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17 August 2022

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Abstract. This article introduces the `xtgranger` command in Stata, which implements the panel Granger non-causality test approach developed by Juodis et al. (2021). This test offers superior size and power performance to existing tests, which stems from the use of a pooled estimator that has a faster $\sqrt{NT}$ convergence rate. The test has several other useful properties; it can be used in multivariate systems, it has power against both homogeneous as well as heterogeneous alternatives, and it allows for cross-section dependence and cross-section heteroskedasticity.

Keywords: Panel data, Granger causality, Nickell bias, Heterogeneous panels, Half-panel Jackknife, Cross-section dependence, `xtgranger`.

1 Introduction

Predictive (Granger) causality and feedback is an important aspect of applied time series and panel (longitudinal) data analysis. Granger (1969) developed a statistical concept of causality between two or more time series variables, according to which, a variable x "Granger-causes" a variable y, if the variable y can be better predicted using past values of both x and y, than using solely past values y. The concept of "Granger-causality" has been widely adopted in economics, medicine, chemistry, physics, biology, engineering, and beyond.

Granger causality is useful also when the data consist of multiple time series, as in the case of panel data. Methods on testing for Granger causality using panel data models, are very well cited and widely available in standard econometric software. Prominent examples include the GMM approach of Holtz-Eakin et al. (1988), which is valid for homogeneous panels with a small number of time series observations (T), and the methods of Dumitrescu and Hurlin (2012) and Emirmahmutoglu and Kose (2011), suitable for heterogeneous, large-T panels. The GMM approach of Holtz-Eakin et al. (1988) has been implemented in Stata by Abrigo and Love (2016) with the command `pvargranger`, whereas the method of Dumitrescu and Hurlin (2012) is available in both EViews and Stata, see e.g. the Stata command `xtgcause` by Lopez and Weber (2017).

Recently, Juodis, Karavias, and Sarafidis (2021) developed a new method for testing the null hypothesis of no Granger causality, which is valid in models with homogeneous or heterogeneous coefficients. The novelty of their approach lies in the fact that under the null hypothesis, the Granger-causality parameters equal zero and thus they are homogeneous. This allows the use of a pooled fixed effects-type estimator for these parameters only, which guarantees a $\sqrt{NT}$ convergence rate, where N denotes the number of cross-sectional units in the panel and T denotes the number of time series observations in the panel.[1] To account for the so-called "Nickell bias" of the pooled estimator, their testing procedure makes use of the Half Panel Jackknife (HPJ) method of Dhaene and Jochmans (2015). The resulting approach works very well under circumstances that are empirically relevant: many cross-section units, a moderate time dimension, heterogeneous nuisance parameters, and high persistence.

The method of Juodis et al. (2021) has a number of advantages relative to existing approaches. In particular, the GMM approach of Holtz-Eakin et al. (1988) is not appealing when T is (even moderately) large. This is due to the well-known problem of using too many instruments, which often renders the usual GMM-based inference highly inaccurate, see e.g. Bun and Sarafidis (2015) and Remark 8 in Juodis and Sarafidis (2021). Moreover, when feedback based on past own values is heterogeneous (i.e. the autoregressive parameters vary across individuals), inferences may not be valid even asymptotically. On the other hand, while the method of Dumitrescu and Hurlin (2012) accommodates heterogeneous slopes under both null and alternative hypotheses, their test statistic is theoretically justified only for sequences where $N/T^2 \to 0$. This implies that when T is sufficiently smaller than N, i.e. $T << N$, this method can suffer from substantial size distortions. In an extended Monte Carlo experiment, Juodis et al. (2021) show that their method outperforms the method of Dumitrescu and Hurlin (2012), in terms of power.

The present paper introduces a new Stata command, `xtgranger`, which implements the Granger non-causality test of Juodis et al. (2021). The command reports the Wald test statistic and its p-value, the null and the alternative hypothesis, as well as regression results with respect to the HPJ bias-corrected pooled estimator. The command offers options for both manual and automatic lag-length selection, using a BIC criterion. The command further allows for cross-sectional dependence and cross-sectional heteroskedasticity in the errors. Finally, the command can test for Granger-causality in equations with multiple relevant variables.[2] The panel must be balanced.

