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# Graphical modelling of multivariate panel data models

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**Abstract**

In this paper, we propose a new approach to both test Granger Causality in a multivariate panel data environment and determine one ultimate "causality path" excluding those relationships which are redundant. For the sake of concreteness, we combine recent developments introduced to estimate Granger causality procedure based on Meta-analysis in heterogeneous mixed panels (Emirmahmutoglu and Kose, 2011 and Dumitrescu and Hurlin, 2012) and graphical models proposed in a growing literature (Spirtes et al, 2000, Demiralp and Hoover, 2003, Eicher, 2007 and 2012) searching iteratively for the existing dependencies between a multivariate set of information. Finally, we illustrate our proposal by revisiting existing studies in the context of panel Vector Autoregressive (VAR) models to the analysis of the fiscal policy-growth nexus

**Keywords**: Granger causality, panel data, causal maps
Clasificación JEL: C33 · C51

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## 1. Motivation

Starting from Granger (1969), the notion of granger causality has been widely applied in the field of econometrics in a very transversal way. The simplicity, adaptability, and transversality of this concept, based on the idea that the cause (a variable X) contains -early- information about the effect (variable Y) that is unique, and is in no other variable (Granger, 2003), may be one of the most determinant reasons justifying such an extraordinary compilation of academic citations.

Although a very high share of total applications is limited to the analysis of potential relationships between a pair of variables, the growing literature has also expanded the concept to more complex frameworks in which multivariate or non-linear models are commonly used.

Particularly, the context of Vector Autoregressive (VAR) models is very suitable for this approach as it intuitively classifies the different indicators included in the analysis as endogenous and exogenous. The former may react to changes in other endogenous variables whereas the latter evolve with no interactions with other variables. Moreover, to be precise when we identify the cause, it allows to test the true existence of a causal relationship by conditioning on (some of) the remaining endogenous variables which may play a role in defining the total impact of "cause" on "effect". For instance, if a third variable is a common cause for both.

On the other hand, graph theoretic method and theory of causal discovering is becoming more popular in the econometric literature. These methods make use of discovery algorithms[1] to find independence patterns on the data. One of its main virtues is that they eliminate the need to impose strict a priori assumptions as a prior ordering of variables (Spirtes et al,, 2000). Although they were originally thought for non-temporal data, studies adapting these techniques to data with a temporal structure have recently been developed. Demiralp and Hoover (2003) show that the PC algorithm can be an effective tool in selecting the contemporaneous causal orders of SVARs. For its part, Eichler (2007, 2012) and Runge (2018) provide a framework that allow the use of path diagrams for inferring the dynamic causal relationship among different variables.

Testing for Granger Causality in the panel data econometric literature has been also addressed more frequently as the availability of this kind of data is being improving in the recent years. The usual and basic method when the variables are stationaries consists in analysing the significance of the block of lags, normally using a Wald test. In this way, the null hypothesis is formulated as zero restrictions in those coefficients. However, on account of different heterogeneity sources, alternative methods have been developed. There is a first group of papers where the parameters of the equations are constant across individuals, meaning that either causality occurs everywhere, or it occurs nowhere in the panel, and those where they can vary (see Holtz-Eakin et al., 1988, Hurlin and Venet, 2001, and Hurlin, 2004). The main drawback is to expect the same causal relationships to occur between all the individuals. As Nair-Reichert and Weinhold (2001) suggest, it is possible that in a heterogenous panel, treated as a homogeneous, the underlying causal relationships between individuals may be missing (see also Hansen and Rand, 2006). They consider a variation of the Mixed Fixed and Random (MFR) model.

The aim of this paper is to propose a new approach for testing Granger Causality in panel data in the context of Vector Autoregressive (VAR) models. Therefore, our proposal allows to extend the number of relevant variables (generally limited to two). Importantly, we propose an alternative procedure based on averaging individual Wald tests statistic of cross-sectional units using the Fisher's transformation framework. By doing so, we follow Dumitrescu and Hurlin (2012) and Emirmahmutoglu and Kose (2011), who test causal relationships in panel data by transforming individual tests into a composite measure[2].

In addition, as a novelty, we apply graph-theoretic methods for causal analysis used in panel data models. We use the PC algorithm in its stable version to select the optimal causal ordering between all possible ones. Thus, another contribution of our work is to link two literatures evolving independently so far.

1 These algorithms can learn causal structures from purely o mostly observational data. For a practical guide see Malinsky and Danks (2018).

2 Averaging individual tests in order to get a statistic for the whole sample has become a common practice in Units Roots framework. See Im et al., (2003).

The plan of the paper is organized as follows. Section 2 sets out our methodology. Section 3 presents an empirical application and, finally, Section 4 provides some concluding remarks.

## 2. Methodological issues[3]

In this section we present the methodology we propose to identify the *true* causation path between the endogenous variables included in a panel VAR model.

We first consider panel VAR ($\tau_i$) model with *p* variables:

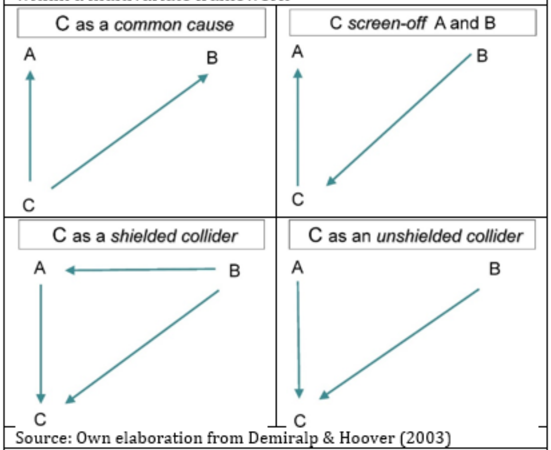
$$y_{i,t} = \mu_i + \sum_{\tau=1}^{\tau_i} \Phi_{i(\tau)} y_{i,t-\tau} + u_{i,t} \qquad i=1,\dots,N;\ t=1,\dots,T$$

The index *i* denotes each cross-sectional unit and *t* denotes the time periods. $\mu_i$ is a ($p\times1$) fixed effects vector and $\Phi_{i,1},\dots,\Phi_{i,\tau i}$ are ($p\times p$) matrices of parameters. $u_{i,t}$ is ($p\times1$) of error terms, which are independently and identically distributed[4]. Finally, $\tau_i$ is the order of the autoregressive process.

