COVID-19 Lockdown and Housing Deprivation Across European Countries

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IMPORTANT

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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 has been intrinsically linked to a deep economic crisis. "Stay-at-home" orders at the beginning of the first wave, partial lockdown in subsequent waves, 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 Appendix 1). Most European countries significantly curbed public life to halt the spread of the COVID-19 outbreak. The resulting shutdown 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).

Inevitably, the economic crisis also translated into a well-being shock (Brodeur et al., 2021) changing inequality and poverty trends in various European Union (EU) countries (Belot et al., 2020; Cantó et al., 2021). 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 measures.

Changes in the distribution of disposable income and in the earnings distribution are not, however, the only type of welfare losses associated with the lockdown. Undoubtedly, one of the most important sources of these losses 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 and gave more relative importance to adequate housing as a fundamental right. Furthermore, differences in the lack of adequate housing conditions in EU countries put forward in Borg (2015) or, more recently, in Dewilde and Decker (2016) and Decker (2017), 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. Second, COVID-19 has replicated existing health inequalities and, in some cases, has increased them, housing being part of this process (Public Health England, 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 losses. The pandemic has also affected mental health issues and households living in precarious housing conditions might be particularly affected (Royal College of Psychiatrists, 2020). Furthermore, viral transmission may be facilitated in densely populated areas and in locations with insufficient social distancing (Lusignan et al., 2020; Chu et al., 2020; Rubin et al., 2020).

Adequately measuring housing conditions in European countries may therefore be a good approximation to the diverse dimension of an important source of decrease in well-being caused by the pandemic. This requires having advanced measurement and interpretation procedures for housing deprivation. 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-27 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 approximately 1% in Finland, Norway and Ireland.

The key question is whether housing conditions were already significantly different among individuals within each country right when the lockdown began. 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 that includes more dimensions than the official Eurostat indicator of severe housing deprivation. 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 Lemmi (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 both within a country and between them. Interpreting deprivation as a phenomenon that has different degrees, allows the focus of public intervention to be placed on two different levels: the possibility of analyzing results focusing on different comparative experiences (which is what we give more weight to), and that of drawing, when necessary, a particular threshold within the deprivation scale. Another advantage is that Fuzzy Sets Analysis works particularly well when theories about the object of study are diverse and the different dimensions that are measured are subject to discussion, as in our case (Ragin, 2000).

In our analysis we use two complementary membership functions, that proposed by Betti and Verma's (2008) and our new proposal, each of them with different levels of compensation between the proportion of individuals who are less deprived than a given individual and diverse shares in the lack of deprivation of all individuals who are less deprived than the person concerned. The former membership function allows for partial compensation while the latter allows for a total one between the proportion of the population and the share in the lack of deprivation of individuals less deprived than a given individual. Thus, we evaluate housing deprivation in the case in which a high proportion of individuals with less deprivation than a given individual in a specific dimension can be compensated by a lower average level of deprivation of those less deprived. On the other hand, under partial compensation, a high proportion of individuals with less deprivation than a given individual in a specific dimension will need a much lower average level of deprivation of those less deprived to get a similar score than in the case of total compensation. In this way we provide two alternatives to check the robustness of results under different degrees of compensation between the proportion of the population and the share in the lack of deprivation of individuals less deprived than a given individual. We also perform a robustness analysis regarding the aggregation of dimensions allowing for different levels of compensation in which a bad performance in one dimension can be offset by good performances in others to different degrees.

We use pre-COVID data (2019) to infer the consequences of the COVID crisis. 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, housing deprivation levels are significantly higher in some Eastern European countries in comparison to the rest of the EU and contrast with the low levels of the index in Nordic countries. 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. Given the variety of dimensions it incorporates and the solution it offers for constructing a synthetic indicator, our approach can be used not only to analyze housing deprivation in a lockdown context but also in more general contexts.

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 and Section 5 concludes.

2. A FUZZY APPROACH FOR THE MEASUREMENT OF HOUSING DEPRIVATION

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 suffer 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.