Notably, by construction `xtgranger` is computationally faster than `xtgcause`, es-

1. The autoregressive parameters and intercepts (fixed effects) are still allowed to be heterogeneous.
2. The command does not consider Granger-causal relations that only exist more than one periods ahead, see e.g. Dufour and Renault (1998).

pecially so when N is relatively large. This is because the former is based on a single, pooled regression, whereas the latter runs N individual regressions and retrieves N individual-specific Wald test statistics, which are subsequently averaged over i.[3]

The `xtgranger` command is applied to a real dataset from the U.S. banking industry, where we perform Granger non-causality tests to examine the type of temporal relation between profitability, cost inefficiency and asset quality. Our results show that past values of inefficiency contain information that helps to predict profitability, while this is not the case for asset quality.

The remainder of the article is organized as follows. In Section 2, we briefly outline the Wald-test approach developed by Juodis et al. (2021). Section 3 describes the syntax of the `xtgranger` command. Section 4 illustrates the command using a real data set. Section 5 concludes.

2 A bias-corrected test for Granger non-causality

We consider the following linear dynamic panel data model:

$$y_{i,t} = \phi_{0,i} + \sum_{p=1}^{P} \phi_{p,i} y_{i,t-p} + \sum_{p=1}^{P} \beta_{p,i} x_{i,t-p} + \varepsilon_{i,t}, \tag{1}$$

for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. Without loss of generality and for ease of exposition, $x_{i,t}$ is assumed to be a scalar. The parameters $\phi_{0,i}$ denote the individual-specific effects, $\varepsilon_{i,t}$ are the errors, $\phi_{p,i}$ denote the heterogeneous autoregressive coefficients, $p = 1, \ldots, P$, and $\beta_{p,i}$ are the heterogeneous feedback coefficients, or Granger causality parameters.

The restriction that the number of lags of $y_{i,t}$ is the same as that of $x_{i,t}$ has the benefit of a minimal computational cost when it comes to lag length selection. Such restriction is also imposed by `xtgcause` and `pvargranger`.

The null hypothesis that $x_{i,t}$ does not Granger-cause $y_{i,t}$ can be formulated as a set of linear restrictions on the parameters in Eq. (1):

$$H_0: \quad \beta_{p,i} = 0, \quad \text{for all } i \text{ and } p. \tag{2}$$

The alternative hypothesis is:

$$H_1: \quad \beta_{p,i} \neq 0 \quad \text{for some } i \text{ and } p. \tag{3}$$

Failure to reject the null hypothesis can be interpreted as $x_{i,t}$ does not Granger-cause $y_{i,t}$.[4] The same applies when $x_{i,t}$ consists of multiple relevant variables and is a $k \times 1$ vector of regressors.

3. To provide some indication of the likely computational gains of our method, in the application of this paper ($N = 450$, $T = 56$) we note that when the maximum number of lags equals 5, `xtgranger` requires roughly one second to test the null hypothesis, whereas `xtgcause` takes about 33 seconds.
4. Obviously, non-trivial power of the test requires that there exist sufficiently many individuals with non-zero coefficients.

The main feature of the above setup, utilised in the Granger non-causality test proposed by Juodis et al. (2021), is that under the null hypothesis $\beta_{p,i} = 0$, for all i and p. In other words, the model is homogeneous in the feedback coefficients. This allows the use of a pooled estimator for $\{\beta_{p,i}\}_{i=1}^{N}$. Pooled estimators have a faster, $\sqrt{NT}$, rate of convergence, which means that they benefit from a larger value of both N and T. However, they are subject to the so-called "Nickel bias". Juodis et al. (2021) propose that this bias is corrected using the half-panel jackknife method of Dhaene and Jochmans (2015). Although bias corrections have been previously shown to reduce the power of tests (Karavias and Tzavalis 2016, 2017), Juodis et al. (2021) demonstrate that this test has very good power in empirically relevant scenarios.