Recent developments on panel data econometrics (Emirmahmutoglu and Kose, 2011 and Hurlin, 2012) has focussed on developing causality tests in a multivariate framework (by conditioning on a third relevant variable). Moreover, it is highly worthy to link these recent developments to those developed in graph theoretic method and theory of causal discovering (see Spirtes *et al*, 2000, for a complete description). In this regard, considering both pieces together of literature help to highlight the relevance of determining the existing links between the different variables in a multivariate framework (see Demiralp & Hoover, 2003, for an extended explanation).

For the clarify of presentation, we consider a vector Y=[A, B, C], where C may be either a third variable of the final result of a more complex network of indirect links between the remaining list of variables included in Y. In the Figure 1 we illustrate the underlying dependencies which may coexist between them. Firstly, looking to the top-left panel it could be the case that C is a common cause shaping the relationship between A and B. Under these circumstances, to omit or include this in-

Figure 1: Theoretical illustration of conditional dependency within a multivariate framework




Source: Own elaboration from Demiralp & Hoover (2003)

Note: C may be just one variable or a more complex structure of indirect links between a set of third variables.

formation in our estimation procedure, will determine the final output and, consequently, the conclusions we may derive from them. Secondly, in the top-right panel, we include an alternative scenario in which the *third* variable(s) also play an important role. Indeed, A and B could be dependant even if there is not a direct link among them, always we identify a variable (C) connecting them throughout an indirect link. Thirdly, in the bottom panels we present two different scenarios in which variable C is a collider, in the sense that arrowhead come together at this point, no matter whether A and B are directly connected (bottom-left) or not (bottom-right), when we condition on C.

Next, we present the stages of our proposal. First, we obtain an aggregate measure that indicates both the intensity and the direction of the movement between the variables included in the analysis. To do so, we follow David (1949), who proposes the following procedure to obtain an overall measure of dominant correlation. First, the author proposes to use Fisher's transformation to normalise the distribution and stabilise the variance of the correlation coefficients in order to make them suitable for combination. Once the coefficients have been normalised, they are averaged to, latter, undo the transformation to obtain the aggregated correlation coefficient that summarises the information contained in the combined correlation coefficients. Formally, the procedure described above is as follows:

Step 1: Let $r_1,\dots,r_N$ be all the correlation coefficients we want to combine. To combine all the correlation coefficients into a common metric (R)[5] we need first the Fisher trans-

3 We have developed a model-independent implementation in Matlab of our methodology. We will make it available upon request by email.

4 $E(u_{i,t}) = 0$; $V(u_{i,t}) = \Sigma u_{i,t}$

5 Proxy to population Correlation

formation of each r_i, which is defined by:

$$z_i = \ln\frac{(1+r_i)}{(1-r_i)}$$

Each $z_i$ is approximately normally distributed with variance $1/T_i$ where $T_i$ is the sample size used to calculate $r_i$.

Step 2: Using these transformations, the summary coefficient ($Z$) of the correlations may be calculated as the sample mean

$$Z = \sum \frac{z_i}{N}$$

This expression is then approximately normally distributed with variance

$$\frac{1}{\sum_{i=1}^{N} T_i}$$

Step 3: Once we have calculated $Z$, we can undo the transformation to summarize the dominant correlation coefficient.

$$R = \frac{e^{2Z}-1}{e^{2Z}+1}$$

With the above statistics we can compute a measure for the whole sample of individual, but we can also calculate it for a subgroup, which can be used as a robustness check and makes easier to find group patterns.

For the next step in our proposal, we carry on the standard causality test, Wald test, which, as commented, consists in testing the significance of the matrix of linear parameters $A_{i,s}$. In the case of Granger non-causality, the null hypothesis for the *i-th* individual is defined as:

$$H_0 : \Phi_{i,\tau} = 0 \text{ for all } i$$

Following, among others, Hurlin (2001) and Emirmahmutoglu and Kose (2011) and with the aim of getting the common measure for the whole panel (jointly with any meaningful subset of units), we carry out Fisher's transformation. Fisher (1932) proposes the following transformation of the individual p-values ($p_i$).

$$\lambda = -2\sum \ln p_i$$

where $p_i$ is the p-value corresponding to the *i-th* individual cross-section. This test has a chi-square distribution with *2N* degrees of freedom. serves to determine the existence of a common causality pattern for the included units.

Once the test is computed for all the units, the process of depuration and obtention of the causal graph is carried out. In this context, we propose to use the PC algorithm in its stable version (Colombo and Maathuis, 2014)[6] to carry out the causality analysis. This is an iterative algorithm based on qualitative information about whether a particular local conditional independence constraint holds as all available information is sequentially included. The algorithm's steps are the following (Demiralp and Hoover, 2003):

1. Start with a graph ***G*** in which each variable is connected by an edge to every other variable (*a complete undirected graph*).

2. Set $n = 0$. Test for nth-order conditional causality between every pair of variables conditioning on every subset of variables size n. (For $n = 0$, the conditioning set is the null set, so that conditional relation is equivalent to unconditional relation.) If a pair of variables is conditionally unrelated, we eliminate the edge between them.

3. Set $n = n + 1$ and repeat successively step 2 until all possible conditionings set have been exhausted. Call the resulting graph **F.**

4. Consider each pair of variables (*X* and *Y*) in **F** that are unconnected by a direct edge but are connected through an undirected path through a third variable (*Z*). Orient *X—Z—Y* as *X* **->***Z* **<-** *Y* if, and only if, *X* and *Y* are dependent when conditioned on every subset of variables, excluding *X* and *Y,* that includes *Z*. Call the resulting graph **F'.**

5. Repeat until no more edges in **F'** can be oriented: if *X* **->** *Z* and *Z* –*Y* and *X* and *Y* are not directly connected, then orient *Z* – *Y* as *Z***->***Y*

6 The main difference between the original version and the sable one is that the stable version of the algorithm maintains the adjacent sets of nodes unchanged at each particular level. Thus, the output is independent with the order of the variables.

To keep things simple, at the final stage of the process, whenever it does exist a robust causal relationship between a pair of variables, there is an edge between them. This edge does not only show the existence of the relationship but also the sense of the link (the variable leading) and the intensity of the relationship (measured in our case as the dominant crossed correlation function).

Note that the above procedure is also valid for any kind of relationship, although in this paper we have focused on causality.

