European Sociological Review, 2018, Vol. 34, No. 2, 121–137
doi: 10.1093/esr/jcx089
Advance Access Publication Date: 22 January 2018
Original Article

Understanding Material Deprivation for 25 EU Countries: Risk and Level Perspectives, and Distinctiveness of Zeros

Selçuk Bedük*

Department of Social Policy and Intervention, University of Oxford, Oxford OX2 6HG, UK

*Corresponding author. Email: selcuk.beduk@spi.ox.ac.uk

Submitted May 2017; revised December 2017; accepted December 2017

Abstract

Existing deprivation scales identify a majority of the population in each European Union (EU) country with zero deprivation. In this article, I hypothesize and test whether scoring zero on a material deprivation scale is a qualitatively different phenomenon to scoring at least one by applying and comparing multiple count models. I then examine how neglecting the distinctiveness of zeros, as the case in conventional models, influences our understanding of deprivation risk (deprived vs. non-deprived) and deprivation level (high vs. low deprivation), specifically regarding their relationship to social class. Consistently across 25 EU countries, the findings show that those with zero deprivation have significantly distinct profiles to those who have at least one deprivation. These results are robust to different weighting and index specifications. I then demonstrate how neglecting the distinctiveness of zeros results in significant underestimation of the strong social class gradient in risk of deprivation, and significant overestimation of the rather weak social class gradient in level of deprivation. Moreover, accounting for the distinctiveness of zeros reveals the conceptual difference between the risk and the level of deprivation given their different determinants, while conventional models identify the same determinants for both. These latter findings are also broadly consistent across 25 EU countries, with some exceptions in countries with very low level of zeros, such as Hungary, Bulgaria, and Romania. Relevant scales with a zero threshold can be used to study deprivation or to measure poverty in the EU yet either with some reconsiderations of conceptual and data problems or using a consistent poverty approach.

Introduction

How do we distinguish deprived from non-deprived, high from low deprivation? How is our understanding of material deprivation affected by these choices? The concept of material deprivation has gained prominence in the literature on poverty and disadvantage owing to the recognized problems of a sole focus on income. Material deprivation (*or deprivation hereafter*) is generally defined as the enforced lack of food, clothing, heating, and certain durables and social activities. These goods and services are assumed to be key conditions of life for social participation (Guio *et al.*, 2016), or can be considered as the necessities for performing expected social roles (Townsend, 1979).

Multiple counting indices are proposed to assess material deprivation consisting of an a priori selected binary items (*inter alia* Whelan and Maître, 2012; Guio *et al.*, 2016). Deprivation items are self-reported enforced lack of goods, deprivation score is the total count of deprived items, and the deprived (vs. non-deprived) is defined based on an arbitrarily assigned threshold on the deprivation score (e.g. having three or more deprived items).[1]

A recent literature analyses the determinants of deprivation using these counting indices. Some scholars focus on exploring the differences in the risk of being deprived (deprived vs. non-deprived), while others focus on explaining the variation in the level of deprivation (low vs. high deprivation). Despite providing substantial evidence on understanding deprivation, these studies neglect a common and important feature of deprivation data. Figure 1 shows the distribution of deprivation for 25 European Union (EU) countries using nine-item index of Whelan and Maître (2012). In all countries, there is a clustering at zero: a majority of the population in almost each country has no deprivation.

The excess of zeros has substantive implications for defining and analysing deprivation.[2] Zero is a conceptually meaningful phenomenon, indicates a state of no deprivation, while even one indicates some level of deprivation. Moreover, the very high prevalence of zeros suggests a distinct data-generating process: people with zero deprivation might have a distinct risk profile than people with at least one deprivation; hence zero might be qualitatively different from counts (one, two . . . nine).

If zeros are qualitatively distinct from counts, (i) zero can be considered as a natural threshold for the analysis of deprivation risk (deprived vs. non-deprived), and (ii) zeros must be excluded from the analysis of deprivation level (low vs. high deprivation). However, conventional models of deprivation risk employ an arbitrarily assigned threshold (usually two (3+)), and the conventional models of deprivation level include zeros into the analysis. Therefore, if zeros are distinct, the conceptual assumptions of conventional models do not hold; thus they might give unreliable estimates and distort our understanding of the risk and the level of material deprivation.

