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Inequality and poverty in the European Union: In search of lost dynamics

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Abstract

This paper analyses the relationships between income inequality, monetary poverty and economic growth for a sample of 30 European economies over the period 2004-2020. To do so, we adopt a novel approach, based on a dynamic analysis that takes into account the variability that can occur in the evolution of these relationships over the period analysed. The proposed panel-VAR model allows us to perform a Granger causality analysis between the variables mentioned. In a second stage, we complete this analysis with the application of the iterative PC algorithm that allows us to interpret the results of the model by defining the corresponding causal graphs. For the empirical analysis we use micro-data from the EU-SILC database for the period 2004-2020. The results obtained show that, for the set of economies analysed, inequality has a positive effect on poverty. Moreover, we also find that this dynamic is reversed, with a double positive causality between these variables. In addition, we do not find evidence of a poverty or inequality reducing effect of economic growth. However, we find that these results differ across countries, depending on the type of welfare state in place.

Keywords: Inequality - Poverty - Economic Growth - Causality - Causal Graphs
JEL Codes: C32 · D31 · E25· I32 · O15

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1. Introduction

In recent years, there has been a surge in the number of papers focusing on the analysis of the effects of poverty and inequality on economic growth. In this paper, we revisit this topic aiming to contribute along the following lines. First, most studies adopt a comparative statics approach, with the causal dynamics perspective being relatively neglected. Second, on the other hand, these issues have been addressed from a bilateral point of view, focusing exclusively on one of the distributional dimensions and its effect on economic growth. Nevertheless, for a proper interpretation of this complex phenomenon, it is necessary to broaden the focus of analysis and include both variables simultaneously, as they not only represent different distributional phenomena, each with its own potential effects on economic growth, but can also affect each other.

This paper proposes a new methodological approach to analyse, from an empirical perspective, the dynamic causal relationships between inequality, poverty and economic growth. The effects of inequality on economic growth have been thoroughly studied, both from a theoretical and empirical point of view. From the theoretical point of view, therefore, we find numerous models that, through different causal mechanisms, predict a positive effect (Bourguignon, 1981; Lazear and Rosen, 1981). Likewise, we also find models that argue for the opposite effect (Bertola, 1993; Alesina and Rodrick, 1994; Persson and Tabellini, 1994; Perotti, 1996). From an empirical point of view, there is no greater consensus on the meaning of the relationship, but one finds different methodological approaches that lead to very different results for different periods and/or societies. Although these differences may stem partially from the empirical strategy adopted, we believe it is of interest to contribute to clarifying the fundamental determinants of the relationships between the dimensions analysed.

As regards the studies that analyse the growth-poverty relationship, although we find numerous studies that define different transmission mechanisms, the studies that attempt to provide empirical support are scarcer in number. Thus, much of the empirical work focuses on calculating the elasticity of the poverty-growth relationship, generally finding an inverse relationship between poverty and growth variables (Adams, 2004; Ravallion and Chen, 1997). We also highlight the pro-poor growth literature, which focuses on identifying whether economic growth has direct effects on individuals with lower incomes or alternatively, whether an unequal distribution of gains would lead to higher levels of poverty (Kakwani and Pernia, 2000; Ravallion, 2004). However, most of these works have a number of common technical features that make them relatively distant from our study. Firstly, the analysis tends to focus on countries at a lower stage of development, with papers looking specifically at advanced European economies being less common. Likewise, the way poverty is measured, typically using common/absolute poverty lines, also differs from the one adopted in this paper, where we rely on relative measures. Finally, it is also recognised in the empirical literature that the intensity of the growth-poverty relationship is influenced by the sectoral composition of growth. In this sense, we believe that adopting a dynamic perspective allows us, to a certain extent, to address the various changes that take place in this context.

The aim of this paper is to analyse the causal relationships linking economic growth, poverty and inequality. To this end, we propose a new approach, novel in some dimensions, which is based on analysing the information present in the data (data driven approach). We construct a yearly frequency database covering 30 European countries (26 EU member states, Switzerland, Iceland, Norway and the United Kingdom) for the period 2004-2020. The set of countries included have different institutional characteristics and welfare states, which allows them to be classified into different groups and to analyse the existence of common patterns in each of them.

Our empirical analysis strategy is structured in the following stages. First, we carry out a first exploratory exercise in which we analyse the direction and magnitude of the co-movements between the different variables. To do so, we calculate the cross-correlation function (CCF) between the different variable pairs for the entire sample and for the different units that compose the sample. In a second stage, we establish our baseline specification, which consists of a panel-VAR model in which we include the variables mentioned above and carry out a causality analysis by studying the p-values obtained after performing a Granger causality test for each of the possible relationships. Finally, all the information is combined with the application of the iterative PC algorithm -

in its stable version, introduced by Colombo and Maathuis (2014)- that allows us to interpret the model results in line with the causal graph literature (Lauritzen and Richardson, 2002; Demiralp and Hoover, 2003; Eichler, 2007). This algorithm provides a useful and novel tool to clarify inconclusive relationships[1] . Such algorithms are based on conditional independence tests to obtain information about the underlying causal structure of a given phenomenon (Spirtes et al., 2000). Doing so, we rely on two branches of literature which, to our knowledge, have hitherto been independent of each other. On the one hand, that which studies causality in panel-var models and, on the other hand, that dedicated to graphical methods.

The advantages of the approach we propose are related to certain methodological difficulties encountered in the existing literature. First, we carry out a dynamic analysis that takes into account the variability that can occur in the evolution of these relationships over the period analysed. Furthermore, our methodological approach does not impose an a priori causal structure, but explores patterns of dependence present in the data, considering the potential existence of all directions of causality. Moreover, the results derived from the approach we apply here are not limited to the study of correlation but are interpretable in terms of causality (Granger-causality). An approach that, at the same time, allows us to increase the number of relevant variables in the analysis, usually reduced to two in causality studies using panel-VAR models. Finally, the versatility of the methodology we propose enables us to obtain results both for the total number of countries in the sample and for different subgroups, which makes it easier to carry out robustness analyses that, in turn, make it possible to identify common patterns.

The rest of the paper is structured as follows: Section two conducts a literature review of both theoretical and empirical works. The third section describes the data used, in addition to an initial descriptive analysis. In section four we present the proposed methodology and in section five we present the results. Finally, the sixth section concludes.

1 Algorithms of this type have been commonly used in other areas of knowledge, although they are increasingly being applied to a variety of economic research questions

2. Literature Review

Although the studies analysing the relationship between inequality, poverty and economic growth are numerous and diverse, one could point to the seminal work of Kuznets (1955) as the starting point for the development of this branch of literature. In an effort to synthesise, and without the intention of being exhaustive, we review the main strands of literature that relate to our study.

Firstly, this work is strongly related to those that analyse the relationship between inequality and economic growth from an analytical point of view. There are several mechanisms that could explain both the positive and negative effects of inequality on economic growth. Thus, we found different theoretical works suggesting different transmission mechanisms through which a negative relationship would occur, which means that inequality cause a disincentive effect on growth. The first of these mechanisms refers to political decisions as a fundamental channel. Faced with a more unequal distribution of income, society would choose to demand policy options that include redistributive policies in their programmes, with capital as the main target, or that reduce reliance on pro-bussisness policies. Therefore, the reduction of economic growth would occur through the implementation of these policies. An alternative, but strongly related, transmission mechanism predicts that social discontent derived from the prevalence of high levels of inequality could translate into episodes of violence and social conflict that would directly damage economic growth, both through institutional credibility and through the destruction of assets. Among this group are the works of Bertola (1993), Alesina and Rodrik (1994), Persson and Tabellini (1994) and Perotti (1996). Finally, we also find work that points to underinvestment in human capital as a reason for lower economic growth, at least below potential growth. Thus, Galor and Zeira (1992) and Galor and Moav (2004) propose a model in which, in the face of financial market imperfections, an unequal distribution means that only those individuals with sufficient wealth can invest in human capital.

A number of causal mechanisms supporting the existence of a positive effect are also found in the theoretical literature. Thus, Kaldor (1955) and Bourguignon (1981) argue that aggregate savings and their effect on capi-

tal accumulation is one of the main drivers of economic growth, and therefore, channelling resources to those with a greater propensity to save, those individuals with greater resources, would have a positive effect on economic growth. We find work predicting that high levels of inequality encourage "hard work" and riskier financial decisions in search of higher returns, potentially having a positive effect on economic growth. (Lazear and Rosen, 1981; Okun, 1975). Similarly, Foellmi and Zweimüller (2006) propose a model in which a more equal distribution results in a disincentive to innovation and thus reduces growth.

Similarly, and directly related to our analysis, we find a large body of work that contributes to the empirical testing of these mechanisms. However, no clear consensus has been reached on the sign or intensity of this relationship. The nature of the empirical work is very heterogeneous, which may be a potential explanation for the divergence of the results obtained. The most significant variations arise mainly from the structure of the data and the estimators used, but also from the database chosen and the inequality measure to be analysed. Thus, the first empirical contributions used cross-sectional data to investigate the sign of this relationship. Among others, the work of Alesina and Rodrik (1994), Persson and Tabellini (1994), Perotti (1996) and Deninger and Squiere (1998) stand out. However, and partly explained by the improved availability of panel data, a large part of the most recent studies makes use of this type of data[2]. Thus, we cite, for example, the studies by Li and Zou (1998), Forbes (2000), Barro (2000)[3]. On the other hand, we also highlight several papers that, pointing to the greater complexity of the relationship suggested in the theoretical models, emphasise a specific aspect of the analysis, with the aim of capturing this complexity. Thus, Voitchovsky (2005) studies the effect of inequality on growth depending on the distribution quintile in which it occurs, finding that it is positive in the higher brackets, while the opposite is true for the lower brackets. In Halter et al. (2014) differentiate between effects that occur in the short term, which are beneficial for growth, and those that operate in the long term, which have the opposite effect. Banarjee and Dufflo (2003) investigate whether the relationship that occurs between the variables is linear, finding that trying to impose this form of relationship does not seem to be supported by the data. Castelló-Climent (2010) distinguishes according to the level of development of the region, finding that the effect is negative in middle- and low-income countries.

