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## Working Paper

### *Exploring the relation between income mobility and inequality at the regional level using EU-SILC microdata<sup>1</sup>*

Zbigniew Mogila<sup>2</sup>, Patricia C. Melo<sup>2</sup>, José M. Gaspar<sup>3</sup>

#### Abstract

This paper investigates empirically the impact of labour-related income inequality on income mobility in French and Spanish NUTS2 regions. We explore whether the negative relation between income inequality and mobility - known as the Great Gatsby Curve - is also present in the short and medium run. Using longitudinal microdata from the EU-SILC, we construct NUTS2-level measures of relative income mobility from transition matrices between income deciles for 2-year and 4-year income trajectories and measures of income inequality based on the Gini index and inter-decile ratios. We then combine these measures with other regional-level factors and implement regression models to test the relation between income inequality and income mobility. The regional perspective allows us to investigate the extent to which territorial heterogeneity may also affect income mobility. The findings from the regression analyses do not provide evidence of a significant relationship between income mobility and income inequality, at least when considering mobility over the short-to-medium term (i.e. up to 4 years).

**Keywords:** income inequality, income mobility, territorial heterogeneity, the Great Gatsby Curve

**JEL codes:** D31, J62

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## 1. Introduction

Since the seminal work by Shorrocks (1978) showing a smoothing-effect of income mobility on income inequality, the relationship between the two phenomena has been widely investigated. In the increasingly growing body of research in the topic, attempts have been made to show whether greater income inequality can be offset by greater upward income mobility. Greater upward income mobility may cushion the negative consequences of inequality, e.g., perceptions about social exclusion. This view was emphasized, among others, by Krugman (1992), who stated that: *“If income mobility were very high, the degree of inequality in any given year would be unimportant, because the distribution of lifetime income would be very even . . .”*. The problem, however, seems to be that high(er) income inequality may act as an obstacle to income mobility, in particular intergenerational mobility. This negative relationship has been described by Alan Krueger (2012) as the Great Gatsby Curve.

The relationship between income mobility and income inequality is complex and multifaceted. However, to this date, much attention has been paid to correlational associations rather than theory-driven causal relations. We merely detect in the literature two attempts to provide reasoning for the relationship between income inequality and mobility. The first hypothesis, presented by Prieto-Rodríguez, Rodríguez and Salas (2008, 2010) draws upon Piketty's (1996) model and proposes that increased social mobility lowers pressure for redistribution, which in turn results in greater income inequality. The second hypothesis relates to the Great Gatsby Curve and has been discussed in several OECD reports (2008, 2011, 2015, 2018). It states that greater inequality might hinder upward social mobility due to the unevenness in initial conditions (e.g., family background) and in the access to resources and opportunities such as education and health services, among other services.

The main objective of our paper is to investigate empirically the impact of labour-related income inequality on income mobility. Following the Great Gatsby Curve view, we hypothesize that higher levels of income inequality might be an obstacle to upward income mobility because they can limit the access of poorer households to the kinds of resources and opportunities (e.g. good schools, good local environment, etc.) crucial for better future socio-economic prospects. We set out to test this hypothesis empirically, in the short to medium terms, using regional-level data for France and Spain from the European Union Statistics on Income and Living Conditions (EU-SILC) and the Eurostat regional database. By implementing the empirical analysis at the regional level, we can also control for territorial heterogeneity, reflected in terms of e.g., degree of urbanisation, educational attainment, economic structure, labour market characteristics as well as social redistribution.

To this end, we start by using the longitudinal EU-SILC microdata to construct indicators of labour income mobility and inequality at the level of NUTS2 regions, which is the most disaggregated geographical unit available in the EU-SILC database. We measure relative income mobility using transition matrices between income deciles for 2-year and 4-year income trajectories over the period 2006-2016, from which we subsequently derive summary indicators for the percentage of individuals who moved up or down along the income distribution. To analyse regional income inequality, we construct measures for the Gini index and inter-decile ratios using the same EU-SILC microdata. By combining the regional-level indicators income mobility and income inequality with other variables from the Eurostat regional database, we then estimate regression models to test whether the degree of income inequality may affect the extent of upward income mobility in the short and medium terms.

This paper contributes to the existing literature by analysing the relation between income inequality and income mobility at the regional level, which has mostly been overlooked up to now, and by taking into account the potential role of regional heterogeneity in this relationship. Consequently, it is an attempt to put income mobility in the debate of regional disparities in the EU. The investigation of the relation between

income inequality on income mobility can also contribute to our understanding of the causes of “*the geography of discontent*” (Los et al., 2017; McCann, 2019) and “*the revenge of the places that don't matter*” (Rodríguez-Pose, 2017). As hypothesized above, higher income inequality may affect negatively movements along the income distribution, which in turn can lead to growing dissatisfaction with the economic system and hurt the foundations of economic growth, social cohesion and even democracy. People’s perception of inequalities may be reduced in the presence of growing upward income mobility. However, if there is little or no upward social mobility, people lose hope in better future prospects and develop feelings of exclusion and stigmatization (OECD, 2018). Hence, having a better understanding of how income inequality may affect upward mobility, the goal of our study, may also be helpful in designing policies aimed at improving upward mobility.

The structure of the paper is as follows. In the next section, we give a brief overview of previous studies of the relationship between income inequality and income mobility. The following section describes the conceptual framework and the empirical strategy of our research. Then, the data are presented with special emphasis on the computation of the measures of income inequality and income mobility. We subsequently present and discuss the results from the regression models. The paper concludes with a summary of our findings.

## **2. Overview of relevant literature**

In an overwhelming majority of empirical studies, the link between income mobility and income inequality is investigated using simple comparisons or correlational analysis. Much attention is paid to the hypothesis that higher income inequality is driven by greater income mobility and, as far as the movement along the socio-economic ladder offsets it, it should not be perceived as a problem (e.g. Freidman, 2009; Krugman, 1992). As Table 1 of Appendix A shows, empirical studies can be divided into those supporting a positive association between income inequality and income mobility (e.g. Prieto-Rodríguez, Rodríguez and Salas, 2008, 2010; Aaberge and Mogstad, 2014; Flinn, 2002; Bayaz-Ozturk et al., 2012; Bowlus and Robin, 2012) and those providing no evidence for the relationship (e.g. Aaberge et al., 2002; Gangl, 2005; Jenkins and Van Kerm, 2006; Alves and Martins, 2012; Chen, 2009). The following paragraphs offer an overview of the main approaches and findings obtained by the studies reviewed.

Whereas there is agreement on the measures of income inequality, typically based on the Gini index, Theil index or income share ratios, there is no consensus with respect to the measurement of income mobility (Fields and Ok, 1999; Jäntti and Jenkins, 2015). Furthermore, the conclusions on the relation between income inequality and income mobility are strongly dependent on the measures used (Jäntti and Jenkins, 2015). We identified four analytical frameworks of measuring income mobility applied in analyses of the relationship between income inequality and income mobility. The first one comes from the seminal work by Shorrocks (1978). According to Shorrocks, mobility is derived from the comparison between short term and longer term measures of inequality. Short-term inequality is calculated as inequality within a given year averaged over time (e.g. weighted average of annual Gini coefficients), whereas long-term inequality is measured as inequality of average earnings over a given period (e.g. Gini coefficient of the average of income over a given period). The ratio between short-term inequality and long-term inequality is taken as a measure of mobility (the Shorrocks ratio “R”). ‘*In essence, mobility is measured by the extent to which the income distribution is equalized as the accounting period is extended*’ (Shorrocks, 1978, 378). The relationship between income mobility and the level of income inequality is, subsequently, determined through comparisons or correlational analysis.

The second approach, presented by Aaberge and Mogstad (2014), proposes a formal representation of income mobility as an equalizer of permanent income inequality. It is referred to as a *mobility curve* and is intended to capture the extent to which changes in individuals’ relative income might equalize the

distribution of permanent income over time. The idea behind the mobility curve consists in comparing two Lorenz curves, one representing the real distribution of permanent income and the other showing the distribution of permanent income in a counterfactual scenario with no mobility. The association between income mobility and income inequality is analysed by comparing and contrasting the estimates of income mobility from the mobility curve approach and the level of income inequality measured by the Gini coefficient.

The third approach to the measurement of income mobility is put forth by Jenkins and Van Kerm (2006) and is based on the decomposition of the change in income inequality, measured by any type of the Gini class indices, into two components. The first component represents income mobility in the form of reranking (i.e. the reshuffling of individuals in the income distribution over time), while the second refers to the pro-poor income growth contribution to income inequality, i.e. showing how redistributive policies favour low-income individuals. The reranking component is taken as the measure of income mobility and is then compared and contrasted with the level of income inequality.