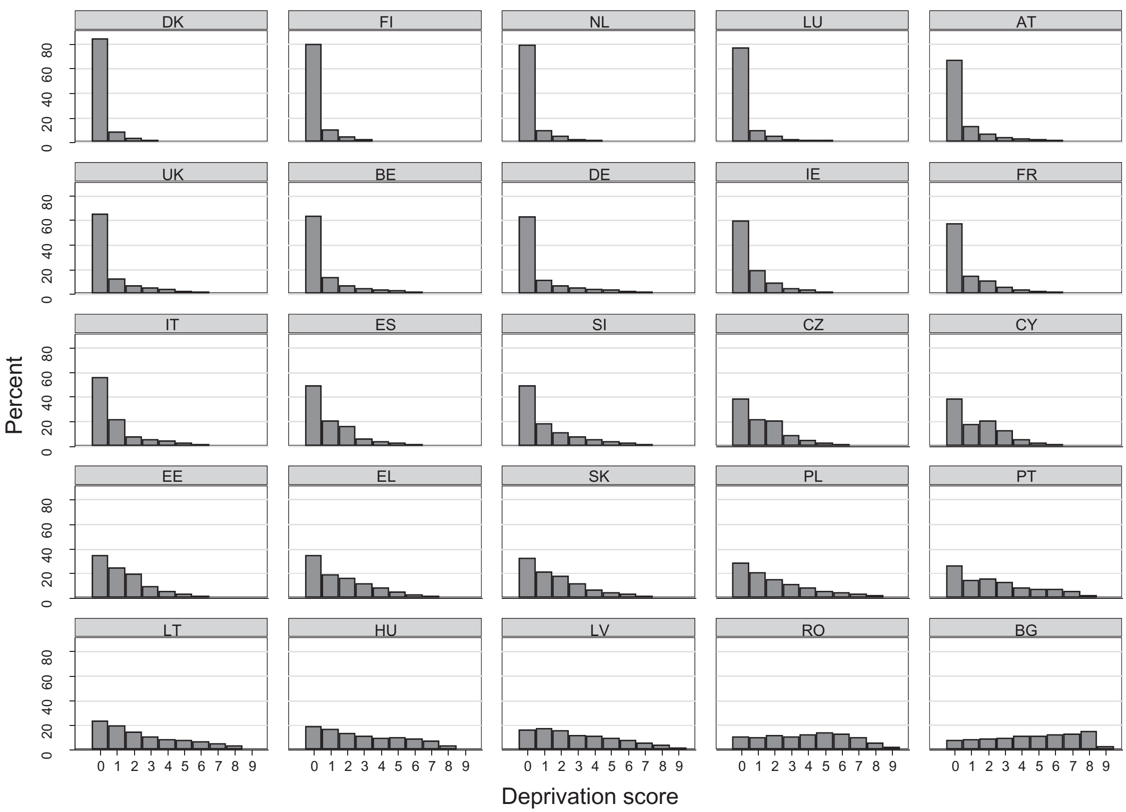

Figure 1. Distribution of deprivation in EU-25 nine-item index of Whelan and Maître
Notes: The histograms reflect the score of nine-item index by Whelan and Maître (2012). See Data and Methodology section for details of the index. Sweden and Malta are excluded due to data problems. The graphs emphasize the excesses of zeros. The number raises around 80 per cent for Denmark, Finland, and The Netherlands.

In this article, the aim is (i) to test the distinctiveness of zeros and (ii) to examine its consequences for understanding material deprivation. *To test the distinctiveness of zeros*, first, I visually compare the risk profiles of deprivation groups (zeros vs. counts) based on an exploratory data analysis; secondly, applying and comparing multiple count models, I formally test whether the models that account for zeros and counts separately fit the data better than the models that account for zeros and counts together.

