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Abstract

There are several avenues through which COVID-19 lockdowns may have potentially increased well-being inequality in European countries. An important one arises from the differences in the housing conditions with which households faced the lockdown. In this paper, we analyse both the degree of housing deprivation and its inequality in European countries when lockdown measures were enacted. We use a fuzzy set approach to measure housing deprivation so that, unlike traditional deprivation approaches, based on a dichotomous variable, we can identify different degrees of housing deprivation for each household in the population. We find similar orderings of housing deprivation dimensions within each country with the highest degree of deprivation in the living space dimension and the lowest one in the standard housing or technology deprivation dimension. However, considering a general housing deprivation index we find that the effects of the lockdown on social well-being have not affected all Europeans equally: Individuals living in Eastern European countries are significantly more housing deprived than those in other EU countries while housing deprivation among their population is more equally distributed than elsewhere. In contrast, individuals living in Nordic countries suffer less from housing deprivation, but their within-country inequality is relatively large.

JEL codes: I31, I32

Keywords: lockdown, COVID-19, housing deprivation, fuzzy sets

1. INTRODUCTION

The COVID-19 pandemic has caused major welfare losses for society. On the one hand, the hundreds of thousands of deceased people in the world mark a before and after in the evolution of our societies. On the other hand, this health crisis is intrinsically linked to a deep economic crisis. “Stay-at-home” orders at the beginning of the first wave, partial lockdown in subsequent waves –the most standard response to the pandemic –, and the drastic shutdown of economic activities in most countries gave rise to a rapid growth in unemployment and social needs.

According to the World Health Organization’s (WHO) data, at some point in 2020 one third of the world population was in some form of lockdown, with their movements actively restricted and controlled by the government. Even if this has been an almost universal strategy, it has been particularly common in European countries, although with different degrees of intensity across the continent (see Table A.1. in the Appendix 1). Most European countries significantly curbed public life to halt the spread of the COVID-19 outbreak. The resulting shutdown has caused remarkable production losses, reaching dimensions that are well beyond the growth slump of previous recessions in the history of the European Union (OECD, 2020; Dorn *et al.*, 2020).

Inevitably, the economic crisis also translated into a well-being shock (Brodeur *et al.*, 2021) changing inequality and poverty trends in various EU countries (Belot *et al.*, 2020; Clark *et al.*, 2020). Regarding the impact on the earnings distribution, ILO (2020) concludes that low-skilled workers in non-essential jobs were the most negatively affected by enforced social distancing and lockdown measure estimating job losses to be over 200 million, with 40% of the global workforce employed in sectors that face high risk of displacement and with limited access to social protection. Some studies have already advanced the possible effects of lockdown on the distribution of earnings in European Union (EU) countries showing remarkable differences in the impacts within countries depending on job and worker characteristics, and across occupations. Adams-Prassl *et al.* (2020) find large differences in the magnitude of the shock between Germany and the US or the UK, where job losses have been particularly high. Palomino *et al.* (2020) estimate that the burden of the pandemic will be disproportionately borne by low-wage earners in European countries which, in the absence of compensating policies, will significantly increase poverty and inequality across Europe. Almeida *et al.* (2020) suggest that over the course of 2020, on average, households’ disposable income in the EU would

fall by -5.9% due to the COVID-19 crisis without discretionary policy measures, and by -3.6% with policy intervention. Their results confirm that the impact of the pandemic is likely to be highly regressive, with the poorest households' being the most severely hit.

Changes in the distribution of disposable income and in the earnings distribution are not, however, the only type of inequality associated with the lockdown. Undoubtedly, one of the most important sources of inequality related to the pandemic has been the decision of confining people for a long time in very different quality housing. When most European countries decided that the whole population – except those working in essential jobs – had to stay at home for a long time, a form of inequality linked to differences in housing conditions was immediately activated. Furthermore, differences in the lack of adequate housing conditions during such a period can further exacerbate inequalities in other basic dimensions of social welfare. First, having adequate housing conditions can itself help contain the spread of illness. The WHO detailed recommendations require that a household environment supports the capacity to protect individuals from the virus. However, as stressed by Brown et al. (2020), this “home environment for protection” is the result of past wealth-constrained choices, and these cannot be easily adjusted in response to the immediate virus threat.

Second, COVID-19 has replicated existing health inequalities and, in some cases, has increased them, being housing part of this process (PHE, 2020; Tinson and Clear, 2020). Overcrowding may amplify infectious and respiratory diseases, damp or mould increase respiratory disease, eczema, asthma, rhinitis, while indoor pollutants may produce asthma, and low temperature is related to respiratory infection, hypothermia, bronchospasm, heart disease (Tunstall, 2020). In general, immune status is affected by underlying health, and underlying health in turn is affected by housing conditions. Therefore, housing deprivation makes COVID-19 magnify well-being inequality. The pandemic is also affecting mental health issues. A survey of over 1,300 mental health doctors from across the UK reveals that 43% of psychiatrists have seen an increase in urgent and emergency cases following the COVID-19 lockdown, and, at the same time, 45% of psychiatrists have seen a fall in their most routine appointments, leading to fears of a ‘tsunami’ of mental illness after the pandemic (Royal College of Psychiatrists, 2020). Households living in precarious housing conditions might be particularly affected. Using data from the UK Household Longitudinal Study, Davillas and Jones (2021) found that

the prevalence of psychological distress increased from 18.5% to 27.7% between the 2019 Wave and April 2020.

Adequately measuring the differences in these housing conditions between and within European countries may therefore be a good approximation to the diverse dimension of an important source of inequality caused by the pandemic. This requires having advanced measurement and interpretation procedures for this type of inequality. Based on EU-SILC information, Eurostat defines a country's severe housing deprivation rate as the share of the population living in a dwelling which is considered as overcrowded, and suffering from at least one of other housing deprivation measures: leaking roof or rot in window frames or floor, lack of bathtub or shower and indoor flushing toilet for sole use of the household, or a dwelling considered too dark. According to this definition, 4% of the EU total population would have been severely housing deprived during the lockdown. However, there are large differences between countries, with a range between 12.7-14.2% in Latvia and Romania and 1% in Finland, Norway and Ireland.

It appears contradictory that, although around three-quarters of Europe's citizens own their own home, the costs of accessing and maintaining a home have continued to rise in the last decade. This does not only jeopardize housing security and quality but can also stand in the way of life projects (Filandri and Olagnero, 2014). It seems also that institutional contexts determine the inter-country variations in housing conditions, with good housing conditions in the 'long-standing' northern EU member states, intermediate conditions in most of the remaining 'long-standing' member states and poor conditions in many of the Eastern European member states (Norris and Shiels, 2007).

The key question is whether these differences in average housing conditions could hide significant inequalities within each country right when the lockdown began. Depending on their extent, the consequences of the lockdown on well-being could be more adverse. To measure this form of inequality, we need a composite indicator of housing deprivation which distribution can be analyzed and summarized in an inequality measure. This paper is motivated by this concern and has two main aims.

First, we propose a robust composite measure of housing deprivation that can help in assessing the different degree of housing deprivation on individuals during the lockdown. Second, we construct a housing deprivation index using this composite measure at the household level that allows us to analyze well-being inequality during the lockdown within each EU country. To do so, multidimensional housing deprivation is treated in the

form of different fuzzy sets applying two complementary membership functions, making use of the methodology introduced by Cheli and Lemi (1995) and updated by Betti et al. (2006) and Lemmi et al (2010). Using this fuzzy methodology we avoid the standard housing deprived/non-deprived dichotomy as housing deprivation is seen as a fuzzy set to which individuals belong to in different degrees. Each dimension of housing deprivation is analyzed separately, and it is also possible to have an overall picture of deprivation in housing conditions. In our analysis we use of two complementary membership functions, Betti and Verma's (2008) and our novel proposal, each of them with different levels of compensation between the share and proportion of individuals who are less deprived than a given individual and the share of all individuals less deprived than the person concerned. The former membership function allows for partial compensation between while the latter for total compensation, providing alternatives to check the robustness of results under different degrees of compensation.

Our findings lend support to the thesis that lockdown decisions affected European countries in different ways given the observed differences in the degree of housing deprivation. According to our index, this degree is especially high in some Eastern European countries in comparison to Nordic countries. Nevertheless, when we focus on the inequality of housing deprivation within countries the result is the reverse: Eastern European countries are significantly more equal in the distribution of housing deprivation among the population and Nordic countries show a relatively large housing deprivation inequality.

Our paper advances knowledge in several respects. While ours is not the first study to examine housing deprivation, our approach adds to previous works the characterization of deprivation as a phenomenon that affects most of the population in a wide variety of degrees, from low (or very low) to high (or very high). This conceptualization allows all individuals to have some level of housing deprivation and improves measures where housing deprivation is defined as a dichotomous state. Furthermore, the use of fuzzy sets facilitates the aggregation of different variables and the combination of different dimensions. As a result, measures are more accurate and less sensitive to irregularities in the distribution function. These richer measures provide us with very valuable information to assist policy design and outreach efforts that may strengthen housing policies aimed at preventing greater inequalities in housing conditions.

The structure of the paper is as follows. The following section presents the details of our fuzzy methodology for the measurement of individual housing deprivation. Section 3 introduces the data and describes the variables used in the analysis. Section 4 discusses the main results of the analysis and Section 5 concludes.

2. A FUZZY APPROACH FOR THE MEASUREMENT OF HOUSING DEPRIVATION

The extensive literature on multidimensional deprivation provides us with a wide range of approaches, which can be rather easily adapted to the case of housing deprivation after a proper selection of the main indicators. Some studies follow a counting approach, while others propose alternative and more complex procedures applied to the observed frequencies, like multivariate statistical techniques.

Among the different alternatives, we opt for a fuzzy approach. The traditional severe housing deprivation definition used by Eurostat is characterized by a simple dichotomization of the population into deprived and non-deprived. According to this criterion, housing deprived individuals are those living in a dwelling which is considered overcrowded, and also suffers from at least one of a list of other housing deprivation conditions: leaking roof or rot in window frames or floor, lack of bath or shower and indoor flushing toilet for sole use of the household, or is considered too dark. A clear advantage of the fuzzy approach compared to the one used by Eurostat is that it preserves the richness of EU-SILC data, by allowing us to consider the degree of housing deprivation both at the individual and country level

The fuzzy approach is characterized by the assumption that housing deprivation is a concept that manifests itself in different degrees rather than as a dichotomous phenomenon – as stated by Chiappero Martinetti (2006) for multidimensional poverty. In this conceptualization, all individuals in a population are subject to housing deprivation, but to a different degree. In this sense, any individual in the population has a risk of housing deprivation. This risk may be very low, low, middle, high, or very high. To measure it we adapt the fuzzy approach introduced by Cheli and Lemmi (1995) and updated by Betti et al. (2006) and Lemmi et al. (2010) for the study of poverty.

