

REndo: An R Package To Address Endogeneity

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1. Background

- The independence between the explanatory variables and the error term is a crucial assumption in regression models. The **endogeneity** problem arises when this condition is not satisfied.
- Most common forms of endogeneity:**
 - omitted variables
 - measurement error
 - simultaneity.
- Instrumental variables (IV) estimation is a common solution to the endogeneity problem. But, **good IV are rare**.
- Internal instrumental variable models (IIV)** are an **alternative** to the IV approach.
- IIV rely on the characteristics of the statistical distribution of the endogenous regressor. **No need for external instruments**.

2. Research question

- How to enable researchers and practitioners to do causal inference with observational data when instrumental variables are lacking?
- Research Objective**
Implement in **R** five of the newest internal instrumental variables methods.

3. Data and Methods

Consider the model

$$Y_t = \beta_0 + \beta_1 W_t + \alpha P_t + \epsilon_t$$

$$P_t = \pi' Z_t + v_t$$

- Y_t dependent variable
- W_t vector of exogenous variables
- P_t endogenous regressor
- Z_t vector of internal instruments $E(\epsilon_t) = 0$ $E(\epsilon_t^2) = \sigma_\epsilon^2$
- ϵ_t structural error, $E(v_t) = 0$, $E(v_t^2) = \sigma_v^2$, $E(\epsilon_t v_t) = \sigma_{\epsilon v}$
- v_t random error,

1. Latent Instrumental Variables

(Ebbes et al., 2005)

- Uses a latent variable model to account for regressor-error dependencies.
- The endogenous regressor is assumed to have two categories with distinct means.
- Allows only one endogenous regressor and no additional explanatory variables.

2. Joint estimation using copulas

(Park and Gupta, 2012)

- Unlike other IIV-methods (e.g. LIV), the copula method does not require the "exclusion restriction" assumption.
- No assumptions imposed on the relationship between Z_t and ϵ_t
- The correlation between the structural and the random error modelled using Gaussian copula.

3. Higher moments

(Lewbel, 1997)

- Build to address measurement error problem, but also other more general regressor-error dependency models.

- Internal instrumental variables can be constructed from the existing variables, using any function $G=G(W)$ with finite third own and cross moments, non-linear in W , as below:
 - $G_t - \bar{G}_t, (G_t - \bar{G}_t)(P_t - \bar{P}_t), G_t - \bar{G}_t, (Y_t - \bar{Y}_t)$
 - $(Y_t - \bar{Y}_t)(P_t - \bar{P}_t), (P_t - \bar{P}_t)^2, (Y_t - \bar{Y}_t)^2$

4. Heteroscedastic errors

(Lewbel, 2012)

- Uses the heteroscedasticity of the errors in a linear projection of the endogenous regressor on the other covariates to solve the endogeneity produced by measurement error.
- Instruments are constructed as simple functions of the model's data: $[Z_t - E(Z_t)]v_t$ where Z_t are a subset of W_t , assumed exogenous. Simple two-stage least squares is used as estimation method.

5. Multilevel GMM

(Kim and Frees, 2007)

- The internal instruments are built exploiting the hierarchical structure of the data.
- Uses the between and within variation of the exogenous variables but only the within variation of the endogenous ones.
- Includes the random and fixed effects estimators as special cases and provides additional estimators between these two extremes.

- The internal instruments constructed can be used in addition to any existing external instrument to increase efficiency.
- The performance of two of these methods, the higher moments and the heteroskedastic errors approaches, relative to the OLS is presented in Figure 1 below.

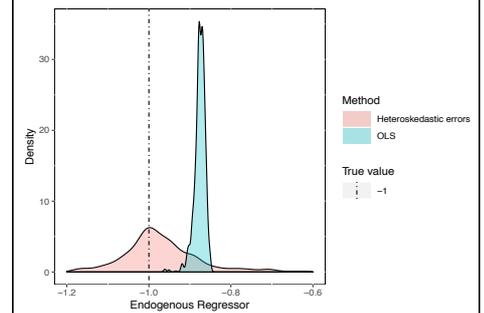
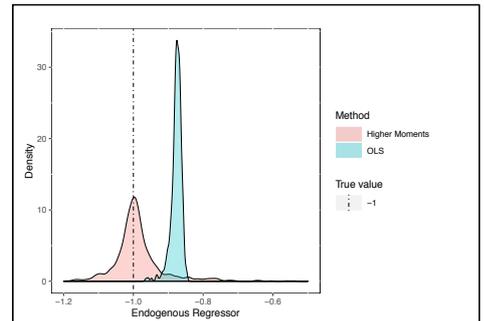


Fig.1: a) Comparison between the higher moments method and OLS, over 1000 simulations b) Comparison between the heteroskedastic errors method and OLS, over 1000 simulations

Method	Model	Assumptions
Latent IV Ebbes et al. (2005)	<ul style="list-style-type: none"> One endogenous variable; No additional regressors; ML estimation. 	<ul style="list-style-type: none"> $P_t \neq N(\cdot, \cdot)$ Z_t discrete, with at least 2 groups with different means. $\epsilon_t \sim N(0, \sigma_{\epsilon_t}^2)$
Copula correction Park and Gupta (2012)	<ul style="list-style-type: none"> Multiple endogenous variables; Additional regressors allowed; ML estimation. 	<ul style="list-style-type: none"> $P_t \neq N(\cdot, \cdot)$, not bi-modal, P_t continuous or discrete, but not Bernoulli, $\epsilon_t \sim N(0, \sigma_{\epsilon_t}^2)$ Z_t skewed, ϵ_t, v_t symmetrically distributed, Third moment of the data exists.
Higher moments Lewbel (1997)	<ul style="list-style-type: none"> One endogenous variable; Additional regressors allowed; Two-stage least squares estimation. 	<ul style="list-style-type: none"> Z_t skewed, ϵ_t, v_t symmetrically distributed, Third moment of the data exists.
Heteroscedastic errors Lewbel (2012)	<ul style="list-style-type: none"> Multiple endogenous variables; Additional regressors allowed; Two-stage least squares estimation. 	<ul style="list-style-type: none"> $cov(W_t, v_t^2) \neq 0$ $E(W_t W_t')$ - not singular $E(W_t \epsilon_t) = E(W_t v_t) = 0$
Multilevel GMM Kim and Frees (2007)	<ul style="list-style-type: none"> The model: $Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + e_{ij}$ $\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j}$ $\beta_{1j} = \gamma_{10}$ GMM estimation 	<ul style="list-style-type: none"> $cov(P_t, \epsilon_t v_t) = 0$ $e_{ij} \sim N(0, \sigma_{e_{ij}}^2)$ $u_{0j} \sim N(0, \sigma_{u_{0j}}^2)$ $cov(X_{ij}, e_{ij}, W_j, u_{0j}) = 0$

Table 1: Description of internal instrumental variables methods in REndo

4. Results

- REndo** offers estimation techniques that *do not require external instrumental variables*.
- Some of the IIV methods come with a set of strong assumptions especially regarding the distribution of the endogenous regressor.
- The IIV methods are in general less efficient than OLS or internal IV methods with good instruments.

5. Conclusion

- The existence of a good external instrumental variable is often questionable.
- Statistical models that **exploit the distribution or the hierarchical structure** of the data make it possible to create instruments from the existing data, with **no need of external instruments**. **REndo**, implements five of these models.

Future research:

- An internal instrumental variable method that addresses endogeneity with a **binary or categorical** dependent variable.
- Integration of **diagnostic tests** for the copula correction and the latent internal variable approaches.

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