To examine the substantive consequences of a possible distinctiveness of zeros, I focus on two questions: (i) Are the risk and level of deprivation socially structured based on social class? (ii) Do the processes that generate deprivation continue to affect the accumulation of deprivation; in other words, are the determinants of the risk and the level of deprivation same? The idea is to compare, based on the questions above, the results of conventional models to the results of a model that account for the distinct zeros. As I argue later, in the presence of distinct zeros, an appropriate modelling strategy for deprivation is using mixture count models, specifically hurdle models. Hurdle models account for two distinct data-generating processes (selection into zeros and determination of the deprivation level), which allow for a flexible and appropriate modelling of both risk and level of deprivation. Using EU-SILC 2009, the analysis is run separately for 25 EU countries given their varying rates of zeros. Therefore, a last question to examine is whether the findings depend on the level of zeros in a country.

Explaining Material Deprivation—Existing Literature, Theory, and Hypotheses

Risk and level perspectives are widely used in the European poverty literature. Deprivation risk is analysed to show different risk profiles of income poverty and material deprivation (Whelan *et al.*, 2004), to choose between alternative poverty measures (Whelan and Maître, 2009) and to examine the impact of individual risk factors and certain institutional factors on the risk of deprivation (Dewilde, 2008; Nelson, 2012). Similarly, deprivation level is studied to question the validity of income poverty thresholds in identifying the most deprived households (Whelan *et al.*, 2001), and to explore individual-level (Layte *et al.*, 2001; Berthoud and Bryan, 2011) and macro-level (Whelan and Maître, 2012; Bárcena-Martín *et al.*, 2014) factors in explaining deprivation level.

Despite the important contributions these studies make in understanding deprivation, two issues are neglected in this literature. First, in explaining the risk of deprivation, the primary concern is typically on the labour market and demographic characteristics, placing greater emphasis on the individual responsibility of poverty, but whether the risk of deprivation is socially structured based on social class attracted rather limited attention (Goldthorpe, 2010). Secondly, deprivation risk and level are used to study similar problems without making a clear distinction between the two, but the two concepts represent different phenomena and whether the same factors determine both processes, and if so why (and if not why not) are important substantive questions.

A theoretical framework based on class and life course risks is helpful in explaining the risk and level of deprivation and forming hypotheses on these two issues (Vandecasteele, 2011). As defined above, deprivation depends on the household's command over resources vis-à-vis their needs. In various life course events such as partnership dissolution, single parenthood, and childbirth, households face higher needs and/or lower economic resources, and hence might experience spells of deprivation. According to this individualistic view, the nature of deprivation is predominantly temporary, persisting until the balance of needs and resources is restored.

A rather more structural view is rooted in class relations, situating material deprivation within the institutionalized social relations through which a highly unequal distribution of economic resources as well as needs are generated and sustained (Townsend, 1979: pp. 409–412; Goldthorpe, 2010). The interest is on identifying the institutions that stratify society into discrete classes given their typical set of constraints and opportunities for life. One such theory defines the class positions based on employment relations, where two distinctions are key (Erikson and Goldthorpe, 1992). The first is among employers, self-employed, and employees, given their relationship to the means of production. The second is among employees based on their type of contract, mainly between *service* and *labour* contracts, distinguished by the differences in human asset and difficulties in monitoring. These two forms of employment regulation might occur in degrees hence *mixed forms* also exist. The theory is operationalized based on an European Socio-Economic Classification (ESEC) scheme which is shown to be a valid measure for comparative use across the EU (Rose and Harrison, 2014). Education and gender are also usually considered as other similar social stratification determinants (Vandecasteele, 2011).

Other important factors such as current income, unemployment, house ownership, and long-term ill-health are endogenous to class and life course variables. In other words, the effects of class and life course variables on deprivation are mediated through low and unstable income, unemployment, ill-health, and tenancy (Borg and Kristensen, 2000; Kurz and Blossfeld, 2004; Goldthorpe and McKnight, 2006; Özcan and Breen, 2012; Pintelon *et al.*, 2013). Yet an important question is whether the class and life course risk effects are partly or totally mediated by these intervening variables, and whether these processes differ for deprivation risk and deprivation level.