The main reason to use a fuzzy approach is that the aggregation of different indicators and the combination of different dimensions is largely simplified by treating each dimension as a degree. The need to divide the population into various discrete groups for

comparison—as the conventional dichotomic analysis requires—is in this way avoided. We can also expect the resulting measures to be much more precise in terms of sampling error as compared to conventional measures where the units are concentrated at the two end points of the distribution (Verma and Betti, 2005). Furthermore, deprivation measures also tend to be less sensitive to local irregularities in the distribution function, and to the particular choice of a threshold that splits the population in two mutually exclusive groups to dichotomize the result.

Fuzzy sets have been used prolifically in the analysis of poverty and living conditions [Cerioli and Zani (1990), Chiappero-Martinetti (1994, 2000), Cheli and Lemmi (1995), Cheli (1995), and Betti and Verma (1999), Vero and Werquin (1997), Giorgi and Verma (2002), Deutsch and Silber (2005), Qizilbash (2006), Betti and Verma (2008), Berti et al. (2014), Betti et al. (2015), D’Agostino et al (2018), Ciani et al. (2019)]. The construction of the fuzzy set measure involves different steps. First, we need to identify the items to be included in the study of housing deprivation that must be meaningful and useful. Second, for each item, we must set a quantitative deprivation indicator in the range [0, 1]. When the item is constituted by a fixed number of categories, as it is the case of all our selected items, it should be then furtherly transformed. For each item we must determine a deprivation score as follows:

$$S_{j,i} = \frac{F(c_{j,i}) - F(1)}{1 - F(1)}, \quad [1]$$

where $c_{j,i}$ – ordered from most to least deprived situations – is the value of the category of the j -th item for the i -th individual and $F(c_{j,i})$ is the value of the j -th item cumulative distribution function function for the i -th individual. . The greater $s_{j,i}$, the less deprived the individual is in such an item.

Third, an exploratory factor analysis to identify the “dimensions” of housing deprivation is performed. The aim is to identify a distinct group of items of housing deprivation describing singular characteristics of housing conditions. These dimensions should be ideally independent from one another and this exploratory factor analysis can be used to select them with that purpose. Additionally, we also rearrange some items in the different dimensions to create more meaningful groups. We then perform a confirmatory factor analysis to test the goodness of fit of the final groupings.

Fourth, we compute the weights of the items contributing to each dimension in each country taking into account two characteristics: the item’s dispersion —deprivation affecting a small proportion of the population is treated as more intense at the individual level—, and the redundancy of the characteristics included in the same dimension —we limit the influence of redundant characteristics.¹

Fifth, the score within each housing dimension is calculated as the weighted mean of items in that dimension h :

$$S_{h,i} = \frac{\sum_{j \in h} w_j s_{j,i}}{\sum_{j \in h} w_j}. \quad [2]$$

Sixth, the membership function for individual i in housing dimension h is defined as:

$$\mu_{h,i} = \frac{(1-F(S_{h,i}))+(1-L(S_{h,i}))}{2}. \quad [3]$$

This function accounts for the proportion of population less deprived than individual i in dimension h and for the share in the lack of deprivation in dimension h of individuals less deprived in that dimension. We propose this new membership function so that the greater the proportion or the share of people less deprived than individual i in housing dimension h the greater $\mu_{h,i}$. Accordingly, as $\mu_{h,i}$ increases from 0 to 1 the deprivation of individual i in housing dimension h also increases. As we aggregate the share and the proportion of the population less deprived than the person concerned in dimension h , total compensation between share and proportion of individuals is allowed. This proposal therefore complements the membership function proposed by Betti and Verma (2008):

$$\mu'_{h,i} = (1 - F(S_{h,i})) (1 - L(S_{h,i})), \quad [4]$$

in which partial compensation between the share and the proportion of the population less deprived than individual i in the dimension h is allowed. We will compare the results of both membership functions to test the robustness of our results.

We then compute the average value of deprivation for each dimension and estimate the level of inequality in each dimension of housing deprivation in every country using one of the most frequently used in empirical analysis, the Gini index. Note that we can easily compute any other inequality index so that in the Appendix 4 we report the results for

¹ For a detailed description of the weight construction, see Garcia-Pardo et al. (2020).

various alternative inequality measures to test if our main conclusions are robust to the inequality index used.

Seventh, an overall country-specific housing deprivation score can then be straightforwardly obtained using the simple average of the dimension scores $\mu_{h,i}$, giving the same weight to all the dimensions, each of which represents a different feature of housing deprivation. The additive aggregation function, μ_{ai} , implies the strong assumption of preference independence. That is, it assumes that it is possible to assess the marginal contribution of each variable separately. This implies full compensation: a poor performance in some indicators can be compensated by sufficiently high values in other indicators.

$$\mu_{ai} = \frac{\sum_{h=1}^H \mu_{h,i}}{H}. \quad [5]$$

With the purpose of overcoming this assumption of full compensation between indicators we propose to equal the individual overall housing deprivation score μ_{Mi} to the highest value within individual housing deprivation dimensions (h),

$$\mu_{Mi} = \max_{h=1, \dots, H} \mu_{h,i}. \quad [6]$$

μ_{Mi} does not allow for any compensation among dimensions and provides alarm signs regarding the individual's worst housing deprivation dimension. In this way, a social planner would have more incentives to improve the dimension with the lowest score if the aggregation procedure were the highest deprivation rather than linear, as it would give her a better chance of improving the position of the country in the ranking.

Nonetheless, different compensation degrees can also be considered at this stage. So, we propose a generalized aggregation index that potentially takes into consideration dimensions other than the worst one. This generalized aggregation measure, denoted as μ_{gi} , is an intermediate (mixed) composite indicator that combines the worst value achieved, μ_{Mi} with the additive aggregation of the values in each dimension, μ_{ai} . In this sense, a bad performance in one dimension can be partially compensated by good performances in others. In this combination, δ is a parameter reflecting intermediate states:

$$\mu_{gi} = \delta \mu_{Mi} + (1 - \delta) \mu_{ai}, \quad \text{with } 0 \leq \delta \leq 1. \quad [7]$$

δ takes values from 0 (full substitutability) to 1 (no substitutability). As $\delta \rightarrow 1$, more importance is given to the dimension in which the individual is more deprived, even though for $\delta < 1$ that dimension would not be the only relevant deprivation dimension.

Finally, we can also estimate the country's average level of overall housing deprivation and its inequality at the overall level, as we have already done previously for each dimension.

3. VARIABLES AND DATA

Adequately measuring housing conditions requires adopting a multidimensional approach as different deprivation dimensions must be considered simultaneously. Eurostat has previously recognized the multidimensional characterization of housing conditions defining the severe housing deprivation rate taking four different aspects into account: overcrowding, leaking roof or rot in window frames or floor, lack of bathtub or shower unit and indoor flushing toilet for sole use of the household, or a too dark dwelling. Although these items are considered in the official EU definition of severe housing deprivation, these are not, however, the only relevant housing conditions that affect a household's wellbeing during a lockdown. With this aim, we will consider additional variables related to living space, technology, environmental and economic stress that can also have a relevant role in the context of a COVID-19 lockdown.

We define housing deprivation as a multidimensional form of unmet basic social housing needs. Since the aim of this paper is to capture the situation of housing deprivation in the context of the COVID-19 lockdown, the choice of elements for this type of deprivation will include not only the basic dimensions that have been commonly used to define housing deprivation, as in the official EU definition – which includes the standard housing deprivation dimension and overcrowding. We also consider other basic social housing needs that become particularly relevant in the context of a lockdown, such as access to technology, environmental issues, economic stress and living space. The methodology used allows us to measure the degree of housing deprivation in each of these dimensions. For example, in the living space dimension we do not only capture whether the household is overcrowded or not – clearly related to its composition and number of household members –, but also the degree of overcrowding. This last aspect is even more relevant given that in a lockdown situation the level of occupancy of the dwelling – in terms of the number of members that reside there and the time they spend in that dwelling – has

changed. The fact of having a garden or any outdoor spaces or the degree of population density of the area in which the household resides also become significantly more relevant.

The best available comparative data source to analyse housing conditions in Europe is the European Survey on Income and Living Conditions (EU-SILC). EU-SILC aims at collecting timely and comparable cross-sectional and longitudinal multidimensional microdata on income, poverty, social exclusion and living conditions. In this paper we use the cross-sectional EU-SILC 2019 for European countries.² The survey questionnaire includes specific questions on housing circumstances that allow for a better understanding of housing conditions in the European context. The choice of these observed items is crucial and often constrained by the available data and the theoretical assumptions. The selected variables and dimensions regarding housing conditions collected in the EU-SILC survey are reported in Figure 1.

< Figure 1 around here >

The first dimension —*standard housing deprivation*— represents the housing context related to housing physical conditions and includes variables such as having a leaking roof, lack of bathtub or a shower or indoor flushing toilet for sole use of the household, or a dwelling considered too dark. Being locked in houses with any of these characteristics makes the health situation worse as these can contribute to increase respiratory related diseases and other health problems.

The second dimension —*living space*— is measured through three items: overcrowded housing, degree of urbanization, and dwelling type. Living in overcrowded dwellings may amplify infectious and respiratory diseases. A dwelling is considered overcrowded when people living there do not have enough rooms for the corresponding size of the household.³ Degree of urbanization classifies local administrative units into three types of area: cities, towns and suburbs, and rural areas. The dwelling type variable classifies houses into detached house, semi-detached or terraced house, apartment or flat in a building with less than ten dwellings, and apartment or flat in a building with 10 or more dwellings. Overcrowded environments, densely populated areas, as well as smaller dwellings types can present a higher risk of spreading the virus.

² See Appendix 2 for the list of countries and observations.

³ See Appendix 3 for a description of variables.

Technology comprises variables indicating whether the dwelling has a computer and at least half of the adults can access the Internet. Many daily elements in a non-lockdown scenario such as work or keeping up with relationships can continue to develop at home while households are confined. However, not all households can access these activities via the internet or other technologies and devices. The two mentioned items are crucial for keeping up with children learning in digital school activities and for adults to work from home during the lockdown.

The *environment and neighborhood* dimension includes the prevalence or absence of crime, violence, pollution and noise. These characteristics are fundamental for the safety of household's members, even under a lockdown. When cities are shut down, it is reasonable to expect that there will be dramatic drops in crime rates but understanding what can happen in practice is challenging. Problems like burglary, robbery and theft are expected to decline. However, staying at home means a higher probability of family violence to occur. It is also plausible that the lockdown can result in increasing antisocial behavior, such as nuisance noise from neighbors.

