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Deprivations rarely come alone. Multidimensional poverty dynamics in Europe

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Abstract
Despite multidimensional poverty measures becoming more popular, little is known about related dynamics at the micro-level. In this paper I propose a framework for the analysis of micro-level dynamics which are inherent to measures of multidimensional poverty. Specifically, in order to explore whether deprivations couple over time, I analyse differences in deprivation transition probabilities between multidimensionally poor and non-poor people. I argue that analysing entries and exits separately is important and that both analyses may be obtained from a single linear model per deprivation indicator. Advantages of the developed approach include that it (i) reflects and summarises relevant mechanisms, (ii) requires only short-run panel data and (iii) is suitable for monitoring purposes. Moreover, the approach may also be applied beyond multidimensional poverty analysis. I illustrate the approach using panel data of the European Union Statistics on Income and Living Conditions (EU-SILC) for more than 20 countries over 2016–2020. The presented evidence suggests that deprivations tend to couple over time. Empirical patterns are broadly time-stable, but vary across countries in magnitude. Implications include that coordinated policy programmes seem critical to overcome entrenched and prevent future deprivations.

Keywords: multidimensional poverty; poverty dynamics; deprivation; EU-SILC; panel data

JEL classification: I32, O52

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1 Introduction

Measures of multidimensional poverty become more popular in both research and practice. International poverty measures are published by UNDP-OPHI (2022) and the World Bank (2022) while more than thirty countries already use a multidimensional poverty index (MPI) as an official poverty measure.[1] Although mostly applied in low and middle income countries (e.g., Alkire and Santos 2014; Alkire, Kanagaratnam, et al. 2022), analyses for richer countries such as the United States, Germany or the European Union (EU) are available, too (e.g. Dhongde and Haveman 2017; Suppa 2018a; Alkire and Apablaza 2017; Weziak-Bialowolska 2016).

Previous work usually draws on individual or repeated cross-sectional data and so dynamics are usually studied as changes over time in aggregate measures (e.g., Alkire, Roche, et al. 2017; Burchi et al. 2022; Alkire, Nogales, et al. 2022). By contrast panel data are rarely used and if so they are analysed in different ways. Some studies exploit the longitudinal structure to measure chronic multidimensional poverty (e.g., Alkire, Apablaza, Chakravarty, et al. 2017; Alkire, Apablaza, and Guio 2021), while others evaluate programs (e.g., Borga and D'Ambrosio 2021). A major constraint for such dynamic analyses is the lack of high-quality panel data for most countries and if available, surveys usually run only for a short period.[2] As a consequence very little is known about multidimensional poverty dynamics at the micro-level. Yet, many theoretically important questions would ideally be addressed with long-run panel data, such as whether and how experienced deprivations in some dimensions beget further deprivations in other dimensions. Building on Apablaza and Yalonetzky (2013) and Suppa (2018a), who examine transitions in multidimensional poverty within the popular Alkire and Foster (2011) approach, the present paper proposes a framework to harness short-run panel data for the analysis of multidimensional poverty dynamics at the micro-level.

Measures of multidimensional poverty build upon deprivation indicators, which capture critical shortfalls in the individual dimensions of human well-being. An important feature of the proposed framework is that it permits to analyse the dynamics among these deprivation indicators of the multidimensional poverty measure itself; in other words measure-inherent dynamics. While related research frequently analyses the links between individual outcomes related to potential deprivations indicators, such as the role of poor housing conditions or material deprivation for poor health (e.g., Angel and Bittschi 2017; Blázquez et al. 2013; Adena and Myck 2014), related dynamics have so far neither been studied in a coherent framework of multidi-

[1] See https://mppn.org/applications/national-measures/ for related applications.

[2] Indeed, for similar reasons first order Markov models became the workhorse for research on monetary poverty dynamics (e.g., Cappellari and Jenkins 2004; Ayllón 2014; Mussida and Sciulli 2022).

mensional poverty, nor jointly for several deprivation indicators.

To illustrate the proposed framework, this paper develops a summary measure, which permits to assess whether, all in all, the deprivations of multidimensional poverty (e.g., low education, poor health or low living standard) tend to couple or decouple over the last year. More specifically, this paper suggests to examine differences in deprivation entry and exit probabilities between poor and non-poor (henceforth *poor* always refers to *multidimensionally* poor). These differences in transitions probabilities allow us to assess whether poor people are (i) more likely to enter a new deprivation and (ii) less likely to leave an existing deprivation than comparable non-poor. The measures of interest can be easily obtained from a single dynamic linear model per deprivation indicator and may be annually computed. Related estimates, therefore, permit to monitor and assess whether dynamics in a particular deprivation indicator have been rather pro- or anti-poor over the last year. Relying on the past poverty status to distinguish transitions rates thus offers a useful summary of individual effects and, moreover, mitigates problems relevant in practice such as small cell-sizes and over-testing. All three advantages of a 'summary index tests' have been previously recognised (e.g., Anderson 2008, p. 1484). The developed framework may also be adapted for other similar purposes, such as an in-depth analysis of country differences in the process of coupling of deprivations or the evaluation of a shock on these processes.

In the empirical analysis, I illustrate this approach using panel data of European Union Statistics on Income and Living Conditions (EU-SILC) for more than 20 countries, over 2016–2020 with an MPI which is broadly consistent with previous work using the same data (e.g., Weziak-Bialowolska 2016; Alkire and Apablaza 2017; Alkire, Apablaza, and Guio 2021). In general the results suggest that deprivations tend to couple, with patterns rather stable over time for most indicators. More specifically, I find that multidimensionally poor people are both less likely to leave an experienced deprivation and more likely to enter an additional deprivation. In other words, deprivations tend to be more persistent for poor people and, at the same time, poor are more prone to further deprivations. I do not find evidence that the main findings systematically differ when poor are required to suffer from a particular deprivation (such as low education). The presented evidence re-enforces the critical role of coordinated policy programmes across departments to effectively overcome multiple deprivation, which has been previously suggested (e.g., Stiglitz et al. 2009, p. 55–56). Nonetheless, I also observe both year-to-year and cross-country variation.

The proposed approach is particular useful for research on multidimensional poverty as it permits to coherently analyse the interplay of its deprivation indicators which so far did not receive much attention. Previous research usually studies statistical associations of variables external to the measure itself, whether in form of disaggregations (e.g., Alkire, Oldiges, et al. 2021), macro-level regressions (Santos et al. 2019; Jindra and Vaz 2019) or micro-level treatment evaluations (Seth and Tutor 2021; Borga and D'Ambrosio 2021). Some studies also rely on mathematical decomposition techniques (Alkire and Foster 2011; Roche 2013). Measure-inherent dynamics have so far been neglected largely because they escape cross-sectional analyses, as the contemporaneous correlation among deprivation indicators is already used for the measurement itself (to identify the multiply deprived as poor). Yet, deprivation indicators are relevant for two reasons. First, they capture critical shortfalls from a normative perspective and are, therefore, an intrinsic part of the measurement exercise itself. Second, deprivations indicators are also instrumentally relevant for achievements in other dimensions of human well-being (e.g., good health is conducive for achieving good education); see Sen (1999, ch. 2) for this distinction. Consequently, methods to study associations among deprivations indicators, which go beyond the measurement itself, are much-needed. In this paper, I suggest to ground analyses of the interplay of the deprivation indicators on their intertemporal correlation, while leaving their contempraneous correlation for the measurement exercise—and that in a way which (i) respects the nature of multidimensional poverty measurement, (ii) provides instructive and novel insights into the coupling processes of deprivations and (iii) is feasible with the available data.

Finally, the presented approach may also be applied beyond multidimensional poverty in other fields which also rely on the Alkire and Foster (2011) approach, such as quality of employment measures (Sehnbruch et al. 2020; Apablaza, Sehnbruch, et al. 2022), women empowerment indices (Alkire, Meinzen-Dick, et al. 2013; Malapit et al. 2019), energy poverty (Nussbaumer et al. 2012) or deprivations in other dimensions (Suppa 2021).

The paper is organised as follows. Section 2 introduces the data and explains how multidimensional poverty may be measured in Europe. Section 3 details the proposed framework and provides both theoretical considerations and the empirical approach. Section 4 shows the results and section 5 provides their discussion. Finally, section 6 offers some concluding remarks.

2 Measuring multidimensional poverty in Europe

The analysed poverty measure is constructed using the Alkire and Foster (2011) approach. Consider $i = 1, \dots, N$ individuals and $t = 1, \dots, T$ periods of time. Further let $y_{ijt} \in \mathbb{R}^+$ denote the $j = 1, \dots, D$ observable achievements relevant for poverty measurement and z_j the critical deprivation thresholds. An individual is deprived in

Table 1. Specification of the multidimensional poverty measure

Dimension	Deprivation indicator	Weight
Health	Self-reported health (Bad or very bad)	1/10
	Limitation in activities due for health problems	1/10
Education	Primary education or less	1/5
Housing	Housing conditions (e.g. leaking roof)	1/10
	Overcrowding index	1/10
Employment	Low work intensity	1/5
Living Standard	Material and social deprivation index	1/10
	Low income (less than 60% of median HH net equiv.)	1/10

Notes: The cross-dimensional poverty cutoff is $k = 1/3$.

achievement j at time t if $d_{ijt} = \mathbb{I}(y_{ijt} < z_j)$, where $\mathbb{I}(\cdot)$ is the indicator function. Let the deprivation score be $c_{it} = \sum_j w_j d_{ijt}$ where $w_j \in (0, 1)$ with $\sum_j w_j = 1$ are the normative weights. Then an individual is considered poor if $poor_{it} = \mathbb{I}(c_{it} \geq k)$, where k with $k \in (0, 1]$ is the cross-dimensional poverty cutoff. Finally, let $Q_t = \{i | poor_{it} = 1\}$ denote the set of all poor people in t and q_t the number of all poor people in t. Then the headcount ratio, which shows the proportion of poor people in the population, is $H_t = \frac{q_t}{N}$. The intensity, which shows the average deprivation among the poor, is $A_t = \frac{1}{q_t} \sum_{i \in Q_t} c_{it}$. The product of both partial indices is the adjusted headcount ratio $M_t = H_t \times A_t$. Additionally, one may obtain deprivation-specific uncensored and censored headcount ratios as $h_{jt} = \frac{1}{N} \sum_i d_{ijt}$ and $\underline{h}_{jt} = \frac{1}{N} \sum_{i \in Q_t} d_{ijt}$, respectively. The former reports the proportion of the population which is deprived in a particular indicator, whereas the latter shows the proportion of the population which is both poor and deprived in that particular indicator. See Alkire, Foster, et al. (2015) for a more comprehensive presentation.

Measure. The multidimensional poverty measure I analyse is broadly in line with previous research using the same data (Weziak-Bialowolska 2016; Alkire and Apablaza 2017; Alkire, Apablaza, and Guio 2021) and may be conceptually integrated into the capability approach and the European framework for of social inclusion indicators (Social Protection Committee 2022). The measure comprises eight deprivation indicator organised in five dimensions; see table 1 for details. The indicator construction largely follows previous research, although low work intensity is measured at the individual level as the poverty measure seeks to identify individuals as poor. The cross-dimensional poverty cutoff is $k = 1/3$ and thus an individual has effectively to suffer from (complete) deprivations in at least two dimensions. The deprivation indicator construction is constrained by the data (i) as some survey modules are only

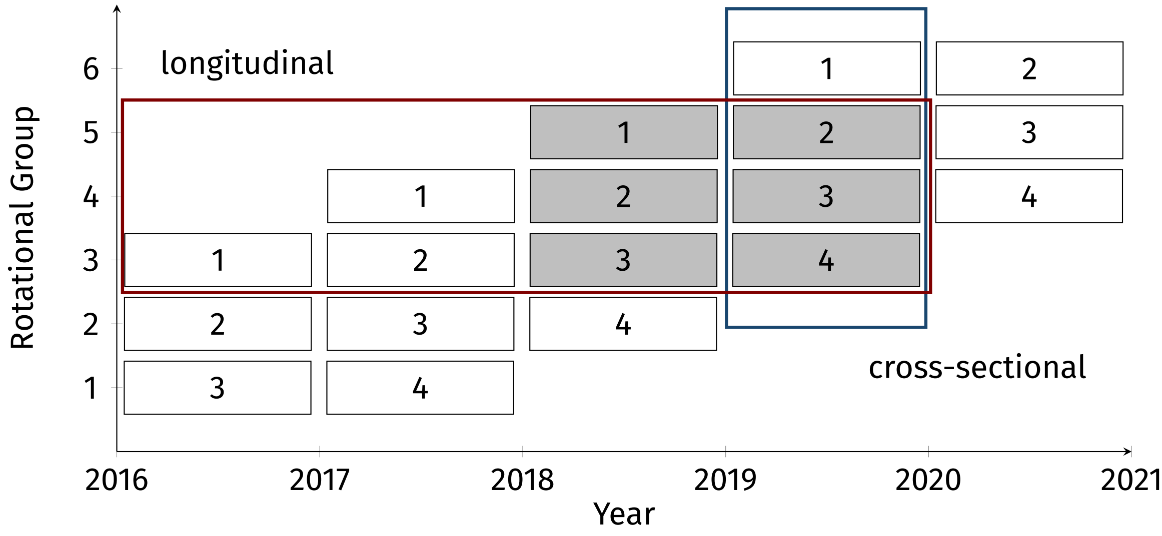

Figure 1. Rotating panel structure. Boxes refer to observations of rotational groups; grey boxes show subsamples used for the analysis of the change to 2019. Further groups ending in 2016 or starting in 2020 are omitted.

collected in individual years (e.g., social activity or detailed wealth information) and (ii) responses to other questions are only distributed with the cross-sectional data (e.g., unmet medical needs, exposure to noise or crime).