Deprivation risk shows differences between deprived and non-deprived, while deprivation level reflects the differences between those with low and high deprivation. If zero is conceptually distinct to counts, then deprivation risk shows differences between zeros and counts, while deprivation level shows differences among counts. Therefore, while deprivation risk examines variance in the whole population, deprivation level focuses on variance among those with at least one deprivation. Based on their study on Ireland, Whelan *et al.* (2007) argue that the social class and education gradients on multiple deprivation are lower than expected because (i) class variables are more powerful discriminating across a general population and (ii) once we focus on the most disadvantaged, the effects of class variables are mediated through rather than accumulated on the effect of other factors (see Vandecasteele, 2011 for similar findings for 13 EU countries).

In this context, hypotheses for the two alleged questions are as followed. Regarding the first question on social class gradient, we expect a systematic variation in deprivation risk by social class, especially among service, mixed, and labour classes, and for deprivation level, the class gradient is expected to be not as strong as in deprivation risk, mainly because the analysis is already focused on the more disadvantaged classes. Regarding the second question on comparing risk and level perspectives, we expect a net effect of all relevant factors on deprivation risk, but for deprivation level, most of the class and life course effects are expected to be mediated; hence net effects might either disappear or diminish.

Two further issues are of relevance to these hypotheses. First, the analyses focus on exploring common regularities across EU countries, although a certain level of country variance is expected in relation to the level of zeros. Still, the expected process and differences between conventional and hurdle models should be more or less consistent across countries.

Secondly, the hypotheses are not expected to apply to conventional models that do not account for the distinctiveness of zeros. Conventional models on deprivation risk typically apply *ad hoc* non-zero thresholds. If zeros are qualitatively distinct as hypothesized, these conventional models underestimate effects of explanatory factors on the risk of deprivation. This is mainly because (i) average differences in explanatory factors are expected to be largest between zeros and others and (ii) in the case of a non-zero threshold (e.g. 3+), non-deprived group includes, in addition to zero, some other count groups (e.g. ones and twos) which dilute average differences between deprived and non-deprived groups. Also, conventional models of deprivation level include zero in the analysis with an assumption that zero is determined by the same process as of counts. If zeros are qualitatively distinct as hypothesized, these conventional models overestimate the effects on level of deprivation. This is mainly because (i) average differences in explanatory factors are expected to be largest between zeros and others, and (ii) when zeros are included into the analysis, the estimates are superfluously raised by differences between zeros and counts, while main interest is explaining the differences among counts.

Data and Methodology

Case Selection

The study aims to generalize over the EU. The analysis is run separately for each country, but for clarity in presentation, the analysis of the consequences of distinct zeros is presented for four countries in the main text, namely, Denmark, Ireland, Portugal, and Hungary. The results for other countries are presented in Supplementary Material, and references are made in the main text where relevant. These four countries are selected based on their level of zeros, each representing a group with similar level of zeros—Denmark from high, Ireland from medium-high, Portugal from medium-low, and Hungary from low group (see Table 1). The four groups show quartiles of the distribution of level of zeros across countries. By comparing the results of these four countries, I investigate the impact of the zero rate in a country on the consequences of neglecting distinct zeros.

Data

EU-SILC 2009 is used for the analysis which includes a special module on material deprivation (ONS, 2011). The unit of analysis is the household reference person (HRP). There are two reasons for this choice: (i) most of the deprivation information is collected at the household level which, in an individual level analysis, might cause

Table 1. Country classification based on rate of zeros

High (First quartile)		Medium-high (Second quartile)				Medium-low (Third quartile)				Low (Fourth quartile)	
DK	**84.1**	AT	66.8	FR	57.6	CZ	38.6	PL	28.5	LT	23.4
FI	80.1	UK	65.4	IT	55.7	CY	38.4	**PT**	**26.3**	**HU**	**18.9**
NL	78.9	BE	63.4	ES	49.3	EE	34.9			LV	16.2
LU	76.9	DE	62.9	SI	49.1	EL	34.5			RO	10.7
		IE	**59.6**			SK	32.6			BG	7.6

Notes: The numbers represent the rate of zeros in the country. Bold are the selected countries.

clustering at the household level; (ii) information on some deprivation items (e.g. clothes, shoes, and social activities) and health indicators is collected only for the HRP in countries such as Denmark, Finland, and The Netherlands.