## 3 An empirical illustration.

In this section we illustrate the use of our proposal. In this regard, we revisit the analysis done in Blanchard and Perotti (2002) and Perotti (2012), on the fiscal policy growth relationship, as it includes some interesting features which may help to value the goodness of our methodology

First, there is not a consensus about the direction of this relationship. On the one hand, fiscal policy has an impact on the economic growth, as it directly affects some of its components. On the other hand, the performance of an economy may force policymakers to react and adopt fiscal measures in order to bring the economy back to a growth path. In this sense, we do not use an identification strategy which impose the relationship between variables but rather adopt a data driven approach.

Second, there is a variety of channels which may alter and influence the fiscal policy-growth nexus. It is commonly believed that changes in taxations are more likely to lead to a reduction in economic growth while an increase in spending can have ambiguous effects. However, the evidence finds that this is not always true.

Third, considering a representative sample of countries may contribute to extract a common pattern shaping this relationship.

However, the reader must take into account that an exhaustive discussion of the results goes beyond the central aims of the paper.

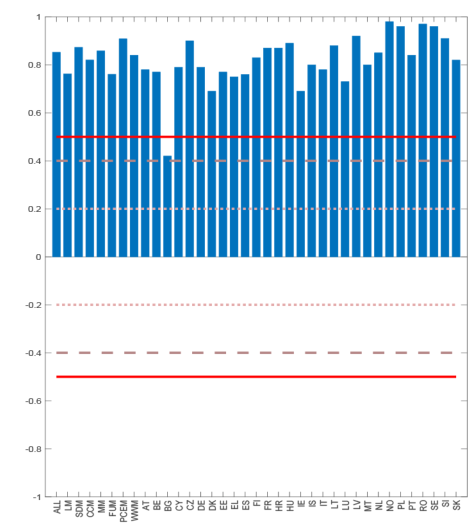
For the sake of concreteness, we consider four indicators: (i) *GDP*, Real *GDP*; (ii) *REV*, General Government Revenues; (iii) *EXP,* General Government Next Expenditures and (iv) *INF*, inflation, over the period 1997-2020 for a selection of advanced economies (mostly belonging to European Union). In concrete, 26 EU member states are included, as well as Iceland, Norway and the United Kingdom. All data are obtained from Eurostat.

In addition, we classify the different economies based on relatively common characteristics of their public systems into the following groups: liberal model (LM- United Kingdom, Ireland and Iceland); conservative-corporatist model (CCM - Austria, Belgium, Germany, France, Switzerland, Luxembourg and Netherlands) social democratic model (SDM- Finland, Sweden, Norway and Denmark); Mediterranean model (MM- Spain, Italy, Greece, Portugal, Malta and Cyprus); post-communist European model (PCEM - Bulgaria, Czech Republic, Hungary, Poland, Slovakia and Slovenia); former USSR model (FUM - Estonia, Latvia and Lithuania ) and finally, weak welfare state model (WWM-Romania).

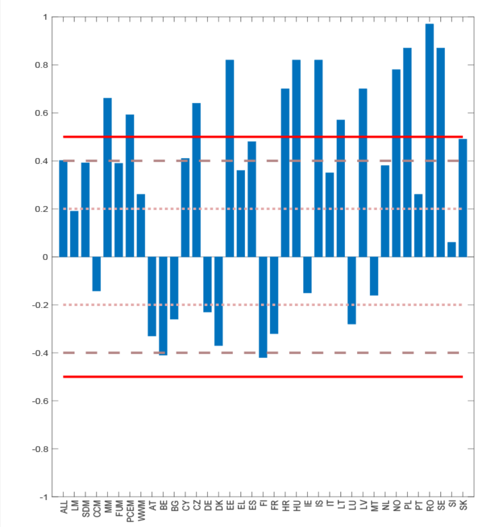
Table 1 provides a detailed overview of the co-movement (CCF) between the different pairs of variables for the aggregate of the whole panel, the different groups and each of the countries included in our sample for the period 1997-2020. According to the literature, the two variables are said to move in the same direction if the maximum value in absolute terms of the estimated correlation coefficient is positive, that they co-move in opposite directions if it is negative, and that they do not co-move if it is close to zero. Thus, we take maximum values of the combined correlations in the ranges 0.20–0.39 and 0.40–0.49 as evidence of weak and moderate correlation respectively. We refer to strong correlation if in absolute terms it is larger or equal to 0.50 and to no correlation if it is lower than 0.19.