The second line of research that relates directly to our work is that which focuses on analysing how poverty is related to economic growth. As with inequality, there is a large theoretical literature that presents different models identifying the potential channels through which this effect would be transmitted. As one of the fundamental thematic lines, we highlight, on the one hand, the works that point to the existence of poverty traps. These are based on the existence of various underlying mechanisms which, on the one hand, prevent part of the population from attaining certain levels of assets and, on the other hand, and fundamentally, reinforce on themselves, thus perpetuating this situation. Thus, on the one hand, some of the mechanisms operate through the personal/psychological characteristics of the poorer population, such as having a higher propensity to consume unproductive goods (Banerjee and Mullainathan, 2010), the need to spend more of their time on ensuring the satisfaction of basic needs or greater risk aversion (Shah et al (2012) and Banarjee (2000), respectively). On the other hand, other mechanisms are based on the existence of resource or credit constraints that result in underinvestment in physical or human capital assets (Banarjee and Newman, 1993). In the most extreme cases, part of the population may suffer from malnutrition, affecting their physical and cognitive performance and thus potential economic growth (Dasgupta and Ray, 1986).

As regards empirical research on the relationship between the two variables, in contrast to analytical models, we find a large number of papers that analyse the impact of economic growth on poverty, especially from the perspective of development economics. Some of this work focuses on analysing the relationship between the growth of the lowest incomes in an economy and average growth, generally concluding that the benefit of economic growth reaches the poor as well as the rest of society (Dollar and Kraay, 2002; Dollar et al., 2016). In turn, Adams (2004) and Ravallion and Chen (1997) estimate the growth-poverty elasticity for a number of develo-

2 In particular, we highlight the influence on the development of the empirical literature of the database published by Deniguer and Squire (1996).

3 More comprehensive literature reviews can be found in Cingano (2014) or Cerra et al. (2021).

ping countries, obtaining an impact ranging between 2% and 3%. Others try to explain the different magnitude of the effect by looking at the type of growth, mainly at the sectoral composition, or at the initial economic conditions. Thus, among others, Loayza and Raddatz (2009) analyse the effect of economic growth on poverty reduction at various levels of disaggregation of production for a group of developing countries. Ferreira et al. (2009) conduct a similar exercise but focusing on Brazil.

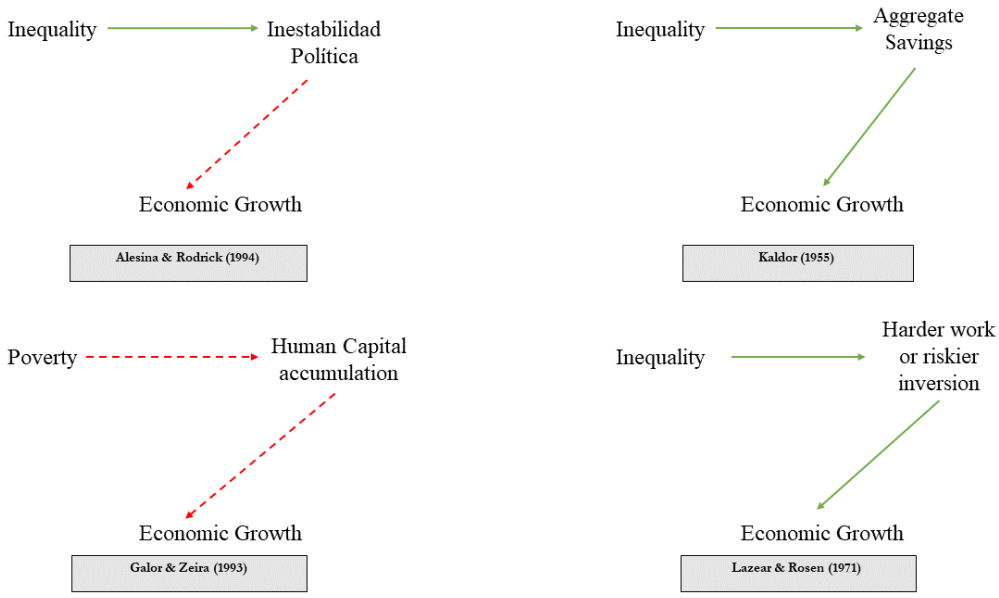
Finally, although somewhat less numerous, we also highlight a branch of the empirical literature that not only takes into account the individual link between some of the distributional variables and economic growth, but also takes into account a possible interaction between these distributional variables. Bluhm et al. (2018) find that the initial level of inequality mitigates the poverty-reducing effect of economic growth for a group of 124 countries. Marrero and Servén (2021), for their part, analyse the links between economic growth and inequality and poverty, considering the possibility of indirect effects through the interaction of the latter two.

3 Data.

The dataset we use to carry out our empirical analysis is drawn from the various releases of cross-sectional microdata from the European Survey of Income and Living Conditions (EUSILC) over the period 2004-2020. This survey is carried out annually and contains, among other things, income data, both at individual and aggregate household level, as well as demographic and social characteristics of households. It is designed as a rotating panel survey, whereby the same household is followed for four consecutive years, with 25% of the sample being renewed each year. Currently, the EU-SILC sample size is approximately 141,000 households and 290,650 individuals for cross-sectional data.

Using this data source offers several advantages compared to other databases commonly found in the literature. Firstly, it minimises the measurement error common in this type of empirical work[4] and enhances compa-

Figure 1. Prior theoretical insights on the links between variables.



Source: Own elaboration

4 Atkinson and Brandolini (2001) point out the potential comparability problems that often arise in such studies when using less consistent databases.

rability between countries, since the questionnaires, data collection, coding of variables and the different weighting systems are harmonised at European level. Although using only this database restricts us both in the number of countries we could include in the sample and in the length of the time interval, we believe that this is compensated by the improvement in the quality and homogenisation of the data. Additionally, this survey presents a broad and detailed coverage of the different sources of household income. This will allow us to identify different income stages, depending on the different intervention of the public sector and, especially, to put the emphasis on the effect of intervention via expenditure or via the tax system. We follow Goerlich (2016) and calculate the following income variables: Market Income, which for each household we add up the total of wages, self-employment income and capital gains; Gross Income, which, on the basis of market income, also includes public and inter-household cash transfers, and, finally, Disposable Income, from which taxes paid by households must be subtracted[5]. In this paper we have opted to take gross income as the benchmark definition of income. The main reason is that it includes income earned by individuals in the market but also old-age benefits[6]. People who receive this benefit as their main source of income would not be included in the market income and this would distort or misrepresent the results obtained in terms of inequality and poverty. Moreover, this strategy allows us to emphasise the role that public intervention has played in changing causal relationships, depending on whether we focus on cash transfers or on the direct tax system.

Based on the different definitions of income mentioned above, we calculate different indicators that allow us to capture the evolution of each of the distributional variables of interest, following the usual standardisations in the literature. We use the Gini index as a measure of income inequality and the Anchored Poverty Rate as a measure of monetary poverty. This poverty measure indicates the percentage of the population below a certain threshold or poverty line, defined as 60% of the median income in each country. It is therefore a measure of relative poverty and, in this analysis, we have decided to consider 2007 as the reference year, as this is the first year for which we have observations for all the countries in the sample. Although it is common in this type of empirical exercise to adopt an absolute measure of poverty, the idea behind our choice is that poverty is a social environment-dependent phenomenon.

The observational unit for the computation of the index is the household, since, on the one hand, we believe that the main decisions regarding income and expenditure are generally taken at household level and, on the other hand, it allows us to exploit all sources of income collected at household level without having to make any assumptions about how these are distributed. Income variables have been adjusted for differences in household size and composition using the OECD equivalence scale. In addition, all indices are obtained using the sampling weights provided by Eurostat. Finally, as a measure of economic growth, we have calculated the rate of real GDP per capita growth.

To sum up, from the calculation of these indices for each country we have constructed the panel data that we will use for our empirical analysis. This is an annual frequency panel with 487 year/country observations for the variables economic growth, income inequality and monetary poverty for 30 European economies over the period 2004-2020[7-8]. Thus, 26 EU member states are included, as well as Switzerland, Iceland, Norway and the United Kingdom. The choice of this period forces us to disregard the data for Serbia and Croatia, as the length of their series is significantly shorter.

3.1 Definition of country groups

In line with the objective of this paper, we have classified the countries[9] in our sample into different groups, based on relatively common characteristics of their public systems, in order to analyse the existence of common patterns. We have used the literature on the different typologies of welfare states, largely influenced by the work of Esping-Andersen (1990), as a frame of reference for the for-

5 Eurostat offers access to different databases of distributional variables. However, in this paper we adopt different definitions of income, so we have had to calculate our indicators from the micro-data.

6 In addition to other income benefits.

7 The length of the series is not the same for all countries included in the sample, so we are working on an unbalanced panel.

8 It should be noted that the data collected in the survey refer to the period prior to the year of publication.

9 The different groupings are carried out on the basis of the country specific results of the different results.

mation of these groups[10]. In it, the author establishes for a group of OECD countries three different types of welfare regimes, according to the degree of decommodification and social stratification, namely the social democratic model, the conservative-corporatist model and the liberal model. Later contributions extend this classification by distinguishing a Southern European or Mediterranean model (Ferrera, 1996) or models specific to post-communist countries (Fenger, 2007).

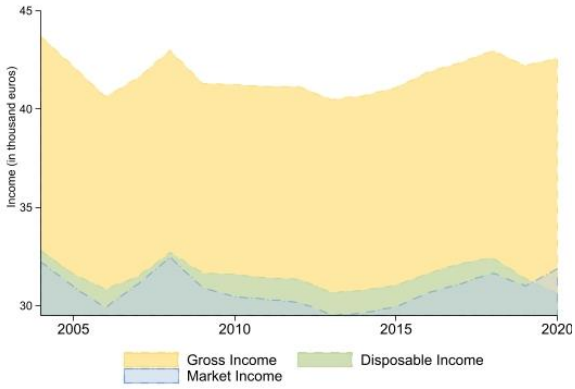
Starting from the seminal Esping-Andersen classification and incorporating the subsequent contributions mentioned above, we have classified the 30 European economies into the following groups: liberal model (LM- United Kingdom, Ireland and Iceland); conservative-corporatist model (CCM - Austria, Belgium, 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).

Although this type of classificatory effort has well-known weaknesses, such as the heterogeneity of the different groups, the assumption that the characteristics of public systems are continuous over time or that the classification responds to ideal types of welfare state, we do believe that it can be useful as an exploratory exercise to identify common trends.

