DID THE COVID-19 PANDEMIC IMPACT INCOME DISTRIBUTION?

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Abstract

This analysis aims to explore how employee income distribution performed during the first year of the COVID-19 pandemic; it further aims to compare it with a pre-pandemic scenario (2019) and with the financial and the sovereign debt crisis. By referring to the EU Labour Force Survey (LFS) database for six EU Member States (Denmark, Estonia, Greece, Ireland, Italy, and Portugal), and by using transition matrices and a selection of mobility indices as empirical tools, the direction and the magnitude of the movement across quantiles experienced by employees are explored. For each of the years under scrutiny, the transition across quintiles is computed between two very close periods (e.g. from one quarter to another). Sudden changes in the structure of the transition matrices and the value of the respective mobility indicators, when observed in comparison with a 'benchmark' year, may be interpreted either as a shock to the economic system, or the (counter) effect of automatic stabilisers and discretionary public policy measures (and as a combination of the two). The direction and the magnitude of the change may depend on different factors, including the kind of crisis, labour market and market income response, along with the design and timing of public policy discretionary cushioning measures. This conclusion emerges from the comparison of results collected for the COVID-19 crisis with those of the Great Recession: Two different kinds of crisis, two different sets of transmission mechanisms from the origin of the crisis to the real economy, two different responses of the labour market and of the public policy intervention. During the COVID-19 crisis, the overall level of income mobility increased, while during the financial crisis and sovereign debt crisis it decreased. The reason lies both in the different magnitude of flows from employment to unemployment and in the type and timing of the measures taken. As for the COVID-19 pandemic vs a pre-pandemic scenario, in-depth observation of the transition matrices and of the relative mobility indices suggests an increase of the overall mobility that is explained by specific movements of the 'upward' and 'downward' movers, as well as from the patterns followed by the proportion of individuals belonging to the single quantiles. When the figures for different indicators are broken down, it seems that there is a general worsening condition of females compared to males, of the youngest (16-29-year-olds) and of employees without tertiary education (ISCED 6-8).

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Introduction

Understanding the effects that the COVID-19 pandemic has had on income inequality (within countries) is attracting a lot of interest. This is also the case in the EU, although in Europe there had not been such a rise in inequality in the last few decades.

Why would COVID-19 impact income inequality? The pandemic shock was completely unexpected and of extraordinary nature. The abrupt and large fall in GDP, of the order of 10 % from one quarter to another, was policy induced (lockdowns) and it had very varied impacts on countries, across sectors and occupations, and more broadly across individuals. However, up to now, the knowledge about the actual distribution of the impact on individuals is rather limited. The main reason for this is the lack of hard data.

Large household surveys (like the Eurostat EU-SILC – Survey on Income and Living Conditions), generally used to analyse income inequality, across all EU countries, are only available with a significant lag (2 to 3 years). Given the paucity of data on actual income, much of the current debate on income inequality is based on expert opinions and alternative solutions in terms of data collection and empirical investigation methodologies, namely ad hoc new surveys, typically, covering a selection of countries, and model-based microsimulations exploiting past data.

The findings are somewhat mixed, but not necessarily contradictory. While some experts claim that the pandemic will increase (market income) inequality because it has exacerbated pre-existing drivers of inequality[1], others point to the impact of the extraordinary government income supports, which are likely to have offset rising market income inequalities[2]. This difference illustrates a general problem concerning research on the impact of COVID-19 income inequality: It is often impossible to disentangle the impact of the policy interventions to contain the spread of the virus and other behavioural changes induced by the pandemic from income support mechanisms. In practice, this means that most research can only describe the outcome of the joint effect of the pandemic and the support measures taken by governments. In addition, the year 2020 was characterised by very sharp changes, often from one month to another, hence annual data tend to mix and dilute the impact of the pandemic and the mitigation measures.

With regards to ad hoc surveys, the most complete and reliable one appears to be the COME-HERE panel survey led by the University of Luxembourg[3] including France, Germany, Italy and Spain, which has been collected since the beginning of the pandemic. Findings based on the survey suggest that income inequality fell from January 2020 to January 2021 in these four countries, because of income support measures. Microsimulation analyses[4], through a complex

[1] See for instance https://www.imf.org/external/pubs/ft/fandd/2021/06/inequality-and-covid-19-ferreira.htm or https://knowledge4policy.ec.europa.eu/diversifying-inequalities_en

[2] See for instance https://www.intereconomics.eu/contents/year/2022/number/1/article/international-inequality-and-the-covid-19-pandemic.html

[3] Clark et al. (2021) https://wwwen.uni.lu/university/news/slideshow/come_here_survey_results_from_luxembourg

[4] See for instance Almeida et al. (2020, 2021), Cantó et al. (2021), Christl at al. (2021, 2022).

model calibrated on past data, simulate the COVID-19 shock and predict an increase in income inequality in the absence of a policy response. However, policy interventions, in the form of changes in the tax and benefit systems, lead to a fall in income inequality. Hence, the results, coming from different strands of the literature, seem to point to a similar conclusion.

Against this background, this paper contributes to the literature by taking a different but complementary approach, relative to those illustrated above. First, it relies on the Eurostat Labour force Survey (LFS), one of the official EU datasets, for which income decile data are gradually becoming available for 2020. The advantage of using the LFS, even if data are not yet available for all EU countries, is that data are accessible upon request to the researcher and the methodology can be reproduced and extended (over time and across more countries as income data become available)[5]. In addition, it allows a comparison of the year 2020 with a pre-COVID-19 period (by selecting a benchmark year) but also with past crises, notably the financial and the sovereign debt crisis. Second, when looking at the policy measures that have been put in place by national governments to stabilise income, and hence which are expected to affect inequality, we realised that the complexity is such that even mapping the measures (before the assessment of their impact) is extremely difficult. The combination of direct transfers, debt relief measures, tax deferral and short-term work schemes affect individuals' income in a very heterogeneous way which is difficult to capture at the aggregate level with a single indicator[6]. Hence, at the cost of increasing complexity in the interpretation of findings, it has been decided not to use standard synthetic indices of income inequality, but rather to look at the whole income distribution in this work[7]. With this in mind, this work looks at income distribution and mobility across income quintiles within the year. While the analysis in this paper does not directly answer the question of whether income inequality has increased or declined, it offers evidence of whether or not individuals originally belonging to a certain income quintile have experienced an improvement or a deterioration (moved to a higher quintile) or a deterioration (moved to a lower quintile) in their income conditions.

Furthermore, this work gives its contribution by using a set of tools belonging to the realms of the ordinal income transition matrices and a selection of the relative mobility index. More precisely, it explores how the income mobility of employees performed in the pandemic scenario (2020) compared to the pre-pandemic scenario (2019). It suggests an ad hoc interpretation of the transition matrices and of relative indices that fit well with the question of how COVID-19 (and the policy response to it) impacted income distribution. In addition, it

[5] From 2021 onwards, the LFS will include a continuous income variable, which will allow an even more accurate and detailed analysis (see Annex 1 for more details). See also the section on Conclusions and further research.

[6] Even focusing on one measure, such as the short-term work scheme, would simplify the aggregate analysis only to a limited extent. The schemes have typically different replacement ratios across the income distribution and do not cover the full scale of wages, they contain caps (on the max amount disbursed) and, often, they tend to interact with other automatic stabilisers.

[7] Indeed, the Gini coefficient or the income quintile share ratio exhibit some limitations, which we consider important in this context. The former is less sensitive to inequality at the tails of the income distribution, while the latter does not take into consideration what happens in the middle of the income distribution.

offers insights on the different parts of income distribution and allows conclusions to be drawn on the regressive/progressive nature of the crisis and its countermeasures. It is worth noting that, when comparing the mobility calculated in two very close periods[8], the difference can be very small. Hence, some abrupt change, from one year to another, observed in the inter-quintile mobility could be associated with extraordinary measures or extraordinary shock. Whether the effect of the shock or the policy measures lead to an increase or a decrease in the income mobility depends on a multiplicity of factors: the sample / population considered (e.g. households, individuals regardless of their work status, or a specific type of worker) as well as the type of policy response. It is also important whether the shock mainly touches wages and salaries or implies, instead, a change in the working status, in particular a transition from employment to unemployment as the extent to which the countermeasures are addressed to those who enter the unemployment status or to those who stay in employment.

Given the focus of the paper on employees, what matters is how the shock and the measures affected wages and salaries. Labour demand decreased in many sectors and at the same time labour supply was affected by those infected by the virus. The combined effect of these two factors altered the number of hours worked to different extents in different sectors and occupations. It may have also modified other aspects of working contracts. Some categories continued to work remotely, but others were completely locked down. Aside from the 'pure' COVID-19 pandemic effect, the design of the countermeasures and in particular of those job retention schemes (JRS) that allow employees to maintain their legal status of employees (short-time work schemes – SWS and wage subsidies – WS) must be considered[9]. JRS, due to their heterogeneity in terms of the specific moment that they started, the length, the eligibility criteria, and the replacement ratio[10] to cite some examples may, in turn, modify the individual earning pattern, pushing toward a transition from one income category to another. The net effect between the shock and the countermeasures is ambiguous, as the latter may not be sufficient to offset the former leading to a change in the position of the individual in the income distribution index. This could be the case if, for example, the real replacement rate of the wage is not 100 %.

Given this general framework, this research plans to explore in depth the changes in income mobility that occurred during the first year of the pandemic and compare them with a pre-pandemic scenario, as well as with the Great Recession. To achieve this aim, we use the EU LFS for a selection of six Member States among which four (Greece, Ireland, Italy, and Portugal) were severely hit by the financial and the public debt crisis. The group also includes Denmark and Estonia, which could be considered as control countries. These two were only marginally affected by the financial crisis and reacted very fast to the COVID-19 pandemic. Estonia suffered quite a deep recession around 2010, but the impact of COVID-19 was rather mild. The selection

[8] In this case the mobility is calculated within the year, but the comparison/changes is evaluated between years.

[9] For a more detailed definition of these schemes please see Drahokoupil and Muller (2021).

[10] Meant as the percentage of the gross or net income covered.

of the countries is also driven by specific data features. The EU LFS allows to obtain more than one observation for the same respondent in the same year (longitudinal data) and includes information about the position of the respondent in the income distribution. These two elements are exploited to construct transition matrices from one quarter to another, within the same year, and to calculate a series of mobility indices. Transition matrices together with mobility indices provide very granular information about the relative position of the portion of employees in the income distribution. In addition, the data allow over-time and cross-country comparisons of both classes of indicators. The study covers the overall population of employees and some breakdowns by demographic aspects, namely gender, age, and educational attainment.

This study is structured as follows: the first section offers a review of the most recent literature that mostly focuses on the development of incomes and income distribution during the pandemic period. The second section is dedicated to a description of the dataset and the empirical methodology. The third section part analyses the results: First, the overall degree of mobility will be considered by comparing the pandemic scenario (2020) with a pre-pandemic scenario (2019) and then the differences between the pandemic scenario and the financial crisis/sovereign debt crisis will be highlighted and explained in light of the different market and public policy responses to the shock. Secondly, income mobility during the COVID-19 pandemic (and compared to the pre-pandemic scenario) will receive in-depth scrutiny. From the cross-country comparison, it is also possible to draw some conclusions about the effect of the job retention scheme measures. Our results, with all the due differences, seem to be in line with some studies conducted with EUROMOD (Christl et al., 2021, 2022). Thirdly, the results of the breakdowns will also be analysed. The fourth section contains the conclusions and provides some suggestions for improving this line of research. In addition, two appendices are included. The first one is methodological and contains further details on the variable used, the sample considered and the construction of the matrices and the computation of indices. The second one includes all the tables that cannot be incorporated in the main text.

