PhD Thesis:

“Social Exclusion in Spain:

Measurement Theory and Application”

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Contents

Introduction

Social exclusion has attracted much attention in recent years in Europe and elsewhere. In fact, the Lisbon Summit committed EU member states to adopt the promotion of social cohesion and inclusion as a strategic goal. But, social exclusion is a new concept in the literature and there is not full agreement on its definition. Moreover, the meaning of social exclusion is often mixed with that of related concepts such as poverty, deprivation and polarization. Social exclusion can be seen as a process that fully or partially excludes individuals or groups from social, economic and cultural networks and has been linked to the idea of citizenship (Lee and Murie, 1999). In fact, social exclusion can be defined as disempowerment at the individual level and as structural obstacles at the social level, which deny some groups access to resources associated with citizenship (Gore, 1997). In particular, social exclusion can be defined as a process, which causes individuals or groups, who are geographically resident in a society, not to participate in the normal activities of the citizens in that society. However, this definition creates some problems. It is argued that non-participation in the normal activities of the society can be a voluntary choice, so the individual can decide to be excluded without feeling in a disadvantageous situation (Burchardt et al., 1999). Moreover, it is not clear which activities have to be considered "normal activities of the citizens in the society".

Atkinson (1988) underlined three main elements characterizing social exclusion: relativity, agency and dynamics. Social exclusion involves the 'exclusion' of people from a particular society, so to judge if a person is excluded or not, we have to observe the person relative to the context of the rest of the society she lives in. Moreover, exclusion implies a voluntary act (agency) and depends on how situations and circumstances develop (dynamic process). So, social exclusion is either a process or a state. Finally, another essential characteristic of social exclusion is its multidimensional nature.

The literature on social exclusion includes studies on specific problems (e.g. long-term unemployment, social networks, etc.), which are taken to be instances of social exclusion, as well as studies tending to develop a general conception of social exclusion. There are also few studies stressing on the average number of years at which the individual is excluded (e.g. Burchardt 2000, Burchart et al. 2002). But, there are no studies focused on changes in the social exclusion distribution over time and on the causes of the dynamic process that leads the individual to be defined as socially excluded, as far as we know. Therefore, this thesis is motived by the need to develop appropriate methods to investigate the dynamics of social exclusion.

Objectives

In order to promote social cohesion and inclusion, the EU states have to identify the individuals most likely to be excluded, who is most likely to remain excluded and who is most likely of becoming excluded. There is a growing literature that focuses on the definition of an appropriate measure of social exclusion and in the identification of who is socially excluded today (e.g. D'Ambrosio and Chakravarty, 2002, Tsaklogou and Papadopoulos, 2001, Nolan, Whelan, Maitre and Layte, 2000). However, none of these measures seem to be completely satisfactory, or based on an adequate theoretical background. Also, there are no satisfactory studies focused on the dynamic process that leads the individual to be defined as socially excluded.

Therefore, the main objectives of this thesis are the following:

- to propose an operational definition of social exclusion paying attention to the border between social exclusion and connected concepts (poverty, deprivation and polarization);
- to suggest a possible approach to select the dimensions of social exclusion, and the items that are suitable to serve as indicators for each dimension, taking due account of the main literature;
- to perform a multidimensional analysis of social exclusion;

- to construct a summary index to measure social exclusion on the basis of some appropriate theoretical assumption;
- to empirically analyse social exclusion dynamics: (i) to investigate if an individual experiencing social exclusion today remains in the same state in successive years (if social exclusion is partially a transitory phenomena), and (ii) to verify the existence of social exclusion persistence and the processes that cause it using the appropriate econometric technique;
- to analyse the Spanish reality on the basis of the proposed theoretical frame using the European Community Household Panel (ECHP);
- to propose a method to compute endogenously the thresholds of a distribution in order to solve the arbitrariness connected with the sensitivity of the proportion of excluded individuals to the particular threshold chosen.

Methodology and main problems

From a theoretical point of view, in order to analyse social exclusion, we need to define it. We also need to specify the dimensions respect to which the individual is excluded or not, the functional form of the synthetic indicator of social exclusion and a method to select the cut-off that distinguishes excluded individuals from not excluded ones.

Since social exclusion is a contested term, we need an operational definition of social exclusion. Thus, we define the social exclusion concept by analysing the main contributions in the literature and identifying the main characteristics of social exclusion.

In order to select the dimensions of social exclusion, we propose to follow the functionings approach proposed by Sen (1985, 1993 and 2000). Functionings represent parts of the state of a person, in particular the various things that he or she manages to do or to be in leading a life. The individual well being, thus, can be seen as an index of the person's functionings. However, some problems emerge in the application of the Sen's approach such as the identification of relevant functionings. We seek to propose some useful criteria to solve these problems.

After the dimensions are selected, we need an “aggregative strategy” in order to construct a summary indicator of social exclusion. This strategy requires specifying the underlying hypotheses on the measurement of functionings, the weighting structure, and the functional form of the indicators. The outcome of an aggregative strategy is, by definition, a complete ordering even if some ambiguity might arise as a result of sensitivity analyses of the underlying hypotheses. Moreover, it may be possible to reduce the degree of arbitrariness by choosing all social exclusion measures that fulfil a set of reasonable postulates. So, we propose to choose a set of criteria for social exclusion measures which in turn implicitly determines a class of measures.

The choice of threshold in any distribution is highly problematic since it can affect the results of the proposed analysis. When we consider more dimensions, as we do in this thesis, we face even more problems since we need to identify a threshold in every dimension. Therefore, we analyse some methodological issues connected with the endogenous determination of thresholds and groups in a distribution.

Social exclusion is a dynamic process. Thus, it is also important to investigate whether the same people are excluded year on year, or whether social exclusion is a short-term phenomenon. Standard statistical techniques are used to study the propensity to social exclusion. In particular, we focus on changes in the individual levels of social exclusion and changes in the individual positions in the distribution of social exclusion. A multivariate panel data analysis is used in order to identify the groups at higher risk of exclusion and to follow the dynamics of exclusion. In particular, we wish to understand if any individual experiencing social exclusion today is much more likely to experience it again. Moreover, we wish to understand the causes that may generate a persistence of social exclusion. From an econometric point of view, analysing the persistence of social exclusion means to analyse the persistence of a discrete choice variable. This leads to some methodological problems connected with the consistent estimation of a non-linear discrete choice model. Thus, the choice of the initial conditions (those found to be excluded in the base year may be a non-random sample) or alternatively of a semi-parametric structure is crucial for the correct estimation. We propose a possible solution and, then, we apply the proposed method to analyse the Spanish reality.

Finally, note that this thesis explores the possibility of a multidimensional analysis of social exclusion using the Sen's capability approach. Multidimensional empirical studies are scarcer in the literature and, indeed, not easy to perform. Each dimension represents an outcome considered important, but interactions between dimensions create a certain number of complications in the analysis. Moreover, a list of relevant dimension is difficult to fulfil and it cannot be exhaustive. Finally, there also exist a certain number of methodological problems in the empirical application of the Sen's capability approach that are widely discussed in the literature. The analysis performed in this thesis gives an original answer to the question, how we can perform a multidimensional analysis.

Thesis structure

This thesis is composed by six chapters. It begins with a discussion of possible answer to the question, what exactly does social exclusion mean? Clarifying the meaning of social exclusion turns out to be quite non-trivial: reading studies and reports on social exclusion reveals a profound confusion among experts. Indeed social exclusion is a "highly problematic" term and it is often confused with similar concepts as deprivation and multiple-poverty. In chapter one, we analyse some key elements of social exclusion and we discuss different approaches to the measurement and understanding of social exclusion and its causes. We also introduce a number of answers to common methodological problems concerning the measurement of social exclusion that allows us to specify our perceptions of "social exclusion" in a working framework useful in the subsequent chapters.

The subject of chapter two is the measurement theory of social exclusion. After clarifying the concept of social exclusion and specifying our working definition, it is still not clear which indicator has to be used to measure social exclusion. By far the most common way of specifying a social exclusion measure is to choose one that, on the face it, has some appealing properties. In this respect, in the social exclusion measurement theory the axiomatic approach is not yet dominant (even if there are a number of promising axiomatic approaches). We believe that axiomatics may turn out to be very fruitful in social exclusion measurement. Therefore, we propose a multidimensional measure of social exclusion requiring its coherence with a certain theoretical background. We also pay attention on the relationship between this measure and the existing axiomatic approaches.

Chapter three and four are about the dynamic of social exclusion. In particular, chapter three analyse the degree of social exclusion mobility. This analysis is motivated by the following observation: if social exclusion is only a transitory phenomenon, social exclusion headcount ratio based on a single year will overestimate the problem. To address this issue, we analyse the extent to which individuals change place in social exclusion distribution over time. In chapter four, we address the issues of the existence of persistence of social exclusion and its causes. In fact, there are two distinct processes that may generate a persistence of social exclusion: heterogeneity (individuals are heterogeneous with respect to some observed and/or unobserved adverse characteristics that are relevant for the chance of experiencing social exclusion and persistence over time) and true state of dependence (experiencing social exclusion in a specific time period, in itself, increases the probability of undergoing social exclusion in subsequent periods). Distinguishing between the two processes is crucial since the policy implications are very different

Chapter five looks at the following methodological problem: how to endogenously group the population in k groups (where also k is endogenously determined). This is a common problem in the poverty literature and it is also extreme relevant in the implementation of our analysis. For example, the endogenous determination of the poverty line could reduce the degree of arbitrariness in analyses based on headcount ratios and poverty gaps. In a multidimensional context, we need the specification of a threshold in every dimension; therefore, an endogenous method to determine such thresholds could be very useful. We discuss a general method to obtain the best population subdivision in k groups, and we propose a “stopping rule” in order to determine the optimal number of groups existing in the population.

Finally, chapter six summarizes the study and draws conclusions regarding the social exclusion measurement theory and the evolution of social exclusion over time in Spain.

Data

In this thesis, we use 1994-2000 Spanish data from European Community Household Panel (ECHP), which is a multi-country comparative household panel survey conducted annually by following the same sample of households and persons in Member States of the European Union. The advantage of the ECHP is that permits to analyse economic and social household conditions from a dynamic point of view. Instead, the main disadvantage is the omission of the homeless populations that could be expected to be socially excluded. As with any data source, we can face sample selection problems: some eligible individuals do not yield an interview. In order to try to correct for the bias that may arise from initial non-response, the obtained sample is weighted to reflect population characteristics such as age, sex, type of dwelling, etc, as closely as possible. Therefore, the analyses reported in this thesis are weighted using the cross-sectional weights available in the ECHP as appropriate. A further problem of non-response specific to panel data arises because respondents at the first wave may fail to give an interview at subsequent waves, so that the remaining sample may be no longer representative. This process is known as attrition. In Spanish data between the 1st and 2nd wave attrition is around 10%, and it is less than 5% between the subsequent waves. We have 11488 individuals (aged 16+) per year in the 4-waves balanced panel and only 8914 individuals per year in the 6-waves balanced panel. A second set of weights, using the more detailed information about individual characteristics available from the most recent interviews, can be used to counter possible attrition bias. Therefore, the longitudinal weights available in the ECHP have been used as appropriate. In chapter 4, we do not use longitudinal weights in any estimation since from an econometric point of view is more efficient not to use sampling weights, as we see later.

1

Understanding Social Exclusion Issues

At the end of 1980s we observed a conceptual shift from poverty to social exclusion. The deep transformations in the economic system in Western countries, and the strong individualism, lead to the emerging of problems not only related to a lack of wealth. A weakening of family ties, an increase in the job precariousness and in the unemployment rate, a growing violation of human rights and a decline in social participation, show the inadequacy of the standard measures of poverty to describe the new reality. The lack of income is not the only relevant aspect anymore. To analyse the new reality, we need to focus not only on economic aspects but also on social and political aspects of the individual day life. A new concept emerges: social exclusion.

Social exclusion is a 'highly problematic' and contested term. Atkinson (1998) recognizes that "reading numerous enquiries and reports on exclusion reveals a profound confusion among experts". However, to clarify the meaning of social exclusion (and inclusion) is necessary and urgent since the EU member states committed themselves to adopt the promotion of social cohesion and inclusion as a strategic goal (Lisbon Summit).

The aim of this chapter is to discuss possible answers to the question, what exactly does social exclusion mean? It then discusses different approaches to the analysis and understanding of social exclusion in order to arrive to an empirical application of its concept in the subsequent chapters. Finally, we wish to highlight the unsolved research issues that motivate this thesis.

In next section, we focus on the meaning of the term social exclusion. In section 1.2, we give an answer to the question, what dimensions of social exclusion are relevant? In section 1.3, we stress on social exclusion as a dynamic concept. In section 1.4, we discuss the links among social exclusion, poverty and deprivation. In section 1.5, we analyse the link between social exclusion and polarization. In section 1.6, we discuss some measurement problems. Conclusions are in the last section.

1.1 On defining social exclusion

The aim of this section is to understand better the meaning of the term social exclusion. In fact, the concept was originated in continental Europe and it was used in different circumstances (and with different meanings). Weber used for the first time the term social exclusion to indicate a process leading one group to secure for itself a privileged position at the expense of some other groups (Parkin, 1979). In France, the term social exclusion was used to indicate the concept of underclass[1]. Recently, the debate on the term social exclusion leads to the following results.

Social exclusion can be seen as a process, which fully or partially excludes individuals or groups from social, economic and cultural networks and has been linked to the idea of citizenship (Lee and Murie, 1999). In fact, social exclusion can be defined as disempowerment at individual level and as structural obstacles at the social level which deny some groups access to resources associated with citizenship (Gore, 1997). In particular, Bhalla and Lapeyre (1999) define social exclusion as a process, which causes individuals or groups, who are geographically resident in a society, not to participate in the normal activities of the citizens in that society.

[1] The “underclass” identifies several generations of people from ethnic minorities, living in ghettos and in receipt of welfare, cut off from the mainstream of the society, and representing a threat to it (Murray 1999).

The above definition has some problems. First, non-participation in the normal activities of the society can be a voluntary choice, therefore, an individual can decide to be excluded without feeling in a disadvantageous situation (Burchardt et al., 1999). In this case, she should not be defined as excluded. Second, we need to define which activities have to be considered "normal activities of the citizens in the society" in order to identify the socially excluded individuals.

Regarding the first problem, Atkinson (1998) points out that social exclusion implies a voluntary act (agency) and depends on how a situation and circumstances develop over time (dynamic process). Social exclusion also involves the 'exclusion' of people from a particularly society. Thus, to judge if a person is excluded or not, we have to observe the individual position relative to the rest of the society she lives in. Therefore, the three main elements characterizing social exclusion are *agency, dynamics and relativy (*Atkinson, 1998). Another essential characteristic of social exclusion is its *multidimensional* nature. In fact, the European Commission (1992 and 1993) suggests that "The concept of social exclusion is a dynamic one, referring both to processes and consequent situations... it also states out the multidimensional nature of the mechanisms whereby individuals and groups are excluded from taking part in social exchanges, from the component practices and rights of social integration and identity... it even goes beyond participation in working life: it is felt and shown in the fields of housing, education, health and access to services".

Atkinson (1998) also points out that the dynamic process called social exclusion leads to a state of exclusion. So, social exclusion is either a process or a state. Bhalla and Lapeyre (1999) identify the state of exclusion with individual deprivation. On the same idea, Sen defines social exclusion as a process leading to deprivation.

According to Sen (2000), social exclusion can be directly a part of the capability approach. [2] In fact, he argues, "Adam Smith's focus on the deprivation involved in 'not being able to appear in public without shame' is a good example of a capability deprivation that takes the form of social exclusion. This relates to the importance of taking part in the life of the community, and ultimately to the Aristotelian

[2] See Appendix I for details about Sen's capability approach

understanding that the individual lives an inescapably 'social' life. Smith's general point that the inability to interact freely with others is an important deprivation in itself (like being undernourished or homeless), and has the implication that some types of social exclusion must be seen as constitutive components of the idea of poverty – indeed must be counted among its core components".

Therefore, social exclusion is 'constitutively' a part of a capability deprivation, but it can also be 'instrumentally' a part of a capability deprivation as cause of diverse capability failures (Sen, 2000). In fact, to be excluded can be itself a deprivation (constitutive relevance). But, exclusion processes can also play a role in causally generating other deprivations that may be ultimately important. In fact, causally significant exclusions cannot be impoverishing in themselves but they can lead to impoverishment of life through their casual consequences (instrumental relevance). So, the different casual patterns become important as in the literature previous analysed. Moreover, as Atkinson identifies agency as characteristic of social exclusion, Sen speaks about active and passive forms of social exclusion. In the first one there is a deliberate attempt to exclude, while in the second one the exclusion is only an involuntary consequence of another action. According to Sen, both forms are important but not in the same measure. Finally, Sen underlines that, on the basis of the above observations, "the real importance of the idea of social exclusion lies in emphasizing the role of relation features in the deprivation of capability and thus in the experience of poverty".

We are now ready to give a working definition of social exclusion that is able to capture all the aspects underlined above. In particular, stressing on agency and on need to analyse social exclusion as a multidimensional process relative to the society under study, we can define social exclusion as follows:

Social exclusion is a multidimensional dynamic process leading to a state of individual exclusion relative to the rest of the society where the she lives in. Social exclusion at a point in time is defined as the impossibility to achieve some relevant functionings (that is, the various things that an individual manages to do or to be in leading a life).

Note that this definition implies that those having the lowest well-being (in other words, the most socially excluded) are those with the lowest achieved functionings.

1.2 Social Exclusion as multidimensional concept

The definition of social exclusion given in the previous section leaves open which dimensions are regarded as relevant. The issue of which are the relevant dimensions to identify an individual as excluded, or how to select them, is subject to ongoing discussion.

Detailed studies on social exclusion have stressed on different "relevant dimensions" revealing a certain degree of confusion among experts. In their literature review on social exclusion, Lee and Murie (1999) identify eight dimensions of social exclusion: labour markets and employment, health, education, welfare markets and poverty traps, exclusion from financial circuits and public utilities, housing markets, neighbourhoods, social networks. The European Commission (2000) when defining social exclusion in terms of the denial or non-realization of social rights, proposes to analyse the different dimensions of social exclusion with the following indicators: distribution of income, share of population below the poverty line before and after social transfers, persistency of poverty, proportion of jobless households, regional disparities, low education, long-term unemployment. Fields like health, housing and homeless, literacy and numeracy, access to essential services, financial precariousness and social participation, are also considered. Burchandt et al. (2001) identify four dimensions: consumption (capacity to purchase goods and services), production (participation in economically or socially valuable activities), political engagement (involvement in local or national decision-making), social interaction (integration with family, friends, cultural groups and community). Finally, Bhalla and Lapeyre (1999) identify three main areas of exclusion: the economic, social and political area. The economic area includes questions of income and production, of access to goods and services from which some people are excluded and others not; the social area analyses relationship issues such as access to public goods and services (e.g. access to education and heath), labour market (e.g. unemployment and precariousness of employment), and social participation (including union membership and local associations); the political area includes aspects connected with personal security, freedom of expression, political participation and equal opportunity.

From the above discussion emerges the lack of a common agreement on the dimensions necessary to analyse social exclusion. Moreover, note that our working definition of social exclusion explicitly assumes that every dimension is a relevant functioning. The question regarding the choice of the relevant functionings has been addressed by Sen (1993, 1988 and 2000). He never provided a complete list, but he gives some guidelines. He argues that social exclusion can cause deprivation through inequality and poverty, labour market exclusion, credit market exclusion, gender-related exclusion, health care exclusion, food market exclusion, etc. Therefore, he underlines some relevant functioning deprivations as unemployment, lack of access to health care, lack of educational opportunities, absences of social safety nets, lack of facilities for disabled persons, credit market exclusion, marketing limitations, political exclusion and relational exclusion. These observations can be seen as the beginning of a wider philosophical debate on the relevant dimensions of well-being. We prefer do not enter in the details of the debate; the interested reader can refer to Nussbaum (1995), Akire (2002) and Robeyns (2002) for further discussion. We prefer to focus on the empirical applications of the Sen's observations made in economics. Brandolini and D'Alessio (1998) and Tsakloglou and Papadopoulos (2001) have explicitly chosen "the relevant functionings" in order to analyse deprivation and exclusion. In particular, Brandolini and D'Alessio define a small number of indicators classified in six relevant dimensions: health, education, employment, housing, social relationship, and economic resources. Tsakloglou and Papadopoulos construct static indicators of deprivation selecting the following relevant functionings: income, living conditions, necessity of life and social relations. Then, they aggregate this information in order to obtain a static indicator of cumulative disadvantage.

Following the suggestions given by Sen, and taking in account the previous empirical applications of the capability approach (Brandolini and D'Alessio, Tsakloglou and Papadopoulos), we select ten relevant functionings. First, Sen indicates poverty as one deprivation caused by social exclusion. Therefore, we identify four relevant functionings as representative of the command over economic resources: "basic need fulfilment", "to reach a certain quality of life", "having an adequate house" and "having an adequate income". Note that we expect the last functioning being positively correlated with the previous ones since a sufficient income indeed helps to meet basic need, to reach a certain quality of life and to have an adequate house, but it also reduces vulnerability due to unexpected events. Conversely, basic needs, quality of life and an adequate house can also be ensured by social relationships (e.g. family support) and not necessarily by income. Second, Sen also indicates labour market exclusion (unemployment), health care exclusion, relational exclusion, lack of educational opportunities, lack of safety and political exclusion as deprivations caused by social exclusion. We select the corresponding functionings: "Being able to perform a paid or unpaid activity", "Being healthy", "Ability to have social relationships", "Possibility to have a basic education", "Living in a safe and clean environment" and "Participation in the political life". These ten functionings seem to be a reasonable (even if not exhaustive) list of functionings. Adding to the list other functionings to take into account other deprivations (as credit market exclusion, gender-related exclusion, food market exclusion, lack of facilities for disabled person, and marketing limitations) could require the availability of an unreasonable quantity of information. Finally, note that this list of functionings is also coherent with the areas of analysis indicated by the literature reviewed above.

1.3 Social Exclusion as a dynamic concept

There is common agreement in the literature on the definition of social exclusion as a dynamic process. The main idea is that social exclusion does not simply arise from an individual or group's current status but it is connected to their background and past. It depends on how a situation and circumstances develop or are expected to develop (Atkinson, 1998). For example, people are considered excluded from the job market, not just because they do not have a current job or income, but because they have few prospects for the future.

The main idea in defining social exclusion as a process is the following. A range of social and economic processes will influence levels of exclusion, and households at similar levels will have arrived at the final position from a variety of different trajectories. In order words, social and economic characteristics affect the individual trajectory; therefore the same individuals can follow different trajectories depending on a variety of events. Events that happen to more individuals can be differently valued by each individual on the basis of her own life experience, and they can generate different processes and different trajectories.

Therefore, using a dynamic approach emphasizes the importance of the factors leading to exclusion. In fact, the focus shifts to the causal analysis of various paths into and out of the state of exclusion.

Burchardt et al. (1999) stressed on the causes that can lead to social exclusion. They classified the factors that affect the individual's ability to perform the "normal activities" of the individual in the society as follows:

- the individual's own characteristics (health, education level, etc.)
- events in the individual life (partnership breakdown, job loss, etc.)
- characteristics of the area she lives in (physical environment, transport links, etc.)
- social, civil and political institutions of society (racial discrimination, welfare state, etc.)

Atkinson (1998) points out the main causes leading to exclusion from the labour market and from consumption. The process leading to exclusion from the labour market can be seen as due to a social security system which induces people to reject labour market participation. Or it can be seen as the outcome of exclusionary behaviour by trade unions or by employers setting a high profit hurdle for job creation. The process leading to exclusion from consumption, instead, can be determinate by the pricing decisions of the suppliers.

It is also possible to analyse how people interact in relation to their economic capacities, resources and risks, and how they organize themselves in groups to include members and to exclude non-members. Olson (1982) agues that stable, peaceful societies tend to accumulate many collusive organizations (distributional coalitions) seeking rents. Thanks to their power, these groups collect advantageous rents, against those individuals who remain excluded from such groups. Thus, the vulnerability of the poor lies in their exclusion from membership of rent-seeking, organized groups. Olson's observations suggest that social exclusion can be seen as the result of the collusive behaviour that had been successfully achieved by the groups characterizing the society. Thus, homogeneous groups on the bases of some characteristics (income, level of education, employment, social status, etc) are formed to offer the members some goods (i.e. insurance, health services, citizen rights, etc.). Moreover, among the members the social relationships result to be strong. Who is excluded cannot benefit from these advantages and does not participate in the social and political life of the group (community).

Numerous studies, as seen above, focus on the interpretations of social exclusion as a dynamic process but empirical treatments are scarcer. Future research should focus on understanding movements in and out of a state of social exclusion. In fact, explaining the dynamics that lead in and out of social exclusion is crucial to understand the causes of exclusion and to formulate anti-poverty policies. Studies on poverty dynamics should be extended to allow for multiple dimensions. The analysis of longitudinal poverty patterns describes different patterns of dynamics in terms of the fixed characteristics of the individual, and identifying who experiences certain types of poverty transition (e.g. Gardiner and Hills, 1999). Transition poverty models examine the chances of exit from, or entry into, poverty as function of observed characteristics of the individuals underlining that experience these events (e.g. Stevens, 1999). Variance component models explain the path of individual income in terms of observed characteristics and other non-observed processes in order to try to discover regularities in the process driving the dynamics (Ducan, 1983; Ducan and Rodgers, 1991). Finally, structural models explain the economic processes that underlie poverty transitions as function of observed and unobserved characteristics of the individual in order to identify the main characteristics, or events, that cause poverty dynamics (Burgess and Propper, 1998).

1.4 Social exclusion, poverty and deprivation

The emerging of a new reality, as emphased in the introduction, led to a development of the traditional concept of poverty. This development involves three main steps: first, from a one-dimensional concept to a multidimensional one; second, from an analysis focused on the lack of resources to an analysis focused on economic, social and political dimensions; and, third from static to dynamic analysis.