3.2 Descriptive comparative analysis

Figure 2 shows the evolution over time of the different income definitions for the total number of countries in the sample for the period 2004-2020. This shows the impact of the financial crisis on the evolution of income and, in particular, on market income, causing it to fall continuously from 2008 until 2014[11], the year in which the economic recovery began. At the same time, it is also noted that, although market income movements are more volatile, this is not fully transmitted to the rest of the income definitions. Thus, we observe that the difference between gross income and disposable income remains relatively constant over the period and the evolution of both income definitions is more stable. This would indicate the key role played by different welfare states in partially absorbing economic shocks.

Figure 2. Evolution of income.



Source: Own elaboration using EUSILC data

Figure 3 shows the evolution of each of the distributional indicators in the different income stages and shows the value at the beginning and at the end of the period. Those countries that are above the bisector have suffered an increase in the values of their indicators and, therefore, a worsening in social welfare, with the further away from the line, the greater the worsening[12]. The following ideas can be drawn from Figure 2. On the one hand, in all four panels it appears that most countries are around the dividing line, so that, in general terms, the reduction in inequality and poverty has not been as expected. Not only that, but some of the countries are in a worse situation than at the beginning of the period. On the other hand, there is a certain symmetry between countries that worsen in terms of inequality and those that worsen in terms of poverty, which could be evidence that there is some relationship between these variables and, therefore, it seems to be convenient to contemplate both variables in this type of empirical exercises. In terms of welfare state typologies, it appears that, in terms of both inequality and poverty, countries that do not worsen are classified in groups associated with more consolidated welfare states.

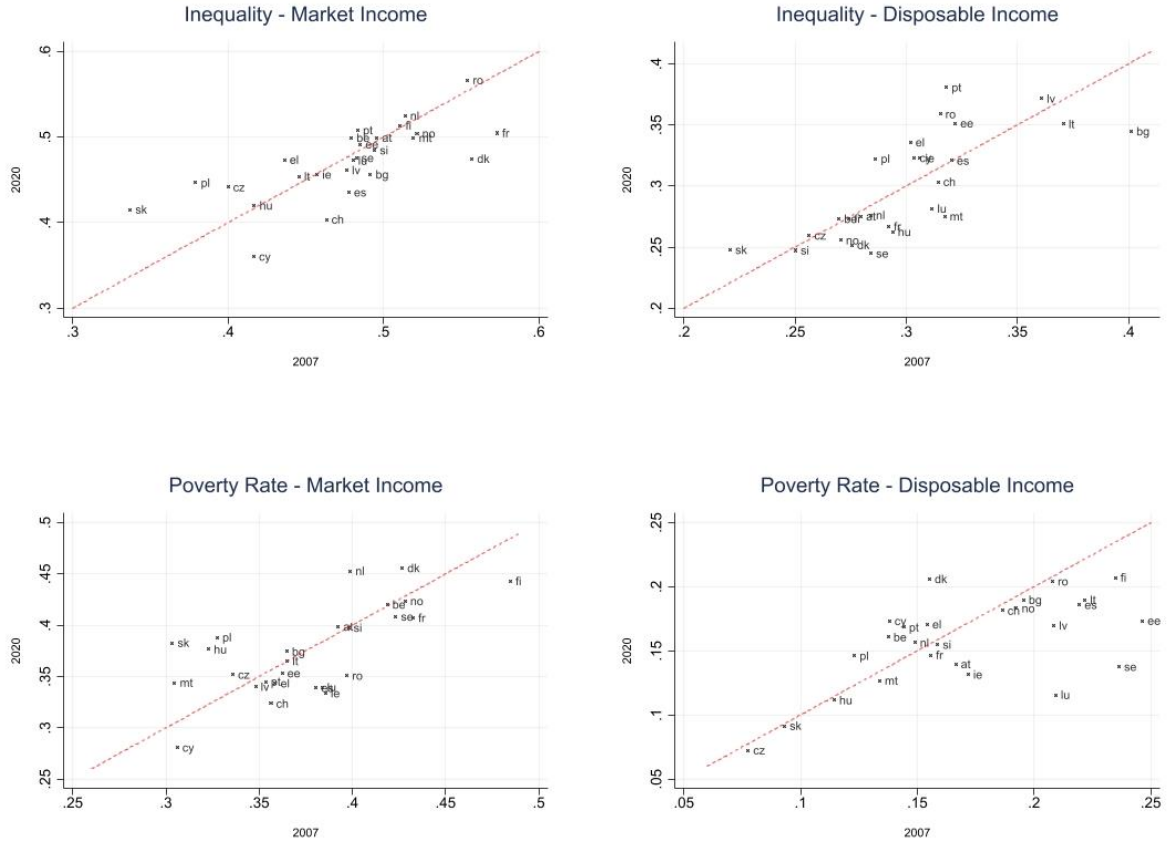
10 It is not the purpose of this paper to analyse in depth the classification proposed in Esping-Andersen (1990). For a more detailed study we refer to Muñoz de Bustillo (2019).

11 It should be noted that some countries started the recovery period earlier than others.

12 Similarly, those countries that fall below the dividing line will have experienced an improvement in their social indicators, with the greater the distance, the greater the magnitude of this improvement.

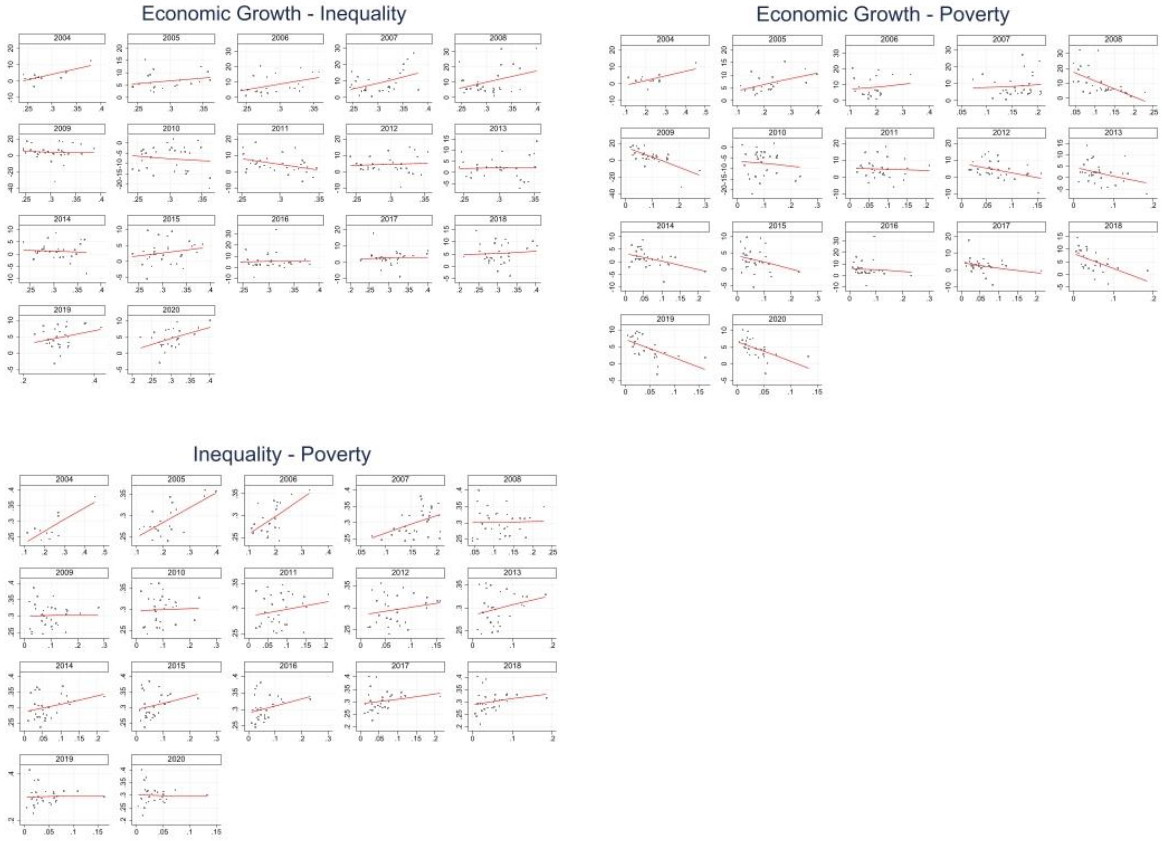
Moreover, in figure 4 we have plotted, for each of the years of the period, the different correlations between our variables of interest. With this exercise, rather than trying to establish the sign of the relationship between them, we highlight the variability of the relationship according to the moment in time on which we focus our attention. In fact, at some points, it can even be seen that at certain times the relationships seem to be reversed. Thus, the correlation between poverty and economic growth is particularly striking. This seems to indicate the relevance of adopting a dynamic approach when analysing the relationship between the different variables.

Figure 3. Gini Index and Poverty Rate: 2004 and 2020.



Source: Own elaboration using EUSILC data

Figure 4. Annual correlation between variables.



Source: Own elaboration using EUSILC data

4 Methodology

4.1 Analysis of co-movement between variables

The first step we take is to 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 later 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:

Let $r_1, \ldots, r_N$ be the correlation coefficients we want to combine. In order to compute them in a common measure, it is necessary to apply the Fisher transformation to each of the individual correlation coefficients (r_i):

$$z_i = 0.5 * \ln \frac{(1+ r_i)}{(1- r_i)} \quad (1)$$

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

Using these transformations, the aggregate coefficient of the correlations can be calculated as the sample mean of the correlations:

$$Z = \sum \frac{z_i}{N} \quad (2)$$

This follows a normal distribution, of variance $1/\sum_{t=1}^{N} \frac{1}{T_i}$.

The last step, once Z has been calculated, is to undo the transformation and thus obtain the aggregate measure representing the dominant correlation coefficient:

$$R = \frac{e^{2z}-1}{e^{2z}+1} \quad (3)$$

4.2 Baseline specification.

The benchmark specification is a multivariate vector autoregressive panel model (P-VAR) in which economic growth, the Gini index and the anchored poverty rate are included. We denote the economic growth rate, income inequality and poverty rate of a country i in a year t by Δy_{it}, G_{it},P_{it} respectively. Thus, our model can be represented as follows:

$$Y_{it} = \mu_i + \Phi(L)Y_{it-1} + \varepsilon_{it} \quad i = 1, \dots, N;\ t = 1, \dots, T \quad (4)$$

Where Y_{it}= $[\Delta y_{it}$,G_{it},$P_{it}]'$, index i refers to each of the countries in our database and t denotes the time period, (L) is the lag operator and $\Phi(L)$ is the polynomial matrix of parameters in (L). ε_{it} is the vector of error terms (3×1) which are independently and identically distributed.