The fourth approach is also based on a decomposition method, but instead of decomposing the change in income inequality (as in the third approach), it is based on the decomposition of income mobility indices. More specifically, it takes income mobility as a combination of an exchange (i.e. positional) component and a structural component. The structural component represents changes in income inequality without any re-rankings, whereas the exchange component allows for re-rankings between individuals across income classes. The structural component has been further decomposed by Van Kerm (2004) into dispersion (i.e. showing how pro-poor income growth is) and growth (isolating the change in income growth which is solely due to the change in the size of the economy) components. This approach uses counterfactual income distributions representing situations when there is no exchange mobility or no structural mobility. Similar decompositions were carried out by Ruiz-Castillo (2003) and Prieto-Rodríguez, Rodríguez and Salas (2008, 2010). In an increasing number of studies looking at the relationship between income inequality and mobility, the latter is based on decomposable indices of the movement in total absolute income proposed by Fields and Ok (1996, 1999).

Whilst the approaches above focus on the mechanical link between income inequality and income mobility by attempting to separate out the effect of positional changes in overall income inequality, there have been very little studies adopting an empirical modelling approach. We identified merely two studies adopting this approach (i.e. Prieto-Rodríguez, Rodríguez and Salas (2008, 2010)). Both studies draw upon Piketty's (1996) hypothesis that greater support for redistribution measures comes from lower social mobility and weaker beliefs that income differences are the result of effort. Following that view, Prieto-Rodríguez, Rodríguez and Salas (2008) argue that increased social mobility lowers pressure for redistribution, which in turn contributes to greater income inequality. They implement nation-wide random coefficients models to estimate the effect of income mobility, and each of its components (growth mobility, dispersion mobility and exchange mobility), on income inequality (measured by the Theil index) and find a positive relationship. The decomposition of income mobility shows that both the structural and positional (i.e. reshuffling) components play an important role in determining the link, but the former has a more dominant role than the later.

Mostly, the literature has viewed income mobility as a component of the overall level of inequality. As noted in the introduction however, there is also a view that high inequality can hinder upward mobility, as depicted by the Great Gatsby Curve and several OECD reports. There have been empirical attempts to look at the link between income inequality and intergenerational income mobility, tracing back to the theoretical model by Becker and Tomes (1979), who presented a unified approach to analysis of within-generation inequality and intergenerational mobility. The model shows factors determining those both categories, namely: family characteristics (e.g. the propensity to invest in children, "endowments" such as: family's race, religion, genes and reputation), the inheritability of endowments, luck, economic growth and taxes and subsidies. Drawing

upon this theoretical concept, attempts have been made to measure intergenerational income mobility using the “intergenerational earnings elasticity”. The measures have been subsequently applied to investigate the correlation between income inequality and intergenerational income mobility. Corak (2006) followed by, e.g., OECD (2008) show that greater income disparities are more like to result in stronger income persistence across generations. This negative empirical association between income inequality at a point in time and intergenerational income mobility has been recently coined as the Great Gatsby Curve (Krueger, 2012). Although the Great Gatsby Curve does not depict a causal relationship, it can be a starting point in investigating the role of income inequality in intergenerational income mobility (Corak, 2013).

This idea that income inequality may act as an obstacle to upward mobility has been put forward by, among others, OECD (2011) by arguing that rising income inequality *“can stifle upward social mobility, making it harder for talented and hard-working people to get the rewards they deserve”*. In addition, OECD (2015) concludes that inequalities in socio-economic outcomes affect access to opportunities in education, health and labour market. Consequently, greater income disparities contribute to lower income mobility. The negative role of income inequality in diminishing income mobility is also found in OECD (2018) where it is shown that: *“(...) high and/or increasing levels of inequality of outcomes, as observed in many OECD and emerging economies, tend to be an obstacle to income and social mobility”*.

Whilst the few studies adopting this view have focused on longer-term intergenerational income mobility, our empirical setting explores whether higher inequality can also act as a potential obstacle to upward income mobility over the short to medium terms. Furthermore, our study adds to the scarce body of research using regional level data to investigate this relation. The following section describes the conceptual framework adopted in our study.

### **3. Conceptual framework and empirical approach**

#### **3.1 Conceptual framework**

Our study focuses on the concept of relative income mobility and is based on the movement (or lack of it) of a given individual along the income distribution. More specifically, we analyse the degree of relative income mobility through the construction of transition matrices between income deciles over a given time period. Based on these matrices, we construct indicators showing what percentage of individuals has moved up or down income deciles over time (see section 4.2). This approach is similar to the concept of social stratification in social sciences (Saunders, 1990). Movements across social strata, or income classes in our case, might affect individuals’ perception of changes in wellbeing more strongly than absolute changes in income. The choice of deciles is justified by data issues, in particular the need to avoid very small sample sizes.

Most importantly, using such a measure of relative income mobility allows us to investigate the hypothesis of whether income inequality may act as a barrier to upward income mobility, as measured by the share of individuals moving up the socio-economic ladder over a given time period. The greater the differences between income classes, the harder it is for individuals to move from one income decile to another. *“A high level of inequality can make the height of the step to climb up appear too high to individuals who are stuck at the bottom.”* (OECD, 2018). Hence, income inequality constitutes a base effect and can act as an obstacle to upward changes of the relative position in the income distribution. This is because it limits access of poorer households to the kinds of opportunities (e.g. good schools, good local environment and health, etc.) crucial for better socio-economic prospects. The aforementioned hypothesis relates somewhat to the rationale behind the Great Gatsby Curve highlighted in section 2 as it puts emphasis upon differences in access to opportunities. We are, however, to test whether income inequality-related mechanisms affecting intergenerational income mobility enter into play in the short run. It is conceivable that structural, e.g. family and neighbourhood-related factors, embedded in income inequality might affect movements along the socio-economic ladder even in a short period of time. The choice of the income mobility measure, i.e.

indicators based on transition matrices, implies the macroeconomic context of our research study. We aim to effectively control for the socio-economic environment in order to be able to assess the pure role of mechanisms associated with the Great Gatsby Curve in shaping intragenerational income mobility. To this end, we pay special attention to urbanisation-related factors as important drivers of both income inequality and income mobility.

There is increasing evidence on a positive association between greater income inequality and urbanisation, in particular for large metropolitan areas (e.g. London, Paris) and cities with greater spatial segregation (OECD, 2018). Previous studies, e.g. Behrens and Robert-Nicoud (2009), Glaeser, Tobio, and Resseger (2009), Royuela, Veneri and Ramos (2014) find an association between urbanisation and wage/income inequality resulting from the fact that larger cities disproportionately attract more people on the tails of the income distribution (i.e. the superstars vs. poorer people) and confer a higher return to skills, thus further attracting the high-skill, high-pay workers at the top of the income distribution.

In addition, the degree of urbanisation appears also to be a relevant factor in determining income mobility. Castro (2011) using a binomial probit model shows that living in an urbanised area is among factors, namely moving from unemployment to employment and higher educational attainment, increasing relative upward income mobility and decreasing movements down the income distribution in Chile. Likewise, Namirembe-Kavuma and Bbaale (2018) indicate that living in a city in Uganda increases household's chances of moving up the income distribution by 26 percentage points and reduces the probability of moving down the economic ladder by 10 percentage points. Again, the results are achieved by applying a binomial probit model to investigate the factors which affect relative income mobility. The findings agree with the hypothesis that cities are places of opportunity, as has been extensively studied in the literature on urban agglomeration economies. However, this literature generally focuses on absolute income mobility (i.e. increases in income level), rather than relative income mobility. There are nonetheless reasons why the scope for relative income mobility may be reduced by greater urbanisation. First, larger cities are more likely to support a greater labour market segmentation in terms of skills and earnings and lead to the creation of "sticky ceilings" with stronger persistence of high-skill-high-pay groups at the top of the distribution (OECD, 2018). Second, changes in the labour market, e.g. due to individuals' expectations of better employment and income opportunities in cities, may affect the labour supply of workers across income groups differently. A proportionally higher increase in the supply of workers in a particular section (e.g. decile) of the occupation and income distribution prevents wages from moving up and may even lead to a reduction in wages. Thus, even though cities tend to offer better employment possibilities, it might occur that the inflow of workers exceeds labour demand contributing to greater unemployment. This is the so-called Todaro paradox (Harris and Todaro, 1970 following: Royuela, Veneri and Ramos, 2014). In accordance with the Philips curve, this inflow of workers may cause a downward pressure on wages, especially for less-skilled jobs. In a recent study, Velthuis, Sissons and Berkeley (2019) investigated the effect of city size on transitions from low to higher pay in British local labour markets and found evidence of limited benefits in wage progression for low earners.