Poverty was initially defined as a static one-dimensional concept that means a low level of material welfare (usually lack of income). Therefore, poverty research initially seeks to identify the individuals whose participation in society is constrained by lack of resources and concentrated on low income as an indicator. The first development of the concept of poverty implied a change in the focus from income to multidimensional disadvantage. Townsend (1979) defines the multidimensional disadvantage as relative deprivation - the absence of those diets, amenities, standards, services and activities, which are common or customary in the society. People are deprived of the conditions of life, which ordinarily define membership of society. In a more recent conceptualisation, deprivation ‘'is viewed as a lack of access to resources and denial of opportunities in areas which most affect people's life chances (particularly education, employment, housing) and ultimately, an inability to participate in those lifestyles, customs and activities which define membership of society'' (Fowell, 1999). Multidimensional poverty analysis has also attracted much attention in recent years focusing on the methodological aspects of a multidimensional measurement analysis (see Bourguignon, 1999).

Until the end of 1990s, research on multiple deprivations broadens the range of indicators but the objective remains an accurate identification of individuals who lack the resources to participate (see Nolan and Whelan, 1996). However, recent studies broaden the concept of multiple deprivation to attempt to identify not only those who lack resources, but also those whose deprivation arises in different ways: through political discrimination, illnesses, cultural identification, lack of social relationships (see for example Brandolini and D'Alessio, 1998).

Finally, the improvement in information technology and the availability of longitudinal data permitted to go from static to dynamic analysis. For example, Whelan, Layte and Maitre (1999, 2000 and 2001) study in recent papers the persistent of deprivation in the European Union. This permitted to better evaluate the efficacy of policies verifying if individuals are permanently (or only temporally) helped out of disadvantage situations.

At this point, we need to find an answer to the following question, what can social exclusion add to the analysis based on the concepts of multiple poverty and deprivation? In fact, social exclusion seems like an old idea in new clothing: it seems to be an attractive way for policy makers to avoid the unpopular words "poverty" and "deprivation". In reality, the concept of social exclusion represents a change in emphasis rather than a change in direction: social exclusion is defined as a wide concept that moves the focus on the necessity of a wider analysis including economic, social and political dimensions, taking a longitudinal view, and allowing for causes of deprivations other than low income.

1.5 Social exclusion and polarization

The concept of social exclusion is linked to the process by which individuals and their communities become polarized, socially differentiated and unequal (ERSC, 1997). Therefore, we observe a link between polarization and social exclusion. We could state that social exclusion implies polarization, or vice versa. But, before discussing it, we better define polarization.

A society is said polarized when the population is grouped into significantly-sized clusters, such that each cluster is very similar in terms of the characteristics of its members, but different clusters have members with very dissimilar characteristics (Esteban and Ray, 1994). Thus, an index of polarization measures the sense of identification of each individual with other individuals who have the same characteristics, and the sense of alienation from the other groups. In different words, we can say that polarization measures the sense of inclusion of an individual in one group, and the sense of exclusion from the other groups.

The existence of groups in the society implies the inclusion of the individual in a group and the exclusion from the other groups. So, a connection between social exclusion and polarization clearly exists. D'Ambrosio and Gradin (2000) suggests using as measure of social exclusion an index of polarization since 'neither the Lorenz-consistent inequality indices nor the measures of poverty are suited for this task'. This suggestion has to be carefully assessed since there is no evidence that social exclusion implies polarization and vice-versa. Intuitively, social exclusion seems to imply some degree of polarization. However, a society can be polarized without the existence of a group of excluded individuals as defined in section 1. So, the concept of social exclusion does not seem to be equal to the one of polarization even if they are clearly linked.

1.6 Measurement problems

A part of the literature focused on constructing multidimensional measures able to capture social exclusion at a certain point in time (e.g. Chakravarty and D'Ambrosio, 2002). This literature faces a certain number of methodological problems:

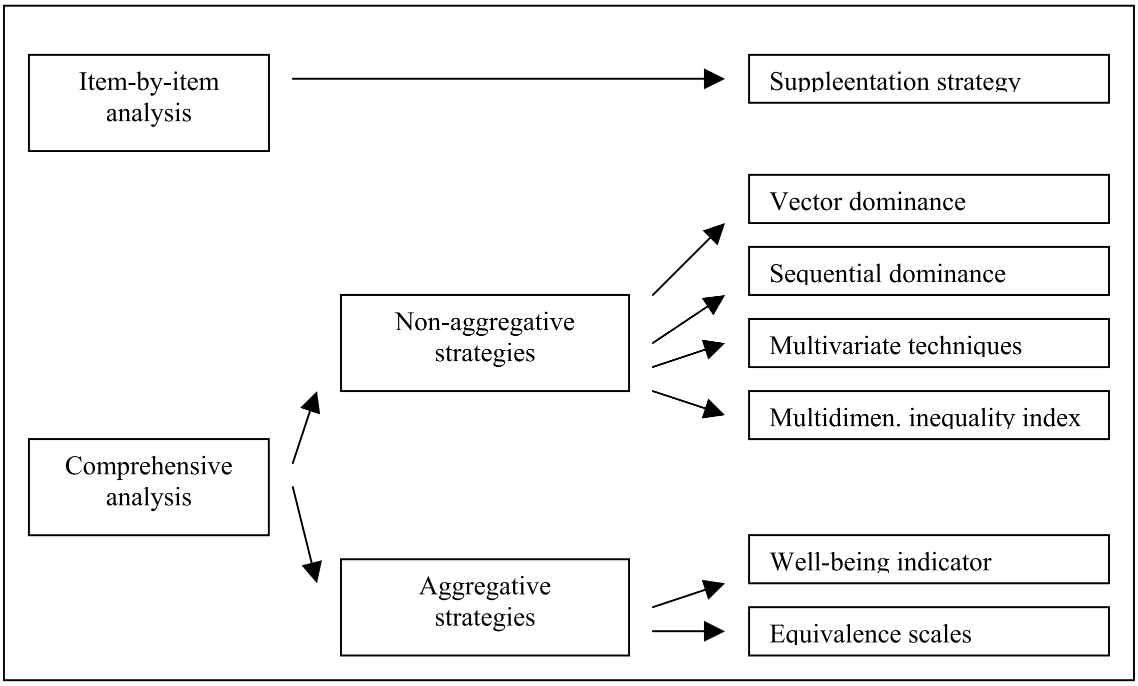
- how to select the dimensions of social exclusion and the items that are suitable to serve as indicators for each dimensions
- how to aggregate and weight them in a summary index to use the information that they contain
- how to select a particular cut-point to distinguish deprived from non-deprived individuals.

The first class of methodological problems was addressed in section 1.2, and it is also discussed later. In this section, we discuss the methodological problems emerging in the aggregation of different dimensions, and in the determination of a cut-point that divides the excluded individuals from the non-excluded.

1.6.1 Aggregation problems

In any empirical analysis of social exclusion, a fundamental decision concerns the way to deal with the multiple dimension of social exclusion. In Figure 1, we can observe different strategies of aggregation. If fact, strategies can be different depending on the purpose of the analysis: the more "structure" we impose to the data, the closer we arrive at a complete cardinal measure of social exclusion.

Figure 1. Strategies to deal with multidimensional analysis



Source: Brandolini and D'Alessio (1998)

It is possible either to investigate the dimensions singly or comprehensively, or to construct a synthetic indicator that resumes the information contained in all the dimensions.

If we wish to analyse the dimensions singly, we could use Sen's supplementation strategy: the attention is directed at the univariate analysis of every dimension, and also at the pattern of cross-correlation. This analysis has the advantage to be simple but it lacks synthesis and it is difficult to draw a well-defined unitary picture.

If we consider all the dimensions comprehensively but without collapsing them in a synthetic indicator (non-aggregative strategies), we need to compare a vector of dimensions. To do so, we can apply one of the following strategies: vector dominance analysis (Gaertner, 1993), sequential dominance analysis (Kendall, 1975, and Sharma, 1996), standard multivariate techniques or multidimensional indexes (Tsui, 1995, and Bourguignon and Chakravarty, 1997).

Finally, we can apply an aggregative strategy constructing a summary index of social exclusion. In this case, we need to specify the underling hypothesis on the weighting structure, the measurement unit and the functional form of the indicators. The result is a complete order but we pay the cost of imposing many restrictions on the data. However, this approach is the one we suggest. In fact, to evaluate policy against social exclusion it is important to have a complete order.

Weighting structure

Weights determine the extension to which different dimensions contribute to well-being, and different weighting structures reflect different views. Mayer and Jencks (1989) suggested equal weights since using different weights for different dimensions implies a certain degree of arbitrariness. Other experts suggest, “to let the data speak for themselves”: the weighting structure is determined by the frequency or by the output of multivariate techniques (as factor analysis, principal components or cluster analysis).[3] Whelan et al. (2001 and 2002), weight each dimension by the proportion of individuals non-deprived in such dimension, following the idea ‘the better a person see the others, the more deprived she feels’. Finally, Bhalla and Lapeyre (1999) stress on the importance that the weights given to the dimensions of social exclusion depend on the degree of development of the country considered. They argue that in industrialized countries the weight given to economic and social dimensions should be almost equal, while in less-developed countries the economic dimension should remain the most important one. In fact, the relational aspect becomes more important in the case of populations that already enjoy access to a survival minimum income.

Each view reported above represents a valid method to weight different dimensions; the choice about the weighting structure reflects the author’s point of view. In particular, we believe that equal weights are not able to discriminate among dimensions that are reputed to play different roles. Therefore, we prefer “to let the data speak for themselves”, and we specially agree with Whelan et al. (2001 and 2002).

[3] See Desai and Shah (1998), Nolan and Whelan (1996), Ram (1982), Maasoumi and Nickelsburg (1988) and Hirschberg et al. (1991) among the others

Functional form of the index and measurement unit

In the literature on multivariate measures of deprivation, individuals' living conditions are often summarized into an index of deprivation. The most popular family of deprivation indices is represented by the additively separable individual function Z_i in the G dimensions:

$$Z_i = \Sigma_g \; w_g \; z(x_{ig})$$

where z(.) is a non-increasing function of the amount x_{ig} possessed by the i-th individual (i=1,…,N) of the attribute (g=1,…,G), and w_g is the weight given to dimension g (equal across individuals). Note that "additivity" can be a reasonable hypothesis especially when some dimensions are represented by binary variables.

Bourguignon and Chakravarty (1997) derived several families of multidimensional measures which satisfy the Pigou-Dalton transfer principle. The latter requires that if we redistribute an attribute from a deprived individual to another one less deprived, the of degree social welfare increases. However, measurement problems emerge if some dimensions are represented by binary variables. In this case, the indices proposed by Bourguignon and Chakravarty cannot be computed. The same kinds of measurement problems emerge when we consider indices that look at complex patterns of interrelation among dimensions (as Maasoumi's index, 1986). Note that in the sub-sequent chapters, we ask the aggregation function to be additively separable since some dimensions will be represented by binary variables.

Finally, note that whereas the measurement unit might not cause any serious problem when the indicators are considered separately, a problem of commensurability can arise when they collapse into a single index. The way in which each attribute is measured depends on the nature of the attribute. So, the measurement unit can be a continuous variable for some attributes and the number of items for other attributes. Possible solutions to measurement problems could be variable standardization, or the application of ordinal criteria to quantitative variables.

Individual possession of attribute g

In most empirical studies,[4] deprivation is represented by binary variables that express the presence or the absence of deprivation. With dichotomised indicators, the situation of an individual in each dimension can be evaluated according to a function $z(x_{ig})$, where x_{ig} is the amount of the g-th attribute possessed by the i-th individual. If $z(x_{ig})$ is equal to one the individual is deprived, otherwise she is not deprived.

$$z(x_{ig}) = \begin{cases} 1 & \text{if } x_{ig} < x_g^* \rightarrow \text{deprived} \\ 0 & \text{if } x_{ig} \geq x_g^* \rightarrow \text{non-deprived} \end{cases}$$

where x_g^* is the cut-point that divides the g-th functioning distribution (assumed to be continuous) in two groups: deprived and non-deprived.

Evaluating deprivations using binary variables we loose information about the quantity or quality. Desai and Shah (1988) suggested measuring deprivation in dimension g using a distance between x_{ig} and the modal value of the g-th attribute:

$$z(x_{ig}) = E[x_{ig}] - x'_{ig}$$

where x'_{ig} is the mode of the distribution of g.

A distance function was also used by Hirschberg et al. (1991). They determined the individual deprivation as the distance between the individual position and the mean in dimension g controlling for the variance of the attribute:

$$z(x_{ig}) = (x_{ig} - \mu_g)/\sigma^2_g$$

where μ_g and σ^2_g are the mean and the variance of the dimension g.

[4] See Townsend (1979), Mark and Lansley (1985), Mayer and Jencks (1989), Nolan and Whelan (1996), Federman et al (1996) among others

Different degrees of deprivation, instead of the dichotomy deprived/non-deprived, are also assumed using the fuzzy sets approach proposed by Cheli and Lemmi (1995). The function z(.) is seen as a "membership" function that may assume a value between 0 and 1 (where value one indicates maximum deprivation). An intermediate value indicates that the individual is "partially" a member of a set of deprived people: The authors represented function z(.) as follows:

$$z(x_{ig}) = \begin{cases} 0 & \text{if } i=1 \\ z(x_{i-1\,g}) - [\,(\,\phi(x_{i\,g}) - \phi(x_{i-1\,g})\,)\,/\,(\,1-\phi(x_{1g}))] & \text{if } 1<i<N \\ 0 & \text{if } i=N \end{cases}$$

where $\phi(.)$ is the cumulative sampling distribution function of the attribute g, and $x_{1g} < \ldots < x_{ig} < \ldots < x_{Ng}$.

Different degrees of deprivation are also computed by Cerioli and Zani (1989). They define two critical values and partial deprivation is computed as a "deprivation gap". The relative distance between the individual position and the cut-point that assesses deprivation is what matters. In this case, z(.) is defined as follows:

$$z(x_{ig}) = \begin{cases} 1 & \text{if } x_{ig} < x_g^* & \rightarrow \text{deprived} \\ (x_g^{**} - x_{ig})/(x_g^{**} - x_g^*) & \text{if } x_g^* \leq x_{ig} < x_g^{**} & \rightarrow \text{partially} \\ 0 & \text{if } x_{ig} \geq x_g^{**} & \rightarrow \text{non-depriv.} \end{cases}$$

where x_g^* and x_g^{**} are the critical values that divide the definitely deprived and the definitely non-deprived.

1.6.2 Cut-point determination

The implementation of the multi-dimensional indices seen above implies the classification of each individual in one of the following exhaustive categories: deprived and non-deprived (or deprived, partially deprived and non-deprived). Therefore, we need to find the attribute levels that group the population in different clusters. These attribute levels are called cut-points.

The definition of the income threshold, that groups individuals in poor or non-poor, has received a lot of attention in the literature. British official statistics suggest using 50% of the mean of the equivalent income distribution as cut point. Eurostat, instead, suggests using 60% of the median, since the median is less sensitive than the mean to outliers. However, both suggestions imply a certain degree of arbitrariness. For example, the sensitivity analysis performed by Tsakloglou-Papadopoulos using different cut-points (50%, 60% and 70% of the median equivalent income) shows that the results are not robust respect to the cut-point.

Going from a uni-dimensional analysis to a multidimensional analysis the arbitrariness increases. In most of the multi-dimensional indices seen above,[5] we need to specify a cut-point for every dimension. Thus, the author can either choose a specific cut-point for every dimension (Burchardt et al., 2001) or she can define all cut-points as a fix proportion of the mean (or median) of every distribution.

Only few attempts to endogenize the cut-points specification exist. Aghevly and Mehran (1981) and Gradin (2000) proposed to define different groups minimizing the differences within groups expressed as the difference between the Gini index of the ungrouped population and the between-group Gini index. This method seems to work quite well but only with continuous distributions that present more than one mode. However, the number of groups is given, so it is arbitrarily decided. Therefore, there is a growing necessity to work on endogenous methods to compute the cut-points of a distribution in order to eliminate the arbitrariness in the actual social exclusion measures.

1.7 Conclusions

This chapter reviews the main contributions to the debate about social exclusion in order to understand better the concept. It emphasises the key features of social exclusion and the ongoing research areas.

[5] For example any multidimensional index based on the specification function of the kind suggested by Townsend (1979), Mark and Lansley (1985), Nolan and Whelan (1996), Cerioli and Zani (1989), etc.

We define social exclusion as a multidimensional dynamic process leading to a state of individual exclusion relative to the rest of the society where the individual lives in. Social exclusion at a point in time is defined as the impossibility to achieve some relevant functionings. This definition has a number of features. First, it allows multiple dimensions and, therefore, implies a specification of the "relevant functionings". Second, the definition regards dynamics as central to the concept of social exclusion. Therefore, the understanding of the individual paths into and out of the state of exclusion and the existence of an eventual persistence of exclusion becomes extremely important.

We emphasised that the analysis of various paths into and out of the state of exclusion has not been explored in the literature. Empirical studies of the causes leading to social exclusion dynamics are rare, and they are limited to the poverty dimension without allowing for multiple dimensions. We also stressed on the necessity of developing an empirical measure of social exclusion and, therefore, on the need to solve a certain number of methodological problems: aggregation and weighting problems and the definition of cut-points. The aim of this thesis is in part to propose answers to these methodological issues.

Appendix I. Sen's capability approach

Sen (1993) suggests a range of alternative concepts of individual welfare, which permit to move from a monetary approach to welfare analysis to a multidimensional analysis of the standard of living. The latter captures the achieved activities and state of being (e.g. having social interaction, having a good nutrition, etc.) of an individual. These achieved activities and states of being are called functionings. In other words, functionings represent parts of the state of a person, in particular the various things that he or she manages to do or to be in leading a life. The capability of a person reflects the alternative combinations of functionings the person can achieve, and from which he or she can choose one collection. The approach is based on a view of living as a combination of various 'doings and beings', with quality of life to be assessed in terms of the capability to achieve valuable functionings.

The individual well-being, thus, can been seen as an index of the person's functionings (Sen, 1985). In fact, commodities possessed by a person are converted into functionings by an individual function (converting function). The functionings considered range from the basic ones (i.e. to be well-nourished) to more complex ones such as to be able to participate in the community life. So, well-being can be seen as an evaluation of the vector of functionings (through an evaluation function).

According to this approach, deprivation in terms of income (inability to buy certain commodities) can become deprivation in terms of capabilities (limiting living opportunity) and it can lead to the impossibility to perform certain social functionings (i.e. appearing in public without shame). Therefore, this approach shifts the focus of the analysis from goods to people, stressing on the relationships between individuals and the community they live in. Finally, note that the capability approach is a multidimensional approach: it considers distinct capabilities and functionings.

The empirical application of the capability approach requires the identification of relevant functionings, the converting function and the evaluation function (Brandolini and D'Alessio, 1998).

The identification of the relevant functionings is discussed in section 1.2. However, note that the conversion from commodities to functioning reflects people's own perception as well as society standard. So, the main problem to consider is that different individuals have different abilities to transform commodities into functioning. Instead, in the specification of the evaluation function the main problem is to evaluate overall combinations of functionings and compare them across people. So, a valuation structure specifying the relevant functioning and their mutual relationship has to be determined.

Finally, note that Sen's approach defines well-being not in terms of 'achieved functioning' but of capabilities. However, the shift in the focus from functionings to capabilities presents some problems. Relevant alternatives to the actual achievement and time patters have to be considered. Moreover, statistically surveys collect only data on fact that actually occurred rather than on fact that could happen or could have happen. So, we have to be content to evaluate achievements functionings as elementary evaluation of the capability notion of well being (Sen 1993).

2

Measuring Social Exclusion:

methodological issues and empirical application

2.1 Introduction

In the first chapter, social exclusion was initially defined as a process that fully or partially excludes individuals or groups from social, economic and cultural networks and has been linked to the idea of citizenship (Lee-Murie, 1999). We highlight that social exclusion can also been seen as a part of the Sen's capability approach, and it can be defined as a process leading to a state of functioning deprivations (Sen, 2000). Remember that functionings represent parts of the state of an individual, in particular the various things that he or she manages to do or be in leading life. The capability of a person reflects the alternative combinations of functionings the individual can achieve, and from which he or she can choose one collection (Sen 1993). Thus, living is viewed as a combination of various "doings and beings", with quality of life to be assessed in terms of the capability to achieve relevant functionings. On the other side, the impossibility to reach a functioning leads to a state of deprivation. Therefore, we arrived at the following working definition of social exclusion: "*social exclusion at a point in time can be defined as the impossibility to achieve some relevant functionings*". Note that this definition has a number of features, as analysed in detail in Chapter 1. First, we need to focus on the relevance of each functioning at a point in time and in a certain space, so social exclusion is a relative concept. Second, social exclusion is a multidimensional concept since we evaluate exclusion on the basis of a vector of relevant functionings.

Third, social exclusion implies agency since every individual has to participate in the society she lives in to reach valuable functionings.

In order to design policies for inclusion, it is important to understand the magnitude of social exclusion. Therefore, we need to define a measure, based on the above definition, able to summarize the state of individual social exclusion. The choice of a particular measure of social exclusion can imply some degree of arbitrariness, and so can imply the conclusion based on that measure. It may be possible to reduce the degree of arbitrariness by choosing measures that fulfil a set of reasonable properties. There is a growing literature on the choice of a set of criteria, which in turn implicitly determines a class of multidimensional measures. (e.g. D'Ambrosio and Chakravarty 2002, Tsui 1999, Chakravarty et al. 1998, Bourguignon and Chakravarty 2003). We wish to reduce the arbitrariness in the measurement of social exclusion by focusing on the relationship between the capability approach and multidimensional measures of social exclusion. No studies have done so, as far as we know.

The main aim of this chapter is to construct a measure of social exclusion that has some appealing features. In particular, in our view any social exclusion measure should be clearly connected to the Sen's capability approach. In particular, we construct a social valuation function following the suggestion given by the Sen's capability approach, and we derive the unique (up to monotonic transformations) index consistent with such social valuation function. This index turns out to be the multidimensional generalization of the Foster-Green-Thorbecke (FGT) index. Therefore, this paper helps to better understand the hypotheses below the use of the FGT index to analyse multidimensional phenomena. As result, we obtain a full specification of the theoretical background behind the measure of social exclusion.

Note that the use of the multidimensional generalization of the FGT index to measure social exclusion permits to analyse the intensity of social exclusion. Therefore, the new element with respect to the existing literature is the change of focus from knowing if an individual is excluded or not, to knowing her degree of exclusion. Therefore, we can evaluate policies, not only comparing changes in the proportion of the population counted as excluded but also, analysing changes in the intensity of social exclusion. As far as we know, multidimensional measures of the intensity of a certain phenomenon are used in poverty analysis but not yet in social exclusion analysis.

In next section, we review the main literature on social exclusion and multidimensional poverty. In section 3, we construct a social valuation function according to Sen's capability approach. In section 4, we derive the unique (up to monotonic transformations) measure of social exclusion consistent with such social valuation function. Section 5 reviews the properties of the multidimensional generalization of the Foster-Green-Thorbecke index. Section 6 presents an empirical application to 1999 Spanish data from the European Community Household Panel (ECHP). Finally, some conclusions are made.

2.2 Literature review

The measurement of social exclusion is actually object of study, and no measure of social exclusion has received unanimous approval. Research on social exclusion has actually taken two branches.

The first branch of literature focuses on the empirical analysis of social exclusion without developing an appropriate theoretical background. In this branch we find some recent applications of Sen's capability approach to the multidimensional analysis of social exclusion. Brandolini and D'Alessio (1998) define a small number of indicators classified in six categories (health, education, employment, housing, social relationship, and economic resources) and they compute them using Italian data for 1995. A low correlation between functioning measures confirms the usefulness of broadening the analysis to non-economic factors. Tsakloglou and Papadopoulos (2001) apply the same kind of analysis in order to identify the population members at high risk of social exclusion in Europe. Following the idea that social exclusion is a dynamic process leading to deprivation, they construct static indicators of deprivation in particular fields (income, living conditions, necessity of life and social relations). Then, they aggregate this information in order to obtain a static indicator of cumulative disadvantage. So, individuals classified as being at high risk of cumulative disadvantage at least twice during the period of three years, are classified as being at high risk of social exclusion.

The second branch of literature focuses on developing an axiomatic approach to the measurement of social exclusion. For example, Chakravarty and D'Ambrosio (2002) identify a class of subgroup decomposable social exclusion measures using a set of independent axioms and, then, they look at the problem of ranking exclusion profiles using exclusion dominance principles under certain restrictions. Bourguignon and Chakravarty (2003) provide a multidimensional poverty measure ordering corresponding to a family of multidimensional poverty measures satisfying a set of intuitive axioms.

The contribution of this chapter could be included in the latter branch of literature: we also derive a measure of social exclusion consistent with theoretical assumptions. However, our focus is different from any axiomatic approach. We investigate the theoretical connection between social exclusion measurement and the capability approach.

2.3 Derivation of the social valuation function

In this section, we follow the suggestion given by the capability approach in order to derive a social valuation function. Assume that we have N individuals and G relevant functionings x_g is the column vector containing N individual observations, defined on the support [0,1], relative to functioning g. Therefore, its transpose is $x'_g=(x_{ig},\ldots, x_{Ng})$. Every individual i has achieved the functioning value of x_{ig} (with g=1,…,G). As mentioned in the previous section, we define the individual deprivation relative to the g-th functioning as the deprivation gap

$$y_{ig} = \max \{ (x^*_{ig} - x_{ig}), 0 \}$$

where the threshold, x^*_{ig} can be defined in a relative way as

$$x^*_{ig} =\xi\ \mu_g$$

where $\xi\in(0,1)$ and $\mu_g=(1/N)\Sigma_i\ x_{ig}$ is the mean for functioning g. In chapter 1, we emphasized that social exclusion is a relative concept (in general, standards of living of a society are expressed in a relative way), therefore the thresholds that determine the degrees of deprivation have also to be expressed in a relative way (see Diaz, 2003, for further discussion).

