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# SOCIAL EXCLUSION AND ECONOMIC GROWTH: AN EMPIRICAL INVESTIGATION IN EUROPEAN ECONOMIES

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The aims of this article are to propose an overall index of social exclusion and to analyze its relationship with economic growth in European countries. We approach social exclusion as a multidimensional phenomenon by a three-mode principal components analysis (Tucker3 model). This method is applied to estimate an indicator of social exclusion for 28 European countries between 1995 and 2010. The empirical evidence shows that in the short run: (1) Granger causality runs one way from social exclusion to economic growth and not the other way; (2) countries with a higher level of social exclusion have higher growth rates of real GDP per capita; and (3) social exclusion has a larger effect than income inequality on economic growth. The policy implication of our analysis is that social inclusion is not a source of economic growth in the short term.

**JEL Codes**: C82, D63, I3, O15, O52

**Keywords**: economic growth, multidimensional index, social exclusion, three-mode principal components analysis

## 1. Introduction

The aims of this paper are: (1) to propose an aggregate overall index of social exclusion in order to assess the intensity and evolution of this phenomenon in European countries; and (2) to analyze its relationship with economic growth in Europe over the period 1995–2010.

Social exclusion is a multidimensional general concept that refers not only to material, economic, or health deprivation, but also to deprivation from social relationships and participation in society. A growing literature addresses the issue of how appropriately an index of overall social exclusion (e.g., Burchardt *et al.*, 1999; Bradshaw *et al.*, 2000; Tsakloglou and Papadopoulos, 2002; Whelan *et al.*, 2002; Chakravarty and D'Ambrosio, 2006; Bossert *et al.*, 2007; Poggi, 2007) can be measured. The assessment of social exclusion by scientific debates has become an even more important task both for understanding and for policy evaluation. In fact, an aggregate index of social exclusion can serve as a useful indicator of both the overall level of social disadvantage and the overall effectiveness of governmental social policies (Micklewright, 2001).

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With regard to the first issue, while proposing quite a new approach for the economic field (i.e., Multiway Principal Component Analysis), we present an overall (macro) index of social exclusion based on five main areas: employment, poverty, income inequality, education, and health. These meta-dimensions include many accepted indicators that have been selected according to the EU approach of social exclusion (e.g., European Commission, 2004, 2008).

With regard to the second issue—analyzing the relationship between social exclusion and growth in European countries—we attempt to broaden the perspective of existing literature. This is made possible by testing the relationship between economic growth and the previously estimated overall index of social exclusion. This analysis is carried out on a dataset by collecting observations for 28 European countries over the period 1995–2010.

The relationship between income inequality and growth has spawned a large theoretical and empirical body of literature (for a survey, see, e.g., Barro, 2000; Forbes, 2000; Kanbur, 2000). In this research, we aim at extending this literature by examining the relationship between economic development and a wider concept of disparities/inequality, that is, social exclusion. The latter captures the multidimensional aspects of (relative) socioeconomic disadvantages more effectively than income inequality and poverty do.

Recent studies point out the role played by social exclusion in economic growth. The increasing scientific interest in this issue has been amplified by greater relevance that the fight of social exclusion has for European institutions. Since the Treaty of Amsterdam (1997) and the launch of *Lisbon's Strategy* (2000), social inclusion has been considered one of the strategic objectives of the EU. Again, in March 2010, the European Council re-launched social cohesion as one of the five key areas of the "Europe 2020 strategy." Due to the greater relevance that social inclusion has for European policies, the literature on social exclusion also has been mainly concerned with problems in European countries (Gore and Figueiredo, 1997; Walker and Walker, 1997; Sen, 2000; Tsakloglou and Papadopoulos, 2002). Following this strand, this article has its geographical focus on Europe. Thus, our results indirectly provide an empirical investigation of the theoretical background of the EU policies, which, in fact, assume a significant positive relationship between social inclusion and economic growth.

The empirical evidence shows that, in the short run, countries with a higher level of social exclusion have higher growth rates of GDP per capita.

This article is organized as follows. The definition and measurement issues related to social exclusion are discussed in Section 2. In Section 3, we outline our proposed framework for the measurement of the overall index of social exclusion and present the results. A summary of the various theories on the relationship between inequality and growth is presented in Section 4.1. Section 4.2 describes the econometric model. Section 4.3 gives the results of the empirical analysis on the relationship between social exclusion and economic growth. Section 5 contains the conclusion. The data available and comparison among alternative approaches to estimate the index of social exclusion are briefly reviewed in the Appendixes.

## 2. Social Exclusion: Definitions and Measurement Issues

### 2.1. *Defining Social Exclusion*

The history of the concept of social exclusion is relatively short, but the literature on the subject is already large and rapidly growing (Flotten, 2006). Several definitions are proposed in the literature; however, in essence, they hold the concept that social exclusion includes a wide range of dimensions of marginalization and exclusion. These dimensions refer, not only to material, economic, or health deprivation, but also to deprivation from social relationships and participation in society.

Essentially four approaches to define social exclusion are proposed in the literature: (1) social exclusion as the lack of participation in social institutions (Duffy, 1995; Rowntree Foundation, 1998; Paugam and Russell, 2000); (2) social exclusion as the denial or non-realization of social, political, and civil rights of citizenship (Room, 1995; de Haan, 2000); (3) social exclusion as an increase in the distance among population groups (Akerlof, 1997); and (4) social exclusion as a process that leads to a state of functioning deprivations (Sen, 1998, 2000).

Social exclusion borrows much from earlier literature on deprivation and poverty, and it is related, but not equivalent, to concepts such as inequality and poverty (Atkinson, 1998; Sen, 1998, 2000; Atkinson *et al.*, 2002; Robila, 2006; Atkinson and Marlier, 2010).[1] Opinions differ over the nature of this relationship. On the one hand, poverty has been described as a cause of social exclusion, in as much as it prevents participation and access to the various networks that can help people into education, homes, jobs, and services (e.g., de Haan, 2000). On the other hand, social exclusion has been considered a cause, or an element, of poverty (e.g., Jordan, 1996). However, social exclusion differs from early "income" poverty, as the last is only concerned with lack of economic resources; whereas social exclusion refers to a broad range of dimensions of deprivation (Berghman, 1995; Atkinson and Marlier, 2010).

The relationship between social exclusion, inequality, and poverty can be usefully considered in the perspective of Sen's *capability approach*. In this perspective, all these concepts deal with functioning disparities or failures, but social exclusion refers to functioning failures in terms of the inability to participate and emphasizes the role of relational features in the deprivation of capability (Sen, 2000). As Sen points out, social exclusion can be constitutively a part of capability deprivation. It happens when one is not able to relate to others and to take part in the life of the community; this can directly impoverish a person's life. For example, persistent exclusion from the labor market or credit access may impoverish a person and cumulatively lead to other deprivations, such as underconsumption, undereducation, or homelessness. However, social exclusion can also be instrumentally a cause of diverse capability failures, inequalities, and poverty. It happens

[1]Notions of multidimensional inequalities and poverty can be found even in Aristotle's *Nicomachean Ethics*, and notions of exclusion and inclusion are an essential part of the concept of poverty defined by Adam Smith in the *Wealth of Nations* (Sen, 1998, 2000). So, "the helpfulness of the social exclusion approach does not lie in its conceptual newness, but in its practical influence in forcefully emphasizing—and focusing attention on—the role of relational features in deprivation" (Sen, 2000, p. 8).

when even significant exclusions may not be impoverishing in themselves, but can lead to the impoverishment of human life through their causal consequences (Sen, 2000).

This article refers to Atkinson and Marlier's (2010, p. 1) definition of social exclusion as "the involuntary, not transitory exclusion of individuals and groups from society's political, economic and societal processes, which prevents their full participation in the society in which they live." According to this description, individuals or groups are excluded when: (1) they suffer disadvantages in terms of education, training, employment, housing, financial resources, health, and so on; (2) their chances of gaining access to socioeconomic relations and to major social institutions that distribute these life chances are low if compared with the others; and (c) these disadvantages persist over time (Room, 1990; Byrne, 1999).

A general consensus has formed around some key attributes of social exclusion. First, social exclusion is a purely relative and relational concept. "Exclusion" refers to a specific society at a specific point in time. It is concerned with comparisons of different individuals or groups and emphasizes the quality of their (socioeconomic) relationships. Individuals can be considered socially excluded only relatively to other members of the specific society in which they live, if there is a major discontinuity in their relationships with the rest of society, a lower degree of social participation, and lack of socioeconomic integration. So, unlike poverty, social exclusion can be only relative (Tsakloglou and Papadopoulos, 2002; Bossert *et al.*, 2007; Scutella *et al.*, 2009). In this comparative context, if the focus is on disparities or deprivation of opportunities, we move in the direction of the idea of poverty as capability deprivation. In a similar way, social exclusion is concerned with the absence of interrelations between the opportunities enjoyed by different members of the community (Sen, 2000).