There is, however, an extensive literature on multidimensional deprivation that 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, such as multivariate statistical techniques.

There are different alternatives to construct synthetic housing deprivation indices using multivariate analysis techniques (see Ayala and Navarro, forthcoming, for a review). Layte et al. (2001) and Whelan et al. (2001) applied factor analysis to a set of deprivation indicators, finding that in addition to the two dimensions of basic and secondary deprivation, there was a third of residential deprivation. Ayala and Navarro (2007) used a latent class model assigning households to different classes, showing that a vector of observed variables –having hot running water, heating, a leaky roof, damp walls or floor, rot in window frames and floors and overcrowding– and the correlations among such variables could be explained by a single latent variable. Other authors have used the latent trait model under item response theory (IRT) to measure poverty ranking assets according to the prevalence of ownership of durables, including housing equipment (Deutsch et al., 2020). Martínez and Navarro (2016) used IRT to analyze a set of indicators of material deprivation, including some of the most common housing indicators.

Another alternative is fuzzy sets theory. This approach interprets deprivation as a phenomenon that appears in different degrees and levels that are difficult to separate and identify instead of as an attribute that one either lacks or possesses (Chiappero-Martinetti, 2000; Betti and Verma, 2008). Using this fuzzy methodology, the standard deprived/nondeprived dichotomy can be avoided, as housing deprivation is seen as a fuzzy set to which individuals belong to in different degrees. In this conceptualization, all individuals in a population are subject to housing deprivation, but to a heterogeneous degree. Comparison of these two alternative methods, latent class models and fuzzy set approaches can be found in Pérez-Mayo (2007).

Among the different alternatives, we opt for a fuzzy approach. The main reason to use a fuzzy approach is that the aggregation of different indicators and the combination of different housing 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. 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.

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), 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)]. Using the integrated fuzzy and relative (IFR) methodology, Ulman and Ćwiek (2020) determined the scale of housing poverty and its determinants in Poland.

To measure the level of housing deprivation 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 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 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. Since factor analysis is usually based on Pearson correlations of continuous variables and problems may occur when the variables are discrete and dichotomous, we use tetrachoric correlations which are better suited to the discrete and dichotomous nature of deprivation data. We use the matrix of tetrachoric correlations as the input for the factor analysis (Guio et. al, 2016; European Comission, Eurostat, 2012). 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, w_j, in each country considering 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. As explained in García-Pardo et al. (2021): $w_j = w_j^a\, w_j^b$, where w_j^a = coeficient of variation of s_j and $w_j^b = 1 - R^2_{s_{j,i}\, s_{-j,i}}$, with n being the number of individuals in the country and $R^2_{s_{j,i}\, s_{-j,i}}$ being the coefficient of determination for a multiple linear regression model in which $s_{j,i}$ is the dependent variable and $s_{1,i}, s_{2,i}, \dots, s_{j-1,i}, s_{j+1,i}, \dots s_{J,i}$ are the independent variables (J being the total number of items in the dimension).

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

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

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

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

This function accounts for the proportion of population less deprived than individual i in dimension h, $1 - F(S_{h,i})$, and for the share in the lack of deprivation in dimension h of individuals less deprived in that dimension, $1 - L(S_{h,i})$, where $L(S_{h,i})$ represents the value of the Lorenz curve of S_h for individual i. 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):

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

in which partial compensation between the share and the proportion of the population less deprived than individual i in the dimension h is allowed. Note that in their formulation, Betti et al. (2006) introduce a parameter α chosen so that the mean of the membership function equals the head count ratio, and the fuzzy monetary measure can be expressed in terms of the generalized Gini measure. As in Betti and Verma (2008), we remove the α parameter and so that the methodology is independent from the anchorage to the headcount ratio. However, this strategy eliminates the possibility of giving more weight to the more deprived statistical units. Beyond that, the choice of the value of α is essentially arbitrary or, at best, is based on some external considerations. 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.

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.

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

where H is the number of dimensions (h=1…H).