Although it is common in this type of empirical exercises to test the significance of the relationship between variables by using instrumental variables (IV) and estimators that rely on this type of procedures, Kraay (2015) points out that the weakness of these instruments is often a common problem and may be affecting the results obtained. In this sense, we believe that the specification of VAR models provides us with a more versatile regression framework, which is in line with the theoretical literature. Finally, to test the existence of a relationship between the variables, we carried out a causality analysis in the Granger sense.

4.3 A Granger causality test in a panel data framework

In order to complete the previous exercise, we examine the concept of causality in greater depth. To do so, we use the definition of causality proposed by Granger (1969) and which has been widely used in the context of autoregressive vector models. The idea behind this concept is quite intuitive: one variable x causes à la Granger to another y if by including the values of the former, it improves the forecast in the latter. In practice, this has resulted in analysing the significance of the coefficient associated with this variable. Although this concept of causality was developed for bivariate and single cross-section time series models, recent developments in econometric techniques have made it possible to adapt this test to a panel data environment. Thus, one of the main advantages that arises from this adaptation is the improvement in the efficiency of the different tests, derived from the greater number of observations and, therefore, degrees of freedom.

Following, among others, Hurlin (2001) and Emirmahmutoglu and Kose (2011), one of the fundamental elements of our methodological proposal consists of calculating a synthetic aggregate from individual measures that allows us to determine the existence of causality between variables for the total sample or any subgroup of cross-section units. In this way, we manage to exploit the common features of the different Welfare States.

To do so, we rely on one of the standard tools in the determination of causality, the Wald test which, as mentioned above, consists of testing the significance of the matrix of linear parameters. In the case of Granger non-causality, the null hypothesis for the *i-th* individual is defined as:

$$H_0: \Phi_i = 0 \text{ for all } i. \quad (5)$$

From the results obtained through this test and, following Emirmahmutoglu and Kose (2011), with the aim of constructing the common statistic for the total sample, we carry out the transformation of the individual p-values (p_i) proposed by Fisher (1932), and obtain the following:

$$\lambda = -2\sum \ln p_i \quad (6)$$

Where p_i is the p-value corresponding to the *i-th* cross-sectional unit. This synthetic statistic λ has a chi-square distribution with 2N degrees of freedom and serves to determine the existence of a common causality pattern for the included units.

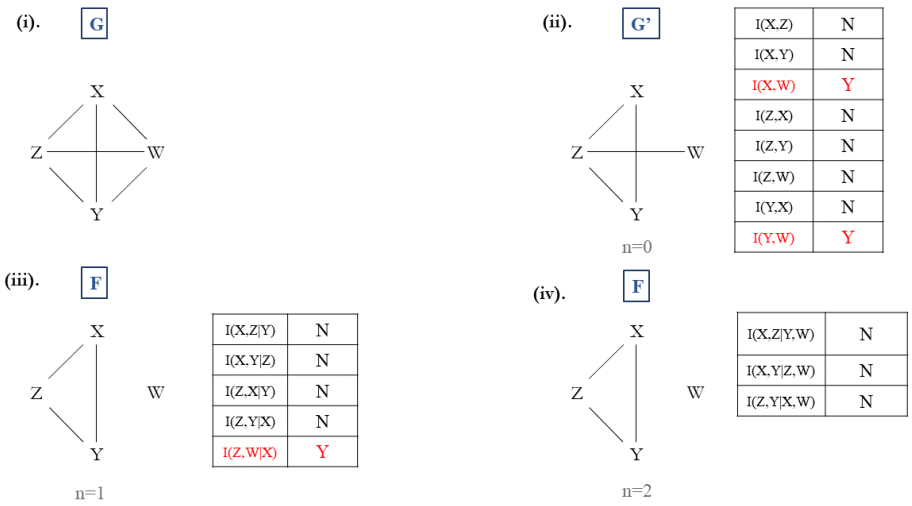
4.4 Application of the causal search algorithm and obtaining causal graphs.

After obtaining for each relationship analysed the different synthetic aggregates representative for the whole panel that allow us to determine the existence, intensity and direction of causality, we proceed to the application of the PC algorithm[13] in its stable version (Colombo and Maathuis, 2012). This implies an iterative process to clarify the genuine flow

13 For a more detailed review on the implementation and application of the algorithm see Spirtes et al. (2000), Pearl (2000), Colombo and Maathuis (2012) and Le et al. (2014).

of causality in case the results obtained are inconsistent or admit of different interpretations. To do so, it uses a mechanism based on specific information about whether or not a certain condition is met (Granger causality in our analysis) as all available information is sequentially included. The application procedure is as follow: (i) First, unconditional (in)dependence tests are carried out between all pairs of variables. (ii) For those pairs of variables where dependence (causality) is detected, the test is repeated, now controlling for another of the variables included in the model. (iii) Sequentially, and if the relationship survives the different tests, the remaining endogenous variables included in the model will be added to the set of control variables. That is, in the last stage, a total of (k-2) variables will be included in the control set. As far as we know, this is the first time this type of algorithm has been used in a panel data environment. In line with the causal graphs literature, which involves a graphical representation of the dependence flows between the different endogenous variables in the model, the above procedure would entail the following. (i) The algorithm starts with a graph G in which all variables are connected to each other. (ii) We set n=0 and analyse the existence of unconditional causality between all pairs of variables. When there is no significant causal relationship, the arrow is removed, thus obtaining the graph G'. (iii) We set n = n + 1 and repeat the tests of independence between those relationships that have survived, but, this time, conditioning on the subset of size n formed by the rest of the adjacent variables, in an iterative manner, until the process is exhausted, obtaining the F graph. (iv) Given X, Y and Z, orient X - Z - Y as X → Z ←Y if and only if X and Y are not independent when conditioned on any subset of variables which, excluding X and Y, includes Z. (v) Repeat the process until there are no nodes left in F that can be oriented.

Figure 5. Stages of the PC algorithm



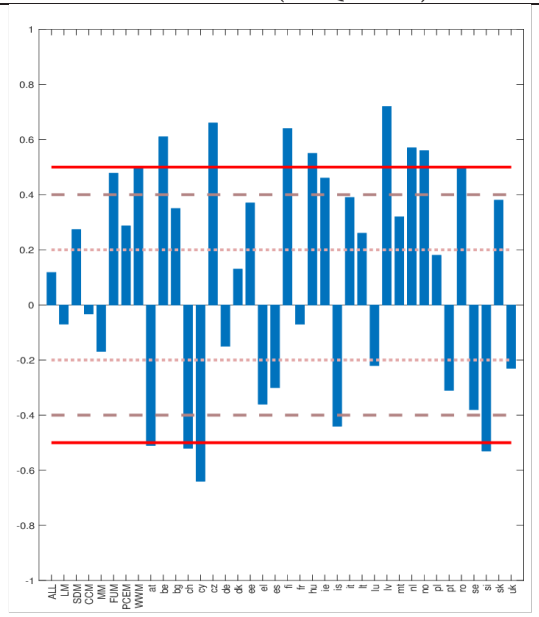
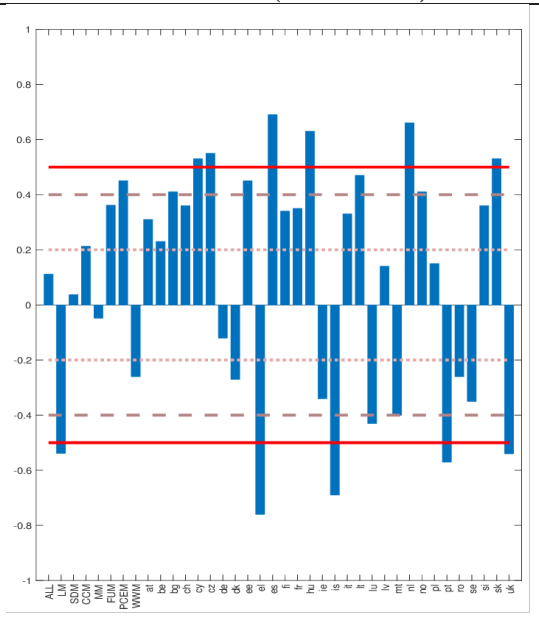
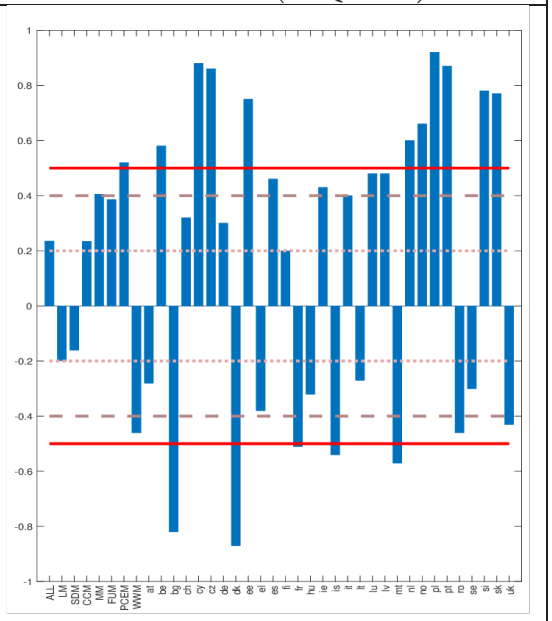
Source: Own elaboration based on Colombo and Maathuis (2014) and Demiralp and Hoover (2003)

For simplicity, this implies performing unconditional causality tests between each of the variables included in the model. Each time one of these tests is significant, it is performed again, but this time controlling sequentially for the rest of the variables in the VAR.

5 Results

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 2004-2020. 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 - L.1 -All Links- Gross Income

ENDO VAR (INQ-GDP)	ENDO VAR (POV-GDP)	ENDO VAR (INQ-POV)
		

Source: Own elaboration using Causality Map Toolbox

Notes: (1) Results obtained from Granger's causality test at 10% of significance level, for the period 2004-2020.