1. Literature review

The COVID-19-induced crisis has drawn much attention to changes in income distribution[11] and the effect of the cushioning measures. It impacted income and income distribution, mainly through labour market dynamics, its transformations, such as those related to remote working[12], and the transitions from one status to another (employed, unemployed, inactive).

[11] Including the analysis of the evolution of overall inequality income indices, quintile analysis, and poverty indices.

[12] Which while being a form of resilience set up in the crisis period, will possibly shape the future structure of the labour market. Also this part of the literature is particularly relevant as it gives hints for understanding how it could be the evolution of income distribution in a near future. Among others, Palomino et al. (2020), referring to the EU Member States, study how wages respond differently to the COVID-19 shock depending on the ease of working remotely and on the relevance on the specific professions in the economy. In a similar vein see also Bonacini et al. (2021) on Italy.

In this context, the changes that occurred in various kinds of income have been considered: labour income, unemployment benefits, and incomes deriving from other kinds of benefits that may support those in employment, unemployment, or inactivity while also considering the 'absorbing shock effect' provided by the household itself. Most studies consider the overall distribution (and where possible, the full set of measures available, including those targeted at households and not directly to individuals), and analyse household (equivalent) disposable income. The main difficulty encountered in this field, especially for the analyses done in Europe, has been the lack of up-to-data income microdata (e.g. EU SILC for the EU Member States). Due to the complexity involved in collecting the data, the microdata required for an in-depth observation of the dynamics of income distribution in a population are generally only available after about 2, or even sometimes 3 years. In response to the extreme necessity of quantifying the effects on poverty and inequality in the COVID-19 period, Eurostat computed some relative indicators with an experimental methodology for the years 2019 and 2020[13].

This section looks at the literature, which analyses the evolution of income[14] distribution during the COVID-19 pandemic and which studies the effect of COVID-19 on market income and disposable income, the difference between the two, and, consequently, the effect of the cushioning measures. Facing the above-mentioned lack of up-to-date microdata, the researchers either collected ad hoc databases or referred to articulated methodologies to include the COVID-19-induced shock into existing datasets such as EU-SILC. Furthermore, this section also considers the literature that provides a cross-country EU perspective in more detail[15].

Clark et al. (2021), using the longitudinal COME-HERE database studied the development of absolute and relative income inequality calculated on household disposable income in France, Germany, Italy and, Spain[16] for the period January 2020 to January 2021, and concluded that inequality rose steadily from January to May 2020, before falling back to pre-COVID levels in September 2020. Income-support measures which counterbalanced the losses that occurred during COVID-19 were addressed to individuals at the bottom of the income distribution, explaining the decrease in income inequality[17]. Menta (2021), in also referring to the COME-

[13] See https://ec.europa.eu/eurostat/cache/experimental_statistics/income-inequality-and-poverty-indicators/Flash-estimates-2020-Country-profiles.html

[14] In a broad sense.

[15] While most of the studies concerning single countries are more accurate and propose interesting methodologies, the comparison between these latter may be too extensive to take into account all the methodological heterogeneities. Regardless the methodology adopted, for the literature exclusively devoted to one of the Members Stated selected in this study see: for Denmark Bennedsen et al., (2020); for Ireland, Beirne et al., (2020), Doorley et al., (2020), O'Donoghue et al., (2020), for Italy Brunori et al., (2020), Carta and De Philippis, (2021), Ceriani et al., (2020), Figari and Fiorio, (2020).

[16] As well as Sweden in Clark et al., 2020.

[17] Other ad hoc data collection for the cross-country perspective have been collected by Adam-Prassl et al. (2020) for Germany (UK and US) for the period March-April 2020 that focus on the probability of job loss and earning loss and their determinants. Also Belot et al. (2020, 2021) collected data in April 2020 for Italy (and the US, UK, China, Japan, and South Korea) to investigate financial and non-financial gain and losses in the first period of the

HERE database, shows that poverty indices increased in the first half of 2020, then fell back in the second half of the year with heterogeneity across the countries considered (France, Germany, Italy and Spain).

A richer strand of literature is based on tax and benefits microsimulation models. Almeida et al. (2020, 2021) and Christl et al. (2021, 2022) use EUROMOD[18] for a cross-country analysis including all 27 Member States with uprating and shocking the EU-SILC database of previous years. Comparing these two groups of studies, the main source of methodological heterogeneity lies in how the COVID-19 shock is accounted for in the microdata: A reweighting procedure based on macro data forecast for Almeida et al. (2020, 2021) and a nowcasting procedure based on the transition of workers to unemployment or monetary compensations[19] for Christl et al. (2021, 2022). Another important difference lies in the fact that while in Almeida et al. (2020, 2021), not all the COVID-19-related policies were considered (because indeed at that time they were not yet ready to be modelled in the EUROMOD policy spine), in Christl et al. (2021, 2022) monetary compensation schemes are included. At the EU-27 level, with regards to household income, Almeida et al. (2021: p. 423) claimed that 'household income would have fallen by -9.3 % due to the impact of COVID-19 without fiscal policy measures, while policy intervention reduced this impact to -4.3 %. In the absence of fiscal policy responses, the COVID-19 pandemic would have a clear regressive effect on household income' and Christ et al. (2021: p. 9) showed that 'market income dropped by more than 5.1 % […]. The drop in disposable income is significantly smaller than market income (1.3 %). The reduction indicates a progressive pattern, with the poorest quintile losing around 0.2 % of disposable income against the 1.9 % loss for the richest quintile.' Using EUROMOD, for Belgium, Italy, Spain (and the UK) Cantò (2021) concluded that government cushioning measures served to mitigate the impact of COVID-19, but while income inequality remained quite constant, the tax and benefit system did not appear to be sufficiently equipped to face the pandemic's poverty-increasing tendency.

2. Data and methodology of the empirical analysis

This section briefly presents the dataset selected, some of its peculiar characteristics, and the main variable of interest. Together they are the most important ingredients of the descriptive statistical methodology, which is based on transition matrices, and a selection of mobility indices. More detailed explanations, including those on the procedures adopted in the microdata management for each of the Member States under scrutiny, are provided in Annex 1 Methodology, while Annex 2 includes the mobility indices referred to the breakdowns.

Data: The database chosen was the EU Labour Force Survey (LFS), as it is the most reliable and updated European household / individual-level survey database, including, among others,

pandemic. (Möhring et al., 2020) concentrated on data collected for Germany in the period March-April 2020 for assessing inequalities in employment trajectories.

[18] The EU tax and benefit micro simulation model.

[19] Via the EUROMOD Labour Market Adjustment (LMA) add-on.

information on individual characteristics, their activity status, and their position within income distribution. Furthermore, the EU LFS microdata has been collected both on a yearly (and quarterly) basis for a long period that allows for both comparisons between a pre-pandemic (2019) and a pandemic scenario (2020) and a comparison with the previous financial crisis (2009)[20], and with the sovereign debt crisis (2010-2012), selecting the most relevant year depending on the Member State under scrutiny. Finally, while, the EU LFS is originally not designed as a panel (i.e. with a longitudinal dimension) it has a rotational structure[21] that permits, for each wave (i.e. within the same year), some longitudinal analysis to be conducted (Mack et al., 2016; Eurostat, 2021a; Eurostat, 2021b). More specifically, observations taken in different quarters[22] for the same individuals within a specific year are considered. The main variable of interest is INCDECIL, the monthly net (take-home) pay[23] of employees[24]. INCDECIL is an ordinal variable ranging between 1 (lowest decile) to 10 (highest decile) recorded per employee[25]. As regards country coverage, the selection had to take into consideration two criteria: i) the actual availability of the INCDECIL variable in 2020[26] and ii) the number of times (minimum 2) the same employee is included in the sample (i.e. provides an observation) within the year. A further selection is based on sample size[27], which may be too small when taking into account the various breakdowns described later. The selection then includes six Member States: Greece, Ireland, Italy, and Portugal (as particularly hit also by the sovereign debt crisis), Denmark as representative of the Northern countries and Estonia as representative of the Baltic countries.

Transition matrices: The availability of the INCDECIL variable, together with the 'within wave' longitudinal dimension of LFS allows for income mobility analysis from one quarter to another within a specific year by using transition matrices. In this specific case, they serve the purpose of computing and visualising the proportion of individuals (employees) moving across income groups (quintiles in ascending order) from one quarter to another.

[20] As the 2008 income distribution information is not available in LFS and 2009 can be considered as a more representative year of the financial recession in Europe.

[21] For example Italy and Estonia, generally have the so called '2-(2)-2' rotation structure: respondents are interviewed in two consecutive quarters, then temporarily are removed for the next two quarters and enter again for the following two quarters. Afterwards they are definitely removed from the survey.

[22] On the selection of the quarters please see Table A.1 4 in Annex 1.

[23] For an exhaustive definition of the labour income in the INCDECIL variable please see Table A.1 1 in Annex 1.

[24] I.e. self-employed and family workers are excluded.

[25] As such, it does not allow to directly construct inequality indices on income variable expressed in classes or continuously (e.g. Gini Index).

[26] In April 2022, the INCDECIL variable was still not filled for 2020 data in the following MS: Austria, Czechia, Germany, Spain, Sweden, Slovenia and Slovakia. Furthermore, the Member States that, at least in 2020, have a number of observations per individual > 1 do not include Belgium, Bulgaria, Czechia, Germany, Spain, Finland, France, Luxembourg, Latvia and the Netherlands. The exercise may be easily extended when the INCDECIL variable is filled in by the missing Member States with a number of observations per individual > 1.

[27] Especially relevant as an analysis based on breakdowns is conducted.

Indicating with *k* the possible 'status' that the individual can belong to and indicating with n_{ij}, where *i, j = 1… k*, the number of individuals who in the sample belong to class *i* at time *t* and to class *j* at time *t + 1*, a transition matrix P of order $k \times k$ (e.g. 5) is defined as:

$$P \equiv \begin{vmatrix} p_{11} & p_{12} & p_{13} & p_{14} & p_{15} \\ p_{21} & p_{22} & p_{23} & p_{24} & p_{25} \\ p_{31} & p_{32} & p_{33} & p_{34} & p_{35} \\ p_{41} & p_{42} & p_{43} & p_{44} & p_{45} \\ p_{51} & p_{52} & p_{53} & p_{54} & p_{55} \end{vmatrix}$$

where each element of the matrix *pij* is calculated as $\left[\frac{n_{ij}}{n_i}\right] \in [0,1]$

Rows are the origin *(t)* and the columns are the destination *(t+1)*. The p_{ij} is estimated, from the empirically observed frequencies, or by the proportion of individuals passing from *i* to *j*. The main diagonal of the transition matrix describes the percentages of individuals defined as 'immovables' or 'stayers' as they remain in their original category. Out of the diagonal, there are the 'movers'. More specifically, when, as in this case, the categories are sorted in ascending order in the upper diagonal there are the 'upward movers' (improving their relative position) while in the lower diagonal there are the 'downward movers' (worsening their relative position). It is worth stressing that, when, for example, considering five quintiles, in the upward movers' group the proportion of respondents moving from the first, the second, the third, and the fourth quintile to a better quintile is included (the fifth quintile cannot further improve, so it is not included). In the downward movers group the proportion of respondents moving from the fifth, the fourth, the third, and the second quintile to a worse quintile is included (the first quintile cannot further worsen unless entering another working status, unemployment or inactivity with possibly a lower income, so they are not included). Additional relevant insights can come from considering single rows. In the first and in the fifth rows are included respectively those that from the first (fifth) quintile move towards a better (worse) position, while in the second, third, and fourth quintiles are included both those that can improve and worsen their position.