Since a vector of functionings, x_i, fully describes the status of a person, well-being can plausibly be seen as an evaluation of such vector (Sen, 1985). The individual valuation of a vector of functionings is simply the evaluation of the degree of functionings achieved by the individual. Therefore, the value given to a vector of functionings is inversely related to the deprivations suffered by the individual. The simplest individual valuation function that we can think of, is a linear combination of the G deprivation values:

$$z_i = -\sum_g w_g y_{ig} \qquad \text{with} \qquad \sum_g w_g = 1 \text{ for all } i=1,..,N$$

where $w_g = [(1-\gamma_g)/(\sum_g (1-\gamma_g))]$ is the weight given to the g-th deprivation value and γ_g is the proportion of deprived people in dimension g. As mentioned in the previous section, we follow the suggestion of the literature about the existence of an inverse relation between the weight and the number of deprived individuals in each dimension.

The social value in the society can be seen as a decreasing function of the individual impossibility of achieving some relevant functionings (impossibility of reaching a certain level of well-being). Therefore, we can simply derive the social valuation function, V, from the individual valuation functions as their sum:

$$V = \sum_i z_i$$

It can be written as:

$$V(x) = -\sum_i \sum_g w_g \max\{(x^*_{ig} - x_{ig}), 0\} \qquad (1)$$

where x is the NxG matrix equal to $(x_1 \mid \ldots \mid x_g \mid \ldots \mid x_G)$ and x_g is the column vector containing the N individual values x_{ig} with i=1…N. Finally, note that this social valuation function has some features:

1) The social valuation function, V, is homogenous of degree one [$V(ax)=aV(x)$ for all $x \in R^{NxN}_{++}$ and $a>0$].

Proof

$$V(ax) = -\sum_i \sum_g w_g \max\{(ax^*_{ig} - ax_{ig}), 0\} = -a\sum_i \sum_g w_g \max\{(x^*_{ig} - x_{ig}), 0\} = aV(x)$$

□

2) The social valuation function, V, is increasing along rays [$V(ax)>V(x)$ for all $x \in R^{NxN}_{++}$ and $a>1$].

Proof

It follows from the homogeneity of degree one.

□

3) The social valuation function, V, is additive and continuous.

2.4 Derivation of the social exclusion index

In this section, we derive the unique (up to monotonic transformations) measure of social exclusion consistent with the social valuation function V(.). This measure turns out to be the multidimensional generalization of the Foster-Green-Thorbecke index. In particular, we prove that the social valuation derived in the previous section implies, under some assumptions, a unique normatively social exclusion ordering: the necessary hypothesis is weakly multi-homotheticity.

First of all, we need to introduce the concept of consistency. Let SE(x) be an index of social exclusion, V(x) our social valuation function and x the functioning matrix, then we define consistency as follows:

Def. (consistency) We shall say that SE and V are mutually consistent if for all matrices x, $x^1 \in R^{NxN}_{++}$ such that $\Sigma_i x_{ig} = \Sigma_i x^1_{ig}$ for all g, we have that

$$SE(x) \leq SE(x^1) \qquad \Leftrightarrow \qquad V(x) \geq V(x^1).$$

Consistency implies that social value depends on "size" and "distribution" of each functioning, therefore we can write the social valuation function in the following way:

$$V(x) = f(-SE(x), \mu) \qquad \text{where} \quad \mu' = (\mu_1, \ldots, \mu_G) \text{ and } x \in R^{NxN}_{++}$$

Second, we need to define some properties:

Def. (weak homothetic) V(.) is weak homothetic when $V(x) \geq V(x^1) \Leftrightarrow V(ax) \geq V(ax^1)$, for all x, $x^1 \in R^{NxN}_{++}$ such that $\Sigma_i x_{ig} = \Sigma_i x^1_{ig}$ for all g and a>0.

Def. (multiplication of a matrix (NxG) and a vector (Gx1) using the operator $\wp$) The operator $\wp$ multiplies the g-th column of the matrix by the g-th element of the vector (g=1…G).

Using the operator $\wp$ we can define V(.) as weak homothetic if $V(x)\geq V(x^1) \Leftrightarrow V(x\wp\lambda)\geq V(x^1\wp\lambda)$, for all x, $x^1\in R^{NxN}_{++}$ such that $\Sigma_i x_{ig}=\Sigma_i x^1_{ig}$ for all g, $\lambda'=a*e$ and a>0. In this case the vector λ has all elements equal to a>0. But we can also define λ as a vector with positive elements, but not necessarily all equal to each other. In this case we speak about a new concept: “weak multi-homotheticity”.

Def. (weak multi-homothetic) V(.) is weak multi-homothetic when $V(x)\geq V(x^1) \Leftrightarrow V(x\wp\lambda)\geq V(x^1\wp\lambda)$, for all x, $x^1\in R^{NxN}_{++}$ such that $\Sigma_i x_{ig}=\Sigma_i x^1_{ig}$ for all g and $\lambda>>0$ ($\lambda\in R^G_{++}$).

Weak multi-homotheticity implies weak homotheticity. It also implies that each functioning distribution has to be weak homothetic. We are now ready to give the first theorem[1] that will permit us to arrive to the social exclusion index.

Theorem I. $V:R^{NxG}\rightarrow R$ is weakly multi-homothetic if and only if there exist functions $f:RxR^G_{++}\rightarrow R$ strictly increasing in its first argument for any $g:R^{NxG}\rightarrow R$ s.t.

$$V(x)=f(g(x\wp\lambda^{-1}), \lambda)$$

Proof

(Necessity) Weak multi-homotheticity requires

$$V(x\wp\mu^{-1})\geq V(x^1\wp\lambda^{-1}) \Leftrightarrow V(x\wp\mu^{-1}\wp\lambda)\geq V(x^1\wp\mu^{-1}\wp\lambda)$$

for all x, $x^1\in R^{NxN}_{++}$ such that $\Sigma_i x_{ig}=\Sigma_i x^1_{ig}$ for all g and $\lambda>>0$.

This is equivalent to require that $V(x\wp\mu^{-1}\wp\lambda)$ be an increasing transformation of $V(x\wp\mu^{-1})$, that is, $V(x\wp\mu^{-1}\wp\lambda)=f(V(x\wp\mu^{-1}), \lambda)$ where V is strictly increasing in its first argument. Choosing $\lambda'=\mu'=(\mu_1,\ldots,\mu_G)$, we obtain $V(x)=f(V(x\wp\mu^{-1}), \mu)$ for all $x\in R^{NxG}$ which clearly implies that exists a function g s.t.

$$V(x)=f(g(x\wp\mu^{-1}), \mu) \text{ for all } x\in R^{NxG}$$

(*Sufficiency*) The poof is straightforward.

$\square$

[1] This is an extension of the Theorem 4 presented in Esteban and Dutta (1992)

This theorem suggests that the natural candidate for the social exclusion index implied by V is simply -$V(x \wp \mu^{-1})$. Moreover, its monotonic transformations are also "good" indices of social exclusion, so we arrive at the social exclusion index as defined in section 3 by the axiomatic approach:

$$SE(x)= (1/N) \sum_i \sum_g w_g \max \{ ((x^*_g - x_{ig})/ x^*_g), 0 \}$$

The last step is to show that the social exclusion index, implied by our social valuation function, is unique up to monotonic transformations. Since the social exclusion ordering is mean invariant by construction, we apply the following theorem[2]: "Let $\geq^{SE}$ and $\geq^{SE1}$ be two social exclusion orderings mean invariant to each other. If $\geq^{SE}$ and $\geq^{SE1}$ are consistent with a given $\geq^{V}$, then $\geq^{SE}$ and $\geq^{SE1}$ are identical". Thus, our social exclusion index is unique (up to monotonic transformations).

Now we are ready to state a second theorem:

> Theorem II. Let the social valuation function be the one represented in (1), then the consistent and unique (up to monotonic transformations) index of social exclusion is:

$$SE(x)= (1/N) \sum_i \sum_g w_g \max \{ ((x^*_g - x_{ig})/ x^*_g), 0 \}$$

Summing up, we derived the unique (up to monotonic transformation) measure of social exclusion consistent with the social valuation function constructed using the capability approach. Note that this index is the multidimensional generalization of the Foster-Green-Thorbecke index (Bourguignon and Chakravarty, 2003)

[2] Esteban and Dutta (1992) Theorem 2

2.5 Properties of the social exclusion measure

Since we have found that our social exclusion measure is a special case of the multidimensional generalization of the FGT index, it satisfies a set of reasonable properties (Bourguignon and Chakravarty, 2003):

- Focus (FOC): for any person i and attribute g such that $x_{ig} \geq x^*_g$, an increase in x_{ig}, given that all other attributes remain fixed, does not change the social exclusion value SE(x).
- Normalization (NOM): if $x_{ig} \geq x^*_g$ for all individuals i and attribute g, then SE(x)=0; moreover, SE(x) ranges between zero and one.
- Monotonicity (MON): for any person i and attribute g such that $x_{ig} < x^*_g$, an increase in x_{ig}, given that all other attributes remain fixed, does not increase the social exclusion value SE(x).
- Principle of population (POP): for all $x \in R^N_+$ and for all integer m>0, SE(x[m])=SE(x).
- Symmetry (SYM): for all $x \in R^N_+$ and for all permutation matrices, P, SE(x)=SE(Px).
- Subgroup Decomposability (SUD): for any $x^1, x^2, \ldots, x^k$ such that $x = Ux^i$, $SE(x)=\Sigma^k_i (N_i/N)\, SE^i(x^i)$ where N^i is the population associated with x^i and $\Sigma^k_i N_i = N$.
- Continuity (CON): for any vector of thresholds $(x^*_1, \ldots, x^*_g, \ldots, x^*_G)$, SE(x) is continuous.
- Weak Transfer Principle (WTRP): all the other things being equal, a pure transfer in the well-being in dimension g of a person above the threshold to someone below it must not increase social exclusion.
- Nondecreasing index under correlation increasing switch (ND): if attribute j can compensate for the lack of attribute g, then increasing the correlation between the two attributes must not decrease the index value.

The first property states that if an individual is not excluded with respect to an attribute, then giving him more of this attribute does not change the intensity of social exclusion even if he is excluded in some other attributes. “Normalization” says that if all individuals in the society are not excluded, then the index takes the value zero. Under “monotonicity”, social exclusion does not increase if the situation of excluded individuals improves. According to the “principle of population”, if we merge two or more identical populations, social exclusion does not change. This property is particularly helpful for intertemporal and interregional comparisons. “Symmetry” demands anonymity: social exclusion should depend on the intensity of the individual level of social exclusion but not on the name of the individual. “Continuity” ensures that small changes in the attribute quantities will not imply an abrupt jump in the value of the social exclusion index. Thus, a continuous social exclusion index will not be oversensitive to minor observational errors on basic need quantities. According to “subgroup decomposability”, if a population is divided into several mutually exclusive subgroups (e.g. defined by geographical regions), then the overall social exclusion is the population share weighted average of the subgroup exclusion levels. This property is particularly interesting from a policy point of view in the sense that it permits us to identify the subgroups that are most afflicted by social exclusion and hence to implement inclusion policies. The “weak transfer principle” is more difficult to figure out in terms of social exclusion. In fact, we should think of a pure transfer of “something” that can affect the well being of a person in one dimension, and not of a pure transfer of well-being. For this reason, we use a weak version of the transfer principle: a pure transfer from a not excluded individual to an excluded person must not increase social exclusion[3]. Finally, the last property was defined by Bourguignon and Chakravarty to take care of the essence of the multidimensional measurement through correlation between attributes. In fact, this property stresses the difference between single and multidimensional measures by taking into account the association of attributes, as captured by the degree of correlation between them: an increase in correlation between two attributes should not decrease social exclusion (Bourguignon and Chakravarty 2002).

2.6 Empirical Analysis

In this section, we present an empirical application of the multidimensional measure of social exclusion derived in the previous sections using 1999 Spanish data from European Community Household Panel (ECHP). The next chapter discusses more in detail the potential of our measure to analyse changes in the distribution of social exclusion.

[3] In the strong version of the transfer principle, such transfer must decrease social exclusion.

In chapter 1, we selected the ten functionings that in our opinion are relevant to analyse social exclusion. These functionings are chosen to be representative of the economic, social and political dimensions of exclusion. Using the available variables, we select the commodities and transform them into functionings. Then, the functionings are aggregated in the social exclusion index as proposed in the previous section.

Functionings

As already emphasised, the identification of functionings is a key point of our analysis, and has to be done having in mind the fully-fledged characterization of well-being (Brandolini and D'Alessio, 1998). Moreover, we have to underline that a complete list of functionings cannot be unequivocally compiled. However, some guidance is offered by Sen (2001), by the "Scandinavian approach to welfare" as proposed by Brandolini and D'Alessio (1998) and by Tsakloglou-Papadopoulos (2001). Thus, following the suggestions of the above literature we have selected ten functionings: "the basic need fulfilment", "having an adequate income", "to reach a certain quality of life", "to have an adequate house", "the ability to have social relationships", "being healthy", "living in a safe and clean environment", "being able to perform a work activity / social status", "possibility to have a basic education" and "participation in the political life". Note that we cannot include in the analysis the last two functionings due to the following problems: first, the educational information does not appear to be very accurate in the Spanish case;[4] second, the ECHP do not contain data about the individual participation in the political life.

Each of the eight remaining dimensions represents a functioning considered important in its own right. This is not to deny that there are intersections between functionings, but rather to emphasize that the achievement of every functioning is regarded as necessary for social inclusion. Conversely, impossibility to achieve any one functioning is sufficient for social exclusion. Note that while some functioning deprivations can be themselves causes of exclusion, other functioning deprivations are only instrumentally causes of exclusion (Sen, 2000). In this second case, deprivations may not be impoverishing in themselves but they can lead to impoverishment of life through their causal consequences. Therefore, the environment conditions and ill health become important dimensions to analyse social exclusion, even if they are not constitutive causes of exclusion.

It is important to underline that every functioning results from the transformation of a vector of items chosen as representative of such functionings. Table 1 summarizes the operationalization of the eight dimensions of social exclusion: it shows the items from the ECHP selected to correspond to each dimension. For each selected item, we assigned to each individual a score ranging from zero to one. A score of one means that the individual can afford the item, has the item or does not have 'the problem'[5]. Instead, a score equal to zero means that the individual is deprived in that item. All the values between zero and one mean an intermediate situation. We aggregate the items corresponding to every functioning by summing up their scores and dividing the result by the number of items. Equal weights are given to all items.[6] Thus, for each functioning, an individual receives a score between zero and one. A score of one means that the functioning has been fully achieved, a score of zero means that the functioning has not been achieved, and intermediate values represents intermediate situations.

Finally, we estimate the correlation between different items belonging to the same dimension, and between different dimensions and we find low degrees of association (see Table 2). Most coefficients are, in absolute value, below 0.2; just a little stronger is the correlation between economic dimensions ("basic needs fulfilment", "having an adequate income", "to reach a certain quality of life" and "having an adequate house"). Except for the correlated "basic needs" and "quality of life", the contemporary presence of two deprivations is rare, suggesting that the indicators tend to capture complementary aspects. In particular, social and economic dimensions seem to capture different aspects of social exclusion.

Social exclusion index

A second aggregation is performed when we compute the index of social exclusion. For the implementation of our social exclusion measure we need to specify the thresholds. Inclusion or exclusion on each of the eight dimensions we selected is clearly a matter of degree. A functioning can be achieved

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[4] We find that about 70% of the sample do not achieve basic education. Probably, the definition of the education levels is not appropriate for the Spanish educational system.

[5] For example, she can afford a durable or she has an indoor flushing toilet or she does not have pollution in the area she lives.

at different levels at a point in time, and any choice about a threshold (below which the individual is counted as deprived) has some degree of arbitrariness. In absence of endogenous rules, we fix the threshold in each dimension equal to the 50% of the functioning distribution mean (ξ=50%). Every individual below the cut-point in dimension g is defined as deprived in that dimension g. Therefore, an individual can be deprived in one or more dimensions. Moreover, we implicitly assume that anyone was able to achieve a valuable functioning would do so. In the appendix, the reader can find more information about the thresholds.

Table 3 shows the proportion of people counted as deprived in every dimension and as socially excluded (headcount ratios). Table 4 gives information about the distribution of deprivation in each dimension and about the distribution of social exclusion. More details about the social exclusion distribution are shown in Table 5. Finally, Figure 1 shows a graphical representation of social exclusion distribution in Spain, 1999.

In Spain in 1999, the average social exclusion is particularly low, about 0.27, [7] while the percentage of the population with a social exclusion value bigger than zero is about 42%. This is due to the presence of a big group of individuals with individual social exclusion values close to zero. Only a small group of individuals presents a little-bit higher level of social exclusion (the maximum individual degree of exclusion registered is 0.48 over one). These results have important implications: the headcount ratio may overestimate the problem. Policies to really be effective in helping the individuals suffering in the heavy disadvantages should focus on the restricted number of people registering the highest degree of exclusion. Therefore, the necessity to monitor policy using measures of the intensity of social exclusion.

Finally, in table 6, we divide the population in sub-groups according to social and geographic individual characteristics. We observe that females have a higher average social exclusion than the population average exclusion. Individuals with less than second stages of education, single parents and couples with three or more children have also a higher average social exclusion. Moreover, we observe that the social

[6] See Brandolini and D'Alessio (1999) for more details about the use of equal weights and alternative weighting structures.

[7] The social exclusion index ranges between 0 and 1. A value of one represents maximum exclusion.

exclusion average in Canary Islands and in South Spain is higher than the national average. These results help to identify population groups at high risk of social exclusion. This is important in order to target policies.

2.7 Conclusion

In this chapter, we derive the unique (up to monotonic transformations) index of social exclusion consistent with the social valuation function constructed using the suggestions given by Sen's capability approach. This index is a special case of the multidimensional generalization of the Foster-Green-Thorbecke index proposed by Bourguignon and Chakravarty (2003). Therefore, the proposed measure of social exclusion also fulfils a set of axiomatic properties that are considered important to analyse a multidimensional phenomena.

In the empirical application, we highlight that our social exclusion measure giving information about the average degrees of social exclusion has to be used to monitor policies together the headcount ratio. About 42% of the sample shows a social exclusion value bigger than zero. However, the average social exclusion results about 0.027 over one. This indicates the existence of a big group of people very close to the border of exclusion: therefore, measures of the intensity of social exclusion seem to be more useful to monitor policies than headcount ratios. Note that we may suspect that the headcount ratio overestimates the problem, if social exclusion could be a transitory phenomenon. We address this issue in detail in the next chapter.

Figure 1. Social exclusion distribution in Spain, 1999

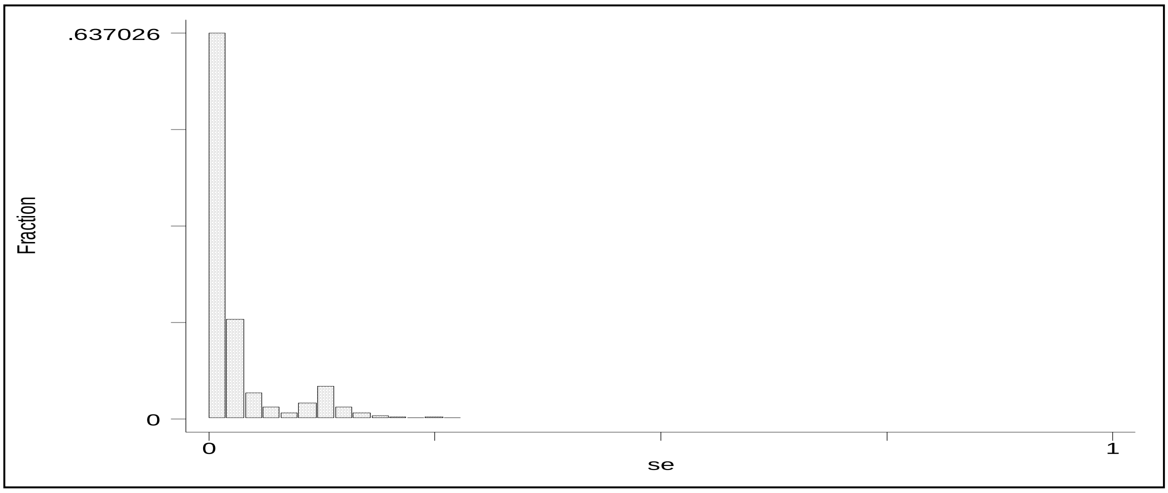


Table 1. Functionings

Basic needs fulfilment (BASIC)
Not eating meat or like every second day (food)
Being unable to buy new, rather than second hand clothes (clothes)
Being unable to pay bills, rents, etc. (afford1)
Having an adequate income (INCOME)
Income
To reach a certain quality of life (QUALITY)
Car or van (car1)
Colour TV (tv1)
Video recorder (vcr1)
Telephone (tel1)
Having friends or family for a drink/meal at least once a month (friends)
Having an adequate house (HOUSING)
Not having indoor flushing toilet (toilet)
Not having hot running water (water)
Not having enough space (space)
Not having enough light (light)
Not having adequate heating facility (heating)
Not having damp walls, floors, foundation... (damp)
Not having leaky roof (roof)
Not having rot in windows frame, floors (rot)
Ability to have social relationships (SOCIAL)
Frequency of talk to the neighbours (talk)
Frequency of meeting people (meet)
Being healthy (HEALTH)
Health of the person in general
Living in a safe and clean environment (LIVING)
Noise from neighbours or outside (noise)
Pollution, grime or other environment problems caused by traffic or industry (poll)
Vandalism or crime in the area (crime)
Being able to perform a paid or unpaid work activity (WORK)
Being unemployed (unemp1)

Note: the variable’s name is in bracket.

Table 2. Correlation matrices

	basic	quality	housing	social	healthy	living	work
basic	1.0000						
quality	0.4171	1.0000					
housing	0.2010	0.2563	1.0000				
social	0.0430	-0.0028	0.0192	1.0000			
healthy	0.1275	0.1701	0.1129	0.0443	1.0000		
living	0.0803	0.0278	0.2045	0.0803	0.0258	1.0000	
work	0.0768	0.0801	0.0700	-0.0156	-0.0696	0.0234	1.0000
income1	0.1625	0.2382	0.1404	-0.0936	0.0868	-0.0070	0.1050

	clothes	food	afford1
clothes	1.0000		
food	0.2840	1.0000	
afford1	0.1762	0.1243	1.0000

	car1	tv1	vcr1	tel1	friends
car1	1.0000				
tv1	0.0832	1.0000			
vcr1	0.2918	0.1543	1.0000		
tel1	0.1564	0.0935	0.2213	1.0000	
friends	0.1742	0.0685	0.1786	0.1312	1.0000

	toilet	water	space	light	roof	damp	rot
toilet	1.0000						
water	0.2719	1.0000					
space	0.0115	0.0422	1.0000				
light	0.0545	0.0435	0.1902	1.0000			
roof	0.1001	0.1246	0.1008	0.1168	1.0000		
damp	0.0741	0.1353	0.1210	0.1311	0.4166	1.0000	
rot	0.1312	0.1447	0.1074	0.1038	0.3569	0.4006	1.0000
heating	-0.0072	-0.0169	0.0134	0.0478	-0.0100	-0.0103	0.0158

	talk	meet
talk	1.0000	
meet	0.2634	1.0000

Table 3. Headcount Ratios

Variable	Exclusion >0 (headcount ratio)
Basic	1.75
Quality	2.02
Housing	1.02
Social	2.03
Health	9.65
Living	13.70
Work	7.46
Income	17.97
SE	42.26

Table 4. Exclusion distribution of every functioning and in aggregate

Variable	Obs	Mean	Std. Dev.	Min	Max		Average exclusion
Basic	13083	.006581	.0524877	0	0.66		.0041836
Quality	13076	.0047898	.0423485	0	1.00		.0050604
Housing	13028	.0022742	.0251666	0	0.73		.0017443
Social	13041	.0065422	.0564945	0	1.00		.0062107
Health	13045	.0364848	.1372905	0	1.00		.0395965
Living	13092	.0527609	.1840817	0	1.00		.0492432
Work	13104	.0746352	.2628118	0	1.00		.0708944
Income	13078	.0587416	.1622698	0	1.00		.0521966
SE	12899	.0293329	.0521904	0	0.43		.0273649

Table 5. Social Exclusion Distribution in Spain (1999)

Percentiles			Main statistics	
1%	0		mean	.02933
25%	0		Variance	.00272
50%	0		Skewness	2.3235
75%	.03274		Kurtosis	9.2956
99%	.22902			

Table 6. Average social exclusion
(cross-sectional weights)

Average social exclusion for the total population		**.0273649**
	% tot	Average social exclusion for the population sub-group
Sex		
Female	47.98	.030458
Male	52.02	.0238124
Age		
16-35	38.40	.029937
36-55	30.75	.0216261
55+	30.84	.0261675
Education		
Third stage of education	18.46	.0202118
Secon stage of education	18.90	.0235594
Less of second stage of education	62.64	.0304580
Household type → single adults		
One person aged 65 or more	3.17	.0245776
One person aged 30-64	1.98	.0229692
One person aged less than 30	0.61	.0355753
Single parent with one or more children (all children aged less than 16)	0.22	.0750135
Single parent with one or more children (at least one child aged 16 or more)	6.92	.0345452
Household type → couples		
Couple without children (at least one person aged 65 or more)	7.41	.0241445
Couple without children (both persons aged less than 65)	5.72	.0213514
Couple with one child (child aged less than 16)	4.30	.0205958
Couple with two children (all children aged less than 16)	6.95	.0240436
Couple with three children or more (all children aged less than 16)	1.79	.0400031
Couple with one or more children (at least one child aged 16 or more)	41.57	.0273587
Other households	19.35	.0294666
Region		
North-west	12.44	.0257706
North- east	10.53	.0185147
Madrid area	12.68	.0264829
Centre	13.49	.0262209
East	26.41	.0247714
South	19.81	.0343219
Canary Islands	4.06	.038137

Appendix 1. Variable construction

In this appendix, we illustrate how we selected the items that had been transformed in functionings. We also illustrate the threshold corresponding to each functioning (computed as the 50% of the mean).

The general health condition (HEALTH) is self-assessed on the scale form “very bad” to “very good”. Thus, a value one is assessed if the individual answers “very good”, and a value zero if he answers “very bad”. Intermediate values are assessed for the answers “good”, “fair” and “bad”.