Second, unlike inequality and poverty, social exclusion is a dynamic concept. Exclusion depends not only on current situations, but also on "prospects for the future" (Atkinson, 1998). Individuals or groups can be considered socially excluded when deprivation, inadequate social relations, and lack of participation persist or may worsen over time. Furthermore, according to Atkinson and Marlier (2010, p. 13), "social exclusion is not only a matter of ex post trajectories but also of ex ante expectations." Within this framework, social exclusion has to be analyzed as a process, and it requires the inclusion of time as an important variable. Therefore, forward-looking indicators are needed (Atkinson, 1998; Tsakloglou and Papadopoulos, 2002; Bossert *et al.*, 2007).

### 2.2. *Measuring Social Exclusion*

Social exclusion, as we have already seen, is a multidimensional concept that focuses on deprivation in different areas. As a consequence, a wide range of indicators of living standards is required to measure an overall index of this phenomenon. Taking this into account, most of the EU countries now produce, often at a micro level, several indicators that are related to the specific areas of individual deprivation and social exclusion: incomes, employment, health, education, and access to housing and other services (Atkinson *et al.*, 2002; Marlier *et al.*, 2007; Scutella *et al.*, 2009).

Indices of overall social exclusion or deprivation are needed both for understanding such a multidimensional phenomenon and for policy evaluation. For example, an aggregate index makes it possible to compare social exclusion levels among different countries, to evaluate the impact of socioeconomic policies implemented by governments, and to measure changes over time and/or across countries. In addition, according to Micklewright (2001), there are at least two obvious arguments for the use of an aggregate measure of poverty and social exclusion: it would summarize the overall picture, thus avoiding the problem of fuzziness of multiple indicators, to allow a more clear understanding to emerge; and it would guarantee a better communication, getting more attention on the field, as happened with the United Nations Development Program's Human Development Index.

In this regard, the multidimensional nature of social exclusion gives rise to a methodological problem of aggregation. It is about how to get a synthetic measure of overall social exclusion from a portfolio of indicators referring to several different areas of deprivation and exclusion, generally defined at the micro level. In some sense, defining a measure of overall social exclusion can be seen as a problem of multivariate analysis (Poggi, 2003).

There is a very substantial body of literature related to the measurement of social exclusion and linked concepts (e.g., Burchardt *et al.*, 1999; Bradshaw *et al.*, 2000; Tsakloglou and Papadopoulos, 2002; Whelan *et al.*, 2002; Atkinson, 2003; Bourguignon and Chakravarty, 2003; Chakravarty and D'Ambrosio, 2006; Daly, 2006; Bossert *et al.*, 2007; Poggi, 2007; Amendola and Dell'Anno, 2008; Hayes *et al.*, 2008; Bossert *et al.*, 2013).

According to Atkinson and Marlier (2010), it is possible to distinguish between two different forms of aggregation of the different dimensions (characteristics) of social exclusion. The first combines different characteristics at the individual level (for example, persons or households), which are aggregated over individuals to form an overall index.[2] The second approach aggregates first across people and then across fields (characteristics) and, thus, utilizes a combination of aggregate indicators (e.g., Atkinson, 2003). These two approaches introduce two methods that measure social exclusion. In fact, the first one, that is predominant in the literature, focuses on multiple deprivations at the individual level, which requires micro-datasets containing information covering the different relevant domains (i.e., empirical analyses are performed using longitudinal data). The latter at the macro level compares the relative dimension of social exclusion across countries and over time (i.e., empirical analyses are performed using a panel dataset of aggregate variables). This article focuses on the latter approach.

Differences between two approaches may exist as a consequence of different nature and methods of micro and macro data collection. In particular, the sizes of

[2]In this strand of literature, there is a line of research that develops an axiomatic approach to the measurement of social exclusion. Among these, Chakravarty and D'Ambrosio (2006) and Bossert *et al.* (2007), similar to this research, estimated the social exclusion in EU member states, respectively, for the periods 1994–98 and 1994–2001.

response bias[3] change by aggregating individual-level data (e.g., based on household panel) instead of using data collected according to the methodology of national accounting. Considering that this kind of measurement bias usually occurs when respondents omit or distort—sometimes unconsciously—answers involving sensitive and private aspects of their life (e.g., mental health, material deprivation, social or political participation), differences in response bias may be relevant to measure a concept as social exclusion. In this sense, the macro approach may reduce the respondent bias on these sensitive questions looking for this information in manifest variations of observable variables (e.g., crude death rate from suicide, inactivity rate, share of people with low educational attainment). However it may have the cost of a more rough approximation of the dimensions of social exclusion.

This argument strengthens the authors' opinion that the two approaches are complementary and interdependent (e.g., macro data are usually based on the characteristics observed at the individual level).

According to UNDP (2011), in this area of research, the literature provides no straightforward algorithm for the construction of a multidimensional social exclusion index for a panel of countries. It rather provides some general guidance and suggestions of good practices in the area (Gordon and Pantazis, 1997; Scutella *et al*., 2009; Atkinson and Marlier, 2010; Alkire and Foster, 2011). In particular, Atkinson and Marlier (2010) provided an overview of the challenges of measuring social exclusion and identified a minimum set of principles for social exclusion indicators. The first principle is that the set of indicators should be balanced across the different dimensions. It implies that the selection should ensure that all the main areas of concern are covered. The second principle is that the indicators should be mutually consistent and that the weights of single indicators in the portfolio should be proportionate. The third principle is that the portfolio of indicators should be as transparent and accessible as possible. This implies that indicators should be easy to read, examine, and understand. In this research, these guidelines are applied for combining indicators into an overall index of social exclusion.

Once the indicators are selected, the key issue of the macro-level index of social exclusion is the method of aggregation.[4] An increasing number of studies use principal components analysis (PCA) to construct aggregate indices of social exclusion or relative deprivation. Among these studies, Cavassini *et al*. (2004) use PCA to construct an index of marginality for regions in Costa Rica; Mangan and Stephen (2007) for regions in Queensland; and Daly *et al*. (2008) and Lewis and Corliss (2009) for regions and states of Australia. We aim at contributing to this line of research by proposing an advancement of PCA (i.e., multi-way PCA) that is more appropriate for aggregating the (multi-)dimensions of social exclusion with panel data.

[3]It is a systematic pattern in the difference between the respondent's answers to a question and the true values.

[4]See Njong and Ningaye (2008) for an overview of the methods of aggregation of a multidimensional index. The study analyzes the index of poverty, but these methods are also appropriate for social exclusion.

## 3. Estimating an Overall Index of Social Exclusion in European Countries

### 3.1. *The Dimensions of the Overall Index of Social Exclusion*

There are no commonly shared definitions and measures of overall social exclusion. Therefore, the proposal of a synthetic index of such a complex phenomenon is not only a noteworthy but also a puzzling task. In order to reduce the arbitrariness of measuring social exclusion, we follow the minimum set of principles for social exclusion indicators proposed by Atkinson and Marlier (2010).

Concerning the first principle, we identify five main dimensions of social exclusion: labor market, poverty, income inequality, education, and health. For each of these dimensions we define, among available data, a balanced number of observed variables for each dimension. As regards the second principle proposed by Atkinson and Marlier (2010), taking into account that method of dimensionality reduction (e.g., Multiple-way Principal Component Analysis, MPCA) estimates the loadings for each variable, the number of variables in each dimension reflects the authors' idea about which are the fundamental determinants of social exclusion.[5] With reference to the third principle, to obtain a transparent, reliable, and accessible index of social exclusion we use only data collected by "institutional" databases. Data published by institutions such as Eurostat assure that data are collected, elaborated, and reported by standard and certified methods.

Although inclusion of more variables may increase the completeness of the estimated latent variable (i.e., social exclusion) a significant trade-off exists between inclusiveness of social exclusion definition and reliability of the estimated index (Atkinson and Marlier, 2010). Thus, we consider it worthwhile to exclude variables with inadequate coverage of European countries or lacking time span.[6] In sum, we fine-tune this choice, balancing the dimensions of social exclusion between social and economic variables on the basis of the quality and availability of data.

With regard to the data source, in 2001 the Laeken European Council developed a system of social indicators to better measure and understand social exclusion in the EU. It proposed a set of common statistical indicators for social inclusion, which allow monitoring in a comparable way to member states' progress toward the agreed EU objectives (Eurostat, 2003). In May 2006, the Social Protection Committee endorsed new best practice criteria for indicator design, and the list was updated in September 2009. The common indicators are currently divided into four strands attached to specific objectives, with some indicators

[5]That is because the relevance of the five dimensions is indirectly determined by the numerousness of variables associated to each dimension. In this sense, we include five variables related to (un)employment status because we consider that it is the most important cause of social exclusion. Similarly, poverty, education, and health (with three variables) are more relevant than income inequality (with two variables). Alternative approaches to fix the weights of dimensions of a multidimensional index have recently been proposed in the literature. For instance, Bellani (2013) proposes a multidimensional deprivation index where the weights of each dimension are based on their perceived importance by members of alternative reference groups. However this approach is not suitable for the macro data approach.