Mobility indices: Four main mobility indices have been selected for performing the analysis; the results are described in Section 3. The first two indices are complementary, the Immobility Ratio (IR) and the Bibby mobility index (M_{BB})[28], as described respectively in equation (1)[29] and equation (2).

$$IR = \frac{trace\ (P)}{k} = \frac{1}{k}\sum_{i=j}^{k} p_{ij} \qquad (1)$$

[28] Bibby (1975).

[29] Reported as in the formulation indicated in Paul (2020).

$$M_{BB} = 1 - \frac{trace\ (P)}{k} \qquad (2)$$

Both the indicators are based on the trace of the transition matrix, namely the main diagonal that records the percentages of individuals that do not change statuses between the two periods under consideration, but while the former focus on the individuals remaining in their original position, the latter, instead focus on the individuals moving away from their original position. Nevertheless, the Bibby mobility index does not take into consideration the distance among the categories.

$$M_B = \frac{1}{k}\sum_{i=1}^{k}\sum_{i=1}^{k}|i-j|\,p_{ij} \qquad (3)$$

To overcome this constraint, the Bartholomew mobility index (M_B) is added (equation 3). This latter is a positional index, also known as 'average jump index' and it is equal to the number of income class boundaries crossed by an individual (whether upwards or downwards). Additional information is provided by the Mobility Index by Paul (2020), in equation 4, which adds to the Bartholomew mobility index some interesting features: being normalised and including a pro-poor weight that attaches higher weights to the mobility of the lowest quintiles and vice versa.[30]

$$M = \frac{\frac{2}{\mathrm{k(k+1)}}\sum_{i=1}^{k}(\mathrm{k}+1-i)\sum_{i\neq j}^{k}|\,\mathrm{i}-\mathrm{j}\,|^{\alpha}\ \mathrm{p}_{ij}}{\left(\frac{2}{k}\right)\sum_{i=1}^{(k-1)/2}|i-k|^{\alpha}+\left(\frac{1}{k}\right)\left(\frac{k-1}{2}\right)^{\alpha}} \qquad (4)$$

While the immobility and overall mobility indices are interesting, additional information can be drawn by separating the contribution of upward and downward mobility (equations 5 and 6) that are similar to the ones indicated in Chattopadyay et al. (2019, page 101, equations 2.2. and 2.3) and in Paul (2020, page 396, equations 13 and 14).

$$M_{BB} = M_{BB_U} + M_{BB_D} \qquad (5)$$

$$M_{BB_U} = \frac{1}{k}\sum_{i=1}^{k-1}\sum_{j=i+1}^{k} p_{ij} \qquad (5.1)$$

$$M_{BB_D} = \frac{1}{k}\sum_{i=2}^{k}\sum_{j=1}^{i-1} p_{ij} \qquad (5.2)$$

$$M_B = M_{B_U} + M_{B_D} \qquad (6)$$

$$M_{B_U} = \frac{1}{k}\sum_{i=1}^{k-1}\sum_{j=i+1}^{k} p_{ij}\,|i-j| \qquad (6.1)$$

$$M_{B_D} = \frac{1}{k}\sum_{i=2}^{k}\sum_{j=1}^{i-1} p_{ij}\,|i-j| \qquad (6.2)$$

Keeping in mind the inability of the Bibby Index and Bartholomew Index to distinguish between upward and downward mobility, they have been broken down into two elements (5.1 and 5.2 for Bibby and 6.1 and 6.2 for Bartholomew) representing the proportion of respondents

[30] For more details on the computation of this index and its features, see Paul (2020).

belonging to the categories of upwards and downwards movers. The sub-indices are conceived to add up to the value of the overall respective indices.

Breakdowns: the COVID-19 pandemic did not homogeneously affect all categories of individuals. To grasp some of the possible differences the sample has been breakdown according to gender and age brackets (15-29-year-olds, 30-54-year-olds, and 55-74-year-olds)and education level (below tertiary and above tertiary, according to the ISCED 11 scale).

3. Results and comments

This section describes the results drawn from the quantile transition matrices and the respective mobility indices. First, the pandemic scenario is compared to a pre-pandemic scenario and the financial crisis/sovereign debt crisis. This first part of the analysis is based on two overall mobility indices. Then a focus on other mobility indices, on specific components of the overall mobility (upward and downward), and the pattern of the specific quintiles is proposed. This to provide also some consideration on the cushioning measures adopted. Transition matrices and the relative indices are then calculated to take into account some breakdowns related to individual characteristics (gender, age, and educational attainment).

For this descriptive statistics exercise, based on cross-year comparisons, the years selected are respectively 2019 and 2020[31] (pre-pandemic and pandemic scenarios), whereas, going back to the Great Recession, 2009 is considered for all the chosen Member States[32] with the addition of the first year of the Economic Adjustment Programme for Greece, Ireland, Italy, and Portugal. Mobility indices are comparable across countries as the underneath definition of the take-home pay of employees is the same (see **Table A.1 1** in Annex 1).

It is worth recalling that the transition matrices and the respective mobility indices, are calculated based on a vary close starting and a destination point in time that a (i.e. transition from one quarter to another) and the comparison between two years is considered. The commentary on the results is based on the following general interpretation: sudden changes in the structure of the inter-quintile transition matrices and the value of the respective mobility indices are symptoms of a shock in the economic system and of the cushioning effect of the automatic stabilisers and the discretionary measures. As, in this case, the sample considered is that of employees, the sign and the magnitude of the change in the mobility of a 'crisis' year compared to a 'normal' one or another 'crisis' year, crucially depends on the nature of the shock, on the way the labour market, and thus the market income, receives the shock, on the structure of the labour market (e.g. in terms of occupation / sector / dimension of the enterprises) and on the type, design and timing of the counteracting public policies. In anticipation of more detailed results, the figures suggest that for employees in the COVID-19

[31] As this latter is the most recent year for which EU LFS provides income data which are disseminated only in the yearly files, notwithstanding they are recorded on a rotational basis.

[32] Denmark, Estonia, Greece, Ireland, Italy and Portugal.

pandemic there has been a general increase in income mobility, whereas in the Great Recession there was a general decrease in income mobility. Further explanations for the reason behind this conclusion will be provided below.

3.1 Employees' income mobility changes between the COVID-19 scenario and the pre-COVID-19 scenario and between the COVID-19 scenario and the Great Recession.

Quantile mobility of employees tends to be higher in the COVID-19 scenario (2020) compared to the pre-COVID-19 scenario (2019), possibly due to changes in the number of hours worked or in other contractual aspects. Various indices point towards this conclusion such as Bibby Index and Bartholomew index.[33] As shown in Table 1, the mobility indices increase for all the Member States under scrutiny except for Denmark.

Table 1. Mobility indices, employee population 16-74-year-olds, 2019, 2020 and percentage points 2019-2020

	Bibby Index			Bartholomew Index		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
DK	31.9	31.8	-0.12	40.85	40.90	0.05
EE	38.2	40.6	2.40	50.26	54.69	4.43
EL	4.2	15.4	11.22	5.67	18.41	12.74
IE	13.1	13.3	0.19	15.74	16.81	1.07
IT	37.4	42.1	4.75	50.07	58.54	8.47
PT	30.0	31.5	1.52	34.02	35.29	1.27

Source: Authors' calculation on Eurostat EU LFS data 2019 and 2020.

Note: The Bibby index varies between 0 and 1 (with 0 maximum immobility and 1 maximum mobility). Bartholomew index has the same lower bound (with 0 maximum immobility), but the upper bound may exceed 1. Here the indices are expressed between 0 and 100.

Nevertheless, in some Member States, the changes in the mobility indices from 2019 to 2020 tend to be marginal. This is possibly due to the negative effect on market income, at least partially, counterbalanced by the positive effect of the job retention schemes. The cross-country heterogeneity is immediately obvious. In terms of ranking, Greece surpasses all other MS, followed by Italy, Estonia, and then Portugal and Ireland. In Denmark, there is no change in mobility between 2019 and 2020.

The employee income mobility recorded in 2020 is generally higher than the one of the Great Recession and the reason is linked to the different effects the two crises had on labour market outcomes as well as to the different countermeasures put in place and their timing.

Table 2 presents the results of the Bibby Index and the Bartholomew Index, comparing 2009 with 2020 for all six Member States[34] under scrutiny and additionally comparing the first year

[33] More indices will be analysed in subsection 3.2.

[34] Except for Portugal which does not have a sufficiently large sample size to construct meaningful transition matrices for 2009.

of the Economic Adjustment Programmes (2010 for Greece[35], 2011 for Ireland and Portugal, and 2012 for Italy) with 2020.

Table 2. Mobility Indices, employee population 16-74-year-olds, 2009, 2010, 2011, 2019 and 2010

	Bibby Index						Bartholomew Index					
	2009	2010	2011	2012	2019	2020	2009	2010	2011	2012	2019	2020
DK	34.57				31.93	31.80	45.25				40.85	40.90
EE	29.65				38.21	40.61	38.00				50.00	55.00
EL	4.27	1.64	3.16		4.17	15.39	4.86	1.85	3.69		5.67	18.41
IE	9.28		7.75		13.11	13.30	11.24		9.25		15.74	16.81
IT	41.28			43.79	37.39	42.14	57.72			60.71	50.07	58.54
PT	n.a.		27.43		29.98	31.51	n.a.		31.84		34.02	35.29

Source: Authors' calculation on EU LFS data, 2009, 2010, 2011, 2012, 2019 and 2020.

Note: The Bibby index varies between 0 and 1 (with 0 maximum immobility and 1 maximum mobility). Bartholomew index has the same lower bound (with 0 maximum immobility), but the upper bound may exceed 1. Here the indices are expressed between 0 and 100.

When comparing 2009 with 2020, both the mobility indices are lower for Estonia, Greece, and Ireland[36]. This also occurs for the Programme Member States in the specific years considered when compared to 2020, with the exception of Italy. In some cases, mobility indices are also lower compared with those of 2019 (the benchmark year) as in the case of Estonia in 2009, of Greece in 2010 and 2011, of Ireland, and of Portugal in 2011. Italy presents a different picture. Indeed, the mobility index is very similar between 2009 and 2020, but the figures recorded in 2012, during the austerity measures (including those related to flexicurity), are even higher than those in 2020. Finally, for Denmark, mobility was lower in the financial crisis than in the COVID-19 crisis[37].

The higher mobility index in the first year of the COVID-19 pandemic compared to the Great Recession can be explained by the fact that the latter leads to a different type of shock in the labour market. The transition is more accentuated from employment to unemployment rather than across income categories for employees. Referring to Eurostat data for the unemployment rate and for the transition rate between employment and unemployment[38], it is intuited a negative correlation between the income mobility for employees and the rate of unemployment or the flow rate from employment to unemployment.

Table 3. Unemployment rate and transitions rate from employment to unemployment, 2009-2020

	Unemployment Rate (15-74, y.o.) expressed as the percentage of population in the labour force											
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
DK	6.40	7.70	7.80	7.80	7.40	6.90	6.30	6.00	5.80	5.10	5.00	5.60
EE	13.50	16.60	12.30	9.90	8.60	7.30	6.40	6.80	5.80	5.40	4.50	6.90

[35] For Greece 2011 has also been added.

[36] Portugal is excluded from this comparison, see note 34.

[37] With the caveat that Denmark, in the third quarter of 2009, had already emerged from the recession with a positive GDP growth.

[38] This is not ideal, as it includes not only employees but also self-employed and other types of workers, but it does provide the directions of the dynamics.