The frequency of talk with people (TALK) and the frequency of meeting people (MEET) are assessed on the scale from “on most days” to “never”. Thus, a value one is assessed if the individual answers “on most days”, and a value zero if he answers “never”. Intermediate values are assessed for the other answers.

The variable INCOME is the transformation of the median equivalent income that assesses the value one to the richest individual and zero to the poorest. The income concept is the net equivalent household income over a full calendar year, and the equivalent scale used is the OECD scale. Moreover, the amounts specified in national currency have been converted to a common units using the PPP for a periods concerned published by Eurostat. In fact, even if our study refers to a single country, we paid special attention to the comparability, over time and across countries, of the results obtained.

The variable AFFORD1 indicates if an individual is able (unable) to pay scheduled mortgage payments, rent, utility bills or to hire purchase instalments during the past twelve months[8]. We assessed a value one if he is able to pay all of them, and value zero if he is unable to pay all of them. Intermediate values are assessed for the intermediate situations.

The variable UNEMP1 is constructed using the ‘main activities status’ of the individual. It assumes value one if the individual is unemployed, and zero otherwise.

[8] It is constructed following the idea proposed by Nolan-Whelan-Maitre-Laype 2001

The level of education (EDUC) is assessed on the following scale: "recognized third level (ISED 5-7)", "second stage or secondary level education (ISED 3)", "Less then second stage of secondary education (ISED 0-2)".

All the other variables are binary. So, they are transformed in order to assume value one if the individual can afford[9] the item and zero otherwise. If the item is a problem (or a negative situation) that the individual wish to avoid, the value one is assessed if he has not the problem.

For the variables that refers to durables (as CAR, TV, …), we assessed value zero if the individual cannot afford the item, and one otherwise. However, we considered the use of durable as 'normal activities of the citizen' only if at least half of the individuals have the durable.

[9] If this information is not available, value one is assessed if the individual has the item

3

Social exclusion mobility in Spain, 1994-2000

3.1. Introduction

We have defined social exclusion as a process leading to a state of multiple functioning deprivations (Sen, 2000). In the previous chapter, we have proposed to measure the intensity of the individual social exclusion (social exclusion gap) using the multidimensional generalization of the Foster-Green-Thorbecke index. We can also compute the social exclusion headcount ratio by computing the proportion of the population that experience deprivation in at least one relevant function (as also done by Burchart, 2000).

Cross-sectional social exclusion rates may overstate the extend of the problem if most individuals do not remain in the same state in successive years. In other words, if social exclusion is only a transitory phenomena, social exclusion headcount ratios based on a single year will overstate the problem. To address this issue, we need to focus on social exclusion dynamics and, in particular, on the degree of mobility. Social exclusion mobility can be seen as changes in the individual state of exclusion. In particular, it can be seen as changes in the individual levels of social exclusion and changes in the individual positions in the distribution of social exclusion.

Few studies have paid attention to the dynamic of social exclusion, and analyses of the degree of mobility are scarcer. No studies analyse changes in the individual position in the distribution of social exclusion, as far as we know. This chapter seeks to contribute to generation of the knowledge about social exclusion dynamics by capturing the extend of social exclusion mobility experienced in Spain from 1994 to 2000 and by identifying the personal attributes and life-course transitions that trigger social exclusion mobility. Therefore, the aim of this chapter is to analyse mobility focusing on individual movements within the distribution between two time periods.

On one hand, there is a lack of studies about social exclusion mobility but, on the other hand, there exist various approximations for the study of income mobility. In section 3.2, we review some basic concepts of income mobility measurement. Section 3.3 describes the methods we apply to analyse social exclusion mobility. Section 3.4 gives information about the data and the construction of the social exclusion distribution. In section 3.5, we report on changes in cross-sectional social exclusion in Spain between 1994 and 2000 and on social exclusion transition. Section 3.6 concludes, summarising our findings.

3.2 Basic concepts of income mobility measurement

Income mobility concerns the changes in economic status from one time period or generation to another (Fields and Ok, 1999). Any study on mobility analyses the time path of a given distribution among the same individuals (or among dynasties) in a given society. In other words, the theory of mobility measurement can be defined as the study of distributional transformations over two-periods. Note that the very notion of income mobility is not well defined: different studies concentrate on different aspects of mobility (e.g. origin dependence, income movements, income growth, etc.). Therefore, income mobility can be seen as a multi-faceted concept, and any attempt to devise a measure that aims to incorporate all aspects of income mobility is destined to failure. Fields and Ok (1999) highlight the key aspects of the income mobility concept, and analyse the axiomatic studies on the measurement of income mobility and the welfarist approaches developed in the context of income mobility measurement in recent years. This literature is reviewed in some details in Fields and Ok, so here we concentrate on some key aspects of income mobility, which are also important in our analysis of social exclusion mobility. In particular, we illustrate the distinction between basic income mobility concepts like transition matrices, relative versus absolute mobility, and between structural versus exchange mobility. The interested reader is referred to Fields and Ok for further details of income mobility literature.

Relative vs. absolute mobility

Relative mobility tells us the extent to which individuals change places in income distribution over time. Note that for all monotonic transformation of the initial distribution such that incomes grow but everyone keeps their positions (or ranks) in the distribution, a relative measure records the same level of mobility in all these transformations (if it records zero mobility, we say that the measure is strong relative).

Absolute mobility is measured as a function of changes in the individual income levels regardless of the ranking of the individuals in the initial distribution and in the final one. Statements about absolute mobility are almost always about changes in the mean of the income distribution, and not about changes in the degree of persistence in income positions. Note that the level of mobility associated with a certain transformation would not be altered if the same amount of money is added to everybody's income in both the initial and the final distribution.

There exists different ways to measure both relative and absolute mobility. For example, relative mobility can be measured using the correlation between the initial year income and the final year income: large values of correlation show a strong inertia and, consequently, a low degree of mobility. It can be also measured using indices based on transition matrices as we explain later. Absolute mobility can be measured, for example, using the indicator of the degree of income change experienced by individuals over a given time interval proposed by Fields and Ok (1996).

Structural vs. exchange mobility

The sociological literature, when referring to intergenerational mobility, has traditionally emphasised the difference existing between the process of mobility caused by an increase in the positions in the upper part of the social scale due to a modification in the income structure (structural mobility) and those which have their origin in the exchange of positions within that scale (exchange mobility). Recent studies have incorporated a third cause of mobility, that which results from the effect of the growth of income.

Attempts have been made in the literature to decompose total mobility into exchange mobility and structural mobility. Markandya (1982) proposes two alternative procedures: to define exchange mobility as the proportion of the change in welfare that could have been obtained if the income distribution stayed constant through time, and let structural mobility be the balance of the total welfare change; or, to define structural mobility as the change in welfare that would have taken place if there had been no mobility, and let exchange mobility be defined as the residual. Fields and Ok (1996) also suggest an indicator that is additively decomposable into two sources: exchange mobility and structural mobility. Chakravarty, Dutta and Weymark (1985) propose a measure of mobility based on the comparison between the welfare associated to the distribution resulting from the aggregation of incomes for two periods to that, which would exist if there had been no mobility. Ruiz-Castillo (2000) reformulates the last measure of mobility in order to identify the three components of mobility: structural, exchange and growth mobility.

Transition matrices

Relativistic approaches to income mobility seem to be dominant in the income mobility literature, and it is common use to measure relative mobility using a transition matrix from the initial period to the final one. The transformation from the initial to the final distribution is defined as the matrix with elements the proportion of people that were in class j in the initial distribution and have now moved to class h. Therefore, the use of transition matrices requires that income classes are previously created in both the initial and the final distributions (often using as cut-points the deciles or quintiles of the distribution). Note that all the measures based on the idea of calculating mobility after the creation of income classes are defined “two stage mobility measures”.[1]

Transition matrices give information about the individuals who have remained in their initial class and, consequently, have not changed their relative position (the “stayers”) and about the individuals who have transited from an income class to another one (the “movers”). Shorrocks (1978) and Bartholomew (1982) propose indices of mobility on the basis of transition matrices. The Shorrocks index quantifies the mobility from a transition matrix through the calculation of its trace, while the Bartholomew index is the

[1] Measures based on the comparison of the whole income distribution at the final time with the distribution at the initial time are defined “one stage mobility measures” (for example, the Fields-Ok index).

weighted mean of the total relative frequencies (where the weights are the distances between income classes).

3.3 Social exclusion mobility: methodology

As seen in the previous section, the analysis of income mobility gives some “tools” to analyse the degree of mobility in a distribution. However, few studies have paid attention to the dynamics of social exclusion and they lack information on the degree of mobility in the distribution of social exclusion. The information connected to intertemporal variation in individual social exclusion levels can be very useful to check if social exclusion is a transitory phenomenon or not. Therefore, we focus on social exclusion mobility and, in particular, on the extent to which individuals changes place in the social exclusion distribution over time. We use the relative approach (that seems to be dominants in the mobility literature) and we highlight the individual probability of exchanging position within the scale (exchange mobility). More precisely, we analyse the individual probability to move from one class to another one performing a “two-stage” analysis. In particular, we use transition matrices to summarize the mobility content of distributional transformations since they provide a simple picture of the “movement” of the individuals among the specific social exclusion classes. Moreover, note that this kind of analysis is shown to be robust to data contamination (Cowell and Schulter, 1998) and permits discussion of a richer pattern of social exclusion mobility than the one that can be embodied within a single class of distance-based index *a la* Fields-Ok. Finally, we analyse both short-term mobility looking to social exclusion transition from time t to time t+1 and medium / long-term mobility studying the transition from time t to time t+6.

More formally, the starting point for the analysis of mobility is the existence of information regarding the distribution of social exclusion for the same individuals in two different periods. Let any distribution of social exclusion be defined over the bounded support [0,1], the population composed of N individuals, with $N \equiv \{1,2,\ldots,n\}$, $\mathbf{x}=(x_1,x_2,\ldots,x_n)$ the initial distribution of social exclusion in ascending order and $\mathbf{y}=(y_1,y_2,\ldots,y_n)$ that corresponding to a second period. Given that the transformation $\mathbf{x} \rightarrow \mathbf{y}$ produces an intertemporal variation in individual social exclusion levels, it is possible to assign to any individual $i \in N$ a vector of social exclusion levels (x_i,y_i) for the whole period. Note that if x_i is equal to zero, the individual *i* is not socially excluded, and x_i =1 indicates the highest level of social exclusion. Intermediate values indicate intermediate levels of social exclusion.

The construction of a transition matrix **P** from time t to time t+k requires that at each period the individuals are grouped in different (and exhaustive) classes. In particular, we classify individuals into five exhaustive classes based on their degrees of social exclusion as follows:

- Class 1: individuals not socially excluded (social exclusion equal to zero)
- Class 2: individuals "not really" excluded (social exclusion bigger than zero and lower than 0.1)
- Class 3: individuals "slightly" excluded (social exclusion bigger than, or equal to, 0.1 and lower than 0.2)
- Class 4: individuals "a bit" excluded (social exclusion bigger than, or equal to, 0.2 and lower than 0.3)
- Class 5: individuals "really" excluded (social exclusion equal to or bigger than 0.3)

Note that often in the income mobility literature classes are normally defined so that there is always the same proportion of individuals in each class: for example, the r-th class correspond to the r-th decile (quintile) of the distribution. But, we cannot define social exclusion classes in this way due to the shape of the social exclusion distribution: in fact, about 50% of the population is not excluded, and about 80% experience social exclusion lower than 0.1 over one. Therefore, the best option is to define absolute classes of social exclusion such that each class includes a sufficient number of individuals[2].

The values on the main diagonal of the transition matrix are the probabilities of being in the same class in the two periods of study, while the off-diagonal values are the probabilities of transition from one class to another one (see Figure 1). Therefore, the jh-th element of the matrix is the probability that an individual belonging to class j at time t has passed to class h at time t+k. This probability can be written as p_{jh} (such that Σ_h p_{jh}=1) and it can be estimated using the row relative frequencies. Note that if there is complete

[2] Note that we are aware of possible problems due to the definition of "absolute" classes. In fact, Fields and Ok (1999) show a paradoxical outcome of a particular transition matrix analysis due to the radically different number of individuals in the defined classes. However, they also stress on a certain number of problems emerging using deciles (or quintile) matrices. Therefore, no classes definition results without problems and, in our case, we can only design absolute classes.

immobility, individuals would never change class (all the off-diagonal values are zero); if movements are random, 20 per cent of each starting group would fall into each ending group.

Figure 1. Transition matrix (P)

		Social exclusion at time t+k					
		1	2	3	4	5	
social exclusion at time t	1	p_{11}	p_{12}	p_{13}	p_{14}	p_{15}	100
	2	p_{21}	p_{22}	p_{23}	p_{24}	p_{25}	100
	3	p_{31}	p_{32}	p_{33}	p_{34}	p_{35}	100
	4	p_{41}	p_{42}	p_{43}	p_{44}	p_{45}	100
	5	p_{51}	p_{52}	p_{53}	p_{54}	p_{55}	100

Note: each probability is multiplied by 100

In the empirical analysis, we highlight some mobility indicators. In particular, p_{55} represents the frequency of socially excluded individuals that have been "really" excluded in both periods. Instead, p_{11} gives us information about the individuals that have never experienced exclusion in the two years of analysis. We can observe downwards mobility by looking at the elements below the diagonal, and upward mobility by looking at the elements above the diagonal (for example, the sum of the row relative frequency above the diagonal, $p_{j+,}$ is an indicator of mobility from class *j* to higher classes). Note that we define downwards mobility when the individual improves her situation: social exclusion decreases (she moves to the lower class). Instead, we have upward mobility when the individual situation worsens off: individual social exclusion increases (she moves to the higher class). Therefore, downwards mobility is a "good" phenomenon, while upward mobility is a "bad" phenomenon.

Note that to perform our analysis we need to kwon the degree of social exclusion of each individual in at least two periods. But, respondents at the first year may fail to give an interview at subsequent years, so that the remaining sample may be no longer representative. This process is known as attrition. Moreover, some eligible individuals could not yield an interview (sample selection problem). In order to try to correct for these sources of bias, the obtained sample can be weighted to reflect population characteristics such as age, sex, type of dwelling, etc, as closely as possible using longitudinal or the cross-section weights as appropriate. We can also check if the exits from the panel are random by grouping individuals in six classes, where the first five are the ones designed above and the sixth class is represented by the individuals that left the panel during the period of analysis. In this way, we can see whether the probability of exit is the same one for every income class or if more excluded individuals have higher probability of leaving the panel.

Finally, transition probabilities may vary from individual to individual depending on certain characteristics and social exclusion dynamics may differ amongst individuals with different characteristics. Therefore, we study the relationship between individuals' attributes and social exclusion mobility. We also perform a multivariate analysis to analyse the simultaneous impacts of different individual attributes on the probability of experiencing downwards mobility.

3.4 Social Exclusion Distribution

Examining changes in mobility over time requires the specification of distributions of social exclusion in at least two periods. Therefore, we need to use a measure of social exclusion able to capture the individual level of social exclusion (exclusion gap). It has to be a multidimensional measure since we have defined social exclusion as a process leading to a state of multiple functioning deprivations. Thus, we also need to define a list of relevant functioning deprivations. These issues have been discussed in the previous chapters.

Remember that we have selected eight relevant functionings: "the basic needs fulfilment", "having an adequate income", "to reach a certain quality of life", "to have an adequate house", "the ability to have social relationships", "being healthy", "living in a safe and clean environment", and "being able to perform a paid, or unpaid, work activity (social status)". Table 1 summarizes the operationalization of the eight dimensions of social exclusion: for each functioning, an individual receives a score between zero and one. A score of one means that the functioning has been fully achieved, a score of zero means that the functioning has not been achieved, and intermediate values represents intermediate situations. More details are given in chapter 2, section 6.

Remember also that we have proposed to measure social exclusion using the following multidimensional generalization of the Foster-Green-Thorbecke index:

$$SE(x)= (1/N) \sum_i \sum_g w_g \max \left\{ ((x^*_g - x_{ig})/ x^*_g), 0 \right\}$$

It is a function of the functioning achievement matrix x and threshold vector x^*. We have defined x as the matrix where each column contains N individuals observations relative to functioning g, for $g=1 \dots G$. Therefore, x_{ig} defines the level of functioning g achieved by individual i. Each element of the vector x^* represents a threshold, that is, the minimal value necessary to be defined as "not deprived" in a certain dimension. Therefore, we have defined as deprived in dimension g any individual $i=1 \dots N$ such that $x_{ig} < x^*_g$. Note that x^*_g has been defined as 50% of the mean of the distribution of functioning g. Finally, the weighting structure has been defined as a decreasing function of the proportion of the deprived individuals in each dimension. That is,

$$w_g = [(1-\gamma_g)/(\sum_g (1-\gamma_g))]$$

where γ_g is the proportion of deprived people in dimension g determined using x_g^* as threshold.

Finally, note that we use 1994-2000 Spanish data from the European Community Household Panel (ECHP). Attrition is an issue: we have 17893 individuals in 1994 and only 8822 individuals remain in the panel in 2000. Therefore, the analyses reported in this paper are weighted using the longitudinal or the cross-section weights available in the ECHP as appropriate.

3.5 Results

Changes in cross-sectional social exclusion, 1994-2000

Table 2a shows the proportion of the population aged 16+ who experience deprivation in each dimension in Spain from 1994 to 2000. Table 2 also reports the proportion of the population who experience positive degrees of social exclusion. In 1994, we find that about 54.5% of the sample is socially excluded at least in one dimension. This proportion decreases during the study period, and only the 37.41% of the sample is socially excluded in 2000. However, the exclusion gap (average individual social exclusion) is only

0.027 (over one) in 1994, and 0.012 in 2000. Therefore, we find a quite high proportion of excluded individuals but a very low degree of exclusion. In other words, a big proportion of excluded individuals is "not really" excluded: about 62% of excluded people in 1994 and about 70% in 2000 (see Table 3 for details). We might suspect that those individuals experience short social exclusion spells or do not experience social exclusion in the successive years. Therefore, we could suspect that social exclusion is partially a transitory phenomenon.

Short-term mobility analysis

To analyse mobility, as explained above, we classify individuals in five social exclusion classes and we construct the transition matrix from time t to time t+k. In particular, to analyse short-term mobility we use transition matrices from time t to time t+1. Table 3 shows the proportion of the population belonging to each class in Spain during the study period: we can immediately notice that the proportion of social excluded people in 2000 in every class in lower than the corresponding one in 1994.

Table 4 shows the transition probabilities for each pair of consecutive waves during the period 1994-2000. Table 5 summarizes the probability of experiencing downwards mobility, upwards mobility or persistence in two sub-sequent years during the study panel. Note that the average probability to experience downwards mobility in 1994 is about 28.5%, but the probability is about 35% if the individual is in class 2 ("not really" excluded) and only about 25% if the individual is in class 5 ("really" excluded). The average probability of experiencing upward mobility in 1994 is lower than the average probability of experiencing downwards mobility: it is only about 14% (but the probability is about 30% if the individual is in class one and only about 4% if the individual is in class five). Finally, the average probability to remain in the same class in 1994 and in 1995 is about 35%, but the probability of persistence is about 70% for individuals in class one and zero for individuals in class five.

The average downwards mobility (as well as the average upwards mobility and the average persistence) changes over time, as we can see in Table 5. Therefore, we need to check if these changes are statistically significant. We can apply a test on the equality of several means to test the hypothesis that several indices computed on independent sample are statistically significant (Ramos, 1999).[3] In particular, we can test the identity of the average downwards mobility (average upwards mobility /average persistence) on a pairwise comparison bases and all at once. The results of these two tests are shown in Table 6 and 7. These tests suggest that the average downwards mobility (average upwards mobility /average persistence) is not statistically different from one year to another one during the study period. Since the average downwards mobility, average upwards mobility and average persistence summarize the information contained in the transition matrices, we would expect the latter also be very similar. However, applying a multinomial test, we find that there are some statistical significant differences among the matrices.[4]

Concluding, we find a high degree of social exclusion mobility in the short-term, an excluded individual has about 30% probabilities to improve her situation in the successive year. Note that an individual has also about 12.6% probabilities to face a worst situation in the sub-sequent year and about 35% to be in the same situation. Therefore, there is some degree of persistence. Moreover, the probabilities of experiencing downwards mobility are higher than the one of experiencing upwards mobility. In other words, the individual situation is more likely to improve (or to remain equal) than to worse in the successive year.

Long-term mobility analysis

Table 8 shows the extend of medium/long-term mobility relative mobility from 1994 to 2000. For example, the first row of the second panel includes those individuals who did not experience social exclusion in 1994. About 73% also did not experience social exclusion in 2000. Likewise, only about 10% of those individuals who were defined as “really” socially excluded in 1994 were also in the class of the most excluded people in 2000. About 80% improved their situations from 1994 to 2000: about 40% had moved in the group of the individuals “slightly” socially excluded, and about 20% had not experienced social exclusion in 2000.

[3] A full description of tests on equality of means can be found, for instance, in Mood et al. (1974), pp. 435
[4] For a full description of a multinomial test see, for instance, Mood et al. (1974), pp. 449 and Amemiya (1985), pp.417

The row relative frequencies reported in the transition matrix can also be read as probabilities of transition from a class to another one or as probabilities of being in the same class in the two years of study. Note that "probability of being in the same class" means the probability that the same individual experience a certain degree of exclusion both in time t and in time t+k. However, we do not mean that the individual remains in the same class during all study period. In other words, the individual is in class h at time t and at time t+k, but she can be in a different class during the period between t and t+k.

Table 9 summarizes probabilities for being in the same class, downwards mobility, and upward mobility for medium-term transition, comparing them with the short-term stationary average values. As we can see in this table, the probability that an individual is in the same class after one year is higher than the probability that she is in the same class t+6 years late. Average upwards mobility is surprisingly higher one-year horizon than over six-years horizon (12.6% versus 10%). Conversely, average downwards mobility is much more high over long-term horizon (79% versus 29.5%). In other words, our analysis seems to suggest that the probability to experience upward mobility decreases when the length of time considered rises while the probability to experience downwards mobility increase when the length of time considered rises. Moreover, the probability of an improvement of the individual situation seems to be much more likely than a worsening of her situation.

Exit from the panel

Table 10 reports the frequencies of exit from the panel during the considered period.[5] About half of the individuals that were in the panel in 1994 are not in the panel in 2000: about 18% of the initial sample leaves the panel after one year. The probability that the most socially excluded individuals leave the panel in 1995 is lower than the probability that not excluded individuals do so (12% versus 18%). But the probability that the most socially excluded individuals leave the panel in 2000 is quite similar to the probability that not excluded individuals do so (51% versus 49%). Individuals that belong to class 3 and 4 seem to have the highest probability to exit from the panel both in 1995 and in 2000. Therefore, the

[5] We compute this frequencies using the unbalanced panel. We also did not use any weights.

probability to leave the panel does not seem to be fully random. To correct this bias, we have used longitudinal weights where appropriate.

Differences across socio-demographic groups

In this sub-section, we analyse the association between socio-demographic attributes of individuals and the incidence of mobility. To do so, we compare social exclusion mobility (and probability of being in the same class in the two period of analysis) in various subgroups, categorised on the basis of sex, education (Table 11), geographical areas of residence (Table 12) and age (Table 13). Note that we analyse mobility from 1994 to 1995 (short-term horizon) and from 1994 to 2000 (long-term horizon).

Males have a higher probability of experiencing downwards mobility than females both over a short and a long horizon. They also have a lower probability of being in the class of the most excluded individuals in both years. Individuals with a high-medium level of education have zero probability of being “really excluded”, while low educated individuals have a positive probability (12,5% over 6 years). The latter experience less downwards mobility.

There is evidence of regional differences. The probability of persistence in the class of the most excluded individuals is positive only in the South region over long horizon and it is about 31,25%. Average downwards mobility across regions over short horizon results different than the one over long horizon: Figure 1 emphasises these differences. Individuals living in the centre have the lowest probability to experience downwards mobility over short horizons, while people living in the south have the lowest probability to experience downwards mobility over long periods. Note that the individuals in Canary Islands have the lowest probability of being in the class of not excluded individuals in both years (Table 12).

Figures 2 and 3 emphasise the results that are subdivided on the basis of age in the base year. Over short periods, mobility monotonically increases with the age of the individual. Instead, over long periods, downwards mobility is high amongst individuals aged between 16 and 24, it decreases amongst individuals aged between 25 and 44, and amongst individuals aged between 45 and 64, and it slightly increases amongst the oldest age group. Likewise, the probability of being in the class of the most excluded individuals in both years has different behaviours over short and long periods. Over short periods, it remains close to zero while, over long periods, it is zero amongst the youngest group, and then it increases to 17% (reaching its maximum) amongst individuals aged 25 to 44. Finally, it decreases amongst older age groups.

Downwards mobility: multivariate analyses

The analyses carried out above are concerned with either a single variable (analysis of the social exclusion mobility) or the link between two variables at a time (e.g. how mobility differs between age-groups). Now, we extend our analysis on the basis of a multivariate analysis that deals with more than two variables simultaneously and we focus on downwards mobility. We use a logit model in order to determine which socio-demographic characteristics of the excluded individuals explain the probability to experience downwards mobility. We also analyse which individual attributes explain the probability to move from inclusion to exclusion. In both case the dependent variable is a binary variable. In the first model, it is equal to one if an excluded individual in 1994 experiences downwards social exclusion mobility in 2000, and zero otherwise. In the second one, the dependent variable is equal to one if a non-excluded individual in 1994 experiences exclusion in 2000, and zero otherwise. Note that we have also considered the possibility to use a multinomial logit model and an ordered logit model to study the marginal effects of every individual attributes on the probability of experiencing downwards mobility (being in the same class and experiencing upwards mobility) if the individual belongs to intermediate exclusion classes.[6] The results do not add much to the below conclusions and, therefore, they are not presented here.