[6]In particular, adding other variables (e.g., social life, political participation) may: (1) cause problems in balancing the five dimensions of social exclusion (in contrast to the first principle); (2) increase the number of missing values; and (3) make it harder to hold the third principle proposed by Atkinson and Marlier (2010) due to mixing data extracted by Eurostat with other sources.

being a part of more than one portfolio. The four strands are as follows: (1) the *overarching indicators*; (2) the *social inclusion indicators*; (3) the *pensions indicators*; and (4) the *health and long-term care indicators*. These strands are structured in three sections: *primary indicators* cover the most important elements, thereby leading to poverty and social exclusion; *secondary indicators* are intended to support the lead indicators and describe other important dimensions of the phenomena; and, finally, a set of *context indicators* have been specified as providing "context" information which helps in interpreting trends in the primary and secondary indicators (Marlier *et al*., 2007).

In this research, we consider the 2011 updating of *Laeken indicators* both as a theoretical background and as a reference data source for our analysis.[7] From this set of indicators, we extract a subset of nine variables, in order to balance the number of indicators over the five EU meta-dimensions of social exclusion and data availability. To have a better picture of the social exclusion phenomenon, we also include seven additional variables.

In conclusion, the dimensions of social exclusion are related to the labor market, poverty, income inequality, education, and health. These dimensions are defined by the following variables (Laeken indicators are marked by asterisks):

(1) *Employment*: inactivity rate, share of temporary employment, total unemployment rate, young unemployment, and long unemployment*.
(2) *Poverty*: at-risk poverty before social transfer*, relative median at-risk-of-poverty gap*, and poverty rate of elderly people*.
(3) *Income inequality*: Gini index*, income quintile share ratio*.
(4) *Education*: adult non-participation in education and training*, early leavers from education and training*, and people with low educational attainment*.
(5) *Health*: infant mortality, suicide rates in people aged 50–54, and suicide rates in people aged 15–19.

The 16 variables are then aggregated into an overall index based on weights that represent the relative importance of sub-indicators in the latent variable so-called "social exclusion." These variables, arranged according to the five dimensions of social exclusion, are summarized in Table 1. Further details on the data source and definitions are provided in Appendix A.

## 3.2. *Three-Mode Principal Components Analysis*

To construct an aggregate measure of overall social exclusion, MPCA is applied. As argued by Leardi *et al*. (2000), MPCA is a dimensionality reduction technique that allows a much easier interpretation of the information present in the dataset, as it directly takes into account its three-way structure. In particular, the Tucker3 model is the most common model for performing three-way PCA (Pardo *et al*., 2004).[8]

[7]For methodology and definition details of Laeken indicators, see Eurostat (2010). Data are retrievable from the Eurostat online database. See Appendix A for details.

[8]Although PCA could be also applied to a three-dimensional dataset (e.g., Countries · Time · Variables) by transforming data, results could be difficult to interpret, because the information of the three modes can be mixed (Pardo *et al*., 2004).

In particular, we propose two models that have not been used earlier within this field of research: the Tucker3 and PARAFAC models. The first one was originally applied by Tucker (1966) in psychometrics and there are numerous examples within other disciplines such as chemometrics (e.g., Henrion, 1994; Pardo *et al.*, 2004). The second one is the parallel factor analysis (PARAFAC), also named "canonical decomposition," proposed simultaneously by Harshman (1970) and Carrol and Chang (1970). Kiers (1991) shows that PARAFAC can be considered a constrained version of Tucker3. The generality of the Tucker model made it an often used model for decomposition, compression, and interpretation in many applications.

The fundamental idea behind (multiple and two-way) PCA is to reduce the dimensionality of a dataset consisting of a larger number of interrelated variables, while retaining as much as possible the variation present in the original dataset. This is achieved by transforming the original data array in a more condensed form. In this sense, the multi-way PCA framework (e.g., Tucker, PARAFAC) generalizes the classical (two-way) PCA solution.

The Tucker method is an extension of PCA to $N$-way data arrays, which preserve the original multi-way structure of the data during model development. The Tucker3 method decomposes the three-way data arrays X into three orthonormal loading matrices, denoted as A (I · P), B (J · Q), C (K · R), and the core matrix G (P · Q · R), which describes the interactions among A, B, and C.[9] In sum notation, Tucker3 becomes

$$x_{ijk} = \sum_{p=1}^{P}\sum_{q=1}^{Q}\sum_{r=1}^{R} a_{ip} b_{jq} c_{kr} g_{pqr} + e_{ijk}, \tag{1}$$

where the values $p$, $q$, and $r$ are the number of components selected to describe the first, the second, and the third mode, respectively, of the data array. The number of factors in each mode is not necessarily the same (i.e., $P \neq Q \neq R$). Each of A, B, and C matrices can be interpreted as a loading matrix in the classical two-way PCA. $g_{pqr}$ denotes the elements ($p$, $q$, $r$) of the core matrix G.

The largest squared elements of G indicate the most important factors that describe X. The core array is another relevant difference between two-way PCA and the Tucker3 model. In standard two-way PCA, there are no interactions among PCs; whereas the Tucker3 model allows such interactions. All loading vectors in one mode (can) interact with all loading vectors in the other modes, and the strengths of these interactions are provided in the core array $g_{pqr}$. Statistically, the squared element $g_{pqr}^2$ reflects the amount of variation explained by the factor $p$ from the first mode; factor $q$ from the second mode; and factor $r$ from the third mode. It is essential to choose a model with a reasonable number of PCs in all directions, because too many PCs results in over-fitting (modeling noise); whereas too few components leads to under-fitting (lack-of-fit) (Jørgensen *et al.*, 2006). The

[9]For a comprehensive analysis of this approach, see Kroonenberg (1983, 2008) and Acar and Yener (2009). The empirical analysis of this research is performed by using N-ways toolbox for MATLAB (downloadable at http://www.models.life.ku.dk/~pih/parafac/chap0contents.htm) and described by Andersson and Bro (2000).

number of factors chosen for the Tucker3 model determines the dimension of the core. We have an optimal dimensionality when the increase in the complexity of the model no longer increases the fit of the model significantly. One can use the development in explained variation as the model increases in dimensionality to indicate the best/simplest model of X. Therefore, the model with the last clear increment in explained variance is usually the one of interest. Appendix B shows the explained variation (sum of squares) of the core for three models: (1,1,1), (2,1,2), and (2,2,2). It confirms that only the first component is sufficient to explain the variation of X. Therefore, our choice is definitely the dimension (1,1,1). It implies that we estimate a matrix of loading vector for "country" dimension A ($28 \cdot 1$), for the "time "dimension B ($16 \cdot 1$), and for variables dimension ($16 \cdot 1$).

With reference to the most parsimonious model (1,1,1), we see that the core element (1,1,1) indicates interaction among factors A1, B1, and C1. By definition, it explains the highest amount of variation. The second core entry multiplied by the vectors (2,1,2) is a rather small part of the total structural information. It supplies the models with an additional 3.3 percent of the total explained variation.

Furthermore, Appendix B shows a rough superdiagonality of core matrixes G (i.e., all the elements of the superdiagonal are null). It has two relevant implications. The first one is that it considers it unnecessary to apply orthogonal core rotations in order to estimate a new solution that can be interpreted more easily. The second implication is that superdiagonality makes it possible to use the simplest three-way model: the PARAFAC model. With the same symbols as in equation (1), the decomposition method in the PARAFAC model is as follows:

$$x_{ijk} = \sum_{p=1}^{P} a_{ip} b_{jp} c_{kp} + e_{ijk}. \tag{2}$$

Obviously, the downside of a more complex structure of the Tucker model, in addition to it being less parsimonious, is that the interpretation of findings involves not only the components themselves for all three modes, but also all interactions between these components. Therefore, we consider it worthwhile to also estimate a PARAFAC model that supports both loading interpretations and verifies the robustness of output.

A simple way of assessing whether the model structure is reasonable is by monitoring the distribution of superdiagonal and off-superdiagonal elements of G. The core consistency diagnostic indicates how well the model is in concert with the distribution of superdiagonal and off-superdiagonal elements of the Tucker3 core. According to Bro (1998), the PARAFAC model is appropriate if all the superdiagonal elements are close to one another and the off-superdiagonal elements are close to zero. We apply the so-called "core consistency diagnostic" (CORCONDIA) proposed by Bro (1998). It is also a helpful test for determining the right number of components. The analysis using CORCONDIA indicates that only two factors are necessary, because the utilization of more factors leads to a great decrease in the core consistency. According to this explorative analysis, Table 1 reports the estimated loadings of the matrix C estimated by Tucker3 (1,1,1), (2,1,2), (2,2,2), and PARAFAC (2,2,2).