### 3.2 Empirical approach

Taking the conceptual framework into consideration, we implement regional-level regression models for the relationship between income inequality and income mobility, as per the equation below:<sup>4</sup>

$$\begin{aligned} IM_i = & \alpha + \beta_1 IE_{i,t_0} + \beta_2 (IE_{i,t_0} * country_i) + \beta_3 (IE_{i,t_0} * tperiod_i) + \beta_4 unemp_{i,t_0} + \beta_5 hedu_{i,t_0} \\ & + \beta_6 lq125_{i,t_0} + \beta_7 socben_{i,t_0} + \beta_8 age_{i,t_0} + \beta_9 durb_i + \beta_{10} country_i \\ & + \beta_{11} tperiod_i + \varepsilon_i \end{aligned} \quad (1)$$

where:

- $IM_i$  - income mobility in region  $i$ ,
- $IE_{i,t_0}$  - income inequality in region  $i$  in  $t_0$ ,
- $unemp_{i,t_0}$  - percentage of unemployment rate in region  $i$  in  $t_0$ ,
- $hedu_{i,t_0}$  - percentage of people having completed tertiary education in region  $i$  in  $t_0$ ,
- $lq125_{i,t_0}$  - specialization scope indicator in region  $i$  in  $t_0$ ,
- $socben_{i,t_0}$  - ratio of social benefits other than social transfers in kind to net disposable income in region  $i$  in  $t_0$ ,
- $age_{i,t_0}$  - percentage of people aged 15-30 in region  $i$  in  $t_0$ ,
- $durb_i$  - set of dummy variables characterizing the rural-urban classification of the NUTS2 region (predominantly urban, intermediate, predominantly rural),
- $country_i$  - dummy variable taken the value of 0 for the federal system of policymaking (Spain) and 1 for the more centralised system (France),
- $tperiod_i$  - indicator of the period over which income mobility is measured, i.e.: 2- or 4-years,
- $\alpha, \beta$  - parameters to be estimated,
- $\varepsilon_i$  - error term.

We define the dependent variable income mobility ( $IM$ ) between 2006-2016 using three measures, namely, the percentage of individuals who did not move decile in the income distribution ( $nmovers$ ), those who moved up one decile in the income distribution ( $up1dec$ ), and those who moved 2 or more deciles up in the income distribution ( $up2plus$ ). Given the four-wave rotational design of the EU-SILC, we can only study individuals' income trajectories up to a maximum of four years over the period 2005-2016. Hence, we measure income mobility only for 2-year (i.e. transitions between  $t-1$  and  $t$ ) and 4-year (i.e. transitions between  $t-3$  and  $t$ ) income trajectories over that period. Similarly, we also experiment with different measures of income inequality, our main variable of interest. We use four main measures of income inequality: Gini Index ( $GI$ ), income ratio between the 90<sup>th</sup> (i.e. 10% richest) and 10<sup>th</sup> (i.e. 10% poorest) percentiles ( $P90/P10$ ), income ratio between the 90<sup>th</sup> and 50<sup>th</sup> percentiles ( $P90/P50$ ), and the income ratio between the 50<sup>th</sup> and 10<sup>th</sup> percentiles ( $P50/P10$ ). Bearing in mind our conceptual framework, with income inequality acting as a base effect for income mobility, we set 2006 as the base year for the explanatory variables. This can also help us avoid distortion caused by the latest international economic crisis. In addition, many of the processes in question – e.g. urbanisation and structural change – exhibit inertia.

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<sup>4</sup> The selection of control variables was determined by indicators of model goodness of fit as well as the evaluation of multicollinearity problems associated with different combinations of the regressors.

In order to account for other relevant regional-level factors, namely urbanisation-related ones, which may also affect income mobility and may be confounded with income inequality, we consider the following covariates in the model specification:

- Human capita (*hedu*) as a proxy for equity of opportunities, measured by the percentage of people having completed tertiary education
- Unemployment rate (*unemp*) as a proxy of changes in supply of and demand for the labour force having an impact on wages and salaries. For instance, high unemployment rates may be associated with lower wages for less-skilled jobs because there is a greater supply of labour available compared to demand. Since this is likely to be more severe for the bottom of the skill and income distribution it could affect income mobility.
- Degree of urbanisation (*durb*) as a proxy for urban agglomeration economies and differences in the quantity and diversity of public services available to residents. We use a 3-level rural-urban classification for predominantly urban regions, intermediate regions, and rural regions (ESPON, 2011).
- Economic specialization scope indicator (*lq125*) as a proxy for relative regional concentration across sectors. Using the structural composition of persons employed we calculate location quotients (LQ) for each sector.<sup>5</sup> Following Coleman (2014), we assume that values of the indicator greater than 1.25 allow us to classify a particular sector to be enough competitive to be an exporter. Subsequently, those branches with the LQ higher than 1.25 are summed up producing the final indicator. In doing so, we are capable of reflecting the scope of specialization of a particular region.
- Redistributive measures (*socben*) approximated by the ratio of social benefits other than social transfers in kind to net disposable income. We use this measure due to data constraints, however, we are aware of its limitations, among which, the limited coverage of redistribution effects.
- Life cycle effect (*age*) measured by the percentage of people aged between 15 to 30 years old. Drawing upon OECD (2018), we select the age-cohort of working population characterised by the greatest changes in individual equivalised disposable income.
- We introduce an additional control variable specifying a country in which a given region is located (*country*) to account for differences in national models of governance, e.g. more federal nature (Spain) or more centralized, top-down character (France) (Smith and Heywood, 2000).
- Income trajectory (*tperiod*) to separate between the two subperiods over which income mobility is measured, namely 2- and 4-year time spans.

In addition, we allow for interactions between the inequality indicators and the country-level ( $IE_{i,t_0} * country_i$ ) and the time span of income mobility ( $IE_{i,t_0} * tperiod_i$ ) to test, respectively, whether the relation between income inequality and mobility differs between the two countries studied and the time period over which income mobility was measured.<sup>6</sup>

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<sup>5</sup> We use 68 2-digit NACE Rev. 1.1 sectors (Business Structural Statistics of Eurostat). For sectors with data missing due to confidentiality reasons, we assumed values 0. It seems to be reasonable taking into account the sense of not publishing confidential data which is to protect information on particular businesses and, consequently, implying a relatively small scale of the production and employment.

<sup>6</sup> The regression models were estimated using the variables in levels. We also estimated a specification using logs, but did not find much difference and thus we opted for the version in levels which presented overall better goodness of fit. The results are available from the authors upon request.

It is important to clarify that whilst our empirical analysis does not establish a causal effect of regional income inequality on regional income mobility, it advances on previous studies making simple comparisons or correlation analyses.

## **4. Data and descriptive analysis**

### **4.1 Data sources**

We use two main data sources: i) the longitudinal sample of the pan-European microdata survey EU Statistics on Income and Living Conditions (EU-SILC) to calculate indicators of income mobility and income inequality at NUTS2 level, and ii) the Eurostat regional database to obtain NUTS2 level variables to be used as control factors in the regression analyses.

The more challenging data-related task consisted of preparing the longitudinal microdata from the EU-SILC survey to calculate indicators of income mobility and income inequality for individuals living in different NUTS2 regions, which we describe in section 4.2. The longitudinal sample of the EU-SILC survey follows a 4-wave rotational design, whereby a release for any given year contains four sub-samples, i.e. rotational groups, which have been in the survey for one, two, three or four years. Given the focus of our research on individual income mobility within NUTS2 regions in France and Spain<sup>7</sup>, we used the panel data component of the EU-SILC for the longest period of data available to date.<sup>8</sup> There are four longitudinal datasets in the EU-SILC: Household Register (H-file); Household Data (D-file); Personal Register (R-file); Personal Data (P-file). The D-file is a register that contains basic information about the household ID, country, region, degree of urbanisation, etc. Likewise, the R-file is a personal register file containing data similar to the H-file but at the individual level (personal ID, country ID, household ID). The H-file contains a rich set of data collected at the household level, while the P-file contains a rich set of personal data, such as net and gross income values for employed individuals or self-employed individuals among many other variables. We use STATA 14 to merge the aforementioned longitudinal datasets in order to obtain a combined household-individual-region dataset for France and Spain, totalling approximately 225,000 and 300,000 observations, respectively, for the period 2006-2016.<sup>9</sup>

EU-SILC provides the longitudinal base weights RB060 (time t), RB062 (time t-1), RB063 (time t-2) and RB064 (time t-3), from the P-file and R-files, respectively, which we use in the foregoing analysis. Whenever a longitudinal weight is missing for an individual who covered a wave of two or four years, we replace the missing value with the weight of the adjacent most current period. Robustness checks were done using several longitudinal weights (including the ones in the GESIS script file reported in Borst (2018)). The results remain by and large invariant under different approaches implying a relatively low attrition.<sup>10</sup>

Representativeness of the NUTS-2 regional components of the EU-SILC datasets for Spain and France and their appropriate stratification are emphasised in the Final Quality Reports for the period 2006-2016 (e.g. Eurostat, 2016) commissioned by the European Commission and concerning, among other things, accuracy and reliability of the EU-SILC national datasets with special emphasis put upon sample design. In addition,

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<sup>7</sup> Ciudad Autónoma de Ceuta (ES63) and Ciudad Autónoma de Melilla (ES64) are left out of the analysis due to the small sample sizes.

<sup>8</sup> Rotational groups remain in the survey for four years (except for the case of France). Each data release contains the most recent observations of the rotational groups that are still active, implying that each year one of the four rotational groups from the previous year is lost and a new one is added. Between year t and t+1 the rotational group overlap is around 75%, 50% between t and t+2, 25% between t and t+3 and zero afterwards. For a more detailed analysis on the rotational design followed by EU-SILC and the selection of rotational groups, we refer the reader to papers such as Atkinson, Guio, and Marlier (2017), Engel and Schaffner (2012).