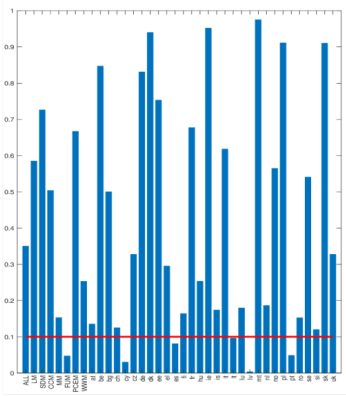
(2) INQ= Gini Index, POV= Anchored Poverty Rate, GDP=Gross Domestic Product.

If we consider gross income, which as mentioned in the introduction will be our benchmark definition of income, we obtain the following: at a first level, for the aggregate of the total sample (ALL), the correlation between the different pairs of variables, although positive in all cases, only exceeds the threshold of 0.2 for the relationship between the inequality and poverty variables. This would indicate that these two variables tend to evolve jointly, albeit with a weak correlation. The rest of the relationships, therefore, do not seem to show a sufficient magnitude to consider some relationship between their movements[14]

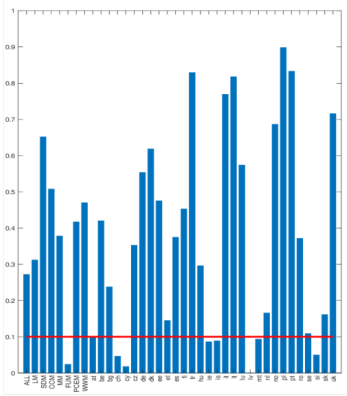
Table 2: P-value Significance - L.1 - Model: Gross Income

Model: Inequality and Economic Growth

Inequality to GDP

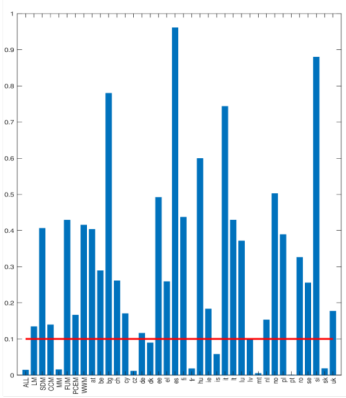


GDP to Inequality

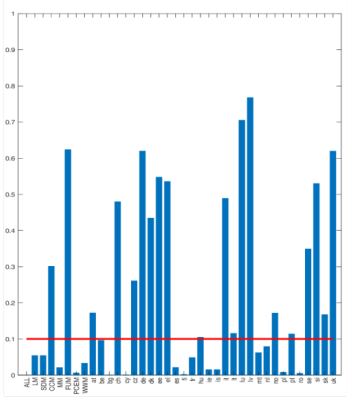


Model: Inequality and Poverty

Inequality to Poverty

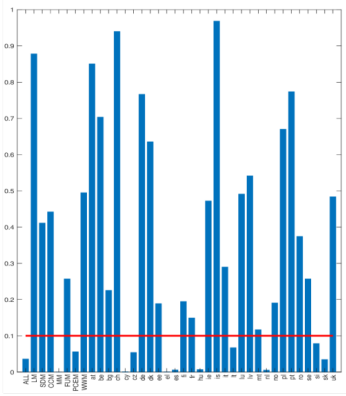


Poverty to Inequality

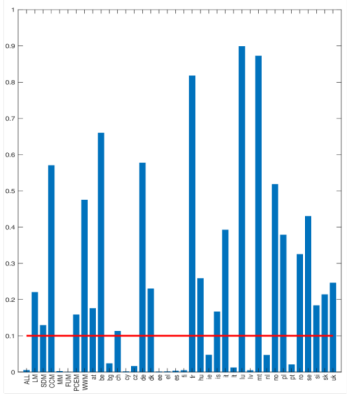


Model: Poverty and Economic Growth

GDP to Poverty



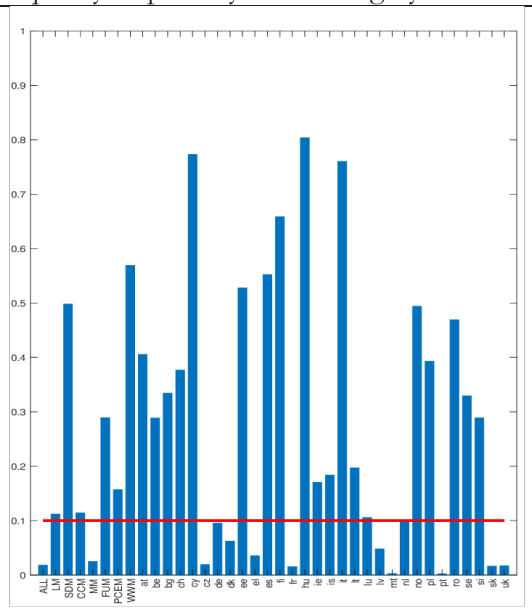
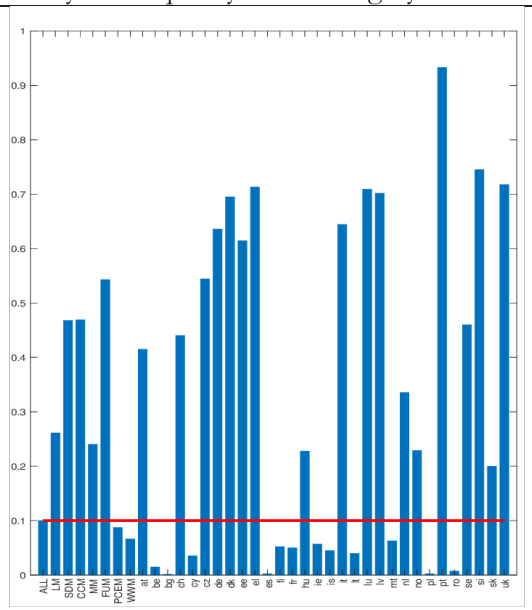
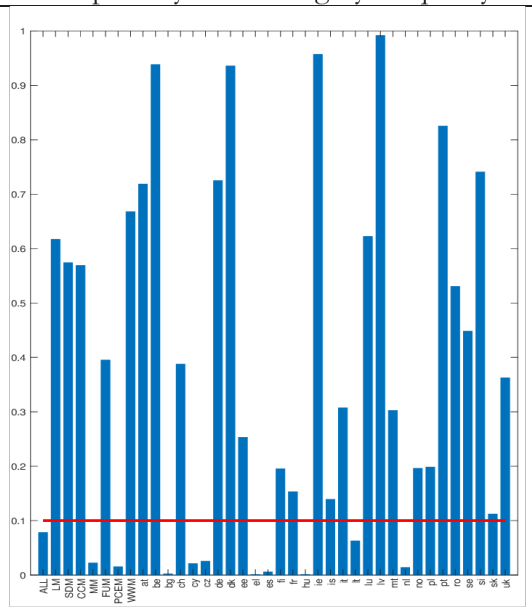
Poverty to GDP



Source: Own elaboration using Causality Map Toolbox
Notes: (1) Results obtained from Granger's causality test at 10% of significance level, for the period 2004-2020.
(2) INQ= Gini Index, POV= Anchored Poverty Rate, GDP=Gross Domestic Product.

14 When interpreting the results of our analysis, it is important to keep in mind the first stage of our methodological proposal, since it is possible that we obtain significance in some of the causality tests between the different pairs of variables, but that we finally disregard it because it does not fall within the bands established for the CCF.

Table 3: P-value Significance - Survival links- Gross Income - Level 2

Inequality to poverty controlling by GDP	Poverty to inequality controlling by GDP	GDP to poverty controlling by inequality
		

Source: Own elaboration using Causality Map Toolbox

Notes: (1) Results obtained from Granger's causality test at 10% of significance level, for the period 2004-2020.

(2) INQ= Gini Index, POV= Anchored Poverty Rate, GDP=Gross Domestic Product.

However, once we look at the rest of the groups or countries individually, we see that the situation is very different, characterised by a marked heterogeneity in both intensity and sign. Thus, for the aggregate of the economies classified as PCEM the correlation is moderate for the relationship between the economic growth variables and the two distributional variables, respectively, and strong for the relationship between poverty and growth. The opposite is true for the group of SDM economies, which have a coefficient below the threshold for correlation for growth-poverty and inequality-poverty and weak for growth. At the same time, the countries in the different classifications do not seem to have a common behaviour at the group level. Thus, the groups that stand out most for their uniformity would be the CCM and the LM. This would suggest that it would be necessary to look at other institutional or economic characteristics in addition to those adopted here in order to capture the different common idiosyncrasies.

The second part of our empirical strategy is to complement the preliminary analysis of co-movement between variables by assessing the significance of various causality tests. In this sense, we have presented in tables 2 and 3 the results obtained for the Granger Causality tests, for level 1 and level 2 respectively. Hence, we can observe that, for the aggregate of the total sample, the relationships between poverty and growth and between poverty and inequality are significant in both directions, while we do not find evidence of a relationship between economic growth and inequality . At first, this would seem to indicate that poverty plays a leading role in shaping the dynamics between the variables. However, taking into account previous results, although the relationship between poverty and growth is significant, the coefficient obtained for the CFF indicates that the magnitude of the effect is so small that it could be considered almost non-existent. Therefore, at a first level, the dynamics are marked by the relationship between the two distributive variables, poverty and inequality.

In table 3, after debugging the relationships by applying the PC algorithm, we observe that, among the relationships that were initially significant, three of them survive. Hence, we find a double causality between the distributional variables of poverty and inequality, plus a very weak effect of economic growth on poverty. From these results, we draw two main conclusions: firstly, over the period studied, economic growth is not an effective tool for reducing inequality and poverty in short term in the economies analysed as a whole. This is congruent with the evolution of the variables described in section 3, where we found that, despite different periods of economic growth, these had not translated into an improvement in distributional indicators (figure 2 and 3). In addition, the double causality between distributional variables may be making more difficult to reverse the worsening general trend observed in poverty and inequality[15].

Finally, table 4 shows the causal graphs generated by combining the information obtained from our causality analysis for the different groups of economies, which graphically represent the dynamics between the different variables. First, we find that the dynamics between variables are very different for the different groups, both in direction or effect and in significance.

Hence, we find that for the LM, SDM and CCM economies there is no causal dynamic between variables, while growth seems to play a key role in shaping the dynamics in the PCEM economies. Tables A.1 and A.2 from the Annex provide the causal graphs calculated for both market and disposable income. The main difference between the three income's definition is found when moving from market to gross income, which may be indicative of the powerful role play by cash transfer in avoiding the negative effects found of poverty on economic growth at market income.