EL	9.80	12.90	18.10	24.80	27.80	26.60	25.00	23.90	21.80	19.70	17.90	17.60
IE	12.60	14.60	15.40	15.50	13.80	11.90	9.90	8.40	6.70	5.80	5.00	5.90
IT	7.90	8.50	8.50	10.90	12.40	12.90	12.00	11.70	11.30	10.60	9.90	9.30
PT	11.20	12.60	13.50	16.60	17.20	14.60	13.00	11.50	9.20	7.20	6.70	7.00

	Transition employment - unemployment expressed as the percentage of total employment											
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
DK	n.a.	n.a.	3.30	3.10	3.10	3.00	2.60	2.60	2.50	2.50	2.30	2.70
EE	n.a.	n.a.	3.30	2.40	3.10	2.50	2.40	2.70	2.20	2.40	2.10	3.50
EL	n.a.	n.a.	5.90	7.80	5.50	2.90	2.50	2.60	2.20	1.60	1.50	2.80
IE	n.a.	n.a.	4.20	3.80	2.80	2.80	2.20	2.00	1.80	n.a.	1.40	2.30
IT	n.a.	n.a.	2.20	2.80	3.10	2.70	2.30	2.50	2.30	2.20	2.00	2.30
PT	n.a.	n.a.	n.a.	6.60	6.00	3.90	3.80	3.50	2.50	2.40	2.40	3.00

Source: Eurostat, codes [une_rt_a] and [lfsi_long_a].

Considering more in detail the Member States under scrutiny and looking at **Table 2** and **Table 3**, in Estonia, in 2009 the mobility index was lower than in 2020 (29.65 vs 40.61 for the Bibby and 38 vs 55 for the Bartholomew), whereas the unemployment rate is much higher (13.50 % vs 6.90 % and the flow rate is not available). For Greece, rate of unemployment in 2009 is lower than in 2020 (9.80 % vs 17.60 %). Nevertheless looking at the whole time series, that peaked in 2014 with a value of 26.6 %, the level of unemployment in 2020 is the same as that registered between 2010 and 2011. The flow rate from employment to unemployment of 2011 it is double compared to that of 2020 (5.9 % vs 2.8 %, and 7.80 % vs 2.8 % for 2012). The picture is similar for Ireland and Portugal: Lower mobility indices in the Great Recession compared to the COVID-19 crisis and a higher rate of unemployment and/or flow rate from employment to unemployment. In Italy, the situation in terms of mobility, unemployment rates and flows from employment to unemployment is very similar across the two crises and the mobility is even higher in 2012 compared to all the other years, as already stressed.

3.2 An in-depth analysis of income mobility during the COVID-19 pandemic

Now the focus is on the dynamics of income mobility during the pandemic vs the pre-pandemic scenario with a closer look at additional mobility indices, highlighting specific aspects about the stayers, the upward and downward 'movers', and the patterns of the individual quintiles within the transition matrices.

Table 4. Mobility indices, employees (16-74 y.o.), 2019, 2020, and percentage points 2019-2020

	Immobility Ratio			Bibby Index			Bartholomew Index			Mobility Index by Paul (2020)		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
DK	68.1	68.2	0.12	31.9	31.8	-0.12	40.85	40.90	0.05	12.79	12.82	0.03
EE	61.8	59.4	-2.40	38.2	40.6	2.40	50.26	54.69	4.43	15.92	17.07	1.14
EL	95.8	84.6	-11.22	4.2	15.4	11.22	5.67	18.41	12.74	1.80	6.35	4.54
IE	86.9	86.7	-0.19	13.1	13.3	0.19	15.74	16.81	1.07	4.90	5.08	0.18
IT	62.6	57.9	-4.75	37.4	42.1	4.75	50.07	58.54	8.47	15.50	18.39	2.89
PT	70.0	68.5	-1.52	30.0	31.5	1.52	34.02	35.29	1.27	12.30	12.38	0.07

Source: Authors' calculation on EU LFS data 2019 and 2020.

Note: Immobility Ratio index ranges between 0 and 1 (with 0 maximum mobility and 1 maximum immobility). The Bibby index and the mobility index by Paul (2020) range between 0 and 1 (with 0 maximum immobility and 1 maximum mobility). Bartholomew index has the same lower bound (with 0 maximum immobility), but the upper bound may exceed 1. Here the indices are expressed between 0 and 100.

- For the Immobility Ratio index, the difference between 2019 and 2020 is always negative and, looking at the stayers (percentage of employees on the matrix diagonal), the difference between 2019 and 2020 is led by a decrease in the stability that concerns all the quintiles (see Table 7, bold figures in the transition matrices). Indeed, the percentage of employees that stays stable in their original category decreases for all the quintiles in Greece and in Italy, for 4 out of 5 quintiles in Estonia, and for 3 out of 5 quintiles for Denmark, Ireland, and Portugal.
- According to the Bibby index, mobility increases in all the Members States under scrutiny with one exception. Compared to 2019, the difference recorded in Greece ranked first (with an increase of 11.22 percentage points) and Italy second (with an increase of 4.75 percentage points). Estonia, Ireland, and Portugal recorded a difference below 3 percentage points. The only exception is a slight decrease in Denmark.

Mobility increased, but generally, the number of categories crossed tends to stay limited in most cases. The Bartholomew index, which measures the average jump and weights for the number of categories crossed, also points toward higher overall mobility. In a cross-country, cross-year comparison a higher / lower index means that the movements occur across more / less distant categories. The jumps across categories are broader for the countries that show higher differences when comparing 2020 with 2019 as in the case of Greece and Italy (as confirmed by looking at the underneath transition matrices in Table *7*). While for the other countries the tendency is of moving through immediately adjacent income categories.

- **The mobility index by Paul (2020), which also considers the pro-poor social preferences[39], increases as do the other indices. This already points to a positive cushioning effect of the measures, especially for the lowest quintile(s).** According to the data, this is the case with Greece and Italy which recorded the highest difference between 2019 and 2020

[39] For a clear explanation of this component in the index please see Annex 1.

(and it may be the case that the replacement wage is lower than 100 % and possibly capped).

As a robustness exercise, 2018, instead of 2019, is considered as an alternative benchmark year, The differences between the pandemic year and the alternative benchmark year are similar and in some cases are more accentuated.

Table 5. Mobility indices, employees (16-74-year-olds), 2018, 2019, 2020, and percentage points 2018-2019 and 2019-2020

	Immobility Ratio					Bibby Index				
	2018	2019	2020	pp 2018-20	pp 2019-20	2018	2019	2020	pp 2018-20	pp 2019-20
Denmark	67.97	68.07	68.20	0.23	0.12	32.03	31.93	31.80	-0.23	-0.12
Estonia	63.49	61.79	59.39	-4.09	-2.40	36.51	38.21	40.61	4.09	2.40
Greece	95.29	95.83	84.61	-10.68	-11.22	4.71	4.17	15.39	10.68	11.22
Ireland	88.76	86.89	86.70	-2.06	-0.19	11.24	13.11	13.30	2.06	0.19
Italy	61.54	62.61	57.86	-3.68	-4.75	38.46	37.39	42.14	3.68	4.75
Portugal	72.73	70.02	68.49	-4.24	-1.52	27.27	29.98	31.51	4.24	1.52
	Bartholomew Index					Mobility Index by Paul (2020)				
	2018	2019	2020	pp 2018-20	pp 2019-20	2018	2019	2020	pp 2018-20	pp 2019-20
Denmark	40.27	40.85	40.90	0.63	0.05	12.18	12.79	12.83	0.64	0.03
Estonia	48.30	50.26	54.69	6.39	4.43	14.37	15.93	17.07	2.70	1.14
Greece	6.94	5.67	18.41	11.46	12.74	2.15	1.81	6.36	4.20	4.55
Ireland	13.66	15.74	16.81	3.15	1.07	4.53	4.90	5.08	0.56	0.18
Italy	51.59	50.07	58.54	6.96	8.47	15.99	15.50	18.39	2.40	2.89
Portugal	30.75	34.02	35.29	4.54	1.27	11.04	12.31	12.38	1.34	0.08

Source: Authors' calculation on EU LFS data 2018, 2019 and 2020.

Note: Immobility Ratio index ranges between 0 and 1 (with 0 maximum mobility and 1 maximum immobility). The Bibby index and the mobility index by Paul (2020) range between 0 and 1 (with 0 maximum immobility and 1 maximum mobility). Bartholomew index has the same lower bound, but the upper bound may exceed 1 (with 0 maximum immobility). All the indices are here expressed between 0 and 100.

Considering that in 2019, some Member States were already on the downward side of the cycle and, since the mobility indices also reflect this aspect, the differences between the pandemic scenario (2020) and the alternative pre-pandemic scenario 2018 are similar or even more accentuated. As shown in Table 5, the differences between the Immobility Ratios calculated in 2020 and those calculated in 2018 are always negative, except for Denmark and with a higher difference (compared to that recorded for 2019-2020) for Estonia, Ireland, and Portugal. Conversely, the differences between the various Mobility Indices calculated in 2020 and those calculated in 2018 are all positive (except for Denmark – only for the Bibby index) with a higher difference (compared to that recorded for 2019-2020) for Estonia, Ireland, and Portugal. While, on the one hand, the analysis of immobility and overall mobility is interesting, further information comes from the analysis of indices relative to upward and downward movers while additional information derives from investigating what happens in each quintile. Before interpreting the results in the Member States it is worth recalling that according to the way the transition matrices are constructed: i) the upward movers' group (above the main diagonal) includes the proportions of individuals belonging to the first, second, third, and fourth quintile

(the fifth is excluded as it can only stay in its original position or worsen its situation); ii) the downward movers' group includes proportions of individuals belonging to the second, the third, the fourth and the fifth quintile (the first is excluded as it can only stay in its original position or improve its situation). Furthermore, considering each quintile separately (to be read from left to right), and excluding the stayers: i) the first row includes those in the first quintile that moved towards a better position; ii) the second, the third, and the fourth rows include both those that improved and worsened their positions (thus, in this context what is relevant is their net improvement or worsening); iii) the fifth row included those in the fifth quintile that moved towards a worsening position.

As a general interpretation, in this context, comparing 2020 with 2019: i) an overall mobility, driven by downward mobility (to the extent that this, in turn, is mainly driven by the downward mobility of the fifth quintile), may be a sign of progressivity of the cushioning effect of the measures adopted; ii) an overall mobility, driven by upward mobility (to the extent that this, in turn, is mainly driven by the upward mobility of the first quintile), in a crisis context is not plausible, nevertheless it could be the case that the cushioning measures allow the first quintile to stay stable or even to improve its situation. iii) **nevertheless, having overall mobility driven by downward mobility, with upward mobility, that compared to a benchmark year stays stable or increases less than the downward mobility, points to a general progressive cushioning effect of the discretionary measures adopted. Specific interpretations depend on the figures relative to the individual Member State and on an in-depth knowledge of the full design of the measures addressed to employees.**

Table 6. Index of upward and downward mobility as components of the Bibby and the Bartholomew indices, 2019, 2020 and percentage points 2019-2020.

	Bibby upward component			Bibby downward component			Bartholomew upward component			Bartholomew downward component		
	2019	2020	pp 2019-20	2019	2020	pp 2019-20	2019	2020	pp 2019-20	2019	2020	pp 2019-20
DK	17.86	16.31	-1.54	14.07	15.49	1.42	22.74	21.36	-1.38	18.11	19.55	1.43
EE	19.56	18.92	-0.64	18.65	21.68	3.03	25.49	25.89	0.40	24.76	28.80	4.03
EL	2.93	5.00	2.06	1.24	10.39	9.16	3.66	6.09	2.43	2.01	12.32	10.31
IE	5.79	7.02	1.23	7.32	6.28	-1.04	7.36	8.91	1.55	8.38	7.91	-0.47
IT	19.58	21.28	1.70	17.81	20.86	3.05	26.22	29.87	3.65	23.85	28.67	4.82
PT	15.49	13.56	-1.93	14.49	17.95	3.45	17.59	15.32	-2.28	16.43	19.97	3.54

Source: Authors' calculation on EU LFS data 2019 and 2020.