TABLE 1
THE LOADINGS OF MATRIX C (VARIABLES)

| | | Tucker3 (1,1,1) | Tucker3 (2,1,2) | | Tucker3 (2,2,2) | | Parafac (2,2,2) | |
|---|---|---|---|---|---|---|---|---|
| | | C1 | C1 | C2 | C1 | C2 | C1 | C2 |
| | *Employment* | | | | | | | |
| EI | Inactivity rate | 0.258 | –0.258 | –0.009 | –0.258 | –0.013 | 0.257 | 0.041 |
| ET | Temporary employment | 0.090 | –0.089 | –0.093 | –0.089 | –0.089 | 0.085 | –0.069 |
| EUT | Total unemployment rate | 0.070 | –0.070 | 0.036 | –0.070 | 0.037 | 0.072 | 0.051 |
| EUY | Young unemployment | 0.153 | –0.153 | 0.032 | –0.153 | 0.035 | 0.154 | 0.067 |
| EUL | Long unemployment | 0.031 | –0.031 | 0.018 | –0.031 | 0.017 | 0.032 | 0.023 |
| | *Poverty* | | | | | | | |
| PR | At risk poverty before social transfer | 0.208 | –0.210 | 0.051 | –0.210 | 0.054 | 0.213 | 0.096 |
| PM | Relative median at-risk-of-poverty gap | 0.178 | –0.178 | 0.010 | –0.178 | 0.009 | 0.179 | 0.046 |
| PE | Poverty rate elderly persons | 0.165 | –0.163 | –0.089 | –0.163 | –0.090 | 0.158 | –0.054 |
| | *Income inequality* | | | | | | | |
| IG | Gini index | 0.247 | –0.247 | –0.001 | –0.247 | 0.001 | 0.247 | 0.053 |
| IQ | Income quintile share ratio | 0.039 | –0.039 | –0.007 | –0.039 | –0.007 | 0.039 | 0.001 |
| | *Education* | | | | | | | |
| ENL | Non participant-life-long learning | 0.768 | –0.771 | 0.112 | –0.771 | 0.116 | 0.776 | 0.275 |
| ELA | Person with low education attainment | 0.271 | –0.267 | –0.666 | –0.267 | –0.670 | 0.233 | –0.599 |
| EE | Early leavers from education and training | 0.140 | –0.135 | –0.310 | –0.134 | –0.317 | 0.118 | –0.282 |
| | *Health* | | | | | | | |
| HAS | Crude death rate from suicide (50–54) | 0.205 | –0.202 | 0.634 | –0.201 | 0.627 | 0.232 | 0.656 |
| HSY | Crude death rate from suicide (15–19) | 0.061 | –0.058 | 0.152 | –0.058 | 0.144 | 0.066 | 0.153 |
| HI | Infant mortality | 0.051 | –0.051 | 0.039 | –0.051 | 0.036 | 0.052 | 0.046 |
| | *Explained variation of x (%)* | 94.582 | 97.447 | | 96.879 | | 96.261 | |

The interpretation of the Tucker3 and PARAFAC models is different. PARAFAC can be interpreted in a similar manner to two-way PCA, whereas the interpretation of Tucker3 results should also take into account the magnitude and sign of the non-zero elements of G. This means that for Tucker3, by comparing loadings from different modes, some attention needs to be paid to the core array, because the magnitude of a direction is given by the core array. For this reason, the signs of C1 loadings estimated by Tucker3 (2,1,2) and C2 of Tucker3 (2,2,2) are opposite to PARAFAC. According to this analysis, we conclude that the results are robust with regard to different Tucker3 dimensions and model specifications (i.e., PARAFAC).

Although the estimated coefficients and the fitting of the three models are very similar, we choose the Tucker3 (1,1,1)—or equivalently the PARAFAC(1) that yields identical results—to extract the factor loadings of the component matrix C (third mode). In particular, (a) Tucker3 explains a significantly higher variance with regard to PCA (94.6 percent instead of 80.6 percent); and (b) the indexes based on Tucker3 (1,1,1) and Tucker3 (2,1,2) have very similar estimated values with a correlation coefficient of 99.8 percent. Thus, as simple is better, Tucker3 (1,1,1) is regarded as the preferred model in terms of trade-off between share of explained variance and model complexity.

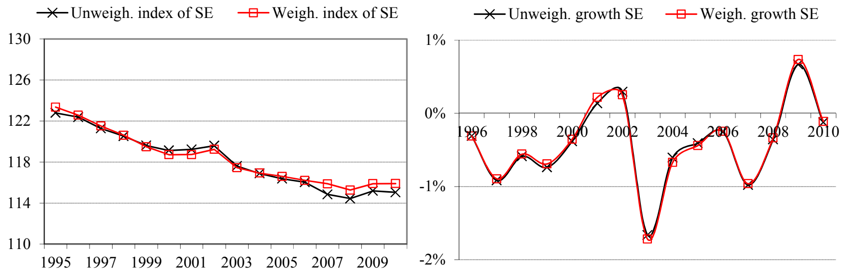


Figure 1. The Dynamics of the Index of Social Exclusion

As concerns the relative weights of the dimensions of social exclusion—by aggregating the squared factor loadings estimated by Tucker3 (1,1,1) in Table 1—we find that education variables account for 68.3 percent of the total explained variance, employment proxies for 10.4 percent, poverty measures for 10.2 percent, income inequality indexes for 6.3 percent, and health indicators for 4.8 percent.

### 3.3. *An Index of Social Exclusion in European Countries*

In this section, the loadings of the vector C of Tucker3 (1,1,1) are employed to calculate a lower dimensional representation of social exclusion. Analogous to two-way PCA, the factor loadings are the correlation coefficients between the 16 proxies of social exclusion and the latent factor. Thus, we estimate the index of social exclusion according to Table 1:[10]

$$SE_{ij} = 0.258 \cdot EI_{ij} + 0.090 \cdot ET_{ij} + \ldots + 0.051 \cdot HI_{ij}, \tag{3}$$

where $i = 1, 2, \ldots, 28$ (countries) and $j = 1995, 1996, \ldots, 2010$.

Figure 1 depicts both trend and growth rate of the European social exclusion index calculated as unweighted and weighted for a population average over the 28 countries of our sample. According to our index, a higher score means a higher level of social exclusion.

Figure 1 reveals a decreasing trend (i.e., negative growth rates) of social exclusion with the exception of the years 2001, 2002 and 2009.

Figure 2 reports the ranking of 28 European countries calculated as normalized averages over the sample period.[11] Country rankings in terms of social exclusion are compared with the levels of income inequality (Gini index). The two indexes show a significant positive correlation (r = 0.62).

Figure 2 clearly depicts the two measures of income inequality and social exclusion; although correlated for construction (see equation (3)), they quantify quite different phenomena.

[10]In order to estimate $SE_{ij}$, we substitute the missing values in the 16 variables of equation (3) with the observations available for the next year(s). Since the missing values are mainly from 1995 to 1997 (529 on 1344 observations), the estimates of the index for these years should be considered cautiously.

[11]$Norm.Index_i = [Index_i - \min(Index_i)]/[\max(Index_i) - \min(Index_i)]$, where *Index* denotes the average of the index of social exclusion or the Gini index for each country. The Gini index was extracted from the Eurostat online database; see Appendix A for details.

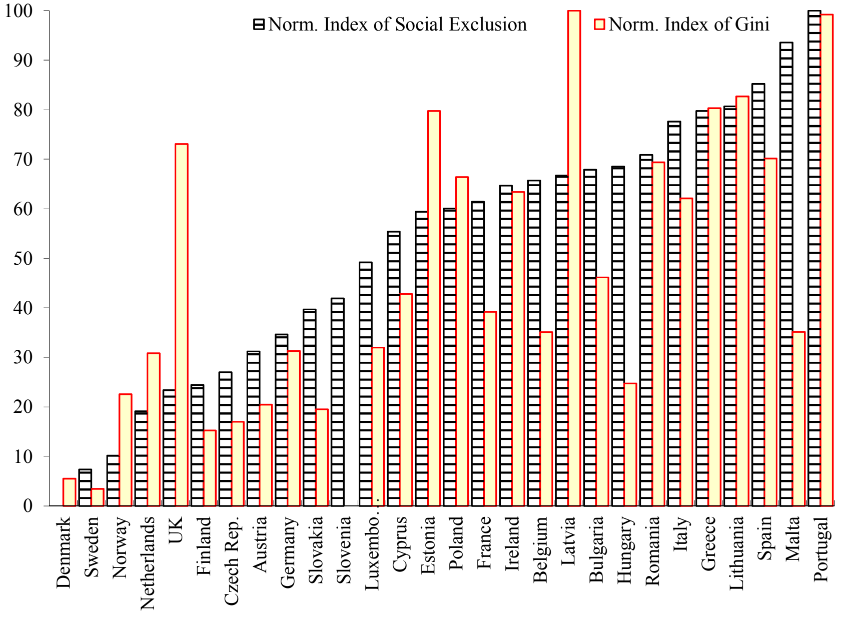


Figure 2. Normalized Indexes of Social Exclusion and Gini (averages 1995–2010)

Table 2 reports values of the social exclusion index for each of the 28 European countries for several years.

According to our index, Scandinavian countries with The Netherlands and United Kingdom exhibit the lowest levels of social exclusion between 1995 and 2010. On the contrary, South European countries (Portugal, Malta, Spain, Greece, Italy) and Lithuania exhibit the highest values. In order to provide a rough evaluation of the effectiveness of the European policies that are aimed at reducing social exclusion, we find that since the declaration of Lisbon's Strategy in 2000, the countries with the best performances in promoting social inclusion are Sweden (–3.4 percent), Romania (–2.4 percent), and Latvia (–1.4 percent); on the opposite side, we have Slovenia (+10.0 percent), Denmark (+8.1 percent), and Cyprus (+7.4 percent).