However, the relevance of our results is not to identify a specific causal model that is supported by one of the previous theoretical paradigms, but rather to point out that there are certain analytical and methodological caveats that should be taken into account when revising such paradigms. If anything is evident from the analysis of our results, it is that they are characterised by a high degree of variability. On the one hand, we observe that depending on the specific countries we look at, we find different causal relationships. Thus, we can highlight, among others, the case of the countries of the conservative corporatist model, in which inequality has a positive effect on

15 This would indicate that there is no evidence of significance in the relationship between these variables in most countries, although this relationship may be significant for specific groups or countries, as in the case of the economies of the FUM group.

poverty, as opposed to the post-communist European model, in which we find that it is economic growth that leads the relationship, having a positive effect on poverty, which extends from poverty to inequality. In this sense, one of the fundamental advantages of the methodological approach we adopt in this paper is that it allows us to directly exploit the individual characteristics of each of the countries without losing the objective of trying to establish common patterns or trends. On the other hand, it is unquestionable that public intervention can be decisive in the final configuration of these relationships, as the causal path varies completely depending on the income stage considered. As we have shown above, there is empirical support to affirm that its result varies depending on whether we consider its function via expenditure (cash transfers) or taking into account, in addition, the effect of the tax system (disposable income). This, in turn, serves as a clue to the importance of focusing on dynamic analysis, since throughout the period analysed, the trends in transfers and revenue collection were very different and were strongly influenced by the evolution of the economic cycle.

On the other hand, our results also indicate that trying to impose an a priori causal structure may be influencing the results obtained in the empirical literature, as not only do we find that the double causality relationship between variables is usually common, but we also observe very diverse causal structures that, to some extent, differ from the established and accepted. Thus, it seems appropriate to be cautious about imposing common, time-constant models for economies that are different from each other.

Table 4: Causality Maps - Gross Income

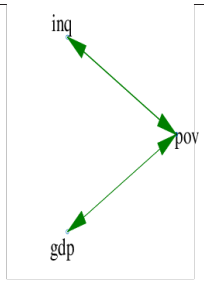
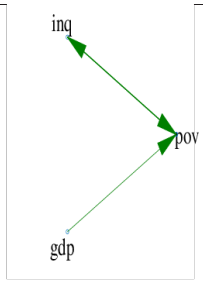
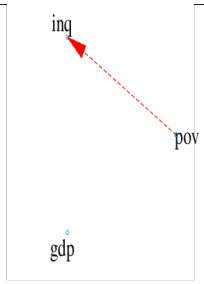
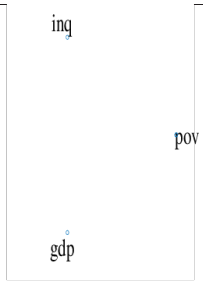
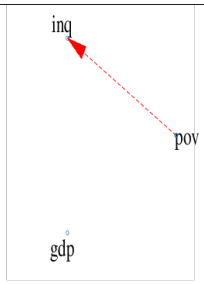
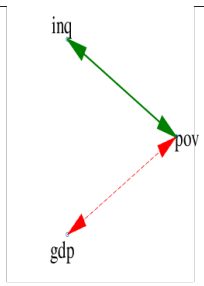
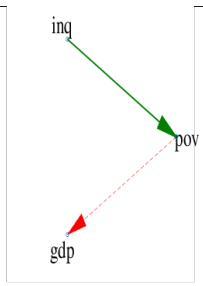
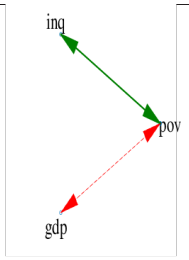
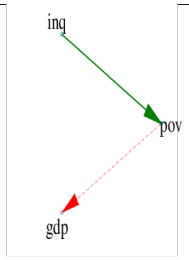
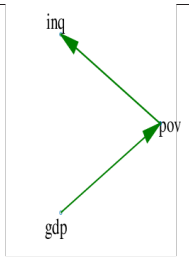
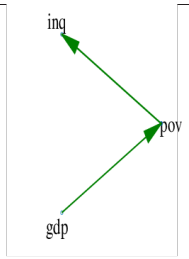
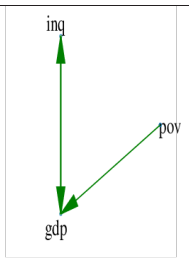
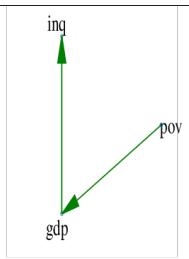
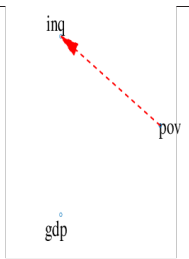
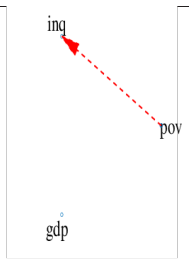
UNIT	L1	L2
ALL		
LM		
SDM		
CCM		

Table 4 (cont): Causality Maps - Gross Income

UNIT	L1	L2
MM		
PCEM		
FUM		
WWM		

Source: Own elaboration using Causality Map Toolbox Notes:
(1) Results obtained from Granger's causality test at 10% of significance level, for the periodo 2004-2020. Solid (Dashed) line indicates that the crossed-correlation between each pair of nodes is positive (negative). Finally, the wider the line, the higher this value.
(2) INQ= Gini Index, POV= Anchored Poverty Rate, GDP=Gross Domestic Product.

6 Conclusions

A proper understanding of the relationships between economic growth and the main distributional variables is essential for the design of effective public policies that allows to achieve certain social objectives. In general, much of the empirical literature that has focused on analysing this relationship has focused on it from a comparative static perspective. However, in order to deepen the analysis and contribute to the understanding of such a complex phenomenon, we believe that it is also necessary to take into account the dynamic evolution of these relationships.

In this paper we carry out a dynamic Granger causality analysis between economic growth, monetary poverty and income inequality for 30 European economies over the period 2004-2020. For this purpose, we use an annual frequency database constructed from EU-SILC micro-data. Our analysis is based on a VAR model for panel data, where we compute different synthetic estimators from the individual statistics. Complementarily, we apply a causal search algorithm that allows us to debug possible incongruent relationships (the PC algorithm) and interpret its results in line with the established in the literature of causal graph.

As shown in the paper, we observe that, for the total sample, the interaction between inequality and poverty plays a key role in shaping the evolution of the distributional dynamics, an effect that is found in most of the stages analysed. Except for market income, we also find a positive effect of economic

growth on poverty, which becomes a double causality relationship for disposable income. We also find that economic growth does not affect the evolution of any of the distributional variable. However, when we classify economies into different typologies of welfare states to study them separately, we find that the previous relationships can change completely, even disappearing for some of the groups.

Some relevant conclusions can be derived from our results. Firstly, it should be emphasised that economic growth does not seem to show an inequality or poverty reducing effect in any of the groups analysed or income definitions analysed. These results, on the one hand, challenge the trickle-down hypothesis, which argues that higher economic growth would benefit, through indirect effects, those households with fewer resources. It also shows us that, in order to reduce poverty and inequality, it is necessary to undertake specific policies and not rely exclusively on policies aimed at enhancing economic growth. Furthermore, for most models, we find evidence of a robust relationship between the two distributional variables, either through direct or indirect effects. Therefore, it seems necessary to take into account the interaction between the two when designing different social policies.

Moreover, we note that the results obtained are sensitive to the specific countries included in each exercise, which has several implications. This suggests that the design of universalist or generalist economic policy recommendations would be less effective than specifically designed public policies for different groups of countries. On the other hand, we also observe that the relationships that we find in the first income stage disappear totally or partially as we move the focus of the analysis to income distributions in which the intervention of the public sector is greater, such as gross income, where cash transfers are include, or disposable income, after the application of the direct taxes considered in the analysis. We can conclude that public intervention would be an effective tool to mitigate possible shocks or adverse effects arising from these relationships, both through expenditure and through the tax system, as far as direct taxation is concerned.

In conclusion, we should emphasise that the main contributions of our work lie in the novelty of the dynamic approach adopted, which we believe can serve to complement and enrich the debate on the matter. Thus, our methodological approach focuses on causal dynamics, relatively forgotten in favour of approaches based on comparative statics, in which the relational sequence appears pre-established. This change of perspective, we believe, allows us to question certain a priori assumed relationships. We should also clarify that we approach the study of causal relationships between growth, inequality and poverty from a neutral perspective, exploring all possible causal flows between variables and without first imposing a sense of causality. In addition, we jointly analyse the relationship between economic growth and the different distributional variables that have often been analysed as separate issues.

6. Referencias

Adams Jr, R. H. (2004). Economic growth, inequality and poverty: estimating the growth elasticity of poverty. *World development*, 32(12), 1989-2014.

Alesina, A., and Rodrik, D. (1994). Distributive politics and economic growth. *The Quarterly Journal of economics*, 109(2), 465-490.

Atkinson, A. B. and Brandolini, A. (2001). Promise and pitfalls in the use of "secondary" data-sets: Income inequality in OECD countries as a case study. *Journal of Economic Literature*, 39(3), 771-799.

Banarjee, A. (2000). The Two Poverties. *Nordic Journal of Political Economy*, 26, 129-141.

Banerjee, A. and Newman, A. F. (1993). Occupational choice and the process of development. *The Journal of Political Economy*, 101(2), 274-298.

Banerjee, A., and Duflo, E. (2003). Inequality and growth: What can the data say? *Journal of Economic Growth*, 8(3), 267-299. 10.3386/w7793

Banerjee, A., and Mullainathan, S. (2010). The shape of temptation: Implications for the economic lives of the poor (No. w15973). *National Bureau of Economic Research*.

Barro, R. J. (2000). Inequality and Growth in a Panel of Countries. *Journal of Economic Growth*, 5(1), 5-32.

Bergstrom, K. (2020). The Role of Inequality for Poverty Reduction. (Policy Research Working Paper;No. 9409). *World Bank*. 10.1596/1813-9450-9409

Bertola, G. (1993) Factor shares and savings in endogenous growth. *American Economic Review* 83(5), 1184-1198.

