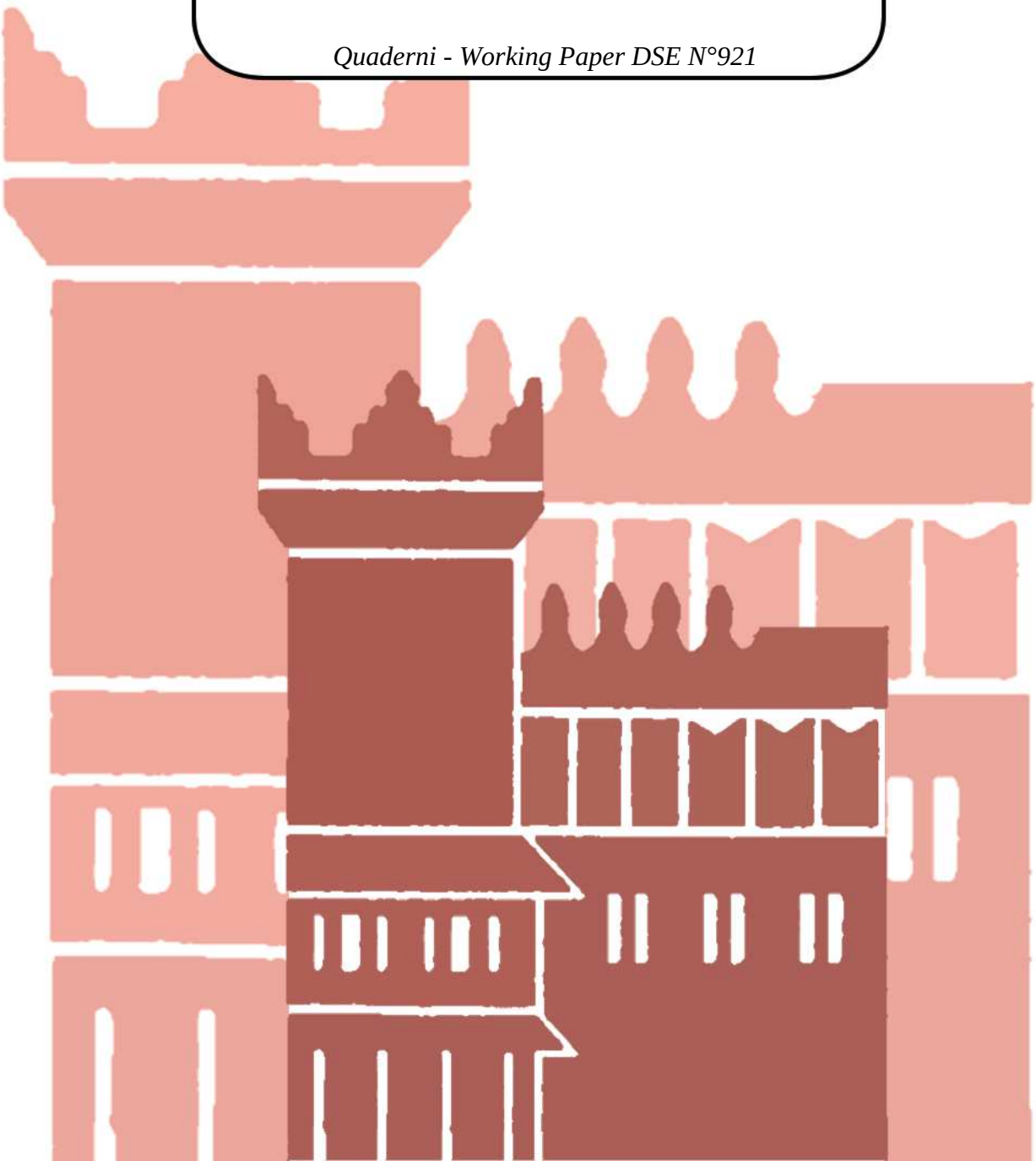

Testing exogeneity of multinomial regressors in count data models: does two stage residual inclusion work?*

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Abstract

We study a simple exogeneity test in count data models with possibly endogenous multinomial treatment. The test is based on Two Stage Residual Inclusion (2SRI). Results from a broad Monte Carlo study provide novel evidence on important features of this approach in nonlinear settings. We find differences in the finite sample performance of various likelihood-based tests under correct specification and when the outcome equation is misspecified due to neglected over-dispersion or nonlinearity. We compare alternative 2SRI procedures and uncover that standardizing the variance of the first stage residuals leads to higher power of the test and reduces the bias of the treatment coefficients. An original application in health economics corroborates our findings.

JEL Classification: C12, C31, C35, I11

Keywords: count data, endogenous treatment, exogeneity test, health care utilization

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1 Introduction

Instrumental variables (IV) methods are the established solution to the problem of endogeneity of regressors in linear models. However, it is well known that IV estimators imply an efficiency loss that might be substantial with respect to Ordinary Least Squares estimators. This explains the great attention received by the Hausman test for endogeneity (1978), and by its computationally simple regression-based form. This consists of a two stages procedure: first stage residuals are computed from reduced form estimation and are then inserted as additional regressors in the second stage equation for the outcome of interest. This method, known as two stage residual-inclusion (2SRI), tests the null hypothesis of exogeneity of a subset of regressors by way of a variable addition test, i.e. checking whether the coefficients of the first stage residuals are equal to zero in the second stage structural equation.

Accounting for endogeneity in non linear models is a challenging issue in econometrics. Wooldridge (2002, 2011) and Terza (2008) point out that the application of IV methods in this context is not straightforward, since two stages estimators are not in general consistent for the structural parameters of interest. Despite some recent contributions suggest distribution free semiparametric approaches (see Abrevaya et al, 2010, and the references cited there), the most common practice to handle endogeneity in the nonlinear framework consists in formulating some parametric distributional assumptions on both the endogenous regressors and the outcome variable. Inference on the parameters of interest and on the exogeneity status of the regressors is performed through Maximum Likelihood (ML) method, its validity requiring correct specification of the model. Wooldridge (2011) shows that in some non linear models with endogenous regressors ML estimation under misspecification -i.e. Quasi ML estimation- has some robustness properties. Wooldridge (2011) also derives a class of two step tests for exogeneity of multiple -and possibly discrete- regressors. The conceptual and computational simplicity of the two step approach to exogeneity testing in nonlinear models makes it extremely appealing for the applied researcher.

We consider here the problem of endogeneity in count data models. The empirical microeconometrics literature, and health econometrics in particular, devoted much attention to this class of non linear models. For instance they are extensively used to represent healthcare demand through the number of doctor visits. Endogeneity is likely to arise due to unobserved heterogeneity affecting both the outcome and the regressors, possibly stemming from unobserved agents'characteristics or misreporting. Deb and Trivedi (1997), Kenkel and Terza (2001), Mullahy (1997), Windmeijer and Santos Silva (1997), Van Ophem (2000), Miranda (2004), Fabbri and Monfardini (2009), Cheng and Vahid (2010), Bratti and Miranda (2011) are some examples dealing with endogenous binary regressors. Recently, some attention has been devoted to the case of count data models with multinomial endogenous regressors. Deb and Trivedi (2006) propose a simulation based full maximum likelihood method for single equation count data models (generalized to the case of multivariate counts by Fabbri and Monfardini, 2011). Zimmer (2010) adopts instead a two step procedure, following the suggestion of Terza et al (2008). This latter study stresses that in many non linear contexts replacing predicted endogenous variables

in the second stage leads to inconsistent estimators, and points to 2SRI to obtain valid inference, including exogeneity tests.

This paper aims at establishing whether exogeneity tests based on 2SRI represent a viable alternative to detect endogeneity in count data models with multinomial endogenous regressors. In this context, 2SRI tests are much easier to implement than maximum likelihood approaches that require simulations and are computationally intensive. We develop a broad Monte Carlo Study to assess the finite sample properties of 2SRI exogeneity tests. In our framework, endogeneity is represented by alternative specific latent factors entering both the count outcome equation and the multinomial treatment model. This formalization of endogeneity is germane to Terza (2008) - based on 2SRI - and Deb and Trivedi (2006) - based on FIML estimation.

Our Monte Carlo experiments produce novel evidence on important features of the 2SRI procedure, enhancing existing simulation studies conducted by Terza (2008) and Staub (2009) for the case of count regressor with dychotomous endogenous explanatory variable.[1] We start by evaluating the performance of different likelihood based tests, namely Wald and Likelihood Ratio, under correct specification and various form of misspecification, ranging from neglecting over-dispersion to neglecting non-linearity. Then we compare alternative 2SRI tests, adopting alternative definitions for the first stage residuals, and spot relevant differences in their performance. This is a relevant aspect, since the first stage estimation involves multinomial discrete choice models, where no consensus exists on the definition of the error term (see Pagan and Vella, 1989). Finally, we bring our conjectures and findings to real data, and apply the 2SRI procedure to an original case study in health economics. We use data from an important French Survey to model the individual annual number of doctor visits allowing for healthcare insurance status to be endogenously determined. The results of this application are coherent with the main finding of our Monte Carlo investigation.

The remaining of the paper is structured as follows. Section 2 sets a general parametric representation of endogeneity in nonlinear models. Section 3 describes the count regression with multinomial endogenous treatment. Section 4 presents the 2SRI estimator/test we study. The design of the Monte Carlo experiment is illustrated in Section 5, together with the simulation results. Section 6 is devoted to the application of the procedure to a model of healthcare demand with endogenous insurance. Section 7 concludes.