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,

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

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, 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:

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

δ takes values from 0 (full substitutability) to 1 (no substitutability). As $\delta \to 1$, 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. There is not a preferred value of δ, and its value is decided by the social planner. In our analysis we provide results for values of δ between 0 and 1 to assess that results are not largely sensitive to this choice.

Finally, we can also estimate the country's average level of overall housing deprivation, 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 the only relevant housing conditions that affect a household's well-being 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, we 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 this context, such as access to technology, environmental issues, economic stress and living space. Given the lack of an official or commonly accepted definition of which dimensions should be considered in a lockdown situation, this is one of the possible contributions of our paper. Being the decision on which dimensions to include inevitably somewhat ad-hoc, the inclusion of the four dimensions is supported by previous studies in the housing deprivation literature. Another alternative could have been to consider the use of information from surveys to the general population on which housing dimensions might be the most relevant in a lockdown situation. Unfortunately, to the best of our knowledge, these surveys are not yet available.

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 in relation to the number of rooms, 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 microdata on income, poverty, social exclusion and living conditions. In this paper we use the cross-sectional EU-SILC 2019 for European countries (See Appendix 2 for the list of countries and observations). 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 (Tinson and Clear, 2020).

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 (See Appendix 3 for a description of variables). Degree of urbanization classifies local administrative units into three types of area: densely, intermediate and thinly populated area. 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 (Awada et al., 2021). It must be noted, however, that some of these relationships might not be so straightforward. For instance, while living in an overcrowded home during a lockdown may be bad for mental health, it could also be that living alone without any human contact in that isolated situation is also a problem.

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 (El-Osta et al., 2021).

The *environment and neighborhood* dimension might be also important when households face a lockdown situation. However, area variables are probably the most difficult to select when measuring individual deprivation. On the one hand, we are restricted by the limited information available in EU-SILC. For example, the data do not include information on variables that have been shown to be relevant in the analysis of urban setting –physical inactivity, diet, harmful alcohol consumption, and smoking– and its relationships with cardiovascular health (Rivera-Navarro et al., 2021) or environmental variables that are also important in explaining physical activity (Rivera Navarro et al. 2020). On the other hand, the variables selected should have a particular impact in a lockdown situation. We have selected 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 (Usher at al., 2020). 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 a worsening of mental health problems (Cheng et al. 2021) even if the main reason to include them is that housing costs are one of the most prominent dimensions, along with housing conditions, housing equipment and neighbourhood quality (Ayala and Navarro, forthcoming). The traditional rationale for considering these costs is to try to measure people's situation with respect to where they live. Although these costs are also strongly correlated with an increased risk of income poverty —when housing costs reach high levels, the ability to cope with other consumption is reduced, and the probability of being poor increases (Saunders, 2017)—, there is growing evidence —at least for some European countries— that higher housing costs are associated with increased living conditions deprivation (Dewilde, 2021).

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

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 another one 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 (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.

The results obtained for the five dimensions of housing deprivation (Table 1, Figures 2 and 3) and the overall housing deprivation (Table 2) following a wide range of aggregation methods ($\mu_{ai,}$ μ_{Mi}, and μ_{gi}) yield important insights into the differences across European countries regarding the degree of housing deprivation. Results for the Betti and Verma (2008) membership function are reported in Appendix 4. Our main conclusions hold under both membership functions, proving the robustness of our findings.

< Table 1 around here >

The *standard housing deprivation* fuzzy measure 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.

The *living space* dimension, which is measured by the overcrowding indicator, 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 the entire household. 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.

Regarding the *technology* dimension, the countries where the degree of deprivation is greatest are Eastern European countries (Romania, Bulgaria and Serbia). In contrast, countries like Norway, Denmark, Luxembourg, Finland, and Switzerland stand out for having the lowest degrees of technology deprivation. 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, there are different degrees of access observed between same-country households which clearly affects individual well-being 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 ―defined on the basis of the indicators available in EUSILC― is not a worrying deprivation dimension for most countries. Its degree is higher in Malta, Greece, Portugal, France and Luxembourg. 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.