<sup>9</sup> The detailed methodology for merging EU-SILC longitudinal datasets is available from the authors upon request.

<sup>10</sup> For more information about the weighting procedure within the EU-SILC datasets refer to Eurostat (2017).

GHK (2010) confirms the representativeness of the NUTS-2 regional sample after weighting for the total population of the region in the case of, among others, France and Spain.

The measures of income mobility and inequality are based on labour income, more specifically, employees' gross earnings from work. As described in Chap. 24 of Atkinson et al. (2017), labour income in the EU-SILC corresponds to the annual gross employee cash or near income: "the monetary component of the compensation in cash payable by an employer to an employee, and it includes the value of any social contributions and income taxes payable by an employee or by the employer on behalf of the employee to social insurance schemes or tax authorities. As a result, we always refer to labour income when using the term income in the paper. In order to compare income over time and across countries, we use the latest information on Harmonized Indices of Consumers Prices (HICP) provided by Eurostat to deflate gross income for cross-year comparison and convert all income values to constant prices of 2015.

The reference sample for the empirical analysis of labour income consists of working age individuals (16-65 years old). We removed all observations referring to non-working individuals during the income reference period as well as those individuals with gross income equal to zero or missing values during the income reference period. To account for the presence of outliers in the distribution of labour income, we use data on minimum wages from Eurostat<sup>11</sup>, at constant prices of 2015, and remove all observations with gross labour income lower than 3/5 of the annual minimum wage. This allows us to account for the existence of part-time workers and thus leads to a lower loss in the number of observations. In addition, following Van Kerm and Alperin (2013), we remove the upper extreme values of the income distribution by dropping values that are 25% higher than the 99<sup>th</sup> percentile. After creating the NUTS2 level indicators of income mobility and inequality produced from the EU-SILC microdata we merged them with other NUTS2 regional data described in section 3.2 and which we summarize in section 4.3.

## **4.2 Measuring income mobility and inequality at regional level using EU-SILC microdata**

### **4.2.1 Income mobility**

We follow the concept of relative income mobility by measuring the positional change of a given individual along the income distribution through the construction of transition matrices between income deciles over 2- and 4-years respectively. We summarize the results using stacked bar charts showing the percentage of individuals who did not move decile in the income distribution, the percentage of individuals who moved to the adjacent decile (i.e., just one decile up and down the income distribution), and the percentage of individuals who moved 2 or more deciles, both up and down the income distribution. Figure 1 and Figure 2 show the degree of income mobility across NUTS2 regions for Spain and France, respectively. Appendix B provides a map and table describing the NUTS2 regions.

Figure 1 shows that there is considerable variation in the extent of income mobility across regions in both Spain and France. In the case of Spain, the higher percentage of non-movers is ranging between 37% and 50% between  $t$  and  $t-1$  for Canarias and Asturias, respectively. Between  $t$  and  $t-3$ , there is greater scope for overall higher income mobility compared to the 2-year period between  $t$  and  $t-1$ , but now we observe that the capital region (Comunidad de Madrid) has the highest percentage of non-movers. In the case of France, the highest percentage of non-movers observed for the capital region Île de France. Comparing the results across countries, we can say that, overall, there appears to be greater variation in the level of mobility across regions in France than in Spain. However, discrepancies in upward mobility across regions were very high in both countries. Figure 2 shows the distribution of the three measures of income mobility, namely, percentage of non-movers, percentage of movers up 1 decile, and percentage of movers 2+ deciles for both countries.

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<sup>11</sup> See [https://ec.europa.eu/eurostat/statistics-explained/index.php/Minimum\\_wage\\_statistics](https://ec.europa.eu/eurostat/statistics-explained/index.php/Minimum_wage_statistics).

Fig. 1 Income mobility in Spain (top) and France (bottom) across NUTS2 regions between t-1 and t (left) and between t-3 and t (right)

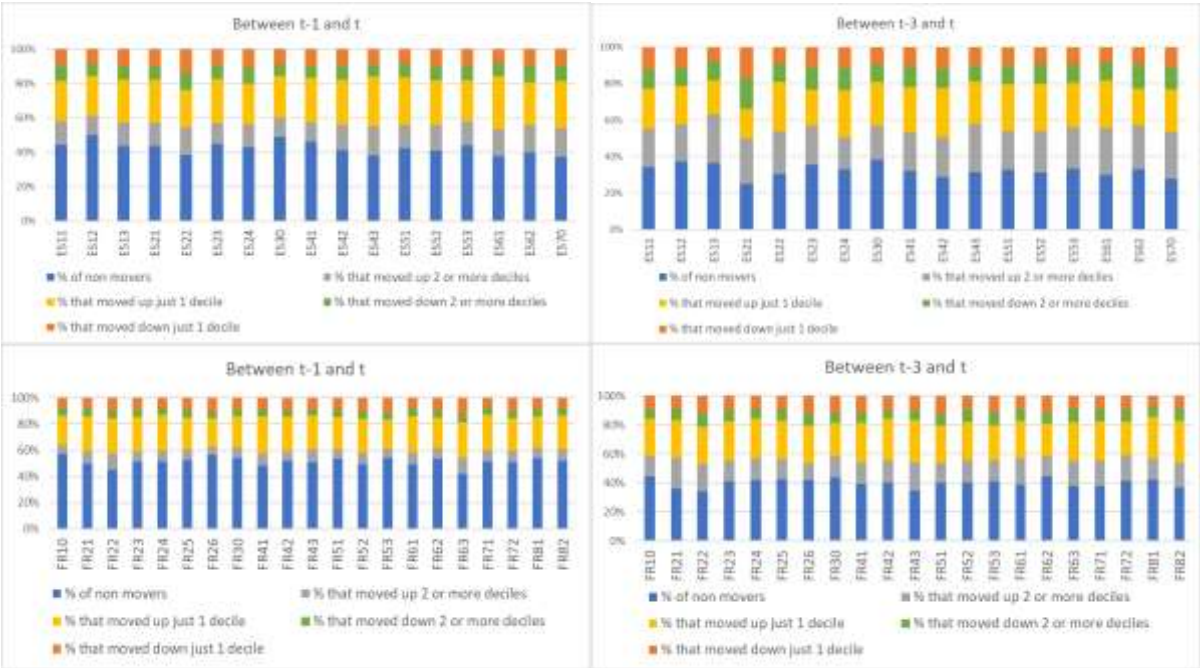
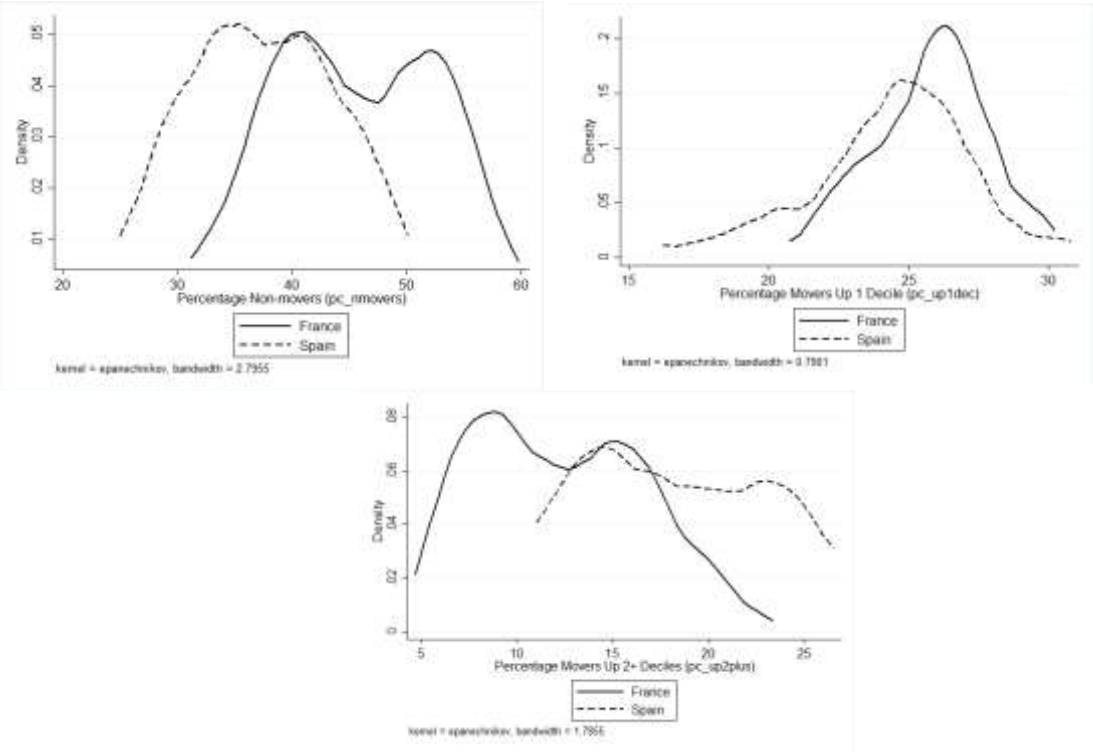