The above arguments are demonstrated as follows. First, rewrite Eq. (1) as:

$$y_{i,t} = \mathbf{z}'_{i,t}\boldsymbol{\phi}_i + \mathbf{x}'_{i,t}\boldsymbol{\beta}_i + \varepsilon_{i,t}, \tag{4}$$

where $\mathbf{z}_{i,t} = (1, y_{i,t-1}, \ldots, y_{i,t-p})'$, $\mathbf{x}_{i,t} = (x_{i,t-1}, \ldots, x_{i,t-p})'$, $\boldsymbol{\phi}_i = (\phi_{0,i}, \ldots, \phi_{p,i})'$ and $\boldsymbol{\beta}_i = (\beta_{1,i}, \ldots, \beta_{p,i})'$. Stacking Eq. (4) over time yields:

$$\mathbf{y}_i = \mathbf{Z}_i\boldsymbol{\phi}_i + \mathbf{X}_i\boldsymbol{\beta}_i + \boldsymbol{\varepsilon}_i, \tag{5}$$

where $\mathbf{y}_i = (y_{i,1}, \ldots, y_{i,T})'$, $\mathbf{Z}_i = (\mathbf{z}_{i,1}, \ldots, \mathbf{z}_{i,T})'$, $\mathbf{X}_i = (\mathbf{x}_{i,1}, \ldots, \mathbf{x}_{i,T})'$ and $\boldsymbol{\varepsilon}_i = (\varepsilon_{i,1}, \ldots, \varepsilon_{i,T})'$. Under the null hypothesis, $\boldsymbol{\beta}_i = \boldsymbol{\beta} = \mathbf{0}$. The pooled least squares estimator of $\boldsymbol{\beta}$ is defined as follows:

$$\hat{\boldsymbol{\beta}} = \left. \sum_{i=1}^{N} \mathbf{X}'_i\mathbf{M}_{\mathbf{Z}_i}\mathbf{X}_i \right)^{-1} \left. \sum_{i=1}^{N} \mathbf{X}'_i\mathbf{M}_{\mathbf{Z}_i}\mathbf{y}_i \right). \tag{6}$$

where $\mathbf{M}_{\mathbf{Z}_i} = \mathbf{I}_T - \mathbf{Z}_i\left(\mathbf{Z}'_i\mathbf{Z}_i\right)^{-1}\mathbf{Z}'_i$. Fernández-Val and Lee (2013) show that under general conditions, and as $N, T \to \infty$ with $N/T \to \kappa^2 \in [0; \infty)$, we have

$$\sqrt{NT}\left(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}_0\right) \to \mathbf{J}^{-1}N\left(-\kappa\mathbf{B}, \mathbf{V}\right), \tag{7}$$

where $\mathbf{J} = plim_{N,T\to\infty}(NT)^{-1}\sum_{i=1}^{N}\mathbf{X}'_i\mathbf{M}_{\mathbf{Z}_i}\mathbf{X}_i$, $\mathbf{V}$ denotes the variance-covariance matrix and $\mathbf{B}$ is the bias arising from the fact that N and T are of the same order.

To remove the bias of the pooled estimator, we employ the half-panel jackknife estimator of Dhaene and Jochmans (2015), which is defined as follows:

$$\tilde{\boldsymbol{\beta}} = \hat{\boldsymbol{\beta}} + \left(\hat{\boldsymbol{\beta}} - \frac{1}{2}\left(\hat{\boldsymbol{\beta}}_{1/2} + \hat{\boldsymbol{\beta}}_{2/1}\right)\right) = \hat{\boldsymbol{\beta}} + T^{-1}\hat{\mathbf{B}}. \tag{8}$$

The bias-corrected estimator then forms the basis of a Wald test for Granger non-causality. In particular, under mild regularity assumptions reported in Juodis et al. (2021), as $N, T \to \infty$ with $N/T \to \kappa^2 \in [0, \infty)$, we have:

$$\hat{W}_{HPJ} = NT\tilde{\boldsymbol{\beta}}'\left(\hat{\mathbf{J}}^{-1}\hat{\mathbf{V}}\hat{\mathbf{J}}^{-1}\right)^{-1}\tilde{\boldsymbol{\beta}} \to \chi^2(P), \tag{9}$$

where $\hat{\mathbf{J}} = (NT)^{-1} \sum_{i=1}^{N} \mathbf{X}_i' \mathbf{M}_{\mathbf{Z}_i} \mathbf{X}_i$.