The last dimension —*economic stress* associated with housing— refers to financial issues reflecting arrears on mortgage or rental payments, arrears on utility bills —related to housing —, and the magnitude of the housing cost to income ratio. The mix of financial stress and bad housing conditions under a lockdown can cause stress and anxiety. As stated before, a worsening of mental health problems could be one of the side effects of COVID-19. For the most vulnerable households, uncertainty around the own financial situation and job insecurity is a key issue during a lockdown. The resulting stress can also lead to unhealthy coping mechanisms, such as excessive smoking or alcohol abuse.

4. RESULTS

With the aim of identifying the dimensions (group of items) of housing deprivation that best determine a relevant feature of housing conditions an exploratory and confirmatory factor analysis is performed. We first accomplish an exploratory factor analysis to provide a preliminary structure of the dimensions and then rearrange some factors in the different dimensions to create more meaningful groups. Finally, we conduct a confirmatory factor analysis to test the goodness of fit of a five-factor structure model as described in Section 3.

Our exploratory factor analysis identified six key dimensions, one of them containing the item leaking roof and damp and rooms too dark, and other containing bath or shower and indoor flushing toilet. Since these four items are usually treated as one dimension in the Eurostat definition of severe housing deprivation, we decided to merge them into only one dimension identified as *standard housing deprivation* as we described in Figure 1. The remaining dimensions correspond to the rest of the variables proposed in the initial hypotheses. To assess the fit of the factor analysis the root mean square residual was computed. If it is equal or below 0.06 —as in our case (0.054)— the fit is considered particularly good. We also computed the root mean squared error of approximation based on the analysis of residuals. Its small value (0.051) indicates a good fit —a very good fit would imply a number below 0.05.

The results obtained for the five dimensions of housing deprivation (Table 1, Figure 2 and 3) and the overall housing deprivation (Table 2) following a wide range of aggregation methods (μ_{ai} , μ_{Mi} , and μ_{gi}) yield important insights into the differences across European countries⁴ regarding the degree of housing deprivation.⁵

< Table 1 around here >

The *standard housing deprivation* fuzzy measure, which includes lack of basic facilities such as having a bathtub or shower unit or toilet inside the dwelling for the sole use of the household, insufficient natural light or having structural problems such as leaks or rot, allows us to overcome the strict division between deprived and non-deprived, preserving the richness of data information. Under the fuzzy approach the degree of standard housing deprivation is one of the lowest among the different dimensions in most EU countries. This is a result of the fact that two of the four items are basic amenities whose possession is highly generalised in Western and Southern European countries, thus their lack is very rare. However, in Eastern EU member states, such as Bulgaria, Romania, Lithuania and Latvia, the incidence of lacking basic sanitary facilities such as a bath or shower or indoor flushing toilet for the sole use of the household can be up to 100 times higher than in other countries. One key finding is precisely that this dimension is one of the dimensions

⁴ Italy is excluded from the analysis because the microdata for 2019 are not yet available in EU-SILC user's database. Germany, The Netherlands and Slovenia are excluded because the variable 'degree of urbanization' is not provided in the EU-SILC user's database in all these countries. The variable 'number of rooms available to the household' is not available for Germany either.

⁵ Results for the Betti and Verma (2008) membership function are reported in Appendix 5. Conclusions remain under both membership functions proving the robustness of our findings.

—jointly with technology— showing greater inequality⁶ in most countries, with an average Gini index of 0.328 for all countries. Nevertheless, there are some significant differences between the countries with highest and lowest inequality values. Among the top five countries with the highest inequality in this housing deprivation dimension we identify Finland, Slovakia, Norway, Czechia, and Sweden. Among the five countries with the lowest inequality levels we have Cyprus, Portugal, Hungary, Latvia and Bulgaria. Inequality in this group varies largely from one country to another.

The *living space* dimension, which is measured by the overcrowding indicator, the degree of urbanization of the dwelling (population density) and the dwelling type, is —unlike the previous one— the dimension that shows the highest degree of housing deprivation. This dimension is especially important because, first, living in a dwelling in a densely populated area is associated with a high spread of COVID-19 (faster transmission in areas that concentrate high volumes of population). Second, living in an overcrowded household doesn't allow individuals to maintain the necessary physical distance and self-isolation so it threatens the health outcomes of entire households. In practice, overcrowded households have also a higher risk of transmitting infectious diseases like COVID-19. Third, during a lockdown it is clearly very different to live in detached houses, which are characterized by wide outdoor space or surrounded by a garden, than in a flat in a building with a lot of dwellings. As mentioned above, living in certain types of dwellings during a strict lockdown can have adverse effects in mental health. Thus, this dimension is crucial for the capacity of dwellings to protect households from the virus, and inequalities in this dimension might exacerbate physical and mental health inequalities.

Our results show that the countries with the highest level of deprivation in this living space dimension are Estonia, Latvia and Lithuania, together with some Southern EU Member States such as Malta and Spain. A striking result is that while this dimension shows the lowest levels of inequality within countries, it is the one where differences between countries in the Gini values are greatest. In this sense, lockdown measures would have led to greater differences in social welfare between European countries through the

⁶ We have computed alternative inequality indexes to Gini such as the Theil index and the P90/P10 index. Results using these indices confirms our main conclusions assuring us the robustness of our results to the choice of inequality index and are reported in Appendix 4.

different levels of deprivation in this dimension during the lockdown period in which the population had to stay at home.

Regarding the *technology* dimension, the countries where the degree of deprivation is greatest are Eastern European countries (Romania, Bulgaria and Serbia). At the other extreme, countries like Norway, Denmark, Luxembourg, Finland, and Switzerland stand out for having the lowest degrees of technology deprivation. However, inequality in this dimension within the latter is much larger, while the opposite occurs in the countries where the degree of this type of deprivation is larger. This is, without a doubt, one of the biggest social problems raised by lockdown strategies. Even in countries where most households can access the internet and have computers at home, the large differences observed between same-country households represents another large source of well-being inequality when households are forced to stay at home for an extended period.

The low mean values of the *environment and neighborhood* fuzzy measure, especially in Croatia, Norway, Estonia, Slovakia and Finland, show that environment and neighborhood is not a worrying deprivation dimension for most countries. Its degree, however, is higher in Malta, Greece, Portugal, France and Luxembourg. As in other dimensions where deprivation was at a low level, inequality in this dimension is high, with values of the Gini index over 0.330. The most unequal countries are Croatia, Slovakia, Norway, Hungary and Estonia while the less unequal are Malta, Greece, Portugal, France and Luxembourg. High inequality levels in environment and neighborhood quality is rather problematic in a situation of lockdown where antisocial behavior, such as nuisance noise from neighbors, can have harmful consequences on the well-being of the individuals being a source of inequality.

The dimension capturing *economic stress associated with housing* is not only of great importance due to the fact that economic stress associated with housing can lead to anxiety and mental health problems, but also because delays in the payment of bills can lead to supply cuts, a very undesirable situation from the social point of view in a situation of lockdown. Particularly serious are the delays in the payment of the rent or the mortgage, since they can lead (if repeated in time) to eviction processes. Similarly, the cost of housing is a very important problem for some social groups, which have to dedicate a large part of their earnings to cover this cost. A key demographical group is young individuals who surely will delay their emancipation processes. The perceived

economic insecurity of a large part of the population due to the lockdown can exacerbate these problems.

The degree of deprivation in this dimension does not seem to be particularly related to the level of income, geographic location or to the intrinsic characteristics of the countries. Among the countries with the highest degree of intensity in this dimension, Greece, Bulgaria, Serbia, Switzerland, Denmark and Norway stand out. On the other hand, those with the greatest inequalities among its inhabitants are Malta, Estonia, France, Finland and Spain. Inequality in this dimension is relatively high but there is still a variety of situations across countries.

The mean degree of the five dimensions by country is shown in Figure 2. The outer line corresponds to the *living space* dimension showing that in all countries it presents the highest degree while *standard housing* deprivation is usually the one with a lowest degree everywhere.

< Figure 2 around here >

Figure 3 presents the Gini index of the fuzzy measure of housing deprivation by country and dimension. In this case, standard housing deprivation levels show the greatest values of within countries inequality in almost all countries. Living space is the dimension more homogeneous within countries although, as mentioned before, its level of deprivation is generally high.

< Figure 3 around here >

Finally, our methodological approach allows us to summarize housing deprivation in European countries in a single indicator (Table 2). We have different alternatives to aggregate the previous measures. The two extremes are the arithmetic mean of the five housing deprivation dimensions and the maximum deprivation. The first one allows full compensation between dimensions, while the second does not allow compensation. There are many other aggregation measures depending on the value of δ in [7]. If we focus on the global situation of housing deprivation (without breaking it down into dimensions) under full compensation among dimensions (arithmetic mean), the countries with the greatest degree of deprivation are a group of Eastern European countries: Bulgaria, Latvia, Serbia, Lithuania and Cyprus. On the other side of the coin, some Nordic countries such as Norway and Finland —together with Croatia— are those with the lowest degree

of deprivation. In turn, the countries with greatest inequality under an arithmetic mean housing deprivation index are Nordic countries (Finland, Norway), while Greece and some of the Eastern European ones —such as Bulgaria, Romania and Serbia— have the lowest levels of housing deprivation inequality. It appears therefore that countries with lower degree of housing deprivation tend to have greater levels of inequality and vice versa.

< Table 2 around here >

Similarly, if we do not allow for compensation among dimensions and focus on the dimension in which each individual is more deprived in (maximum), the greatest degree of housing deprivation continues to appear in a variety of Eastern countries —Bulgaria, Romania, Latvia and Serbia. At the other extreme, Northern countries —such as Finland and Norway— show the lowest degree, as we previously found when using an arithmetic mean. As for the arithmetic mean, we effectively observe once more a negative association between levels of deprivation and inequality in housing deprivation: countries with lower levels of housing deprivation have higher levels of inequality.

Finally, we present the results for the generalized aggregation index, which is a mixed composite indicator that can be built for different values of δ . Figure 4 shows how the generalized aggregation index change for different degrees of compensation, from full compensation ($\delta = 0$, arithmetic mean) to no compensation ($\delta = 1$, maximum). Countries with larger slopes have results on housing deprivation that are more sensitive to the degree of substitution across dimensions. By contrast, countries with smaller slopes have more homogeneous degree of deprivation across dimensions. In general, country rankings are very stable regardless of the compensation level, with Bulgaria, Latvia and Serbia leading the ranking (highest degree of housing deprivation) and Norway and Finland registering the lowest degree of housing deprivation.