Note: The Bibby components may range between 0 and 1, whereas the Bartholomew components have the same lower bound, but the upper bound may exceed 1 (with 0 maximum immobility). The sum of the upward and the downward component for each index sum to the overall value of the relative index. All the indices are here expressed between 0 and 100.

The downward mobility drives the overall mobility. Upward mobility either decreases or increases less than the downward mobility[40]. The downward component of the Bibby and

[40] This implies that, in relative terms, there are more employees that are worsening their position comparing to those that are improving. Again, it is recalled that in the former group the first quintile is excluded whereas in the latter the fifth quintile is excluded.

Bartholomew indices is higher in 2020, compared to 2019, in Denmark, Estonia, Greece, Ireland, Italy and Portugal (with the only exception of Ireland in the Bibby). The upward components of the two indices are higher in 2020 compared to 2019 in Greece, Ireland, and Italy, (but the increases are always more moderate than those ones in the downward mobility) in both cases, these results can be read as a form o progressivity of the cushioning measures.

Considering, even more in-depth, the dynamics of the individual quintiles in more depth, it can be concluded that the patterns[41] of the first and the fifth quintiles point to the progressive design of the measures.

Table 7. Transition matrices, 2019 and 2020

DENMARK (DK)											
	From Q_t to Q_{t+1} 2019						From Q_t to Q_{t+1} 2020				
Quintiles	1	2	3	4	5	Quintiles	1	2	3	4	5
1	**0.81**	0.13	0.03	0.02	0.01	1	**0.80**	0.13	0.03	0.02	0.01
2	0.09	**0.62**	0.21	0.05	0.03	2	0.13	**0.61**	0.19	0.06	0.02
3	0.03	0.17	**0.56**	0.20	0.04	3	0.03	0.18	**0.58**	0.16	0.04
4	0.02	0.04	0.16	**0.61**	0.17	4	0.01	0.04	0.16	**0.63**	0.15
5	0.01	0.02	0.03	0.14	**0.80**	5	0.01	0.02	0.04	0.15	**0.78**
ESTONIA (EE)											
	From Q_t to Q_{t+1} 2019						From Q_t to Q_{t+1} 2020				
Quintiles	1	2	3	4	5	Quintiles	1	2	3	4	5
1	**0.72**	0.19	0.05	0.03	0.02	1	**0.69**	0.19	0.05	0.03	0.03
2	0.19	**0.57**	0.16	0.06	0.02	2	0.19	**0.55**	0.19	0.05	0.02
3	0.05	0.18	**0.48**	0.24	0.05	3	0.06	0.20	**0.51**	0.19	0.04
4	0.04	0.05	0.20	**0.54**	0.17	4	0.02	0.06	0.25	**0.52**	0.15
5	0.02	0.02	0.05	0.14	**0.78**	5	0.03	0.02	0.07	0.19	**0.69**
GREECE (EL)											
	From Q_t to Q_{t+1} 2019						From Q_t to Q_{t+1} 2020				
Quintiles	1	2	3	4	5	Quintiles	1	2	3	4	5
1	**0.95**	0.03	0.01	0.00	0.00	1	**0.82**	0.15	0.02	0.00	0.00
2	0.01	**0.95**	0.03	0.01	0.00	2	0.08	**0.88**	0.02	0.01	0.00
3	0.00	0.01	**0.97**	0.01	0.01	3	0.04	0.29	**0.65**	0.01	0.01
4	0.00	0.01	0.01	**0.95**	0.04	4	0.01	0.01	0.05	**0.91**	0.02
5	0.00	0.01	0.01	0.01	**0.97**	5	0.00	0.01	0.01	0.03	**0.96**
IRELAND (IE)											
	From Q_t to Q_{t+1} 2019						From Q_t to Q_{t+1} 2020				
Quintiles	1	2	3	4	5	Quintiles	1	2	3	4	5
1	**0.93**	0.04	0.02	0.01	0.00	1	**0.91**	0.06	0.02	0.01	0.00
2	0.06	**0.85**	0.07	0.02	0.01	2	0.05	**0.84**	0.08	0.02	0.01
3	0.01	0.10	**0.82**	0.06	0.01	3	0.01	0.03	**0.85**	0.09	0.02
4	0.01	0.01	0.09	**0.83**	0.06	4	0.01	0.01	0.07	**0.86**	0.05
5	0.00	0.00	0.01	0.08	**0.91**	5	0.01	0.01	0.02	0.10	**0.86**
ITALY (IT)											
	From Q_t to Q_{t+1} 2019						From Q_t to Q_{t+1} 2020				
Quintiles	1	2	3	4	5	Quintiles	1	2	3	4	5
1	**0.76**	0.16	0.05	0.03	0.01	1	**0.71**	0.17	0.06	0.04	0.02
2	0.14	**0.57**	0.19	0.07	0.03	2	0.18	**0.51**	0.19	0.08	0.04
3	0.04	0.18	**0.52**	0.20	0.07	3	0.06	0.21	**0.46**	0.20	0.07
4	0.02	0.07	0.19	**0.53**	0.18	4	0.03	0.08	0.20	**0.50**	0.19
5	0.01	0.03	0.06	0.15	**0.75**	5	0.01	0.04	0.07	0.17	**0.72**

[41] By pattern here is meant the way the proportion of employees is distributed in a specific quintile. A better pattern means that the proportion of those improving is increasing compared to a benchmark year, while a worsening pattern means that the proportion of those worsening is increasing compared to a benchmark year.

PORTUGAL (PT)											
	From Q_t to Q_{t+1} 2019						From Q_t to Q_{t+1} 2020				
Quintiles	1	2	3	4	5	Quintiles	1	2	3	4	5
1	**0.63**	0.30	0.05	0.01	0.00	1	**0.66**	0.28	0.05	0.01	0.00
2	0.26	**0.57**	0.15	0.02	0.00	2	0.30	**0.54**	0.14	0.01	0.00
3	0.05	0.16	**0.67**	0.12	0.00	3	0.06	0.19	**0.67**	0.08	0.00
4	0.01	0.02	0.13	**0.73**	0.12	4	0.01	0.01	0.17	**0.71**	0.10
5	0.00	0.00	0.01	0.10	**0.89**	5	0.00	0.00	0.00	0.15	**0.85**

Source: Authors' elaboration based on Eurostat EU LFS data 2019 and 2020.

More specifically:

- **The mobility of the first quintile in 2020 shows the same or a better pattern in all the Member States considered when compared to the one recorded in 2019.** In Denmark, the pattern is very similar while it is better in the remaining countries (Estonia, Greece, Ireland, and Italy). The only exception is Portugal where the pattern of the first quintile is worse (see the first row of each transition matrix in **Table 7**).
- **The mobility of the fifth quintile in 2020 shows a worse pattern in all the Member States considered when compared to the one recorded in 2019.** In this case, there are no exceptions.
- In terms of magnitude in the 2019-2020 difference, the Member States rank in the following order: The proportion of upward movers is highest in Greece, followed by Italy, Ireland and Estonia. While the proportion of downward movers is highest in Estonia, followed by Ireland, Portugal, Italy, and Greece. These results are in line with those proposed by Christl et al. (02/2021, cfr. Page 10, Table 2) which show the net loss in terms of disposable income. The authors highlight that the loss of the first quintile is always lower than the loss of the fifth quintile and they interpret these results as a sign of the regressive nature of the discretionary public policy measures applied, especially of the monetary compensation schemes. While the ranking found here is not always exactly the same (possibly due to the different samples considered, as they refer to household income) the size of the difference between the proportion of upward movers in the first quintile and the proportion reflects the differences in disposable income losses of Christl et al. (cfr. 02/2021, Page 10, Table 2)
- **The pattern of the third quintile tends to show the following recurrent patterns: The proportion of downward movers tends to be higher in 2020 compared to 2019 across the Member States considered. This may be the result of the specific design of the measures (*inter alia* the rate of wage replacement, as well as the presence of 'caps' to the level of wage replaced)[42].** In Denmark, which is the most stable, the proportion of upward movers

[42] For example, in Italy, is generally said that 80 % of the gross salary is covered, nevertheless the coverage is capped, implying that, de facto, the replacement rate may be substantially below 80 % for most workers. Indeed, the 'Cassa Integrazione Guadagni' ('in deroga'), that, in the explanation of Ceriani et al. (2020, p. 29), is a wage supplementation scheme 'for softening the impact of economic cycles on the labour market, allowing firms to keep their full workforce, who can work shorter hours while waiting for better economic conditions' in 2020, has

outweighs the proportion of downward movers in 2019, whereas the proportion of upward movers perfectly balances the proportion of upward movers in 2020. A common element across the other Member States is that the proportion of downward movers in the third quintile recorded in 2020 is always higher than the one recorded in 2019 (except for Ireland). Looking at the third row of each couple of transition matrices by country this is clearly visible for Estonia, Italy and Portugal. It is more evident in Greece where, while in 2019 there was almost perfect immobility in the third quintile, in 2020, the downward movers' proportion increased (29 % and 4 % of the third quintile ending up in the second and first one respectively).

- **As regards the second quintile is concerned the results are mixed and, overall, the proportion of upward movers is not that different when comparing 2020 and 2019.** In Estonia, Ireland and Italy there is a slight increase in the proportion of the upward movers. The remaining countries register a slight decrease.
- **As regards the fourth quartile the proportion of downward movers tends to be higher in 2020 compared to 2019.** This is the case for Estonia, Italy, Portugal, and Greece, Denmark stays stable, and in Ireland the proportion of downward movers is slightly lower.

3.3 Income mobility by individual characteristics

As far as breakdowns are concerned, three basic demographic individual characteristics are considered, – gender, age, and level of education.

The proportion of women worsening their relative position is higher compared to that of men, possibly because, during the pandemic, they were more concentrated in the most affected productive sectors. Comparing 2020 with 2019, this conclusion is not immediate if one refers to the overall mobility. Indeed the overall mobility for women is higher only in Ireland (see **Table A.2 4** in Annex 2). Nevertheless, more in-depth scrutiny suggests that the proportion of women belonging to the group of downward movers is always higher compared to that of the previous year and compared to that of men. See Bibby and Bartholomew downward indices) for Estonia, Greece, marginally Ireland, Italy and marginally Portugal in **Table A.2 2**, **Table A.2 3**, **Table A.2 5**, **Table A.2 6** in Annex 2). The only exception is for Denmark, where males have marginally worsened their relative position (see **Table A.2 1** in Annex 2).

Younger employees (16-29) record higher mobility compared to employees belonging to other age classes (30-54 and 55-74). While this may be an expected outcome even in a benchmark year, during the pandemic period it is even more pronounced, possibly because younger people have less stable contracts or lower degree of seniority and, are thus, possibly not fully covered by the cushioning measures. Member States are heterogeneous: comparing 2020 and 2019, while overall mobility is higher for 16-29 year olds for all the Member States, in Greece, Italy, and Portugal it can be seen that this is driven by the downward mobility (see **Table A.2 3**, **Table**

a threshold of EUR 2 159. Income below the threshold can be compensated to a maximum of EUR 939, while incomes above the threshold can be compensated to a maximum of EUR 1 129.