When the errors are assumed to be homoskedastic along both time and cross-sectional dimensions, then

$$\hat{\mathbf{V}} = \hat{\sigma}^2 \hat{\mathbf{J}}, \tag{10}$$

with the variance estimator given by

$$\hat{\sigma}^2 = \frac{1}{N(T-1-P)-P} \sum_{i=1}^{N} \left(\mathbf{y}_i - \mathbf{X}_i \hat{\boldsymbol{\beta}} \right)' \mathbf{M}_{\mathbf{Z}_i} \left(\mathbf{y}_i - \mathbf{X}_i \hat{\boldsymbol{\beta}} \right). \tag{11}$$

On the other hand, if the errors are cross-sectionally heteroskedastic,

$$\hat{\mathbf{V}} = \frac{1}{N(T-1-P)-P} \sum_{i=1}^{N} \mathbf{X}_i' \mathbf{M}_{\mathbf{Z}_i} \hat{\boldsymbol{\varepsilon}}_i \hat{\boldsymbol{\varepsilon}}_i' \mathbf{M}_{\mathbf{Z}_i} \mathbf{X}_i. \tag{12}$$

The model in (1) can allow for weak cross-section dependence as in Sarafidis and Wansbeek (2012) and Dumitrescu and Hurlin (2012). Under weak cross-sectional dependence, the HPJ estimator $\tilde{\boldsymbol{\beta}}$ remains consistent but $\hat{\mathbf{V}}$ in the above equations is not. In this case, an estimator for $\hat{\mathbf{V}}$ is obtained by using the pairs bootstrap as in Gonçalves and Kaffo (2015). Unreported Monte Carlo simulations show that this approach works well in finite samples.

3 The `xtgranger` command

3.1 Syntax

`xtgranger` *depvar* [*indepvars*] [*if*] [*in*] [, *options*]

Data must be `xtset` before using `xtgranger`. The panel must be balanced.

3.2 Options

`lags(#)` specifies the number of lags of of dependent and independent variables to be added to the regression. If `lags(#)` is not specified, the default is `lags(1)`.

`maxlags(#)` specifies the upper bound of lags. The BIC criterion is used to select the number of lags that provides the best model fit.

`het` allows for cross-sectional heteroskedasticity.

`nodfc` does not apply the degrees of freedom correction in Eq. (11) and Eq. (12). This option is mostly useful under cross-sectional heteroskedasticity.

`bootstrap` employs a bootstrap variance estimator in the HPJ Wald statistic with the current seed and 100 repetitions. This is useful in the presence of weak cross-sectional dependence.

`bootstrap(`*reps*`, seed(`*seed*`)` employs a bootstrap variance estimator in the HPJ Wald statistic with the custom set *seed* and *reps* repetitions.

`sum` presents results on the sum of the estimated feedback coefficients. This option can be useful when $P > 1$.

3.3 Stored results

Scalars

`e(N)`	number of units
`e(T)`	number of time periods
`e(p)`	number of lags
`e(BIC)`	BIC values
`e(W_HPJ)`	the Wald statistic
`e(pvalue)`	p-value for the HPJ Wald test

Matrices

`e(b_HPJ)`	the HPJ coefficient estimator
`e(Var_HPJ)`	the variance-covariance matrix of the HPJ estimator
`e(b_Sum_HPJ)`	sum of the HPJ estimates of the feedback coefficients
`e(Var_Sum_HPJ)`	the variance of the sum of the HPJ estimators

3.4 Postestimation commands

`predict` can be used after `xtgranger`. The syntax for predict is:

`predict newvar` [*if*] [*in*] [, *residuals xb*]

`residuals` calculates the residuals.

`xb` calculates the linear prediction on the partialled out variables.

4 Example

4.1 Estimation of the determinants of banks' capital adequacy ratios

To illustrate the `xtgranger` command, we perform Granger non-causality tests and examine the type of temporal relation between profitability, cost efficiency and asset quality in the U.S. banking industry. We draw a random sample of 450 U.S. bank holding companies (BHC), each one observed over 56 time periods, namely 2006:Q1-2019:Q4. The data are publicly available and they have been downloaded from the Federal Deposit Insurance Corporation (FDIC) website.[5]

5. See https://www.fdic.gov/.

We focus on the following model:

$$ROA_{i,t} = \phi_{0,i} + \sum_{p=1}^{P} \phi_{p,i} ROA_{i,t-p} + \sum_{p=1}^{P} \beta_{1,p,i} INEFFICIENCY_{i,t-p} + \sum_{p=1}^{P} \beta_{2,p,i} QUALITY_{i,t-p} + \varepsilon_{i,t}, \quad (13)$$

for $i = 1, \ldots, N(= 450)$ and $t = P + 1, \ldots, T(= 56)$.