First model. We analyse which individual characteristics explain the probability of experiencing downwards mobility. The sample includes only excluded individuals at time t: we do not consider the non-excluded people in 1994 because they cannot experience downwards mobility by definition. Table 14 gives the results for the logit model: the results are reported in terms of coefficients, marginal effects and

[6] The top and the bottom classes have to be excluded in this kind of analysis since not all kinds of transitions are possible in these classes. Mobility in the top and bottom classes has to be separately analysed using logit models.

standard errors. The individual characteristics that we consider in order to explain downwards social exclusion mobility are sex, age, education (high, medium or low level), changes in cohabitation status (from single to couple, and vice versa), persistence in the same cohabitation status (as couple), changes in the number of children in the household (from zero to some children and an increase in the number of children), and geographical areas of residence (north-west, north-east, Madrid’s area, centre, south, Canary Islands and east). Also dummies representing the social exclusion classes are included in the analysis (no dummies represent the top and the bottom class). The reference group is the group of males aged between 25 and 45, medium educated, single and without children in both period, and living in the Madrid’s area.

Among all variables representing a change in socio-demographic characteristics, only individuals who remained living as a couple are more likely to experience downwards social exclusion mobility in comparison with the reference group. Males have a slightly higher probability to improve their situation than females. Likewise, high-educated people have a higher probability to experience downwards mobility, while low educated people have a lower probability to experience downwards social exclusion mobility. Moreover, the higher is the degree of social exclusion experienced by the individual in 1994, the smaller is the probability to experience downwards social exclusion mobility. Finally, note that the probability that an excluded individual in 1994 is in a better situation in 2000 is quite high: it is about 50%.

Second Model. We study which individual attributes explain the probability of experiencing some degrees of social exclusion in 2000 if the individual is not excluded in 1994. Table 15 reports the results for the logit model in terms of coefficients, marginal effects and standard errors. As in the previous model, the explanatory variables are sex, age, education, changes in cohabitation status, persistence in the same cohabitation status, changes in the number of children in the household, and geographical areas of residence. Also the reference group is the same one: group of males aged between 25 and 45, medium educated, single and without children in both period, and living in the Madrid’s area. The probability of experiencing exclusion in 2000 (if the individual is not excluded in 1994) is very high: it is about 70%. Only few covariates are statistically significant. Males have lower probabilities to experience social exclusion. While, people with low-level education and individuals leaving in Canary Islands have higher probabilities to experience social exclusion.

3.6 Conclusions

Much of the debate on social exclusion focuses on those people who are excluded at a point in time; this would be appropriate if social exclusion was essentially a permanent state of affairs. But this is unlikely to be the case. Therefore, the focus of this chapter is on social exclusion mobility. We look at evidence produced from Spanish longitudinal data in order to document people's experiences of social exclusion over time. We argue that social exclusion can partially be a transitory phenomenon and we need to investigate the transition probabilities to provide insights into the nature of the dynamic that underlie social exclusion.

We find an average social exclusion rate (positive degree of exclusion) about 47 per cent over the period of study. At one extreme it may mean that those same 47 per cent of individuals are always excluded; at the other extreme every individual may have a bit less than one in two chance of being excluded at any time. In both cases social exclusion is a relevant issue but the nature of the problem we face is clearly dependent on which of these is closer to the truth.

Analysing Spanish data from 1994 to 2000, we obtain some interesting results. *First*, an individual experiencing a high degree of exclusion in a certain point in time has higher probability to experience it again when the length of the time considered rises. However, a worsening in the individual situation is less likely over a long horizon than over a short one. *Second*, the probability of an improvement of the individual situation is much more likely than a worsening of her situation. *Third*, we observe an extremely high degree of downwards mobility: social exclusion seems to be in part a transitory phenomenon.

In order to understand who experiences social exclusion downwards mobility, we look at the events associated with decreasing the social exclusion degree or moving out of exclusion. In particular, we focus on family structured events (as marriage, divorce, number of children) and socio-demographic attributes (as sex, age, education level, area of residence). We mainly find that females, individuals with low-education and older individuals have a lower probability to improve their situations over the study period.

Future research could investigate other sets of events associated with social exclusion mobility as employment-related events (e.g. labour market participation) and/or events associated with changes in the tax-benefit system. Moreover, we should not be content simply to measure social exclusion and characterize the events associated with social exclusion transition. In addition, we should like to understand the dynamics of the underlying processes, which lead into and out of poverty. In particular, we should like to analyse if an individual experiencing social exclusion today is more likely to experience exclusion tomorrow. This is necessary to understand the causes of social exclusion, and to formulate anti-exclusion policies. In next chapter we focus on the processes leading to social exclusion.

Figure 1. Downwards social exclusion mobility by geographical regions (average)

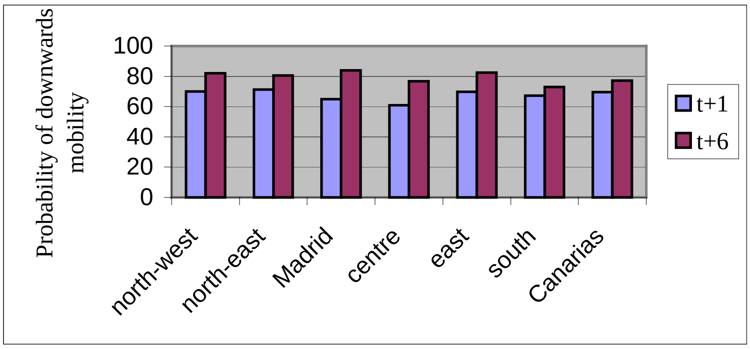


Figure 2. Social exclusion downwards mobility by age groups (average)

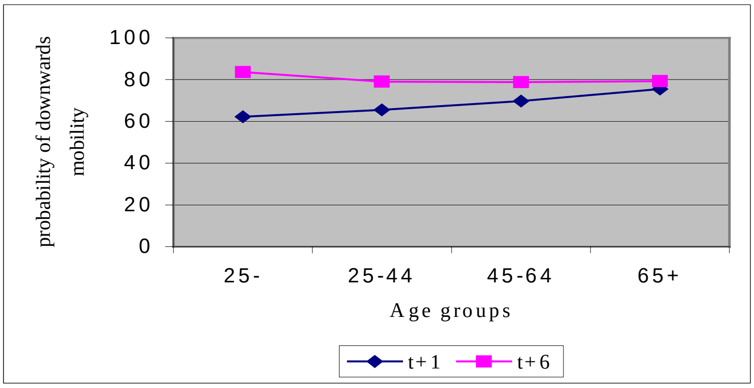


Figure 3. Social exclusion probability of being in the same class in the two period of study by age groups (p_{55})

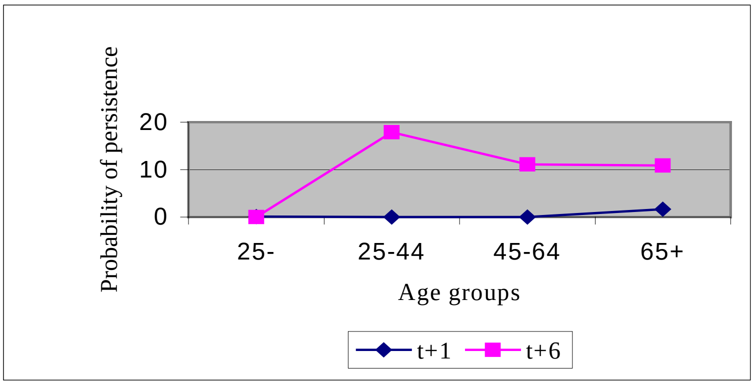


Table 1. Functionings

Basic needs fulfilment (BASIC)
Not eating meat or like every second day (food)
Being unable to buy new, rather than second hand clothes (clothes)
Being unable to pay bills, rents, etc. (afford1)
Having an adequate income (INCOME)
Income
To reach a certain quality of life (QUALITY)
Car or van (car1)
Colour TV (tv1)
Video recorder (vcr1)
Telephone (tel1)
Having friends or family for a drink/meal at least once a month (friends)
Having an adequate house (HOUSING)
Not having indoor flushing toilet (toilet)
Not having hot running water (water)
Not having enough space (space)
Not having enough light (light)
Not having adequate heating facility (heating)
Not having damp walls, floors, foundation... (damp)
Not having leaky roof (roof)
Not having rot in windows frame, floors (rot)
Ability to have social relationships (SOCIAL)
Frequency of talk to the neighbours (talk)
Frequency of meeting people (meet)
Being healthy (HEALTH)
Health of the person in general
Living in a safe and clean environment (LIVING)
Noise from neighbours or outside (noise)
Pollution, grime or other environment problems caused by traffic or industry (poll)
Vandalism or crime in the area (crime)
Being able to perform a paid or unpaid work activity (WORK)
Being unemployed (unemp1)

Note: the variable's name is in bracket.

Table 2. Cross-sectional social exclusion: headcount ratios

Deprivation headcount ratios:	1994	1995	1996	1997	1998	1999	2000
Basic (>0)	2.38 %	1.54 %	1.52 %	1.15 %	1.06 %	1.75 %	1.05 %
Quality (>0)	5.27 %	4.52 %	3.66 %	3.16 %	2.36 %	2.02 %	0.91 %
Housing (>0)	1.52 %	0.90 %	1.40 %	0.77 %	0.55 %	1.02 %	0.30 %
Social (>0)	2.83 %	2.03 %	2.36 %	2.21 %	2.25 %	2.55 %	1.55 %
Healthy (>0)	14.08%	12.12%	11.23%	10.91%	11.06%	9.65 %	10.07%
Living (>0)	23.60%	21.54%	18.51%	17.42%	15.64%	13.70%	10.82%
Work (>0)	9.47 %	10.76%	11.47%	10.32%	8.94 %	7.46 %	6.48 %
Income (>0)	18.36%	17.70%	16.67%	18.85%	18.28%	17.97%	15.95%
SE headcount (SE>0)	54.54%	51.70%	48.79%	47.91%	46.00%	43.96%	37.41 %
SE gap $\in [0,1]$	0.028	0.028	0.027	0.026	0.027	0.027	0.012

Table 3. Cross-sectional social exclusion: social exclusion classes (%)

SE classes	1994	1995	1996	1997	1998	1999	2000
1) Not excluded	45.46	48.30	50.38	51.29	54.07	57.67	62.59
2) Not really excluded	33.93	31.37	30.38	31.34	30.58	28.96	26.03
3) Slightly excluded	18.16	18.26	16.97	15.50	13.80	12.09	10.50
4) A bit excluded	2.10	1.86	2.06	1.69	1.43	1.16	0.72
5) Really excluded	0.35	0.21	0.20	0.18	0.12	0.12	0.17

Table 4. Short-term transition matrices (balanced panels)

	SE 1995					
SE 1994	1	2	3	4	5	
1	**70,26**	19,72	9,45	0,54	0,04	100
2	35,38	**47,28**	16,01	1,24	0,10	100
3	22,95	30,41	**42,03**	4,30	0,32	100
4	5,67	29,93	45,43	**15,09**	3,88	100
5	25,08	50,66	22,61	1,65	**0,00**	100

	SE 1996					
SE 1995	1	2	3	4	5	
1	**70,86**	20,97	7,98	0,19	0,00	100
2	36,18	**46,81**	15,27	1,65	0,11	100
3	25,28	28,25	**40,74**	5,24	0,49	100
4	10,79	23,92	36,98	**24,18**	4,13	100
5	0,00	24,00	53,00	23,00	**0,00**	100

	SE 1997					
SE 1996	1	2	3	4	5	
1	**70,49**	22,08	7,22	0,21	0,00	100
2	35,91	**48,14**	14,61	1,20	0,14	100
3	26,37	30,16	**37,84**	5,25	0,39	100
4	5,28	31,59	46,83	**12,93**	3,38	100
5	0,00	15,42	52,34	28,04	**4,21**	100

	SE 1998					
SE 1997	1	2	3	4	5	
1	**73,19**	20,58	6,08	0,14	0,01	100
2	37,78	**47,69**	13,27	1,15	0,11	100
3	28,40	30,42	**36,44**	4,31	0,43	100
4	6,09	29,12	48,66	**15,23**	0,90	100
5	0,00	19,35	18,71	62,58	**0,00**	100

	SE 1999					
SE 1998	1	2	3	4	5	
1	**74,69**	18,63	6,43	0,25	0,00	100
2	40,59	**46,69**	11,57	1,11	0,05	100
3	30,26	32,43	**33,70**	3,36	0,26	100
4	9,04	35,08	37,52	**13,87**	4,66	100
5	29,14	9,27	56,29	5,30	**0,00**	100

	SE 2000					
SE 1999	1	2	3	4	5	
1	**79,04**	15,46	5,36	0,12	0,01	100
2	41,29	**47,57**	10,62	0,49	0,03	100
3	31,32	29,46	**34,93**	3,59	0,70	100
4	10,12	23,93	48,46	**11,75**	5,75	100
5	0,00	46,15	18,46	29,23	**6,15**	100

Table 5. Short-terms transition probabilities

Downwards mobility						
	A	B	C	D	E	F
	1994-5	1995-6	1996-7	1997-8	1998-9	1999-0
P_{2-}	35,38	36,18	35,91	37,78	40,59	41,29
P_{3-}	26,68	26,77	28,26	29,41	31,35	30,39
P_{4-}	27,01	23,90	27,90	27,96	27,21	27,50
P_{5-}	25,00	25,00	23,46	25,16	25,00	23,46
average	28,52	27,96	28,88	30,08	31,04	30,66
Upwards mobility						
	A	B	C	D	E	F
	1994-5	1995-6	1996-7	1997-8	1998-9	1999-0
P_{1+}	29,74	29,14	29,51	26,81	25,31	20,96
P_{2+}	17,34	17,02	15,95	14,53	12,73	11,14
P_{3+}	4,62	5,73	5,63	4,74	3,61	4,29
P_{4+}	3,88	4,13	3,38	0,90	4,66	5,75
average	13,90	14,01	13,62	11,74	11,58	10,53
Persistence						
	A	B	C	D	E	F
	1994-5	1995-6	1996-7	1997-8	1998-9	1999-0
P_{11}	70,26	70,86	70,49	73,19	74,69	79,04
P_{22}	47,28	46,81	48,14	47,69	46,69	47,57
P_{33}	42,03	40,74	37,84	36,44	33,70	34,93
P_{44}	15,09	24,18	12,93	15,23	13,87	11,75
P_{55}	0,00	0,00	4,21	0,00	0,00	6,15
Average	34,93	36,52	34,72	34,51	33,79	35,89

Table 6. Test on equality of two means

Downwards mobility	A-B	B-C	C-D	D-E	E-F
T	0,153	0,242	0,319	0,219	0,073
Upwards mobility					
T	0,012	0,044	0,215	0,021	0,153
Persistence					
T	0,262	0,302	0,034	0,113	0,321

Table 7. Test on equality of several means

Statistics	Downwards mob.	Upwards mobility	Persistence
T	0,173	0,072	0,0062

Table 8 Long-term transition matrix (balanced panels)

SE 1994	SE 2000 1	2	3	4	5	
1	**73,11**	20,32	6,44	0,09	0,04	100
2	53,72	**35,87**	9,67	0,65	0,09	100
3	48,88	29,41	**20,18**	1,46	0,08	100
4	36,70	33,90	24,79	**3,69**	0,92	100
5	20,24	13,13	41,22	15,07	**10,33**	100

Table 9. Transition probabilities from t=1994 to 2000

Transition probability	**t+1***	**2000**
Probability of being in the same class		
P_{11}		73,11
p_{55}		10,33
average persistence	35.06	28.63
Upwards mobility		
P_{1+}		26,89
P_{2+}		10,41
P_{3+}		1,54
P_{4+}		0,92
average downwards mobility	12.56	9,94
Downwards mobility		
P_{2-}		53,72
P_{3-}		78,28
P_{4-}		95,39
P_{5-}		89,57
average upward mobility	29.52	79,24

(*) Stationary probabilities

Table 10. Transition matrices (unbalanced panels)

SE 1994	SE 1995 1	2	3	4	5	out	
1	58,62	15,57	7,24	0,42	0,04	**18,11**	100,00
2	29,51	38,70	12,54	1,04	0,10	18,11	100,00
3	17,79	24,14	32,32	3,36	0,29	22,09	100,00
4	4,52	22,87	35,11	11,44	2,66	23,40	100,00
5	20,63	41,27	22,22	3,17	0,00	**12,70**	100,00

SE 1994	SE 2000 1	2	3	4	5	out	
1	37,25	11,00	3,15	0,07	0,02	**48,50**	100,00
2	25,64	18,98	4,76	0,30	0,03	50,29	100,00
3	19,39	13,72	8,50	0,91	0,03	57,45	100,00
4	10,90	15,16	10,37	1,60	0,27	61,70	100,00
5	14,29	7,94	17,46	6,35	3,17	**50,79**	100,00

Transition probabilities	1995	2000

to leave the panel		
Average*	18,88	53,74
p1out	18,11	48,50
P5out	12,70	50,79

Table 11. Transition probabilities from t=1994 to 2000

Transition probability	**1995**	**2000**
Female		
P_{11}	68,45%	71,46%
P_{55}	3,33%	10,00%
average downwards mobility	66,79%	75,35%
Male		
P_{11}	72,11%	74,84%
P_{55}	0,00%	7,69%
average downwards mobility	67,34%	80,07%
High-med. Education		
P_{11}	74,81%	79,25%
P_{55}	0,00%	0,00%
average downwards mobility	70,06%	85,46%
Low Education		
P_{11}	67,50%	69,42%
P_{55}	1,92%	12,50%
average downwards mobility	65,92%	77,35%

Table 12. Regional transition probabilities from t=1994 to 2000

Transition probability	**1995**	**2000**
North-west		
p11	69,61%	77,40%
p55	0,00%	0,00%
Average downwards mobility	69,92%	82,08%
North-east		
p11	76,27%	75,73%
p55	0,00%	no obs.
average downwards mobility	71,31%	80,64%
Madrid Area		
p11	67,16%	76,00%
p55	0,00%	0,00%
average downwards mobility	64,81%	83,89%

Centre		
p11	72,64%	70,33%
p55	0,00%	0,00%
average downwards mobility	60,95%	76,84%
East		
p11	70,42%	73,67%
p55	0,00%	0,00%
average downwards mobility	69,76%	82,51%
South		
p11	67,18%	67,23%
p55	0,00%	31,25%
average downwards mobility	67,24%	72,85%
Canary Islands		
p11	63,58%	54,84%
p55	0,00%	0,00%
average downwards mobility	69,58%	77,11%

Table 13. Transition probabilities by age-groups

Transition probability	**1995**	**2000**
age 16-24		
p11	67,00%	72,81%
p55	0,13%	0,00%
average downwards mobility	62,20%	83,59%
age 25-44		
p11	74,11%	75,97%
p55	0,00%	17,86%
average downwards mobility	65,52%	79,08%
age 45-64		
p11	67,90%	70,59%
p55	0,00%	11,11%
average downwards mobility	69,81%	78,79%
age 65+		
p11	70,26%	73,12%
p55	1,64%	10,87%
average downwards mobility	75,56%	79,29%

Table 14. Multivariate analysis of long-term downwards social exclusion mobility: Logit estimates

Log likelihood = -2929.8579
Pseudo R2 = 0.0489
Obs = 4446
Y=pr(y)= 0.4891

downwards mobility	**Coef.**	**Std. Err.**	**dy/dx**	**Std. Err**
sex (=1 if male)	0.1818*	.0629	0.0454*	0.0157
aged under 25	0.0844	.1065	0.0211	0.0266
aged over 45	-0.3420**	.0745	-0.0854**	0.0186
high education	0.6550**	.1419	0.1603**	0.0332
low education	-0.3274**	.0989	-0.0816**	0.0246
single to couple	-0.2084	.2917	-0.0517	0.0718
couple to single	-0.1048	.1401	-0.0261	0.0349
couple to couple	-0.4071**	.0736	-0.1010**	0.0181
no child to children	0.4354	.2283	0.1077	0.0551
more children	-0.1178	.1626	-0.0293	0.0404
class 2	0.9836	.4025	0.2386	0.0921
class 3	0.6008	.4045	0.1488	0.0983
class 4	-0.0618	.4430	-0.0154	0.1102
north-west	-0.0403	.1388	-0.0100	0.0346
north-east	0.1338	.1497	0.0334	0.0375
centre	-0.2525	.1388	-0.0627	0.0343
east	0.2478	.1348	0.0618	0.0335
south	-0.1893	.1322	-0.0471	0.0329
Canary Islands	-0.5021*	.1604	-0.1229*	0.0381
Constant	-0.0502	.4376	------------	---------

Note: the reference individual is a male aged between 25 and 45, with medium education, single and without children in both periods, and living in the Madrid area.

(**) level of significance at 1%
(*) level of significance at 5%

Table 15. Multivariate analysis of long-term upward mobility from non-exclusion in 1994 to exclusion in 2000: Logit estimates

Log likelihood = -23864.392
Pseudo R2 = 0.0245
Obs = 4147
Y=pr(y)=0.73011

upwards mobility	**Coef.**	**Std. Err.**	**Dy/dx**	**Std. Err.**
sex (=1 if male)	-0.2105*	0.0709	-0.0414*	0.0139
aged under 25	0.3240	0.1254	0.0672	0.0271
aged over 45	0.2296	0.0845	0.0452	0.0166
high education	-0.2993	0.1394	-0.0561	0.0248
low education	0.4013**	0.1059	0.0767**	0.0196
single to couple	0.2147	0.3291	0.0442	0.0707
couple to single	0.2113	0.2035	0.0435	0.0435
couple to couple	0.0069	0.0814	0.0013	0.0160
no child to children	-0.2057	0.2245	-0.0387	0.0403
more children	0.3336	0.1666	0.0695	0.0367
north-west	0.0925	0.1481	0.0184	0.0300
north-east	-0.0552	0.1429	-0.0108	0.0277
centre	0.2680	0.1424	0.0549	0.0302
east	0.1949	0.1388	0.0394	0.0287
south	0.3169	0.1468	0.0655	0.0317
Canary Islands	0.8330**	0.1998	0.1879**	0.0490
Constant	-1.6873**	0.1943	--------	--------

Note: the reference individual is a male aged between 25 and 45, with medium education, single and without children in both periods, and living in the Madrid area.

(**) level of significance at 1%
(*) level of significance at 5%

4

Does persistence of social exclusion exist in Spain?

4.1 Introduction

Social policy debates have often focused on social exclusion dynamics in recent years in Europe and elsewhere. As we have seen, social exclusion can be seen as a process that, fully or partially, excludes individuals or groups from social, economic and cultural networks and has been linked to the idea of citizenship (Lee-Murie, 1999). Therefore, social exclusion is a multidimensional process leading to a state of exclusion.

In order to promote social cohesion and inclusion (as explicitly required by the Lisbon Summit), the EU states have to identify not only the individuals most likely to be excluded but also who is most likely to remain excluded and who is most likely to become excluded. As we seen in chapter one, there is a growing literature that focuses on the definition of an appropriate measure of social exclusion and on the identification of who is socially excluded today (e.g. D'Ambrosio – Chakravarty 2002, Tsaklogou-Papadopoulos 2001, Nolan- Whelan-Maitre-Layte 2000). Other studies analysed the degree of exclusion by number of dimensions and by duration (e.g. Burchardt 2000, Burchardt et al. 2002). But, as far as we know, no studies have focused on the causes of the dynamic process that leads the individual to be defined as socially excluded.

Questions regarding the causes of social exclusion persistence ought to be central in the debate on policies addressing social exclusion. In fact, if social exclusion persists for many years, policymakers and others have good reasons for concern over the causes of such long-term exclusion. In addition, since government programs frequently provide assistance to those excluded in a certain dimension, it is important to document the efficacy of such policies and, therefore, we need to verify if the individual is permanently, or only temporally, helped out of social exclusion.

The aim of this chapter is to analyse the causes behind the dynamic process that we call social exclusion. In particular, we wish to understand if an individual experiencing social exclusion today is much more likely to experience it again. Moreover, we wish to understand better the process that may generate persistence of social exclusion.

Persistence of social exclusion may arise from individual heterogeneity. That is, individuals could be heterogeneous with respect to characteristics that are relevant for the chance of experiencing social exclusion. In this case, an individual experiencing social exclusion in any point of time because of adverse characteristics will also be likely to experience social exclusion in any other period because of the same adverse characteristics. These adverse characteristics can be observed (e.g. sex, level of education, household status) or unobservable. In the latter case, we speak about unobserved heterogeneity as a cause that may generate persistence of social exclusion.

Social exclusion can also be due to a process called true state of dependence. That is, experiencing social exclusion in a specific time period, in itself, increases the probability of undergoing social exclusion in subsequent periods (Heckman, 1978).

Distinguishing between the two processes is crucial since the policy implications are very different. If persistence of social exclusion is (at least partly) due to a true state of dependence, then it makes sense to force the individual out of social exclusion at time *t* in order to reduce her chance of experiencing exclusion in the future. Thus, it is logical to intervene on the dimensions that (at least partly) generated the true state of dependence in order to break the “vicious circle”. But if persistence of social exclusion is due only to unobserved heterogeneity any short-time policy aimed at forcing the individual out of social exclusion at time *t* is not really effective. In fact, forcing the individual out of social exclusion today does not affect her adverse characteristics, and therefore does not reduce her chance of experiencing social exclusion spells in subsequent periods.

This chapter contributes to the literature on social exclusion in the following three ways. First, it provides an analysis of social exclusion persistence identifying the causes of exclusion: true state of dependence, unobserved heterogeneity and/or observed heterogeneity. Previous studies on social exclusion identify the population members at high risk of social exclusion and present tabulations about the duration of social exclusion. However, they do not analyse, as we do, the processes that can lead to social exclusion persistence. Thus, we provide estimates of the extent to which the experience of social exclusion today increases the risk of being socially excluded in the future (true state of dependence), while controlling for differences in observed and unobserved characteristics between individuals (heterogeneity). Second, we consider eight dimensions as components of social exclusion. Previous studies on income, and earnings, suggest analysing true dependence controlling for observed and unobserved heterogeneity. These studies focus only on one dimension: income or earnings. Instead, we perform a multidimensional analysis using an aggregate measure of social exclusion and studying every dimension separately. Third, we apply an econometric technique that has never been applied to neither social exclusion nor income, as far as we know. This technique, proposed by Wooldridge 2002, estimates consistently a logit model with both lagged dependent and exogenous variable to distinguish between two different sources of dynamics, true state dependence and heterogeneity.