The dimension capturing *economic stress associated with housing* is not only of great importance because economic stress associated to housing problems 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 must 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 country. Among the countries with the highest degree of intensity in this dimension, Greece, Bulgaria, Serbia, Switzerland, Denmark and Norway stand out.

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 >

Finally, our methodological approach allows us to summarize housing deprivation in European countries into a single indicator (Table 2). We have different alternatives to aggregate the previous measures. The two extremes of this methodological choice are either using the arithmetic mean of the five housing deprivation dimensions or using the maximum deprivation level in any dimension. The first one allows full compensation between dimensions, while the second does not allow compensation at all. 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, where a bad performance in one dimension can be completely offset by good performances in others), 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.

< 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.

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 3 shows how the generalized aggregation index changes 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 under different aggregation criteria 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 3 around here >

These differences in housing deprivation across countries warn us about the problems that the lockdown strategy can cause in the medium term in terms of well-being. 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. This result shows that the effects of the lockdown on social well-being may not have affected all Europeans equally and emphasizes the need of government measures that promote decent housing.

5. CONCLUDING REMARKS

There are several avenues through which COVID-19 lockdowns can potentially affect well-being. The channels through which this effect may take place are far less clear. Households' access to work and education are two of the most important drivers of the reduction in well-being both in the short and medium term. Nevertheless, there are other relevant side effects of keeping individuals at home. An important one arises from the housing conditions with which households faced the lockdown. Housing deprivation led to immediate decreases in well-being across households when lockdown measures were enacted. Additionally, the lack of adequate housing conditions during lockdowns can also exacerbate deprivation in other well-being dimensions.

Analysing the degree of housing deprivation 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 to 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.

Second, conclusions are robust to the type of membership function chosen so that different degrees of compensation (between the proportion of the population and the share in the lack of deprivation of individuals less deprived than a given individual) do not change results significantly. Moreover, conclusions are also robust to the alternative ways one can aggregate the information of each dimension allowing for different levels of compensation.

These findings can assist policymakers in formulating policies and outreach efforts that may prevent the decrease 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 that in some countries the degree of housing deprivation is still very high. 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.

Given that housing problems can affect health outcomes –both public health problems arising from inadequate housing conditions and mental health problems associated with economic stress– some of the countries with a higher level of housing deprivation should promote policies aimed at improving housing conditions as a way to improve multidimensional well-being. These policies should encompass not only the improvement of the indicators used by Eurostat but also the broader set of dimensions that we consider in this paper.

Our work may also be useful to open newlines of research. The empirical analysis can be much richer and provide key hints for policy design if we disaggregate indicators by population groups. Moreover, specific dimensions could be used as predictors of specific outcomes in a meaningful way. For instance, a technological deprivation index, could predict the level of individual future education achievement.

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Figure 1. Dimensions and variables