2 A parametric representation of endogeneity in non-linear models

We consider the non linear conditional mean of the outcome y:

[1] In a related work Kapetanios (2010) analyses through a Monte Carlo study the peformance of some new Hausman-type tests for exogeneity in nonlinear threshold models.

$$E[y_i|\mathbf{x}_i, \mathbf{x}_{ei}, \mathbf{q}_i] = M(\mathbf{x}_i\boldsymbol{\beta} + \mathbf{x}_{ei}\boldsymbol{\beta}_e + \mathbf{q}_i\boldsymbol{\lambda}) \quad (1)$$

$$= M(\mathbf{x}_i\boldsymbol{\beta} + \sum_{s=1}^{S}\gamma_s x_{eis} + \sum_{s=1}^{S}\lambda_s q_{is}) \quad (2)$$

where $M(\cdot)$ is a non-linear function, $\mathbf{x}_i$ is a set of K exogenous regressor, $\mathbf{x}_{ei}$ is a set of S covariates (either discrete or continuous) possibly correlated with a set of S unobservable confounders $\mathbf{q}_i$, hence endogenous. Following Terza et al. (2008), we represent endogeneity of regressors $\mathbf{x}_{ei}$ by an idiosyncratic influence of the same latent factors $\mathbf{q}_i$ on both y_i and $\mathbf{x}_{ei}$ in possibly non linear reduced form regressions:

$$x_{esi} = r_s(\mathbf{z}_i\alpha_s) + q_{si} \quad s = 1, ..., S \quad (3)$$

where $\mathbf{z}_i = [\mathbf{x}_i \ \mathbf{w}_i]$, and $\mathbf{w}_i$ is a set of at least S instrumental variables satisfying all the necessary assumptions.

In this setting, the hypothesis of exogeneity of regressors x_{esi}, $s = 1, ..., S$ can be formulated as:

$$H_0 : \lambda_1 = \lambda_2 = ... = \lambda_S = 0$$

Taking a fully parametric approach to inference, let the density of the outcome conditionally to endogenous regressors, exogenous covariates and latent factors be:

$$f(y_i|\mathbf{x}_i, \mathbf{x}_{ei}, \mathbf{q}_i)$$

and the marginal density of endogenous regressors conditionally to exogenous covariates $\mathbf{x}_i$, identifying instruments $\mathbf{w}_i$ and latent factors $\mathbf{q}_i$ be denoted as:

$$g(\mathbf{x}_{ei}|\mathbf{x}_i, \mathbf{w}_i, \mathbf{q}_i)$$

The two above distributions can be combined into a joint distribution of the type:

$$Pr(y_i, \mathbf{x}_{ei}|\mathbf{x}_i, \mathbf{w}_i, \mathbf{q}_i) = f(y_i|\mathbf{x}_i, \mathbf{x}_{ei}, \mathbf{q}_i) \times g(\mathbf{x}_{ei}|, \mathbf{x}_i, \mathbf{w}_i, \mathbf{q}_i) \quad (4)$$

Unobservability of $\mathbf{q}_i$ can be handled by way of some parametric distributional assumptions, taking them as *i.i.d* draws from density $h(\mathbf{q}_i)$. Their distribution is integrated out via simulation, obtaining the joint density of the observable variables:

$$Pr(y_i, \mathbf{x}_{ei}|\mathbf{x}_i, \mathbf{w}_i) = \int f(y_i, \mathbf{x}_{ei}|\mathbf{x}_i, \mathbf{w}_i, \mathbf{q}_i)h(\mathbf{q}_i)d\mathbf{q}_i \quad (5)$$

Estimation is performed maximizing a simulated log-likelihood function. Provided that the factor loading parameters $\lambda_1, \lambda_2, ..., \lambda_S$ are identified, a test for exogeneity of the vector $\mathbf{x}_{ei}$ can be carried out with the usual maximum likelihood-based tests. This is a full information maximum likelihood (FIML) procedure since all equations are jointly estimated,

and it is well known to achieve asymptotic efficiency properties under correct distributional assumptions. Notice, however, that efficiency comes with an heavy computational cost.

An easier test for exogeneity of $\mathbf{x}_{ei}$ can be carried out resorting to the so called two stage residual inclusion procedure (2SRI). Two Stages Residual Inclusion and Two Stages Prediction Substitution (2SPS) are the non-linear counterparts of the linear Two Stages Least Squares (2SLS) approach. While 2SPS substitutes the endogenous regressors in the structural equation with their consistent estimates obtained in the first stage (mimicking 2SLS in the nonlinear case), 2SRI keeps the endogenous regressors in the outcome equation and substitutes the unobservable confounders with residuals obtained from the reduced equation. Wooldridge (2002) and Terza et al. (2008) emphasize that, when the conditional expectation is nonlinear, 2SPS is generally an inconsistent procedure, while 2SRI allows to get consistent estimates of the structural equation parameters.[2] In our case of full parametric assumptions the 2SRI approach involves separate maximum likelihood estimation of both the first and the second stage equations (and it amounts to limited information maximum likelihood, cf. Wooldridge, 2011).
After estimation of the reduced form equations, predictors of the endogenous regressors are obtained as:

$$\hat{x}_{esi} = r_s(\mathbf{z}_i\hat{\alpha}_s) \tag{6}$$

Residuals, which estimate q_{si}, are computed as follows:

$$\hat{q}_{si} = x_{esi} - r_s(\mathbf{z}_i\hat{\alpha}_s) \tag{7}$$

and are plugged inside the structural equation. The parameters λ_s $s = 1, ..., S$ are the coefficients associated to the estimated residuals $\hat{q}_{si}$, so that the exogeneity test amounts to a variable addition test in the second stage equation, which can be easily performed with likelihood-based tests.

When the functions $M(\cdot)$ and $r_s(\cdot)$ in (1) and (3) are linear, 2SRI coincides with the regression-based exogeneity test proposed by Hausman (1978), thus the 2SRI procedure can be seen as an extension of the Hausman test to the non-linear framework. Notice that the non linear function $r_s(\cdot)$ allows for endogenous regressors of different nature in $\mathbf{x}_{ei}$, including multinomial treatment. In this case (3) will describe its relationship with the unobservable confounders as a multinomial response model.

Testing exogeneity of $\mathbf{x}_{ei}$ with 2SRI is a more practical alternative with respect to FIML approaches. However, little is known about its properties in finite samples. Is the two step procedure reliable, so that practitioners can exploit its computational advantages? Are there ways to conduct 2SRI outperforming alternative possibilities? In the following sections we answer to these questions. Despite we analyse the specific case of a count

[2] The proof of consistency is carried out by Terza et al. (2008) using the theory of two stages optimization estimators, of which 2SRI can be seen as a special case.

outcome, some results of ours might also be informative for other nonlinear models with potentially endogenous multinomial regressors.

3 A count data model with endogenous multinomial treatment

In the Data Generating Processes we will specify in the next section, the multinomial treatment affects the count outcome equation trough $\mathbf{d}_i$, a set of J dummies for the $J+1$ mutually exclusive alternatives in the choice set. Endogeneity is pinned down using the same alternative specific latent factors q_{ij}, in the treatment and the outcome equations. This formulation adapts the proposal of Deb and Trivedi (2006) to the general representation of endogeneity presented in the previous section.

Let the density for the count outcome conditionally to exogenous variables, treatment and latent factors be written as:

$$f(y_i|\mathbf{x}_i, \mathbf{d}_i, \boldsymbol{q}_i) = f\left(\mu_i, \boldsymbol{\theta}\right) \tag{8}$$

In order to accomodate for overdispersion in the data, $f(\cdot)$ is assumed as a Negative Binomial type-2 density function with rate parameter μ. Thus, (8) can be re-written as:

$$f(y_i|\mathbf{x}_i, \mathbf{d}_i, \boldsymbol{q}_i) = \frac{\Gamma(y_i+\psi)}{\Gamma(\psi)\Gamma(y_i+1)}\left(\frac{\psi}{\mu_i+\psi}\right)^{\psi}\left(\frac{\mu_i}{\mu_i+\psi}\right)^{y_i} \tag{9}$$

where ψ is the overdispersion parameter, and the conditional mean for the outcome takes the usual exponential form:

$$\mu_i = E(y_i|\mathbf{x}_i, \mathbf{d}_i, \boldsymbol{q}_i) = exp\left(\mathbf{x_i'}\boldsymbol{\beta} + \sum_{j=1}^{J}\gamma_j d_{ij} + \sum_{j=1}^{J}\lambda_j q_{ij}\right) \tag{10}$$

In the above equation $\mathbf{x_i}$ is a vector of exogenous observable characteristics of individual i which do not vary among alternatives, and $\boldsymbol{\beta}$ is the conformable vector of coefficients. The multinomial treatment enters the model trough $\mathbf{d_i}$, the set of J dummies, d_{ij} indicating the treatment alternatives. $\mathbf{q_i}$ is a vector of J unobservable latent factors q_{ij}, with associated factor loadings λ_j, which potentially affect both the outcome and the treatment, generating endogeneity in the outcome model.

The equation for the multinomial treatment is derived from a random utility model, according to which each individual chooses the treatment which maximizes her indirect utility. Indirect utility for individual i from alternative j can be expressed as follows:

$$V_{ij}^{*} = \mathbf{z_i'}\boldsymbol{\alpha}_j + q_{ij} \tag{11}$$

where $\mathbf{z}_i$ is a vector including the exogenous covariates in $\mathbf{x}_i$ in (10) plus a set of instruments, and $\boldsymbol{\alpha}_j$ is the vector of associated parameters for the alternative j. Alternative j is chosen by individual i iff $V_{ij}^* \geq V_{ik}^*, \forall k \neq j$. The dummy d_{ij} in (10) takes value 1 if alternative j is chosen, 0 otherwise. Utility from alternative $j = 0$ is normalized so that $V_{i0}^* = 0$.