$ROA_{i,t}$ stands for the "Return on Assets", and is used as a measure of profitability; in particular, it is defined as annualized net income expressed as a percentage of average total assets. $INEFFICIENCY_{i,t-p}$ presents a measure of cost inefficiency, which has been constructed from a stochastic cost frontier model using a translog function form.[6] Finally, $QUALITY_{i,t-p}$ represents the quality of banks' assets and is computed as the total amount of loan loss provisions expressed as a percentage of assets. Thus, a higher level of loan loss provisions indicates lower quality.

We start by testing if the pair of $INEFFICIENCY$ and $QUALITY$ Granger-causes ROA. Subsequently, we consider univariate tests, by modelling ROA as a function of $INEFFICIENCY$ and $QUALITY$ separately. Throughout, we allow for a maximum of 4 lags of the dependent variable and the covariates. The following results are obtained:

```
. xtset cert time
. xtgranger roa inefficiency quality, maxlags(4) het
Juodis, Karavias and Sarafidis (2021) Granger non-causality Test
-------------------------------------------------------------------------------
Number of units= 450                          Obs. per unit (T) = 55
Number of lags = 1                            BIC               = -34257.34
-------------------------------------------------------------------------------
JKS non-causality test
H0: Selected covariates do not Granger-cause roa.
H1: H0 is violated.
HPJ Wald test  : 30.2387
p-value        : 0.0000
-------------------------------------------------------------------------------
BIC selection:
    lags = 1, BIC = -34257.336*
    lags = 2, BIC = -33371.195
    lags = 3, BIC = -32727.595
    lags = 4, BIC = -32715.923
-------------------------------------------------------------------------------
               Results for the Half-Panel Jackknife estimator
       Cross-sectional heteroskedasticity-robust variance estimation
-------------------------------------------------------------------------------
             | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+-----------------------------------------------------------------
inefficiency |
         L1. |   .2562039   .0572807     4.47   0.000     .1439358     .368472
```

6. See Section 5 in Juodis et al. (2021) for more details.

```
     quality |
         L1. |  -.0162294   .0444754    -0.36   0.715    -.1033996    .0709409
------------------------------------------------------------------------------
```

As we can see, the null hypothesis that cost inefficiency and asset quality do not Granger-cause profitability is rejected at the 5% level of significance. The optimal number of lags equals 1 according to the BIC criterion.[7] The option `het` requests computing cross-sectional heteroskedasticity-robust standard errors.

In addition to the Wald test statistic, the command also reports regression results with respect to the HPJ bias-corrected pooled estimator. The regression output above indicates that the test outcome may be driven by $INEFFICIENCY$. To shed some light on this issue, we test for Granger non-causality for each variable separately using univariate tests. We obtain the following output:

```
. xtgranger roa inefficiency, maxlags(4) het
Juodis, Karavias and Sarafidis (2021) Granger non-causality Test
------------------------------------------------------------------------------
Number of units= 450                         Obs. per unit (T) = 55
Number of lags = 1                           BIC               = -33295.8
------------------------------------------------------------------------------
JKS non-causality test
H0: inefficiency does not Granger-cause roa.
H1: inefficiency does Granger-cause roa for at least one panelvar.
HPJ Wald test  : 24.3174
p-value        : 0.0000
------------------------------------------------------------------------------
BIC selection:
    lags = 1, BIC = -33295.799*
    lags = 2, BIC = -32170.227
    lags = 3, BIC = -31112.604
    lags = 4, BIC = -30724.676
------------------------------------------------------------------------------
               Results for the Half-Panel Jackknife estimator
       Cross-sectional heteroskedasticity-robust variance estimation
------------------------------------------------------------------------------
             | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
inefficiency |
         L1. |   .2549723   .0517052     4.93   0.000     .1536319    .3563127
------------------------------------------------------------------------------

. xtgranger roa quality, maxlags(4) het
Juodis, Karavias and Sarafidis (2021) Granger non-causality Test
------------------------------------------------------------------------------
Number of units= 450                         Obs. per unit (T) = 55
Number of lags = 1                           BIC               = -33816.06
```