Empirical Model

The main analysis is based on the nine-item index of Whelan and Maître (2012) *(WM hereafter)*. The index score is calculated as a raw sum of nine binary deprivation items described in Appendix. Following the common practice, threshold for deprivation is selected as being deprived on three or more items. Presented in Supplementary Material, the main analysis is repeated for two other deprivation scales (e.g. weighted WM and 13-item index of Guio *et al.* (2016)) to test sensitivity to weighting and index specification.

Informed by the theoretical framework, the following explanatory variables are used. *Social class* is constructed based on the ESEC using the two-digit ISCO codes. Originally 10-class schema, given the problems of constructing the schema with two-digit codes, ESEC 5 class version with an inclusion of the 'excluded (never worked)' category is employed.[3] The five classes are named based primarily on their employment relations, as the gradient is expected to be between salariat, mixed, and labour classes. Income variable is the household disposable income, equivalized using OECD scale and used in a log form in the regressions. The education variable is three-category version of ISCED, reflecting the highest educational level attained.[4] Other variables such as gender, unemployment, being single parent, having three children or more, disability and chronic health problems in the household, and being a tenant are constructed as binary variables. Also, age is included as a control variable.[5] See Table A1 for descriptive statistics for all variables.

Missing Data

Missing data for the main variables of interest are presented for the whole sample and separately for each country in Tables A1 and A2. Sweden is excluded due to significant missing cases (around 30 per cent) on the deprivation scale, and so as Malta due to coding problems in social class variable. For the whole sample, the missing rate for the deprivation scale is 2 per cent, for other variables lower than 1 per cent, and in total around 4 per cent. For the United Kingdom, around 8 per cent has missing data on the deprivation scale, but social class and income distributions of the missing and non-missing samples are very similar. For The Netherlands, Denmark, and France, around 3–4 per cent has missing information on social class but a similar distribution of deprivation with the non-missing sample. Therefore, the analysis is held based on non-missing cases.

Count Models

Count models are extensively used for analysing count outcomes, for example, in studies of fertility behaviour (e.g. number of children) (Parrado and Morgan, 2008), labour market outcomes (e.g. unemployment spells, number of job changes) (Andress, 1989), and healthcare utilization (e.g. number of doctor visits) (Deb and Trivedi, 1997). The most basic count model, Poisson model (PM), assumes equal conditional variance and mean:

$$\mu_i = E(y_i \mid x_i) = \exp(x_i\beta) = \lambda_i.$$

$$Var(y_i \mid x_i) = \lambda_i.$$

Yet, usually the data are over-dispersed: conditional variance exceeds conditional mean. Three reasons for overdispersion are unobserved heterogeneity, dependence of observations, and the existence of more than one data-generating processes (Cameron and Trivedi, 2013). More advanced models such as negative binomial model

(NBM) includes unobserved heterogeneity with an additional parameter(δ_i):

$$\mu_i = E(y_i \mid x_i \ , \ \epsilon_i) = \exp(x_i\beta + \epsilon_i) = \exp(x_i\beta) \ \delta_i.$$

The distribution of δ is gamma with one parameter$v$; then $E(\delta_i) = 1$, $Var(\delta_i) = \frac{1}{v} = \alpha^{-1}$, where α is the dispersion parameter. In both of these models, zeros are still modelled together with the counts assuming that they are determined by the same data-generating process.