## 4. Social Exclusion and Economic Growth

This section analyses the relationship between social exclusion and economic growth in Europe over the period 1995–2010. Section 4.1 summarizes theoretical explanations that may explain how social exclusion affects growth. Section 4.2 describes the empirical model. Section 4.3 discusses the results.

### 4.1. *What Does the Theoretical Literature Say?*

The relationship between economic disparities and economic development has been explored in many empirical studies, which mainly focus on the relationship between income distribution and growth (e.g., Aghion *et al.*, 1999; Temple,

TABLE 2

THE INDEX OF SOCIAL EXCLUSION FOR EACH COUNTRY

| | 1995 | 2000 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | Averages 1995–2010 | Averages Gr. 1995–2010 |
|---|---|---|---|---|---|---|---|---|---|---|
| Austria | 115.9 | 110.7 | 105.5 | 104.6 | 104.3 | 104.0 | 103.7 | 103.6 | 109.2 | –0.74% |
| Belgium | 131.2 | 124.5 | 121.1 | 121.3 | 120.1 | 119.5 | 119.7 | 119.1 | 123.8 | –0.63% |
| Bulgaria | 126.3 | 126.8 | 121.3 | 123.2 | 123.6 | 123.8 | 125.3 | 125.9 | 124.7 | 0.00% |
| Cyprus | 124.8 | 122.9 | 120.0 | 116.5 | 114.3 | 112.7 | 114.1 | 113.8 | 119.5 | –0.60% |
| Czech Republic | 107.2 | 107.3 | 109.1 | 108.1 | 106.1 | 104.7 | 106.6 | 106.0 | 107.5 | –0.07% |
| Denmark | 100.4 | 99.5 | 91.9 | 89.8 | 91.4 | 91.8 | 92.0 | 91.4 | 96.1 | –0.61% |
| Estonia | 131.8 | 121.2 | 118.6 | 113.3 | 112.9 | 113.6 | 118.0 | 116.4 | 121.2 | –0.80% |
| Finland | 112.8 | 107.2 | 103.7 | 104.0 | 101.6 | 102.3 | 102.9 | 100.2 | 106.4 | –0.78% |
| France | 126.9 | 123.9 | 120.0 | 119.8 | 118.6 | 117.6 | 119.1 | 119.9 | 122.0 | –0.37% |
| Germany | 114.8 | 110.1 | 109.7 | 109.9 | 110.3 | 109.0 | 108.6 | 108.3 | 110.7 | –0.39% |
| Greece | 137.9 | 132.7 | 125.6 | 126.3 | 125.0 | 123.3 | 123.3 | 124.4 | 129.8 | –0.68% |
| Hungary | 131.1 | 125.8 | 123.7 | 126.8 | 121.4 | 122.5 | 122.3 | 122.1 | 125.0 | –0.46% |
| Ireland | 130.7 | 125.8 | 120.2 | 117.4 | 117.6 | 116.9 | 118.4 | 119.2 | 123.4 | –0.60% |
| Italy | 136.2 | 128.3 | 127.2 | 125.7 | 124.9 | 124.2 | 124.8 | 124.6 | 128.9 | –0.59% |
| Latvia | 127.9 | 122.0 | 121.1 | 121.9 | 118.2 | 125.4 | 128.6 | 123.7 | 124.3 | –0.18% |
| Lithuania | 133.6 | 134.5 | 126.7 | 125.1 | 121.0 | 123.0 | 126.9 | 128.2 | 130.1 | –0.26% |
| Luxembourg | 127.9 | 115.3 | 112.1 | 116.5 | 117.7 | 114.4 | 105.7 | 110.3 | 116.9 | –0.92% |
| Malta | 136.6 | 140.1 | 133.5 | 133.0 | 132.4 | 131.4 | 130.7 | 130.5 | 135.6 | –0.30% |
| Netherlands | 112.3 | 104.2 | 103.2 | 101.9 | 100.5 | 99.5 | 100.1 | 100.7 | 104.2 | –0.72% |
| Norway | 100.7 | 101.2 | 98.2 | 104.1 | 100.3 | 98.0 | 100.3 | 100.4 | 100.4 | 0.00% |
| Poland | 120.4 | 121.1 | 124.9 | 122.0 | 118.5 | 117.3 | 118.9 | 118.5 | 121.4 | –0.10% |
| Portugal | 142.6 | 139.2 | 137.7 | 136.5 | 136.5 | 134.5 | 133.2 | 133.4 | 138.3 | –0.44% |
| Romania | 123.7 | 123.3 | 130.6 | 130.6 | 130.8 | 128.2 | 127.4 | 126.3 | 126.0 | 0.15% |
| Slovakia | 111.8 | 113.9 | 114.7 | 112.0 | 109.2 | 109.9 | 112.5 | 114.6 | 112.8 | 0.18% |
| Slovenia | 120.4 | 118.3 | 110.1 | 108.6 | 107.0 | 105.9 | 107.4 | 106.6 | 113.8 | –0.80% |
| Spain | 142.4 | 132.4 | 126.1 | 125.4 | 124.0 | 124.9 | 127.2 | 128.3 | 132.1 | –0.68% |
| Sweden | 95.8 | 96.0 | 102.3 | 104.2 | 102.0 | 100.0 | 102.1 | 99.2 | 99.2 | 0.25% |
| UK | 114.3 | 107.2 | 99.6 | 100.1 | 105.6 | 106.0 | 105.2 | 105.6 | 105.9 | –0.50% |
| *Unw. averages* | 122.8 | 119.1 | 116.4 | 116.0 | 114.8 | 114.4 | 115.2 | 115.0 | 118.2 | |
| *Unw. Growth aver.* | | –0.43% | –0.38% | –0.41% | –0.25% | –0.98% | –0.36% | 0.67% | –0.12% | –0.41% |

*Note*: The remaining values ('94,'96,'97,'98,'99,'01,'02,'03,'04) are available upon request from the authors.

1999; Barro, 2000; Kanbur, 2000; Banerjee and Duflo, 2003; Knowles, 2005; Ehrhart, 2009). Notwithstanding, it still remains a puzzle in terms of: (1) the sign of correlation; (2) the nature of this relation (short term or long term); and (3) whether causality runs from economic growth to inequality and/or vice versa.

Various theoretical explanations have been suggested that explain how inequality could affect growth. Ehrhart (2009) classifies this literature into two main strands: (1) political economy explanations, and (2) purely economic explanations.

With reference to political economy explanations, the first group of models argues that a greater degree of inequality motivates more social demand for redistribution throughout the political process (e.g., Bertola, 1993; Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Perotti, 1996). Typically, the transfer payments and the associated taxation will distort economic decisions, and, through this channel, the inequality would reduce the growth. The second group of models (also known as "socio-political unrest theory" by Barro, 2000) hypothesizes that high economic disparities cause "political instability" (Alesina and Perotti, 1994, 1996) and motivate the poor to engage in crime and disruptive activities (Bourguignon, 1999). Through these dimensions of socio-political unrest, more inequality tends to reduce overall productivity and economic growth.

With reference to "purely economic" explanations, in the first approach, the hypothesis of a (negative) relationship between inequality and growth is due to the presence of imperfect capital markets (Galor and Zeira, 1993; Aghion *et al.*, 1999). This proposition assumes that a more unequal distribution of assets means that an increased number of individuals does not have access to credit and, thus, cannot carry out productive investments. Through this channel, inequality would reduce growth rate. According to the so-called "endogenous fertility approach," income inequality noticeably reduces the future growth rate because of the positive effect of inequality on the overall rate of fertility (e.g., Becker *et al.*, 1990; Galor and Zang, 1997). Thus, a worsening in inequality jointly generates a rise in the fertility rate and a drop in the rate of investment in human capital, and this reduces the future growth rate of GDP per capita. The third approach claims that a more unequal distribution of incomes results in smaller domestic markets (Murphy *et al.*, 1989). The size of home demand is, thus, too small to generate markets large enough to fully develop local industries or to attract foreign direct investments. Following this approach, inequality reduces growth rate as a consequence of a lower exploitation of the economies of scale and of incentives to foreign direct investment.

In our view, "political economy explanations" and "purely economic arguments," originally proposed to explain the relationship between income inequality and economic growth, can also be applied to the wider concept of social exclusion.

In conclusion, our proposal is to analyze the relationship between inequality and growth by means of a broader measure of *social exclusion* referring to the distribution of income, economic, and social opportunities as well as access to several (social) citizenship rights (Marshall, 1950).

This wider approach to inequality and growth analysis also finds support in Ehrhart's (2009) conclusions. According to this survey, only the models of "political instability" and "endogenous fertility" find less controversial data validation. Thus, since the agents' decision processes are significantly affected by social factors included in the notion of social inclusion, we assume that social exclusion may be much more relevant for affecting political instability and fertility decisions of economic agents than (just) income distribution.

### 4.2. *Empirical Model*

The empirical analysis of the relationship between the overall index of social exclusion and economic growth is pursued by different econometric approaches. It aims at verifying whether the theoretical arguments behind the relationship between (income) inequality and growth are empirically validated, irrespective of whatever wider concept of inequality (i.e., social) is applied.