Data. The subsequent analyses use the official micro data of the European Union Statistics on Income and Living Conditions (EU-SILC) for 22 countries, which are widely used for monitoring purposes of various social inclusion indicators in the European Union (Eurostat 2021; Wirth and Pforr 2022).[3] The target population are private households and their current members. The analysis draws on the longitudinal component of the data with a period of observation of 2016–2020. Using earlier data rounds would imply additional compromises for the deprivation indicator construction. The EU-SILC follows a rotating panel structure. Each year a new sub-sample (also called rotational group) starts and its respondents are followed for some time until they are eventually replaced by new sub-sample. Countries may have four or more rotational groups. Each subgroup is supposed to be representative of the entire population in a particular year and would allow, e.g., a cross-sectional estimate for that year. Figure 1 illustrates the rotating panel structure of the EU-SILC for a country with four rotational groups.

The EU-SILC is distributed in two variants. The cross-sectional component of the data for a particular year comprises all four subsamples observed in that year from different rotational groups (see the blue box in figure 1 for the 2019 cross-section). The estimation of a cross-sectional quantity (e.g., the poverty rate in a particular year)

[3]Specifically, I use EU-SILC release 1 in 2022 (DOI: 10.2907/EUSILC2004-2020V.2).

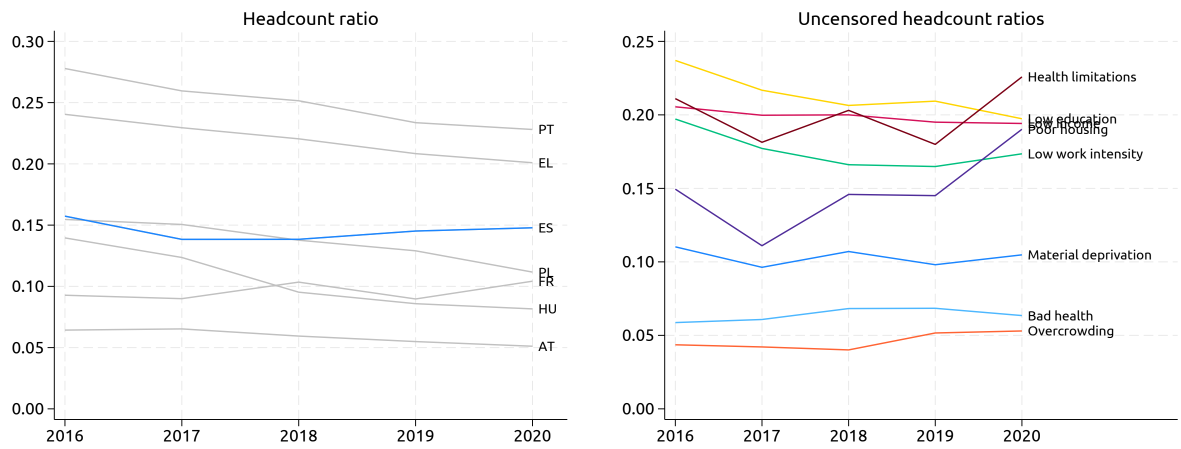

Figure 2. Headcount ratio and uncensored headcount ratios for Spain

would use all four available subsamples for efficiency reasons. The longitudinal component of the data for a particular year comprises all observations of those three rotational groups which have been previously observed, too (see the red box in figure 1 for the 2019 longitudinal sample). An estimate which explicitly draws on the panel-component, such as the proportion of people poor in both current and previous period, may only use three subsamples (as the fourth group just started and does not provide any information for previous years). Similarly, estimating the proportion of people poor in the current period who were also poor in all three previous periods would have to be based on a single rotational group (in figure 1 rotational group 3 would allow such an estimate for 2019.)

The objective of the present paper is to analyse year-to-year changes and test specific hypotheses in this context. For more precise estimates, e.g., in the analysis of the change to 2019, I therefore use a balanced 2-year panel comprising all rotational groups observed in those two years (grey boxes in figure 1). All analyses use the longitudinal weights for a balanced 2-year panel as provided by Eurostat, which account for complex survey design, non-response adjustments (including panel attrition) usually by rotational group, age groups sex and region for most countries.[4] Using EU-SILC data from 2016–2020, I can analyse four changes (from 2016–2017 to 2019–2020).

The subsequent empirical analysis focuses on Spain to streamline the presentation while results for other countries are largely deferred to the appendix. Before turning to actual analysis, figure 2 shows basic estimates for Spain and selected countries to provide context. In terms of the headcount ratio (left figure) Spain experiences an incidence of about 15% throughout the period of observation. Instead, other countries

[4]As the EU-SILC is based on ex-ante output harmonization national statistical offices who share the survey data with Eurostat may opt for slightly different survey designs and different non-response adjustments, for instance.

with initially higher or similar headcount ratios reduce their incidence by about 5%-points. Portugal or Greece, for instance, have higher incidences whereas, e.g., Hungary and Poland have initially similar incidences. Turning to the indicator-specific uncensored headcount ratios, the right-hand graph in figure 2 suggests slight reductions for some indicators (e.g., low education and work intensity) and slight increases for others (e.g., overcrowding). A salient observation is certainly the increase in poor housing conditions and limitations through health in 2020, which is most likely related to then unfolding covid pandemic. However, results for 2020 should be interpreted with caution, as the pandemic and related policy-responses also induced considerable changes in the interview mode.

3 Framework

3.1 Theoretical considerations

Multidimensional poverty measures capture overlapping deprivations and, moreover, permit to measure poverty conceptualised as *multiple* deprivation. Various mechanisms may result in coupling of deprivations. For instance, low education may first result in more and longer spells of unemployment and material deprivation, which then together also deteriorate health over time. Such indicator dynamics have been previously studied, however, neither coherently in multidimensional poverty framework, nor jointly for several indicators.

More specifically, previous research lends support for associations of every possible combination of two deprivation indicators, even though the identification of the causal direction or specific mechanisms has been ignored for a long time; for health outcomes, for instance, see Smith (1999) and Fuchs (2004). More recent studies, however, seek to provide estimates permitting a causal interpretation. For instance, with respect to health outcomes Angel and Bittschi (2017) explore the effect of housing conditions, Blázquez et al. (2013) the effect of material deprivation and Drydakis (2015) the role of unemployment. Increasingly available panel data also permit to study deprivation entries and exits separately (e.g., Adena and Myck 2014), which is a concern that also figures prominently monetary poverty dynamics since Bane and Ellwood (1986).

Taken together deprivations in general may steadily accumulate over the time if (i) each deprivation features a certain persistence, (ii) already experienced deprivations involve further deprivations, (iii) existing deprivations make leaving other deprivations more difficult or a combination thereof. In practice individuals may be subject to several mechanisms at the same time and, moreover, some of those mechanisms may only slowly unfold their effect over time (e.g., health deterioration). Additionally, some deprivations, such as low education may function as moderators of one or more other mechanisms. Specifically, education is considered in both economics and sociology for a long time to improve individuals' decision making when facing changing circumstances, including economic shocks (Fullan and Loubser 1972; Schultz 1975). In line with this, Riddell and Song (2011) find higher education to increase the re-employment probability conditional on being unemployed beforehand. Modelling and analysing all these relations explicitly would put extremely high demands on the data (including the structure of long-running panel). Instead, one way to summarise the previous considerations is to expect poor people (who experience multiple deprivation by definition) to be more likely to enter a particular deprivation, which they do not experience than comparable non-poor (who neither suffer from that deprivation). Likewise, one may expect poor people to be less likely to leave a particular deprivation than comparable non-poor who do, however, experience that particular deprivation. See Suppa (2018b) for similar, but more ad-hoc hypotheses.

One advantage of formulating hypotheses with respect to the poverty status, which essentially pools various deprivation-specific mechanisms, is that it allows for general assessments summarising recent deprivation entry and exits patterns. Other advantages include that a focus on the poverty status may help to mitigate issues of small cell sizes (which is often related to marginally significant results) and over-testing. Indeed, all three advantages of 'summary indices' at the microlevel have been recognised in previous research (Anderson 2008). Naturally, where needed this summary may be unpacked to explore specific mechanisms for entries or exits of a particular deprivation.

Conditional probabilities of interest. In order to formulate these hypotheses more formally, it is helpful to introduce the following four transition probabilities.

$$\Pr(d_{ijt} = 1 \mid poor_{it-1} = 0 \ \wedge \ d_{ijt-1} = 0) \tag{CP.1}$$

$$\Pr(d_{ijt} = 1 \mid poor_{it-1} = 1 \ \wedge \ d_{ijt-1} = 0) \tag{CP.2}$$

$$\Pr(d_{ijt} = 0 \mid poor_{it-1} = 0 \ \wedge \ d_{ijt-1} = 1) \tag{CP.3}$$

$$\Pr(d_{ijt} = 0 \mid poor_{it-1} = 1 \ \wedge \ d_{ijt-1} = 1) \tag{CP.4}$$

Equations (CP.1) and (CP.2) are the deprivation entry probabilities for non-poor and poor individuals, respectively. Instead, equations (CP.3) and (CP.4), are the deprivation exit probabilities for non-poor and poor individuals, respectively.

Hypotheses. The main hypotheses may then be formulated as follows. First, since poor individuals are by definition already deprived in several other deprivations in $t-1$, one may also expect them to be more likely to enter a new deprivation j in t, which they do not experience in $t-1$, compared with non-poor and who were also not j-deprived in $t-1$. So the first hypothesis, expressed as a difference in deprivation entry probabilities is

$$\begin{aligned}\Delta_j^{\text{entry}} &= \Pr(d_{ijt} = 1 \mid poor_{it-1} = 1 \;\wedge\; d_{ijt-1} = 0)\\ &\quad - \Pr(d_{ijt} = 1 \mid poor_{it-1} = 0 \;\wedge\; d_{ijt-1} = 0) > 0.\end{aligned} \tag{H.1}$$

Second, since poor by definition already experience several other deprivations, they may be less likely to leave deprivation j they already experience in $t-1$, than non-poor who are deprived in j in $t-1$. So the second hypothesis, expressed as a difference in deprivation exit probabilities is

$$\begin{aligned}\Delta_j^{\text{exit}} &= \Pr(d_{ijt} = 0 \mid poor_{it-1} = 1 \;\wedge\; d_{ijt-1} = 1)\\ &\quad - \Pr(d_{ijt} = 0 \mid poor_{it-1} = 0 \;\wedge\; d_{ijt-1} = 1) < 0.\end{aligned} \tag{H.2}$$

Third, a priori there is no reason to expect the poverty status to play quantitatively the same role for both deprivation entries and exits. Specifically, poverty may increase the deprivation entrance probability *more* or *less* than it reduces the deprivation exit probability. Evidence in support of either direction would suggest to distinguish deprivation entries and exits in any analysis. Thus, the third hypothesis is that the absolute value of the increase in the deprivation entrance probability is not equal to the absolute value of the decrease in the deprivation exit probability, or formally

$$\mid \Delta_j^{\text{entry}} \mid \neq \; \mid \Delta_j^{\text{exit}} \mid. \tag{H.3}$$

Fourth, if deprivations are persistent, then the current deprivation status depends on the past deprivation status. Given the formalisation above, a fourth hypothesis to explore in this context is whether current deprivation status depends on past deprivation status ($\Pr(d_{ijt} \mid d_{ijt-1})$), which would reflect the persistence of deprivations. If deprivations are persistent then people deprived in $t-1$ are more likely to be deprived in t than non-deprived or formally

$$\Pr(d_{ijt} = 1 \mid d_{ijt-1} = 1) > \Pr(d_{ijt} = 1 \mid d_{ijt-1} = 0). \tag{H.4}$$

The subsequent empirical analyses will seek to reject the respective null hypotheses of equality in all four cases.