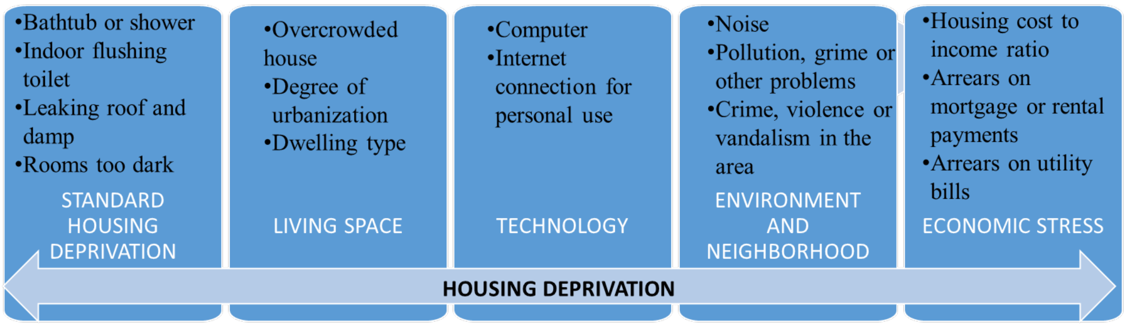
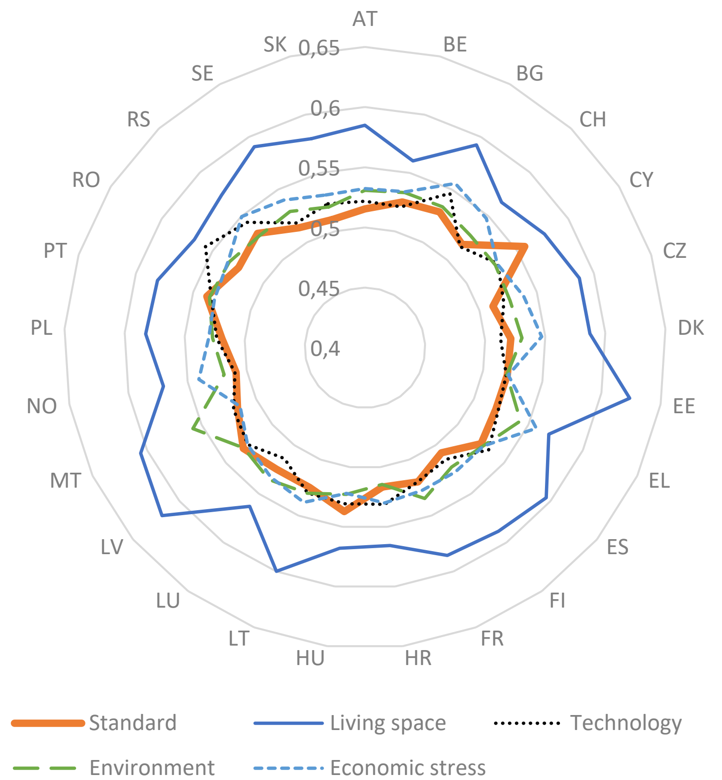
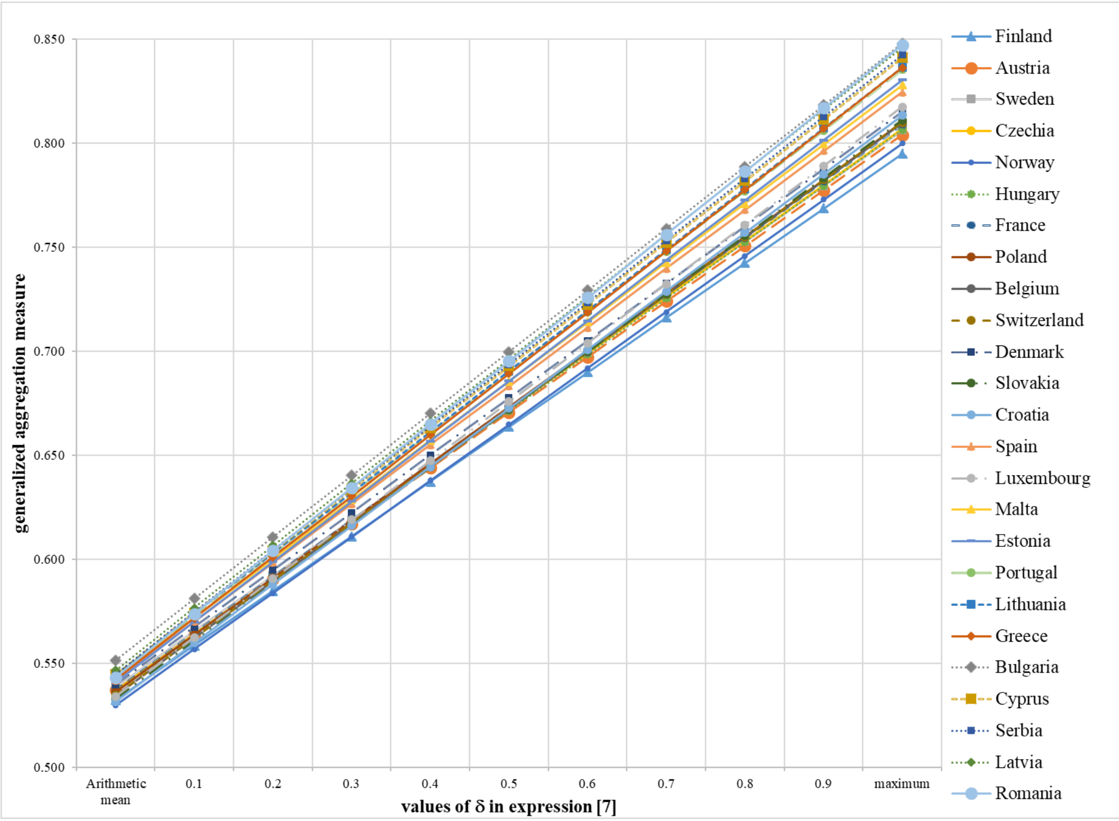