We specify q_{ij} as $i.i.d$ Type 1 Extreme Value erros (logistic after normalization). This amounts to assume a Multinomial Logit (MNL) representation for the probability of the treatment, which can be written as follows:

$$Pr\left(d_{ij}|\mathbf{z}_i\right) = \frac{exp\left(\mathbf{z}_\mathbf{i}'\boldsymbol{\alpha}_j\right)}{1 + \sum_{k=1}^{J} exp\left(\mathbf{z}_\mathbf{i}'\boldsymbol{\alpha}_k\right)} \quad for \;\; j = 0, 1, ..., J \tag{12}$$

4 The 2SRI estimator

4.1 First stage

In multinomial discrete choice models there is no consensus about the definition of errors and residuals. With our notation, let $\widehat{Pr}\left(d_{ij}|\mathbf{z}_i\right)$ be the predicted probability of choosing alternative j, obtained after estimation of a multinomial response model. The most obvious definition of residuals is what we name, following Cameron and Windemejer (1996) *raw residuals* (adopted for example by Terza et al.,2008 and Staub, 2009):

$$\widehat{q}_{ij}^{R} = d_{ij} - \widehat{Pr}\left(d_{ij}|\mathbf{z}_i\right) \quad for \;\; j = 0, 1, ..., J \tag{13}$$

Alternatively, Pagan and Vella (1989) suggest a standardized version of the residuals, with unit variance, we call *standardized residuals*

$$\widehat{q}_{ij}^{S} = \widehat{Pr}\left(d_{ij}|\mathbf{z}_i\right)^{-1/2}\left(1 - \widehat{Pr}\left(d_{ij}|\mathbf{z}_i\right)\right)^{-1/2}\left(d_{ij} - \widehat{Pr}\left(d_{ij}|\mathbf{z}_i\right)\right) \quad for \;\; j = 0, 1, ..., J \tag{14}$$

In the absence of any guidance on the choice between these two alternatives, in our Monte Carlo study we will compare them, to find out whether standardization improves the performance of the exogeneity test.

4.2 Second stage

Once the MNL for treatment is estimated, we have available two types of residuals for each alternative (raw, R, and standardized, S), based on expressions (13) and (14), say:

$$\widehat{q}_{ij}^{r} = d_{ij} - \widehat{Pr}\left(d_{ij}|\mathbf{z}_i\right) \quad for \;\; j = 0, 1, ..., J \;\; r = R, S$$

These residuals are then added to structural equation for the outcome, substituting for the unobservable latent factors, so that equation (10), describing the conditional mean for y, can be re-written as follows:

$$E(y_i|\mathbf{x}_i, \mathbf{d}_i, \hat{\boldsymbol{q}}_i^r) = exp\left(\mathbf{x_i'}\boldsymbol{\beta} + \sum_{j=1}^{J}\gamma_j d_{ij} + \sum_{j=1}^{J}\lambda_j \widehat{q}_{ij}^r\right) \quad r = R, S \tag{15}$$

This second stage model is estimated via maximum likelihood and the exogeneity test for the hypothesis $H_0 : \lambda_1 = ... = \lambda_J = 0$ is carried out through Wald, Likelihood ratio and Lagrange Multiplier tests under three different specification scenarios.

4.2.1 Correct specification

The conditional density is assumed to be the NB2 distribution (9), with conditional mean (10).

4.2.2 Neglecting over-dispersion: Poisson estimator

The conditional density is assumed to be a Poisson distribution, setting $\psi = 0$ in the NB2 distribution (9), while mantaining the same formulation (10) for the conditional mean. Despite this specification does not allow for the existing overdispersion of the data, the Poisson PML estimator is still consistent for the conditional mean of the outcome, which remains the same. Estimating the model with this alternative version of the 2SRI estimator allows us to assess the robustness of the Poisson specification under different degrees of overdispersion of the outcome.

4.2.3 Neglecting non linearity: OLS estimator

The equation describing the conditional mean for y is substituted by the following linear approximation:

$$E(y_i|\mathbf{x}_i, \mathbf{d}_i, \hat{\boldsymbol{\tau}}_i) = \mathbf{x_i'}\boldsymbol{\beta} + \sum_{j=1}^{J}\gamma_j d_{ij} + \sum_{j=1}^{J}\lambda_j \widehat{q}_{ij}^r \;\; r = R, S \tag{16}$$

In this setup the exogeneity test is conducted through a F test. This will allows us to evaluate to what extent the count nature of the outcome can be ignored resorting to the linear approximation.

5 The Monte Carlo Study

In order to investigate the finite sample properties of the 2SRI exogeneity tests, we run simulations under different Data Generating Processes (DGPs) described below.[3]

[3]The study has been conducted using STATA 12. Programming code and user-written routines are available on request.

5.1 Experimental design

Random utilities are computed by way of a discrete choice model; the $j-th$ status dummy assumes value 1 if its utility has the highest value among the $J+1$ alternatives, 0 otherwise. After having generated the dummies representing the multinomial treatment, the conditional expectation of the count dependent variable, y, is obtained by random sampling from a Negative Binomial type-2 distribution. This is obtained as a Poisson-Gamma mixture with parameter $\lambda_i = \mu_i \nu_i$, where μ_i is the conditional mean of a Poisson random variable, taking the usual exponential form, and ν_i is a random draw from a Gamma distribution. The number of alternatives in the multinomial treatment model, $J+1$, is set to three: $j = 0, 1, 2$, so that only two dummies are included inside the conditional mean for the outcome.

In order to evaluate size and power properties of the exogeneity tests, we build two different DGPs under endogeneity and exogeneity of the multinomial treatment. Both DGPs we analyse include logistic latent factors, but they differ for the degree of overdispersion. Under DGP2 the count variable is set to be much less overdispersed - i.e. its variance is closer to its mean, compared to the count variable generated under DGP1.[4] The sample size, N, is set to 5.000 observations, which is a realistic size for application of count data models to microeconometric data. The size and power properties of the 2SRI exogeneity tests are evaluated on 5.000 replications of the test statistics.

The following table describes the distribution of the pseudo random variables and the parameter values in our experimental setting.

[4] We obtain these pattern by increasing the scale parameter of the mixing gamma distribution and by lowering the constant inside the conditional mean of the count, as detailed in the table describing the experimental design.

Description of experimental design	
DGP 1, DGP 2	
d_{i1}	$= 1$ if $V_{i1}^* = \max(V_{i0}^*, V_{i1}^*, V_{i2}^*)$, $= 0$ otherwise
d_{i2}	$= 1$ if $V_{i2}^* = \max(V_{i0}^*, V_{i1}^*, V_{i2}^*)$, $= 0$ otherwise
V_{i0}^*	$=0$
V_{i1}^*	$= 0.025 + 0.5\, obs_i + 0.5 inst1_i + -0.25\, inst2_i + q_{i1}$
V_{i2}^*	$= 0.25 + 0.1 obs_i + 0.5 inst1_i + 0.5\, inst2_i + q_{i2}$
obs_i	i.i.d $N(0,1)$, observable characteristic
$inst1_i$	dummy variable, $I[U(0,1) < 0,5]$ - first instrument
$inst2_i$	$N(0,1)$ - second instrument
q_{1i}, q_{2i}	i.i.d draws from a logistic density
$f(y_i \mid \mathbf{x}_i, \mathbf{d}_i, \mathbf{q}_i)$	$= \frac{\Gamma(y_i+\psi)}{\Gamma(\psi)\Gamma(y_i+1)} \left(\frac{\psi}{\mu_i+\psi}\right)^{\psi} \left(\frac{\mu_i}{\mu_i+\psi}\right)^{y_i}$
Mixing distribution ν_i	$Gamma(\psi, \frac{1}{\psi})$
μ_i	$= exp(k + \beta_{obs}\, obs_i + \gamma_{d1}\, d_{i1} + \gamma_{d2}\, d_{i2} + \lambda_1\, q_{i1} + \lambda_2\, q_{i2})$
	$\beta_{obs} = 0.5; \gamma_{d1} = 0.4; \gamma_{d2} = 0.8$
Endogenous treatment	$\lambda_1 - 0.1; \lambda_2 = -0.5$
Exogenous treatment	$\lambda_1 = \lambda_2 = 0$
DGP 1	$\psi = 1; k = 1$
DGP 2	$\psi = 3; k = -1$

In Appendix 1 we report basic descriptives of the treatment dummy variables and of the count variables under the different DGPs. Notice that the marginal probability distribution of the dummies is kept constant over the different data generation processes. DGP2 involves a much lower degree of overdispersion than in DGP1, as it can be observed comparing the variance and the mean of the two count variables. Concomitantly, under DGP2 the count variable displays the "excess of zeros" pattern wich is often encountered in applications.

5.2 Results

5.2.1 Exogeneity Test

In Table 1 we report rejection frequencies over the 5000 Monte Carlo replications of the three asymptotycally equivalent Wald, Likelihood Ratio (LR) and Lagrange Multplier (LM) tests under correct specification of the estimated model, i.e. when the estimated model is NB2. We present two versions of the Wald test, the first of which is based on a Murphy-Topel corrected Variance-Covariance Matrix. This is evaluated taking into account that the model estimated in the second stage involves generated regressors, namely the first stage estimated residuals. We have derived the correction when the first stage model is multinomial adapting the procedure suggested by Hole (2006).[5] The Table reveals a general very good performance of all 2SRI tests, in terms of both size and power for both

[5] Analytical results and STATA code are available upon request.

analysed DGPs. If we compare the test performance among the two definitions of residuals we notice an improvement of power properties of Wald corrected test when switching from "raw" to "standardized" version. A very slight power gain is associated to the use of standardized residuals also for the non corrected version of the Wald for the LM test. The improved general performance with standardized residuals is an interesting pattern we spot here and in the following results, and to which will devote further attention later.

Table 1 here

Table 2 presents the results concerning the effects on exogeneity tests of the first misspecification we study. The tests are here obtained estimating a Poisson regression model while both DGPs involve a NB2 process. As the count variable exhibits greater overdispersion under DGP1 than under DGP2, the Poisson estimator, which assumes equidispersion, is "more misspecified" under DGP1. In this latter scheme, the bad consequences of misspecifying overdispersion are serious for all tests but Lagrange Multiplier, which proves to be fairly robust, with higher power still obtained with standardized residuals. The empirical size of the Wald test evaluated without Murphy-Topel correction, and that of the Likelihood Ratio test are dramatically affected by misspecification of overdispersion, with rejection frequencies that imply huge probabilities of first type error (reject exogeneity when this is true). Moreover, the Wald test with corrected variance is found to loose any power of spotting true endogeneity. The robustness of LM test means that the quantities involved in its computation (score function of the unrestricted model, restricted estimator) are less affected by overdispersion parameter than the quantities involved in LR (restricted and unrestricted loglikelihood functions) or non-corrected Wald tests (unrestricted estimator). Some different mechanism is instead likely to affect the Wald test based on Murphy Topel variance, annihilating both its size and power properties. Under DGP2, on the contrary, all tests display reasonable empirical size and power. Remarkably, the best power results of corrected Wald test and LM are still achieved resorting to standardized residuals, confirming the pattern already spotted under correct specification.