3.2 Empirical approach

3.2.1 Binary model

One way to obtain all the conditional probabilities introduced in the previous section is to fit a binary choice model for different subsamples (i.e. individuals who enter and leave a deprivation, respectively) and subsequently estimate the average predicted probabilities evaluated at the respective d_{ijt-1} and $poor_{it-1}$. Formally these models can be written as

$$\Pr(d_{ijt} = 1) = F(\alpha_1 + \beta_1\, poor_{it-1} + \epsilon_{1ijt}) \quad \forall d_{ijt-1} = 0 \quad \forall j \tag{1}$$

$$\Pr(d_{ijt} = 0) = F(\alpha_0 + \beta_0\, poor_{it-1} + \epsilon_{0ijt}) \quad \forall d_{ijt-1} = 1 \quad \forall j \tag{2}$$

where $F(\cdot)$ is a cumulative distribution function. Equation (1) is a model for deprivation entries (the analysed event is deprivation) and may be estimated using a sample of observations who are not deprived in indicator j in $t-1$. Instead, equation (2) is a model for deprivation exits (the analysed event is non-deprivation) and may be estimated using a sample of observations who are deprived in indicator j in $t-1$. Using these models the average predicted entry probabilities for poor and non-poor may be obtained as $F(\alpha_1 + \beta_1)$ and $F(\alpha_1)$. Their difference corresponds to partial effect of $poor_{it}$ on the deprivation probability:

$$\frac{\Delta \Pr(d_{ijt} = 1)}{\Delta poor_{it-1}} = F(\alpha_1 + \beta_1) - F(\alpha_1) \tag{3}$$

Instead of estimating models (1) and (2) separately, joint estimation is preferable. Besides efficiency gains, all three hypothesis may be explored based on a single estimation.

First, observe that equation (1) models the deprivation event, whereas equation (2) models the non-deprivation event. In binary choice models, however, the parametrization of the event probability also implies the parametrization of the complementary probability. Accordingly β_0 (from model (2)) may also be used to compute the complementary (staying deprived) probability $\Pr(d_{ijt} = 1)$. Effectively, only the signs of the coefficients would change. Introducing, moreover, the past deprivation status and its interaction with the past poverty status gives a combined flexible model, which allows to analyse deprivation exits and entries, as follows

$$\Pr(d_i = 1) = F(\alpha + \beta poor_{it-1} + \gamma d_{it-1} + \delta poor_{ijt-1} \times d_{ijt-1} + \epsilon_{it}) \quad \forall j \tag{4}$$

3.2.2 Linear probability model

The main interest of this paper is to explore hypotheses related to differences in conditional probabilities, which are essentially differences in particular average predicted probabilities. As the linear probability model (LPM) often approximates the partial effects of explanatory variables well (Wooldridge 2010, p.562–565) and related hypothesis testing is also straightforward (if heteroskedasticity-robust standard errors are used), I focus on estimates of the LPM below. Additionally, table A.2 in the appendix shows that both the LPM and a logit model produce nearly identical average predicted probabilities (the first 3 decimals digits of both point estimate and its standard error are usually identical). The linear model may be written as follows:

$$\Pr(d_{ijt} = 1) = \alpha + \beta poor_{it-1} + \gamma d_{ijt-1} + \delta poor_{ijt-1} \times d_{ijt-1} + \epsilon_{it} \quad \forall j \tag{5}$$

Besides a slightly faster estimation, one advantage of the linear model is that average predicted probabilities can be directly obtained from the coefficients of the model, i.e.

$$\Pr(d_{ijt} = 1 \mid poor_{it-1} = 0 \ \wedge \ d_{ijt-1} = 0) = \alpha \tag{6}$$

$$\Pr(d_{ijt} = 1 \mid poor_{it-1} = 1 \ \wedge \ d_{ijt-1} = 0) = \alpha + \beta \tag{7}$$

$$\Pr(d_{ijt} = 0 \mid poor_{it-1} = 0 \ \wedge \ d_{ijt-1} = 1) = 1 - (\alpha + \gamma) \tag{8}$$

$$\Pr(d_{ijt} = 0 \mid poor_{it-1} = 1 \ \wedge \ d_{ijt-1} = 1) = 1 - (\alpha + \beta + \gamma + \delta) \tag{9}$$

Note that the deprivation exit probabilities are obtained as complementary probabilities from the model estimates.

Coefficient Interpretation How are the different coefficients now to be interpreted? First, γ reflects the role of past deprivation for current deprivation. For a persistent deprivation $\gamma > 0$. Instead, β reflects the role past poverty for current deprivation. Assuming the coefficient of the interaction term $\delta = 0$ for the moment, $\beta > 0$ means that poor are more likely to enter the deprivation *and* less likely to leave the deprivation. The coefficient of the interaction term δ permits, however, the role of past poverty on current deprivation status (as captured by β) to differ for deprivation entries and exits. Specifically, a positive (negative) δ would mean that past poverty status is quantitatively more (less) important for deprivation exits than for deprivation entries. Importantly $\delta \neq 0$ also suggests to analyse deprivation entries and exits separately. An interesting special case is $\beta + \delta = 0$, which means that the poverty status increases the deprivation entry probability, but does not affect the deprivation exit probability. Conversely, $\beta = 0$ and $\delta > 0$ suggests that past poverty is irrelevant for deprivation entries but decreases the probability for deprivation exits.

Finally, the measures of interest, the differences of entry and exit probabilities between poor and non-poor can be easily computed using the coefficients of the linear model as

$$\Delta_j^{\text{entry}} = \beta \tag{10}$$
$$\Delta_j^{\text{exit}} = -(\beta + \delta). \tag{11}$$

4 Results

4.1 Transition rates

Before turning to the regression results, figure 3 shows the overall deprivation exit and entry rates for Spain over time. In general deprivation entry rates tend to be relatively smaller than exit rates. This observation partly follows from different reference populations, which is relatively large for entry probabilities (all people who are not deprived in a particular indicator) and relatively small for exit probabilities (people who are already deprived in that indicator). Since deprivation indicators frequently identify smaller proportions of the population, this pattern can be expected to be observed more generally. Moreover, the level of transition rates vary by indicator, too. For instance, exit rates for low income or low work intensity are about 0.3 whereas those for material deprivation and housing quality are about 0.5 and 0.6 in 2019 (both declining from even higher levels), respectively. Deprivation entry rates tend to be 0.1 or less. Subsequent analyses explore these transition rates further and in particular their relation with the multidimensional poverty status in the previous period.

4.2 Coefficients

Table 2 presents estimates for the coefficients of the linear model for Spain in 2019, see table A.1 for three further examples (Austria, Belgium and Poland). Several important observations emerge. First, past deprivation status is usually highly relevant for current deprivation status; the estimate of the related coefficient $\hat{\gamma}$ is positive and significant at the 1%-level in most instances. Moreover, the estimate for the coefficient of the past poverty status $\hat{\beta}$ is positive and significant in most instances, as well. Seen individually, it only refers to deprivation entries; for deprivation exits the estimated coefficient of the interaction term ($\hat{\delta}$) is to be taken into account as well. The results for this interaction term are of particular interest at this stage as it allows us to assess whether the subsequent analysis should report results separately for de-

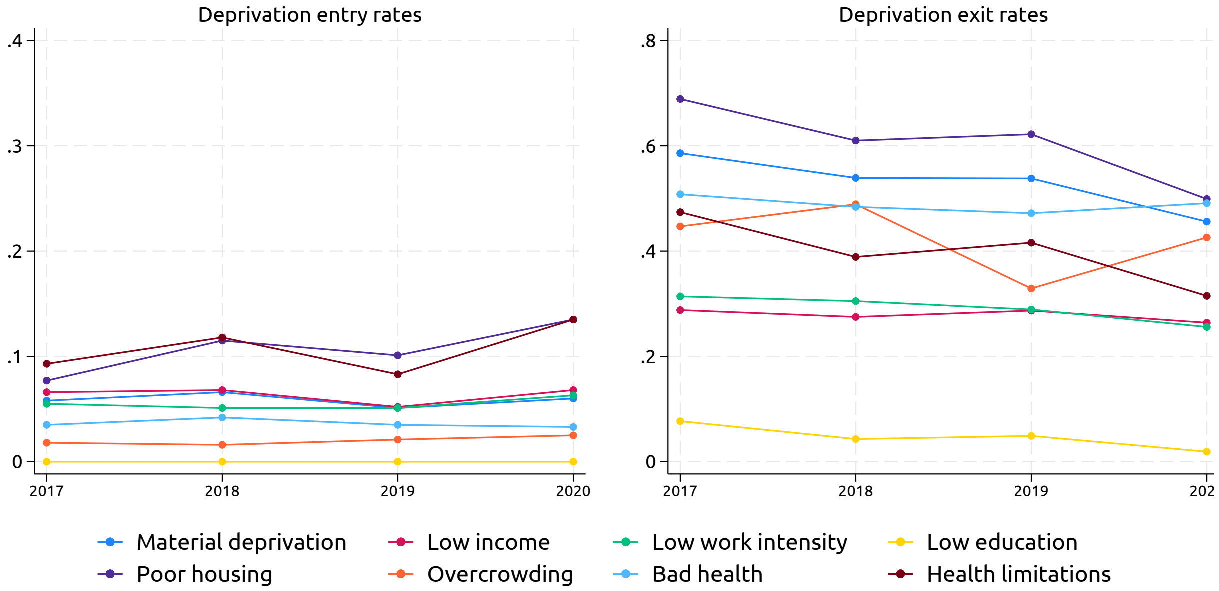

Figure 3. Transition rates over time in Spain by deprivation indicator

Table 2. Estimated coefficients - linear model

Spain 2019

	(1) MD	(2) LI	(3) LWI	(4) LE	(5) PH	(6) OC	(7) BH	(8) HL
poor	0.14***	0.07***	0.01	0.02*	0.11***	0.03***	0.07***	0.07***
	(0.014)	(0.012)	(0.012)	(0.009)	(0.013)	(0.007)	(0.010)	(0.015)
dep	0.30***	0.61***	0.59***		0.26***	0.58***	0.41***	0.40***
	(0.025)	(0.015)	(0.018)		(0.017)	(0.032)	(0.034)	(0.015)
poor x dep	0.05	0.05**	0.14***		-0.04	0.12**	0.05	0.15***
	(0.035)	(0.024)	(0.026)		(0.030)	(0.047)	(0.042)	(0.026)
Obs.	14824	14824	14824	3599	14824	14824	14824	14824
Entries	597	567	552	0	1175	230	511	1013
Exits	873	880	713	182	1496	200	553	1373

Notes: Dependent variables are material deprivation (MD), low income (LI), low work intensity (LWI), low education (LE), poor housing (PH), Overcrowded (OC), bad health (BH), health limitations (HL); cells show point estimates for coefficients of linear model with standard errors in parentheses; columns in panels are separately estimated; explanatory variables refer to poverty and deprivation status in $t-1$; indicated levels of significance are *** for $p < 0.01$, ** for $p < 0.05$ and * for $p < 0.1$, respectively.

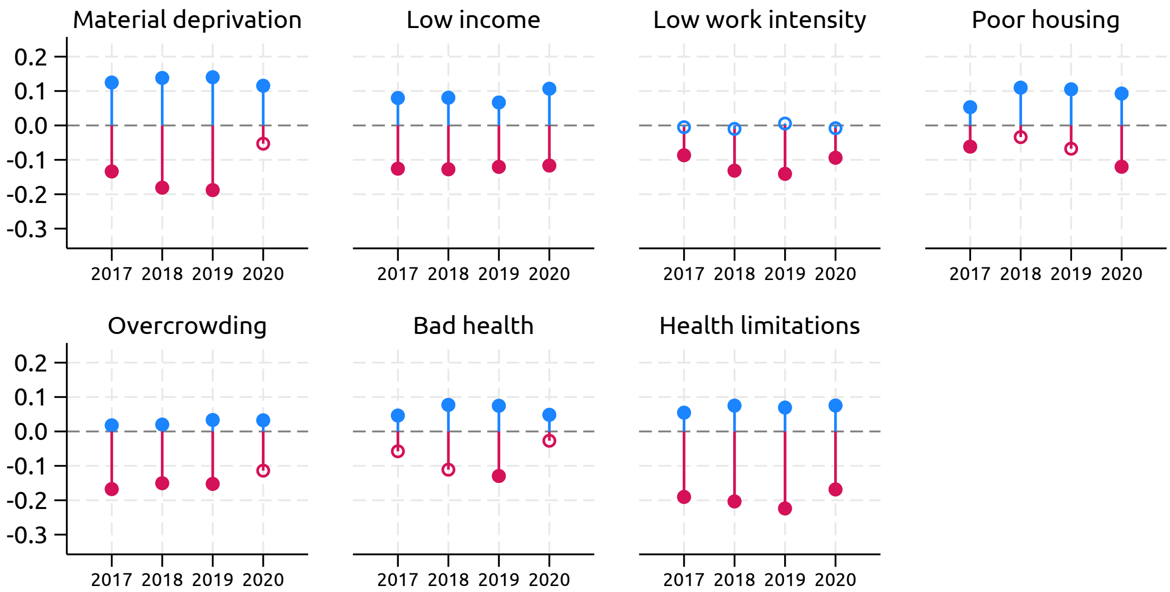

Figure 4. Differences in deprivation entry and exit probabilities in Spain. Dots show differences in deprivation entry (•) and exit (•) probabilities between poor and non-poor, hollow markers insignificance.

privation entries and exits. Table 2 shows that estimated coefficients of interaction terms are often positive and sometimes insignificant or even negative. Note that if either deprivation entries or exits are not observed, neither γ nor δ can be estimated for lack of information (e.g, as in the case of low education). This issue of small cell sizes surfaces also in other countries and becomes by tendency more relevant for better off countries and smaller samples or both.