Figure 2. Mean degree of housing deprivation by dimensions and country, 2019



Source: Authors' calculations using EU SILC, 2019.

Figure 3. Housing deprivation for different compensation degrees between dimensions



Source: Authors' calculations using EU SILC, 2019.

Table 1. Mean values in various dimensions of housing deprivation, 2019

Country	*Standard housing deprivation*	*Living space*	*Technology*	*Environment and neibourhood*	*Economic stress associated with housing*
Austria	0.515	0.585	0.522	0.531	0.532
Belgium	0.525	0.560	0.521	0.533	0.534
Bulgaria	0.529	0.592	0.546	0.534	0.556
Switzerland	0.518	0.566	0.515	0.528	0.547
Cyprus	0.557	0.576	0.531	0.528	0.530
Czechia	0.512	0.587	0.521	0.527	0.539
Denmark	0.521	0.587	0.513	0.531	0.547
Estonia	0.520	0.624	0.519	0.520	0.521
Greece	0.520	0.569	0.522	0.543	0.557
Spain	0.525	0.595	0.533	0.528	0.528
Finland	0.508	0.589	0.515	0.523	0.528
France	0.520	0.586	0.520	0.535	0.528
Croatia	0.517	0.566	0.531	0.514	0.530
Hungary	0.537	0.568	0.531	0.523	0.522
Lithuania	0.525	0.600	0.530	0.530	0.538
Luxembourg	0.525	0.563	0.514	0.535	0.533
Latvia	0.531	0.619	0.526	0.531	0.527
Malta	0.517	0.606	0.521	0.558	0.515
Norway	0.509	0.570	0.510	0.519	0.540
Poland	0.519	0.583	0.523	0.527	0.530
Portugal	0.538	0.581	0.534	0.536	0.531
Romania	0.524	0.568	0.557	0.533	0.535
Serbia	0.530	0.574	0.543	0.528	0.550
Sweden	0.514	0.591	0.518	0.529	0.540
Slovakia	0.510	0.579	0.523	0.521	0.531

Source: Authors' calculations using EU SILC, 2019.

Table 2. Mean values of aggregated housing deprivation degree, $\mu_{\alpha i}$ and μ_{Mi}, 2019

Country	Arithmetic mean $\mu_{\alpha i}$	Maximum μ_{Mi}
Austria	0.537	0.804
Belgium	0.535	0.810
Bulgaria	0.551	0.848
Switzerland	0.535	0.810
Cyprus	0.545	0.841
Czechia	0.537	0.807
Denmark	0.540	0.815
Estonia	0.541	0.831
Greece	0.542	0.836
Spain	0.542	0.825
Finland	0.532	0.795
France	0.538	0.809
Croatia	0.532	0.814
Hungary	0.536	0.807
Lithuania	0.545	0.837
Luxembourg	0.534	0.817
Latvia	0.547	0.846
Malta	0.543	0.828
Norway	0.530	0.800
Poland	0.536	0.810
Portugal	0.544	0.835
Romania	0.543	0.847
Serbia	0.545	0.843
Sweden	0.538	0.806
Slovakia	0.533	0.811

Source: Authors' calculations using EU SILC, 2019.