Two main limitations affect this analysis: (1) the small time dimension of the dataset (1995–2010), and (2) the structural break of the recent economic crisis (2008–09). Thus, the analysis on the long-run properties of the relationship between social exclusion and growth should be considered with caution.

The econometric analysis starts by testing logarithms of GDP per capita and the index of social exclusion for the presence of unit roots. We apply the Levin *et al.* (2002) panel unit root tests, which also accounts for the structural break in 2008–09. Accordingly, we find that both growth rates of GDP per capita (Ggdp) and the levels of social exclusion do not have a common unit root process.[12] It means that we cannot validate the existence of a systematic co-movement in the long run between social exclusion and economic growth. Thus, if a statistical link between social exclusion and GDP's growth exists, it may have only short-run characteristics. Subsequently, Granger causality tests that are adapted to the panel structure of datasets are run to determine whether causality runs from social exclusion to economic growth and/or vice versa.

We carry out Granger (1969) causality tests in a context of panel data, to test whether previous changes in one variable help in explaining current changes in other variables. However, a bi-variate framework without considering other relevant variables may lead to a spurious causality. Therefore, this study adopts a multivariate dynamic autoregressive model.

Since the two variables employed in the Granger test should be stationary, we employ the growth rate of GDP per capita (Ggdp) and the level of social exclusion (SE). We also include period dummies for the structural break of the economic crisis (2008 and 2009) and a set of control variables to reduce potential omitted-variables bias. These are some potential causes of economic growth (i.e., foreign direct investment, population being more than 65 years of age, level of GDP, and index of openness at the international trade) and social exclusion (i.e., tertiary school enrolment). See Appendix A for the sources of data. However, when fixed effects are included in regressions (4) and (5), then several of these control variables

[12]We also apply a battery of tests detecting for individual unit root processes so that unit root may vary across cross-sections: for growth rates of GDP per capita we reject the hypothesis of individual unit root processes while for the level of social exclusion index the null hypothesis cannot be rejected. As a consequence, we also perform Pedroni's and Westerlund's test of cointegration on these two variables. The results have ambiguous findings with a prevalence to support no cointegration. Conclusively, as these diagnostics have low power when the time dimension is small as in our dataset (T = 16), we opt to investigate on the short run properties of relationship between growth and social exclusion because it is definitely more suitable to our sample size.

become statistically insignificant. As a result, we omit to report these extended specifications later on. Finally, we run two regressions, including cross-country dummies, a dummy for economic recessions (Dummy '08/'09), an index of international trade openness (T_open), for economic growth regression (4), and the gross enrolment rate of tertiary school (Sch3), for social exclusion regression (5):

$$(4) \qquad Ggdp_{ij} = \alpha_0 + \sum_{l=1}^{m} \alpha_l Ggdp_{ij-l} + \sum_{l=1}^{m} \beta_l SE_{ij-l} + \gamma_1 Dcrisis_i + \gamma_2 T\_open_{ij} + c_i + u_{ij}$$

$$(5) \qquad SE_{ij} = \alpha_0 + \sum_{l=1}^{m} \alpha_l SE_{ij-l} + \sum_{l=1}^{m} \beta_l Ggdp_{ij-l} + \gamma_1 Dcrisis_i + \gamma_2 Sch3_{ij} + c_i + u_{ij},$$

where Ggdp is the first difference of the logarithm of GDP per capita. The $\chi^2$ (Wald) statistics for the joint hypothesis: $H_0$: $\beta_1 = \ldots\ldots = \beta_m = 0$ is the usual test that is used to investigate for the presence of Granger causality. In particular, we fix the length of lags (*m*) equal to two in order to save degrees of freedom.

According to redundant fixed effects and the Hausman test for correlated random effects, the best model specification for (4) and (5) is a fixed-effect model that includes cross-country and time dummies. Accordingly, we consider two specifications of the least-squares dummy variable (LSDV) estimator: an LSDV one way with a dummy for 2008 and 2009, and an LSDV with periods' and countries' fixed effects (LSDV two ways). Since Nickell (1981) demonstrates that the LSDV estimator is not consistent for a finite time dimension, three further econometric strategies are applied to check the robustness of econometric results: (1) Kiviet's (1995) approach to correct (downward) biased estimates in the LSDV estimator with a lagged dependent variable (LSDVC); we report bias-corrected LSDV estimators using the bias approximations in Bruno (2005a), who extends the results by Bun and Kiviet (2003) and Kiviet (1995) to unbalanced panels; (2) linear generalized method of moments (GMM) estimators proposed by Arellano and Bond (1991)—First Differences GMM; and (3) Arellano and Bover (1995) and Blundell and Bond (1998)—System GMM (2 steps). Following Roodman (2009a, 2009b), one of the main drawbacks in implementing the dynamic panel GMM estimator is that too many instruments can overfit endogenous variables and fail to remove their endogenous components. Roodman (2009a) suggests two main techniques for overcoming this issue: first, to use only certain lags instead of all available lags for instruments; and second, to combine instruments through addition into smaller sets (so-called "instruments collapsing"). We apply both of them: lags 2 (lag 1) through 7 (6) are included for the equation in differences, and lags 1 (lag 0) through 7 (6) are used for the level equation for endogenous (predetermined) variables. In particular, to implement the GMM approach in equations (4) and (5), lagged variables are treated as endogenous; control variables (trade openness and tertiary school enrolment) are handled as predetermined; and dummies are considered exogenous. To verify the reliability of the GMM estimates, the robust version of Sargan's (1958) test (Hansen J-statistic) is applied to check for the validity of instrumental variables. Since we have an unbalanced panel with gaps, the sample is maximized by using the forward orthogonal deviation

(Arellano and Bover, 1995) instead of the first-difference approach. Finally, we report standard error estimates computed by Windmeijer's (2005) finite-sample correction for the two-step covariance matrix.

Unfortunately, there is no general consensus in the literature on how identify the best choice of panel estimator given the dimensions of the dataset used here. In particular, the most utilized dynamic panel estimator with endogenous regressors—the GMM approach—is designed for situations with few time periods (T) and many cross-sectional units (N), but our dataset does not hold this structure as it has only 28 cross-units and relatively many time periods. Thus, in spite of the applied techniques to reduce the instrument set (i.e., limiting the lag depth and "collapsing" the instrument set), dynamic GMM may still be inconsistent as the number of instruments becomes too large with T = 16. This concern is more relevant for system GMM because it uses more instruments than the difference GMM, thus estimates based on Arellano and Bover (1995) and Blundell and Bond (1998) should be considered cautiously. An additional source of bias for the estimates calculated by the first difference GMM occurs when the individual series shows a high degree of persistence. In this case the instruments available for the equations in first-differences are likely to be weak (Bond, 2002). It is the case of the regression 5 where the coefficient of the lagged index of social exclusion ($\alpha_1$) is about 0.85.

In conclusion, given the dimensions of our dataset and the high persistence of the index of social exclusion, a clear best choice of panel estimator is not available. However, some useful indications to address this issue are provided by Judson and Owen (1999) and Buddelmeyer *et al.* (2008). These studies run Monte Carlo simulations on a range of different estimators of panel data model with fixed effects in order to compare their biases. Matching the dimension of our dataset to Judson and Owen (1999) and Buddelmeyer *et al.* (2008) simulations, reveals that the best-performing estimator may be Kiviet's bias-corrected LSDV estimator. However, LSDVC assumes strictly exogenous regressors, thus to extend our analysis to endogenous regressors, the first difference GMM and the system GMM can be regarded as the most reliable estimators for regressions 4 and 5, respectively.

### 4.3. *Empirical Findings*

The results of regressions (4) and (5) are shown in Tables 3 and 4, respectively. In order to check robustness of findings for each estimator, we report estimates based on two different techniques to aggregate the dimensions of social exclusion, i.e., PCA and MPCA.[13] In general, this test confirms that the findings are robust to the choice of the method to combine the dimensions of social exclusion.

Findings of Table 3 show that, with exclusion of the system GMM model, the Wald tests reject the null hypothesis that the coefficients of social exclusion ($\beta_i$) are jointly equal to zero in both the MPCA and PCA index. Accordingly, social exclusion Granger causes real GDP growth. Empirical outcomes show a statistically not significant impact of the lagged social exclusion's value on the growth at the time $t$ but a positive effect of social exclusion on the growth rate after two years

[13]See Appendix C for details on PCA and a comparison of alternative measures of social exclusion. Estimated output based on MPCA (2,1,2) is not reported for the sake of brevity. These results are qualitatively very similar to MPCA (1,1,1).