Broadly speaking the results suggest, that (i) the poverty status is usually relevant for both deprivation entries and exits, (ii) quantitatively past poverty is more important for deprivation exits than for deprivation entries in most instances, (iii) the evidence supports persistence of deprivations, (iv) specific results may vary with country and year and (v) small cell sizes may even matter to the extent that occasionally coefficients cannot be estimated at all.

4.3 Differences in entry and exit probabilities

Country-specific evidence. Instead of analysing individual model coefficients one may also directly explore differences in deprivation entry and exit probabilities between poor and non-poor for each indicator over time, as shown in figure 4 for Spain. See figure A.1 for all other countries. Several observations are salient. For instance, figure 4 reveals a certain stability over time for most indicators, although estimates may vary from year-to-year to some extent. Furthermore, in many instances a quantitatively different role of poverty for deprivation entries and exits is apparent. More specifically, past poverty status tends to decrease deprivation exit probabilities more than it increases deprivation entry probabilities, which corresponds to the previously observed positive coefficient for the interaction terms. Another way to interpret this finding is to view deprivations as more persistent for the poor than for non-poor. In some cases, estimated differences are also insignificant (low work intensity) or missing (education). The latter follows from observing insufficient transitions (see also above).

A more in-depth rationalization of observed patterns may have to rely on country-specific trends or circumstances (e.g., the business cycle). For instance, most countries experienced a pronounced decline in the unemployment rate between 2013 and 2019. According to the Eurostat, Spain reduced its unemployment rate by some 12%-points (cf. fig. A.2), which may result in fewer unemployment entries in general and explain the insignificant difference in low work intensity deprivation in particular. During this massive unemployment reduction in Spain the poor were, however, less likely to leave deprivation in low work intensity.

Cross-country evidence To which extent are these patterns observed in other European countries as well? Figure 5 shows the differences in transition probabilities for deprivations between poor and non-poor individuals in the previous year across different countries and years. Reddish dots show the difference in deprivation exit probabilities and are usually significantly negative ($p < 0.01$), indicating that individuals poor and j-deprived in $t-1$ are less likely to leave deprivation j than non-poor and j-deprived individuals (insignificant estimates are represented by hollow markers). Bluish dots, in turn, show the difference in deprivation entry probabilities and are usually significantly positive ($p < 0.01$), indicating that individuals who were poor and not j-deprived in $t-1$ are more likely to enter deprivation j than individuals non-poor and non-j-deprived in $t-1$.

Moreover, figure 5 also shows median entry and exit probabilities for each indicator (depicted as black X). The median entry probability difference for material deprivation is, for instance, about 0.1, meaning that typically poor in $t-1$ are 10%-points more likely to enter this deprivation than non-poor (conditionally on being non-deprived in $t-1$). Instead, the median exit probability difference for material deprivation suggests that poor are usually 15%-points less likely to leave this deprivation. More generally, it is not uncommon to observe differences in exit probabilities between -0.5 and -0.2 across indicators and differences in entry probabilities between 0.05 and 0.1. Indeed, by tendency, differences in exit probability are larger than in entry probability, suggesting poverty to play a particular important role in impeding to leave deprivations.

Finally, figure 5 also illustrates two exceptions. First, some indicator-country-year

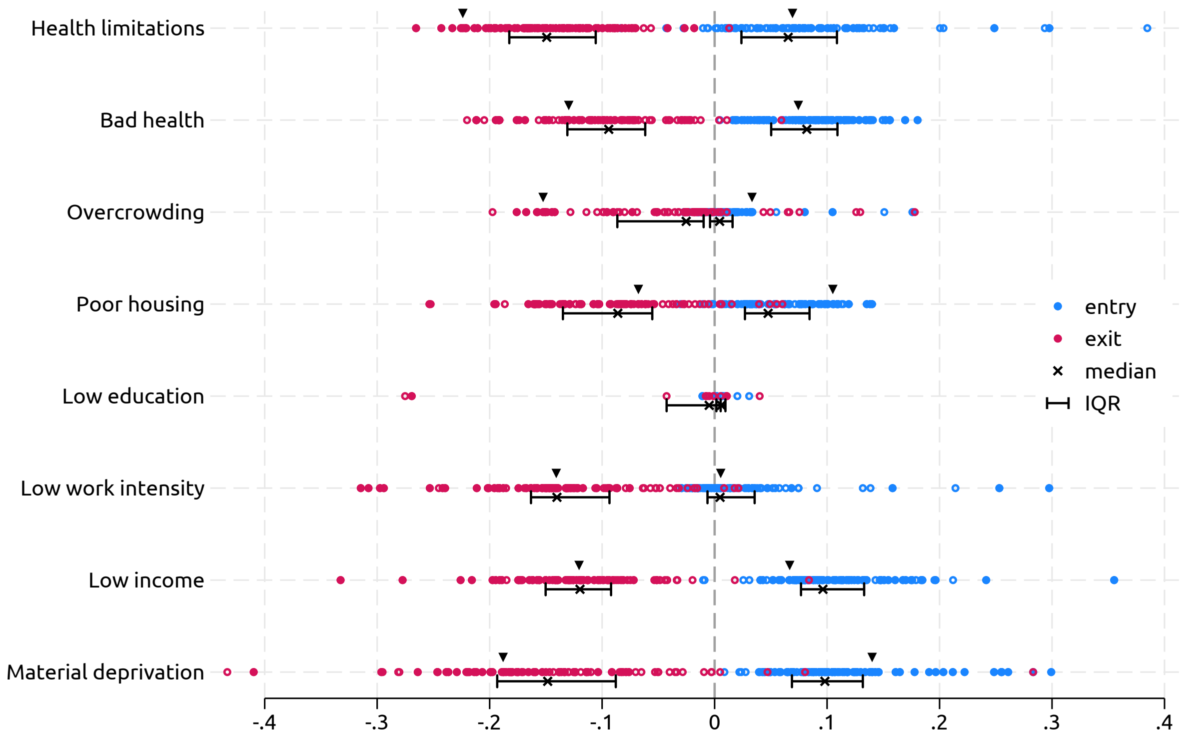

Figure 5. Differences in deprivation transition probabilities across countries and years. Figure shows differences in deprivation entry (•) and exit (•) probabilities between poor and non-poor, hollow markers indicate insignificance; ▼ indicates vales for Spain in 2019; pooled estimates for all countries and 4 year-to-year changes.

combinations result in insignificant differences (e.g., for education), which largely follows from insufficient observations (cf. entry and exit observations in table 2). Second, and perhaps more interestingly, for some indicator-country-year combinations of the difference estimate turns out to be significant with the 'wrong sign' (e.g., for entry probabilities into low-work-intensity deprivation). As several phenomena may produce such a finding, identifying the exact mechanism requires further in-depth analysis. A pronounced economic downturn may, for instance, force otherwise not-deprived individuals to substantially reduce working hours. Section 5 will return to this issue.

4.4 Effect heterogeneity in poverty profiles

Poverty has many faces and multidimensional poverty may originate from very different combinations of deprivations. While Suppa et al. (2022) propose an in-depth analysis of deprivation profiles and bundles, for the present context deprivation-specific censored headcount ratios together with the incidence of poverty already provide important insights and are shown in figure 6 for Spain in 2019. Specifically, censored deprivation rates vary between 2–10% which implies, together with an incidence of 15%, that each deprivation indicator usually afflicts less than half of the poor. Put dif-

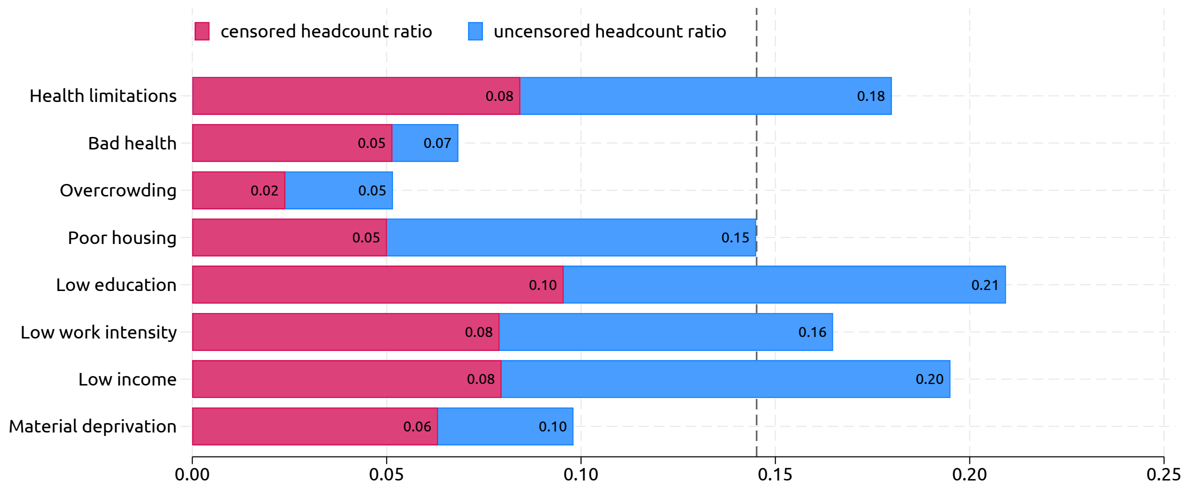

Figure 6. Censored and uncensored headcount ratios in Spain 2019. Dashed line is headcount ratio.

ferently, there is no deprivation indicator which all of the poor suffer from. Moreover, figure 6 also shows that censored headcount ratios are in part considerably smaller than their uncensored counter parts, which implies that there is no deprivation which immediately entails poverty either. This evidence suggests that poverty (understood as multiple deprivation) does manifest in many different shapes and forms.

The approach proposed in this paper relies on the poverty status to offer a summarising assessment of whether deprivations further coupled or perhaps even decoupled over the last year. Occasionally, one may however also wish to unfold the embodied effect heterogeneity to some extent. For instance, one may wonder whether the observed patterns actually only originate from deprivation in a single indicator which happens to be widespread among many of the poor, such as low education (which afflicts about two thirds of the poor according to figure 6). Similarly, one may ask whether experiencing a particular deprivation results in systematically higher or lower probabilities to enter or leave another specific deprivation. Given that different mechanisms related to different indicators are to be expected, the question is to which extent the focus on the poverty status may obscure instructive effect heterogeneity. More specifically, one may thus ask whether conditional on being already poor in $t-1$, the probability to enter a further deprivation j differs with the presence of a deprivation in some indicator ι. Formally, one would seek to reject the hypotheses that

$$\begin{aligned} &\Pr(d_{ijt} = 1 | poor_{it-1} = 1 \land d_{ijt-1} = 0 \land d_{i\iota t-1} = 0) \\ = &\Pr(d_{ijt} = 1 | poor_{it-1} = 1 \land d_{ijt-1} = 0 \land d_{i\iota t-1} = 1) \quad \forall j \neq \iota \end{aligned} \tag{H.5}$$

and

$$
\begin{aligned}
&\Pr(d_{ijt} = 0 | poor_{it-1} = 1 \wedge d_{ijt-1} = 1 \wedge d_{\iota t-1} = 0)\\
&= \Pr(d_{ijt} = 0 | poor_{it-1} = 1 \wedge d_{ijt-1} = 1 \wedge d_{i\iota t-1} = 1) \quad \forall j \neq \iota
\end{aligned} \tag{H.6}
$$

In order to test these hypotheses one may modify model (5) to include interaction terms for each occurrence of $poor_{it-1}$ with the deprivation in an indicator ι and thus estimate

$$
\begin{aligned}
\Pr(d_{ijt}) = \alpha + \beta poor_{it-1} + \beta^{\iota} poor_{it-1} \times d_{i\iota t-1} + \gamma d_{ijt-1}\\
+ \delta poor_{ijt-1} \times d_{ijt-1} + \delta^{\iota} poor_{ijt-1} \times d_{ijt-1} \times d_{i\iota t-1} + \epsilon_{it} \qquad \forall j \neq \iota
\end{aligned} \tag{12}
$$

Testing for systematically different transition probabilities related to the presence of a deprivation ι amounts to testing the null hypotheses $\hat{\beta}^{\iota} = 0$ and $\hat{\beta}^{\iota} + \hat{\delta}^{\iota} = 0$, respectively.[5]

Figure 7 illustrates such an analysis by exploring whether the role of poverty for deprivation entries and exits differs systematically if poverty involves deprivation of education. More specifically, figure 7 shows estimated differences between persons who are education deprived and those who are not conditional on being poor using several years of Spanish data. Broadly speaking, results suggest that in most cases there is no significant difference. While significant differences can be observed in some years for some indicators, the sign of the difference cannot be immediately rationalised. The reason is that non-deprivation in education in this analysis does not imply that those individuals necessarily experience a lower deprivation score, since after all the analysis conditions on being poor. In summary, I do not find evidence that results systematically differ for poor who experience deprivation in education compared with poor who do not. The lack of statistical power may however caution against too strong conclusions.