In the next section, we shortly review the main literature about income (and earnings) dynamics as well as studies about social exclusion dynamics. In section 3, we operationalize the definition of social exclusion and we define our binary measure of social exclusion. In section 4, we analyse how social exclusion evolves over time in Spain. In section 5, we present the dynamic model that we use to analyse the persistency of social exclusion. In section 6, the empirical results are given. In section 7, we discuss the robustness of our analysis performing sensitivity analysis in order to consider eventual problems on the definition of social exclusion. The last section concludes.

2. Social exclusion dynamics: a review

Nowadays, a lot of studies focus on social exclusion mainly suggesting an appropriate definition of social exclusion and/or proposing an adequate social exclusion measure. However, only few of them pay attention to analyse its dynamics.

Burchardt (2000) looks across different dimensions of social exclusion at a single point in time, and traces the course individuals follow over time. She finds that exclusion on a particular dimension (consumption, production, political engagement or social interaction) increases the exclusion on the same dimension in the following year. In a more recent study, Burchardt, Le Grand and Piachaud (2002) extended the analysis of Burchardt (2000) proposing a multidimensional dynamic measure of social exclusion to monitor the effectiveness of government policies. The empirical analysis in both studies is made using British data from the BHPS. [1]

Tsakloglou and Papadopoulos (2001) identify the population members at high risk of social exclusion in Europe. Following the idea that social exclusion is a dynamic process leading to deprivation, they construct static indicators of deprivation in particular fields (income, living conditions, necessity of life and social relations). Then, they aggregate this information in order to obtain a static indicator of cumulative disadvantage. So, individuals classified as being at high risk of cumulative disadvantage at least twice during the period of three years, are classified as being at high risk of social exclusion.

Nolan, Whelan, Layte and Maitre had produced a certain number of articles about poverty, mobility and persistence of deprivation [2]: they mainly analyse persistence using tabulation of the duration of deprivation and poverty. The empirical analysis is a comparative study across European countries done using the European Community Household Panel (ECHP).

The general message that comes from the literature surveyed above is that approaches to the analysis of social exclusion dynamics mainly focus on the duration of social exclusion and on the identification of individuals at high risk of exclusion, without taking into account movements into and out of social

[1] British Household Panel Survey
[2] Social exclusion can be seen as a process leading to a state of deprivations (Sen, 2000)

exclusion and the causes leading to exclusion. Therefore, the main contribution of our study is to analyse the causes leading to social exclusion. The analysis is performed by extending dynamic methods, normally used to explore income and poverty dynamics, to understand social exclusion.

Jenkins (2000) describes four main types of dynamic models that have been applied in income and poverty dynamics literature to data. The first type of models describes different patterns of poverty dynamics in terms of the fixed characteristics of the individual, and it identifies who experiences certain types of poverty transition (e.g. Gardiner and Hill, 1999). The second approach examines the chances of exit from, or entry into, poverty as function of observed characteristics of the individuals underlining that experiences these events. In other words, it emphasizes which individual types are more likely to exit from, or entry in, poverty (e.g. Huff Stevens, 1999). The third approach seeks to explain the path of individual income in terms of observed characteristics and other non-observed processes in order to try to discover regularities in the process driving poverty dynamics. The final approach is to model the economic processes that underlie poverty transitions as function of observed and unobserved characteristics of the individual in order to identify the main characteristics, or events, that cause poverty dynamics (e.g. Burgess and Propper, 1998).

These approaches are reviewed is some detail in Jenkins (2000), so here we focus on the latter method which we have adopted. The aim of this chapter, as explained in the introductory section, is to analyse the causes leading to social exclusion persistence (unobserved heterogeneity and true state of persistence). Therefore, we need to model social exclusion allowing for a complex lag and error structure to capture dynamics. Recent papers, as Stevens (1999), Devicienti (2000) and Capellari and Jenkins (2002), focus on the question of unobserved heterogeneity and true state of dependence in poverty dynamics, and on the related issues of endogeneity of initial conditions and panel attrition. Related models have been also applied to transitions into and out of low earnings (e.g. Stewart and Swaffield 1999). Trivellano et al. (2002) also test for true state of dependence, in presence of unobserved heterogeneity, using Italian panel data. We propose an alternative solution to the problem of modelling unobserved heterogeneity and true state of dependence, as we explain in depth in section 4.

3. Definitions and data

We have defined social exclusion as a process that fully or partially excludes individuals or groups from social, economic and cultural networks in the society they live in. Social exclusion can also been seen as a part of the Sen's capability, and it can be defined as a process leading to a state of functioning deprivations (Sen, 2000). Therefore, the "process" of social exclusion produces a "state" of exclusion that can be interpreted as a combination of some relevant deprivations. In this chapter, we use the following working definition of social exclusion:

"An individual is defined as socially excluded in a specific point in time if she is deprived of one or more relevant functionings".

This definition refers to the "state" of social exclusion, and it implies that an individual is defined as socially excluded at time *t* if she is deprived in at least one dimension, where every dimension represents one functioning. Note that this definition is slightly different from the definition used in the previous chapters: now we are defining social exclusion as a binary variable where the individual can be classified as excluded or as not excluded. No intermediate values are possible. The main reason to do so is to be able to obtain consistent estimators of the two processes leading to exclusion (without to complicate too much the econometric framework).

To construct an indicator of the individual state of social exclusion based one the above working definition, we used the first six waves (1994-99) of the European Community Household Panel (ECHP). We use a balanced panel composed by 8914 individuals aged 16+. Cross-sectional and longitudinal weights are used as appropriate. But, note that we do not use weights in any estimation since from an econometric point of view is more efficient not to use sampling weights, as we see later.

The above working definition implies the following methodological problems in the construction of a binary measure of social exclusion. First, the choice of the relevant functionings (dimensions) and the items representing them. Second, the identification of deprived individuals. Third, the aggregation of the relevant functionings in a binary measure of social exclusion. The first and the second issues have been already discussed in chapter 2, section 6. Table 1 lists the functionings used in the analysis. The aggregation issue is treated below.

Remember that, for convenience, we have chosen a deprivation threshold (cut-point) for each dimension at a point in time equal to the 50% of the functioning distribution mean. Note that issues about the arbitrariness in the choice of the thresholds are addressed in Section 7, where a sensitivity analysis is performed. Now we combine the information about each dimension deprivations in a binary measure of social exclusion. For each individual, the score of such measure is one if the individual is socially excluded and zero otherwise. Finally, as we have already stressed, our working definition of social exclusion implies that any deprivation in one functioning is sufficient for social exclusion. Therefore, an individual is counted as socially excluded at time *t* if she is deprived in at least one dimension.

3. Evidence of Social Exclusion and its persistence

Table 2 shows the proportion of the population aged 16+ who fell below the threshold in each dimension through the panel. In 1994, we find that about 54.5% of the sample is socially excluded at least in one dimension. High deprivation rates are observed in the following dimensions: “living in a safe and clean environment”, “having an adequate income”, “being healthy”, and “being able to perform a work activity”. All of them, except “having an adequate income”, describe non-economic aspects of social exclusion. However, the proportion of the population counted as excluded is sensitive to the particular threshold chosen in every dimension: the higher the threshold, the more people result deprived in a certain dimension and, therefore, the more people appear socially excluded. So possibly of more interest than the level of social exclusion is the relationship between dimensions at a point in time and the pattern of exclusion over time.

Looking across dimensions of exclusion at a single point in time, we notice that less than 18% of people results deprived in at least two dimensions in 1993, less than 4% in a least three dimensions and only less than 1.05% of the individuals results deprived in more than three dimensions. As observed by Burchardt et al. (2002) studying the U.K., there is no evidence of a concentration of individuals who are excluded in all dimensions.

Connection over time in social exclusion is quite strong: social exclusion in one year is strongly associated with social exclusion in the following year (the correlation is about 0.4), and the association is only slightly lower in the subsequent years. Figure 1 shows how deprivation evolves over time in every dimension. The deprivation rate observed in 1999 results lower than the one registered in 1994 in every dimension, but deprivation monotonically decreases only in the dimensions “reaching a certain quality of life” and “living in a safe and clean environment”. Figure 2 shows the evolution of social exclusion during the panel period: it decreases over time resulting about 10% lower at the end of the panel (see also Table 2).

Table 3 shows the pattern of exclusion of the individuals that are excluded for one wave or more during the panel. As time progresses, an increasing proportion of the sample has some experience of exclusion, and, correspondingly, a decreasing proportion has never experienced exclusion during the panel. About 83% of the sample experienced social exclusion in at least one dimension and at least in one wave during the panel, but about 13% of the sample is excluded in at least one dimension in all the waves. The proportion of the sample that experiences some exclusion, but is not excluded throughout, is an indication of the degree of mobility. So, we observe a high degree of mobility in the sample through the panel. Note that we also observe a strong persistence in social exclusion since about 13% of the population is counted as excluded in all waves during the panel.

Focusing our attention on the duration and the frequency of the exclusion spells, we note that about 25% of the population experiences exclusion spells not longer than one year, but 10.33% of them experiences multiple spells (see Table 4). About 13% of the entire sample experiences multiple spells during the panel. But, only about 25% of the population experiences exclusion spells longer than 3 years.

Finally, looking to the sample structure of the excluded in the panel, we can note that about 27% of the excluded individuals are females and only about 21% of excluded are males. We also observe that about

14.30% of the excluded population is aged between 16 and 35, about 14.73% is aged between 36 and 56, and about 17% is aged 65+. Moreover, about 10% of the excluded individuals have a high or medium level of education: 37.41% of the individuals counted as excluded does not have the second level of education (see Table 5).

5. The Model

In this section, we use an econometric model in order to obtain more information about the persistence of social exclusion. As I have mentioned above, there are two processes that can generate persistence: unobserved heterogeneity and true state of dependence. In the first process, individuals could be heterogeneous with respect to characteristics that are relevant for the chance of experiencing social exclusion and persistence over time. In this case, an individual experiencing social exclusion at any point in time because of (unobserved) adverse characteristics will also be likely to experience social exclusion in any other period because of the same adverse characteristics. In the second process, experiencing social exclusion in a specific time period, in itself, increases the probability of undergoing social exclusion in subsequent periods. Remember that, for each individual, the score on the social exclusion indicator is equal to one if the individual is excluded, and zero otherwise. The number of individuals aged 16+ with complete observations during the panel (N=8914) is large and the number of periods, T, is fixed (T=0,…,5).

From an econometric point of view, analysing the persistence of a discrete choice variable, and in particular the presence of true state of dependence and unobserved heterogeneity, leads to some methodological problems connected with the consistent estimation of a non-linear model. Thus, the choice of the initial conditions or alternatively of a semi-parametric structure is crucial for the correct estimation (Honore, 1993).

In general non-linear panel data models have received little attention because it is not possible to difference out individual specific effects as it is the practice for linear models. Thus, if the individual specific effects are not run out, the estimation will not be consistent. There are essentially two approaches to deal with this problem: the random effects approach and the fixed effects approach.

In the random effects approach, one parameterises the distribution of the individual specific effects conditional to the exogenous explanatory variables. The estimation of the model can be done by a pseudo-maximum likelihood method that ignores the panel structure of the model. Under suitable regularity conditions, this will lead to a consistent and asymptotically normal estimator. The model results to be fully parameterised and the initial conditions have to be also specified. A simple solution to the initial conditions problem, in dynamic non-linear panel data models with unobserved heterogeneity, is given by Wooldrigde (2002). He proposed finding the individual specific effect distribution conditional on the initial value (and the observed history of strictly exogenous explanatory variables). He treats the general problem of estimating average partial effects, and shows that simple estimators exist for important special cases.

In the fixed effects approach, one attempts to estimate the parameters making only minimal assumptions on the individual specific effects. If there are at least four time periods, and the exogenous explanatory variables are not included, Chamberlain (1985) has shown that the parameters of a dynamic logit model can be estimated by considering the distribution of the data conditional on a sufficient statistic for the individual specific effect (conditional likelihood estimation). Honore and Kyriazidou (2000) generalized this to the case where the logit model was also allowed to contain exogenous explanatory variables.

The choice between random effects and fixed effects model is fully discussed in Honore (2002). He argues that “estimating a random effects panel data model results in a fully specified model in which one can estimate all the quantities of interest, whereas fixed effects panel data models typically result in the estimation of some finite dimensional parameter from which one cannot calculate all functions of the distribution of the data. Moreover, random effects models will usually lead to more efficient estimators of the parameters of the model if the distributional assumptions are satisfied. On the other hand, violation of the distributional assumption in a random effects model will typically lead to inconsistent estimation of the parameters. The fixed effects model imposes fewer such assumptions. Based on this, it seems that if the main aim of an empirical exercise is to judge the relative importance of a number of variables, or to statistically test whether certain variables are needed, and if efficiency is not too much of an issue, then fixed effects approach is preferable because it will be less sensitive to distributional assumptions. On the other hand, if one wants to use the model for prediction or for calculating the effect of various 'what-if is', then a random effects model would be preferable".

Since we wish to use a model that, in a future, could be used for estimating the impact of a specific policy, we concentrate our attention to random effects models. In particular, we follow the approach proposed by Wooldridge (2002) to estimate consistently the parameters. Moreover, we estimate the average partial effects in order to determine the importance of the dynamics in the model, and not only to test whether there is dynamics. This approach has also some computing advantages, if we consider a dynamic logit model (as appropriate in our case), a standard random effects software can be used to estimate the parameters and the average effects. [3]

Dynamic Logit Model

In the previous section, we constructed an individual indicator of the state of exclusion. It indicates the presence or the absence of an exclusion state: we assess the value of one if exclusion occurs and the value of zero if it does not. To analyse how this static indicator evolves over time, we use a dynamic panel data logit model.

For a random draw i from the population, and t=1,2,3,4,5, the conditional probability that exclusion occurs is

$$P(y_{it} = 1 \mid y_{it-1}, \ldots, y_{io}, c_i) = \phi(\rho y_{it-1} + c_i). \qquad (1)$$

where the functional form of ϕ is a logistic distribution, the dependent variable y_{it} is the exclusion state of individual i at time t, ρ is a parameter to be estimate and c_i is the individual specific effect.

The assumptions implied by this equation are the following: first, the dynamics are first order, once c_i is conditioned on; second, the unobserved effect is additive inside the distribution function, ϕ. As suggested

[3] For futher details see Wooldridge (2002).

by Wooldridge (2000), the parameters in (1) can be consistently estimated by specifying a density for c_i given the exclusion initial condition y_{i0}. Therefore, we assume that

(2) $$c_i \mid y_{i0} \sim \text{Normal}\,(a_0 + a_1\, y_{i0} + \mathbf{z}_i\, \mathbf{a}_2\, ,\, \sigma^2_a\,)$$

where $\mathbf{z}_i$ is the row vector of all time constant explanatory variables, a_0, a_1 and $\mathbf{a}_2$ are parameters to be estimated and σ^2_a is the conditional standard deviation of c_i. Note that the vector $\mathbf{z}_i$ appears in (2), and not in equation (1), because otherwise we could not identify the coefficients on time constant covariates.

Given (1) and (2), we can write the conditional density for the conditional distribution as

$$f(y_{it}\, , \ldots, y_{\,iT} \mid y_{io}\, , c_i\, ;\rho) = \Pi_{\,t}\, \{\phi\, (\rho y_{it-1} + c_i\,)^{yt}\, .\, [1\text{-}\phi\, (\rho y_{it-1} + c_i\,)]^{1-yt}\}$$

When we integrate this with respect to the normal distribution in (2), we obtain the density of $(y_{it}\, , \ldots, y_{\,iT} \mid y_{io}\, , c_i\, ;\rho)$. Then, we maximize the density obtained (likelihood) in order to estimate the parameters ρ, a_0, a_1, $\mathbf{a}_2$, σ^2_a. The estimation is consistent only under the assumption that the model is correctly specified.

In the model, the value of ρ determines if the exclusion sequence $\{y_{it}\}$ features true state of dependence. In other words, it determines if experiencing exclusion in a specific time period, in itself, increases the probability of undergoing social exclusion in subsequent periods. In particular, if $\rho>0$, then experiencing exclusion at time t-1, $y_{it-1}=1$, increases the chance to experience exclusion at time t ($y_{it}=1$). Moreover, the estimate of a_1 is of interest in its own right, since it tells us the direction of the relationship between the individual specific effect and the initial conditions. Finally, the estimate of σ^2_a gives us information about the size of the dispersion accounted by unobserved heterogeneity.

Finally, note that the method proposed by Wooldridge (2002) requires a balanced panel. Therefore, we may face not only attrition problems (as already underlined) but also selection problems. Wooldridge's method derives the density conditional on (y_{i0} , z_i) and it has some advantages in facing selection and attrition problems. In particular, it allows selection and attrition to depend on the initial conditions and, therefore, it allows attrition to differ across initial levels of exclusion. In particular, individuals with different initial status are allowed to having different missing data probabilities. Thus, we consider selection and attrition without explicitly model them as a function of initial conditions. As a result, the analysis is less complicated and it compensates the potential lost of information from using a balanced panel. Similar comments apply to stratified sampling: any stratification that is function of (y_{i0} , z_i) can be ignored in the conditional MLE analysis since it is more efficient not to use any sampling weights (Wooldridge, 2002).

6. Empirical results

We discuss the results in three stages. First, we present the estimates of the true state of dependence and the heterogeneity. Second, we analyse the importance of the dynamics in the model. Third, we discuss the estimated impact of each dimension on social exclusion.

Estimates of persistence

Using the dynamic logit model in section 5, we present in Table 6 the conditional maximum likelihood estimates (and the asymptotic standard errors) for the following two cases. First, we consider as the only explanatory variable the lag of social exclusion (model 1). Second, in order to explicitly control for some observed heterogeneity we include some time-constant variables (models 2 and 3).

In model 1, after controlling for the unobserved effect, the coefficient on the lagged social exclusion is statistically very significant. The initial value of social exclusion is also very important, and it implies that there is substantial correlation between the initial condition and the unobserved heterogeneity. In fact, the coefficient on initial social exclusion (1.7) is much larger than the coefficient on the lag (0.4). Moreover, the estimate of the conditional standard error of c_i (σ_a) is equal to 1.3 and it is statistically different from zero: this means that there is much unobserved heterogeneity.

In model 2, we include some time-constant variables (Model 2 in Table 6): since in model 1 we observe much unobserved heterogeneity, we wish to explicitly control for the heterogeneity that we can observe. The time-constant covariates are sex (equal to one if male), the level of education (high or medium), the year dummies (to capture an eventual trend), the age at time zero, the cohabitation status at the initial period (with or without children in the household),[4] the presence of one or more individuals in the household at the initial period and being a lone parent at the initial period. Interestingly, even after time constant variables are included, there is much unobserved heterogeneity that cannot be explained by the covariates: the estimated σ_a is still equal to 1.3. We also observe true state of dependence and high correlation between the initial condition and the unobserved heterogeneity, as in model 1. However, model 2 has a better fit. Among the time constant variables included, the level of education (high and medium) seems to reduce significantly the probability to experience social exclusion while being lone parent seems to increases the chance to be excluded. Moreover, the coefficients of the year dummies (wave2,..,wave5) suggest that social exclusion decreases over time.

In model 3, we also included region dummies to take into account geographical differences (see Table 7 and 8). The European Household Panel divides Spain in seven regions: North - West, North – East, Madrid’s region, Centre, East, South, and Canary Islands. Using simple descriptive techniques, we observe the lowest social exclusion rate in the North East (about 33%) and the highest rate in Canary Islands (about 61%). Estimating model 3, we also find that an individual living in South Spain and, especially, in Canary Islands has higher probabilities to experience social exclusion than one living in the Madrid’s region. Instead, an individual living in the North West, in the East and, specially, in the North East has lower probabilities to be socially excluded than one living in the Madrid area. Finally, note that even after region dummies are included, the estimate of the true state of dependence and the estimate of unobserved heterogeneity are still very statistically significant.

One general lesson from the estimation of the previous models is that there is great individual heterogeneity (observed and unobserved) in the possibility to experience social exclusion. A second general lesson from the results discussed above is that there is a non-trivial part of social exclusion persistence that may be ascribed to past exclusion. These results are similar to the ones reported by Cappellari and Jenkins (2002a) that analyse income dynamics for the UK in the 1990s. Note that these

[4] The variables “cohabitation without children”, “cohabitation and children”, “old individual in the household” and “lone parent” could be also designed as time variant variable; however, it would not add much to the analysis but it would make the model much more complicated: including a time-variant explainatory variables implies the necessity to also include T indicator variables and, therefore, we could end up with too much covariates (for details see Wooldridge, 2002).

finding are of policy relevance: policies focused on getting people out of social exclusion and policies focused on keeping individuals out of social exclusion once out are both relevant policies.

Importance of the dynamics and impact of observed heterogeneity

In order to determine the importance of the dynamics in the model, and not just to test whether there are dynamics, we estimate average partial effects. We determine the magnitude of partial effects to analyse the importance of any state of dependence. In the same way, we can investigate the impact of any observed heterogeneity on the probability to experience social exclusion. The average partial effects on the response probability are based on

$$E\,[\,\phi\,(\,\rho\, y_{t-1} + c_i\,)]$$

where the expectation is with respect to the distribution of c_i. A consistent estimator of the previous expected value was proposed by Wooldridge 2002, and it is the following:

$$N^{-1}\sum_{i=1}^{N}\phi\left(\hat{\rho}_{\kappa}\; y_{t-1} + \hat{a}_{0\kappa} + \hat{a}_{1\kappa}\; y_{i0} + z_i\, \hat{a}_{2\kappa}\right)$$

where the κ subscript denotes multiplication by

$$\left(1+\hat{\sigma}_a^{\,2}\right)^{-1/2}$$

and the parameters are estimated using the conditional MLEs.

Using this estimator, we estimate the probability of being excluded in 1999 given that the individual is or is not excluded in 1998. The difference is an estimate of the state of dependence of being socially excluded. The probability to experience social exclusion in 1999 given that the individual is excluded in 1998 is 0.42, while it decreases to 0.29 if the individual is not excluded in 1998. Thus, the estimate of the state dependence of social exclusion is about 0.126 (Table 6).

For a high educated individual that was excluded in 1998, the estimated probability of experiencing social exclusion in 1999 is 0.166. The probability to be socially excluded in 1999, having been excluded in 1998, is much higher if the individual does not have a high level of education: about 0.4486. Moreover, for an individual with a high level of education, that was not excluded in 1998, the probability to experience social exclusion is very close to zero (0.06) but it is equal to 0.31 if the individual does not have a high level of education. Finally, we note that for a single parent the probability to be excluded in 1999 is about 0.7 if he was excluded in 1998, and it is about 0.57 if he was not (see Table 6).

Hence, individuals excluded at a certain point in time have a higher probability to experience social exclusion in the future than non-excluded individuals. This probability appears related to differences in observed individual characteristics.

Impact of each dimension on social exclusion

In Table 9, we consider the impact of each dimension on social exclusion. The main idea is to decompose the social exclusion initial value in its 8 components (the dimensions initial conditions) in order to understand which component affects more the probability to experience social exclusion. We still observe true state of dependence, high correlation between initial conditions and unobserved heterogeneity, and much unobserved heterogeneity. Education still reduces the probability to experience exclusion, being single parent increases it and social exclusion still decreases over time. The estimates of all initial deprivations, with exception of initial housing deprivation, result statistically significant. To better see the implications of the estimates, we examine the probabilities of experiencing social exclusion in 1999 that result from the model estimated in Table 9. The various estimated probabilities are summarized in Table 10. The following initial deprivations imply the highest probabilities to be socially excluded (>0.53): not being able to reach a certain quality of life, not being healthy, not being able to perform work activities or/and being poor. In Table 11, we analyse the relation between estimated state of dependence and initial deprivations. The main result is that all the initial deprivations (except initial housing deprivation) appear related to social exclusion persistence over time. In particular, the above mentioned initial deprivations affect more the estimated probability to experience social exclusion in 1999 if the individual is socially excluded in 1998. Therefore, public policies to reduce social exclusion should focus on reducing single dimension deprivations in order to decrease the individual probability to experience social exclusion.

7. Sensitivity analysis

In this section, we report on the robustness of our results to variation in some hypothesis underlying the model presented in the previous sections. First, we consider what happens when we use alternative definitions of social exclusion. Second, we test the robustness of the cut-points chosen.

Operazionalizing the definition of social exclusion has implied to take a certain number of arbitrary decisions as the selection of the relevant functionings and the number of deprivations needed to define the individual excluded. Therefore, we consider the following alternative definitions of social exclusion. First, we omit the functioning "having an adequate income" in the construction of the social exclusion variable supposing that the dimensions "basic need fulfilment", "to reach a certain quality of life" and " to have an adequate house" are fully able to capture the economic features of social exclusion. Second, we use the following working definition: "an individual is defined as socially excluded at time *t* if he is deprived in at least *two* relevant functionings". Using the first alternative definition, the headcount ratios and the persistence rates are lower than the ones presented in the previous section, but the dynamics has the same behaviour. Using the second alternative definition, the probability to be excluded in 1999, being excluded in 1998, is much lower than the one observed in section 5 as well as the estimated state dependence (but still statistically different from zero). Therefore, we conclude that the implications due to the existence of true state of dependence and unobserved heterogeneity are still valid (see Table 12).

Finally, note that the definition of the dimension cut-points that was utilized so far was inspired by definitions used in Britain's official income statistics. However, its choice is arbitrary in essence (Atkinson, 1987). This motivated us to re-estimate the model using alternative definitions of the cut-points: 40% and 60% of the mean distribution. The comparisons of the results suggest that the higher the cut-points the higher the persistence and deprivation rates in every dimension. Therefore, the level of social exclusion is sensitive to the chosen cut-points. However, the estimated state of dependence results statistically equivalent for all considered cut-points. Thus, we can conclude that our results about the state of dependence are robust to cut-points ranging between 40% and 60% (see Table 12).