TABLE 3

Dependent Variable: Growth Rate of Real GDP

| | LSDV One-way | | LSDV Two-way | | LSDVC | | GMM 1st-diff. | | GMM-sys (2-steps) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | PCA | Tucker3 | PCA | Tucker3 | PCA | Tucker3 | PCA | Tucker3 | PCA | Tucker3 |
| $Ggdp_{t-1}$ | 0.342*** | 0.383*** | 0.420*** | 0.454*** | 0.511*** | 0.553*** | 0.375*** | 0.456*** | 0.446*** | 0.491*** |
| | (5.65) | (6.62) | (5.45) | (5.88) | (8.59) | (9.17) | (5.27) | (7.77) | (8.22) | (9.83) |
| $Ggdp_{t-2}$ | −0.150* | −0.194** | −0.143 | −0.196** | −0.163*** | −0.219*** | −0.076 | −0.159** | −0.227** | −0.143 |
| | (−1.73) | (−2.22) | (−1.59) | (−2.19) | (−3.25) | (−4.53) | (−0.75) | (−2.10) | (−2.16) | (−1.47) |
| $SE_{t-1}$ | −0.018 | −0.035 | 0.073 | 0.011 | 0.106 | 0.028 | −0.624* | 0.118 | 0.096 | 0.051 |
| | (−0.12) | (−0.43) | (0.51) | (0.14) | (0.86) | (0.37) | (1.79) | (0.77) | (0.42) | (0.41) |
| $SE_{t-2}$ | 0.364** | 0.177** | 0.190* | 0.13* | 0.159 | 0.077 | 0.297* | 0.178** | 0.223 | 0.01 |
| | (2.54) | (2.31) | (1.90) | (1.69) | (1.34) | (0.99) | (1.71) | (2.13) | (1.14) | (0.91) |
| Dummy ('08/'09) | −5.665*** | −5.803*** | | | | | −4.814*** | −5.640*** | −5.585*** | −6.050*** |
| | (−14.77) | (−14.81) | | | | | (−5.56) | (−8.93) | (−8.09) | (−8.79) |
| T_open | 0.095*** | 0.097*** | 0.062*** | 0.066*** | 0.058*** | 0.060*** | 0.195*** | 0.181*** | 0.090*** | 0.083** |
| | (8.21) | (8.14) | (4.16) | (4.26) | (3.90) | (3.98) | (4.79) | (3.83) | (3.12) | (2.09) |
| Observ.(countries) | 380 (28) | | 380 (28) | | 380 (28) | | 350 (28) | | 380 (28) | |
| Fixed effects | Countries | | Countries & Years | | Years | | | | | |
| Robust S.E. | Cross-section weights | | Cross-section weights | | Kiviet | | Robust[a] | | Windmeijer | |
| Adj-$R^2$ | 0.622 | 0.606 | 0.686 | 0.673 | | | | | | |
| Durbin-Wats. | 2.153 | 2.144 | 2.035 | 2.031 | | | | | | |
| Wald test $\beta_i$ (p-v.) | 0.000 | 0.001 | 0.001 | 0.022 | 0.001 | 0.090 | 0.006 | 0.024 | 0.131 | 0.817 |
| GMM diagnostics | | | | | | | | | | |
| AR(2) (p-value)[b] | | | | | | | 0.805 | 0.368 | 0.206 | 0.246 |
| # instruments | | | | | | | 22 | 22 | 26 | 26 |
| Hansen test | | | | | | | 0.069 | 0.046 | 0.134 | 0.113 |
| GMM instruments for levels (p-value)[c] | | | | | | | | | | |
| Exclud. Gr.[d] | | | | | | | | | 0.066 | 0.048 |
| Difference[e] | | | | | | | | | 0.883 | 0.980 |
| IV: (p-value)[c] | | | | | | | | | | |
| Exclud. Gr.[d] | | | | | | | 0.065 | 0.039 | 0.113 | 0.111 |
| Difference[e] | | | | | | | 0.306 | 0.404 | 0.526 | 0.287 |

*Notes*: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Constant term and fixed effects are not reported. The numbers in parentheses are the t-ratios.

The Robust Covariance method known as Panel Corrected Standard Error (Beck and Katz, 1995), is applied to compute standard errors that are robust to heteroscedasticity across cross-sections but not to general correlation of residuals. For LSDVC the Kiviet (1995) correction estimator is applied. The consistent estimator chosen to initialize the bias correction is the Anderson and Hsiao (1982) estimator. We apply xtlsdvc STATA's command (Bruno, 2005b).

[a]Standard errors are robust to heteroscedasticity and arbitrary patterns of autocorrelation within countries.

[b]Arellano–Bond test for AR(2) in first differences.

[c]Difference-in-Hansen tests of exogeneity of instrument subsets. P-values greater than usual significance levels imply that we can not reject null that the instruments used in GMM and IV parts are valid.

[d]Hansen test excluding group. The null hypothesis is that excluded instruments, as a group, are not correlated with independent variables (those which were assumed to be endogenous).

[e]The null hypothesis is that the instruments are exogenous.

(with the exception of LSDVC and the GMM-system). This result means that, in the short run, the hypotheses of negative relationship between the level of social exclusion and economic growth—i.e., the above entitled "political instability" and "endogenous fertility" theories—are not empirically supported.

Taking into account the lack of robustness of these findings, any economic explanation should be interpreted with caution. Tentatively, (1) the statistically not significant impact of the lagged social exclusion's value on growth at time $t$ provides evidence that the interactions between these two phenomena have to be analyzed in the long run. It is reasonable to assume that the effects of social exclusion on growth (e.g., through political instability and changes in fertility rate) require a longer time span. (2) The statistically not significant impact of the social exclusion at $t-2$ on growth obtained by LSDVC and the GMM-system suggests that not conclusive results are obtained by this analysis. However, if a correlation between these two variables exists, it is positive. In this circumstance two possible reasons may explain this finding. On the one hand, a higher level of social exclusion may have a positive impact upon growth (after two years) as a consequence of the expansion of government expenditures related to social welfare programs (e.g., welfare subsidies, education spending, public housing). Thus, a higher level of social exclusion encourages expansionary fiscal policy and stimulates the economy. On the other hand, a decrease in the level of social exclusion may have a negative impact on growth because the costs to promote social integration (e.g., distortionary taxation of financing public expenditures) may outweigh the positive benefits of social inclusion in human capital accumulation. These arguments[14] may explain the lack of a negative effect of promotion of social inclusion upon economic growth in the short run. However, the overall effect upon future growth is undetermined because it likely occurs out of the time horizon of the empirical model. According to Herzer and Vollmer (2012), panel cointegration techniques are the most suitable approach to address this issue. By means of this econometric approach, they find that income inequality has a negative long-run effect on income per capita (and thus long-run growth). However, this econometric technique cannot be applied in this study as the cointegration method cannot be implemented with short data spans.

Results of Wald tests in Table 4 suggest that, with exclusion of the LSDV one way and the GMM-system including the PCA index of social exclusion, the null hypothesis cannot be rejected. Accordingly, economic growth does not Granger-cause social exclusion at conventional significance levels.

In conclusion, there is empirical evidence that Granger causality runs one way from social exclusion to Ggdp and not the other way. This implies that, in the short run, the promotion of social inclusion has a negative impact on economic growth instead of vice versa.

The last step of our empirical analysis involves a comparison of these results with the effect of income inequality on growth rates. In this sense, we aim at investigating whether the EU institutions' policy to promote economic growth while looking at the social disparities instead of the income inequality is

[14]They are similar to the transition mechanisms proposed by Sylwester (2000) to explain a negative association between income inequality and economic growth.