Such analyses of effect heterogeneity thus likely suffer from similar limitations as the analysis of individual indicators, namely that cell sizes may prove critically small and the few observed deprivation entries among the poor have to be further divided according to their specific deprivations (as already suggested in the discussion of table 2). On the one hand, this challenge may be seen as one of insufficient data and not as a limitation of the principle approach. On the other hand, one may expect to

[5]Indeed, other approaches to examine effect heterogeneity may be explored too. For instance, one may also argue for an interaction of the deprivation status of j in $t-1$ with the deprivation status of ι in $t-1$. Another option would be to create different classes based on deprivation profiles as discussed in Suppa et al. (2022). Alternatively, one may also entire discard the poverty status and exclusively study deprivation indicators with potentially numerous interactions instead.

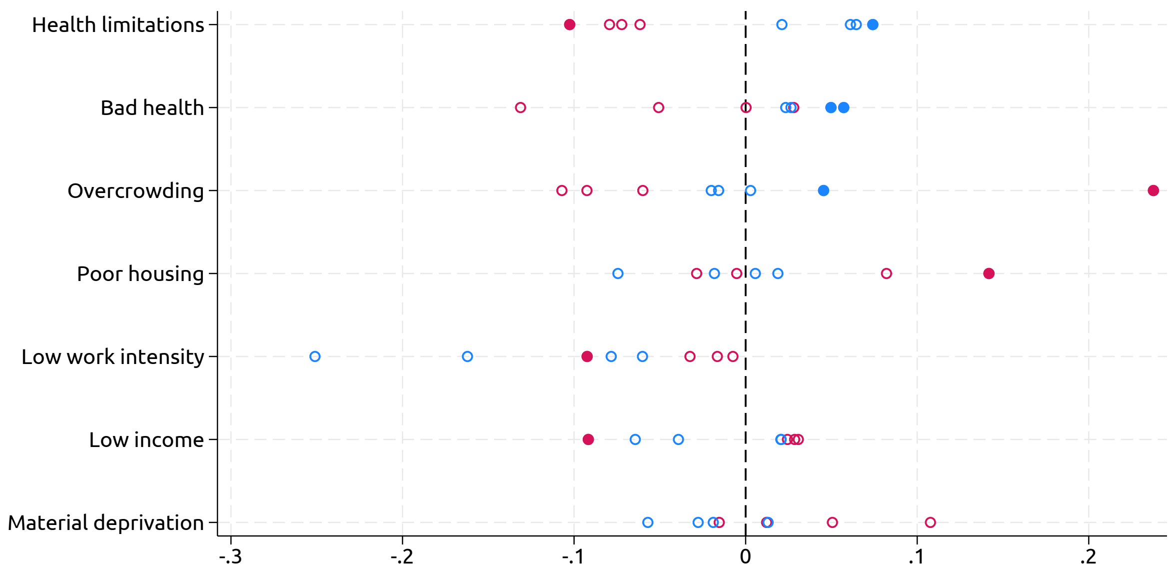

Figure 7. Difference in transition probabilities for educational deprivation conditional on being poor in Spain. Dots show difference in deprivation entry (•) and exit (•) probabilities between people who are deprived in education and those who are not, conditional on being poor; hollow markers indicate insignificance.

frequently encounter this issue in practice, as deprivation indicators usually refer to relatively small proportions of the population. The focus on the (past) poverty status, as explored in this paper may, therefore, provide a promising alternative to overcome this issue, while offering a meaningful and coherent interpretation in terms of more general patterns within the overall measurement framework.

5 Discussion

All in all, did deprivations over the last year further couple, remain the same or perhaps even decouple? To answer this question I suggest to analyse annually computed differences in deprivation entry and exit probabilities between poor and non-poor. I provide four remarks on what these information may reflect and which conclusions are supported.

First, the adopted approach does not feature any identification strategy to isolate correlation which would permit a causal interpretation. While the timing structure of the dynamic model does purge contemporaneous correlation of multidimensional poverty and its deprivations (it ignores both other deprivations and poverty in t), important sources of endogeneity remain. More specifically, poverty and deprivation status in $t-1$ may be mechanically related, simultaneously determined or both. In particular, observed or unobserved heterogeneity (e.g., personality traits, ability or effort) may be correlated with the poverty status. Addressing such endogeneities is

Table 3. Interpretation of transitions probabilities differences

Description	Δ_j^{entry}	Δ_j^{exit}
anti-poor	> 0	< 0
neutral	$= 0$	$= 0$
pro-poor	< 0	> 0

left for future research.

Second, as discussed in section 3.1 each pair of indicators may be related by one or more mechanisms and some deprivations may, moreover, function as moderators (e.g., low education). Additionally, in-depth analysis of deprivation interlinkages suggests that multidimensional poverty usually comprises different deprivation profiles (Suppa et al. 2022). As a consequence several mechanisms which are related to different indicators may all be jointly operative and result in the observed differences in transition probabilities. The approach to rely on the poverty status as the main distinction for the proposed analysis (which requires multiple deprivation in the first place) seeks to provide a useful summary of those dynamics.

Third, the presented evidence suggests in general rather stable patterns over time for most indicators, although there is year-to-year variation, too. Moreover, occasionally transition probability differences are insignificant or may even have the 'wrong' sign in some years (e.g., low work intensity). How may such patterns be rationalised? Recall that poor might be more likely to enter an additional deprivation for very different reasons, which include mechanisms related to their already experienced deprivations (as discussed above). On the one hand, many of these mechanisms are in some sense more structural and relate, for instance, to the functioning of the healthcare system (e.g., in terms of required resources and entitlements), the functioning of insurance markets or hiring protocols and practices of employers. On the other hand, differences in transition probabilities may also change with macro-economic developments (e.g., the business cycle as discussed above) or specific policy measures. Consider, for instance, a perfectly targeted policy measure which only helps to overcome low work intensity for the poor. If large enough, such a policy may render the poor even *more* likely to leave the deprivation than the non-poor. The interplay of structurally related processes, relevant macro-economic trends and various policies may then produce patterns such as the observed.

Based on the previous considerations differences in the transition probabilities may be understood as a "net effect" of the various factors operative in a particular year and thus be interpreted as summarised in table 3. Specifically, observing $\Delta^{entry} > 0$ and $\Delta^{exit} < 0$ each suggest deprivations to couple and transitions probabilities to be at the disadvantage of the poor, so *anti-poor*. If instead, $\Delta^{entry} = 0$ and $\Delta^{exit} = 0$ transitions or trends may be considered as *neutral*. Finally, $\Delta^{entry} < 0$ or $\Delta^{exit} > 0$ would mean that trends have been *pro-poor* and deprivations decoupled during the period of observation. In this sense both statistics may be used for monitoring purposes on a annual basis (while making use of the information of the panel component).

Finally, overcoming deprivations is important by-itself. A well-constructed multidimensional poverty measure relies on deprivation indicators, which already reflect normatively undesirable shortfalls. The presented evidence, however, additionally suggests that non-deprivation in one indicator may help to prevent further deprivation in other indicators. Put differently, non-deprivation in one dimension is also instrumentally relevant for improving human well-being in another dimension; see Sen (1999) for a discussion of intrinsic and instrumental relevance of dimensions of human well-being. The presented evidence, therefore, also resonates well with research on monetary poverty dynamics, which concludes that preventing people from falling into poverty in the first place may be an effective measure due to substantial state-dependence (Biewen 2014).

6 Concluding Remarks

To illuminate dynamics of multidimensional poverty at the micro level this paper proposes a framework to analyse the interplay of its deprivation indicators, i.e. measure inherent dynamics. Specifically, I suggest to analyse differences in deprivation entry and exit probabilities between (multidimensionally) poor and non-poor. Annually computed differences in these transition probabilities emerge as a useful summary measure to assess whether, all in all, deprivations further couple, evolve neutrally or perhaps even decouple over the last year. The presented approach may be applied using short-run panel data. An illustration with EU-SILC data suggests, broadly speaking, rather stable patterns over time for most indicators and largely supports the idea that initial deprivations beget further deprivations. An important implication of the presented evidence is that coordinated programmes and measures across policy fields are critical for both overcoming already experienced deprivations and preventing entry into new deprivations. Moreover, there is also both year-to-year and cross-country variation, which may be further explored in more depth by future research.

The proposed analysis seeks to better understand multidimensional poverty dynamics and illuminate how the joint distributions of deprivations is changing over time. The principle approach may, however, also be used in settings not directly concerned with multidimensional poverty, since technically the underlying MPI is not required.

One may, for instance, study whether individuals with a low working intensity are less likely to leave and more likely to enter income poverty. Indeed, the basic approach might even be adapted to socio-demographic variables. For instance, one could study whether young or old persons are more likely to enter or leave income poverty. Such applications seem worth exploring as the current use of the longitudinal component of the EU-SILC for informing policy has been questioned (Jenkins and van Kerm 2014) and, moreover, indicators on transitions may be included in the social inclusion portfolio (Social Protection Committee 2022, p. 84)

The proposed analysis has also limitations. First, while the evidence may be rationalised with recourse to several mechanisms or sources, other factors such as unobserved heterogeneity (e.g., personality traits, effort or ability) cannot be ruled out. On the one hand it may seem acceptable for a summary measure to reflect the influence of these factors, too. On the other hand, some of these factors may be beyond the reach of policymakers and thus unnecessarily compromise policy relevance. Second, the presented analysis may not sufficiently address sample attrition, which may be an issue in some countries more than in others. Since usually poor and deprived respondents are more likely to leave the survey, deprivation exits and entries of the poor are presumably over- and underestimated, respectively. Consequently, differences in transition probabilities may draw an overly optimistic picture and thus be rather seen as lower bound estimates. Naturally, both correlated heterogeneity and panel attrition may be addressed in future research. Besides addressing these limitations, future research may also explore cross-country differences and the impact of shocks in more depth where data permits in order to identify social structures and arrangements which encourage, reduce or prevent the accumulation of deprivations.

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A Additional tables

Table A.1. Estimated coefficients - linear model

Austria 2019

	MD	LI	LWI	PH	OC	BH	HL	LE
poor	0.26***	0.18***	0.13**	0.03	0.10***	0.09***	0.14*	0.02*
	(0.034)	(0.051)	(0.058)	(0.022)	(0.037)	(0.031)	(0.073)	(0.011)
dep	0.80***	0.60***	0.52***	0.42***	0.73***	0.48***	0.58***	0.36***
	(0.132)	(0.022)	(0.032)	(0.024)	(0.022)	(0.029)	(0.013)	(0.137)
poor x dep	-0.17	-0.06	0.01	0.11*	-0.02	-0.02	-0.05	-0.06
	(0.154)	(0.067)	(0.076)	(0.063)	(0.057)	(0.068)	(0.080)	(0.167)
Obs.	6898	6898	6898	6898	6898	6898	6898	6898
Entries	152	198	187	259	198	230	679	31
Exits	4	283	210	353	128	237	634	30

Belgium 2019

	MD	LI	LWI	PH	OC	BH	HL	LE
poor	0.25***	0.04***	0.01	0.01	0.01**	0.07***	0.05*	-0.01
	(0.019)	(0.016)	(0.013)	(0.006)	(0.007)	(0.016)	(0.027)	(0.021)
dep	0.87***	0.50***	0.63***	0.87***	0.86***	0.49***	0.57***	
	(0.066)	(0.019)	(0.028)	(0.011)	(0.025)	(0.031)	(0.014)	
poor x dep	-0.25***	0.15***	0.16***	0.02	-0.08*	0.12***	0.13***	
	(0.075)	(0.033)	(0.035)	(0.023)	(0.045)	(0.043)	(0.033)	
Obs.	8695	8695	8695	8695	8695	8695	8695	935
Entries	520	310	181	47	79	314	792	0
Exits	10	563	236	171	72	268	588	78

Poland 2019

	MD	LI	LWI	LE	PH	OC	BH	HL
poor	0.07***	0.08***	-0.00	0.02**	0.03***	-0.01***	0.09***	0.06***
	(0.009)	(0.011)	(0.006)	(0.007)	(0.007)	(0.004)	(0.011)	(0.015)
dep	0.40***	0.58***	0.70***		0.54***	0.91***	0.57***	0.60***
	(0.028)	(0.014)	(0.018)		(0.018)	(0.006)	(0.017)	(0.011)
poor x dep	0.09**	0.07***	0.08***		0.10***	0.04***	0.02	0.09***
	(0.036)	(0.022)	(0.024)		(0.027)	(0.009)	(0.025)	(0.021)
Obs.	19798	19798	19798	2986	19798	19798	19798	19798
Entries	437	1277	323	0	487	255	1000	1602
Exits	754	1070	543	34	868	321	938	1278

Notes: Dependent variables are material deprivation (MD), low income (LI), low work intensity (LWI), low education (LE), poor housing (PH), Overcrowded (OC), bad health (BH), health limitations (HL); cells show point estimates for coefficients of linear model with standard errors in parentheses; columns in panels are separately estimated; explanatory variables refer to poverty and deprivation status in $t - 1$; indicated levels of significance are *** for $p < 0.01$, ** for $p < 0.05$ and * for $p < 0.1$, respectively.