Table 2 here

Table 3 reports the results obtained when the estimated model is linear, thus neglecting the count nature of the dependent variable. Performing the test within OLS estimation delivers very misleading results. It proves quite important to implement the test specifying a count density, rather than resorting to the linear approximation of the conditional mean implyed by linear regression. Empirical sizes are generally much higher than their nominal counterparts, hindering any reasonable inference on the exogeneity status. Similarly to the Poisson estimator case, failure of the test in recognizing exogeneity of the treatment is likely due to the inability of the estimator to fit the overdispersed structure of the data. Indeed, over-rejection of the true exogeneity hypothesis is less pronounced, despite still serious, under DGP2, where the count is less overdispersed.

Table 3 here

5.2.2 Comparing raw and standardized first stage residuals

In this section we analyse more carefully the different finite sample performance of the exogeneity tests obtained including the two alternative definitions of residuals in the second stage, i.e. raw versus standardized. In Figures 1 and 2 in Appendix 2 empirical power is plotted against nominal size for different values of the latter. The interesting part of the plot is for small values of nominal size that will be chosen in practice (usually nominal size is set below 0.10). The higher power of the test obtained standardizing the first stage residuals is a clear pattern for all test statistics under both DGPs, confirming that there is a gain in using the standardized residuals.

To get some insights on the source of this gain we exploit our simulation setting to compare the generated errors of the discrete choice model and their two alternative estimates represented by raw and standardized residuals respectively. To this purpose, we perform the following elaborations. First, we regress the generated errors used to simulate the two random utilities attached to alternatives 1 and 2 (named latent 1 and latent 2 in the following graphs) against the two alternative definitions of residuals. In the upper part of Figure 3 in Appendix 2 we plot the true latent errors versus the fitted latent errors obtained using as regressor the two alternative definitions of residuals. In the bottom part, we plot together the density of the true latent errors, the raw residuals and the standardized residuals.

Taken together, these plots reveal that standardizing the variance of the residuals allows for a better overlap with the range of possible values assumed by the latent error component. Indeed, standardization will always increase the variance of raw residuals, which is lower than one by definition. This represents a possible explanation for the better ability of the standardized residuals to approximate the latent utility error and for the better performance of the exogeneity tests based on this definition of residuals.

5.2.3 Some remarks on the coefficients estimators

As a by-product of our analysis on the properties of the exogeneity test, we report in Tables A2-A3 in Appendix 3 the mean of the estimated coefficients and their standard errors obtained trhough the 5000 replications of the Monte Carlo experiments. We draw our attention on the behaviour of the dummy coefficients estimators which represent the treatment effects of interest. The coefficients display little bias under exogeneity when the estimation is based on either NB2 (Table A2) or Poisson (Table A3), confirming its well known consistency property under correct specification of the conditional mean.[6] However, inference on the treatment coefficients is -not surprisingly- much more difficult under endogeneity. Here, the treatment coefficients exhibit some bias, despite the quite large sample considered ($N = 5000$), with different magnitude across DGPs and estimated models. In order to get a measure of the total bias of the two treatment coefficients we build a synthetic measure given by the sum of the absoute value of the bias over the two coefficients. Figure 4 plots the distribution of this measure of total bias of the second stage

[6] We do not include for brevity results on OLS estimators, which turn out to be tremendously biased.

ML estimators across estimated models and DGPs. Interestinlgy, the bias is always lower when estimation involves the standardized version of the first sage residuals, corroborating the inference gain already spotted for the exogeneity test. A final remark concerns the Murphy Topel correction. As expected, the corrected standard errors are higher than their non corrected counterpart, but become excessively high in the presence of misspecification. This calls for some caution before basing inference on the modified variance estimator in applied contexts.

6 An application to healthcare demand

Count data models with possibly multinomial endogenous treatment arise quite easily in the Health Economics literature. Here demand naturally comes as a count (for physician visits or hospital admissions) and polichotomous health insurance status is an endogenous treatment of paramount interest. To provide a vivid example of how the two alternative 2SRI strategies fare in the applied econometrics practice we revisit and update the French case study on the effect of complementary health insurance on health care utilization originally explored by Buchmueller et al. (2004).

Social Security insurance (Sècuritè Sociale) financed out of personal income tax covers most of individual healthcare expenditure for legal residents of France. Co-pay are customarily levied for general practitioner or specialist visits, hospital stay, or prescription drugs to moderate moral hazard. To get rid of most of these copayments French citizens purchase complementary health insurance (CHI) on a voluntary basis (individually purchase) or within an employer-sponsored set-up (employer insured). CHI plans enroll 85% of the French population and fund about 13% of total health care expenditure. Similarly to Buchmueller et al. (2004) our exercise aims at assessing the impact of the CHI status on physician visits' utilization. We differ in that we allow for a differential impact of the individually purchased and the employer provided CHI with respect to the benchmark case of no complementary coverage. Accounting for endogeneity of the treatment and modeling the dependent variable as a count represent the biggest improvements on the previous study.

We use data from the 2006 wave of the Enquète sur la Santé et la Protection Sociale (ESPS), a national household survey conducted by IRDES. The full sample contains data for 22725 individuals. We restrict our analysis to individuals aged between 25 and 75. After excluding those who have not completed the 'health' section of the questionnaire or have missing data on key regressors we end up with a final estimation sample of 6455 observations. Table 4 presents the distributions of our utilization measure, i.e. counts for visits to any physician (in the 12 months before the interview), and the treatment variable, i.e. availability of a Complementary Health Insurance. 55% of the sample receives CHI as part of work total compensation while 34% purchases it deliberately in the market. 6% of the sample is covered by CMU-C (Couverture Maladie Universelle Complementaire). This plan was introduced in 2000 by the French Government to improve the non-elderly poor access to health care. CMU-C beneficiaries are asked no co-pay at the point of use. Eligible

individuals are those with a household income below a given threshold (€587 per adult equivalent per month in 2005, see Grignon, Perronnin and Lavis, 2008). Upon control for income per adult equivalent we assume this CHI status as conditionally exogenous.

Table 4 here

Descriptive statistics for the regressors we control for in our models are provided in Table 5. Their extended name is self-explanatory on their definition.

Table 5 here

The Complementary Health Insurance status according to employer-based or individually purchased vis-a-vis being either covered by CMU-C or not covered is modeled as a Multinomial Logit. Following Buchmuller et al. (2004), professional occupational variables and labour market status are used as instruments - and therefore excluded from the visit equation, to avoid indentification being based only on non-linearity. The usual argument here is that different employment sectors offer different opportunities to enroll into complementary health insurance schemes and also attract individuals with different degrees of risk aversion (Fabbri and Monfardini, 2011). Estimated coefficients (presented in Table 6) are coherent with theoretical predictions and previous empirical research in the field. Income is a good predictor for the CHI status according to a conventional hump shaped relation.

Table 6 here

Table 7 here

Table 7 contains the estimation results for the count regression. Most of the estimated coefficients exhibit the expected signs. The most prominent are those related to health status: self-assessed health, suffering from chronic conditions or from some limitation in daily activities. All of them testify that worse health positively correlates with healthcare consumption. Notice, however, that these effects are likely biased by self-reporting (see Bago d'Uva et. al. 2011). Consumption rises, as expected, as the individual ages. Moreover being highly educated is positively correlated with healthcare consumption, a common finding in the literature. The first column displays estimates obtained under exogeneity of health insurance, the second and third columns contain the second stage results with inclusion of raw residuals, with variance matrix non corrected and corrected respectively, while the third and fourth columns corresponds to inclusion of standardized residuals. Under exogeneity, we find significant moral hazard effects arising from supplemental insurance coverage either employer provided or individually purchased. Both types of complementary coverage are associated to a 21-24% increase in the conditional mean number of visits with respect to the baseline case of no complementary insurance. Once we allow for the endogeneity of the insurance status results differ depending on the definition of residuals adopted. Following the guidelines emerged from our Monte Carlo Study,

we look at the results obtained with standardized residuals with non corrected standard errors. We find support to an identification assumption frequently adopted in the literature since Ettner (1997): adverse selection is typically argued to be a minor problem for employer-provided coverage, while being possibly not negligible for individually purchased plans. Employer insured dummy proves to be exogenous to visits while a positive partial correlation between standardized first stage residuals and visits' counts purport the view that individuals are adversely selected into personally purchased plans.

The outcome of different exogeneity tests appears at the bottom of Table 7. The most striking feature is represented by the different conclusions implied by the alternative definition of residuals adopted. While exogeneity of health insurance is not rejected according to raw residuals inclusion, whatever the test approach used, the opposite conclusion is reached with the standarized version of the residuals, with the exception of the Wald corrected test. Since we have reasons to believe that health insurance is endogenous (on both theoretical grounds and existing empirical evidence), we reconcile this result with the higher power displayed in the Monte Carlo study by the 2SRI tests using standardized residuals.

7 Concluding remarks

We study two stages residuals inclusion (2SRI) approach to testing exogeneity of multinomial treatment in count data models. The procedure involves estimating the residuals from a discrete choice model, and plugging them as additional variables in the structural count regression, where their joint significance can be tested with likelihood based inference.