7. Assuming that the maximum number of lags is 4, we tested the residuals for remaining serial correlation of order up to 3 using the community contributed Stata command `xtqptest` by Wursten (2018). We did not find evidence of residual serial correlation (p-value=0.089). The commands for getting these results are:
`predict epsilonres, residuals` and `xtqptest epsilonres, lags(3) force`.

```
-------------------------------------------------------------------------------
JKS non-causality test
H0: quality does not Granger-cause roa.
H1: quality does Granger-cause roa for at least one panelvar.
HPJ Wald test  : 0.2090
p-value        : 0.6476
-------------------------------------------------------------------------------
BIC selection:
    lags = 1, BIC = -33816.061*
    lags = 2, BIC = -32649.24
    lags = 3, BIC = -31479.433
    lags = 4, BIC = -30607.217
-------------------------------------------------------------------------------
              Results for the Half-Panel Jackknife estimator
      Cross-sectional heteroskedasticity-robust variance estimation
```

	Coefficient	Std. err.	z	P>|z|	[95% conf. interval]	
quality						
L1.	-.0201426	.0440637	-0.46	0.648	-.1065059	.0662207

The output on the top (bottom) corresponds to the Granger non-causality univariate test of the relationship between profitability and cost inefficiency (asset quality). The null hypothesis that $INEFFICIENCY$ does not Granger-cause ROA is rejected at the 5% level of significance. This implies that past values of $INEFFICIENCY$ contain information that helps to predict ROA over and above the information contained in past values of ROA. On the other hand, one fails to reject the null hypothesis that $QUALITY$ does not Granger-cause ROA.

In order to illustrate further options of the `xtgranger` command, we split the sample into two groups according to their asset size, where the partitioning is determined based on the kmeans clustering algorithm available in Stata. Subsequently, we test for Granger non-causality for the smallest banks in the sample, using data from 2011:Q1 onwards, which corresponds to Quarter 1 of the first year following the enactment of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010.[8] We obtain the following results:

```
. xtgranger roa inefficiency quality, maxlags(4) het sum, if cluster==2 & time>20
Juodis, Karavias and Sarafidis (2021) Granger non-causality Test
-------------------------------------------------------------------------------
Number of units= 183                         Obs. per unit (T) = 34
Number of lags = 2                           BIC               = -10307.93
-------------------------------------------------------------------------------
JKS non-causality test
H0: Selected covariates do not Granger-cause roa.
```

8. The Dodd-Frank Act (DFA) is a US federal law enacted during 2010, aiming “to promote the financial stability of the United States by improving accountability and transparency in the financial system, to end “too big to fail”, to protect the American taxpayer by ending bailouts, to protect consumers from abusive financial services practices, and for other purposes”; see https://www.cftc.gov/LawRegulation/DoddFrankAct/index.htm. In a nutshell, the DFA has instituted a new failure-resolution regime, which seeks to ensure that losses resulting from bad decisions by managers are absorbed by equity and debt holders, thus potentially reducing moral hazard.

```
H1: H0 is violated.

HPJ Wald test  : 36.3572
p-value        : 0.0000
-----------------------------------------------------------------------------
BIC selection:
    lags = 1, BIC = -10249.44
    lags = 2, BIC = -10307.934*
    lags = 3, BIC = -9788.8299
    lags = 4, BIC = -9963.9685
-----------------------------------------------------------------------------
       Sum of Half-Panel Jackknife coefficients across lags (lags>1)
       Cross-sectional heteroskedasticity-robust variance estimation
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
inefficiency	.4906756	.2405474	2.04	0.041	.0192113	.9621398
quality	-.1765458	.1235961	-1.43	0.153	-.4187897	.0656981

As before, the null hypothesis that $INEFFICIENCY$ and $QUALITY$ do not Granger-cause ROA is rejected at the 5% level of significance. Note that the optimal number of lags equals 2. The option `sum` requests reporting the sum of the lags of the regression coefficients, for each variable.

5 Concluding Remarks

`xtgranger` implements the Granger non-causality test of Juodis, Karavias, and Sarafidis (2021). The command reports the Wald test statistic and its p-value, the null and the alternative hypotheses, as well as regression results with respect to the HPJ bias-corrected pooled estimator. The command offers options for both manual and automatic lag-length selection, using a BIC criterion. Moreover, the command allows for cross-section dependence and cross-section heteroskedasticity in the errors.

6 Acknowledgement

Financial support from the Netherlands Organization for Scientific Research (NWO) under research grant number $451 - 17 - 002$ is gratefully acknowledged by Artūras Juodis. Jan Ditzen acknowledges financial support from the Italian Ministry MIUR under the PRIN project Hi-Di NET - Econometric Analysis of High Dimensional Models with Network Structures in Macroeconomics and Finance (grant 2017TA7TYC).

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