Table A.2. Average predicted probabilities: linear probability versus logit model.

Belgium 2019

	d_msdi		d_in60		d_lwi_s		d_hqua		d_ovrc		d_ghlt		d_hlim		d_educ	
	lin	log	lin	log	lin	log	lin	log	lin	log	lin	log	lin	log	lin	log
non-poor & non-dep	0.039	0.039	0.039	0.039	0.024	0.024	0.005	0.005	0.009	0.009	0.035	0.035	0.116	0.116		
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)		
non-poor & dep	0.914	0.914	0.540	0.540	0.653	0.653	0.875	0.875	0.868	0.868	0.524	0.524	0.686	0.686	0.919	0.919
	(0.066)	(0.066)	(0.019)	(0.019)	(0.028)	(0.028)	(0.011)	(0.011)	(0.025)	(0.025)	(0.031)	(0.031)	(0.013)	(0.013)	(0.013)	(0.013)
poor & non-dep	0.294	0.294	0.082	0.082	0.035	0.035	0.012	0.012	0.023	0.023	0.107	0.107	0.168	0.168		
	(0.019)	(0.019)	(0.016)	(0.016)	(0.013)	(0.013)	(0.006)	(0.006)	(0.007)	(0.007)	(0.016)	(0.016)	(0.026)	(0.026)		
poor & dep	0.916	0.916	0.729	0.729	0.820	0.820	0.904	0.904	0.803	0.803	0.716	0.716	0.872	0.872	0.910	0.910
	(0.030)	(0.030)	(0.021)	(0.021)	(0.018)	(0.018)	(0.019)	(0.019)	(0.037)	(0.037)	(0.025)	(0.025)	(0.015)	(0.015)	(0.017)	(0.017)

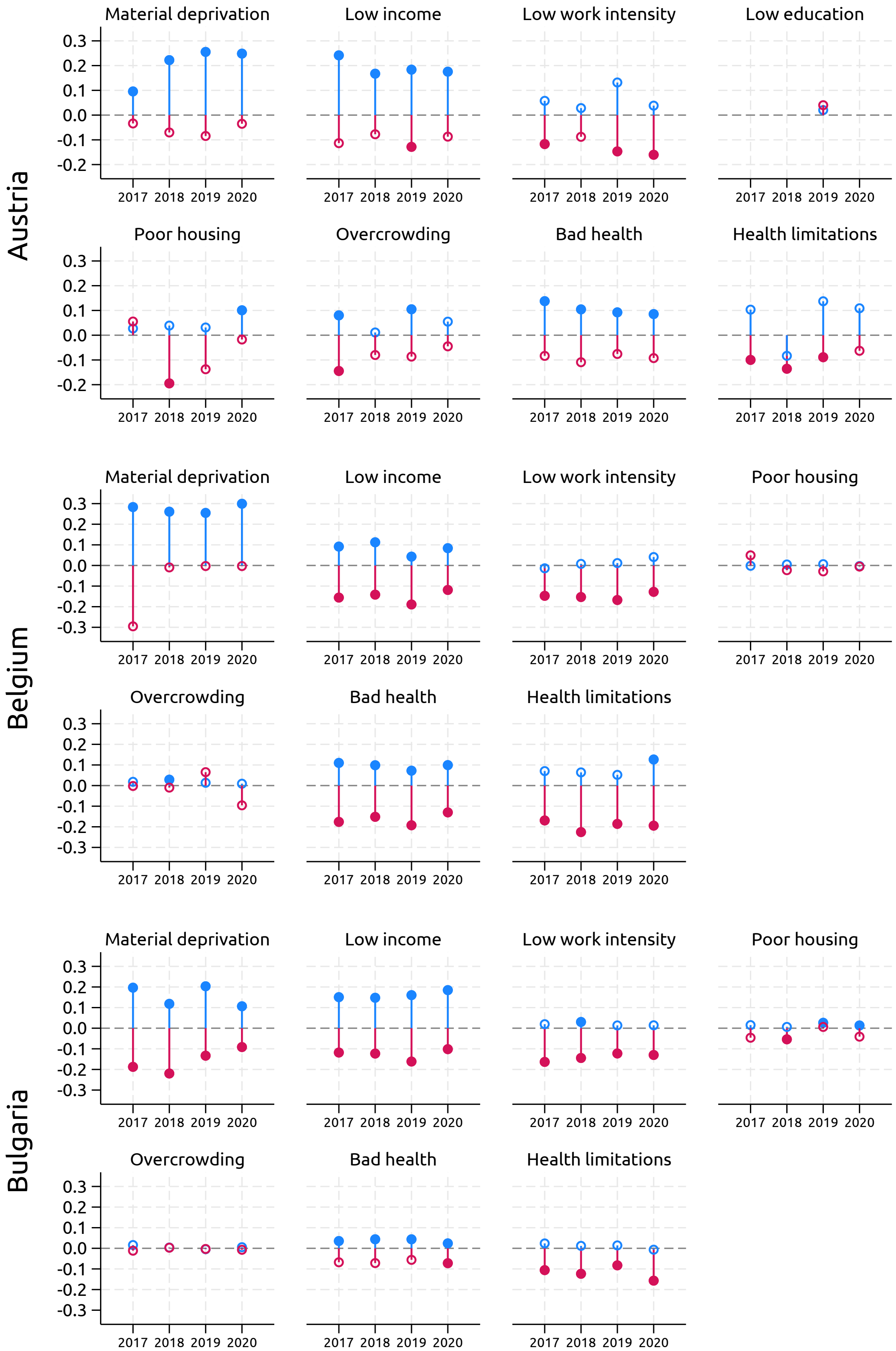
Poland 2019

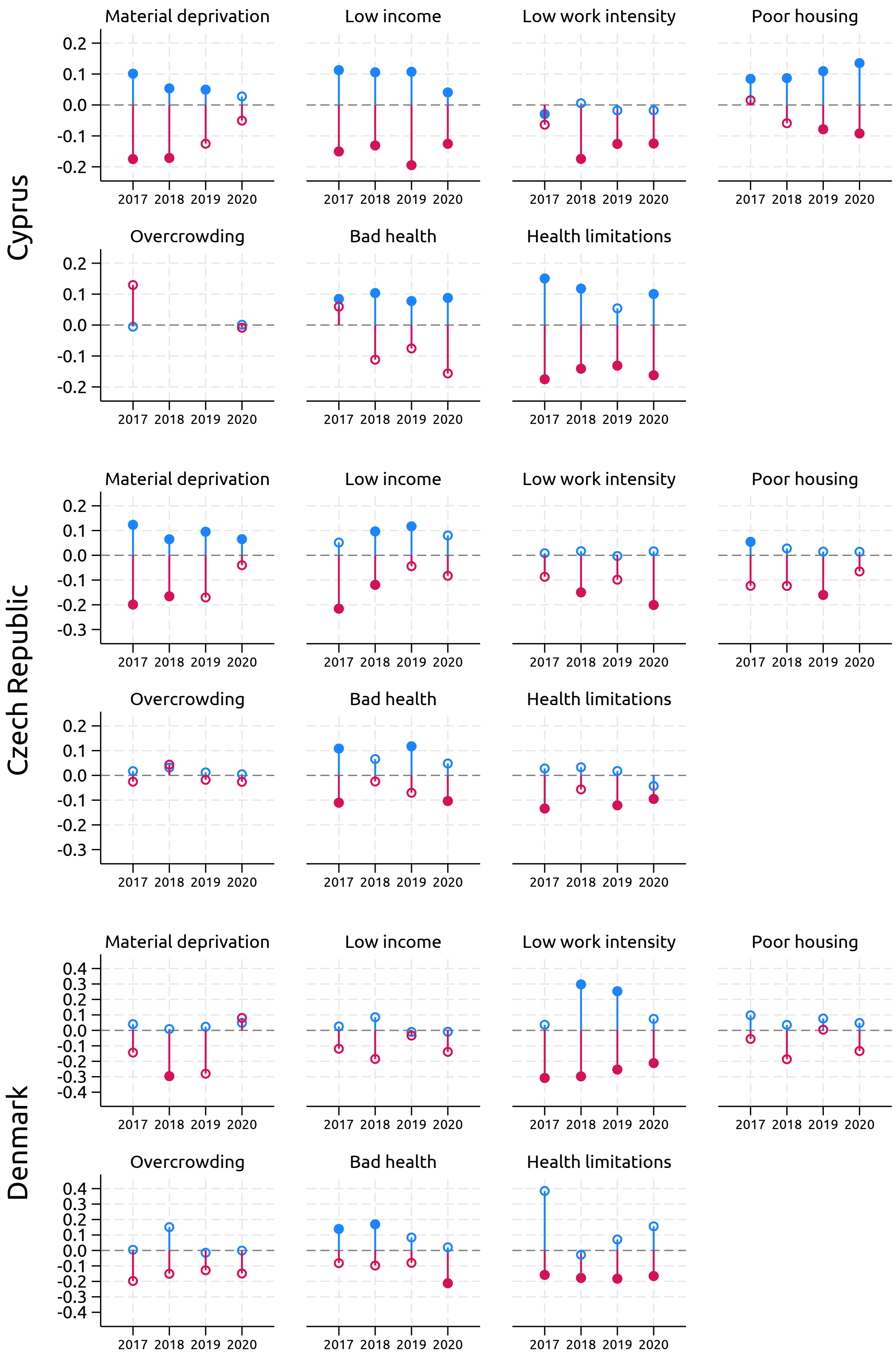
	d_msdi		d_in60		d_lwi_s		d_educ		d_hqua		d_ovrc		d_ghlt		d_hlim	
	lin	log	lin	log	lin	log	lin	log	lin	log	lin	log	lin	log	lin	log
non-poor & non-dep	0.016	0.016	0.064	0.064	0.020	0.020			0.027	0.027	0.022	0.022	0.045	0.045	0.094	0.094
	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
non-poor & dep	0.416	0.416	0.641	0.641	0.723	0.723	0.977	0.977	0.567	0.567	0.930	0.930	0.620	0.620	0.691	0.691
	(0.028)	(0.028)	(0.014)	(0.014)	(0.018)	(0.018)	(0.006)	(0.006)	(0.018)	(0.018)	(0.005)	(0.005)	(0.017)	(0.017)	(0.011)	(0.011)
poor & non-dep	0.085	0.085	0.139	0.139	0.020	0.020			0.059	0.059	0.011	0.011	0.135	0.135	0.155	0.155
	(0.009)	(0.009)	(0.011)	(0.011)	(0.005)	(0.005)			(0.007)	(0.007)	(0.003)	(0.003)	(0.011)	(0.011)	(0.015)	(0.015)
poor & dep	0.576	0.576	0.785	0.785	0.798	0.798	0.992	0.992	0.696	0.696	0.957	0.957	0.729	0.729	0.844	0.844
	(0.020)	(0.020)	(0.013)	(0.013)	(0.014)	(0.014)	(0.004)	(0.004)	(0.019)	(0.019)	(0.007)	(0.007)	(0.015)	(0.015)	(0.010)	(0.010)