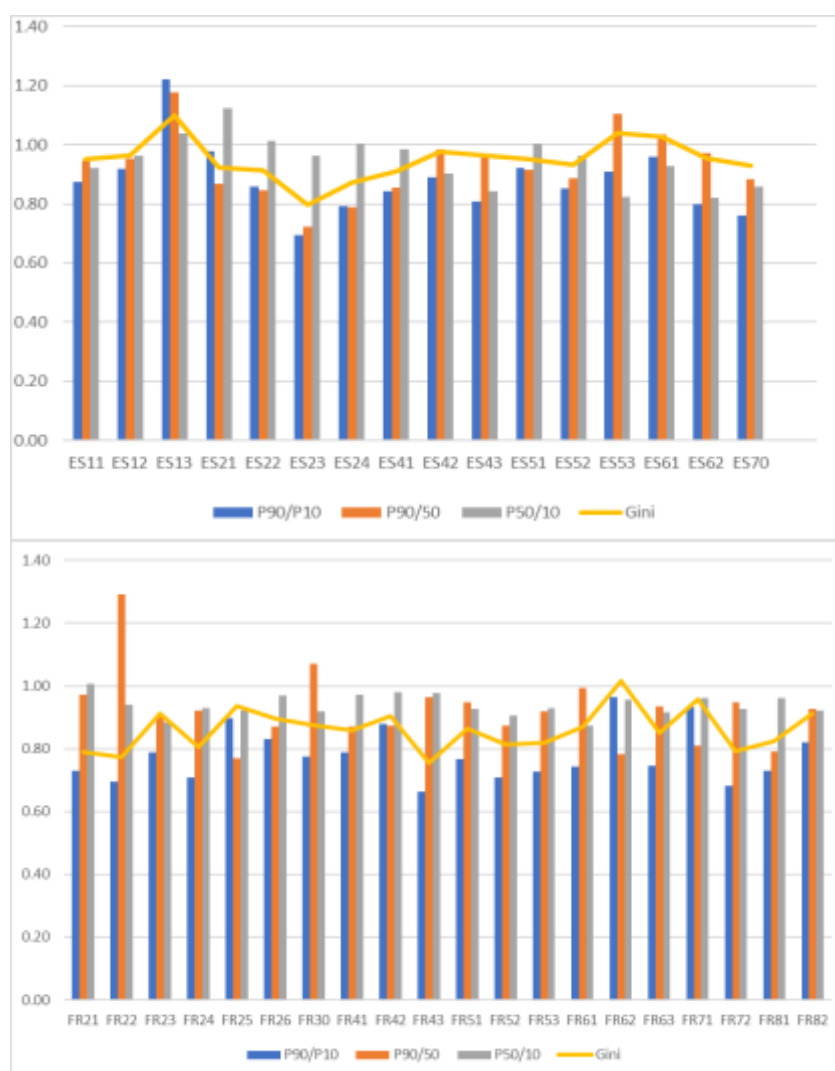
Fig. 2 Distribution of the share of individuals who do not move decile (top-left), move up 1 decile (top-right), move up 2 or more deciles (bottom-center)



#### 4.2.2. Income inequality

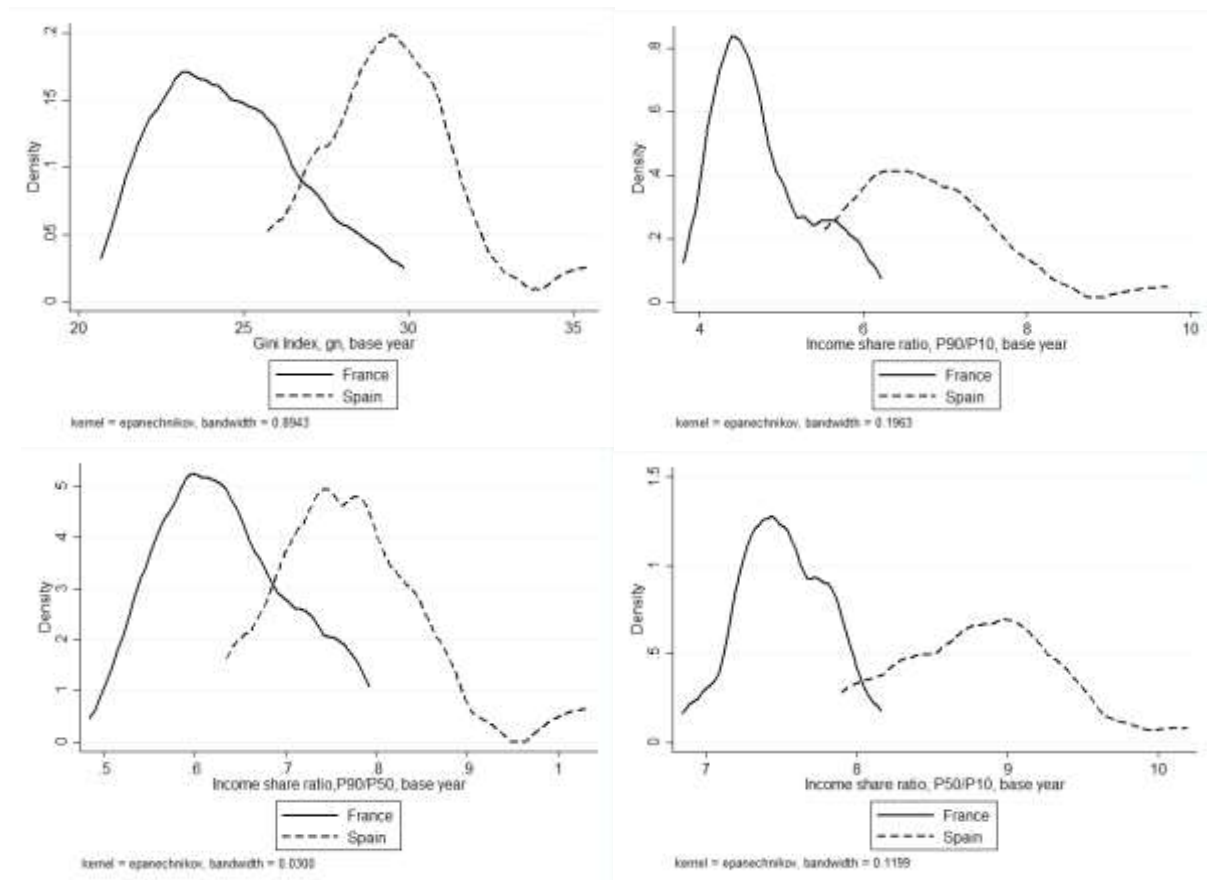
Figure 3 reports the income share ratios and Gini index for Spain and France as an index number with fixed base for the capital region, while Figure 4 shows the distribution of regional inequality using the three indicators. In both cases, we observe that there is considerable regional variation in the level of income inequality across regions and that the highest gap between the richest and poorest 10% (P90/P10) are observed for the capital regions.

Fig. 3 Income ratios and Gini index by region in relation to the capital region for Spain in 2006 (top panel) and France in 2007<sup>12</sup> (bottom panel)



<sup>12</sup> We avoid 2006 due to possible discrepancies in the number of observations.

Fig. 4 Distribution of the Gini index (top-left) and income share ratios P90/P10 (top-right), P90/P50 (bottom-left) and P50/P10 (bottom-right) in base year



#### 4.3 Regional factors affecting income mobility

Table 1 provides basic descriptive statistics for the regional variables used in the econometric analysis. As mentioned earlier, we use the base year 2006 in order to assess how initial (base) conditions affect income mobility.<sup>13</sup>

Table 1. Descriptive statistics for French and Spanish NUTS2 regions

Variable	Obs <sup>1</sup>	Mean	Median	CV <sup>2</sup>	Min	Max
nmovers - individuals who did not move income decile in t-1 (%)	38	47.43	49.00	11.82	37.36	57.00
up1dec - individuals who moved up one income decile in t-1 (%)	38	25.39	25.46	8.24	21.53	30.77
up2plus – individuals who moved 2 or more income deciles in t-1 (%)	38	11.11	10.43	29.00	6.50	17.02
nmovers - individuals who did not move income decile in t-3 (%)	38	36.60	36.96	13.62	25.00	44.84
up1dec - individuals who moved up one income decile in t-3 (%)	38	24.90	25.73	11.74	16.24	29.40

<sup>13</sup> In the case of France, we use the Gini coefficient, P90/P10, P90/P50 and P50/P10 for 2007 instead of 2006 due to data discrepancies mentioned earlier.