**Table 1: CCF - All Links - LEVEL 1**

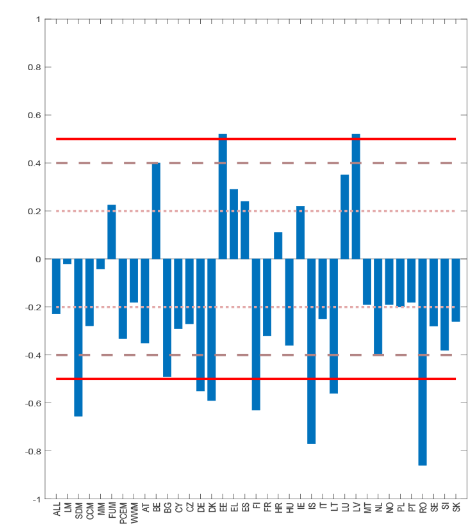
ENDO VARS (GDP-REV): GDP→REV



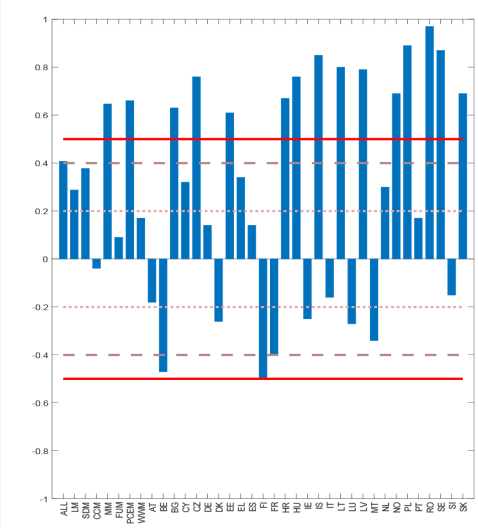

ENDO VARS (GDP-EXP): GDP→EXP



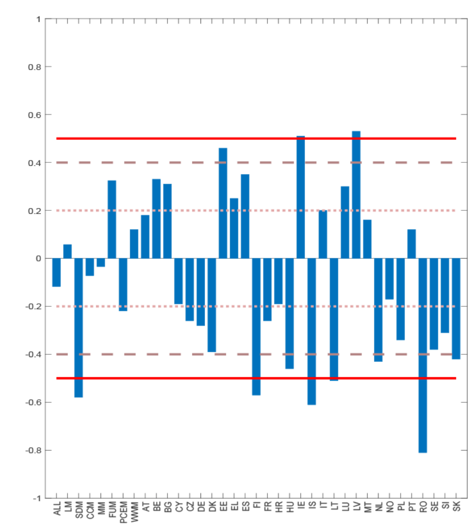

ENDO VARS (GDP-INF): GDP→INF



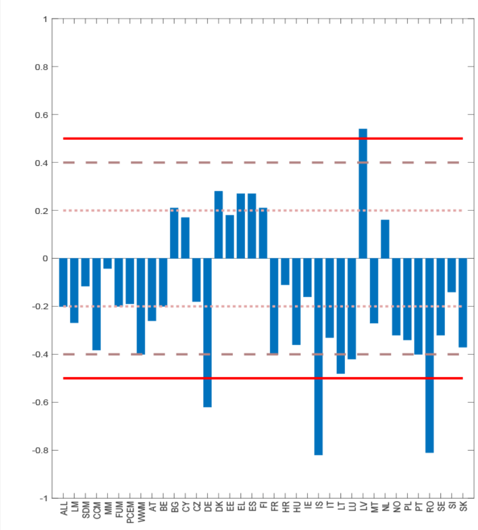

ENDO VARS (REV-EXP): REV→EXP




ENDO VARS (REV-INF): REV→INF

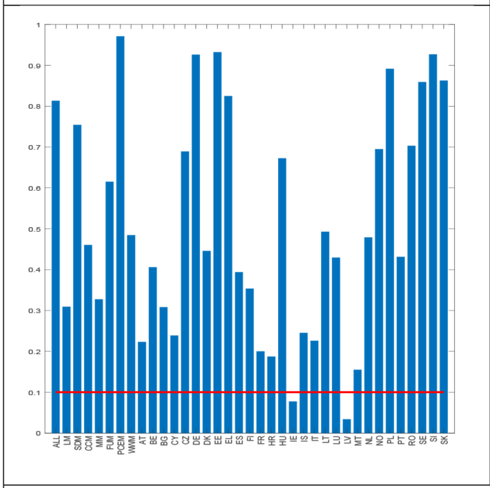
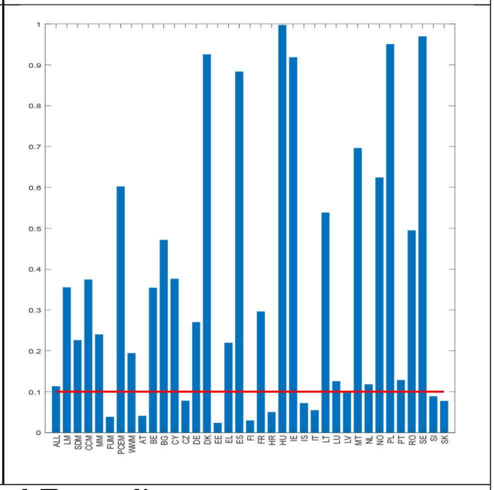
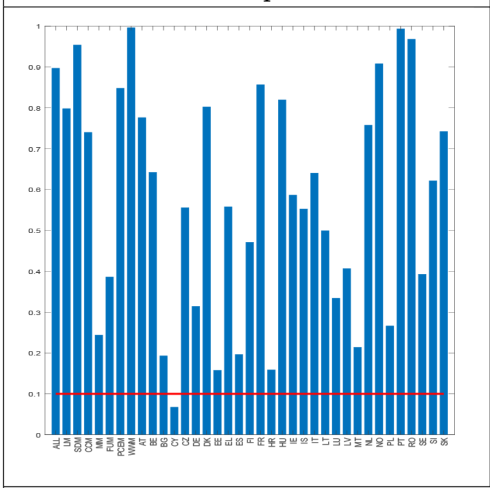
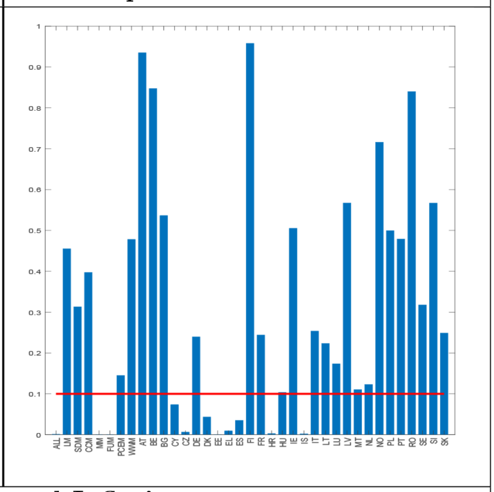
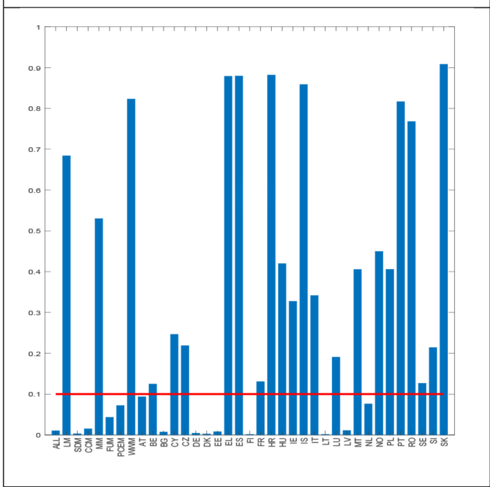
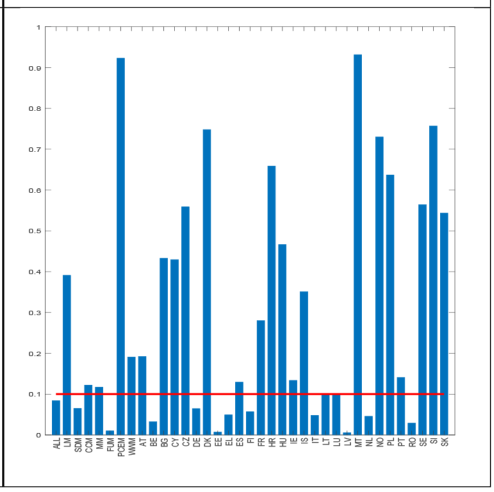