The results of our Monte Carlo study show that 2SRI exogeneity tests using Wald, LR and LM approaches have good finite sample properties when the distribution of the outcome is correctly specified. In this case, all tests display proper empirical size and power. We then analyse the performance of 2SRI under misspecification of the second stage model. We find that the LM test is the only robust procedure when we ignore overdispersion, but this is a strong feature of the data. We also find evidence that in order to apply 2SRI exogeneity tests the practitioners should avoid neglecting nonlinearity and performing OLS estimation.

We investigate also the properties of the testing procedure as sensitive to two alternative definitions of residuals: raw and standardized. We observe that the power of the test is generally higher using standardized residuals, which exhibit an higher variance and represent a better fit of the discrete choice model errors. Furthermore, resorting to standardized residuals leads to a smaller bias of the endogenous treatment dummies coefficients.

The patterns emerging from the Monte Carlo investigation are quite revealing when we bring the 2SRI method to real data on a leading case study in health economics: the modeling of visits' count with endogenous health insurance choice. In our empirical analysis, all tests based on standardized residuals are able to detect endogeneity, while

the use of raw, non-standardized residuals leads to the - most likely wrong - opposite conclusion that health insurance choice is exogenously determined.

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Appendix 1

Table A1: Summary statistics of dependent variables generated in Monte Carlo Study

Distribution of treatment binary variables

	DGP1		DGP2	
	Endogeneity	Exogeneity	Endogeneity	Exogeneity
% of 1				
d0	17.08	17.08	17.08	17.08
d1	39.56	39.56	39.56	39.56
d2	34.36	34.36	34.36	34.36

Distribution of outcome count variable - y

	DGP1		DGP2	
	Endogeneity	Exogeneity	Endogeneity	Exogeneity
Mean	7.11	5.39	0.93	0.75
Variance	199.86	59.10	3.92	1.25
% of values				
0	21.84	19.68	55.64	55.04
1	14.42	14.58	24.54	27.32
2	10.90	12.54	9.56	10.60
3	8.08	8.02	4.72	3.96
4	6.36	6.90	2.32	1.82
5	5.24	6.18	1.16	0.70
6	3.66	4.92	0.66	0.22
7	3.58	3.92	0.32	0.10
8	2.72	3.58	0.30	0.18
9	2.60	2.90	0.22	0.06
10	1.90	2.32	0.06	0
>10	18.70	14.46	0.42	0

Note: summary statistics are computed on the 5000 observations of the first replication of the experiment

Appendix 2

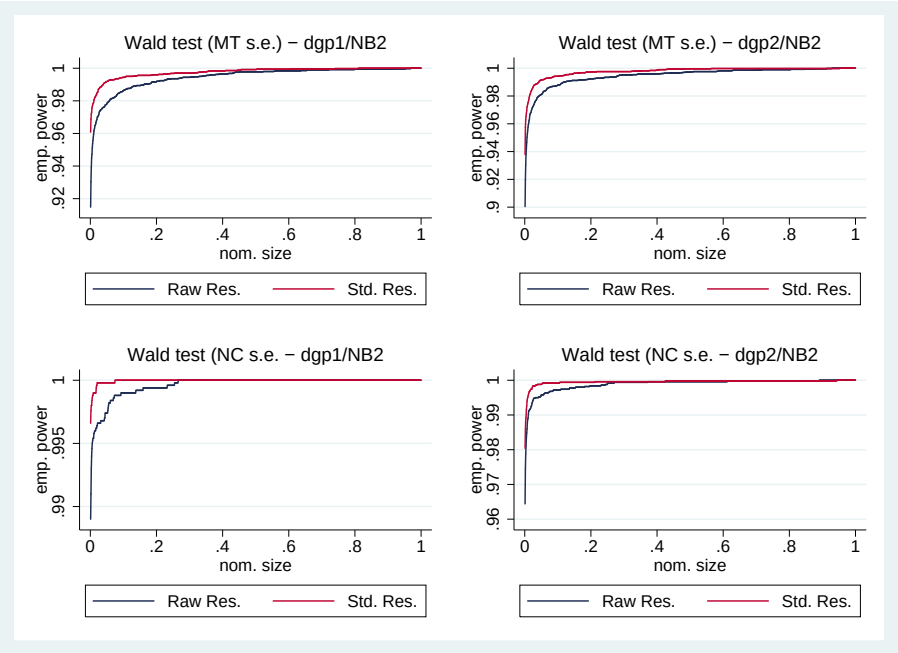


Figure 1: Empirical power plot of Wald tests using raw and standardized residuals

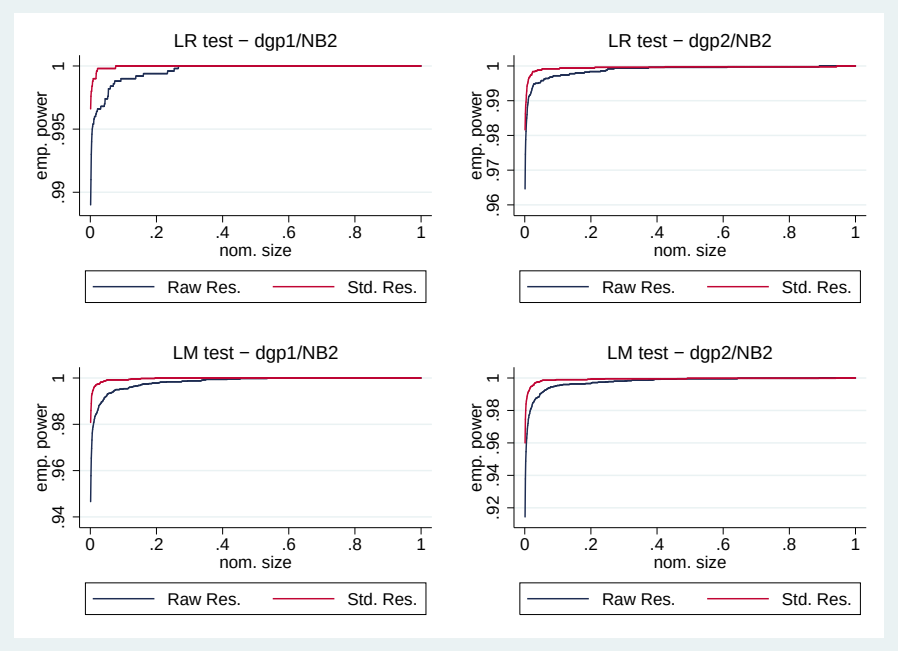


Figure 2: Empirical power plot of LR and LM tests using raw and standardized residuals

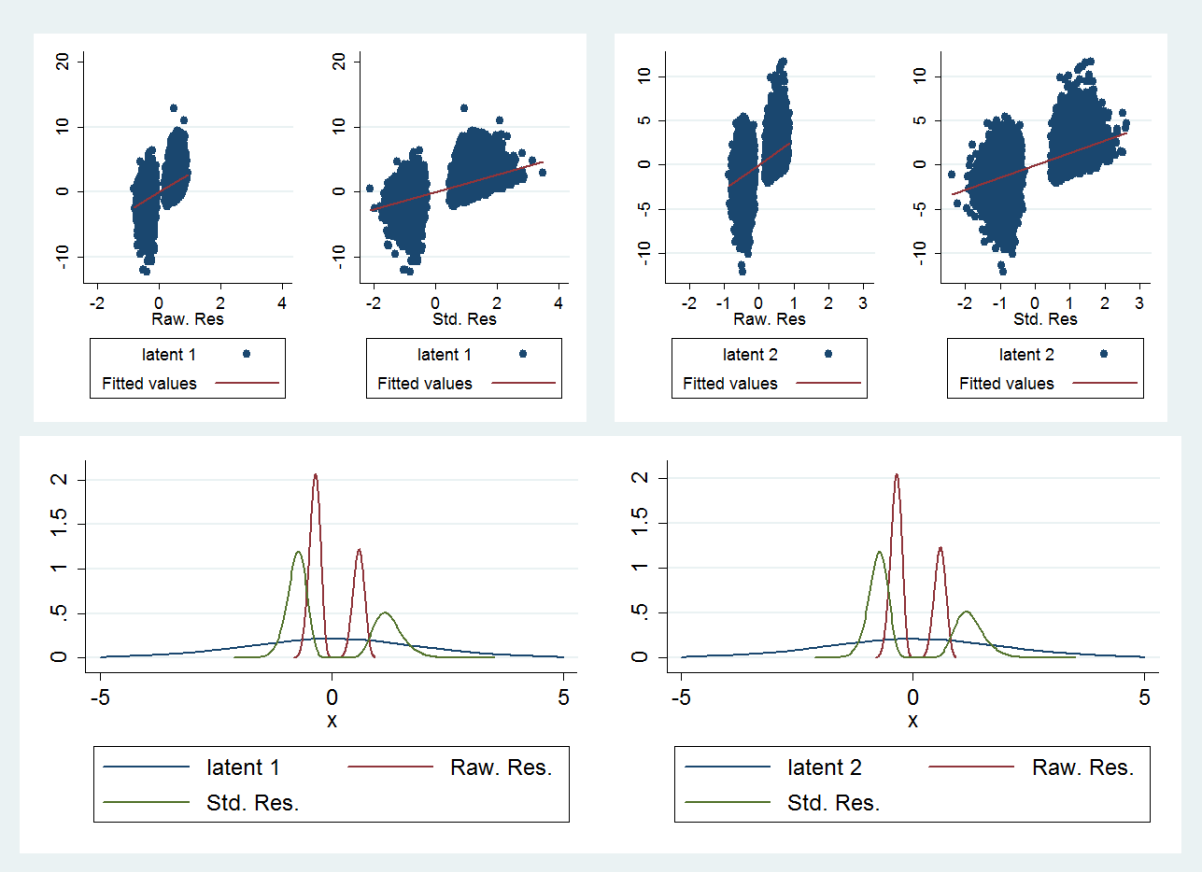


Figure 3: True latent factors against estimated residuals

Appendix 3

Table A2: NB2 estimator: outcome equation coefficients

DGP 1

			Raw Residuals					
	True Values			Exogeneity			Endogeneity	
	Exog.	Endog.	Mean	S.E. (NC)	S.E. (MT)	Mean	S.E. (NC)	S.E. (MT)
γ_{d1}	0,4	0,4	0,3990	0,3730	0,3757	0,6160	0,4432	0,7695
γ_{d2}	0,8	0,8	0,7982	0,2989	0,3012	0,8253	0,3533	0,6010
β_{obs}	0,5	0,5	0,5002	0,0280	0,0282	0,5031	0,0335	0,0572
λ_1	0,0	-0,1	0,0014	0,3757	0,3784	-0,8571	0,4463	0,7712
λ_2	0,0	-0,5	0,0023	0,3022	0,3044	-1,6839	0,3574	0,6065