A.2 5 and Table A.2 6 in Annex 2) while in Ireland the proportion of younger people improving their relative position is higher (than those in other age groups and the one recorded in 2019), possibly because of targeted measures. In Estonia, not only the youngest but also those aged 55-74 are in the group of those worsening their relative position (see Table A.2 2). In Denmark changes are marginal, but they are also higher for the group of downward movers (see Table A.2 1 in Annex 2).

Employees without tertiary education (ISCED 0-5) show more mobility compared to those with tertiary education (ISCED 6-8). While this may be an expected outcome in a benchmark year, during the pandemic it is even more pronounced, as employees without tertiary education may be in occupations where the degree of remote working is lower. In all the Member States, to a different extent, the highest mobility recorded in 2020 compared to 2019, is always due to the proportion of downward movers increasing (see Table A.2 1, Table A.2 2, Table A.2 3, Table A.2 *4*, Table A.2 5, Table A.2 6 in Annex 2).

4. Conclusion and further development of research

This study, using the LFS 2020 data, employs transition matrices and a selection of relative mobility indices to offer a detailed description of employees' income distribution in the first year of the COVID-19 pandemic. These empirical tools give detailed information on the direction and the extent to which employees move across classes of income. A comparison with a benchmark year (2019) gives insight into how important mobility is. Furthermore, the analysis of the transitions of the individuals across each quintile allows conclusions to be drawn on the effect of the pandemic shock and the cushioning measures addressed to employees, in terms of income improvement or deterioration, hence on the progressivity (if any) of the policy response measures.

As expected, we find that inter-quintile income mobility in 2020 is higher than in 2019 (and even more than in 2018) in all countries under consideration, except for Denmark. For most of the countries concerned, it is even higher than in the specific years of the sovereign debt crisis. This can be explained by the fact that the shock was very abrupt and concentrated in one year.

Based on the transition matrices, comparing 2020 with the 2019 benchmark year we find a similar or better pattern for those belonging to the first quintile (lowest income class) and a similar pattern for the upward movers of the second quintile. By contrast, data suggest a worsened pattern for the downward movers of the third, the fourth, and the fifth quintiles. It is assumed that it is unlikely to observe an improvement in the income distribution of the lowest classes of income during the pandemic. Because of this, such upward mobility in the first quintile, (and to a certain extent in the second quartile) compared to the benchmark year, is explained by measures targeted at the poorest part of the distribution. The highest mobility (downward in the remaining classes) is likely to be a mix of the 'pure' pandemic-crisis effect and the fact that the cushioning measures are not designed to benefit these latter classes. Interestingly, this is also the case for the third quintile and, to a certain extent the second,

where possibly the broadest part of the population in absolute terms is concentrated. These results are broadly in line with the existing literature.

Some limits of this analysis concern the country and the time coverage. These issues may be partially addressed when the 2021 data of LFS will be available. This availability will also allow a continuous income variable rather than an ordinal one to be studied. Furthermore, individual or cross-country analysis may be performed starting from the national LFS that already embeds this type of information (for example Carta and De Philippis, 2021, used LFS for a microsimulation exercise in Italy). As frequently stated, this study addresses a very specific group, – employees – which might be considered a limitation. Nevertheless, in future research it is also possible to extend the analysis to a sample including self-employers, exploiting imputation techniques (as in Carta, 2020). Results would be probably different as it is known that this group compared to that of employees, has been hit harder by the COVID-19-induced crisis (whether or not the cushioning measures are considered). Methodologically, there may be improvements also in the construction of indices of mobility by referring to a 'Bartholomew-type' of indicators, with adding a normalisation/decomposition procedure as the one suggested in Paul (2020).

From a policy perspective, the question of whether the cushioning measures were able to counteract the regressive nature of the shock, should be answered by considering a longer period than the one we cover, including 2021. COVID-19 was an extraordinary event and the measures designed were applied over a limited time frame, JRS measures were phased out in most countries by the end of 2021. Yet, there is little doubt that the pandemic left the labour market strongly changed, and changes, of structural nature, in the income distribution, may emerge soon.

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Annex 1. Methodology details

Table A.1 1 LFS selected variables, codes, definitions and notes.

Code	Definition and notes
INCDECIL[43]	Monthly (take-home) pay from the main job The variable is relative exclusively to employees (i.e. self-employed and family workers are excluded). The variable is considered compulsory starting in 2009, nevertheless, the Member States are allowed a delay in the transmission of the variable up to 21 months when administrative data are used for its compilation. INCDECIL is constructed starting from a question asking to the employee either to declare his/her precise income (and then the income is imputed to a specific class) or to indicate the income class (decile) he/she belongs to and that is presented by the interviewer. Thus the final variable INCDECIL is, indeed an ordinal one ranging from 1 to 10 where 1 is the lowest decile and 10 is the highest decile. For example, in Italy 2018, 2019 and 2020, the ten classes of monthly take-home pay from the main job were: i) less than 500; ii) from 500 to 799; iii) from 800 to 950; iv) From 951 to 1.050; v) from 1.051 to 1.200; vi) from 1.201 to 1.400; vi) from 1.401 to 1.700, viii) from 1.701 to 2.000; ix) 2.001 to 3.000; more than 3.000. INCDECIL data may suffer from cross-country comparability issues, but for the selected Member States here considered it seems not to be the case. For specific national definitions of the income used to construct the INCDECIL variable the questionnaires of the individual Member States can be consulted at the following documentation page: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_labour_force_survey_-_documentation#Core_questionnaires Note 1: In this exercise, the deciles have been merged into quintiles to make the analysis smoother. Note 2: From 2021 Q1 it will be available the variable INCGROSS (Gross monthly pay from the main job) will be expressed in Euro (see Eurostat, 2021b).
SEX	Gender (males and females)
AGE	There are 20 age groups ranging from 0 y.o. to 95 and older. Note: In this exercise, are exclude a priori those belonging to age groups 2 (0-4 y.o.), 7 (5-9 y.o.), 12 (10-14 y.o.), 77 (75-79 y.o.), 82 (80-84 y.o.), 87 (85-89 y.o.), 92 (90-94 y.o.), 97 (95 years of age and older). Breakdown in three groups: 16-29, 30-54 and 55-74. As it can be the case that the individual during the year changes the age group he/she belong, the group observed in the first period is considered.

[43] "Purpose: To measure the effects of individual (sex, age) and labour market characteristics (professional status, occupation, activity) on monthly income. Definition: The monthly (take-home) pay is the pay after (provisional, subject to revision later) deduction of income tax and National Insurance Contributions. It includes regular overtime, extra compensation for shift work, seniority bonuses, regular travel allowances and per diem allowances, tips and commission, compensation for meals.

Implementation rules: i) Data should refer to the last monthly pay received before the reference week. In case the person has started a new job it should be the present month; ii) Income from investments – assets, savings, stocks and shares should not be included in monthly wages and salaries; iii) Holiday bonuses (13th and/or 14th month) and fringe benefits should be considered dividing their amount by 12; iv) If the job is an occasional job for a short period, the amount should be an estimate of the total earnings from all similar jobs in that month; v) The first decile (code 01) should refer to people with lowest wages, the 10th (code 10) should refer to people with highest wages; vi) In case of collection of exact salary, the deciles should be calculated and provided once data for the whole year are collected, checked, and corrected from the non-response; vii) In case of collection of data by earning bands, member states should define these earning bands based on deciles using other statistical sources on wages (e.g. Structural Earnings Surveys)". Eurostat, 2016, p. 139. In Eurostat (2016) are also suggested some good practices for the collection of this variable.

HAT11LEV	Highest educational attainment level (ISCED 11) In LFS there are 12 ISCED level breakdowns: 0 Early childhood education ('less than primary' for educational attainment); 100 ISCED 1 primary education; 200 ISCED 2 (incl. ISCED 3 programmes of duration of less than 2 years) lower secondary education; 300 ISCED 3 programme of duration of 2 years and more without possible distinction of access to other ISCED levels; 302 ISCED 3 programme of duration of 2 years and more sequential (i.e. access to next ISCED 3 programme only); 303 ISCED 3 programme of duration of 2 years and more terminal or giving access to ISCED 4 only; 304 ISCED 3 with access to ISCED 5 6 or 7; 400 ISCED 4 – post secondary non-tertiary education; 500 ISCED 5 – short-cycle tertiary education; 600 ISCED 6 – bachelor's or equivalent level; 700 ISCED 7 – master's or equivalent level; 800 ISCED 8 – doctoral or equivalent level. Note: In this study, the level of education is divided in two groups: ISCED 0-5 and ISCED 6-8. As it can be the case that the individual during the year changes the ISCED group he/she belong, the group observed in the first period is considered.
STAPRO	Professional Status (0 Self-employed with or without employees, 3 Employee, 4 Family workers, 9 Not applicable). Note: Among the different types of workers the variable INCDECIL is recorded only for Employees, thus the classes under 0 and 4 are non considered. Nevertheless, for some of the Member States considered there are many missing values in INCDECIL even when STAPRO = 3
HHNUM HHSEQNUM QHHNUM	Serial number of the household Sequence number in the household Serial number of households in each quarter Note 1: These variables have been used to create both a unique identifier to trace the same individual across the various quarters in the same year and an additional variable to identify the specific quarter in which the observation was collected. Note 2: From 2021 on, LFS will include a new variable (Eurostat 2021b) IDENT ('identifier should be unique for a person across datasets. It is assigned to a person the first time he/she joins the LFS sample. It should be independent from the household the person belongs to, so that if the person changes household, the IDENT identifier won't change'). The variable will allows following/tracking the individual respondents across reference quarters, reference years, and across the different LFS databases. In addition to HHNUM and HHSEQNUM, this variable should allow countries to send unique national identifiers which can be used for longitudinal checks and analyses.

Table A.1 2 Availability of INCDECIL variable and the maximum number of observations for the same individual in the yearly LFS files, 2009, 2010, 2011, 2012, 2018, 2019, and, 2020.

	INCDECIL variable available							Maximum number of individual observation in yearly dataset						
	2009	2010	2011	2012	2018	2019	2020	2009	2010	2011	2012	2018	2019	2020
DK	yes	yes	yes	yes	yes	yes	yes	4	4	4	4	4	4	4
EE	yes	yes	yes	yes	yes	yes	yes	2	2	2	2	2	2	2
EL	yes	yes	yes	yes	yes	yes	yes	4	4	4	4	4	4	4
IE	yes	yes	yes	yes	yes	yes	yes	4	4	4	4	4	4	4
IT	yes	yes	yes	yes	yes	yes	yes	3	2	2	2	2	2	2
PT	yes	yes	yes	yes	yes	yes	yes	4	4	4	4	4	4	4

Source: Authors' description and calculation on LFS data, 2009-2012 and 2018-2020.

As shown in Table A.1 2, among the selected ones, there are two Member States (Estonia and Italy) for which the maximum number of observations is two, whereas there are Denmark, Greece, Ireland and Portugal for which the maximum number of observation is four.

Table A.1 3 Structure of the observations collected for the same individual in a specific year.

Groups with a maximum of two observations per individual or groups with two observations in an MS with a maximum of four observations						
Observations in	Q1 and Q2	Q1 and Q3	Q1 and Q4	Q2 and Q3	Q2 and Q4	Q3 and Q4
Groups with three observations per individual in an MS with a maximum of four observations per individual						
Observations in	Q1, Q2 and Q3		Q1, Q2 and Q4	Q1, Q2 and Q3		Q2, Q3 and Q4
Groups with a maximum of four observations per individual						
Observations in	Q1, Q2, Q3 and Q4					

Source: Authors' description based on LSF data.