The robustness of country rankings allows us to think that those with high levels of housing deprivation when the reference is the worst dimension have also high levels of housing deprivation in other dimensions. Moreover, as compensation across dimensions is reduced (greater δ) the levels of housing deprivation are more disperse —fanning out lines—, showing that when the worst dimension criterion is used, the performance of countries is more distant apart. In this way, countries should detect the most common

worst housing deprivation dimension and focus their efforts on that dimension to reduce their housing deprivation distance with other countries.

< Figure 4 around here >

These differences in housing deprivation warn us about the inequality problems that the lockdown strategy can cause in the medium term. To the direct effects of income reduction that may result from the increase in unemployment or the reduction of working hours due to the obligation of staying at home, we must add the social welfare losses caused by the lockdown of households in dwellings and environments of very different quality.

5. CONCLUDING REMARKS

There are several avenues through which COVID-19 lockdowns can potentially increase well-being inequality. The channels through which this increase may take place are far less clear. Households' inequalities in access to work and education seem the most important drivers of the growth of well-being differences. Nevertheless, there are other relevant side effects of keeping individuals at home. An important source of inequality arises from the differences in the housing conditions with which households faced the lockdown. Inequalities in housing deprivation led to immediate increases in well-being inequalities across households when lockdown measures were enacted. Additionally, differences in the lack of adequate housing conditions during lockdowns can also exacerbate inequalities in other well-being dimensions.

Analysing the degree of housing deprivation and inequalities in the different dimensions involved is therefore a major topic of public concern. There is a need for research that provides us with a more complete picture of the conditions in which households in different countries had to face the lockdowns. In this article, we have tried to narrow the gap in the literature by using an innovative approach to housing deprivation that allows researchers to identify the different degrees of housing deprivation both at the individual and the social level. Fuzzy measurement allows us to obtain much more valuable conclusions than if we were restricted to the dichotomy between states —deprived versus non-deprived— imposed by traditional housing deprivation approaches. We have also defined different dimensions of housing deprivation that can be analysed separately.

Two different questions arise in connection with the analysis performed. The first one is related with the similar orderings of housing deprivation dimensions within each country.

Indeed, in most countries, the dimension with the highest degree of deprivation is living space, while the opposite occurs with standard and technology housing deprivation. However, there is no common pattern of countries according to the different dimensions, with very varied situations depending on the housing deprivation dimension analysed, so that these differences lead us to argue that the effects of the lockdown on social well-being measured from this perspective have not affected all Europeans equally.

In addition to the differences between countries in the degree of housing deprivation, a second question studied has been the extent of inequality in this form of deprivation within each country. In general, the dimensions where we find a low degree of housing deprivation are those that show the highest levels of inequality. Something similar occurs with countries, since those that have a lower degree of housing deprivation in most dimensions also show higher levels of within-country inequality in those dimensions. Regarding inequality in housing deprivation, it is generally lower in Eastern and Southern European countries than elsewhere in the EU and higher in the Nordic countries compared to the rest of the continent. While the former would face greater difficulties in a scenario in which households have to stay at home, the lockdown would have in them a smaller effect on inequality in this dimension of well-being.

These findings can assist policymakers in formulating policies and outreach efforts that may prevent the increase of inequality in relevant dimensions of well-being when households are forced to stay at home. Although lockdown measures are extraordinary, the vulnerability to the possible appearance of new viruses forces us to anticipate what the social consequences of the possible strategies to combat them may be. Our results confirm both that in some countries the degree of housing deprivation is still very high and that inequality in these conditions is very large in others. In the absence of policies to correct both problems, the generalization of new lockdown measures could aggravate the social welfare losses associated with pandemic shocks.

References

- Adams-Prassl, A., Boneva, T., Golin, M. and Rauh, C. (2020): Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys. IZA DP No. 13183.
- Almeida, V., Barrios, S., Christl, M., De Poli, S., Tumino, A. and van der Wielen, W. (2020): Households' income and the cushioning effect of fiscal policy measures during the Great Lockdown. JRC Working Papers on Taxation and Structural Reforms No 06/2020.
- Belot, M., Choi, S., Jamison, J. C., Papageorge, N. W., Tripodi, E., and Van den Broek, E. (2020) "Unequal consequences of COVID-19 across age and income: representative evidence from six countries." *COVID Economics*, 38, 196-217.
- Berti, F., D'Agostino, A., Lemmi, A., and Neri, L. (2014): Poverty and deprivation of immigrants vs. natives in Italy. *International Journal of Social Economics*, 41: 630–649.
- Betti, G., and Verma, V. (2008): Fuzzy measures of the incidence of relative poverty and deprivation: a multidimensional perspective. *Statistical Methods and Applications*, 12: 225–250.
- Betti, G., Cheli, B., Lemmi, A., Verma, V. (2006): Multidimensional and longitudinal poverty: an integrated fuzzy approach. In: Lemmi, A., Betti, G. (eds.) *Fuzzy Set Approach to Multidimensional Poverty Measurement*, 111–137. Springer, New York
- Betti, G., Verma, V. (1999): Measuring the degree of poverty in a dynamic and comparative context: a multidimensional approach using fuzzy set theory. *Proceedings of the ICCS-VI, Lahore, Pakistan*, 11, 289–301.
- Betti, G.; Gagliardi, F.; Lemmi, A.; Verma, V. (2015): Comparative measures of multidimensional deprivation in the European Union. *Empirical Economics*, 49: 1071–1100.
- Brodeur, A., Clark, A.E., Flèche, S., and Powdthavee, N. (2021): "COVID-19, Lockdowns and Well-Being: Evidence from Google Trends." *Journal of Public Economics*, 193.
- Brown, C.S., Ravallion, M. and Van de Walle, D. (2020): Can the world's poor protect themselves from the new Coronavirus? NBER Working Paper 27200.
- Ceroli, A., and Zani, S. (1990): A fuzzy approach to the measurement of poverty. In: Dagum, C., Zenga M (eds) *Income and wealth distribution, inequality and poverty, studies in contemporary economics*. Springer, Berlin, 272–284.
- Cheli, B. (1995): Totally fuzzy and relative measures in dynamics context. *Metron*, 53, 83–205
- Cheli, B. and Lemmi, A. (1995): A totally fuzzy and relative approach to the multidimensional analysis of poverty. *Economic Notes*, 24: 115–134.
- Chiappero-Martinetti, E. (1994): A new approach to evaluation of well-being and poverty by fuzzy set theory. *Giornale degli Economisti e Annali di Economia*, 53: 367–388.
- Chiappero-Martinetti, E. (2000): A multidimensional assessment of well-being based on Sen's functioning approach. *Rivista Internazionale di Scienze Sociali*, 108: 207–236.
- Chiappero-Martinetti, E. (2006): Capability approach and fuzzy set theory: description, aggregation and inference. In: Lemmi, A., Betti, G. (eds.) *Fuzzy Set Approach to Multidimensional Poverty Measurement*. Springer, New York.

- Ciani, M., Gagliardi, F., Riccarelli, S., Betti, G. (2019): Fuzzy Measures of Multidimensional Poverty in the Mediterranean Area: A Focus on Financial Dimension. *Sustainability*, 11, 143.
- Clark, A.E., D'Ambrosio, C. and A. Lepinteur, (2020): "The Fall in Income Inequality during COVID-19 in Five European Countries", ECINEQ WP 565.
- Davillas, A. and Jones, A. (2021): The First Wave of the COVID-19 Pandemic and Its Impact on Socioeconomic Inequality in Psychological Distress in the UK. IZA DP No. 14057.
- D'Agostino, A., Giusti, C. & Potsi, A. (2018): Gender and Children's Wellbeing: Four Mediterranean Countries in Perspective. *Child Indicators Research*, 11: 1649–1676.
- Deutsch J. and Silber, J. (2005): Measuring multidimensional poverty: an empirical comparison of various approaches. *Rev Income Wealth*, 51: 145–174.
- Dorn, F., Fuest, C., Göttert, M., Krolage, C., Lautenbacher, S., Lehmann, R., Link, S., Möhrle, S., Peichl, A., Reif, M., Sauer, S., Stöckli, M., Wohlrabe, K., and Wollmershäuser, T.: (2020): The economic costs of the coronavirus shutdown for selected European countries: A scenario calculation. *EconPol Policy Brief* 25.
- Filandri, M. and Olagnero, M. (2014): Housing Inequality and Social Class in Europe. *Housing Studies*, 29: 977–993.
- Giorgi, L., and Verma, V. (2002) European social statistics: income, poverty and social exclusion, 2nd report. Office for Official Publications of the European Communities, Luxembourg
- International Labor Organization (2020): ILO Monitor 2nd edition: COVID-19 and the World of Work. Geneva: ILO.
- Layard, R., Clark, A., De Neve, J.-E., Krekel, C., Fancourt, D., Hey, N., and O'Donnell, G. (2020): "When to release the lockdown: A wellbeing framework for analysing costs and benefits." Centre for Economic Performance, Occasional Paper No. 49.
- Lemmi, A., Verma, V., Betti, G., Neri, L., Gagliardi, F., Tarditi, G., Ferretti, C., Kordos, J., Panek, T., Szukielojc'-Bien'kun'ska, A., Szulc, A., Zieba, A. (2010): Multidimensional and fuzzy indicators developments. Project Small Area Methods for Poverty and Living Conditions Estimates. No. EU-FP7-SSH-2007–2011.
- Norris, M. and Shiels, P. (2007): Housing inequalities in an enlarged European Union: patterns, drivers, implications. *Journal of European Social Policy*, 17: 65–76.
- OECD (2020): "Evaluating the initial impact of COVID-19 containment measures on economic activity", Economics Department, OECD, Paris.
- Palomino, J.C, Rodríguez, J.G. and Sebastian, R. (2020): Wage inequality and poverty effects of lockdown and social distancing in Europe. *European Economic Review*, 129: 1-25.
- Public Health England (2020): Disparities in the risk and outcomes of COVID-19. London: PHE.
- Qizilbash, M. (2006): Philosophical accounts of vagueness, fuzzy poverty measures and multidimensionality. In: Lemmi, A., Betti, G. (eds) *Fuzzy set approach to multidimensional poverty measurement*. Springer, New York, 9–28.
- Royal College of Psychiatrists (2020): Psychiatrists see alarming rise in patients needing urgent and emergency care and forecast a 'tsunami' of mental illness: <https://www.rcpsych.ac.uk/news-and-features/latest-news/detail/2020/05/15>.

Tinson, A. and Clear, A. (2020): Better housing is crucial for our health and the COVID-19 recovery. Health Foundation.

Tunstall, B. (2020): Housing and COVID-19: disease risk, lockdown effects and medium-term issues. Cabinet Office seminar 11th June 2020.