Variable	Obs <sup>1</sup>	Mean	Median	CV <sup>2</sup>	Min	Max
up2plus – individuals who moved 2 or more income deciles in t-3 (%)	38	18.97	18.42	22.02	11.89	26.55
GI – Gini index (%)	38	0.27	0.26	12.26	0.22	0.35
P90/P10	38	5.68	5.58	23.05	4.00	9.73
P90/P50	38	0.70	0.68	15.46	0.51	1.03
P50/P10	38	8.09	7.86	9.68	6.97	10.19
hedu –human capital (%)	38	25.53	23.30	23.28	17.60	41.80
unemp - unemployment rate (%)	38	8.16	7.65	24.38	5.40	13.30
lq125 - specialization scope (number of sectors)	38	15.05	15.00	20.60	8.00	22.00
socben - ratio of social benefits other than social transfers in kind to net disposable income (%)	38	29.92	32.33	24.68	18.02	39.57
age – life cycle effect (%)	38	19.19	19.09	8.12	16.39	22.98

<sup>1</sup> Obs: Observations. <sup>2</sup>CV: Coefficient of variation.

## 5. Results and discussion

Tables 2-4 present the results from the regression models for each measure of income mobility: percentage of non-movers (table 2), percentage of movers up 1 decile (table 3), and percentage of movers 2+ deciles (table 4). Each table presents eight models, one for each measure of income inequality (i.e. Gini index and the three income share ratios discussed earlier) using two model specifications. The first model specification (*reduced-specification*) includes only covariates for income inequality, its interactions with the country level and the time period as well as degree of urbanisation. The second model specification (*full-specification*) comprises the extended set of regional control variables. Adding regional controls allows us to test whether the relation between income inequality and income mobility is affected, and if so how, by regional heterogeneity.

Even though the reduced-specification models 1-3, 10 and 12 indicate a weak association between income inequality and income mobility, after controlling for a broader regional socio-economic context the main relationship ceases to be statistically significant. The only exception is model 16, which shows a negative relation between income inequality (i.e. P50/P10 income share ratio) and mobility (i.e. percentage of individuals who moved up one decile), but this is statistically significant only at 10% level of significance. The analysis of the interactions between income inequality and the country and time span reveals that the association between income inequality and the percentage of those who moved up one decile (models 15-18) is greater when income mobility is measured over a 2-year period compared to a 4-year period, while there seem to be no differences between the two countries.

Overall, the main conclusion is that there is very weak evidence of a significant relationship between income mobility and income inequality in the short to medium terms (i.e. over 2-year and 4-year periods). In other words, we do not find support for the hypothesis that greater income inequality hinders movements along the income distribution, irrespective of whether income mobility is measured using the percentage of non-movers (models 5-8) or the percentage of those who moved up only one decile (models 13-16) and those



who moved up at least two deciles (21-24). This conclusion is also robust to the measure of income inequality used. Consequently, our findings are closer to the literature providing no evidence for the relationship between income inequality and mobility (e.g., Aaberge et al., 2002; Gangl, 2005; Jenkins and Van Kerm, 2006; Alves and Martins, 2012; Chen, 2009), in contrast to the studies proposing that income inequality can act as an obstacle to income mobility, as shown by the Great Gatsby Curve, or the studies implying the positive association (e.g. Prieto-Rodríguez, Rodríguez and Salas (2008 and 2010)).

When interpreting our outputs, one should however have in mind that we measure income mobility over the short (i.e. 2-years) and medium (i.e. 4-years) terms and based on transitions between income deciles. This measure conceals within-decile income movements, which go unnoticed. Furthermore, we should also bear in mind that we analyse income mobility and inequality using earnings as the only proxy of income, which is likely to undervalue the extent of overall income or wealth inequality. Garnero, Hijzen and Martin (2016), for instance, show that the relationship between income inequality and income mobility is strongly affected by considering only individuals who are continuously employed or, alternatively, movements between employment and unemployment. Taking into account other income sources (e.g. capital dividends, land rents) could possibly affect the link between income mobility and income inequality. When allowing for different sources of income, or even extending the analysis to include wealth and social inequality, we could investigate more precisely the extent to which inequality limits the access of poorer households to the kinds of opportunities such as good schools, good local environment and health, etc., which are crucial for better socio-economic prospects. In addition, the relatively short(er) term income trajectories (up to 4 years) might be insufficient to capture tendencies in the trajectories along the income distribution.

As for the effects of the other regional covariates, included in the full-specification models, we observe a relatively small increase in the goodness of fit of these models. Specifically, the results provide no evidence that levels of income mobility vary significantly according to degree of urbanisation. This may partially be a result of using a very aggregate spatial scale (i.e. NUTS2) which is likely to omit and average out a lot of regional heterogeneity. In addition, some models show a negative association between human capital and income mobility (models 5-8 and 13-16), which is counterintuitive given education role as a social elevator. Our measure of human capital only accounts for overall level of higher education, and not how accessible or well-distributed education is. If human capital grows disproportionately faster across higher income deciles this might pose a barrier for individuals from lower parts of the socio-economic ladder. The remaining results for the extent of economic specialization and the ratio of social benefits other than social transfers in kind to net disposable income are significant only in some model specifications and at the 10% level preventing us from making any definite inferences.

As already noted in section 4, the results confirm that income mobility is higher for the longer time-span of 4-years compared to the 2-year time-span (models 1-3, 5-7, 9-16, 18 and 22). The longer the period, the greater the chance to observe income changes and their impact on relative income mobility. Even though we merely consider the difference between income mobility for 2-year and 4-year income trajectories, the results seem to be in line with those presented in OECD (2018) which imply an increase in income mobility between 4- and 9-years. To some extent, our outcomes might also support life cycle (or age-specific) effects on income mobility, i.e. capturing the impact of age composition on income changes, as found by Gangl (2005).

Finally, the results provide no evidence of country-specific differences in regional income mobility. Although this is a 'catch-all' variable of time-invariant country-level heterogeneity, it may suggest that the federal system of governance, characteristic of Spain, does not correlate with greater regional-level income mobility, *ceteris paribus*, in comparison to the more top-down centralised regime prevailing in France. To be able to make informative comparisons, however, this specific dimension of our analysis would need a more detailed investigation in the future.

Table 2. Pooled OLS results for non-movers as the dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GI	0.5217** (0.2417)				0.2530 (0.2340)			
France*GI	0.2521 (0.3272)				0.2969 (0.3469)			
2year*GI	-0.1349 (0.2388)				-0.1349 (0.2152)			
P90/P10		1.1212* (0.6103)				0.4507 (0.5312)		
France*P90/P10		1.4601 (0.9419)				1.4067 (1.1385)		
2year*P90/P10		-0.1980 (0.6224)				-0.1980 (0.5812)		
P90/P50			13.2993** (5.7494)				6.8133 (5.6468)	
France*P90/P50			8.1699 (8.4598)				7.3141 (8.5828)	
2year*P90/P50			-5.0477 (7.0014)				-5.0477 (6.1015)	
P50/P10				0.5232 (1.5430)				-0.4543 (1.6631)
France*P50/P10				0.8814 (2.0736)				1.8007 (2.4091)
2year*P50/10				0.3491 (1.0895)				0.3491 (1.1037)
Intermediate (ref. urban)	1.5227* (0.8660)	1.4832* (0.8715)	1.5276* (0.8739)	1.3126 (0.9300)	1.1970 (0.8718)	1.1314 (0.8765)	1.2957 (0.8662)	1.1424 (0.9242)
Rural (ref. urban)	0.3985 (1.0624)	0.1631 (0.9809)	0.1705 (1.0493)	-1.2071 (0.9859)	0.4383 (0.9944)	0.1528 (0.9598)	0.3684 (0.9886)	-0.4527 (1.1417)
unemp					-0.3312 (0.2575)	-0.2996 (0.2609)	-0.3011 (0.2570)	-0.2870 (0.2824)
hedu					0.2356* (0.1253)	0.2195* (0.1283)	0.2535** (0.1232)	0.2847** (0.1232)
lq125					-0.2179 (0.1416)	-0.2446* (0.1383)	-0.2202 (0.1423)	-0.2926** (0.1424)
socben					0.3733* (0.1909)	0.3636* (0.1870)	0.3572* (0.1972)	0.3633* (0.1899)
age					0.4859 (0.4320)	0.3940 (0.4584)	0.4764 (0.4393)	0.3720 (0.5228)
France (ref. Spain)	4.3073 (8.9642)	3.5391 (5.2102)	4.7279 (5.9518)	3.1799 (16.2377)	-0.8837 (10.0911)	-0.4205 (6.5730)	1.8386 (6.8544)	-7.7150 (18.6722)
2year (ref. 4year)	14.4456** (6.4008)	11.9572*** (3.5211)	14.3435*** (4.8893)	8.0076 (8.7197)	14.4456** (5.8110)	11.9572*** (3.3163)	14.3435*** (4.3319)	8.0076 (8.8590)
Constant	16.1564** (6.9169)	23.8721*** (3.7075)	21.2944*** (4.3139)	26.9060** (12.9480)	3.8204 (13.1361)	10.6841 (13.5683)	5.8071 (12.6842)	16.4617 (21.2130)
Observations	76	76	76	76	76	76	76	76
Adjusted R-squared	0.8271	0.8266	0.8248	0.8060	0.8418	0.8408	0.8405	0.8357