Spain 2019

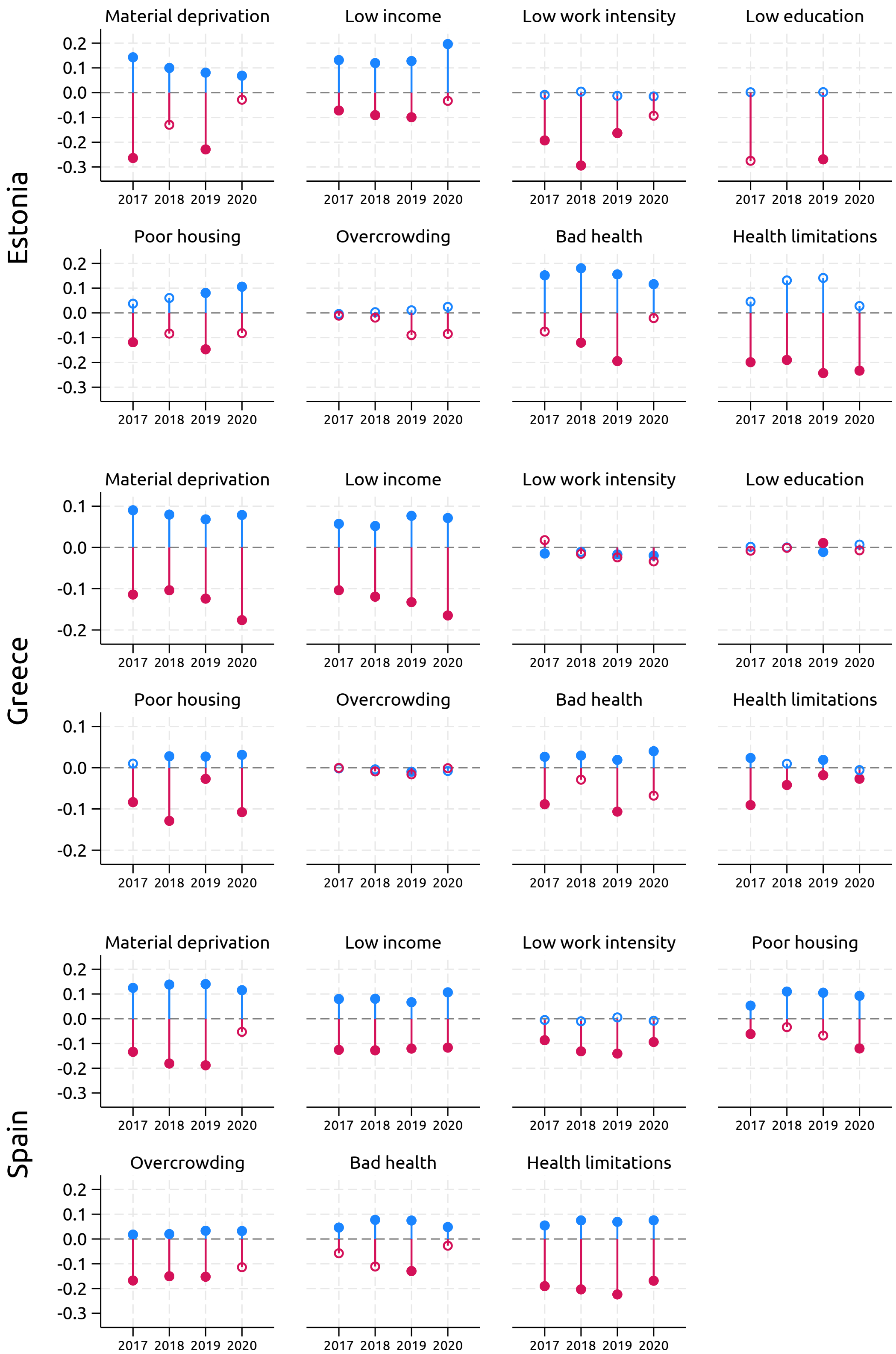
	d_msdi		d_in60		d_lwi_s		d_educ		d_hqua		d_ovrc		d_ghlt		d_hlim	
	lin	log	lin	log	lin	log	lin	log	lin	log	lin	log	lin	log	lin	log
non-poor & non-dep	0.038	0.038	0.046	0.046	0.051	0.051			0.089	0.089	0.016	0.016	0.026	0.026	0.077	0.077
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)			(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
non-poor & dep	0.342	0.342	0.661	0.661	0.643	0.643	0.944	0.944	0.352	0.352	0.600	0.600	0.432	0.432	0.482	0.482
	(0.025)	(0.025)	(0.015)	(0.015)	(0.017)	(0.017)	(0.007)	(0.007)	(0.016)	(0.016)	(0.032)	(0.032)	(0.034)	(0.034)	(0.015)	(0.015)
poor & non-dep	0.178	0.178	0.113	0.113	0.057	0.057			0.194	0.194	0.049	0.049	0.101	0.101	0.146	0.146
	(0.014)	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)			(0.013)	(0.013)	(0.007)	(0.007)	(0.010)	(0.010)	(0.014)	(0.014)
poor & dep	0.529	0.529	0.781	0.781	0.784	0.784	0.959	0.959	0.420	0.420	0.752	0.752	0.562	0.562	0.706	0.706
	(0.020)	(0.020)	(0.014)	(0.014)	(0.015)	(0.015)	(0.005)	(0.005)	(0.022)	(0.022)	(0.033)	(0.033)	(0.022)	(0.022)	(0.015)	(0.015)

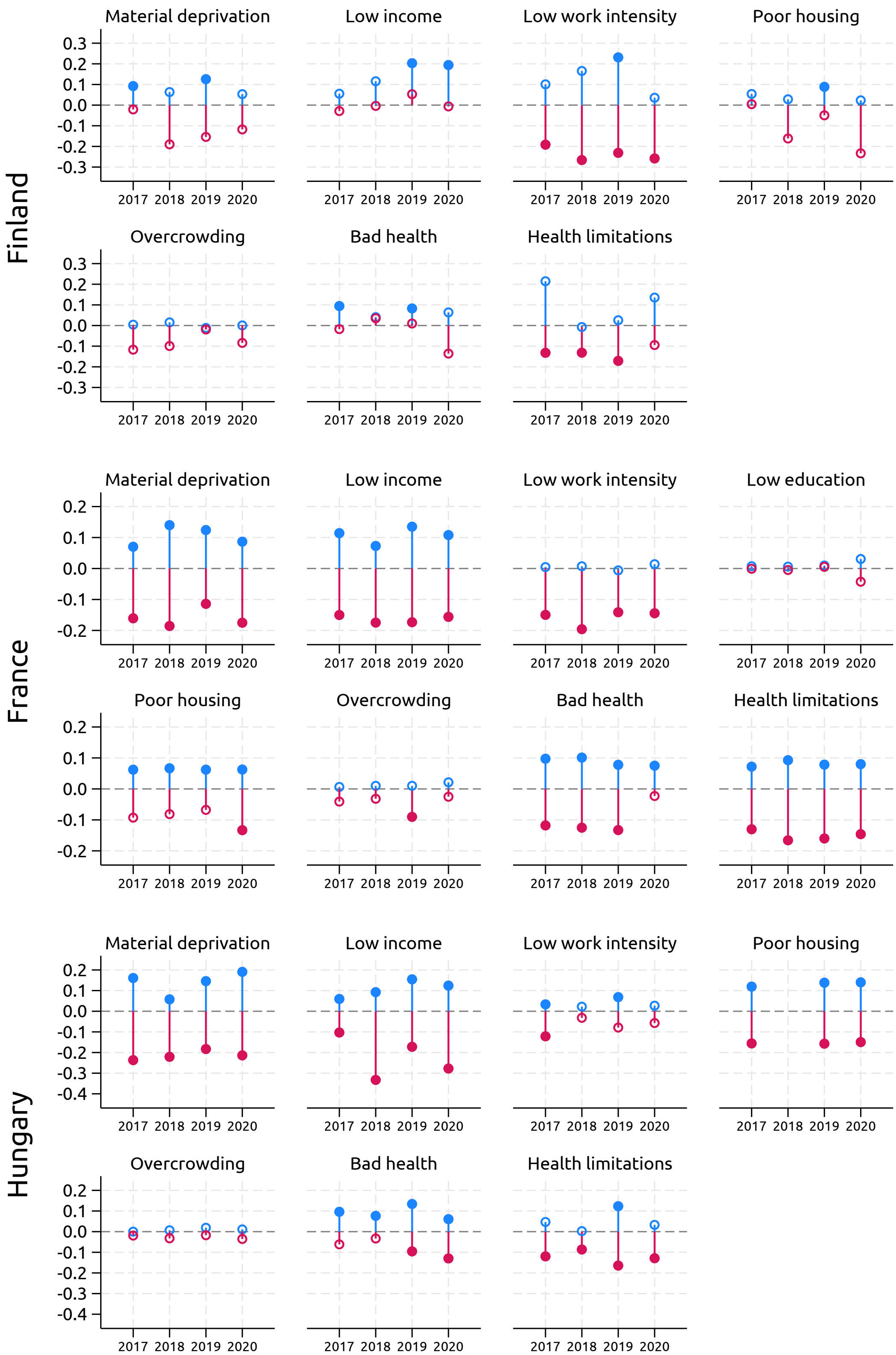
Figure A.1. Further results



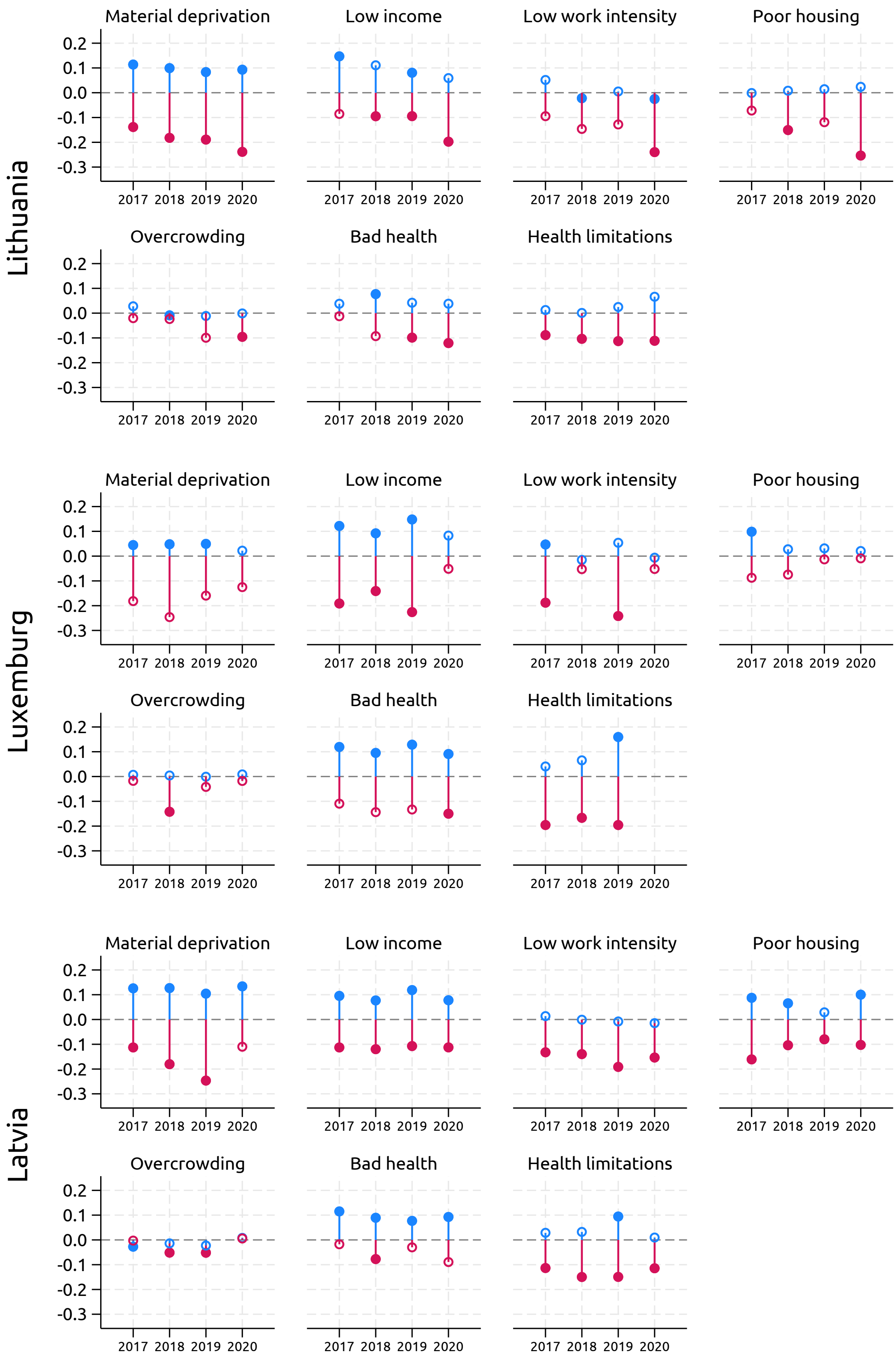


Cyprus
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
0.2
0.1
0.0
-0.1
-0.2
2017 2018 2019 2020
Czech Republic
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
0.2
0.1
0.0
-0.1
-0.2
-0.3
2017 2018 2019 2020
Denmark
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
0.4
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
2017 2018 2019 2020


Estonia
Material deprivation
Low income
Low work intensity
Low education
Poor housing
Overcrowding
Bad health
Health limitations
Greece
Material deprivation
Low income
Low work intensity
Low education
Poor housing
Overcrowding
Bad health
Health limitations
Spain
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
0.2
0.1
0.0
-0.1
-0.2
-0.3
2017 2018 2019 2020



Finland
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
France
Material deprivation
Low income
Low work intensity
Low education
Poor housing
Overcrowding
Bad health
Health limitations
Hungary
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
0.3
0.2
0.1
0.0
-0.1
-0.2
-0.3
-0.4
2017 2018 2019 2020