Hurdle models assume a two-stage process: (i) the probability of zero is usually modelled with a binary logistic model, and (ii) for the ones crossed the 'hurdle' of zero, the level of deprivation is modelled by a zero-truncated PM or zero-truncated NBM. The binary and count parts can be assumed as two separate components allowing the process determining zeros to be distinct from the process generating counts (Cameron and Trivedi, 2013). *Therefore, if the zeros are distinct, we expect a better fit for the hurdle compared to standard PM and NBM*. The preference between Hurdle Poisson Model (HPM) and Hurdle Negative Binomial Model (HNBM) depends on whether further unobserved heterogeneity exists in the model.[6]

Analytical Strategy

To test the distinctiveness of zeros, primarily, risk factors (Y) are plotted against the deprivation score (X) which can help detect the distinctiveness of zero group visually. Secondly, multiple count models are compared in terms of their model fit. A better model fit in hurdle vis-à-vis standard PM or NBM is an indication of a distinct data-generating process for zeros.

Three statistical tests are used to select between models (Cameron and Trivedi, 2013; Long and Freese, 2014). The first is the likelihood ratio test of the dispersion parameter α. The null hypothesis is $\alpha = 0$, in which case NBM equates to PM. Therefore a significant test value shows overdispersion and a preference for NBM over PM. The second is the Vuong test, a maximum likelihood test for non-nested models used to choose between hurdle and standard count models. The Vuong statistic $\frac{LL(HNBM) - LL(NBM \ \ or \ \ PM)}{sd / \sqrt{n}}$ where LL is assumed to have a standard normal distribution, so a value higher than 1.96 shows a preference for hurdle model, while lower than -1.96 shows a preference for standard count model (Poisson or negative binomial). AIC- and BIC-corrected versions of the Vuong test proposed by Desmarais and Harden (2013) which account for the differences in the number of parameters are also used in the analysis. The third is the likelihood ratio test to choose between HPM and HNBM. In addition, information criteria (AIC and BIC) are examined between the models (Kuha, 2004).

To answer the two substantive questions, the conventional models of risk and level (logit and ordinary least squares (OLS)) as well as the best-fit count model are run and compared based on both significance and effect size. For comparability between models, average marginal effects (AMEs) are used.[7] To examine the differences across countries with different levels of zeros, the models are run separately for each country.

Are Zeros Distinct?

To test the distinctiveness of zeros, first, the risk profiles of each deprivation group are explored visually; secondly, count models are compared using formal statistical tests.

Exploratory Data Analysis: Risk Profiles of Deprivation Groups

Figure 2 shows the average equivalized household disposable income for each deprivation group for 14 countries (see Supplementary Material for other countries). The graphs reveal an interesting curve linear trend consistent across countries. The average income of the zero group is significantly above the median income, which drops below median in the first count, and for the subsequent counts, slightly decreases but stays above 60 per cent of median income (this pattern is more apparent in high and medium-high than in medium-low and low countries). More importantly, this curve linear trend, where the slope is the highest for the first count, is observed not only for income but also for social class, education, and ill-health (see Supplementary Material).[8]

These results have three important implications. First, due to the significant fall (or jump for negative risk factors) at the first count, risk profile of zero deprivation group is separated and significantly different from other count groups. For example, in Ireland, average household income of the zeros is above 30,000 euros, while it is between around 15,000 and 20,000 euros for all other groups. Secondly, despite a decreasing (or increasing) trend over higher deprivation groups, risk profiles of the count groups are very similar to each other. For example, group average incomes are generally between the country median income and relative income poverty line (60 per cent of median). Thirdly, given the curve linear bivariate relationships between deprivation and risk factors, a bulk of the variation comes from the differences between zeros and counts, and not from the differences among counts. This shows that identified risk factors are mostly useful in explaining the risk than the level of deprivation.