Notes. Standard errors in parentheses. Statistical significance: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 3. Pooled OLS results for the models with the percentage movers up one decile as the dependent variable

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
GI	-0.3133 (0.2102)				-0.0769 (0.2303)			
France*GI	-0.0863 (0.2576)				-0.1301 (0.2560)			
2year*GI	0.3512** (0.1581)				0.3512** (0.1515)			
P90/P10		-1.1662** (0.4627)				-0.5374 (0.4424)		
France*P90/P10		-0.0972 (0.7313)				0.0194 (0.7493)		
2year*P90/P10		1.0357** (0.3922)				1.0357*** (0.3699)		
P90/P50			-8.2223 (5.1656)				-3.2438 (5.8576)	
France*P90/P50			-3.9295 (6.6484)				-3.5220 (6.2958)	
2year*P90/P50			10.9251** (4.5052)				10.9251** (4.3669)	
P50/P10				-2.4973** (1.0695)				-1.7681* (1.0408)
France*P50/P10				1.9789 (1.3755)				1.8477 (1.4570)
2year*P50/10				1.5928** (0.7446)				1.5928** (0.7000)
Intermediate (ref. urban)	-1.0395 (0.7166)	-1.0322 (0.6945)	-1.0452 (0.7220)	-1.0028 (0.6710)	-1.0583 (0.6969)	-1.0794 (0.7041)	-1.0648 (0.6818)	-1.1956 (0.7666)
Rural (ref. urban)	-0.5882 (0.8757)	-0.5225 (0.7892)	-0.5615 (0.8595)	-0.2119 (0.7059)	-0.8075 (0.8265)	-0.7805 (0.8034)	-0.8261 (0.8149)	-0.9536 (0.9584)
unemp					0.1392 (0.1892)	0.1313 (0.1881)	0.1379 (0.1892)	0.0756 (0.1823)
hedu					-0.2271** (0.0885)	-0.2176** (0.0880)	-0.2242** (0.0847)	-0.2078** (0.0871)
lq125					0.0654 (0.1087)	0.0702 (0.1064)	0.0668 (0.1082)	0.0842 (0.1173)
socben					-0.2508* (0.1478)	-0.2242 (0.1419)	-0.2506 (0.1506)	-0.2245* (0.1340)
age					-0.2200 (0.3609)	-0.1985 (0.3665)	-0.2238 (0.3690)	-0.2934 (0.3616)
France (ref. Spain)	2.8745 (7.1466)	0.5265 (4.0507)	3.5099 (4.8118)	-15.7910 (10.8299)	6.8451 (7.4500)	2.7432 (4.2144)	5.7136 (5.0021)	-12.3079 (11.1154)
2year (ref. 4year)	-8.9194** (4.1744)	-5.3925** (2.1932)	-7.1110** (3.1238)	-12.4035** (5.9124)	-8.9194** (4.0624)	-5.3925** (2.1231)	-7.1110** (3.0984)	-12.4035** (5.5674)
Constant	33.4310** * (6.1287)	32.0149** * (2.9095)	30.6014** * (4.0399)	46.0306** * (9.0126)	41.3964** * (11.3803)	41.4017** * (10.7106)	41.6807** * (10.6354)	55.3643** * (14.2546)
Observations	76	76	76	76	76	76	76	76
Adjusted R-squared	0.1046	0.1495	0.1051	0.1661	0.2002	0.2195	0.2022	0.2278

Notes. Standard errors in parentheses. Statistical significance: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 4. Pooled OLS results for the models with the percentage movers 2+ deciles as the dependent variable

	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
GI	0.1138 (0.2444)				0.2554 (0.2462)			
France*GI	-0.3934 (0.2584)				-0.5414* (0.2899)			
2year*GI	-0.1709 (0.1707)				-0.1709 (0.1661)			
P90/P10		0.2293 (0.5731)				0.7033 (0.5429)		
France*P90/P10		-1.1536* (0.6785)				-1.6145* (0.8288)		
2year*P90/P10		-0.5682 (0.4231)				-0.5682 (0.4126)		
P90/P50			4.6747 (6.2272)				7.2382 (6.3948)	
France*P90/P50			-12.2532* (6.5604)				-14.2090* (7.4127)	
2year*P90/P50			-5.4767 (5.1831)				-5.4767 (5.0104)	
P50/P10				-0.3473 (0.8311)				0.9639 (0.9706)
France*P50/P10				0.5989 (1.3276)				-0.5860 (1.6615)
2year*P50/10				-0.9245 (0.6527)				-0.9245 (0.6949)
Intermediate (ref. urban)	-0.6153 (0.5813)	-0.6133 (0.5696)	-0.6318 (0.5783)	-0.5568 (0.5662)	-0.3176 (0.6537)	-0.3000 (0.6571)	-0.3953 (0.6488)	-0.4492 (0.7253)
Rural (ref. urban)	0.1892 (0.7634)	0.3494 (0.7020)	0.2592 (0.7231)	0.9220 (0.5903)	0.4913 (0.7249)	0.7111 (0.7186)	0.5125 (0.7129)	0.8887 (0.7974)
unemp					0.1833 (0.1759)	0.1820 (0.1762)	0.1597 (0.1764)	0.1521 (0.1839)
hedu					-0.0880 (0.0706)	-0.0871 (0.0735)	-0.0961 (0.0694)	-0.1203 (0.0745)
lq125					-0.0696 (0.0987)	-0.0538 (0.0965)	-0.0603 (0.0961)	-0.0411 (0.1061)
socben					-0.1781 (0.1175)	-0.1632 (0.1162)	-0.1736 (0.1199)	-0.1115 (0.1187)
age					0.0541 (0.2891)	0.1213 (0.3033)	0.0417 (0.2927)	0.1097 (0.3082)
France (ref. Spain)	3.5551 (7.1440)	-0.9512 (3.9345)	1.7312 (4.6930)	-12.0918 (10.2938)	9.8207 (8.4023)	4.0178 (4.9351)	5.1372 (5.7349)	-0.4744 (12.9465)
2year (ref. 4year)	-3.2823 (4.5135)	-4.6337* (2.3649)	-4.0505 (3.5782)	-0.3769 (5.1680)	-3.2823 (4.4061)	-4.6337* (2.3205)	-4.0505 (3.4735)	-0.3769 (5.5152)
Constant	19.4516*** (6.9416)	21.3176*** (3.6677)	19.1763*** (4.5991)	25.8502*** (6.9590)	19.6636** (9.6537)	20.6327** (8.8532)	22.1037** (8.5408)	17.1396 (12.4813)
Observations	76	76	76	76	76	76	76	76
Adjusted R-squared	0.8521	0.8534	0.8524	0.8496	0.8631	0.8648	0.8626	0.8559

Notes. Standard errors in parentheses. Statistical significance: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## 6. Conclusion

The paper contributes to ongoing research on the relationship between income inequality and income mobility by adopting a regional perspective for NUTS2 regions in France and Spain. Using the longitudinal component of the EUSILC dataset, we compute indicators of income mobility and income inequality, which we then combine with other regional-level data in regression models. The findings from the regression analyses provide no evidence of a significant relationship between income mobility and income inequality. In other words, it is not confirmed that greater income inequality hinders movements along the income distribution, particularly upward income mobility. This conclusion is robust regardless of the indicators used to measure both income inequality and income mobility.

At least two aspects should be kept in mind when interpreting our results. First, the analysis focuses only on labour-related income, i.e. employees' earnings, which is likely to underestimate the extent of total income, or wealth inequality. Second, the analysis only considers short-to-medium term income mobility (i.e. 2-year and 4-year), and thus is not likely to fully capture the mechanisms underlying and affecting intergenerational social mobility as reflected by the Great Gatsby Curve. The latter can be more directly related to inequality in the access, particularly of poorer households, to opportunities and resources crucial for better future socio-economic prospects, namely good schools, good local environment and health services, etc. Consequently, the results obtained in our analysis should be interpreted with caution and in this specific context.

Concerning other regional-level factors, there is mixed evidence on the nature and direction of their association with income mobility. While increased urbanisation tends to be associated with higher absolute income mobility (i.e. higher wage levels), we do not find significant evidence of a positive relation between increased urbanisation and relative upward mobility. This result requires, however, further investigation at a lower level of spatial disaggregation (i.e. sub-NUTS2 regions) to avoid the averaging out of territorial specificities. Insights derived from a spatially disaggregated analysis (e.g. at NUTS3 level) could considerably improve our knowledge about the relationship between income inequality and income mobility. Unfortunately, however, the EUSILC does not provide any information at the geographical level.