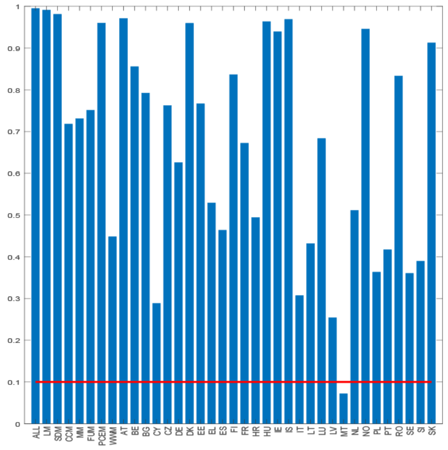
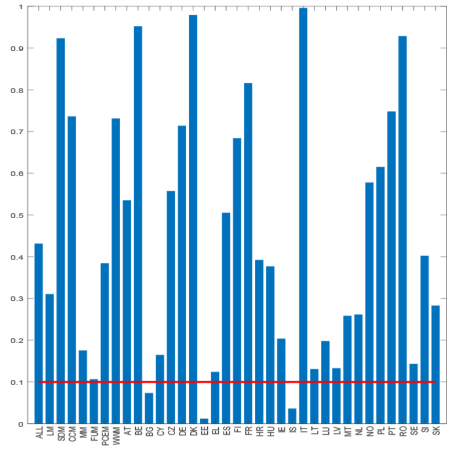
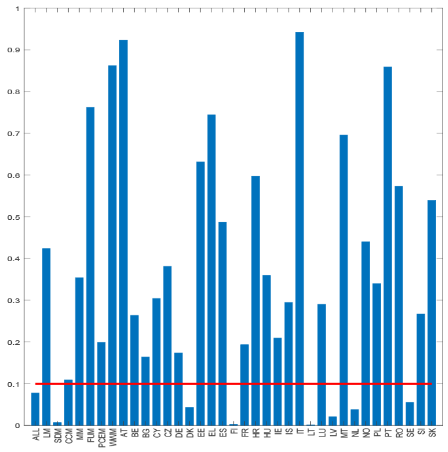
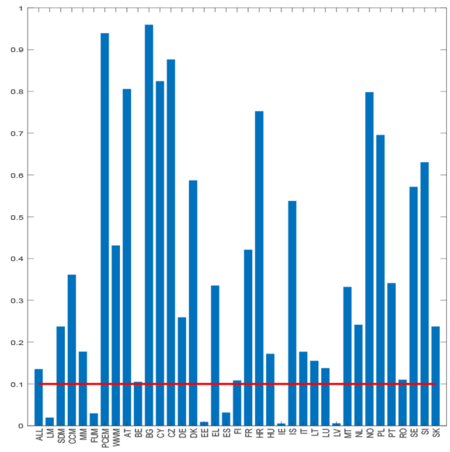
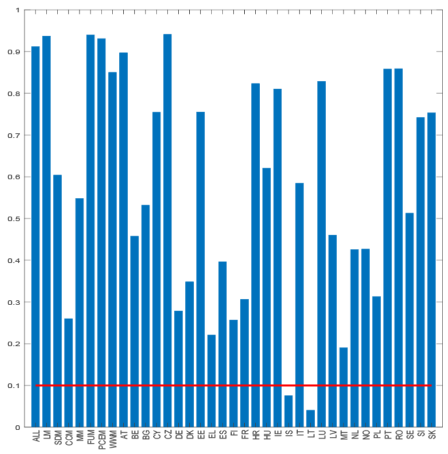
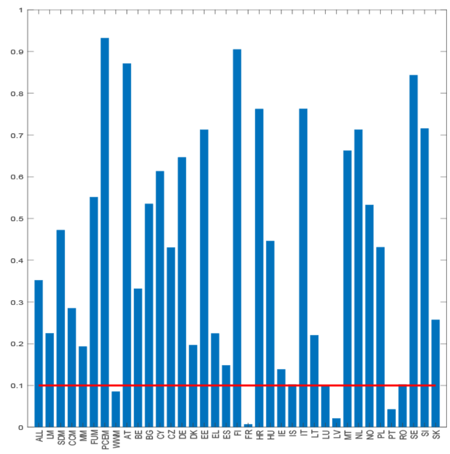

ENDO VARS (EXP-INF): EXP→ING

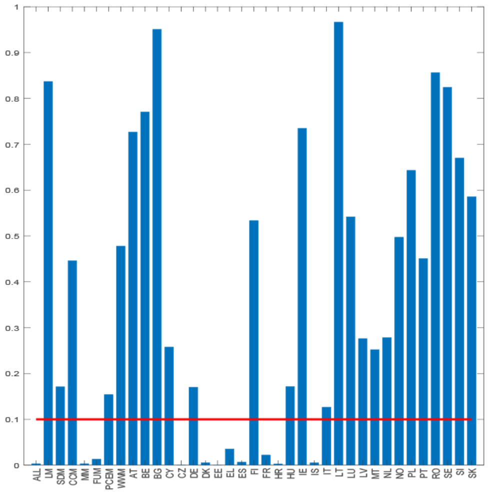
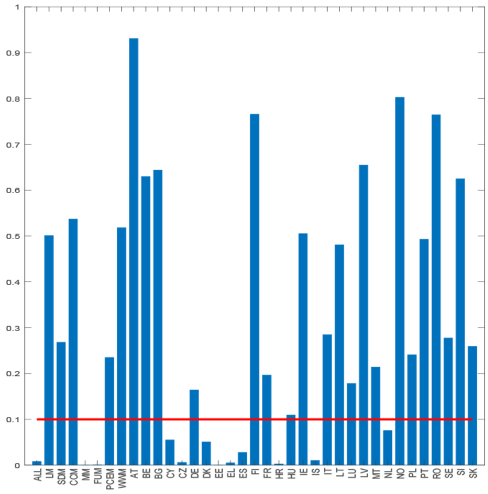
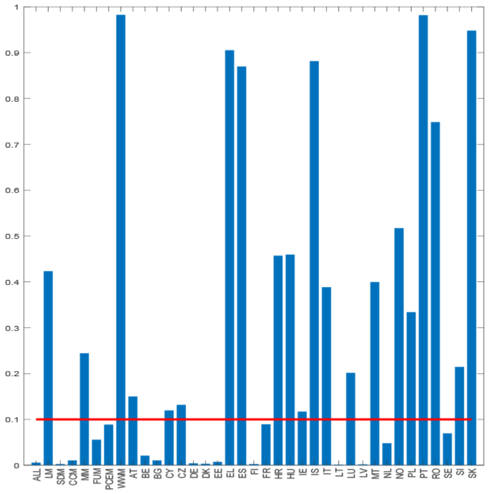
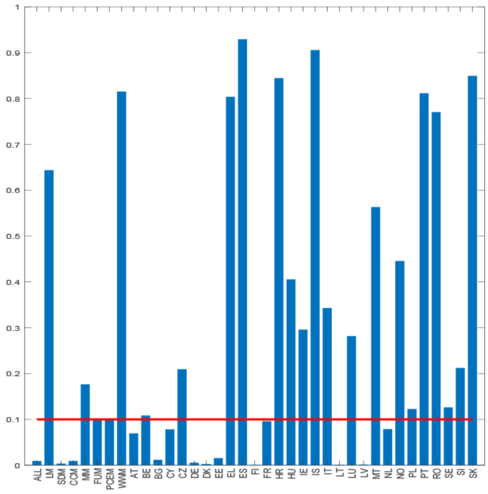
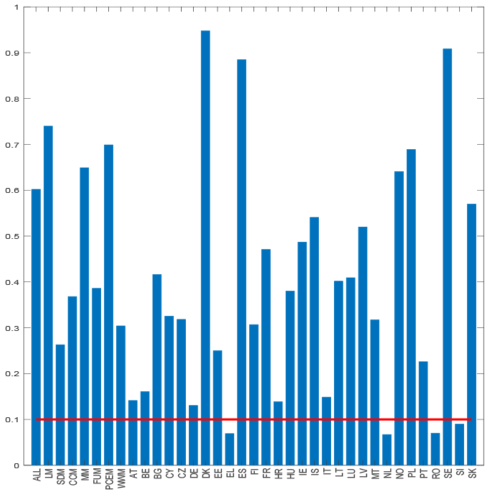
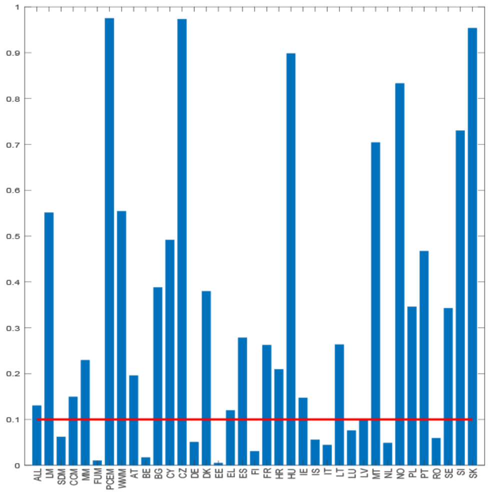