Verma, V., and Betti, G. (2005): Sampling errors for measures of inequality and poverty. Invited paper in classification and data analysis—book of short papers, 175–179. CLADAG, Parma, 6–8 June.

Vero, J., and Werquin, P. (1997): Reexamining the measurement of poverty: how do young people in the stage of being integrated in the labour force manage (in French). *Economie et Statistique*, 8–10: 143–156.

Figure 1. Dimensions and variables

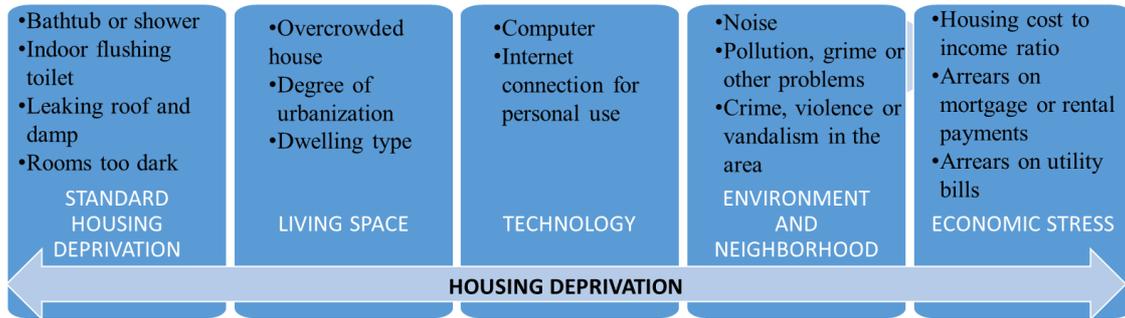
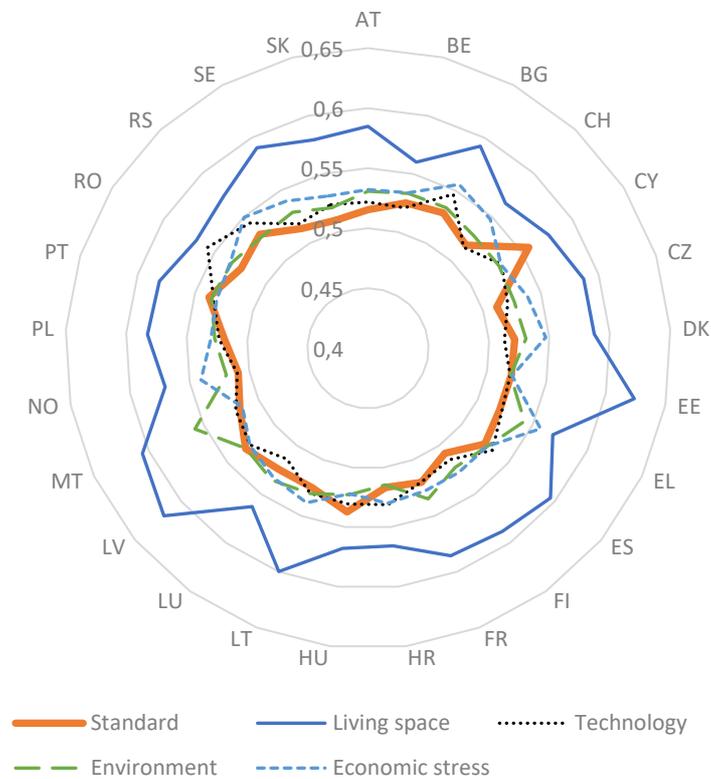
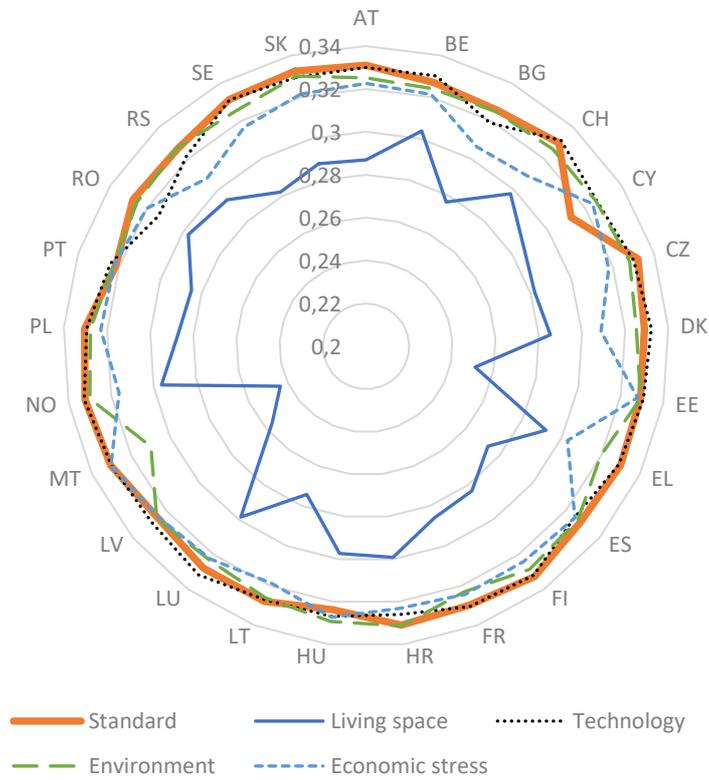


Figure 2. Mean degree of housing deprivation by dimensions and country, 2019



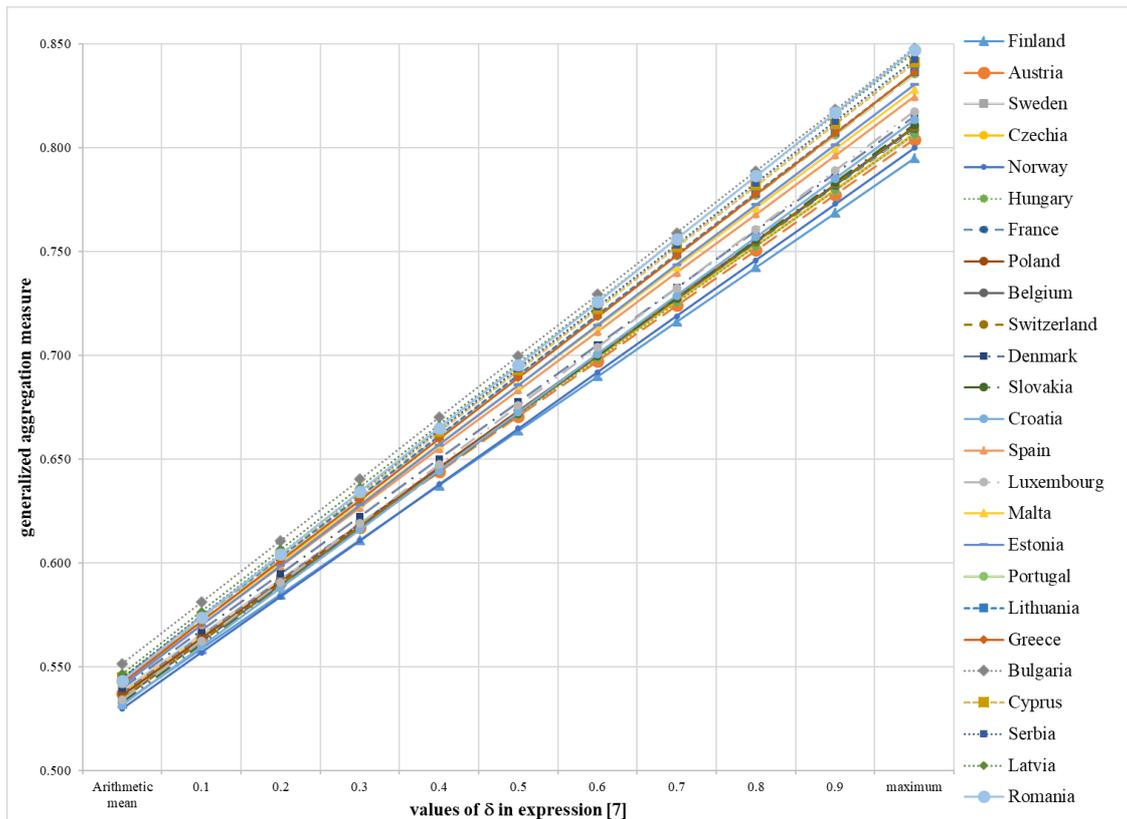
Source: Authors' calculations using EU SILC, 2019.

Figure 3. Gini index of the degree of housing deprivation by dimensions and country, 2019



Source: Authors' calculations using EU SILC, 2019.

Figure 4. Housing deprivation for different compensation degrees



Source: Authors' calculations using EU SILC, 2019.

Table 1. Mean values and Inequality levels (Gini index) in various dimensions of housing deprivation, 2019

Country	<i>Standard housing deprivation</i>		<i>Living space</i>		<i>Technology</i>		<i>Environment and neighbourhood</i>		<i>Economic stress associated with housing</i>	
	Mean	Gini	Mean	Gini	Mean	Gini	Mean	Gini	Mean	Gini
Austria	0.515	0.331	0.585	0.287	0.522	0.330	0.531	0.325	0.532	0.323
Belgium	0.525	0.327	0.560	0.304	0.521	0.330	0.533	0.324	0.534	0.321
Bulgaria	0.529	0.326	0.592	0.277	0.546	0.319	0.534	0.325	0.556	0.306
Switzerland	0.518	0.330	0.566	0.298	0.515	0.332	0.528	0.326	0.547	0.309
Cyprus	0.557	0.312	0.576	0.286	0.531	0.326	0.528	0.326	0.530	0.324
Czechia	0.512	0.332	0.587	0.282	0.521	0.330	0.527	0.328	0.539	0.318
Denmark	0.521	0.329	0.587	0.285	0.513	0.332	0.531	0.325	0.547	0.309
Estonia	0.520	0.329	0.624	0.251	0.519	0.331	0.520	0.329	0.521	0.328
Greece	0.520	0.330	0.569	0.292	0.522	0.329	0.543	0.320	0.557	0.303
Spain	0.525	0.329	0.595	0.273	0.533	0.325	0.528	0.327	0.528	0.325
Finland	0.508	0.333	0.589	0.283	0.515	0.332	0.523	0.329	0.528	0.324
France	0.520	0.330	0.586	0.286	0.520	0.331	0.535	0.323	0.528	0.324
Croatia	0.517	0.331	0.566	0.299	0.531	0.326	0.514	0.331	0.530	0.323
Hungary	0.537	0.324	0.568	0.297	0.531	0.327	0.523	0.329	0.522	0.327
Lithuania	0.525	0.328	0.600	0.274	0.530	0.327	0.530	0.326	0.538	0.319
Luxembourg	0.525	0.328	0.563	0.299	0.514	0.332	0.535	0.323	0.533	0.323
Latvia	0.531	0.325	0.619	0.256	0.526	0.329	0.531	0.326	0.527	0.325
Malta	0.517	0.331	0.606	0.244	0.521	0.330	0.558	0.310	0.515	0.330
Norway	0.509	0.332	0.570	0.296	0.510	0.333	0.519	0.330	0.540	0.316
Poland	0.519	0.330	0.583	0.287	0.523	0.329	0.527	0.328	0.530	0.323
Portugal	0.538	0.322	0.581	0.285	0.534	0.324	0.536	0.323	0.531	0.322
Romania	0.524	0.328	0.568	0.297	0.557	0.314	0.533	0.325	0.535	0.320
Serbia	0.530	0.327	0.574	0.294	0.543	0.321	0.528	0.327	0.550	0.307
Sweden	0.514	0.331	0.591	0.282	0.518	0.331	0.529	0.325	0.540	0.317
Slovakia	0.510	0.332	0.579	0.288	0.523	0.330	0.521	0.330	0.531	0.321

Source: Authors' calculations using EU SILC, 2019.