Lithuania
Luxemburg
Latvia
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
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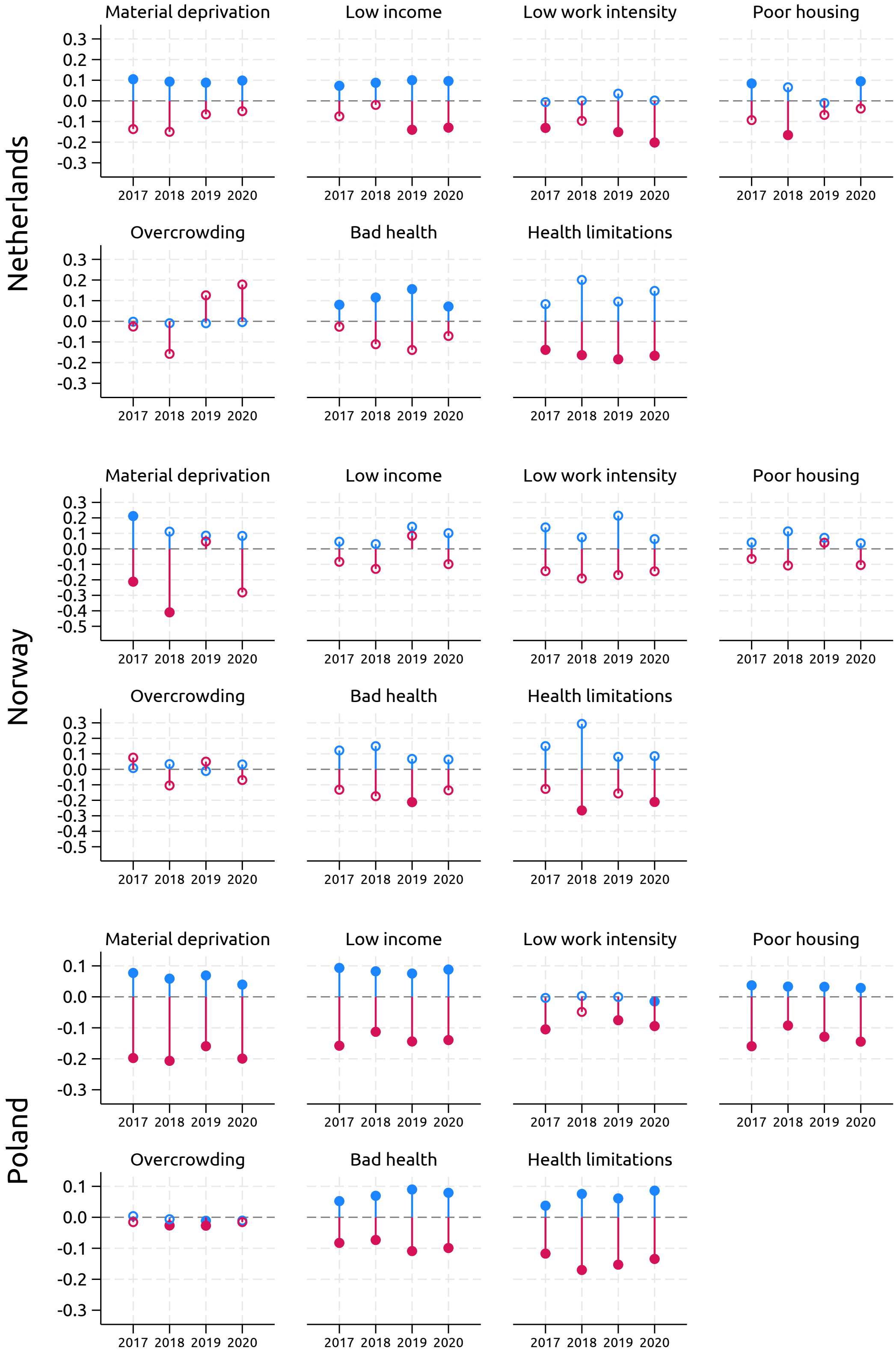
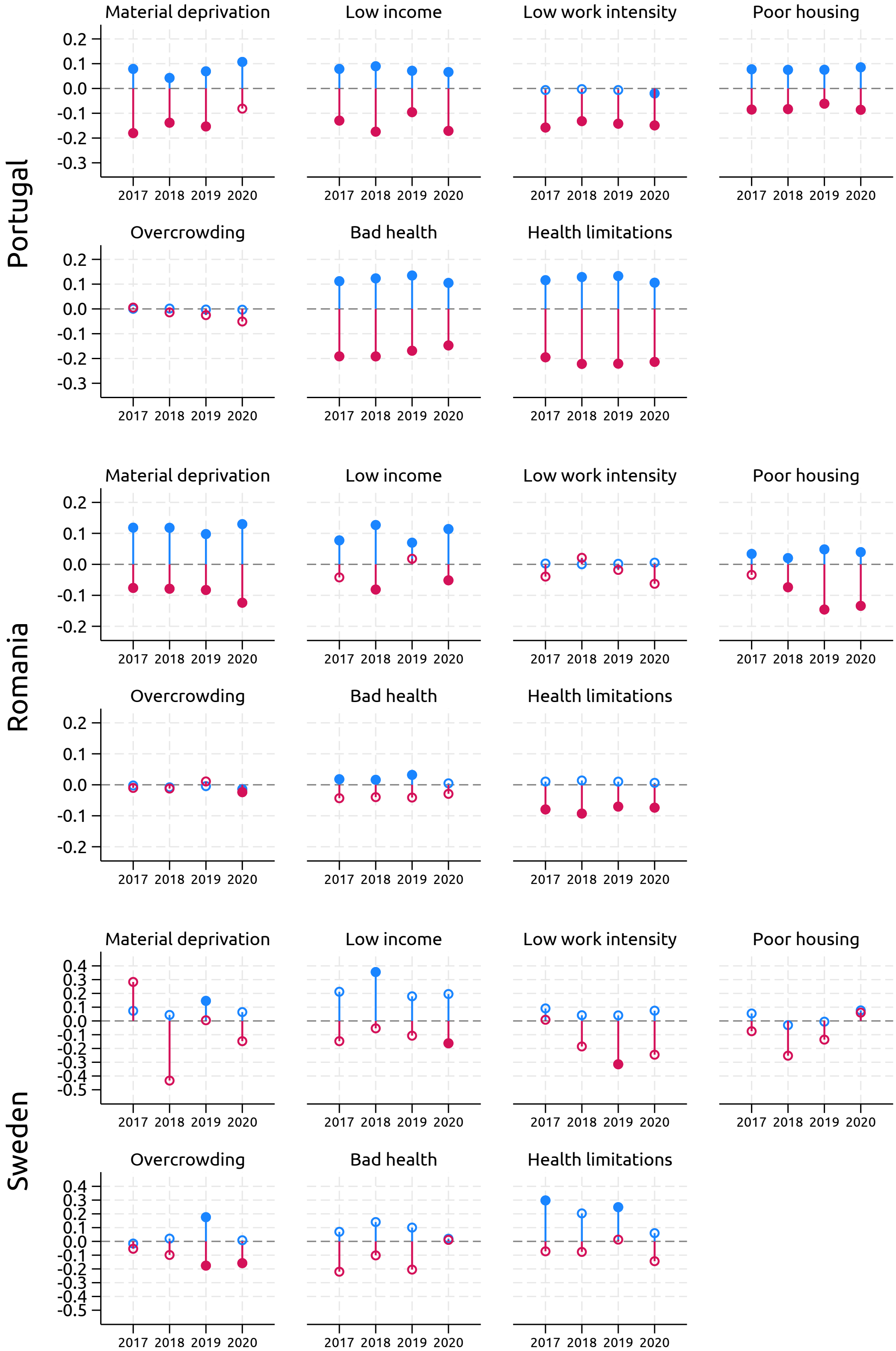
0.1
0.0
-0.1
-0.2
-0.3
2017 2018 2019 2020


Netherlands
Norway
Poland
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
2017 2018 2019 2020


Portugal
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
0.2
0.1
0.0
-0.1
-0.2
-0.3
2017 2018 2019 2020
Romania
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
0.2
0.1
0.0
-0.1
-0.2
2017 2018 2019 2020
Sweden
Material deprivation
Low income
Low work intensity
Poor housing
Overcrowding
Bad health
Health limitations
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0.1
0.0
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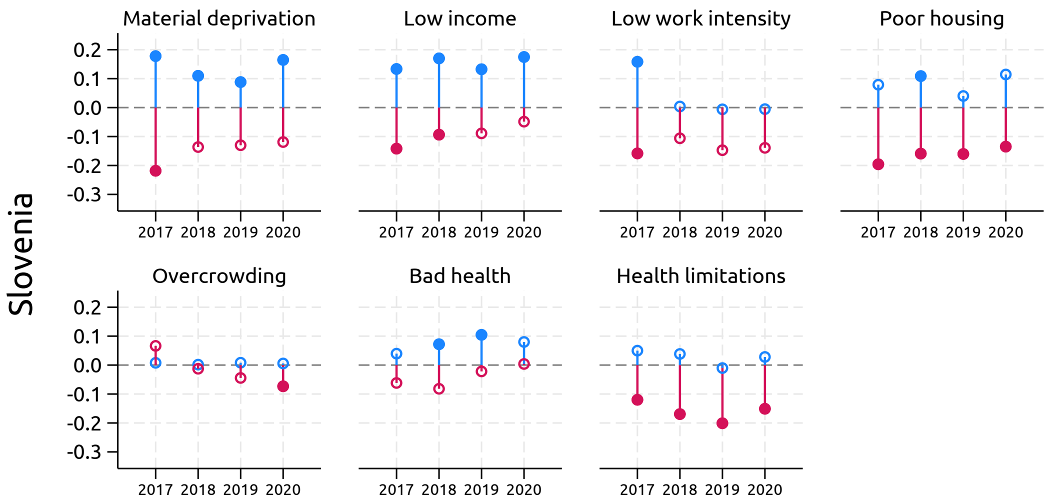
-0.2
-0.3
-0.4
-0.5
2017 2018 2019 2020



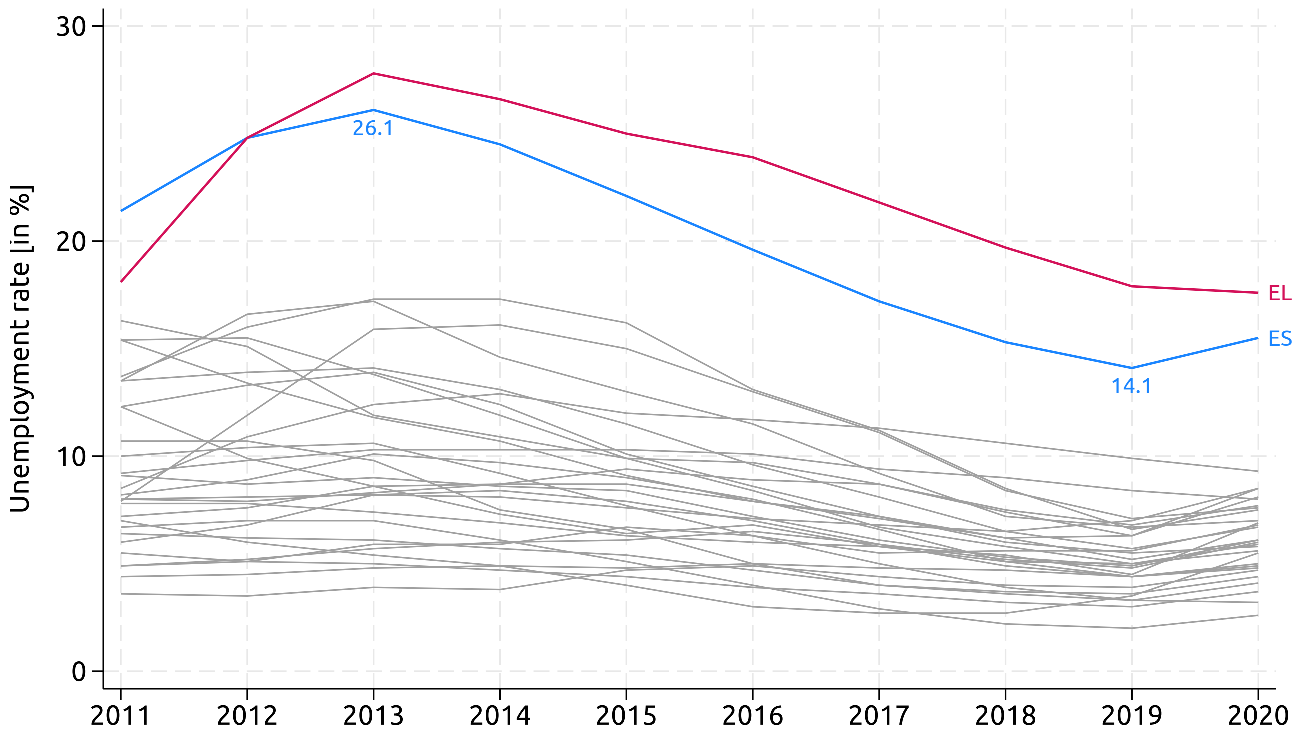


Figure A.2. Unemployment rate in selected EU countries. Highlighted countries are Spain (ES) and Greece (EL). Source Eurostat (online code TPS00203) source dataset: UNE_RT_A.