- For the Members States whose maximum number of observation for the same individual is two, six subgroups are identifiable and mutually exclusive (namely the individuals belonging to one subgroup does not belong to another subgroup). There are those replying in i) Q1 and Q2; ii) Q1 and Q3; iii) Q1 and Q4; iv) Q2 and Q3; v) Q2 and Q4; vi) Q3 and Q4 (see Table A.1 3 first row).
- For the Member States whose maximum number of observations for the same individual is four, there are also groups with three and two observations (as four is, indeed the maximum, but not also the minimum). So in these case we have a more complicated structure that sees:
  - The group with a maximum number of two observations (see Table A.1 3 first row) include six mutually exclusive subgroups (namely the individuals belonging to one subgroup does not belong to another subgroup). There are for which the observation is available in i) Q1 and Q2; ii) Q1 and Q3; iii) Q1 and Q4; iv) Q2 and Q3; v) Q2 and Q4; vi) Q3 and Q4.
  - The group with a maximum number of three observations (see Table A.1 3 second row) includes four mutually exclusive subgroups (namely the individuals belonging to one subgroup does not belong to another subgroup). There are those for which the observation is available in i) Q1, Q2 and Q3; ii) Q1, Q2 and Q4; iii) Q1, Q3 and Q4; iv) Q2, Q3 and Q4.
  - The group with a maximum number of four observations is only one with observations in Q1, Q2, Q3 and Q4. (see Table A.1 3 third row).

In this exercise it has been decided, within every single year, to refer to a generic transition between Q_t and Q_{t+1} when constructing the transition matrices. It is acknowledged the importance of a specific couple of quarters, as the timing of lockdowns and of the cushioning measures present a certain degree of heterogeneity. Nevertheless, in general, taking into account the specific couples of quarters would have generated a large amount of transition matrices, and complicated the analysis, especially for the Member States with a maximum of four observations (that, as said, includes also the groups with only two or three observations). For this reason, the observations captured in some quarters (and some other quarters) have been considered as collected in the generic quarters Q_t and Q_{t+1} according to the criteria shown in Table A.1 4.

Table A.1 4 Structure of the observation of the observations collected for the same individual in a specific year and transformation of the specific quarters in generic quarters Qt and Qt+1.

Groups with a maximum of two observations per individual or groups with two observations in the MS with a maximum of four observations						
Observations in	Q1 and Q2	Q1 and Q3	Q1 and Q4	Q2 and Q3	Q2 and Q4	Q3 and Q4
Transformation in	$Q1 = Q_t$ $Q2 = Q_{t+1}$	$Q1 = Q_t$ $Q3 = Q_{t+1}$	$Q1 = Q_t$ $Q4 = Q_{t+1}$	$Q2 = Q_t$ $Q3 = Q_{t+1}$	$Q2 = Q_t$ $Q4 = Q_{t+1}$	$Q3 = Q_t$ $Q4 = Q_{t+1}$
Groups with three observations per individual in the MS with a maximum of four observations per individual						
Observations in	Q1, Q2 and Q3		Q1, Q2 and Q4	Q1, Q3 and Q4		Q2, Q3 and Q4
Transformation in	$Q1 = Q_t$ $Q2 = Q_{t+1}$		$Q1 = Q_t$ $Q4 = Q_{t+1}$	$Q3 = Q_t$ $Q4 = Q_{t+1}$		$Q2 = Q_t$ $Q4 = Q_{t+1}$
Groups with a maximum of four observations per individual						
Observations in	Q1, Q2, Q3 and Q4					
Transformation in	$Q1 = Q_t$ $Q4 = Q_{t+1}$					

Source: Authors' description based on LSF data and description of the recording of the individual quarters.

The choice made (among other possible) tend to balance the number of observations across quarters. Of course, the same procedure has been applied in all the years considered. Once having obtained a generic Q_t and Q_{t+1} for each individual, those belonging to the groups of two, three and four have been grouped to give back the sample, which size per each MS, is shown in Table A.1 *5*.

Table A.1 5 Sample size of the employees included in 2, 3 or 4 interviews.

DENMARK*	*2 int*	*3 int*	*4 int*	*2,3, and 4 int*	ESTONIA	*2 int*	*3 int*	*4 int*	*2,3, and 4 int*
2009	17206	0	0	17206	2009	2915	n.a.	n.a.	2915
2010					2010				
2011		*not considered*			2011		*not considered*		
2012					2012				
2018	15300	0	0	15300	2018	4454	n.a.	n.a.	4454
2019	13297	0	0	13297	2019	4509	n.a.	n.a.	4509
2020	14813	0	0	14813	2020	4810	n.a.	n.a.	4810
GREECE*	***2 int***	***3 int***	***4 int***	***2,3, and 4 int***	**IRELAND***	***2 int***	***3 int***	***4 int***	***2,3, and 4 int***
2009	5174	5012	7108	17294	2009	3459	2658	1255	7372
2010	4839	4931	6912	16682	2010		*not considered*		
2011	4544	4121	4683	13348	2011	2453	1841	953	5247
2012		*not considered*			2012		*not considered*		
2018	3233	2936	4543	10712	2018	2772	1506	194	4472
2019	3636	3304	4541	11481	2019	3055	1721	708	5484
2020	5583	1877	3547	11007	2020	2564	1450	554	4568
ITALY	***2 int***	***3 int***	***4 int***	***2,3, and 4 int***	**PORTUGAL***	***2 int***	***3 int***	***4 int***	***2,3, and 4 int***
2009	62495	n.a.	n.a.	62495	2009	414	610	1507	2531
2010		*not considered*			2010		*not considered*		
2011					2011	4432	3865	3118	11415
2012	55770	n.a.	n.a.	55770	2012		*not considered*		
2018	57972	n.a.	n.a.	57972	2018	4733	4039	4052	12824
2019	57433	n.a.	n.a.	57433	2019	4350	3863	3795	12008
2020	50072	n.a.	n.a.	50072	2020	3500	2906	3250	9656

Source: Authors' computation based on LSF data 2009-2020.

Note: n.a. stays for not available as it can be the case that for some Member States even when the STAPRO variable equals 3 (employee) the INCDECIL value is missing (see also Table A.1 1). 'Not considered' reflects, instead, the year selected/not selected as a better representative of the sovereign debt crisis.

Annex 2. Mobility indices for breakdowns: gender, age and level of education

Table A.2 1. Mobility indices for breakdowns: gender, age and level of education, 2019, 2020 and percentage points 2019-2020, Denmark.

DENMARK

	Immobility Ratio			Bibby Index		
Employees	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	68.1	68.2	0.12	31.9	31.8	-0.12
Males	64.6	65.4	0.85	35.4	34.6	-0.85
Females	70.2	70.1	-0.17	29.8	29.9	0.17
Aged 15 to 29	59.6	58.3	-1.33	40.4	41.7	1.33
Aged 30 to 54	65.0	65.2	0.20	35.0	34.8	-0.20
Aged 55 to 74	68.5	69.2	0.70	31.5	30.8	-0.70
Lower education	65.7	64.8	-0.92	34.3	35.2	0.92
Higher education	66.0	66.8	0.78	34.0	33.2	-0.78
	Bartholomew Index			Mobility Index, by Paul (2020)		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	40.85	40.90	0.05	12.79	12.83	0.03
Males	47.75	46.09	-1.65	15.53	14.85	-0.68
Females	36.15	37.08	0.93	10.79	11.28	0.48
Aged 15 to 29	57.12	57.67	0.55	14.22	14.70	0.48
Aged 30 to 54	46.67	47.61	0.93	16.09	16.61	0.52
Aged 55 to 74	40.77	39.87	-0.90	13.18	12.70	-0.48
Lower education	45.21	46.62	1.40	12.90	12.96	0.07
Higher education	44.31	45.64	1.33	15.85	16.72	0.88
	Bibby upward component			Bibby downward component		
Employees	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	17.86	16.32	-1.54	14.07	15.49	1.42
Males	20.89	18.30	-2.59	14.55	16.30	1.75
Females	15.50	14.72	-0.77	14.28	15.22	0.94
Aged 15 to 29	13.60	13.35	-0.25	26.81	28.40	1.58
Aged 30 to 54	22.25	20.97	-1.28	12.73	13.81	1.08
Aged 55 to 74	18.31	15.84	-2.47	13.24	15.01	1.77
Lower education	16.20	14.82	-1.39	18.12	20.43	2.31
Higher education	23.36	21.31	-2.05	10.60	11.87	1.27
	Bartholomew upward component			Bartholomew downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	22.74	21.36	-1.38	18.11	19.55	1.43
Males	28.54	25.18	-3.36	19.21	20.92	1.71
Females	18.35	18.36	0.01	17.80	18.72	0.92
Aged 15 to 29	17.03	16.96	-0.07	40.10	40.71	0.61
Aged 30 to 54	30.41	30.05	-0.36	16.26	17.56	1.29
Aged 55 to 74	23.78	21.22	-2.55	16.99	18.64	1.65
Lower education	20.50	18.92	-1.58	24.72	27.70	2.98
Higher education	31.30	31.40	0.11	13.01	14.24	1.23

Source: Authors' elaboration based on Eurostat EU LFS data 2019 and 2020.

Table A.2 2. Mobility indices for breakdowns: gender, age and level of education, 2019, 2020 and percentage points 2019-2020, Estonia.

ESTONIA

	Immobility Ratio			Bibby Index		
Employees	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	61.8	59.4	-2.40	38.2	40.6	2.40
Males	58.2	57.8	-0.40	41.8	42.2	0.40
Females	63.7	60.0	-3.67	36.3	40.0	3.67
Aged 15 to 29	61.8	55.2	-6.63	38.2	44.8	6.63
Aged 30 to 54	60.9	58.4	-2.47	39.1	41.6	2.47
Aged 55 to 74	61.0	60.5	-0.50	39.0	39.5	0.50
Lower education	59.7	57.4	-2.29	40.3	42.6	2.29
Higher education	63.1	59.6	-3.46	36.9	40.4	3.46
	Bartholomew Index			Mobility Index, by Paul (2020)		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	50.26	54.69	4.43	15.93	17.07	1.14
Males	58.40	58.00	-0.40	19.70	18.80	-0.91
Females	46.18	53.70	7.51	13.96	16.30	2.33
Aged 15 to 29	51.84	61.19	9.34	15.80	20.07	4.27
Aged 30 to 54	51.63	56.99	5.36	17.08	18.64	1.56
Aged 55 to 74	51.05	54.35	3.30	15.08	14.81	-0.27
Lower education	53.96	57.24	3.28	16.24	16.73	0.49
Higher education	48.84	56.39	7.55	16.18	19.06	2.88
	Bibby upward component			Bibby downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	19.56	18.92	-0.64	18.65	21.68	3.03
Males	23.40	22.05	-1.35	18.44	20.19	1.76
Females	17.11	16.66	-0.46	19.22	23.35	4.13
Aged 15 to 29	19.73	20.18	0.45	18.44	24.62	6.18
Aged 30 to 54	22.12	21.40	-0.72	17.00	20.19	3.19
Aged 55 to 74	15.68	14.58	-1.10	23.36	24.96	1.60
Lower education	18.62	17.48	-1.14	21.65	25.09	3.43
Higher education	21.19	21.99	0.80	15.72	18.38	2.66
	Bartholomew upward component			Bartholomew downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	25.49	25.89	0.40	24.76	28.80	4.03
Males	33.86	31.27	-2.60	24.54	26.74	2.20
Females	20.67	22.48	1.81	25.51	31.22	5.70
Aged 15 to 29	25.47	29.33	3.86	26.37	31.86	5.49
Aged 30 to 54	29.24	30.62	1.38	22.39	26.37	3.98
Aged 55 to 74	20.19	18.09	-2.10	30.86	36.26	5.40
Lower education	23.85	22.99	-0.86	30.11	34.25	4.14
Higher education	28.72	32.37	3.65	20.12	24.02	3.90

Source: Authors' elaboration based on Eurostat EU LFS data 2019 and 2020.