Bluhm, R., de Crombrugghe, D. and Szirmai, A. (2018). Poverty accounting. *European Economic Review*, 104, 237-255. https://doi.org/10.1016/j.euroecorev.2018.03.003

Bourguignon, F. (1981). Pareto superiority of unegalitarian equilibria in Stiglitz'model of wealth distribution with convex saving function. *Econometrica: Journal of the Econometric Society*, 49(6), 1469-1475. https://doi.org/1911412

Castelló-Climent, A. (2010). Inequality and growth in advanced economies: An empirical investigation. *Journal of Economic Inequality*, 8(3), 293-321. 10.1007/s10888-010-9133-4

Cerra, V., Lama, R. and Loayza, N. (2021). Links between growth, inequality, and poverty: a survey. (Policy research working paper 9603.) *World Bank Group*

Cingano, F. (2014). Trends in Income Inequality and its Impact on Economic Growth, *OECD Social, Employment and Migration Working Papers*, No. 163, https://doi.org/10.1787/5jxrjncwxv6j-en.

Colombo, D. and Maathuis, M. H. (2014). Order-independent constraint-based causal structure learning. *J. Mach. Learn. Res*., 15(1), 3741-3782

Dasgupta, P. and Ray, D. (1986). Inequality as a determinant of malnutrition and unemployment: Theory. *The Economic Journal* , 96(384), 1011-1034. 10.2307/2233171

David, F. (1949). The moments of the z and F distributions. *Biometrika*, 36(3), 394–403.

Deininger, K. and Squire, L. (1996). A new data set measuring income inequality. *The World Bank Economic Review,* 10(3), 565-591. 10.1093/wber/10.3.565

Deininger, K. and Squire, L. (1998). New ways of looking at old issues: inequality and growth. *Journal of Development Economics*, 57(2), 259-287.

Demiralp, S. and Hoover, K. D. (2003). Searching for the causal structure of a vector autoregression. *Oxford Bulletin of Economics and Statistics*, 65(s1), 745-767. 10.1046/j.0305-9049.2003.00087.x

Dollar, D. and Kraay, A. (2002). Growth is Good for the Poor. *Journal of Economic Growth*, 7(3), 195-225.

Dollar, D., Kleineberg, T. and Kraay, A. (2016). Growth still is good for the poor. *European Economic Review*, 81, 68-85. 10.1016/j.euroecorev.2015.05.008

Eichler, M. (2007). Granger causality and path diagrams for multivariate time series. *Journal of Econometrics*, 137(2), 334-353. 10.1016/j.jeconom.2005.06.032

Emirmahmutoglu, F. and Kose, N. (2011). Testing for granger causality in heterogeneous mixed panels. *Economic Modelling*, 28(3), 870-876. 10.1016/j.econmod.2010.10.018

Esping-Andersen, G. (1990). The three worlds of welfare capitalism. *Princeton University Press*.

Fenger, M. (2007). Welfare regimes in Central and Eastern Europe: Incorporating post-communist countries in a welfare regime typology. *Contemporary Issues and Ideas in Social Sciences*, 3(2), 1-30.

Ferreira, F. H. G., Leite, P. G. and Ravallion, M. (2010). Poverty reduction without economic growth? *Journal of Development Economics*, 93(1), 20-36. 10.1016/j.jdeveco.2009.06.001

Ferrera, M. (1996). The "Southern Model" of Welfare in Social Europe. *Journal of European Social Policy*, 6(1), 17–37. https://doi.org/10.1177/095892879600600102

Foellmi, R. and Zweimüller, J. (2006). Income distribution and demand-induced innovations. *The Review of Economic Studies*, 73(4), 941-960. 10.1111/j.1467-937X.2006.00403.x

Forbes, K. (2000). A reassessment of the relationship between inequality and growth. *The American Economic Review*, 90(4), 869-887.

Fosu, A. K. (2017). Growth, inequality, and poverty reduction in developing countries: Recent global evidence. *Research in Economics*, 71(2), 306-336. doi:10.1016/j.rie.2016.05.005

Galor, O. and Moav, O. (2004). From physical to human capital accumulation: Inequality and the process of development. *The Review of Economic Studies*, 71(4), 1001-1026.

Galor, O. and Zeira, J. (1993). Income distribution and macroeconomics. *The Review of Economic Studies,* 60(1), 35-52.

Goerlich. F. J. (2016). Distribución de la renta, crisis económica y políticas redistributivas. *Fundacion BBVA.*

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37(3), 424-438. 10.2307/1912791

Halter, D., Oechslin, M. C. and Zweimüller, J. (2014). Inequality and growth: The neglected time dimension. *Journal of Economic Growth*, 19(1), 81-104. doi:10.1007/s10887-013-9099-8

Hurlin, C. and Venet, B. (2001). Granger causality tests in panel data models with fixed coefficients. *Cahier de Recherche EURISCO*, September, Université Paris IX Dauphine.

Kakwani, N. and Pernia, E. M. (2000). What is pro-poor growth?. *Asian Development Review*, 18(1), 1-16.

Kaldor, N. (1955). Alternative theories of distribution. *The Review of Economic Studies,* 23(2), 83-100. https://doi.org/2296292

Kraay, A. (2015). Weak instruments in growth regressions: implications for recent cross-country evidence on inequality and growth. (Working Paper 7494) *World Bank Policy Research*.10.1596/1813-9450-7494

Kraay, A. and McKenzie, D. (2014). Do poverty traps exist? Assessing the evidence. *The Journal of Economic Perspectives*, 28(3), 127-148. 10.1257/jep.28.3.127

Lauritzen, S. L. and Richardson, T. S. (2002). Chain graph models and their causal interpretations. *Journal of the Royal Statistical Society*. Series B, Statistical Methodology, 64(3), 321-348. 10.1111/1467-9868.00340

Lazear, E. and Rosen, S. (1981). Rank-order tournaments as Optimum Labor contracts. *The Journal of Political Economy*, 89(5), 841-864.

Le, T. D., Hoang, T., Li, J., Liu, L., Liu, H. and Hu, S. (2016). A fast PC algorithm for high dimensional causal discovery with multi-core PCs. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 16(5), 1483-1495.

Li, H. and Zou, H. (1998). Income inequality is not harmful for growth: Theory and evidence. *Review of Development Economics*, 2(3), 318-334. 10.1111/1467-9361.00045

Loayza, N. V. and Raddatz, C. (2010). The composition of growth matters for poverty alleviation. *Journal of Development Economics*, 93(1), 137-151

Marrero, G. A. and Servén, L. (2021). Growth, inequality and poverty: A robust relationship? *Empirical Economics*, 1-67. 10.1007/s00181-021-02152-x

Muñoz de Bustillo, R. (2019). Mitos y realidades del Estado de Bienestar. *Alianza Editorial,* Madrid

Okun, A. M. (1975). Equality and efficiency: The big tradeoff. *Brookings Institution Press*.

Perotti, R. (1996). Growth, income distribution, and democracy: What the data say. *Journal of Economic Growth.* 1(2), 149-187. 10.1007/BF00138861

Persson, T. and Tabellini, G. E. (1994). Is inequality harmful for growth?. *The American Economic Review*, 84(3), 600-621.

Ravallion, M. (2004b). Pro-poor growth: A primer. (World Bank Policy Research Working Paper 3242). *World Bank*.

Ravallion, M. and Chen, S. (1997). What can new survey data tell us about recent changes in distribution and poverty?. *The World Bank Economic Review*, 11(2), 357-382.

Shah, A. K., Mullainathan, S. and Shafir, E. (2012). Some consequences of having too little. *Science*, 338(6107), 682-685.

Spirtes, P., Glymour, C. N., Scheines, R. and Heckerman, D. (2000). Causation, Prediction, and Search. *MIT press*.

Voitchovsky, S. (2005). Does the profile of income inequality matter for economic growth?: Distinguishing between the effects of inequality in different parts of the income distribution. *Journal of Economic Growth*. 10(3), 273-296. 10.1007/s10887-005-3535-3