			Standardized Residuals					
	True Values			Exogeneity			Endogeneity	
	Exog.	Endog.	Mean	S.E. (NC)	S.E. (MT)	Mean	S.E. (NC)	S.E. (MT)
γ_{d1}	0,4	0,4	0,4052	0,2751	0,2760	0,3919	0,3225	0,5099
γ_{d2}	0,8	0,8	0,8025	0,2274	0,2282	0,6484	0,2700	0,3929
β_{obs}	0,5	0,5	0,4998	0,0236	0,0236	0,5163	0,0280	0,0434
λ_1	0,0	-0,1	-0,0024	0,1304	0,1308	-0,2994	0,1525	0,2427
λ_2	0,0	-0,5	-0,0010	0,1105	0,1109	-0,7258	0,1314	0,1928

DGP 2

			Raw Residuals					
	True Values			Exogeneity			Endogeneity	
	Exog.	Endog.	Mean	S.E. (NC)	S.E. (MT)	Mean	S.E. (NC)	S.E. (MT)
γ_{d1}	0,4	0,4	0,3978	0,4757	0,4789	0,6685	0,5351	0,7506
γ_{d2}	0,8	0,8	0,7990	0,3935	0,3964	0,8506	0,4363	0,6008
β_{obs}	0,5	0,5	0,5002	0,0337	0,0340	0,5020	0,0392	0,0539
λ_1	0,0	-0,1	0,0043	0,4778	0,4811	-0,9242	0,5396	0,7540
λ_2	0,0	-0,5	0,0027	0,3964	0,3991	-1,7203	0,4417	0,6095

			Standardized Residuals					
	True Values			Exogeneity			Endogeneity	
	Exog.	Endog.	Mean	S.E. (NC)	S.E. (MT)	Mean	S.E. (NC)	S.E. (MT)
γ_{d1}	0,4	0,4	0,4023	0,3603	0,3616	0,4168	0,3919	0,5250
γ_{d2}	0,8	0,8	0,8030	0,2947	0,2957	0,6717	0,3408	0,4311
β_{obs}	0,5	0,5	0,5000	0,0287	0,0288	0,5158	0,0332	0,0437
λ_1	0,0	-0,1	-0,0003	0,1718	0,1724	-0,3189	0,1867	0,2514
λ_2	0,0	-0,5	-0,0007	0,1416	0,1421	-0,7423	0,1663	0,2126

Note: N. of replications of the Monte Carlo experiment (R) = 5.000; Saple size for each replication (N) = 5.000. Raw residuals and Standardized residuals are computed after estimation of the first stage equations using, respectively, $\hat{\tau}_{ij} = (d_{ij} - \hat{p}_{ij}),\ for\ j = 0, 1, 2$ and $\hat{\tau}_{ij} = \hat{p}_{ij}^{-1/2}(1 - \hat{p}_{ij})^{-1/2}(d_{ij} - \hat{p}_{ij}),\ for\ j = 0, 1, 2$

Table A3: Poisson estimator: outcome equation coefficients

DGP 1

			Raw Residuals					
	True Values			Exogeneity			Endogeneity	
	Exog.	Endog.	Mean	S.E. (NC)	S.E. (MT)	Mean	S.E. (NC)	S.E. (MT)
γ_{d1}	0,4	0,4	0,3990	0,1562	0,3619	0,7218	0,1348	34,5135
γ_{d2}	0,8	0,8	0,7979	0,1304	0,2937	0,8864	0,1129	29,8503
β_{obs}	0,5	0,5	0,5000	0,0108	0,0306	0,5027	0,0092	2,5398
λ_1	0,0	-0,1	0,0022	0,1568	0,3638	-0,9984	0,1361	34,4247
λ_2	0,0	-0,5	0,0030	0,1312	0,2972	-1,7700	0,1143	29,7677
			Standardized Residuals					
	True Values			Exogeneity			Endogeneity	
	Exog.	Endog.	Mean	S.E. (NC)	S.E. (MT)	Mean	S.E. (NC)	S.E. (MT)
γ_{d1}	0,4	0,4	0,4075	0,1193	0,2161	0,4274	0,0988	17,8274
γ_{d2}	0,8	0,8	0,8050	0,0971	0,1901	0,6919	0,0892	15,9219
β_{obs}	0,5	0,5	0,4996	0,0092	0,0234	0,5171	0,0079	1,6498
λ_1	0,0	-0,1	-0,0031	0,0569	0,1042	-0,3345	0,0473	8,3807
λ_2	0,0	-0,5	-0,0021	0,0465	0,0947	-0,7584	0,0436	7,8442

DGP 2

			Raw Residuals					
	True Values			Exogeneity			Endogeneity	
	Exog.	Endog.	Mean	S.E. (NC)	S.E. (MT)	Mean	S.E. (NC)	S.E. (MT)
γ_{d1}	0,4	0,4	0,3967	0,4247	0,4307	0,7345	0,3665	3,1866
γ_{d2}	0,8	0,8	0,7983	0,3548	0,3598	0,8932	0,3070	2,4532
β_{obs}	0,5	0,5	0,5001	0,0293	0,0297	0,5017	0,0251	0,2390
λ_1	0,0	-0,1	0,0053	0,4263	0,4323	-1,0137	0,3699	3,1558
λ_2	0,0	-0,5	0,0032	0,3569	0,3619	-1,7804	0,3107	2,5267
			Standardized Residuals					
	True Values			Exogeneity			Endogeneity	
	Exog.	Endog.	Mean	S.E. (NC)	S.E. (MT)	Mean	S.E. (NC)	S.E. (MT)
γ_{d1}	0,4	0,4	0,4020	0,3243	0,3266	0,4323	0,2687	2,1853
γ_{d2}	0,8	0,8	0,8032	0,2642	0,2662	0,6942	0,2427	1,6916
β_{obs}	0,5	0,5	0,4999	0,0249	0,0251	0,5166	0,0214	0,1928
λ_1	0,0	-0,1	-0,0001	0,1547	0,1559	-0,3381	0,1288	1,0658
λ_2	0,0	-0,5	-0,0009	0,1264	0,1274	-0,7613	0,1185	0,8510

Note: N. of replications of the Monte Carlo experiment (R) = 5.000; Saple size for each replication (N) = 5.000. Raw residuals and Standardized residuals are computed after estimation of the first stage equations using, respectively, $\hat{\tau}_{ij} = (d_{ij} - \hat{p}_{ij}),\ \ for\ \ j = 0, 1, 2$ and $\hat{\tau}_{ij} = \hat{p}_{ij}^{-1/2}(1 - \hat{p}_{ij})^{-1/2}(d_{ij} - \hat{p}_{ij}),\ \ for\ \ j = 0, 1, 2$

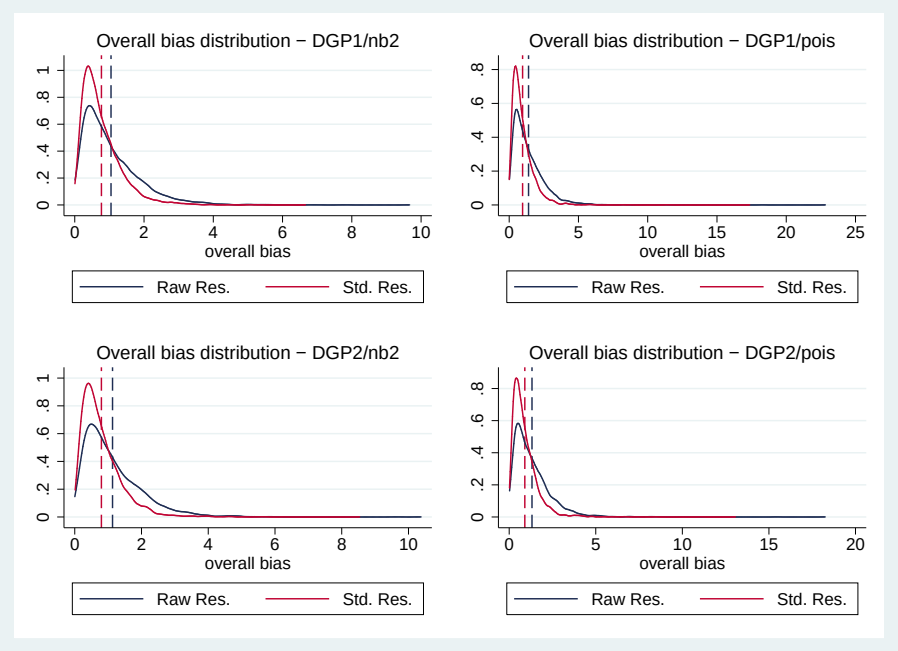


Figure 4: Overall bias of endogenous dummies coefficients using raw and standardized residuals

Table 1: NB2 estimator: rejection frequencies of exogeneity tests

Wald Test (Murphy Topel correction)

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,0084	0,9594	0,0078	0,9788	0,0080	0,9576	0,0082	0,9752
0,05	0,0460	0,9782	0,0426	0,9918	0,0420	0,9810	0,0472	0,9914
0,10	0,0916	0,9862	0,0956	0,9944	0,0876	0,9878	0,0932	0,9942

Wald Test (no correction)