Table 2. Mean values and Inequality levels (Gini index) of aggregated housing deprivation degree, μ_{ai} and μ_{Mi} , 2019.

Country	Arithmetic mean μ_{ai}		Maximum μ_{Mi}	
	Mean	Gini	Mean	Gini
Austria	0.537	0.212	0.804	0.136
Belgium	0.535	0.210	0.810	0.130
Bulgaria	0.551	0.187	0.848	0.094
Switzerland	0.535	0.211	0.810	0.128
Cyprus	0.545	0.193	0.841	0.103
Czechia	0.537	0.213	0.807	0.132
Denmark	0.540	0.209	0.815	0.123
Estonia	0.541	0.208	0.831	0.113
Greece	0.542	0.186	0.836	0.107
Spain	0.542	0.208	0.825	0.117
Finland	0.532	0.224	0.795	0.142
France	0.538	0.210	0.809	0.131
Croatia	0.532	0.212	0.814	0.128
Hungary	0.536	0.216	0.807	0.132
Lithuania	0.545	0.199	0.837	0.108
Luxembourg	0.534	0.211	0.817	0.125
Latvia	0.547	0.196	0.846	0.098
Malta	0.543	0.200	0.828	0.112
Norway	0.530	0.221	0.800	0.137
Poland	0.536	0.215	0.810	0.132
Portugal	0.544	0.193	0.835	0.107
Romania	0.543	0.188	0.847	0.098
Serbia	0.545	0.190	0.843	0.101
Sweden	0.538	0.215	0.806	0.134
Slovakia	0.533	0.216	0.811	0.129

Source: Authors' calculations using EU SILC, 2019.

APPENDIX 1 Table A.1.1. country response measures to COVID-19 (1st Wave)

		Ban on all events	Closure of day care institutions	Closure of higher educations	Closure of primary schools	Closure of secondary schools	Closure of public spaces of any kind	Private gathering restrictions	Closure of restaurants, cafes/bars	Stay-at-home recomen-dations	Stay-at-home orders (general population)	Stay-at-home orders (partial)
Austria	S		16/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020	10/03/2020	16/03/2020	
	E		04/05/2020	30/09/2020	18/05/2020	03/06/2020	14/05/2020	30/04/2020	15/05/2020	15/03/2020	30/04/2020	
Belgium	S		01/05/2020	13/03/2020	13/03/2020	13/03/2020	13/03/2020	18/03/2020	13/03/2020	10/05/2020	18/03/2020	
	E		02/06/2020	20/09/2020	17/05/2020	17/05/2020	03/05/2020	30/06/2020	07/06/2020	31/08/2020	09/05/2020	
Bulgaria	S	08/03/2020	13/03/2020	13/03/2020	13/03/2020	13/03/2020	13/03/2020	08/03/2020	13/03/2020			
	E	14/05/2020	21/05/2020	31/05/2020	14/09/2020	14/09/2020	17/05/2020	30/06/2020	31/05/2020			
Croatia	S	19/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020	19/03/2020	19/03/2020	19/03/2020		17/03/2020	
	E	18/04/2020	11/05/2020	29/03/2020	10/05/2020	29/03/2020	28/05/2020	17/05/2020	11/05/2020		05/05/2020	
Cyprus	S	10/03/2020	10/03/2020	10/03/2020	10/03/2020	10/03/2020	13/03/2020	31/03/2020	16/03/2020		24/03/2020	04/05/2020
	E	24/06/2020	09/06/2020	11/05/2020	21/05/2020	10/05/2020	03/05/2020	03/05/2020	20/05/2020		03/05/2020	21/05/2020
Czechia	S		11/03/2020	11/03/2020	11/03/2020	11/03/2020	17/03/2020	12/03/2020		16/03/2020	22/10/2020	
	E		11/05/2020	10/05/2020	10/05/2020	07/06/2020	23/04/2020	11/05/2020		24/04/2020	03/12/2020	
Denmark	S		16/03/2020	16/03/2020	16/03/2020	16/03/2020	28/04/2020	18/03/2020	18/03/2020			14/03/2020 ^a
	E		15/04/2020	31/07/2020	15/04/2020	18/05/2020	17/05/2020	14/06/2020	17/05/2020			NA
Estonia	S		11/03/2021	16/03/2020	16/03/2020	16/03/2020	12/03/2020	12/03/2020			12/03/2020	
	E		NA	17/05/2020	17/05/2020	17/05/2020	16/05/2020	17/05/2020			17/05/2020	
Finland	S			18/03/2020	18/03/2020	18/03/2020	18/03/2020		18/03/2020		16/03/2020 ^a	
	E			04/08/2020	14/05/2020	04/08/2020	31/05/2020		31/05/2020		22/06/2020 ^a	
France	S		16/03/2020		16/03/2020	16/03/2020	16/03/2020	17/03/2020	16/03/2020		17/03/2020	12/05/2020
	E		01/06/2020		22/06/2020	10/05/2020	10/05/2020	15/06/2020	01/06/2020		11/05/2020	02/06/2020
Germany	S	23/03/2020	13/03/2020		13/03/2020	13/03/2020	16/03/2020		23/03/2020		17/03/2020	06/05/2020
	E	10/05/2020	14/05/2020		03/05/2020	03/05/2020	04/05/2020		04/05/2020		05/05/2020	29/06/2020
Greece	S		11/03/2020		11/03/2020	11/03/2020	14/03/2020	19/03/2020	14/03/2020	27/02/2020	23/03/2020	
	E		01/06/2020		01/06/2020	10/05/2020	03/05/2020	03/05/2020	31/05/2020	22/03/2020	04/05/2020	
Hungary	S	16/03/2020	25/03/2020	25/03/2020	16/03/2020	16/03/2020	13/03/2020		28/03/2020	21/03/2020	27/03/2020	
	E	11/06/2020	02/06/2020	18/05/2020	01/06/2020	01/06/2020	18/05/2020		18/05/2020	26/03/2020	18/05/2020	
Ireland	S	24/03/2020	12/03/2020	12/03/2020	12/03/2020	12/03/2020	12/03/2020	24/03/2020	24/03/2020	18/05/2020	27/03/2020	12/03/2020
	E	28/06/2020	29/06/2020	20/09/2020	24/08/2020	31/08/2020	26/03/2020	28/06/2020	29/06/2020	26/06/2020	17/05/2020	23/03/2020
Italy	S	09/03/2020	10/03/2020	10/03/2020	11/03/2020	04/03/2020	24/12/2020				10/03/2020	
	E	11/06/2020	10/06/2020	10/06/2020	14/09/2020	16/06/2020	06/01/2021				04/05/2020	

Latvia	S		17/03/2020	17/03/2020	17/03/2020	26/10/2020	17/03/2020		17/03/2020		12/05/2020	
	E		10/06/2020	31/08/2020	31/08/2020	NA	11/05/2020		11/05/2020		10/06/2020	
Lithuania	S	12/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020		16/03/2020	16/03/2020		
	E	31/05/2020	26/04/2020	24/05/2020	24/05/2020	31/05/2020	NA		22/04/2020	16/06/2020		
Luxembourg	S	16/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020		18/03/2020	20/04/2020	
	E	24/05/2020	24/05/2020	24/05/2020	NA	11/05/2020	04/05/2020	29/05/2020		19/04/2020	11/05/2020	
Malta	S	13/03/2020	13/03/2020	13/03/2020	13/03/2020	13/03/2020	18/03/2020		18/03/2020		28/03/2020 ^a	
	E	NA	30/06/2020	30/06/2020	30/06/2020	30/06/2020	21/05/2020		21/05/2020		NA	
Netherlands	S	23/03/2020	16/03/2020	12/03/2020	16/03/2020	16/03/2020	15/12/2020	23/03/2020	15/03/2020	18/03/2020	13/03/2020 ^a	11/05/2020
	E	31/05/2020	10/05/2020	14/06/2020	10/05/2020	01/06/2020	02/03/2021	30/06/2020	31/05/2020	10/05/2020	26/06/2020 ^a	01/06/2020
Norway	S	12/03/2020	12/03/2020	12/03/2020	12/03/2020	12/03/2020	12/03/2020	02/06/2020	12/03/2020		12/03/2020 ^a	
	E	06/05/2020	20/04/2020	14/06/2020	26/04/2020	11/05/2020	31/05/2020	NA	31/05/2020		01/06/2020 ^a	
Poland	S		12/03/2020	12/03/2020	12/03/2020	12/03/2020	14/03/2020	02/04/2020	14/03/2020	19/04/2020	24/03/2020	08/03/2020 ^a
	E		06/05/2020	24/05/2020	24/05/2020	24/05/2020	14/03/2020	29/05/2020	17/05/2020	04/05/2020	18/04/2020	NA
Portugal	S	04/05/2020	16/03/2020	16/03/2020	16/03/2020	16/03/2020	13/03/2020	03/05/2020	15/03/2020		19/03/2020	
	E	11/11/2020	17/05/2020	17/05/2020	14/09/2020	17/05/2020	17/03/2020	NA	17/05/2020		02/05/2020	
Romania	S	16/03/2020	16/03/2020	16/03/2020	18/03/2020	22/03/2020	16/03/2020	18/03/2020			25/03/2020 ^a	22/03/2020
	E	14/06/2020	14/06/2020	14/06/2020	13/05/2020	NA	01/06/2020	31/05/2020			14/05/2020 ^a	13/05/2020
Slovakia	S	10/03/2020	16/03/2020	16/03/2020	30/03/2020	16/03/2020	12/03/2020					
	E	03/06/2020	31/05/2020	09/06/2020	31/05/2020	31/05/2020	20/05/2020					
Slovenia	S		12/03/2020	12/03/2020	12/03/2020	12/03/2020	14/03/2020	19/03/2020		19/03/2020	20/10/2020	
	E		17/05/2020	17/05/2020	03/06/2020	17/05/2020	28/04/2020	17/05/2020		04/05/2020	NA	
Spain	S	14/03/2020	12/03/2020	12/03/2020	12/03/2020	12/03/2020	14/03/2020		14/03/2020	09/03/2020	14/03/2020	04/05/2020
	E	01/06/2020	27/08/2020	27/08/2020	27/08/2020	27/08/2020	03/05/2020		03/05/2020	13/03/2020	03/05/2020	11/05/2020
Sweden	S	14/06/2020		18/03/2020		18/03/2020						01/04/2020 ^a
	E	NA		15/06/2020		15/06/2020						22/10/2020 ^a
Switzerland	S	20/03/2020		16/03/2020	16/03/2020	16/03/2020	16/03/2020	20/03/2020	16/03/2020			16/03/2020 ^a
	E	05/06/2020		11/05/2020	11/05/2020	11/05/2020	10/05/2020	05/06/2020	06/06/2020			NA

S: date of start; E: date of end; ^a: stay-at-home recommendations for risk groups or vulnerable populations.