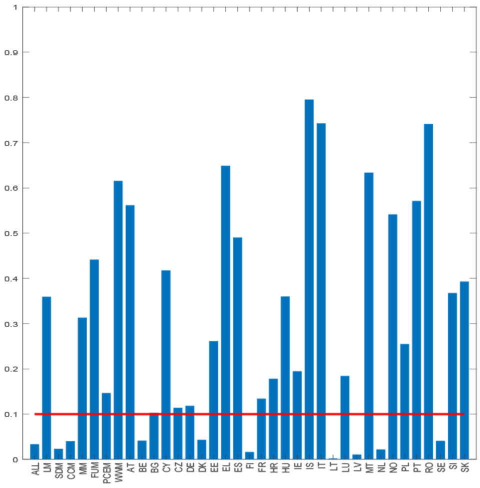
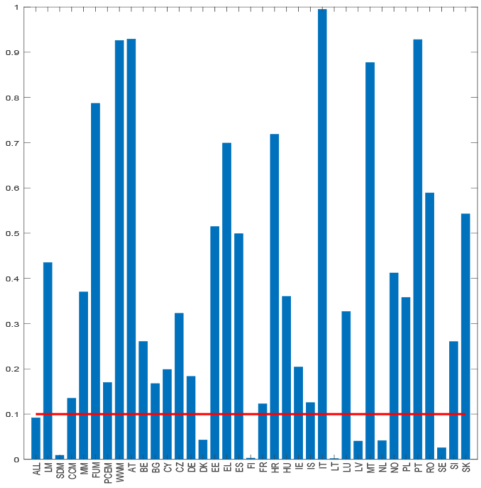

Source: Own elaboration using Causality Map Toolbox
Notes: (1) Results obtained from Granger's Causality test at 10 % of significance level, for the period 1997-2020.
(2) EXP= Government Expenditures, REV=Government Revenues, GDP= Gross Domestic Product, INF=Inflation.

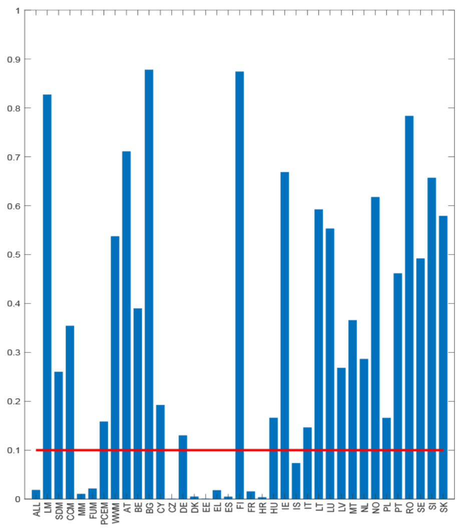
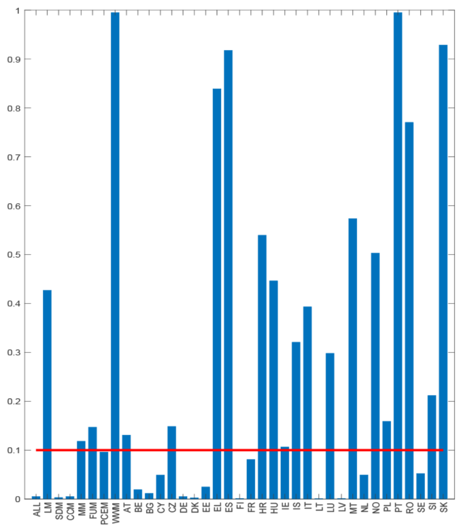
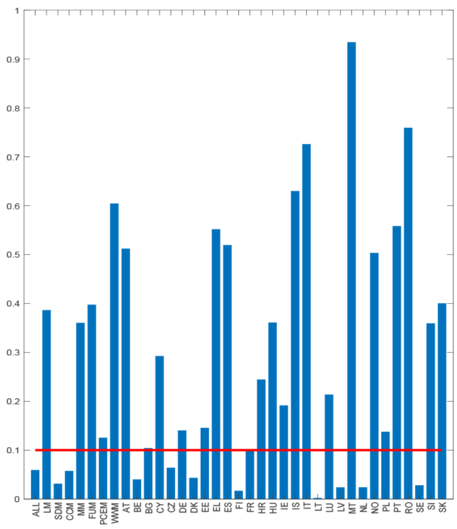
We can see that for the whole panel (All), different pairs of variables tend to move in the same direction such as *GDP* and *REV, GDP* and *EXP* and *REV* and *EXP*. Of those three, we found a strong correlation for the former and moderate for the two remaining pairs. On the other hand, *GDP* and *INF*, *EXP* and *INF* and *REV* and *INF* tend to move on opposite directions, with a not strong enough coefficient (no correlation) for the later and moderate for the formers. This first approximation serves as a clue to explore possible causal relationships.