Conclusions

The aim of this chapter was to study the dynamics of social exclusion in Spain from 1994 to 1999. There are two opposite explanations for the often observed empirical regularity according to which individuals who have experienced social exclusion in the past are more likely to experience that event in the future. One explanation is that as a consequence of experiencing exclusion future choices are altered (true state of dependence). A second explanation is that individuals may differ in certain characteristics, observed and/or unobserved, that influence their probability of experiencing exclusion (heterogeneity).

Using descriptive techniques, we show that about 13% of the population is counted as excluded in at least one dimension in all years from 1994 to 1999 in Spain and about 83% of the sample experienced social exclusion in at least one dimension and in at least one wave during the panel. The high proportion of the sample that experiences some exclusion, but is not excluded throughout, suggests a great degree of mobility into and out of social exclusion. Moreover, note that the proportion of the sample counted as socially excluded is much bigger than the one counted as poor: therefore, social exclusion highlights a problem that involves more people than income poverty.

Looking to the persistence of social exclusion over time, we do find evidence of individual heterogeneity and true state of dependence, even after controlling for observed individual differences. Observed individual characteristics and individual initial conditions appear also strictly related to the probability to experience social exclusion.

Our analysis contribute to understand a little bit better the extent of social exclusion in Spain, and can be used to improve policies to reduce social exclusion. In fact, policies can be focused on getting people out of social exclusion or on keeping individuals out of social exclusion once out. Our results highlight the necessity of both kinds of policies. Moreover, our analysis underlines as certain areas (e.g. education, health, etc.) are more relevant than others to prevent people from falling into social exclusion.

In our view, this chapter represents a first step in order to better understand the causes leading to social exclusion. Further research could focus on the use of the framework presented in this chapter to monitor existing policies and to calculating the effects of alternative policies on social exclusion. In fact, prediction seems to be the logical direction in which research should go.

Figure 1. Dynamics in every dimension

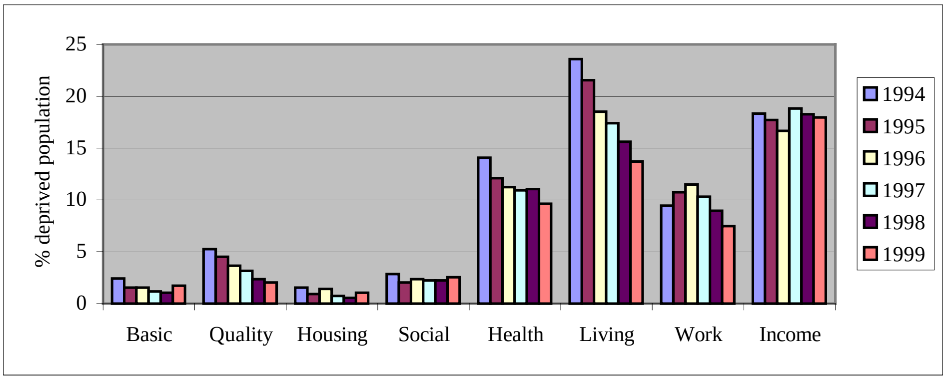


Figure 2. Social Exclusion Dynamics

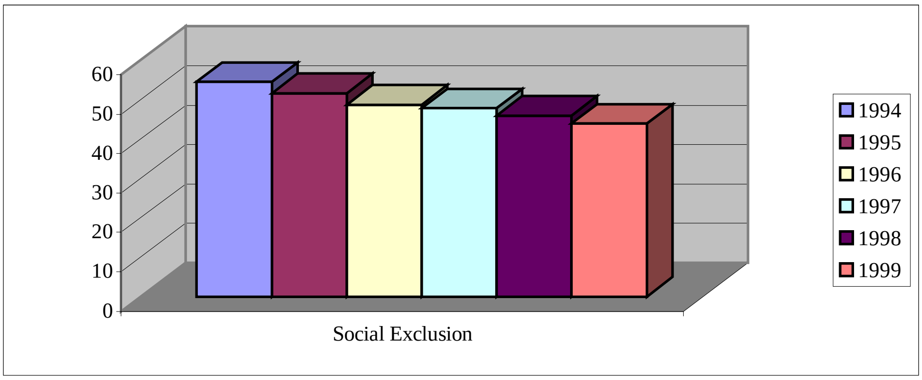


Table 1. Functionings

Basic needs fulfilment (BASIC)
Not eating meat or like every second day
Being unable to buy new, rather than second hand clothes
Being unable to pay bills, rents, etc.
Having an adequate income (INCOME)
Income
To reach a certain quality of life (QUALITY)
Car or van
Colour TV
Video recorder
Telephone
Paying for a week's annual holiday
Having friends or family for a drink/meal at least once a month
Having an adequate house (HOUSING)
Not having indoor flushing toilet
Not having hot running water
Not having enough space
Not having enough light
Not having adequate heating facility
Not having damp walls, floors, foundation...
Not having leaky roof
Not having rot in windows frame, floors
Ability to have social relationships (SOCIAL)
Frequency of talk to the neighbours
Frequency of meeting people
Being healthy (HEALTH)
Health of the person in general
Living in a safe and clean environment (LIVING)
Noise from neighbours or outside
Pollution, crime or other environment problems caused by traffic or industry
Vandalism or crime in the area
Being able to perform a paid or unpaid work activity (WORK)
Being unemployed

Note: Each item represent a good affordable, a good holds or the absence of a problem for at least the 50% of the sample.

Table 2. Headcount ratio - Weighted sample (cross sectional weights)

HEADCOUNT RATIO

	1994	1995	1996	1997	1998	1999
Basic	2.38	1.54	1.52	1.15	1.06	1.75
Quality	5.27	4.52	3.66	3.16	2.36	2.02
Housing	1.52	0.90	1.40	0.77	0.55	1.02
Social	2.83	2.03	2.36	2.21	2.25	2.55
Healthy	14.08	12.12	11.23	10.91	11.06	9.65
Living	23.60	21.54	18.51	17.42	15.64	13.70
Work	9.47	10.76	11.47	10.32	8.94	7.46
Income	18.36	17.70	16.67	18.85	18.28	17.97
SE	54.54	51.70	48.79	47.91	46.00	43.96

Table 3. Persistence (longitudinal weights):

	Basic	Quality	Housing	Social	Healthy	Living	Work	Income	SE
Never excluded	93.38	90.49	96.45	91.20	73.16	56.38	76.22	59.59	17.17
Excluded 1 wave	5.46	5.14	2.79	6.57	9.94	16.23	9.89	12.70	15.11
Excluded 2 waves	0.74	1.85	0.29	1.32	5.04	9.42	5.54	8.13	13.92
Excluded 3 waves	0.27	0.98	0.22	0.49	3.98	8.03	3.75	6.15	14.04
Excluded 4 waves	0.08	0.97	0.16	0.32	3.19	4.52	2.52	6.04	13.30
Excluded 5 waves	0.06	0.52	0.08	0.07	2.92	3.87	1.39	3.98	13.23
Excluded 6 waves	0	0.05	0.02	0.03	1.77	1.55	0.69	3.41	13.22

Table 4. Persistence – subsequent years – and multiple spells

Individuals excluded in j consecutive years in:	one ore more	% of individuals experiencing the following # of spells:		
	%	One	Two	Three
only 1year	25.56	15.23	8.02	2.31
2 years	17.61	15.22	2.39	---
3 years	12.81	12.81	---	---
4 years	7.71	7.71	---	---
5 years	4.63	4.63	---	---
6 years	13.22	13.22	---	---

Table 5. Characteristics of the sample

	% tot	% of the tot population that is socially excluded
Sex		
Female	53.15	27.07
Male	46.85	21.46
Age		
16-25	15.02	7.10
26-35	16.59	7.20
36-45	18.79	7.73
46-55	15.53	7.03
56-65	16.93	8.37
65+	17.14	8.26
Lone parent	0.37	0.27
Couple without children	15.20	7.73
Couple with children	19.34	8.18
Education		
High level	12.82	4.39
Medium level	16.57	6.73
Low level	70.61	37.41
At least one person aged		
65+ in the household	19.14	9.34

Table 6. Social Exclusion – 6 waves balanced panel

	Model 1		Model 2	
se	Coef	Std. Err	Coef.	Std. Err.
se_lag (ρ)	0.4834**	0.0343	0.4586**	.0352046
se0 (a_1)	1.7092**	0.0462	1.6577**	.0470765
edu_h0			-0.9499**	.0634124
edu_m0			-0.4703**	.0579092
sex			-0.0996*	.0391625
age0			-0.0036**	.0013668
old0			-0.0554	.1148726
cc0			-0.0319	.0522191
cwc0			0.1249	.1177814
single0			1.0904**	.3212533
wave2			-0.0772*	.039314
wave3			-0.1047**	.0394217
wave4			-0.2423**	.0393452
wave5			-0.3662**	.0393187
_cons	-1.3943**	0.0294	-0.7954**	.0823838
sigma_a	1.3139**	0.0296	1.3098**	.0302728
Log likelihood	-24397.886		-23202.452	

Note: se_lag = social exclusion at time t-1; se0 = social exclusion at the initial period; edu_h0 = high level of education; edu_m0 = medium level of education; cwc0 = cohabitation without children; cc0 = cohabitation and children, old0 = old individual in the household and single0 = lone parent; wave i =

dummy variable of the wave i (the first wave is wave zero). All the variables are time constant variable at the initial period, unless differently specified.

Estimated probability of being socially excluded in 1999 given that the individual is or is not excluded in 1998.

.	excluded 1998	not excluded 1998	estimated dependence
probability	0.4185	0.2916	0.1269

Probability of being excluded in 1999 if …

.	excluded 1998	not excluded 1998
high education	0.1660	0.0615
otherwise	0.4486	0.3193

.	excluded 1998	not excluded 1998
single parent	0.7011	0.5754
otherwise	0.4174	0.2904

Table 7. Regional differences – headcount ratios

Exclusion	North-West	North-East	Com. Madrid	Centre	East	South	Canary Islands
SE	46.24%	33.36%	43.36%	48.27%	41.40%	54.84%	61.13%
Basic	0,72%	0,48%	0,48%	1,21%	0,66%	1,70%	7,25%
Quality	3,78%	0,96%	1,04%	5,00%	1,74%	4,74%	6,71%
Housing	1,34%	0,51%	0,63%	1,26%	0,16%	0,45%	1,08%
Social	1,42%	1,05%	2,32%	1,33%	1,97%	1,73%	3,35%
Health	15,79%	9,89%	6,75%	13,36%	10,97%	13,93%	15,53%
Living	14,09%	12,59%	26,77%	8,75%	20,46%	15,95%	23,89%
Work	7,34%	6,17%	7,35%	7,55%	6,68%	12,54%	7,83%
Income	17.02%	9.31%	8.37%	26.07%	9.83%	27.12%	28.32%

Table 8. Regional differences – 6 waves balanced panel

	Model 3	
se	Coef.	Std. Err.
se_lag	0.4575**	.0351711
se0	1.5787**	.0465527
edu_h	-0.9008**	.0630247
edu_m	-0.4376**	.0575788
sex	-0.0982*	.0387147
age	-0.0028*	.0013544
old	-0.0258	.1135326
cc	-0.0559	.0518272
cwc	0.0767	.1163954
single0	1.0042**	.3177836
wave2	-0.0775*	.0393159
wave3	-0.1059**	.0394199
wave4	-0.2431**	.0393487
wave5	-0.3668**	.0393242
North-West	-0.1997*	.0795023
North East	-0.6077**	.0793418
Centre	-0.0396	.0780843
East	-0.3387**	.0747151
South	0.1592*	.0767638
Canarias	0.3789**	.1033336
_cons	-0.6437**	.1002111
sigma_a	1.2819**	.0299696
Log likelihood	= -23101.352	

Note: for the variable explanation see Table 6

Table 9. Estimation specifying the effect of each dimension on the probability to be excluded

se	Coef.	Std. Err.
se_lag	0.4805**	.0347857
basic0	0.4281**	.1362487
quality0	1.0924**	.0919919
housing0	0.1924	.1608001
social0	0.7570**	.1547137
health0	1.2322**	.0621426
living0	1.0743**	.048633
work0	1.1472**	.074938
income0	1.2816**	.0529865
edu_h0	-0.8089**	.0613832
edu_m0	-0.3650**	.055713
sex	-0.0958*	.0377421
age0	-0.0034*	.001376
old0	-0.0506	.1112991
cc0	-0.0124	.0500585
cwc0	0.1408	.1137412
single0	0.8975**	.3131783
wave2	-0.0770*	.0390712
wave3	-0.0958*	.0391705
wave4	-0.2384**	.0391193
wave5	-0.3615**	.0391023
_cons	-0.7733**	.080938
sigma_a	1.2341**	.0296985
Log likelihood	= -23287.742	

Note: for the variable explanation see Table 6

Table 10. Probability to be excluded in 1999 if the individual is initially deprived

Deprived in 1994 in:	Probability to be socially excluded in 1999:
Basic	0.36.81
Quality	0.5307
Housing	0.3143
Social	0.4497
Health	0.5419
Living	0.4753
Work	0.5353
Income	0.5380

Table 11 Estimated probabilities

Estimated probability of being socially excluded in 1999 given that the individual is or is not excluded in 1998.

.	excluded 1998	not excluded 1998	estimated dependence
probability	0.2733	0.1426	0.1307

Probability of being excluded in 1999 if …

.	excluded 1998	not excluded 1998	estimate dependence
excluded in basic	0.3681	0.2067	0,1614
not excluded in basic	0.2712	0.1404	

.	excluded 1998	not excluded 1998	estimate dependence
excluded in quality	0.5307	0.3326	0,1981
not excluded in quality	0.2584	0.1275	
.	excluded 1998	not excluded 1998	estimate dependence
excluded in housing	0.3143	0.2727	0,0416
not excluded in housing	0.1696	0.1421	
.	excluded 1998	not excluded 1998	estimate dependence
excluded in social	0.4497	0.2695	0,1802
not excluded in social	0.2708	0.1408	
.	excluded 1998	not excluded 1998	estimate dependence
excluded in health	0.5419	0.3351	0,2068
not excluded in health	0.2289	0.1080	
.	excluded 1998	not excluded 1998	estimate dependence
excluded in living	0.4753	0.2847	0,1906
not excluded in living	0.2215	0.1086	
.	excluded 1998	not excluded 1998	estimate dependence
excluded in work	0.5353	0.3373	0,1980
not excluded in work	0.2518	0.1254	
.	excluded 1998	not excluded 1998	estimate dependence
excluded in income	0.5713	0.3261	0,2452
not excluded in income	0.2518	0.0914	

Table 12. Sensitivity analysis

Alternative definitions

Estimated probability of being socially excluded in 1999 given that the individual is or is not excluded in 1998.

.	excluded 1998	not excluded 1998	estimated dependence
SE without income dimension	0.2382	0.1328	0.1054
SE (in at least 2 dimensions)	0.2382	0.1328	0.1054

Cut-Points

% SE	1994	1995	1996	1997	1998	1999
Cut-points: 40% of the mean	36.97	35.52	33.62	33.42	30.42	28.60
Cut-points: 60% of the mean	48.86	45.94	43.14	41.11	37.11	34.43
% individuals excluded in all waves (persistence)						
Cut-points: 40% of the mean						7.46
Cut-points: 60% of the mean						14.19

Estimated prob. of being socially excluded in 1999 given that the individual is or is not excluded in 1998

.	excluded 1998	not excluded 1998	estimated dependence
cut-points: 40% of the mean	0.2087	0.0941	0.1146
cut-points: 60% of the mean	0.5530	0.4096	0.1434

5

Endogenous population subgroups

5.1 Introduction

The aim of this chapter is to suggest a method to find endogenously the points that group the individuals of a given distribution in k clusters, where k is endogenously determined. These points are the cut-points. Thus, we need to determine a partition of the N individuals into a number k of groups, in such way that individuals in the same group are as alike as possible, but as distinct as possible from individuals in other groups.

This chapter is motivated by the necessity to groups the population in different clusters to measure poverty, deprivation, social exclusion and polarisation. However, notice that the necessity to identify a certain number of groups in a given population exists not only in economics. In areas as medicine, psychology, soil science, ecology and taxonomy, the partition of the population into groups is necessary to make some inferences about property of "natural" groups (Krzanowsky, 1988).

Identifying poor individuals implies to group individuals in different income classes, and to decide which classes have to be considered poor. In particular, the implementation of common measures of poverty (e.g. headcount ratio, poverty gap) requires the identification of every individual as poor or as non-poor. If an individual is represented by her income level, she is defined poor if her income is below a certain income level. This income level (poverty line) is a cut-point that groups the population in two income classes: poor and non-poor individuals. The poverty line is often identified using an exogenous cut-point set up equal to a percentage of the median, or the mean, of the equivalent income distribution (e.g. Eurostat suggests a cut-point equal to the 60% of the median equivalent income). However, this identification is arbitrary: the proportion of the population counted as poor is sensitive to the particular threshold chosen (the higher the threshold, the more people will appear under it). Therefore, we need to endogenously determine the poverty line in order to find non-arbitrary income classes.

As in the implementation of the poverty measures, the measurement of multidimensional poverty, deprivation and social exclusion implies the necessity to group the population in different clusters. In particular, when we perform a multi-dimensional analysis the arbitrariness of the results grows with the number of dimension considered: two dimensions imply the definition of two cut-points (one for each dimension), three dimensions imply three cut-points, and so on. Therefore, we also need endogenous cut-points to eliminate arbitrariness in the analysis.

For the implementation of the polarisation measure suggested by Esteban-Ray (1994), it is necessary to determine an accurate k-spike representation of the population. Therefore, k groups (often income classes) are identified by the definition of k-1 cut-points. Gradin (2000) endogenously computed the subdivision of the population into groups for a given number of groups. Now, the only arbitrary element is the number of groups existing in the population.

In the applications like the ones above, emerge the necessity to define k groups and, therefore, to identify k-1 cut-points. Thus, we face two problems:

- the identification of the best subdivision of the population into a given number k of groups, and
- the determination of the best value of k (the optimal number of groups)

To solve the first problem, we need to formulate an objective function that quantifies the adequacy of a given partition of the population into k groups, and then to find the partition optimising this objective function. Various objective functions have been suggested in the literature, but we found particularly interesting the one proposed by Aghevly and Mehran (1981), and applied to polarisation by Gradin

(2000). Taking as given the number of groups, they proposed to minimise the differences within groups expressed as difference between the Gini index of the ungrouped population and the between-group Gini index. Since the Gini index of the ungrouped population is fixed, we only need to maximize the between-group Gini index to get the best partition of the population in a given number of groups. This method is fully explained in section two.

To solve the second problem, the usual approach adopted is to repeat the optimisation of the objective function for k=2,3,4,… groups, and to choose the value of k at which the final partition appears to be the "best". This criterion is called stopping rule. Mariott (1971) and Krzanowsky (1988) proposed stopping rules based on the optimisation of the within-group covariance. However, we observe the lack of satisfactory stopping rules in cluster analysis applications, and the lack of stopping rules in economic applications, in particular in the determination of income classes. Therefore, we start from the best subdivision of the population into a given number k of groups according to Aghevly and Mehran (1981) and Gradin (2000), and we define an appropriate stopping rule. In other words, our contribute is to find "a criteria" to define the number of groups existing in the literature.

The chapter is organized as follows. In section two, we analyse a general method to compute the best partition of the population in k groups. In particular, we focus on the procedure proposed by Aghevly and Mehran (1981) and Gradin (2000). In section three, we formulate an adequate stopping rule. In section four, some examples are presented to show how the proposed general method and stopping rule work. Finally, section five concludes the chapter.

5.2 K endogenous population subgroups: a general method.

In this section, we propose a general method to identify the best subdivision of the population into a given number k of groups. The problem is the following: given data on a distribution, we wish to group the data into k groups in such way that differences are minimised within the groups and maximised between the groups. Differences can be measured by an inequality index. Therefore, we need some criteria to choose the adequate index.

We assume the number of groups existing in the population is given and equal to k. We consider a particular distribution F of the population over the bounded support $[a,b]$. Each individual i is represented by an attribute x_i. We have n individuals such that $x_1<x_2<\ldots<x_n$. We wish to find endogenously the cut-points, y_1, $y_{2,\ldots}y_{k-1}$, that groups the population in k clusters such that $a<y_1<y_2<\ldots<y_{k-1}<b$ and n_j are the individuals in the j-th group, $[y_{j-1},y_j)$. The cut-points gives us a partition such that

$$n_1 \cup n_2 \ldots \cup n_k = n \qquad \textit{and} \qquad n_1 \cap n_2 \ldots \cap n_k = \phi$$

Note that individual i belongs to the j-th group if, and only if, $x_i \in [y_{j-1},y_j)$. Moreover, note that the group construction implies no-overlap among group ranges.

Our aim is to identify k groups in the population such that the dispersion internal to every group is minimum. Thus, we need to minimise the sum of the internal group dispersions, and the internal group dispersion can be measured by the within-group inequality.

The overall dispersion can be expressed as a weighted sum of the dispersion inside each subgroup plus a term capturing the between-group dispersion. Thus,

(1) $$\mathrm{I}_{tot}=\Sigma_j^k \, \mathrm{q}_j \mathrm{I}_j+\mathrm{I}_b$$

where I_j measures the inequality in group j, I_{tot} measures the overall inequality, I_b measures the between-group inequality, and q_j depends on the population and income share going to subgroup j and on the group position.

For a given distribution the overall inequality is fixed. Therefore, to minimise the sum of the internal group dispersions ($\Sigma_i \mathrm{q}_j \mathrm{I}_j$) is equivalent to maximise the dispersion between groups (I_b). In other words, minimising the within-group differences implies maximising the between-group differences. The best population subdivision in k groups is, therefore, computed by maximising the between group differences (I_b). Our objective function is the between-group dispersion measured by the between-group inequality.

The partition into k groups that maximises the objective function is the optimal partition and it minimises the within-group dispersion.

For the implementation of the procedure to select the best partition, we need to choose an inequality measure. The latter has to be capable to be transformed in an additively decomposable index.

The decomposition of the overall inequality, in the sum of the group inequalities plus the between-group inequality, is possible using indices of the Generalised Entropy families and their monotonic transformations (Shorrocks, 1984). Thus, without imposing specific constrains, the only index, that can be used to measure dispersion, is an entropy index. However, the Gini index is decomposable, in the sense of equation (1), when the group ranges do not overlap (Lambert-Aronson, 1993). Since we are interested in determining non-overlapping partitions, we can also use as dispersion measure some kind of indices not belonging to the Generalised Entropy family, but decomposable. In particular, we can use the Gini index without imposing further constrains. However, we cannot use grouping conditions based on the variance as proposed by Mariott (1971) and Krzanowski (1988).

The choice of the index to use is an important point in our analysis and can lead to some numerical differences. To make this choice we satisfy the following requirement:

Requirement 1. The inequality index, I, has to be decomposable in sense of equation (1).

The indices satisfying Requirement 1, as seen above, are the ones of the Generalised Entropy family and the Gini index when the group ranges do not overlap. We choose to use the latter since it has already been used to group populations into different clusters by Aghevli and Meran (1981) and Gradin (2000). They minimised the within-group dispersions that are equal to the difference between the Gini index of the ungrouped distribution (G) and the between-group Gini index. It means to minimise the error due to grouping in the estimation of the Gini index from grouped data. Moreover, since G is fixed, to minimise the within-group dispersion implies to maximise the between-group Gini index.

Choosing as measure of inequality the Gini index, our problem reduces to find the k-1 cut-points, $y_1 \ldots y_{k-1}$, that maximise the between-group dispersion (G_b):

(2) $$\text{Max}\{G_b(k)\}=\text{Max}\{(1/2n^2\mu)\,\Sigma_i^k\,\Sigma_j^k\, n_i n_j\,|\mu_i-\mu_j|\}$$

where μ_j is the mean of group $[y_{j-1},y_j)$ and n_j is the corresponding population share. We define $G^*_b(k)$ as the optimum value of $G_b(k)$ for a partition into k groups. In other words, $G^*_b(k)$ is obtained grouping the population in k groups using the optimal cut-points $y^*_1 \ldots y^*_{k-1}$.

Properties

The cut-points computed maximizing the between-group Gini index have some useful properties. First, if we multiply all the individual attributes by the same parameter, the cut-points of the new distribution are equal to the old cut-point multiplied by the above parameter. Second, the cut-points depend from the individual attributes, but they do not depend on the name of the individuals. Third, if we merge two or more identical populations, we would like the cut-points to not change.

Property 1a. Be $y^*=(y^*_1,\ldots,y^*_{k-1})$ the vector of the optimal cut-points of the distribution $x=< x_1,..., x_N >$, then $ay^*=(ay^*_1,\ldots,y^*_{k-1})$ will be the vector of optimal cut-points of the distribution $ax=< ax_1,..., ax_N >$, for all a>0.

Proof.

1) Define Y equal to the set of all possible cut-points vector $y=(y_1,\ldots,y_{k-1}) \in R^k$

1) To compute the cut-points, we select the partition such that the Gini between, G_b, is maximum. In other words, be $y^*=(y^*_1,\ldots,y^*_{k-1}) \in Y$ the optimal cut-points vector, we have

$G_b(y^*;x)>G_b(y;x)$ for all $y\in Y$ and $y\neq y^*$.

2) Let's consider the following transformation of the original distribution $x\in R^N$:

$ax=< ax_1,...,ax_N>$ with a>0

3) G_b is homogenous of degree zero: for all a>0,

$G_b(y;ax) = (1/2(an)^2 a\mu)\ \Sigma_i^k \Sigma_j^k\ an_i an_j\ |a\mu_i - a\mu_j| = (1/2n^2\mu)\ \Sigma_i^k \Sigma_j^k\ n_i n_j\ |\mu_i - \mu_j| = G_b(y;x)$

4) Since G_b is homogenous of degree zero, we have

$G_b(y;ay) = G_b(y)$ for all $y \in Y$

then ay* is obviously the cut-point of the new distribution.

□

Property 1b Grouping the two distributions, < x_1,..., x_N > and < ax_1,..., ax_N > (with a>0), in k clusters, the population share going into each group will be the same for both distributions.