Source: Data on country response measures to COVID-19 (European Centre for Disease Prevention and Control).

APPENDIX 2

Table A.2.1. Countries and observations, 2019

Country	Country code	Observations
Austria	AT	12,239
Belgium	BE	15,433
Bulgaria	BG	16,959
Switzerland	CH	15,652
Cyprus	CY	10,828
Czechia	CZ	19,021
Denmark	DK	11,766
Estonia	EE	15,064
Greece	EL	39,768
Spain	ES	38,710
Finland	FI	22,922
France	FR	25,740
Croatia	HR	19,436
Hungary	HU	14,995
Lithuania	LT	11,269
Luxembourg	LU	9,958
Latvia	LV	10,819
Malta	MT	9,527
Norway	NO	14,243
Poland	PL	44,949
Portugal	PT	33,027
Romania	RO	16,791
Serbia	RS	16,090
Sweden	SE	12,690
Slovakia	SK	14,623
		472,519

Source: EU SILC, 2019.

APPENDIX 3

Variable definitions:

Overcrowded dwelling: number of rooms – number of rooms needed according to sum of one room for the household; one room per couple in the household; one room per single person aged 18 and more; one room per pair of single people of the same gender between 12 and 17 years of age; one room per single person between 12 and 17 years of age and not included in the previous category and one room per pair of children under 12 years of age.

Degree of urbanization: 1. Densely populated areas, 2. Intermediate area, 3. Thinly populated areas. Densely populated area: Contiguous grid cells of 1km² with a density of at least 1 500 inhabitants per km² and a minimum population of 50000. Intermediate area: Clusters of contiguous grid cells of 1km² with a density of at least 300 inhabitants per km² and a minimum population of 5000. Thinly populated area: Grid cells outside urban clusters. See variable DB100 definition in EU-SILC for definition of categories.

Dwelling type: 1. Apartment or flat in a building with 10 or more dwellings, 2. Apartment or flat in a building with less than 10 dwellings, 3. Semi-detached or terraced house, 4. Detached house. See variable HH010 in EU-SILC for definition of categories.

Bathtub or shower unit in dwelling: 1. No, 2. Yes, shared, 3. Yes, for sole use of the household.

Indoor flushing toilet: 1. No, 2. Yes, shared, 3. Yes, for sole use of the household.

Leaking roof and damp: the dwelling has a problem with a leaking roof and/or damp ceilings, dampness in the walls, floors or foundation and/or rot in window frames and doors: 1. Yes 2. No

Dwelling too dark: There is not enough daylight coming through the windows: 1. Yes, 2. No

Computer: the household does not have a computer because it cannot afford it (enforced lack) or for other reasons: 1. No, other reason 2. No, cannot afford 3. Yes.

Internet connection for personal use at home: 1. at least half of adults have no internet connection 2. Less than half of adults have no internet connection.

Noise from neighbors or from the street: 1. Yes, 2. No

Pollution, grime or other environment problems: 1. Yes, 2. No

Crime, violence or vandalism in the area: 1. Yes, 2. No

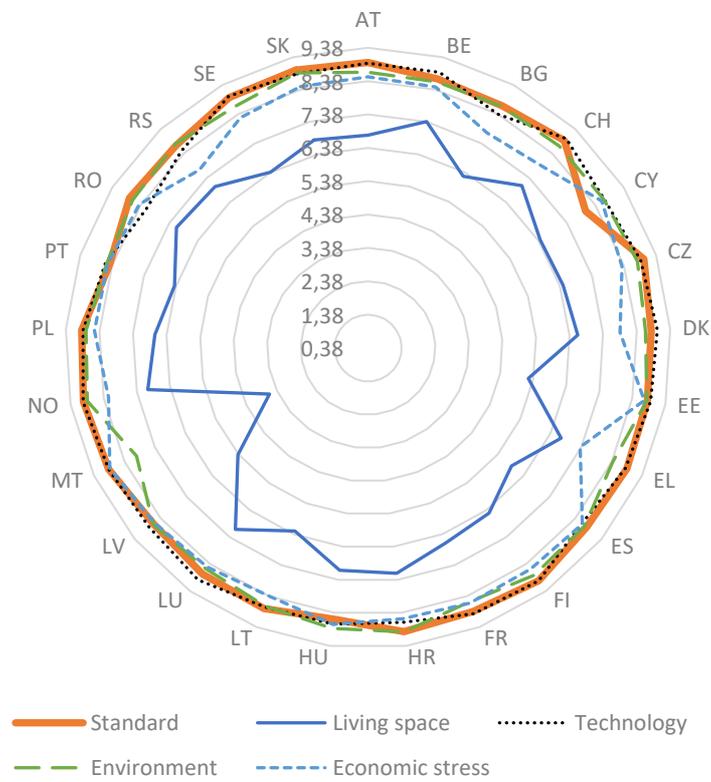
Housing cost to income ratio: Share of total housing cost (rent, mortgage principal and interest payments, cost of utilities, etc.) net of housing allowances in the total disposable household income (net of housing allowances): 1. Greater or equal to 40%, 2. Greater or equal to 30 and smaller to 40% 3. Greater or equal to 20% and smaller to 30% 4. Less than 20%

Arrears on mortgage or rental payments: household has been in arrears on mortgage or rental payments in the past 12 months: 1. Yes, twice or more, 2. Yes, once, 3. No

Arrears on utility bills: household has been in arrears on utility bills in the past 12 months: 1. Yes, twice or more, 2. Yes, once, 3. No

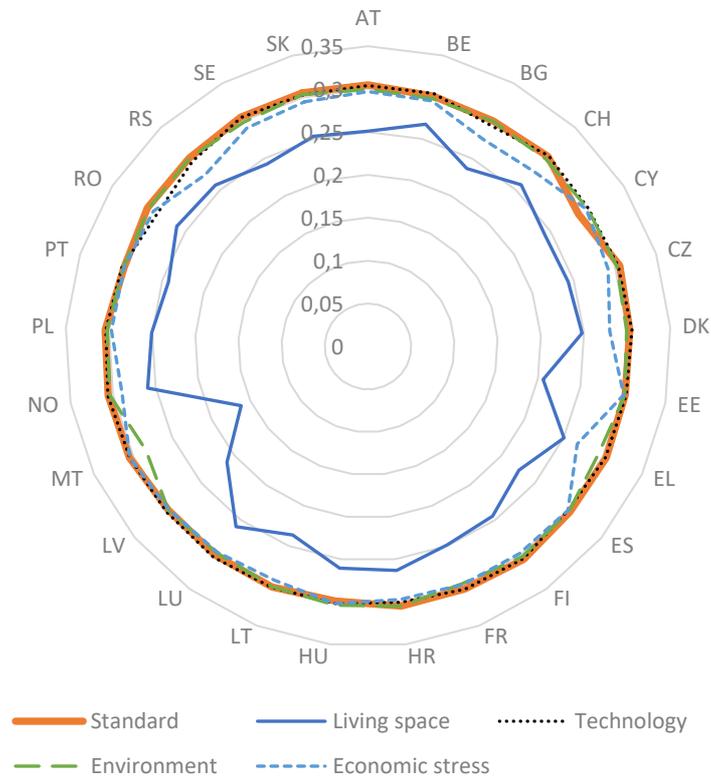
APPENDIX 4

Figure A.4.1. P90/P10 index of the degree of housing deprivation by dimensions and country, 2019



Source: Authors' calculations using EU SILC, 2019.

Figure A.4.2. Theil index of the degree of housing deprivation by dimensions and country, 2019



Source: Authors' calculations using EU SILC, 2019.

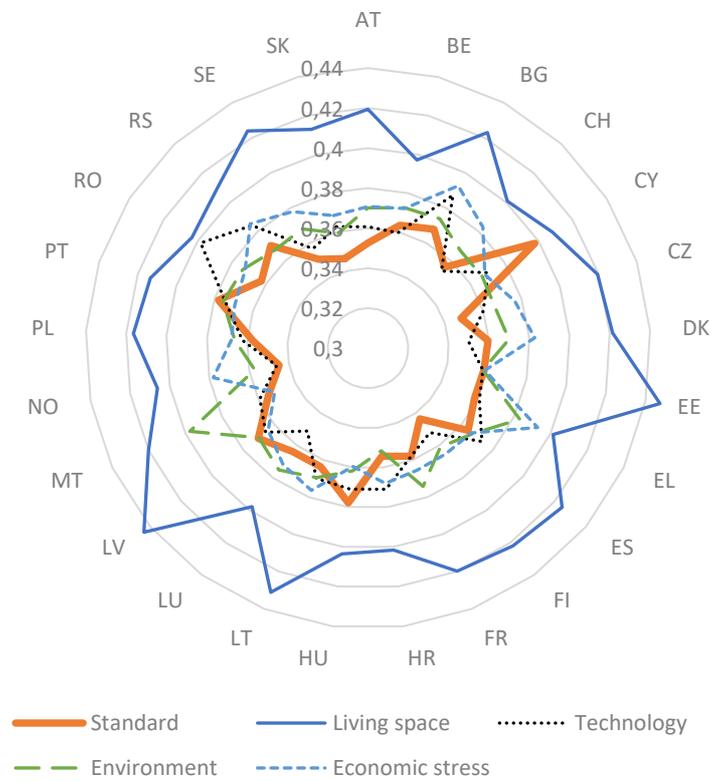
APPENDIX 5. RESULTS FOR THE BETTI AND VERMA (2008) MEMBERSHIP FUNCTION.