| Table 2: P-value Significance - Level 1 | |
|---|---|
| Model: GDP and Revenues | |
| GDP and Revenues | Revenues and GDP |
|  |  |
| Model: GDP and Expenditures | |
| GDP and Expenditures | Expenditures and GDP |
|  |  |
| Model: GDP and Inflation | |
| GDP and Inflation | Inflation and GDP |
|  |  |

| Table 2 (cont): P-value Significance - Level 1 | |
|---|---|
| Model: Revenues and Expenditures | |
| Revenues and Expenditures | Expenditures and Revenues |
|  |  |
| Model: Revenues and Inflation | |
| Revenues and Inflation | Inflation and Revenues |
|  |  |
| Model: Expenditures and Inflation | |
| Expenditures and Inflation | Inflation and Expenditures |
|  |  |
| Source: Own elaboration using Causality Map Toolbox<br>Notes: (1) Results obtained from Granger's Causality test at 10 % of significance level, for the period 1997-2020.<br>(2) EXP= Government Expenditures, REV=Government Revenues, GDP= Gross Domestic Product, INF=Inflation. | |

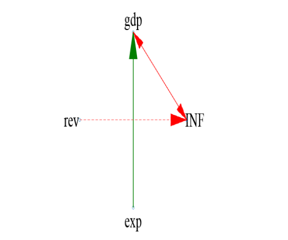
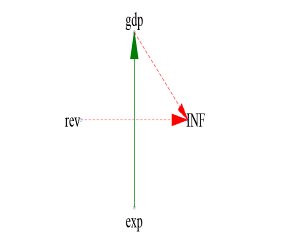
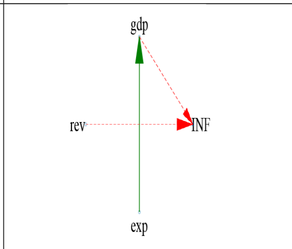
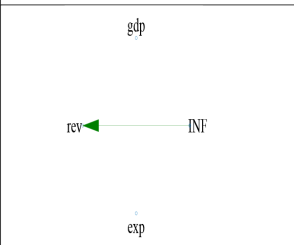
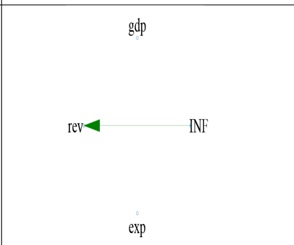
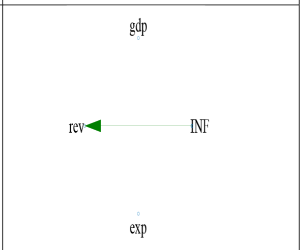
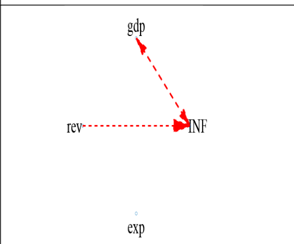
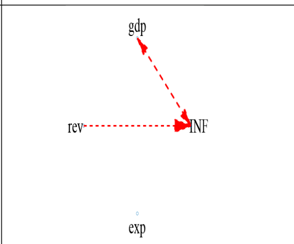
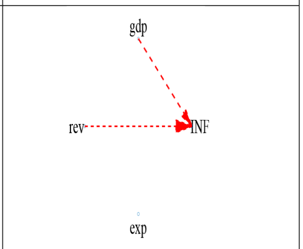
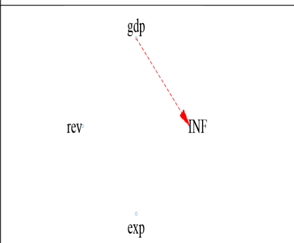
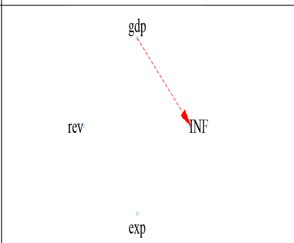
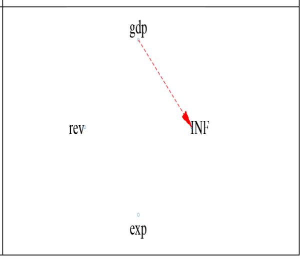
| Table 3: P-value Significance - Level 2 - Survival Links | |
|---|---|
| Expenditures and GDP controlling by Revenues | Expenditures and GDP controlling by Inflation |
|  |  |
| GDP and Inflation controlling by Revenues | GDP and Inflation controlling by Expenditures |
|  |  |
| Inflation and GDP controlling by Revenues | Inflation and GDP controlling by Expenditures |
|  |  |

| Table 3 (cont): P-value Significance - Level 2 - Survival Links | |
|---|---|
| **Revenues and Inflation controlling by GDP** | **Revenues and Inflation controlling by Expenditures** |
|  |  |
| Source: Own elaboration using Causality Map Toolbox<br>Notes: (1) Results obtained from Granger's Causality test at 10 % of significance level, for the period 1997-2020.<br>(2) EXP= Government Expenditures, REV=Government Revenues, GDP= Gross Domestic Product, INF=Inflation. | |