Table A.2 3. Mobility indices for breakdowns: gender, age and level of education, 2019, 2020 and percentage points 2019-2020, Greece.

GREECE

	Immobility Ratio			Bibby Index		
Employees	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	95.8	84.6	-11.22	4.2	15.4	11.22
Males	95.2	84.4	-10.85	4.8	15.6	10.85
Females	96.3	84.6	-11.71	3.7	15.4	11.71
Aged 15 to 29	93.2	79.0	-14.18	6.8	21.0	14.18
Aged 30 to 54	95.8	84.4	-11.31	4.2	15.6	11.31
Aged 55 to 74	95.9	86.3	-9.60	4.1	13.7	9.60
Lower education	95.1	83.0	-12.10	4.9	17.0	12.10
Higher education	96.2	85.4	-10.82	3.8	14.6	10.82
	Bartholomew Index			Mobility Index, by Paul (2020)		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	5.67	18.41	12.74	1.81	6.36	4.55
Males	6.43	18.89	12.46	2.24	6.58	4.34
Females	5.21	18.10	12.89	1.48	6.23	4.75
Aged 15 to 29	13.52	29.28	15.76	2.69	8.29	5.59
Aged 30 to 54	5.69	18.65	12.96	1.85	6.45	4.59
Aged 55 to 74	5.17	16.28	11.11	1.88	5.83	3.95
Lower education	7.33	21.39	14.05	1.99	6.69	4.70
Higher education	4.95	17.20	12.25	1.78	6.51	4.73
	Bibby upward component			Bibby downward component		
Employees	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	2.93	5.00	2.06	1.24	10.39	9.16
Males	3.68	5.70	2.02	1.12	9.95	8.83
Females	2.26	4.45	2.19	1.42	10.94	9.52
Aged 15 to 29	2.24	4.25	2.01	4.55	16.71	12.17
Aged 30 to 54	3.05	5.23	2.18	1.19	10.33	9.13
Aged 55 to 74	3.27	4.61	1.33	0.81	9.08	8.27
Lower education	2.94	4.68	1.74	1.98	12.34	10.36
Higher education	3.03	5.94	2.91	0.78	8.69	7.91
	Bartholomew upward component			Bartholomew downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	3.66	6.09	2.43	2.01	12.32	10.31
Males	4.74	6.87	2.13	1.69	12.01	10.33
Females	2.70	5.45	2.75	2.51	12.65	10.14
Aged 15 to 29	2.89	4.81	1.92	10.63	24.47	13.84
Aged 30 to 54	3.81	6.40	2.59	1.88	12.25	10.37
Aged 55 to 74	4.08	6.05	1.97	1.09	10.23	9.14
Lower education	3.65	5.63	1.98	3.69	15.76	12.07
Higher education	3.87	7.51	3.64	1.08	9.69	8.61

Source: Authors' elaboration based on Eurostat EU LFS data 2019 and 2020.

Table A.2 4. Mobility indices for breakdowns: gender, age and level of education, 2019, 2020 and percentage points 2019-2020, Ireland

IRELAND

	Immobility Ratio			Bibby Index		
Employees	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	86.9	86.7	-0.19	13.1	13.3	0.19
Males	86.3	87.8	1.48	13.7	12.2	-1.48
Females	86.3	85.1	-1.27	13.7	14.9	1.27
Aged 15 to 29	86.1	80.2	-5.89	13.9	19.8	5.89
Aged 30 to 54	87.0	86.8	-0.16	13.0	13.2	0.16
Aged 55 to 74	86.6	86.6	-0.02	13.4	13.4	0.02
Lower education	86.1	85.4	-0.66	13.9	14.6	0.66
Higher education	86.2	85.9	-0.29	13.8	14.1	0.29
	Bartholomew Index			Mobility Index, by Paul (2020)		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	15.74	16.81	1.07	4.90	5.08	0.18
Males	17.47	16.84	-0.63	6.06	5.48	-0.57
Females	16.20	18.23	2.02	4.69	5.16	0.47
Aged 15 to 29	16.50	24.76	8.27	4.70	6.35	1.65
Aged 30 to 54	15.72	17.48	1.76	4.94	5.60	0.66
Aged 55 to 74	16.26	15.51	-0.75	4.99	4.23	-0.76
Lower education	16.54	19.14	2.60	4.68	4.98	0.30
Higher education	18.10	18.25	0.15	6.22	5.86	-0.37
	Bibby upward component			Bibby downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	5.79	7.02	1.23	7.32	6.28	-1.04
Males	8.03	7.36	-0.67	5.69	4.88	-0.81
Females	4.91	6.88	1.98	8.76	8.05	-0.71
Aged 15 to 29	3.87	10.07	6.20	10.06	9.76	-0.31
Aged 30 to 54	6.33	7.61	1.27	6.72	5.60	-1.11
Aged 55 to 74	5.03	5.29	0.26	8.37	8.13	-0.24
Lower education	4.84	5.36	0.52	9.09	9.23	0.14
Higher education	7.40	8.92	1.53	6.43	5.19	-1.24
	Bartholomew upward component			Bartholomew downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	7.36	8.91	1.55	8.38	7.91	-0.47
Males	11.11	10.48	-0.63	6.36	6.35	0.00
Females	5.96	8.35	2.39	10.25	9.88	-0.37
Aged 15 to 29	4.93	11.46	6.54	11.57	13.30	1.73
Aged 30 to 54	8.09	10.18	2.09	7.62	7.30	-0.33
Aged 55 to 74	6.30	6.27	-0.03	9.96	9.25	-0.72
Lower education	5.70	6.67	0.97	10.84	12.47	1.63
Higher education	10.79	11.80	1.00	7.31	6.46	-0.85

Source: Authors' elaboration based on Eurostat EU LFS data 2019 and 2020.

Table A.2 5. Mobility indices for breakdowns: gender, age and level of education, 2019, 2020 and percentage points 2019-2020, Italy.

ITALY

	Immobility Ratio			Bibby Index		
Employees	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	62.6	57.9	-4.75	37.4	42.1	4.75
Males	58.9	53.6	-5.24	41.1	46.4	5.24
Females	64.7	60.0	-4.69	35.3	40.0	4.69
Aged 15 to 29	54.4	49.8	-4.53	45.6	50.2	4.53
Aged 30 to 54	63.0	57.7	-5.28	37.0	42.3	5.28
Aged 55 to 74	63.6	59.8	-3.86	36.4	40.2	3.86
Lower education	61.4	56.4	-5.08	38.6	43.6	5.08
Higher education	62.7	58.3	-4.45	37.3	41.7	4.45
	Bartholomew index			Mobility Index, by Paul (2020)		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	50.07	58.54	8.47	15.50	18.39	2.89
Males	56.86	67.16	10.30	18.90	22.72	3.83
Females	46.83	54.59	7.76	13.77	16.19	2.42
Aged 15 to 29	66.33	74.39	8.06	17.85	20.10	2.25
Aged 30 to 54	49.76	59.19	9.43	15.46	18.63	3.16
Aged 55 to 74	48.26	55.60	7.34	15.07	17.78	2.71
Lower education	51.85	61.31	9.45	15.40	18.42	3.02
Higher education	52.27	59.70	7.44	18.15	21.00	2.84
	Bibby upward component			Bibby downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	19.58	21.28	1.70	17.81	20.86	3.05
Males	24.71	26.50	1.79	16.41	19.86	3.46
Females	15.74	17.70	1.95	19.53	22.27	2.74
Aged 15 to 29	17.25	18.13	0.88	28.37	32.02	3.65
Aged 30 to 54	19.61	21.53	1.92	17.44	20.79	3.36
Aged 55 to 74	20.10	21.77	1.67	16.28	18.46	2.19
Lower education	18.76	20.23	1.46	19.80	23.42	3.62
Higher education	24.02	26.66	2.63	13.27	15.09	1.82
	Bartholomew upward component			Bartholomew downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	26.22	29.87	3.65	23.85	28.67	4.82
Males	34.99	39.93	4.94	21.87	27.23	5.36
Females	20.27	23.63	3.36	26.57	30.96	4.40
Aged 15 to 29	22.33	24.37	2.03	44.00	50.03	6.03
Aged 30 to 54	26.54	30.51	3.98	23.22	28.68	5.46
Aged 55 to 74	27.01	30.93	3.91	21.25	24.67	3.42
Lower education	24.76	28.09	3.34	27.10	33.21	6.11
Higher education	35.31	40.42	5.11	16.96	19.29	2.33

Source: Authors' elaboration based on Eurostat EU LFS data 2019 and 2020.

Table A.2 6. Mobility indices for breakdowns: gender, age and level of education, 2019, 2020 and percentage points 2019-2020, Portugal.

PORTUGAL

	Immobility Ratio			Bibby Index		
Employees	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	70.0	68.5	-1.52	30.0	31.5	1.52
Males	67.2	66.4	-0.83	32.8	33.6	0.83
Females	71.4	69.7	-1.75	28.6	30.3	1.75
Aged 15 to 29	61.8	61.6	-0.16	38.2	38.4	0.16
Aged 30 to 54	69.8	68.3	-1.49	30.2	31.7	1.49
Aged 55 to 74	73.3	70.3	-3.06	26.7	29.7	3.06
Lower education	68.8	66.2	-2.59	31.2	33.8	2.59
Higher education	67.0	68.6	1.67	33.0	31.4	-1.67
	Bartholomew Index			Mobility Index, by Paul (2020		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	34.02	35.29	1.27	12.31	12.38	0.08
Males	38.32	38.23	-0.09	14.34	13.76	-0.58
Females	31.74	33.79	2.05	11.32	11.75	0.43
Aged 15 to 29	45.68	43.00	-2.67	15.06	14.15	-0.91
Aged 30 to 54	34.18	35.73	1.55	12.46	12.47	0.01
Aged 55 to 74	29.43	32.16	2.72	10.45	11.48	1.03
Lower education	35.51	37.94	2.43	12.28	12.65	0.37
Higher education	41.54	37.20	-4.34	16.19	13.81	-2.38
	Bibby upward component			Bibby downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	15.49	13.56	-1.93	14.49	17.95	3.45
Males	18.57	16.20	-2.37	14.19	17.39	3.21
Females	13.94	12.12	-1.82	14.65	18.22	3.57
Aged 15 to 29	18.21	14.61	-3.60	20.01	23.76	3.76
Aged 30 to 54	16.08	14.12	-1.96	14.11	17.56	3.45
Aged 55 to 74	11.83	11.34	-0.48	14.83	18.37	3.54
Lower education	14.21	12.66	-1.55	16.99	21.12	4.13
Higher education	22.83	19.07	-3.76	10.20	12.30	2.10
	Bartholomew upward component			Bartholomew downward component		
	2019	2020	pp 2019-2020	2019	2020	pp 2019-2020
All	17.59	15.32	-2.28	16.43	19.97	3.54
Males	21.99	19.01	-2.98	16.33	19.22	2.89
Females	15.39	13.32	-2.08	16.35	20.47	4.13
Aged 15 to 29	21.05	16.60	-4.44	24.63	26.40	1.77
Aged 30 to 54	18.34	16.00	-2.34	15.83	19.72	3.89
Aged 55 to 74	12.89	12.65	-0.25	16.54	19.51	2.97
Lower education	15.99	14.27	-1.71	19.52	23.67	4.14
Higher education	29.99	23.05	-6.94	11.55	14.15	2.60

Source: Authors' elaboration based on Eurostat EU LFS data 2019 and 2020.