ANNEX

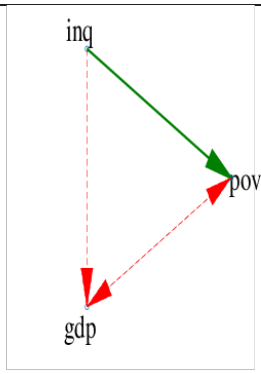
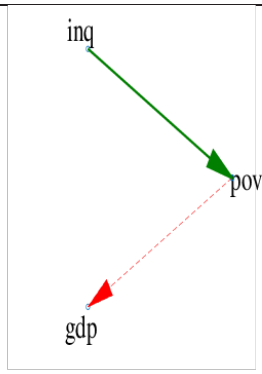
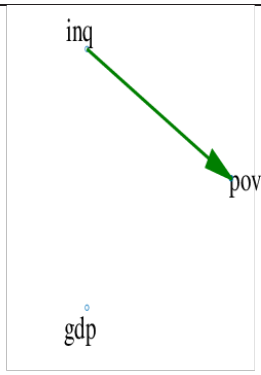
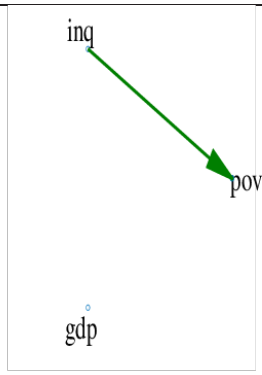
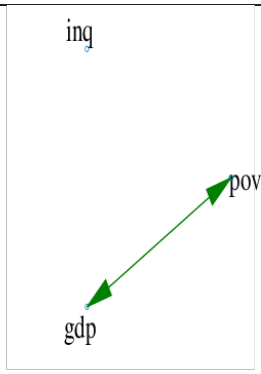
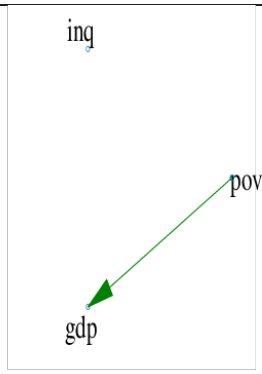
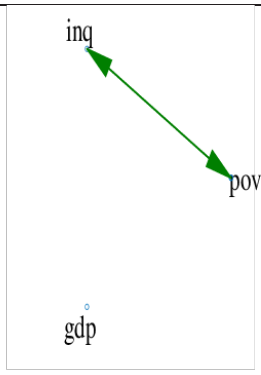
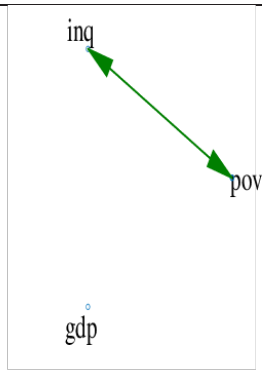
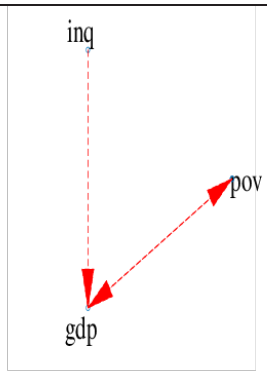
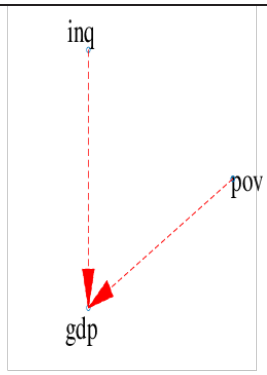
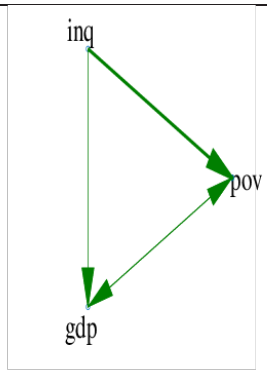
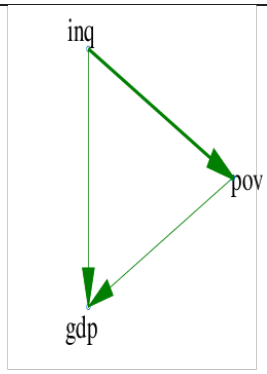
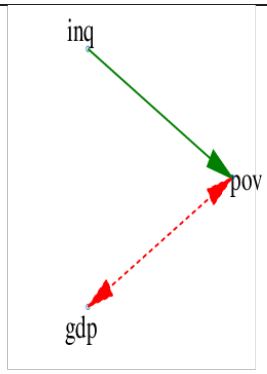
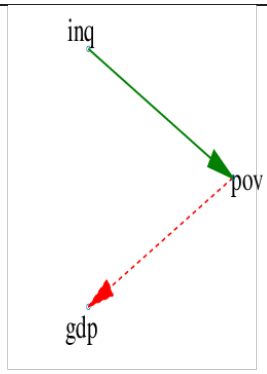
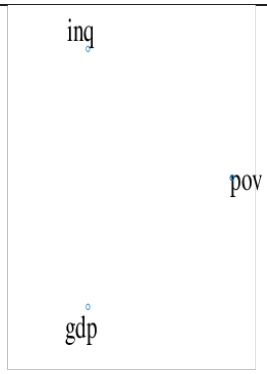
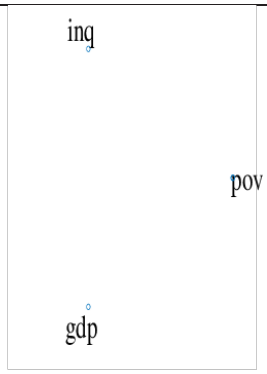
Table A.1: Causality Maps - Market Income		
UNIT	L1	L2
ALL		
LM		
SDM		
CCM		

Table A.1 (cont): Causality Maps - Market Income		
UNIT	L1	L2
MM		
PCEM		
FUM		
WWM		

Source: Own elaboration using Causality Map Toolbox Notes:
(1) Results obtained from Granger's causality test at 10% of significance level, for the periodo 2004-2020. Solid (Dashed) line indicates that the crossed-correlation between each pair of nodes is positive (negative). Finally, the wider the line, the higher this value.
(2) INQ= Gini Index, POV= Anchored Poverty Rate, GDP=Gross Domestic Product.

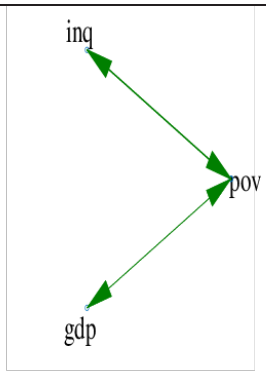
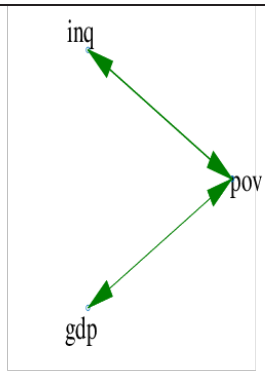
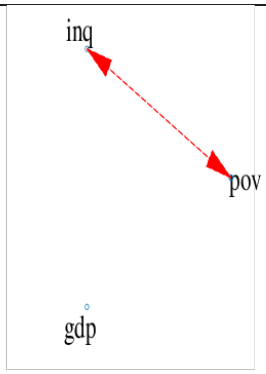
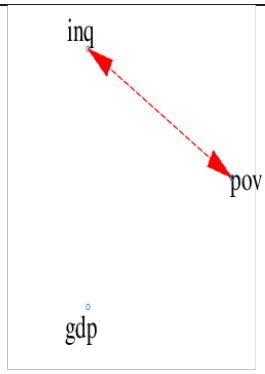
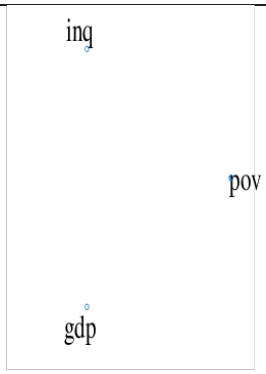
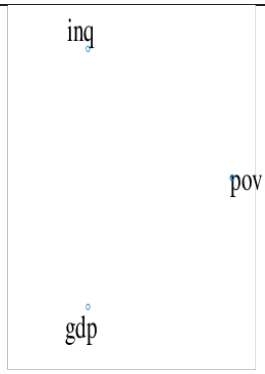
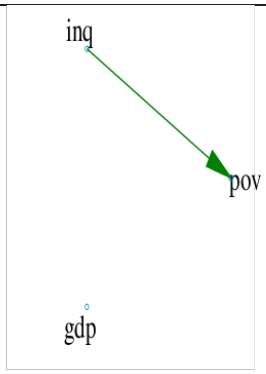
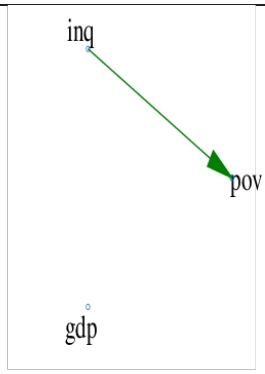
Table A.2: Causality Maps - Disposable Income		
UNIT	L1	L2
ALL		
LM		
SDM		
CCM		

Table A.2 (cont): Causality Maps – Disposable Income		
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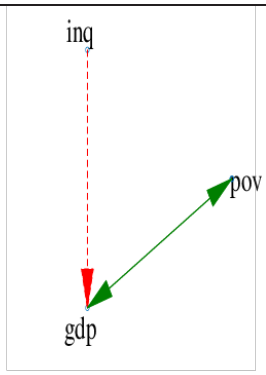
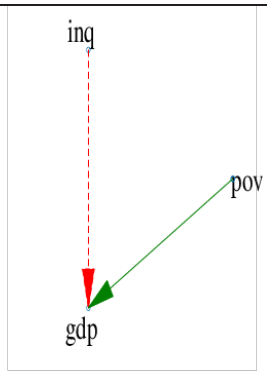
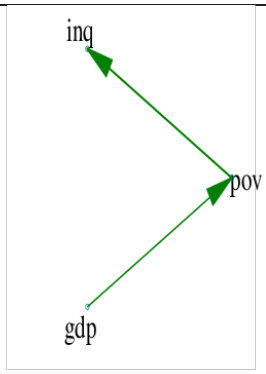
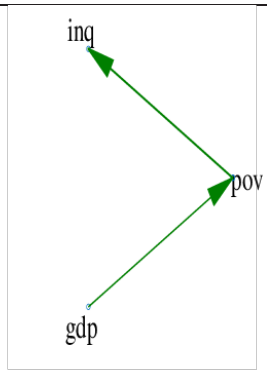
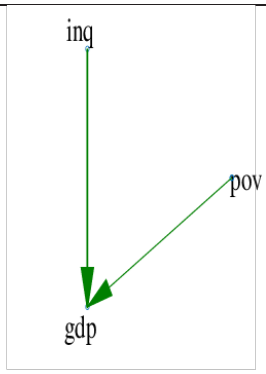
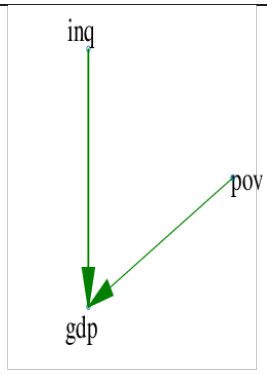
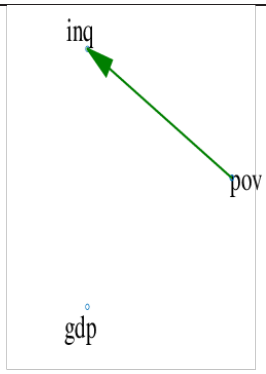
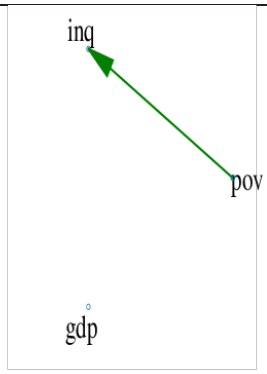
MM		
PCEM		
FUM		
WWM		

Source: Own elaboration using Causality Map Toolbox Notes:
(1) Results obtained from Granger's causality test at 10% of significance level, for the periodo 2004-2020. Solid (Dashed) line indicates that the crossed-correlation between each pair of nodes is positive (negative). Finally, the wider the line, the higher this value.
(2) INQ= Gini Index, POV= Anchored Poverty Rate, GDP=Gross Domestic Product.

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OP 02/17 Braña, Francisco J.; Molero, José: *The economic role of the State on the Spanish democratization and "development" process. A case of success?*

OP 01/16 Borrell, Josep; Mella, José María; Melle, Mónica; Nieto, José Antonio. *"¿Es posible otra Europa? Debate abierto."*