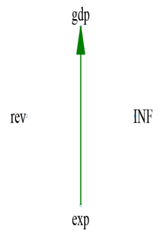
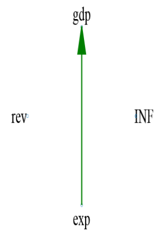
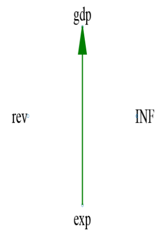
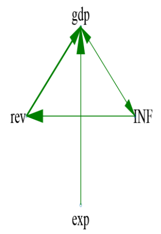
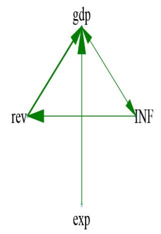
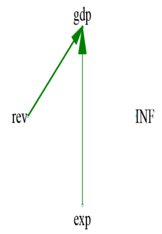
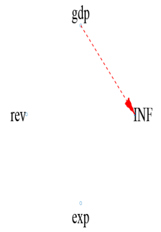
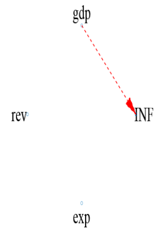
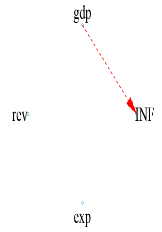
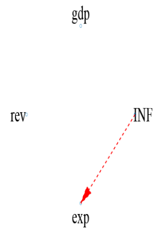
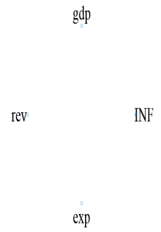
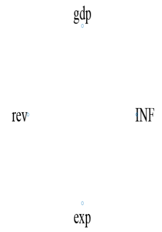
| Table 4: P-value singnificance - Level 3 - Survival Links | | |
|---|---|---|
| **Expenditures to GDP controlling by Revenues and Inflation** | **GDP to Inflation controlling by Revenues and Expenditures** | **Revenues and Inflation controlling by GDP and Expenditures** |
|  |  |  |
| Source: Own elaboration using Causality Map Toolbox<br>Notes: (1) Results obtained from Granger's Causality test at 10 % of significance level, for the period 1997-2020.<br>(2) EXP= Government Expenditures, REV=Government Revenues, GDP= Gross Domestic Product, INF=Inflation. | | |

The second part of our empirical strategy is to complement the preliminary analysis of the co-movement between variables by assessing the significance of various causality tests. In this sense, we have presented in tables 4, 5 and 6 the p-values obtained for the Granger Causality tests, for level 1, level 2 and level 3 respectively. It also includes the individual p-values of each cross-sectional unit, which can help to know the precise situation for each country of our sample in the case for a selection of links, jointly with the p-value used as a reference to indicate that a significant effect is reached. Table 2 shows that, at a first level, only four pairs of relationships result significant for the whole panel, the unconditional causal relationship between *INF* and *GDP*, which is significant in both directions; and the unconditional causal link of *EXP* to *GDP* and *REV* to *INF*[7]. Table 3, which represent level 2, shows that the link between *INF* and *GDP* is only present in the bivariate model and does not remain significant when controlling for *EXP*, which leads to eliminate the possibility of a *true causal relationship*. However, the rest of the relationships found at level 1 does remain significant. Finally, Table 4 shows the p-values for level 3, which implies repeating the causality test for each significant pair of variables found at level 2, but now controlling for the rest of the variables included in the model. We can observe that the all links found at the previous levels survive to the last stage of the algorithm. However, we must remind that although the relationship between *REV* and *INF* is significant, the coefficient obtained for the *CFF* indicates that the magnitude of the effect is small so that it could be considered a weak link in terms of intensity. To sum up, for the whole panel, we can observe that *EXP* is leading the causal path, having a positive effect over *GDP*. At the same time, *GDP* presents a negative causal effect over *INF*, which closes the path.

**Table 5: Causality maps**

| Unit | L1 | L2 | L3 |
|---|---|---|---|
| ALL |  |  |  |
| LM |  |  |  |
| SDM |  |  |  |
| CCM |  |  |  |

7 We can see how the value obtained for the group (ALL) is below the reference p-value confirming the presence of causality for the whole group of countries. However, this conclusion should not be extrapolated to every country as some of the individual p-values do not allow to reject the null hypothesis.

| Table 5 (cont): Causality maps | | | |
|---|---|---|---|
| Unit | L1 | L2 | L3 |
| MM |   |   |   |
| FUM |   |   |   |
| PCEM |   |   |   |
| WWM |   |   |   |

Notes: (1) Results obtained from Granger's Causality test at 10% of significance level, for the periodo 1997-2020. Solid (Dashed) line indicates that the crossed-correlation between each pair of nodes is positive (negative). Finally, the wider is the line, the higher is this value.
(2) EXP= Government Expenditures, REV=Government Revenues, GDP= Gross Domestic Product, INF=Inflation.

Finally, table 5 shows the causal graphs generated by combining the information obtained from our causality analysis for different groups of economies, which graphically represent the final causal path between the different variables. We can observe that the negative effect of *GDP* over *INF* is present in most of the groups, which could be indicating that this causal relationship is found in most of the countries. However, it also reflects the benefits of our methodology, as it captures the different situations of each group. For example, in Liberal Market economies, we can observe a link between *INF* to *REV* that is particular of these economies.

So, although for the whole sample we observe that *EXP* leads the causal chain with a positive effect on *GDP*, which, at the same time, has a negative effect on *INF*, we can observe that, in this exercise, different patterns between variables are present, depending on which countries we study. Even though the variety of results obtained could be the subject of further discussion, this goes beyond the central aim of the paper.

## 4 Concluding remarks.

In the last decades, granger causality has become a transversal concept mostly included in the default toolkit of applied analysts. Particularly, for those interested in time series analysis. The number of alternatives to implement it has grown significantly over the years, but the same basic, flexible idea still operates. As Granger (2003) highlighted, this concept relied on the idea that the cause (a variable X) contains -early- information about the effect (variable Y) that is unique and is in no other variable. These two elements (determination of flow and identification of genuine causes) are included in our proposal in a very intuitive way. On the one hand, considering a multivariate framework allows to control for the main endogenous variables of the model. Particularly, in the context of a Vector Autoregressive (VAR) model. On the other hand, using the PC iterative algorithm allows to clarify any ambiguity in the causality flow and, at the same time, reject any spurious relationship potentially emerged in reduced versions of the full model (as the bivariate ones).

Moreover, we also have contributed to the grounds of applied econometrics by combining graphic-theoretic methods proposed by Spirtes (2000), Demiralp & Hoover (2003) and Eicher (2007, 2012), among others to panel data models which helps to identify common patterns of causality for a representative set of crossed-section units, something very meaningful for specific scenarios like countries, as it allows to interpret the results in a more general way.

Finally, our illustration on the fiscal policy-growth nexus also help to obtain added value compared to previous approaches which only focussed on the impact of the fiscal policy indicators on growth, leaving out all possible flows of causality which may be affecting the results.

To conclude, we think that this approach may be applied to very different issues and datasets. On the top of that, several studies published using reduced models (bilateral/trilateral) may be revisited with our proposal, to check and extend their findings. Thus, the potentialities for future research aver very promising.

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