TABLE 4

Dependent Variable: The Index of Social Exclusion

| | LSDV One-way | | LSDV Two-way | | LSDVC | | GMM 1st-diff. | | GMM-sys (2-steps) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | PCA | Tucker3 | PCA | Tucker3 | PCA | Tucker3 | PCA | Tucker3 | PCA | Tucker3 |
| $Ggdp_{t-1}$ | –0.097** | –0.048 | –0.095** | –0.047 | –0.092** | –0.021 | –0.088** | –0.096 | –0.146** | –0.082 |
| | (–2.54) | (–0.83) | (–2.30) | (–0.76) | (–2.12) | (–0.28) | (–2.10) | (–1.51) | (–2.68) | (–1.10) |
| $Ggdp_{t-2}$ | 0.049 | 0.167*** | 0.015 | 0.107 | 0.018 | 0.100 | 0.007 | 0.092 | 0.074* | 0.072 |
| | (1.20) | (2.63) | (0.35) | (1.65) | (0.34) | (1.17) | (0.25) | (1.40) | (1.86) | (0.99) |
| $SE_{t-1}$ | 0.921*** | 0.740*** | 0.907*** | 0.738*** | 0.925*** | 0.793*** | 0.890*** | 0.848*** | 1.000*** | 0.833*** |
| | (11.56) | (10.79) | (12.10) | (10.82) | (13.06) | (12.08) | (6.40) | (6.52) | (7.67) | (8.43) |
| $SE_{t-2}$ | –0.194** | –0.014 | –0.196*** | –0.038 | –0.162** | –0.014 | –0.234*** | –0.033 | –0.041 | 0.042 |
| | (–2.48) | (–0.22) | (–2.66) | (–0.58) | (–2.54) | (–0.18) | (–3.45) | (–0.62) | (–0.41) | (0.60) |
| Dummy ('08/'09) | 0.728*** | 0.229 | | | | | 0.821*** | 0.739 | 0.952* | 0.731 |
| | (3.58) | (0.65) | | | | | (–3.31) | (1.52) | (2.94) | (1.65) |
| School_3 | –0.027*** | –0.050*** | –0.012 | –0.018 | –0.017 | –0.009 | –0.046* | –0.050 | 0.007 | –0.024 |
| | (–3.17) | (–3.63) | (–1.07) | (–0.93) | (–1.00) | (–0.32) | (–1.98) | (–1.67) | (0.61) | (–0.92) |
| Observ.(countries) | 341 (28) | | 341 (28) | | 341 (28) | | 309 (27) | | 341 (28) | |
| Fixed effects | Countries | | Countries & Years | | Years | | | | | |
| Robust S.E. | Cross-section weights | | Cross-section weights | | Kiviet | | Robust[a] | | Windmeijer | |
| Adj-$R^2$ | 0.955 | 0.974 | 0.961 | 0.976 | | | | | | |
| Durbin-Wats. | 2.050 | 2.049 | 2.043 | 2.054 | | | | | | |
| Wald Test $\beta_i$ (p-v.) | 0.039 | 0.030 | 0.053 | 0.258 | 0.100 | 0.505 | 0.129 | 0.198 | 0.012 | 0.440 |
| GMM diagnostics | | | | | | | | | | |
| AR(2) (p-value)[b] | | | | | | | 0.764 | 0.501 | 0.425 | 0.388 |
| # instruments | | | | | | | 22 | 22 | 26 | 26 |
| Hansen test | | | | | | | 0.313 | 0.422 | 0.251 | 0.346 |
| GMM instruments for levels (p-value)[c] | | | | | | | | | | |
| Exclud. Gr.[d] | | | | | | | | | 0.515 | 0.367 |
| Difference[e] | | | | | | | | | 0.056 | 0.315 |
| IV: (p-value)[c] | | | | | | | | | | |
| Exclud. Gr.[d] | | | | | | | 0.257 | 0.413 | 0.257 | 0.306 |
| Difference[e] | | | | | | | 0.783 | 0.340 | 0.266 | 0.561 |

*Notes*: See Table 3.

empirically supported. To perform this analysis, we estimate regressions (4) and (5), substituting the index of social exclusion with the Gini index (Gini) and the income quintile share ratio (IQ). Appendix D summarizes the results for LSDV one way, LSDVC with period fixed effects, and the GMM-system.

Findings of this analysis suggest not to reject the hypothesis of no-Granger causality between income inequality (e.g., Gini index and income quintile share ratio) and the growth rate of GDP per capita. Thus, we do not find empirical validation of a statistically significant Granger relationship between the measures of inequality and economic growth in the short run. Accordingly, the assumption of this research to analyze the Granger-causality between growth and social exclusion instead of growth and income inequality is empirically supported.

The results for the inexistent relationship between income inequality and growth are not new in the literature. As several surveys show, the findings of this strand of empirical research are mixed. Many studies observe that inequality reduces economic growth (e.g., Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Clarke, 1995; Alesina and Perotti, 1996; Deininger and Squire, 1998; Knowles, 2005; Davis, 2007). Other researches find a positive relationship between inequality and economic growth (e.g., Partridge, 1997; Li and Zou, 1998; Forbes, 2000; Castelló-Climent, 2004). Other ones, similarly to Kuznets (1955), find evidence for a non-linear correlation—for example, U-inverted shaped) (e.g., Barro, 2000; Banerjee and Duflo, 2003; Pagano, 2004; Voitchovsky, 2005; Bengoa and Sanchez-Robles, 2005; Barro, 2008; Castelló-Climent, 2010; Charles-Coll, 2010). Finally, there are studies which find no statistical significance or a non-conclusive nexus (e.g., Lee and Roemer, 1998; Castelló and Doménech, 2002; Panizza, 2002).

Banerjee and Duflo (2003) identify three main sources of bias that allow us to explain the inconclusiveness of results in this strand of literature: (1) the measurement errors in data on inequality; (2) the choice of estimator approach; and (3) the non-linearity of the relationship between the level of inequality and growth.

Similarly, Ehrhart (2009) distinguishes two main reasons behind these controversial results. First, the statistical relationship between income inequality and growth may reflect the effect of omitted variables. For instance, Birdsall *et al.* (1995) sustain that the strong negative correlation is due to the omission of an educational variable (primary and secondary school enrolment rates). Perotti (1996) claims that the negative correlation between inequality and growth is not robust to the inclusion of the variable measuring the share of people over 65 years of age. Birdsall *et al.* (1995) and Fishlow (1996) find that inclusion of regional dummy variables makes the income inequality variable insignificant in the growth regression.

The second issue of empirical analyses according to Ehrhart's (2009) classification matches with Banerjee and Duflo's (2003) hypothesis that the vast majority of research studying the impact of income inequality on economic growth does not measure inequality in a consistent manner as a consequence of lacking comparable data. Knowles (2005) states that studies predating the release of the Deininger and Squire (1996) dataset include data of dubious quality.

In this scenario, we check if our results of inconclusive findings can be explained by the same arguments proposed by this literature. In particular, checking for Banerjee and Duflo's (2003) hypotheses, we control whether the not statistically insignificant relationship between income inequality and growth: (1) is due to measurement errors in data—by using two alternative indexes of inequality; (2) depends on the choice of estimator approach—by using three alternative estimators; or (c) it is due to non-linearity—by including a quadratic term of the measures of income inequality in the models. However, the finding of a not statistically significant relationship is robust to all these checks.

In conclusion, on the question of whether income inequality is harmful or beneficial for growth, our data comply with evidence of irrelevant short run nexus. In spite of this, we guess that by using a long-term perspective this finding may change. As recently shown by Herzer and Vollmer (2012), by using panel cointegration techniques to investigate the long-run effect of income inequality on growth, the effect of the inequality on per-capita income is statistically significant.

## 5. Conclusions

This article pursues a twofold objective. From a methodological point of view, the article proposes an aggregate overall index of social exclusion, estimated through a relatively new approach to this issue (i.e., MPCA). Atkinson *et al.* (2002) and Atkinson and Marlier (2010) outline the essential properties of the indicators of the social index (e.g., unambiguous, robust, responsive to policy without being subject to manipulation, consistent with international standards, balanced across the different dimensions, and readily understood by lay members of the community). We attempt to follow their recommendations by using macro data published by Eurostat for 28 European countries over the period 1995–2010.

The rationale behind the proposed index reflects the conviction that the quantification of an overall index of social exclusion is an essential step in assessing the economic relevance of this phenomenon. We consider as helpful a synthetic measure of social exclusion in terms of a communication strategy. In fact, a solo index allows us to overcome one frequent criticism of these non-monetary indicators. It is what they lack that has made GDP a success: the powerful attraction of a single headline figure allowing simple comparisons of socioeconomic performance over time or across countries (Stiglitz *et al.*, 2009). Hopefully, this work will play a role in this scientific debate.

Looking at the country-by-country analysis, for the year 2010, Scandinavian countries (Denmark, Sweden, Finland, Norway) exhibit the lowest levels of social exclusion. On the contrary, some South European countries (Portugal, Malta, Spain) and Lithuania exhibit the highest values. Looking at time trends, one can see that there has been a decrease in the overall index of social exclusion. This reveals the efficacy of national and European policies to promote social inclusion. In particular, these policies have been very effective in decreasing the level of social exclusion between 2000 and 2010 in Slovenia, Austria, Cyprus, and Finland. Conversely, Sweden, Romania, Latvia, Slovakia, and Bulgaria are the only five European countries in which social exclusion increased in the last decade.

The second goal of this article consists of analyzing the short run relationship between social exclusion and economic growth. In this sense, we provide a rough assessment on the effectiveness of Lisbon's Strategy agenda. Initially, we test whether social exclusion causes economic growth or vice versa in the Granger sense. Results show that there is a (not very robust) statistically significant relationship of Granger causality between social exclusion and economic growth but not vice versa. Atkinson and Marlier (2010, p. iii) state that "Promoting social integration and inclusion will create a society that is safer, more stable and more just, which is an essential condition for sustainable economic growth and development"; thus, this research does not find empirical evidence that supports this view in the short run.

In general, this article has sought to extend the embryonic literature on the issues of measurement of the social exclusion and on the relevance of this phenomenon on the economic development in Europe. With regard to the latter issue, it is worth noting that the theoretical literature has not analyzed the possible mechanisms linking social exclusion to economic growth. We make a first attempt to fill this gap, drawing on some strands of literature on income inequality. In this perspective, we also find that, in the short run, social exclusion has a larger effect than income inequality on economic growth. However, further research needs to explicate the long run mechanisms through which social exclusion matters for economic growth.

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## Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web-site:

**Appendix A:** Database
**Appendix B:** The core matrix with dimensionality (1,1,1), (2,1,2) and (2,2,2)
**Appendix C:** Alternative estimates of Social Exclusion Index
  **Table 5:** Principal component analysis
  **Table 6:** Countries' ranking for MPCA and PCA approaches
  **Figure 3:** The dynamic of the normalised index of social exclusion
**Appendix D:** Regressions with indexes of income inequalities