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,0114	0,9954	0,0096	0,9990	0,0096	0,9890	0,0108	0,9954
0,05	0,0520	0,9974	0,0482	0,9998	0,0472	0,9958	0,0506	0,9988
0,10	0,1008	0,9990	0,1014	1,0000	0,0946	0,9972	0,1008	0,9992

Likelihood Ratio Test

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,0112	0,9954	0,0096	0,9990	0,0098	0,9894	0,0106	0,9954
0,05	0,0520	0,9974	0,0480	0,9998	0,0472	0,9958	0,0502	0,9988
0,10	0,1006	0,9990	0,1016	1,0000	0,0946	0,9972	0,1006	0,9992

Lagrange Multiplier Test

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,0124	0,9806	0,0108	0,9954	0,0104	0,9720	0,0100	0,9910
0,05	0,0544	0,9924	0,0498	0,9990	0,0484	0,9906	0,0510	0,9982
0,10	0,1022	0,9954	0,1032	0,9992	0,0952	0,9954	0,1042	0,9990

Note: N. of replications of the Monte Carlo experiment (R) = 5.000; Saple size for each replication (N) = 5.000. Raw residuals and Standardized residuals are computed after estimation of the first stage equations using, respectively: $\hat{\tau}_{ij} = (d_{ij} - \hat{p}_{ij}),\ \ for\ j = 0, 1, 2$ and $\hat{\tau}_{ij} = \hat{p}_{ij}^{-1/2}(1 - \hat{p}_{ij})^{-1/2}(d_{ij} - \hat{p}_{ij}),\ \ for\ j = 0, 1, 2$

Table 2: Poisson estimator: rejection frequencies of exogeneity tests

Wald Test (Murphy Topel correction)

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,0000	0,0000	0,0000	0,0000	0,0174	0,7370	0,0208	0,8194
0,05	0,0076	0,0000	0,0006	0,0000	0,0816	0,8454	0,0900	0,8940
0,10	0,0456	0,0000	0,0190	0,0000	0,1462	0,8896	0,1562	0,9206

Wald Test (no correction)

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,5494	0,9998	0,5498	0,9998	0,0258	0,9966	0,0298	0,9988
0,05	0,6696	1,0000	0,6822	0,9998	0,0932	0,9980	0,1010	0,9994
0,10	0,7362	1,0000	0,7412	1,0000	0,1628	0,9986	0,1690	0,9994

Likelihood Ratio Test

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,5494	0,9998	0,5494	0,9998	0,0260	0,9966	0,0260	0,9966
0,05	0,6696	1,0000	0,6696	1,0000	0,0928	0,9980	0,0928	0,9980
0,10	0,7362	1,0000	0,7362	1,0000	0,1632	0,9986	0,1632	0,9986

Lagrange Multiplier Test

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,0128	0,9118	0,0124	0,9626	0,0100	0,9372	0,0098	0,9750
0,05	0,0524	0,9660	0,0586	0,9884	0,0482	0,9740	0,0494	0,9918
0,10	0,1072	0,9776	0,1104	0,9946	0,0940	0,9834	0,1034	0,9960

Note: N. of replications of the Monte Carlo experiment (R) = 5.000; Saple size for each replication (N) = 5.000. Raw residuals and Standardized residuals are computed after estimation of the first stage equations using, respectively: $\hat{\tau}_{ij} = (d_{ij} - \hat{p}_{ij}),\ \ for\ j = 0, 1, 2$ and $\hat{\tau}_{ij} = \hat{p}_{ij}^{-1/2}(1 - \hat{p}_{ij})^{-1/2}(d_{ij} - \hat{p}_{ij}),\ \ for\ j = 0, 1, 2$

Table 3: OLS estimator: rejection frequencies of exogeneity tests

F Test (Murphy Topel correction)

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,1092	0,5480	0,2698	0,6214	0,0854	0,6326	0,2248	0,7202
0,05	0,3060	0,7438	0,5348	0,8082	0,2536	0,8056	0,4704	0,8638
0,10	0,4438	0,8264	0,6746	0,8738	0,3752	0,8704	0,6114	0,9116

F Test (no correction)

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,1258	0,5780	0,3028	0,6566	0,1002	0,6600	0,2468	0,7448
0,05	0,3188	0,7576	0,5530	0,8244	0,2652	0,8172	0,4838	0,8760
0,10	0,4520	0,8352	0,6820	0,8830	0,3848	0,8780	0,6198	0,9192

Lagrange Multiplier Test

	DGP 1				DGP 2			
	Raw Residuals		Standardized Residuals		Raw Residuals		Standardized Residuals	
Nom. Size	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power	Emp. Size	Emp. Power
0,01	0,1258	0,5780	0,3030	0,6566	0,1002	0,6604	0,2468	0,7450
0,05	0,3190	0,7578	0,5534	0,8248	0,2660	0,8174	0,4840	0,8762
0,10	0,4520	0,8352	0,6822	0,8830	0,3850	0,8780	0,6202	0,9196

Note: N. of replications of the Monte Carlo experiment (R) = 5.000; Saple size for each replication (N) = 5.000. Raw residuals and Standardized residuals are computed after estimation of the first stage equations using, respectively: $\hat{\tau}_{ij} = (d_{ij} - \hat{p}_{ij}),\ \ for\ j = 0, 1, 2$ and $\hat{\tau}_{ij} = \hat{p}_{ij}^{-1/2}(1 - \hat{p}_{ij})^{-1/2}(d_{ij} - \hat{p}_{ij}),\ \ for\ j = 0, 1, 2$

Table 4: Descriptive statistics of the dependent variables

Treatment Variable

	Mean	Std. Dev.	Min.	Max.
Employer Insured	0,5549	0,4970	0	1
Individually Purchased	0,3374	0,4729	0	1
Uninsured	0,1077	0,3100	0	1

Utilization Measure

	Mean	Std. Dev.	Min.	Max.
Total N. of Consultations	5,2311	5,9175	0	104

Sample Distribution

Value	Freq.	Percentage	Cum. Perc.
0	717	11,11	11,11
1	788	12,21	23,32
2	892	13,82	37,13
3	684	10,6	47,73
4	734	11,37	59,1
5	491	7,61	66,71
6	461	7,14	73,85
7	299	4,63	78,48
8	241	3,73	82,22
9	145	2,25	84,46
10	160	2,48	86,94
More than 10	113	13.06	1,00
Total	6.455	100	

Table 5: Descriptive statistics of the regressors

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Demographic Characteristics				
Male	0,4973	0,5000	0	1
Age	46,4632	13,0897	25	74
Married	0,8215	0,3829	0	1
Children	0,5859	0,4926	0	1
Family size	3,0223	1,2843	1	10
Education				
No school	0,0116	0,1072	0	1
Primary school	0,1287	0,3349	0	1
Secondary school	0,3565	0,4790	0	1
High school	0,1686	0,3744	0	1
Higher education	0,3249	0,4684	0	1
Other/unknown education	0,0098	0,0983	0	1
Income				
HH Income / Comsumption Unit	1616,662	938,655	45,560	15033,330
	Quintile			
	1st	944,450		
	2nd	1293,810		
	3rd	1622,670		
	4th	2138,890		
	5th	15033,330		
Income Unknown	0,0541	0,2262	0	1

Table 5: Descriptive statistics of the regressors

Variable	Mean	Std. Dev.	Min.	Max.
Health Characteristics				
Self Assessed Health: Poor-Fair	0,2059	0,4044	0	1
Self Assessed Health: Good	0,5774	0,4940	0	1
Self Assessed Health: Excellent	0,2167	0,4120	0	1
Chronic Condition	0,2542	0,4355	0	1
Limitation with daily activities	0,1431	0,3502	0	1
Smoker	0,2682	0,4430	0	1
Former Smoker	0,2968	0,4569	0	1
Light Smoker	0,0730	0,2601	0	1
Heavy Smoker	0,0858	0,2801	0	1
Labor Market Status				
Inactive	0,0593	0,2363	0	1
Unemployed	0,0736	0,2611	0	1
Retired	0,1766	0,3814	0	1
Employed	0,6905	0,4623	0	1
Professional Occupation				
Private Employee	0,6945	0,4607	0	1
Private Employee - Blue Collar	0,2561	0,4365	0	1
Private Employee - White Collar	0,3182	0,4658	0	1
Privare Employee - Executive	0,1148	0,3188	0	1
Self Employed	0,1038	0,3050	0	1
Self Employed - Farmers	0,0313	0,1741	0	1
Self Employed - Artisans	0,0248	0,1555	0	1
Self Employed - Commerce & Industry	0,0197	0,1389	0	1
Self Employed - Profession	0,0175	0,1312	0	1
Self Employed - Other	0,0105	0,1021	0	1
Public Sector Employee	0,2017	0,4013	0	1
Public Sector - level 1	0,0218	0,1462	0	1
Public Sector - level 2	0,1284	0,3346	0	1
Public Sector - level 3	0,0499	0,2177	0	1
?????				
Exempted - any	0,1600	0,3667	0	1
Exempted due to Long Term Desease	0,1196	0,3245	0	1
Exempted due to other reasons	0,0564	0,2307	0	1
CMU Complementaire	0,0576	0,2331	0	1
Regime Generale	0,8768	0,3286	0	1
Observations	**6455**			

Table 6: MNL model for Complementary Health Insurance

VARIABLES	Employer Insured	Individually Purchased
Male	-0.229*	-0.252**
	[0.121]	[0.121]
Age	0.161***	0.028
	[0.042]	[0.041]
Age^2	-0.002***	-0.000
	[0.000]	[0.000]
Married	1.282***	0.844***
	[0.162]	[0.161]
Children	0.265	0.191