Table A.5.1. Mean values and Inequality levels (Gini index) in various dimensions of housing deprivation, 2019

Country	<i>Standard housing deprivation</i>		<i>Living space</i>		<i>Technology</i>		<i>Environment and neighbourhood</i>		<i>Economic stress associated with housing</i>	
	Mean	Gini	Mean	Gini	Mean	Gini	Mean	Gini	Mean	Gini
Austria	0.353	0.495	0.419	0.439	0.361	0.493	0.370	0.485	0.371	0.481
Belgium	0.363	0.488	0.397	0.460	0.360	0.494	0.373	0.484	0.372	0.480
Bulgaria	0.368	0.486	0.423	0.430	0.387	0.476	0.374	0.485	0.393	0.462
Switzerland	0.356	0.494	0.401	0.454	0.353	0.497	0.367	0.487	0.383	0.465
Cyprus	0.398	0.465	0.408	0.442	0.371	0.487	0.367	0.487	0.369	0.484
Czechia	0.348	0.498	0.420	0.435	0.360	0.494	0.366	0.490	0.376	0.475
Denmark	0.360	0.492	0.421	0.438	0.350	0.498	0.370	0.485	0.383	0.465
Estonia	0.358	0.492	0.447	0.405	0.358	0.495	0.358	0.492	0.359	0.490
Greece	0.358	0.493	0.401	0.448	0.361	0.492	0.383	0.477	0.393	0.460
Spain	0.364	0.491	0.425	0.428	0.373	0.485	0.367	0.488	0.366	0.486
Finland	0.344	0.499	0.422	0.436	0.352	0.497	0.361	0.491	0.365	0.484
France	0.358	0.493	0.420	0.439	0.358	0.494	0.374	0.482	0.366	0.484
Croatia	0.354	0.495	0.402	0.455	0.371	0.486	0.352	0.496	0.368	0.483
Hungary	0.378	0.483	0.403	0.452	0.371	0.488	0.362	0.492	0.359	0.489
Lithuania	0.364	0.490	0.431	0.426	0.370	0.488	0.370	0.487	0.376	0.476
Luxembourg	0.364	0.490	0.398	0.455	0.351	0.497	0.375	0.482	0.372	0.481
Latvia	0.371	0.485	0.444	0.409	0.366	0.491	0.370	0.486	0.364	0.485
Malta	0.355	0.494	0.420	0.415	0.359	0.494	0.398	0.464	0.351	0.494
Norway	0.345	0.498	0.406	0.451	0.346	0.499	0.357	0.494	0.378	0.473
Poland	0.357	0.494	0.416	0.440	0.362	0.492	0.366	0.490	0.368	0.482
Portugal	0.378	0.480	0.413	0.440	0.374	0.484	0.375	0.482	0.370	0.482
Romania	0.363	0.490	0.403	0.452	0.398	0.468	0.374	0.486	0.372	0.479
Serbia	0.370	0.488	0.409	0.447	0.384	0.479	0.367	0.489	0.385	0.465
Sweden	0.351	0.496	0.424	0.435	0.357	0.496	0.368	0.486	0.378	0.473
Slovakia	0.346	0.498	0.413	0.440	0.363	0.493	0.359	0.494	0.369	0.480

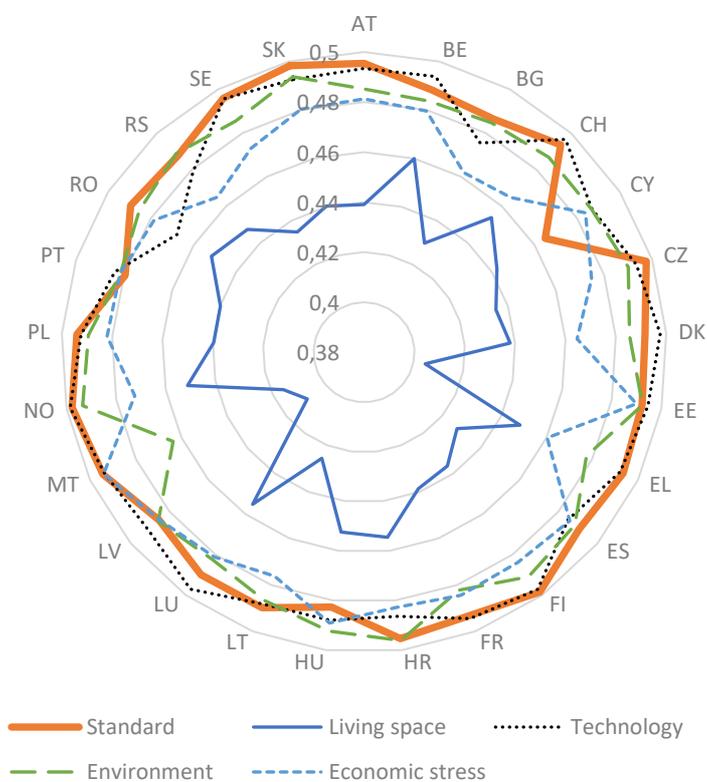
Source: Authors' calculations using EU SILC, 2019.

Figure A.5.1. Mean degree of housing deprivation by dimensions and country, 2019



Source: Authors' calculations using EU SILC, 2019.

Figure A.5.2. Gini index of the degree of housing deprivation by dimensions and country, 2019



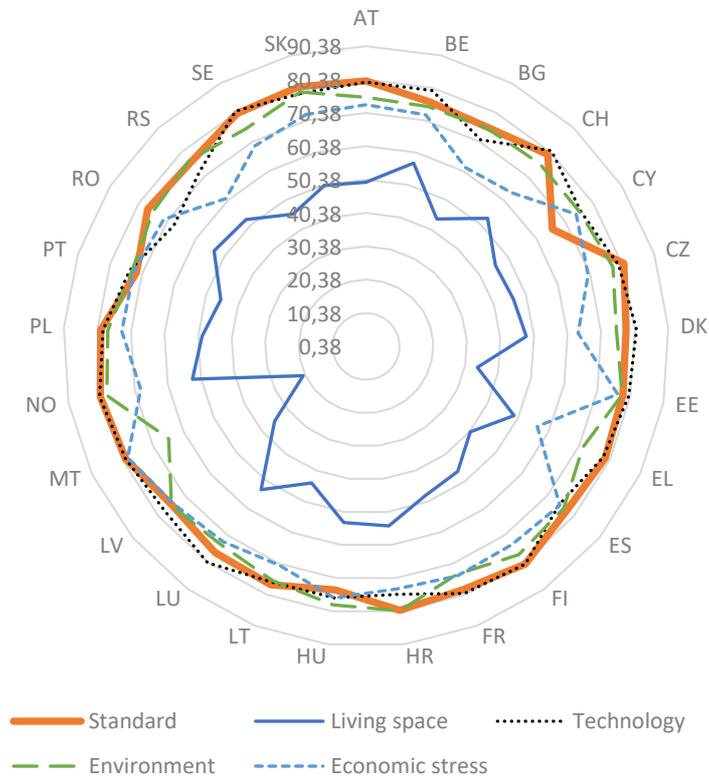
Source: Authors' calculations using EU SILC, 2019.

Table A.5.2. Mean values and Inequality levels (Gini index) of aggregated housing deprivation, 2019.

Country	Arithmetic mean		Maximum	
	Mean	Gini	Mean	Gini
Austria	0.375	0.308	0.689	0.224
Belgium	0.373	0.307	0.697	0.214
Bulgaria	0.389	0.271	0.741	0.167
Switzerland	0.372	0.308	0.695	0.214
Cyprus	0.382	0.277	0.736	0.176
Czechia	0.374	0.309	0.692	0.221
Denmark	0.377	0.307	0.700	0.210
Estonia	0.376	0.299	0.719	0.196
Greece	0.379	0.273	0.728	0.185
Spain	0.379	0.299	0.714	0.198
Finland	0.369	0.324	0.677	0.235
France	0.375	0.306	0.695	0.216
Croatia	0.369	0.304	0.703	0.211
Hungary	0.375	0.313	0.692	0.219
Lithuania	0.382	0.285	0.731	0.183
Luxembourg	0.372	0.305	0.707	0.207
Latvia	0.383	0.280	0.740	0.173
Malta	0.377	0.291	0.715	0.195
Norway	0.366	0.320	0.684	0.227
Poland	0.374	0.309	0.698	0.217
Portugal	0.382	0.279	0.727	0.183
Romania	0.382	0.269	0.745	0.169
Serbia	0.383	0.276	0.736	0.176
Sweden	0.375	0.313	0.692	0.222
Slovakia	0.370	0.309	0.698	0.213

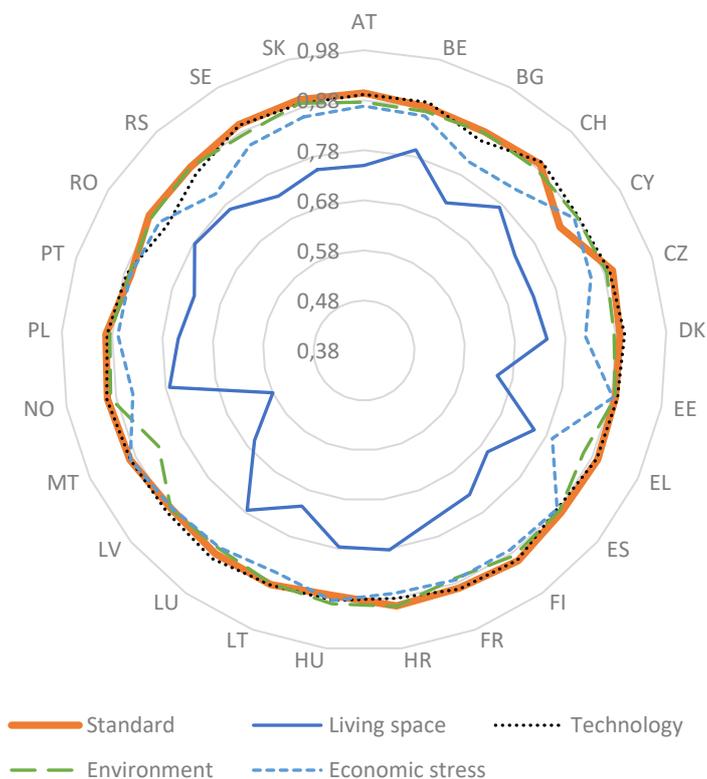
Source: Author's calculations using EU SILC, 2019.

Figure A.5.3. P90/10 index of the degree of housing deprivation by dimensions and country, 2019



Source: Author's calculations using EU SILC, 2019.

Figure A.5.4. Theil index of the degree of housing deprivation by dimensions and country, 2019



Source: Author's calculations using EU SILC, 2019.