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## Appendix A

**Table 1. Review of selected empirical studies on the relationship between income inequality and intragenerational income mobility**

Research	Income mobility measure	Income inequality measure	Income measure	Geographical scope	Time period	Empirical strategy	Outcomes
Aaberge et al. (2002)	Shorrocks approach	Gini coefficient	(1) earnings of those who had strictly positive earnings in every year; (2) the market income of individuals over the time period; and (3) the disposable income of individuals.	Denmark, Norway, Sweden, the US	1980-1990	Comparison of Shorrocks indices with the inequality levels	No evidence of a positive relationship between inequality and mobility
Jenkins and Van Kerm (2006)	Decomposition of the change in the Gini coefficient into the reranking and progressivity components	Gini coefficient	Post-tax post-transfer annual income of the household	The US and West Germany	1980s and 1990s	Decomposition of the change in the Gini coefficient into the reranking and progressivity components. The reranking component (income mobility) is then compared and contrasted with the level of income inequality.	Both countries experienced pro-poor income growth. This inequality-decreasing effect was, however, offset by changes in the income reranking. Their findings do not show that greater income inequality goes with greater mobility.
Van Kerm (2004)	The indices of social mobility, proposed by Fields and Ok (1999). Total mobility is decomposed into: mobility due to economic growth, mobility produced by dispersion and exchange mobility resulting from reranking	No explicit measure employed	Post-tax post-transfer disposable household income	Belgium, Western Germany and the USA	1985-1997	Decomposition of income mobility indices into two basic sources: mobility induced by a change of the income distribution shape and mobility induced by a re-ordering of individuals in the income pecking order. No explicit measure of income inequality employed, however, the group of analysed countries (the USA with relatively great income inequality versus the EU countries with relatively low income disparities) allows us to easily evaluate the relationship between income inequality and income mobility using comparisons.	The positive relationship between income mobility and income inequality).

**Table 1. Continued.**

Research	Income mobility measure	Income inequality measure	Income measure	Geographical scope	Time period	Empirical strategy	Outcomes
Prieto, Rodríguez and Salas (2008)	The indices of social mobility, proposed by Fields and Ok (1999). In addition, following Van Kerm (2004), total mobility is decomposed into: mobility due to economic growth, mobility produced by dispersion and exchange mobility resulting from reranking.	Theil index	Household equivalent income (European Community Household Panel)	15 EU countries	1993–2000	Random coefficients models with the Theil inequality index as a dependent variable. Separate models were estimated for total mobility, growth mobility, dispersion mobility and exchange mobility as explanatory variables. Three mobility intervals were taken into account (1, 3 and 5-year mobility).	The positive relationship between income inequality and income mobility.
Prieto-Rodríguez, Rodríguez and Salas (2010)	The indices of social mobility, proposed by Fields and Ok (1999). In addition, following Van Kerm (2004), total mobility is decomposed into: mobility due to economic growth, mobility produced by dispersion and exchange mobility resulting from reranking.	Theil index	Household equivalent income (European Community Household Panel)	NUTS-1 regions from: Belgium, France, Ireland, Italy, Greece, Spain, Portugal, Australia, Finland, Germany, United Kingdom. NUTS-0 - Denmark, the Netherlands and Luxemburg. NUTS-2 regions from Portugal.	1994–2001	A hierarchical linear model with fixed-effects for both the regional and country levels with the Theil inequality index as a dependent variable. Separate models were estimated for total mobility, growth mobility, dispersion mobility and exchange mobility as explanatory variables. Three mobility intervals were taken into account (1, 3 and 5-year mobility).	The positive relationship between income inequality and income mobility.
Aaberge and Mogstad (2014)	Mobility curve concept	Gini coefficient	The sum of pre-tax market income from wages and self-employment.	The US, the Nordic countries and Germany	1980s	The association between income mobility and income inequality is analysed through comparing and contrasting the estimates of income mobility from the mobility curve approach and the level of income inequality measured by the Gini coefficient.	They find that the US –with greater income inequality– was characterized by higher income mobility than the other countries studied. However, there was only a slight difference.

**Table 1. Continued.**

Research	Income mobility measure	Income inequality measure	Income measure	Geographical scope	Time period	Empirical strategy	Outcomes
Garnero, Hijzen and Martin (2016)	Shorrocks approach	Gini coefficient, Theil index, the mean logarithmic deviation (MLD), Palma indices	Earnings and unemployment benefits	24 countries	2004-2011	Correlational analysis	The positive link between earnings inequality and earnings mobility is found only on the tails of the distribution (for the P90/P10 and P50/P10 indices) whereas there is no significant association when the Gini coefficient is applied. When movements in and out of employment are not taken into account, the relationship between earnings mobility and inequality becomes negative or insignificant.
Gangl (2005)	Shorrocks approach	Gini coefficient, Theil index, the mean logarithmic deviation (MLD)	Equalized post-tax post-transfer household income	11 EU countries and the US	1992-1997	1) Comparison of Shorrocks indices with the inequality levels and 2) the regression model to decompose income inequality into a component of permanent incomes and into the dynamic components of real income growth, life-cycle trends, heterogeneous income trends, and transitory variance in incomes.	No significant difference between the EU and the US in terms of income mobility even though there is a visible gap in cross-sectional income inequality.
Alves and Martins (2012)	Shorrocks approach and the decomposition of income inequality following Jenkins and Van Kerm (2006)	Gini coefficient	Individual equivalent income	The EU countries with a special focus on Portugal	2005-2009	1) Comparison of Shorrocks indices with the inequality levels and 2) Inequality decomposition following Jenkins and Van Kerm (2006).	No relation between the level of inequality and the contribution of income mobility to the reduction in inequality in the EU countries. The contribution of progressive growth to the reduction of inequality was offset by the re-ranking of individuals in the income distribution.
Bowlus and Robin (2012)	A flexible model of individual earnings dynamics is constructed that isolate positional mobility from structural one. Using the flexible model, they simulate individual employment and earnings trajectories given base-year earnings (1998) and construct lifetime annuity value distributions for each country. The ratio of lifetime inequality to base-year inequality is a measure of equalization mobility.	See column 2.	Earnings	The United States, the United Kingdom, France, Germany, and Canada	1990s	Comparison of equalization mobility to the inequality levels.	The positive relationship between income mobility and income inequality.

Source: Own elaboration.

## Appendix B

As reported by Eurostat (2013 version), the names and codes of NUTS2 regions are given by the following table and we further provide a regional map for NUTS2 regions within each country.

### Spain

**Table I: NUTS2 regions in Spain and corresponding codes**

Code	NUTS	Version	Name
ES11	NUTS2	2013	Galicia
ES12	NUTS2	2013	Principado de Asturias
ES13	NUTS2	2013	Cantabria
ES21	NUTS2	2013	País Vasco
ES22	NUTS2	2013	Comunidad Foral de Navarra
ES23	NUTS2	2013	La Rioja
ES24	NUTS2	2013	Aragón
ES30	NUTS2	2013	Comunidad de Madrid
ES41	NUTS2	2013	Castilla y León
ES42	NUTS2	2013	Castilla-la Mancha
ES43	NUTS2	2013	Extremadura
ES51	NUTS2	2013	Cataluña
ES52	NUTS2	2013	Comunidad Valenciana
ES53	NUTS2	2013	Illes Balears
ES61	NUTS2	2013	Andalucía
ES62	NUTS2	2013	Región de Murcia
ES63	NUTS2	2013	Ciudad Autónoma de Ceuta (ES)
ES64	NUTS2	2013	Ciudad Autónoma de Melilla (ES)
ES70	NUTS2	2013	Canarias (ES)

*Source: Eurostat.*

Figure 1: NUTS2 region map for Spain



Source: Eurostat - GISCO, 07/2018

## France

**Table II: NUTS2 regions in France and corresponding codes**

Code	NUTS	Version	Name
FR10	NUTS2	2013	Île de France
FR21	NUTS2	2013	Champagne-Ardenne
FR22	NUTS2	2013	Picardie
FR23	NUTS2	2013	Haute-Normandie
FR24	NUTS2	2013	Centre (FR)
FR25	NUTS2	2013	Basse-Normandie
FR26	NUTS2	2013	Bourgogne
FR30	NUTS2	2013	Nord - Pas-de-Calais
FR41	NUTS2	2013	Lorraine
FR42	NUTS2	2013	Alsace
FR43	NUTS2	2013	Franche-Comté
FR51	NUTS2	2013	Pays de la Loire
FR52	NUTS2	2013	Bretagne
FR53	NUTS2	2013	Poitou-Charentes
FR61	NUTS2	2013	Aquitaine
FR62	NUTS2	2013	Midi-Pyrénées
FR63	NUTS2	2013	Limousin
FR71	NUTS2	2013	Rhône-Alpes
FR72	NUTS2	2013	Auvergne
FR81	NUTS2	2013	Languedoc-Roussillon
FR82	NUTS2	2013	Provence-Alpes-Côte d'Azur
FR83	NUTS2	2013	Corse
FRA1	NUTS2	2013	Guadeloupe
FRA2	NUTS2	2013	Martinique
FRA3	NUTS2	2013	Guyane
FRA4	NUTS2	2013	La Réunion
FRA5	NUTS2	2013	Mayotte

Source: Eurostat.

Figure II: NUTS2 region map for France



Source: Eurostat - GISCO, 07/2018