Table 6: MNL model for Complementary Health Insurance

VARIABLES	**Employer Insured**	**Individually Purchased**
	[0.191]	[0.192]
Familysize	-0.193***	-0.294***
	[0.069]	[0.071]
Secondary School	0.401*	0.495**
	[0.230]	[0.229]
High School	0.633**	0.591**
	[0.285]	[0.285]
Higher Education	0.427	0.325
	[0.284]	[0.283]
Other / Unknown Education	-0.701	-0.235
	[0.465]	[0.452]
Income per C.U. - 20th - 40th percentile	0.457**	0.446**
	[0.201]	[0.197]
Income per C.U. - 40th - 60th percentile	1.323***	0.864***
	[0.249]	[0.247]
Income per C.U. - 60th - 80th percentile	1.661***	1.125***
	[0.295]	[0.291]
Income per C.U.- 80th - 100th percentile	1.449***	0.642**
	[0.296]	[0.298]
Income Uknown	0.687***	0.545**
	[0.263]	[0.254]
Self Assessed Health Status - Good	0.141	0.198
	[0.164]	[0.165]
Self Assessed Health Status - Poor-Fair	-0.183	-0.005
	[0.230]	[0.228]
Chronic Condition	0.260	0.141
	[0.189]	[0.188]
Limited with Daily Activities	-0.152	-0.219
	[0.206]	[0.204]
Former Smoker	0.199	0.123
	[0.156]	[0.158]
Light Smoker	-0.189	-0.051
	[0.231]	[0.232]
Heavy Smoker	-0.541***	-0.577***
	[0.196]	[0.195]
Inactive	-0.963***	-0.503**
	[0.239]	[0.240]
Unemployed	-2.340***	-0.958***
	[0.197]	[0.180]
Retired	-0.141	0.337
	[0.344]	[0.343]
Private Employee	0.811*	0.004
	[0.461]	[0.433]
Private Employee - white collar	0.267	0.254
	[0.170]	[0.170]
Private Employee - executive	0.420	-0.114
	[0.282]	[0.287]
Public Sector Employee	1.033*	0.320
	[0.600]	[0.572]
Public Sector Employee - level 2	0.423	0.312
	[0.473]	[0.469]
Public Sector Employee - level 3	0.153	-0.267
	[0.588]	[0.597]

Table 6: MNL model for Complementary Health Insurance

VARIABLES	**Employer Insured**	**Individually Purchased**
Self Employed - artisans	-0.122	-0.290
	[0.495]	[0.469]
Self Employed - commerce & industry	0.282	-0.236
	[0.530]	[0.497]
Self Employed - profession	-0.373	-0.140
	[0.563]	[0.537]
Self Employed - other	-0.762	-0.558
	[0.647]	[0.618]
Exempted - long term desease	-0.039	-0.053
	[0.227]	[0.224]
Exempted - other	-0.790***	-0.760***
	[0.280]	[0.271]
CMU complementaire	-4.196***	-4.944***
	[0.388]	[0.470]
Regime Generale	0.358	0.014
	[0.267]	[0.262]
Constant	-4.108***	0.304
	[0.967]	[0.921]
Observations	6,455	6,455
Pseudologlik	-4.534.387	-4.534.387

Note: Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Negative Binomial 2 regressions for total numberof consultations (G.P. + specialists)

VARIABLES	**Exogenous**	**Raw Res. (NC s.e.)**	**Raw Res. (MT s.e.)**	**Std. Res. (NC s.e.)**	**Std.Res. (MT s.e.)**
Employer Insured	0.2097***	0.0206	0.0206	0.3522***	0.3522***
	[0.067]	[0.190]	[0.220]	[0.114]	[0.131]
Individually Purchased	0.2407***	-0.1305	-0.1305	0.1369*	0.1369
	[0.068]	[0.315]	[0.339]	[0.082]	[0.110]
Male	-0.5030***	-0.5012***	-0.5012***	-0.4894***	-0.4894***
	[0.027]	[0.027]	[0.033]	[0.026]	[0.027]
Age	-0.0383***	-0.0440***	-0.0440***	-0.0370***	-0.0370***
	[0.008]	[0.009]	[0.010]	[0.008]	[0.010]
Age ^2	0.0004***	0.0004***	0.0004***	0.0003***	0.0003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Married	0.1044**	0.0759	0.0759	0.0778	0.0778
	[0.050]	[0.056]	[0.083]	[0.050]	[0.056]
Children	-0.0402	-0.0509	-0.0509	-0.0442	-0.0442
	[0.047]	[0.047]	[0.082]	[0.047]	[0.050]
Family Size	-0.0205	-0.0186	-0.0186	-0.0109	-0.0109
	[0.019]	[0.020]	[0.026]	[0.020]	[0.023]
Secondary School	0.0499	0.0449	0.0449	0.0304	0.0304
	[0.040]	[0.041]	[0.043]	[0.042]	[0.046]
High School	0.0522	0.0411	0.0411	0.0257	0.0257
	[0.050]	[0.051]	[0.062]	[0.049]	[0.053]
Higher Education	0.1804***	0.1662***	0.1662***	0.1655***	0.1655***
	[0.046]	[0.046]	[0.049]	[0.047]	[0.052]
Other / Unknown Education	0.0924	0.1101	0.1101	0.0930	0.0930
	[0.116]	[0.117]	[0.116]	[0.116]	[0.120]
HH Inc./ CU: 2nd quintile	0.0388	0.0211	0.0211	0.0187	0.0187
	[0.049]	[0.052]	[0.053]	[0.049]	[0.061]
HH Inc./ CU: 3rd quintile	-0.0199	-0.0625	-0.0625	-0.0448	-0.0448
	[0.047]	[0.054]	[0.057]	[0.049]	[0.058]
HH Inc./ CU: 4th quintile	-0.0597	-0.1086*	-0.1086*	-0.0912*	-0.0912
	[0.048]	[0.056]	[0.060]	[0.051]	[0.061]
HH Inc./ CU: 5th quintile	0.0114	-0.0435	-0.0435	0.0090	0.0090
	[0.057]	[0.062]	[0.082]	[0.061]	[0.068]
HH Inc./ CU: unknown	-0.0747	-0.0973	-0.0973	-0.0952	-0.0952
	[0.062]	[0.065]	[0.066]	[0.062]	[0.065]
Self Assessed Health Status: Good	0.3170***	0.3166***	0.3166***	0.3098***	0.3098***
	[0.037]	[0.037]	[0.048]	[0.037]	[0.043]

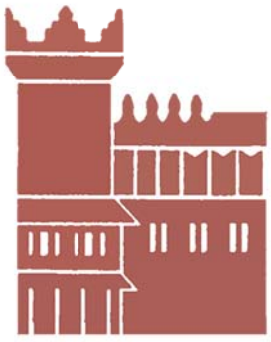
Table 7: Negative Binomial 2 regressions for total numberof consultations (G.P. + specialists)

VARIABLES	**Exogenous**	**Raw Res. (NC s.e.)**	**Raw Res. (MT s.e.)**	**Std. Res. (NC s.e.)**	**Std.Res. (MT s.e.)**
Self Assessed Health Status: Poor-Fair	0.6768***	0.6837***	0.6837***	0.6760***	0.6760***
	[0.058]	[0.059]	[0.096]	[0.058]	[0.060]
Chronic Condition	0.3261***	0.3234***	0.3234***	0.3208***	0.3208***
	[0.032]	[0.032]	[0.044]	[0.032]	[0.039]
Limitation with Daily Activities	0.3826***	0.3841***	0.3841***	0.3893***	0.3893***
	[0.041]	[0.042]	[0.047]	[0.042]	[0.045]
Former Smoker	0.1451***	0.1412***	0.1412***	0.1444***	0.1444***
	[0.028]	[0.028]	[0.037]	[0.028]	[0.030]
Light Smoker	0.0369	0.0419	0.0419	0.0369	0.0369
	[0.054]	[0.054]	[0.056]	[0.053]	[0.072]
Heavy Smoker	0.0183	0.0299	0.0299	0.0375	0.0375
	[0.061]	[0.061]	[0.063]	[0.062]	[0.086]
Exempted - long term desease	0.2496***	0.2506***	0.2506***	0.2497***	0.2497***
	[0.044]	[0.044]	[0.045]	[0.044]	[0.054]
Exempted - other	0.1582***	0.1778***	0.1778***	0.1967***	0.1967***
	[0.061]	[0.064]	[0.065]	[0.061]	[0.066]
CMU complementaire	0.2269***	0.4116	0.4116	0.4016***	0.4016***
	[0.088]	[0.271]	[0.293]	[0.113]	[0.128]
Regime Generale	0.1009**	0.0739	0.0739	0.1016**	0.1016**
	[0.041]	[0.046]	[0.046]	[0.043]	[0.050]
Ist Step "Raw" Res. - Outcome 1		0.1615	0.1615		
		[0.175]	[0.198]		
Ist Step "Raw" Res. - Outcome 2		0.3509	0.3509		
		[0.308]	[0.343]		
Ist Step "Standardized" Res. - Outcome 1				-0.0492	-0.0492
				[0.037]	[0.042]
Ist Step "Standardized" Res. - Outcome 2				0.0211**	0.0211
				[0.010]	[0.017]
Constant	1.7696***	2.0852***	2.0852***	1.7276***	1.7276***
	[0.181]	[0.276]	[0.290]	[0.218]	[0.256]
ln (alpha)	-0.7249***	-0.7259***	-0.7259***	-0.7284***	-0.7284***
	[0.041]	[0.041]	[0.089]	[0.041]	[0.040]
Observations	6,455	6,455	6,455	6,455	6,455
Exogeneity tests					
Wald test		2.806	1.891	5859**	2.019
Wald test - p value		0.246	0.388	0.053	0.364
LR test		4.097	4.097	14338***	14338***

Table 7: Negative Binomial 2 regressions for total numberof consultations (G.P. + specialists)

VARIABLES	**Exogenous**	**Raw Res. (NC s.e.)**	**Raw Res. (MT s.e.)**	**Std. Res. (NC s.e.)**	**Std.Res. (MT s.e.)**
LR test - p value		0.129	0.129	0.001	0.001
LM test		3.403	3.403	8620**	8620**
LM test- pvalue		0.182	0.182	0.013	0.013

Note: *** p<0.01, ** p<0.05, * p<0.1



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