Proof

It is obvious consequence of property 1a.

□

Property 2 The cut-point does not depend on the name of the individuals.

Proof

It follows since for all $x \in R^N_+$ and for all permutation matrices, P, we observe the same G_b

□

Property 3 The cut-point is replicant invariant

Proof.

It follows since for all $x \in R^N_+$ and for all integer m>0, $G_b(x[m]) = G_b(x)$

□

Property 4 For the uniform distribution, the optimal groups have equal size, equal population share and $|\mu_j - \mu_{j+1}| = 1/k$

Proof.

See Aghevli and Meran, 1981

□

5.3 Stopping Rule

In this section, we propose a stopping rule to determine the optimal number of groups, k*. The idea is to repeat the optimisation of the objective function for k=2,3,4,… groups, and to choose the value of k at which the final partition appears to be the "best". To determine the best final partition, we need to define a function, A_k, depending on the objective function (G^*_b) and from the number of groups (k). Such function should remain approximately constant over k for data from a uniform population. But, the optimal subdivision into k groups should provide a large increase in A_k if the data are from a population that is strongly grouped round k clusters. Hence, we suggest using A_k as basis for the stopping rule: the optimum value of k is the value that yields the maximum in A_k.

The main idea is the following. We can face two situations: a one-group distribution and a k-group distribution (k>1). On the border between these two situations, we find the uniform distribution. Thus, we need a function A_k able to tell us in which situation we are. For example, we should like A_k to be less than zero if the distribution is one-group distribution, and to be positive if we have a k-spike distribution. But, if the distribution is uniform, we should like A_k be equal zero for all k. Therefore, requiring A_k approximately zero for all k when the distribution is uniform, we obtain the following effects. First, if the dispersion in our distribution is smaller than the one in the uniform distribution, A_k will be smaller than zero: we face a one-group distribution. Second, if the dispersion in our distribution is bigger than the one in the uniform distribution, A_k will be bigger than zero: we face a k-group distribution (k>1).

We need to specify the following function:

$$A_k = A(G^*_b, k)$$

Axiom For uniform data, as k varies the function value A_k should remain constant.

Suppose $x_1, x_2, \dots, x_n$ are uniformly distributed. If k=1, the between-group dispersion is equal zero, since we have only one group in the population: $G^*_1=0$. If k>1, the subdivision of the distribution into k groups is optimum when the groups have equal size, equal population share and $|\mu_j-\mu_{j+1}|= 1/k$ (property 4). Thus, we observe:

$G^*_1=0$

$G^*_2=2\,(1/ k^3)$ with k=2

$G^*_3= 2\,(1+1+2) / k^3$ with k=3

$G^*_4= 2\,(1+1+1+2+2+3) / k^3$ with k=4

…

$G^*_k= [2\, \Sigma_j^{k-1} j(k-j)] / k^3$

Hence, the subdivision of a uniform distribution into k groups, increases G^*_1 by the following term:

$$[2\, \Sigma_{j=1}^{k-1} j(k-j))] / k^3$$

For uniform data, this implies:

$$G^*_k - [(2\, \Sigma_j^{k-1} j(k-j)) / k^3] = G^*_1 = 0 \qquad \text{for all integer } k>1$$

Theorem The function A_k must have the following specification:

$$A_k= c\, [G^*_k - [(2\, \Sigma_j^{k-1} j(k-j)) / k^3]] \qquad \textit{with } c \in R_{++}$$

Then, we can define the following stopping rule.

Stopping Rule The optimal value of k is the value that maximises A_k.

5.4 Examples and performance

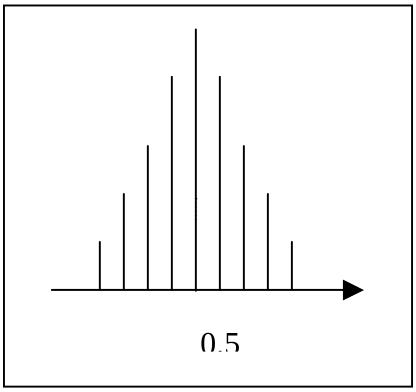
In this section, we consider five simple distributions in order to show how the proposed method works. In the first example, we consider one-spike distribution; in the second one, we study a two-spike distribution; in the third one, we analyse a three-spike distribution; in the fourth example, we show an example where the increment in the function A is stronger when the population results clearly grouped into two clusters. We also analyse how the method works using real data (example five). Finally, we perform an experiment in order to better evaluate the performance on the stopping rule.

Example 1.

Let's consider the distribution

x=(0.1, 0.2, 02, 0.3, 0.3, 0.3, 0.4, 0.4, 0.4, 0.4, 0.5, 0.5, 0.5, 0.5, 0.5, 0.6, 0.6, 0.6, 0.6, 0.7, 0.7, 0.7, 0.8, 0.8, 0.9)

It is a one-group distribution as we can observe in the follow figure:



The results for the maximization of the between-group Gini index, for k=2 and k=3, are showed in the table below. We observe that A_k is less than zero for all k>1, which implies that our distribution is a one-group distribution.

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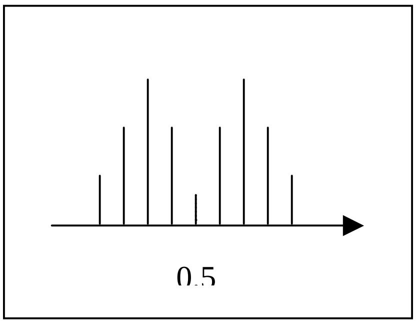
	cut-points		A_k
k=1	---		0
k=2	0.5		-0.09
k=3	0.4; 0.7		-0.0979

Example 2

Let's consider the distribution

x=(0.1, 0.1, 0.1, 0.2, 02, 0.2, 0.2, 0.2, 0.3, 0.3, 0.3, 0.4, 0.5, 0.6, 0.7, 0.7, 0.7, 0.8, 0.8, 0.8, 0.8, 0.8, 0.9, 0.9, 0.9)

It is a two-group distribution as we can observe in the follow figure:



The results for the maximization of the between-group Gini index, for k=2 and k=3, are shown in the following table. We observe that the stopping rule selects k=2. In other words, A_k is maximum for the subdivision of the distribution into two groups.

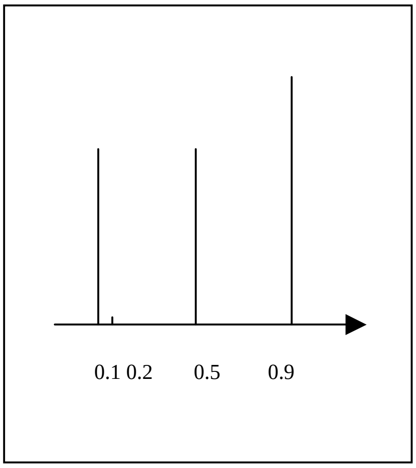
	cut-points	G_b	A_k
k=1	---	---	0
k=2	0.6	0.272	0.022
k=3	0.4; 0.8	0.30048	0.0044837

Example 3

Let's consider the distribution

X	n times
0.1	13
0.2	1
0.5	13
0.9	20

It is a three-group distribution as we can observe in the follow figure:



The results for the maximization of the between-group Gini index, for k=2,3,4 are shown in the table below. We observe that the stopping rule selects k=3. In other words, A_k is maximum for the subdivision of the distribution into three groups.

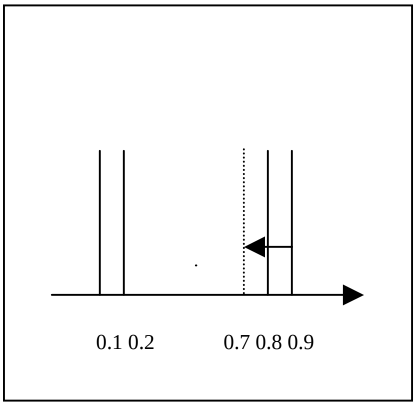
	cut-points	G_b	A_k
K=1	---	0	0
K=2	0.9	0.2668	0.0168
k=3	0.5; 0.8	0.3253	0.0290
k=4	0.2;0.5;0.9	0.3264	0.0139

Example 4

Let's consider the following distributions, x1 and x2:

x1	n times	x2	n times
0.1	13	0.1	13
0.2	13	0.2	13
0.8	13	0.7	13
0.9	13	0.8	13

In both distributions, the individuals are clearly grouped around two clusters. But, in the second distribution the dispersion between the two groups is lower than in the first distribution. If these distributions are income distribution, we could think the second distribution as the results of income reductions of the richest individuals (see Figure below). As result, the two groups in the second distribution are closer on the x-axis than the groups in the first distribution.



X1	cut-points	G_b	A_k
K=1	---	0	0
K=2	0.8	0.350	0.1000
K=3	0.2; 0.8	0.363	0.0663
K=4	0.2;0.8;0.9	0.375	0.0625
X2	cut-points	G_b	A_k
K=1	---	0	0
K=2	0.7	0.333	0.088
K=3	0.7; 0.8	0.347	0.051
K=4	0.2;0.7;0.8	0.361	0.049

Using our stopping rule, we confirm that we face in both cases a two-spike distribution (k=2). As expected, the Gini between (for k=2) in the first distribution is higher then the one in the second distribution. Moreover, we can observe that the function A_k (for k=2) in the first distribution is also higher that the one in the second distribution. This is due to the following properties:

Property $A_k(x_1)>A_k(x_2)$ if and only if $G_k(x_1)>G_k(x_2)$ for a given k

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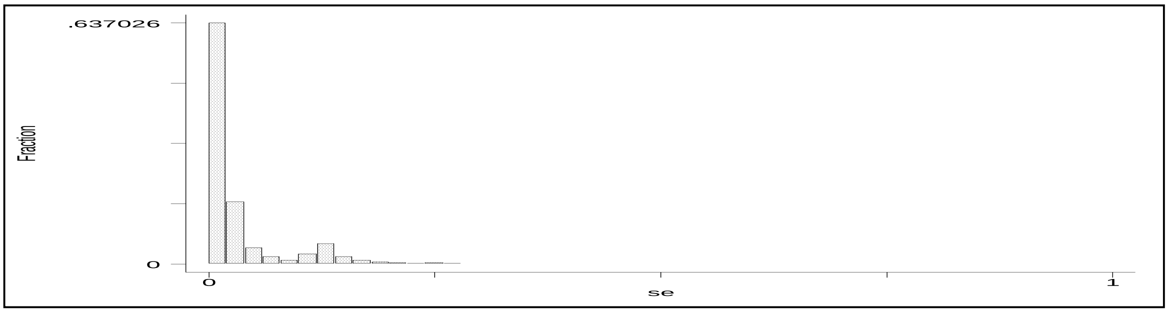
It is a obvious consequences of the fact that $A_k(x_1)-A_k(x_2)=c(G_k(x_1)-G_k(x_2))$ □

Example 5: social exclusion distribution

To investigate the performance of the proposed stopping rule on non-ideal data, it is necessary to apply the rule to real data. Observing the graph below representing the distribution of social excluded individuals studied in chapter two, we immediately notice the existence of at least two groups. We apply our method to check this intuition. In the table below, we report the value of A_k for k=1, 2 and 3.

Social exclusion distribution in Spain, 1999



	cut-points	G_b	A_k
K=1	---	0	0
K=2	0.0274665	0.6370	0.386966
k=3	0.0102; 0.0275	0.6591	0.312541

The maximum value of A_k is at k=2; therefore, the data are classified into two groups. This result confirms our intuition. It also identifies the group of individuals that experiments the most severe exclusion.

5.5 Conclusions

We proposed a new method to determine k-1 endogenous points that groups the population in k subgroups, where the number of groups (k) is endogenous.

The problem is the following: given data on a distribution, we wish to group the data into k groups in such way that differences are minimised within the groups and maximised between the groups. Since differences can be measured by an adequate inequality index, we need some criteria to restrict the possible index set. A possible method is to minimise the weighted sum of the internal group dispersion or, equivalently, to maximise the between-group dispersion. Since the dispersion can be approximately using an inequality measure, we need some axioms to be able to restrict the inequality index set. As result, the latter set is composed only by two indices: Theil index and Gini index. Therefore, maximising the between-group Gini index it is possible to find the optimal partition of the distribution in k groups, with k given.

We proposed a method that endogenously determines the optimal number of groups, k*. This method is called stopping rule. The idea is to repeat the optimisation of the objective function for k=2,3,4,… groups, and to choose the value of k at which the final partition appears to be the "best". To determine the best final partition, we defined a function, A_k that remains approximately constant over k for data from a uniform population. We proposed to use A_k as basis for the stopping rule: the optimum value of k is the value that yields the maximum A_k.

We presented some simple examples to illustrate how the proposed method works on ideal data and on real data. In future research we plan to use experimental methods to evaluate the performance of the stopping rule. Note that results should never be accepted uncritically but should always be examined to make sure they are meaningful. Graphical analysis is useful to do so. Moreover, it should always be remembered that we cannot use our method to determine two, or more, groups in a unimodal distribution (as it is often the case of income distributions). This chapter suggests a method to deal with multimodal distributions classifying individuals belonging to different populations in different groups. Further research is necessary to study how to group individuals belonging to the same cluster in k sub-groups.

6

Conclusions

6.1 Introduction

In this concluding chapter, we set out the central thrust of the argument put forward in this thesis, review the key findings, and discuss their implications for social exclusion measurement, anti-exclusion policy, and further research. Despite its importance, there is remarkably little consensus among scientists on the definition of “social exclusion” and, therefore, on the best way to measure it. Our aim in this thesis has been to address key problems regarding how to identify an adequate measure of social exclusion and how to analyse social exclusion dynamics. We then proceeded to develop an approach to measurement which was in accord with the working definition of social exclusion (considering also the previous literature), and we used it to establish if social exclusion was partially transitory, and to study eventual dependence paths that exclusion might generate. Our analysis has been useful to better understand social exclusion in general, and could give important suggestions on how to design policy.

Our point of departure has been the previous literature on social exclusion (i.e. Burchardt et al., 2001; Chakravarty and D’Ambrosio, 2002; Tsakloglou and Papadopoloos, 2001), deprivation (i.e. Nolan and Whelan, 1996; Brandolini and D’Alessio, 1998) and multi-dimensional poverty (i.e. Burgouignon and Chakravarty, 2003). On this basis, we have defined social exclusion as a multidimensional dynamic process leading to a state of individual exclusion relative to the rest of the society where the individual lives in. Social exclusion at a point in time has been defined as the impossibility to achieve some relevant functionings. We have stressed on the fact that this definition has a number of features. First, it allows multiple dimensions and, therefore, implies a specification of the “relevant functionings”. Second, to judge if an individual is excluded or not, we have to observe her position relative to the rest of the society she lives in. Third, it depends on how a situation and circumstances develop over time (dynamic process). The analysis of these features, specially the last one, has been central in this thesis.

6.2 Key findings

The earlier chapters of this thesis have presented new evidence on the extent of social exclusion and its dynamics over time in Spain. While using Spanish data, the findings highlight conceptual and methodological issues and casual processes that are of quite general relevance. In fact, we have addressed some relevant methodological problems connected with the measurement of social exclusion (i.e. defining the relevant dimensions of exclusion, and the endogenous determination of the threshold that divides excluded and non-excluded individuals), we have focused on the measurement issues, and we have studied the causes leading to social exclusion analysing its dynamics.

Detailed studies on social exclusion have stressed on different “relevant dimensions” revealing a certain degree of disagreement among experts. We have followed the suggestions given by Sen (taking also into account the previous empirical applications of the capability approach). Therefore, each relevant dimension has represented a relevant functioning. In particular, we have compiled a reasonable (but not exhaustive) list of eight functionings representing the command over economic resources (basic needs fulfilment, to reach a certain quality of life, having an adequate house and having an adequate income), labour market exclusion, health care exclusion, relation exclusion and lack of safety. We have found that these dimensions seem to capture complementary aspects of social exclusion: in fact, the correlation between different dimensions was low, and the contemporary presence of two deprivations was rare. For each dimension, we have computed a threshold that divides individuals in deprived and not-deprived. This threshold has been exogenously computed. Note that we have also addressed the issue of the endogenous determination of the threshold, but only in the last chapter of this thesis.

The choice of the functional form able to adequately measure exclusion is not easy. We have proposed to use a special case of the multidimensional generalization of the Foster-Green-Thorbecke index. The main reason has been its consistency with a social valuation function, which in turn has been consistent with Sen's capability approach. Therefore, this index fulfils not only a set of axiomatic properties, as highlighted by Bourguignon and Chakravarty (2003), but it is also able to operazionalize Sen's capability approach. Note that this index is adequate to capture the multidimensionality of social exclusion and gives us information about the intensity of exclusion.

We have found that about 54% of the sample was socially excluded in 1994 (that means about the 54% of the sample was excluded in at least one dimension). Exclusion rates decreased over time and, in 1999, the proportion of individuals defined as excluded was about 43%. We have found that about 13% of the population was counted as excluded in at least one dimension in the study period and about 83% of the sample experienced social exclusion in at least one dimension and in at least one wave during the panel. Indeed, these rates are very high (even if they are consistent with the findings of other studies) but before arriving to any conclusion we should analyse social exclusion better. In fact, social exclusion is a much more complex issue than the one described by the above headcount ratios. Observing the social exclusion intensity we have found very low average social exclusion: in 1994 is about 0.028 over one. This means that only a small group of excluded individuals exhibited heavy exclusion (but never higher than 0.5 over one). This is a first indication that we cannot only relay on the headcount ratios to describe social exclusion. We need more information. We need to investigate if social exclusion is partially a transitory phenomenon and if social exclusion persistence is an issue. We also need to know if observable individual characteristics and/or initial conditions are associated with higher probability of exclusion.

The understanding of the social exclusion dynamics and, in particular, the individual paths into and out of the state of exclusion and the existence of an eventual persistence of exclusion have been the main focus of this thesis (since these topics have not been satisfactorily explored by the literature). In particular, we have reported on changes in the individual position in the social exclusion distribution over time and on social exclusion persistence, highlighting which methodology better describes social exclusion dynamics.

First, we have performed a detailed analysis of social exclusion mobility following the relative approach and using transition matrices (two-stage analysis). The main advantages of using transition matrices are the following: first, two-stage analysis provides a simple picture of the “movement” of the individuals among the specific social exclusion classes and, second, it is shown to be robust to data contamination. This kind of analysis have shown that social exclusion was partially a transitory phenomenon: about 30% of the individuals in the sample improved their situations in one year and about 79% from 1994 to 2000.

Second, we have focused on the causes leading to social exclusion process. We did find that an individual experiencing exclusion today was more likely to experience exclusion tomorrow due to both individual heterogeneity (individuals are heterogeneous with respect to some observed and/or unobserved adverse characteristics that are relevant for the chance of experiencing social exclusion and persistence over time) and true state of dependence (experiencing social exclusion in a specific time period, in itself, increases the probability of undergoing social exclusion in subsequent periods). Note that some observed individual characteristics and individual initial conditions (e.g. education levels, initial health, etc.) appeared also strictly related to the probability to experience social exclusion. The analysis has been done estimating a dynamic non-linear panel data model. We have used the random effects approach to obtain a fully parameterised model in which we have been able to estimate the quantities of interest. Note that this approach seems to be preferable to the fixed effects approach if one wants to use the model for prediction or for calculating the effect of various ‘what-ifs’. In order to solve initial condition problems typical of random effects models, we have applied the solution proposed by Wooldridge (2002). This approach also permitted us to implicitly model attrition and it is an alternative approach to the one proposed by Jenkins and Capellari (2002).

6.3 The implications

The results set out in this thesis have serious implications for the way social exclusion should be analysed and on how anti-exclusion policy should be designed. In short, policy should focus on multiple dimensions, the headcount ratios should not be the only instruments used to monitor policy, and policy should focus both on moving individuals out of exclusion (even over the first year of exclusion) and keeping them out once they are out.

Social exclusion implies the use of a much wider range of indicators of deprivation or inability to participate in the society (inability to reach valuable functionings) than income poverty. The emphasis is not anymore on the monetary aspects of individual disadvantages. But in Spain, policy still focuses mainly on helping income poor individuals and reducing unemployment (Pita-Yanez, 2003). This means that the focus of policy is only on two over eight dimensions. What about the other dimensions? The national health program exists in Spain, but it does not succeed in improving the health status of many individuals. Can it be improved to reach the need of the more disadvantaged individuals? Could housing and education policies be implemented so as to reduce geographical concentration of exclusion? For instance, the government could offer economic incentives to move excluded households to non-excluded areas, or offer good students the possibility to study in regions where the rate of exclusion is low: this kind of policies have been positively used in US. Could safety and environmental conditions be improved? A more complex set of policy is need to address social exclusion than the existent one, and the impact of a single dimension on the probability of experiencing social exclusion has to be carefully monitored. Every dimension seems to describe complementary aspects of social exclusion: we cannot assume that improving income levels will improve outcomes in other dimensions.

Monitoring policy is a further issue. The evidence that have been presented in this thesis shows how conclusions on the extent of social exclusion can be different using headcount rates or an index of social exclusion intensity. Both measures seem to be necessary to understand the extent of exclusion and the impact of policy. In fact, the information given by these measures are complementary to understand social exclusion, and both have to be considered to have a full picture. But, new questions rise in our mind. Should we reduce the number of excluded individuals or the intensity of individual exclusion? Are policies really different according to the aim? Should we focus only on the most excluded individuals? Who are the most excluded individuals? Are the ones registering the highest levels of exclusion, or the ones excluded year after year? Indeed, policy makers have to make a certain number of choices, we can only suggest new ways to analyse social exclusion in order to understand it better.

The notion of social exclusion implies dynamics and a wide time horizon. Therefore, the chances of developing effective policies will be greater if we improve the understanding of the processes leading to exclusion. Social exclusion for an individual at one period becomes a constraint on her in the next period. However, there are different circumstances in which people find themselves socially excluded. Social exclusion may be a transitory phenomenon (a “blip” in an otherwise satisfactory trajectory) or it may be permanent with someone socially excluded year after year. Since social exclusion in Spain seems to be partially transitory and only few individuals seem to be consistently excluded, we could be tempted to infer that social exclusion is not a major concern because it is mainly temporary. But this could be a mistake since we also find a substantial group of people (about 80%) that experience some degree of exclusion in at least one year during the study period. We suggest that the scale of the “social exclusion problem” is only reduced slightly by discounting transitory observations of social exclusion. We face a new and worrying problem: the majority of the population experience some trouble during the study period and experiencing such trouble increases their probability to experience it again in the future. Therefore, it is very important to study carefully the target of anti-exclusion policy. Dynamics should be analysed to better understand the groups at which policy should focus and the factors that may affect exclusion the most. We cannot restrict policy only to those who had been in need over a substantial period. Of course, this would reduce the chances of committing mistakes by helping who was not needy. But, we have seen that being socially excluded at a point in time increases the risk of being persistently excluded; therefore, it would make sense to tackle the problems of all individuals who experience social exclusion (even over the first year) without delay.

Studying social exclusion dynamics may not necessarily change much the scale of the problem, or even the identification of the groups, which might need help. But in designing welfare institutions it does allow differentiating the kind of the intervention for those particular circumstances. Hills (2002) summarizes four kind of policy: (i) prevention of an event or reduction of the risk of entering an undesiderable state (e.g. education or training programs); (ii) promotion of exit or escape (e.g. welfare-to-work policies); (iii) protection from the impact of an event (e.g. paying benefits to those who become unemployed); (iv) propulsion away from the adverse circumstances by reinforcing the benefits of exit (e.g. policies to ensure that the next career move is upwards). The first two of these affect the risk of adverse or favourable events, while the third and the fourth change the consequences of negative events. We do not want to suggest that a certain kind of intervention is better than the others. We just wish to stress on the necessity to find the answer about "the most appropriate policy" in the dynamic analysis of social exclusion. Our results suggest that the risk of adverse events is higher in some groups, and negative events have the consequences of increasing the probability to experience exclusion in the future. Therefore, all four kinds of policies are required to successfully combat social exclusion. For example, prevention is better than a cure in high-risk groups: education programs can reduce the exclusion risk for the group of individuals with low education levels. But, if an individual is transitorily unable to perform a paid activity (e.g. she lost her job), protection policies and welfare-to-work policy are required to reduce the risk to enter in the social exclusion 'vicious circle': employment benefits reduce the risk to experience income deprivation and welfare-to-work strategies help the individual to be able to perform work activities. In other words, we define social exclusion as a complex phenomenon involving a certain number of dimensions, therefore, the set of policies required to address exclusion are also complex and have to focus both on getting people out of exclusion and on keeping high-risk individuals out.

Another way to see how the identification of the processes leading the social exclusion dynamics may affect the kind of policy to implement is the following one. Policies can also be classified into (Hills, 2002): (i) those which change individual characteristics in a way which lasts (such as education and training) and (ii) if there is "initial state dependence" in the system (that is, if where one starts matters) changing the right elements of people's initial state has long-term effects. As stressed above, successful policies addressing social exclusion should combine both kinds of strategies.

Summarising, taking a dynamic perspective may lead to stress on some policies rather than others, even if it does not change them entirely. Therefore, studying social exclusion dynamics can indeed change the ways in which we think about policy and hence the response to disadvantage. However, whether it does so in practice is a different issue. We report evidence that allow changing policy emphasis, but only time can tell whether policy will continue focusing mainly on the cross-sectional distribution of income and on income redistribution across life cycle, or other kind of policies will gain importance (e.g. education, health, housing, etc.).

Finally, note that our stress has been in highlighting some important lessons derived from a detailed analysis of social exclusion dynamics in general. But, social exclusion dynamics is a result, and a combination, of economic and social deprivations dynamics. Therefore, future research should also analyse the dynamics in every relevant dimension of social exclusion. Studying how individuals move in every dimension distribution over time, and understanding the exclusion processes in every dimension, is required to design an appropriate set of policies able to successful reduce social exclusion. In other words, this thesis highlights the guidelines to structure a set of policies able to combat social exclusion; but, future research should focus on every dimension (specially on the dimensions that most affect social exclusion in general) in order to specify which particular policy should be included in the general framework suggested by this thesis.

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