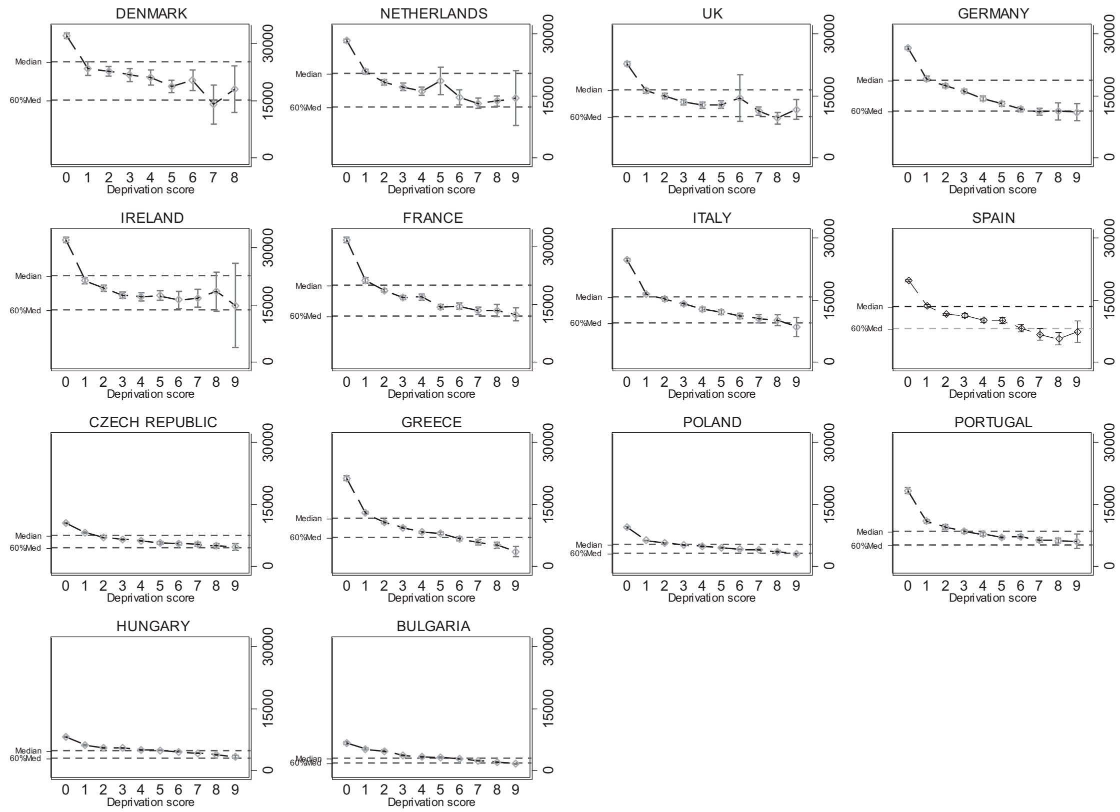

Figure 2. Average income levels for each deprivation group across 14 EU countries
Notes: The figure shows the average disposable equivalized household income for each deprivation group. The bars show 95% of confidence interval. The figures show that consistently across countries, the zero deprivation groups have significantly higher average incomes which then significantly drops for the first count group and then marginally decreases for subsequent groups but generally stays between the median and 60% of median income for all count groups. See Supplementary Material for other countries and risk factors.

Comparing Count Models

If zeros are distinct, zeros should be modelled separately, and hence, hurdle models should fit the data better than standard count models. To formally examine this, PM, NBM, HPM, and HNBM are compared using multiple statistical tests.

As shown in Table 2, for all 25 EU countries, (i) the dispersion parameters (α) are significantly higher than 0 and the likelihood ratio tests are significant, indicating a preference for the NBM over PM (except Bulgaria); (ii) Vuong statistics are positive and bigger than 1.96, showing a preference for hurdle model,[9] and (iii) likelihood ratio test between HNBM and HPM shows a significant result showing a preference over HNBM model (except Cyprus, Romania, and Bulgaria). AIC and BIC values also suggest a similar result (see Appendix, Table A3): for all countries the lowest AIC and BIC values are for the HNBM (or HPM for Cyprus, Romania, and Bulgaria).

These results give strong supporting evidence to the hypothesis that zeros are generated by a distinct process than counts; thus zero deprivation represents a qualitatively distinct phenomenon. As described in Supplementary Material, these analyses are also repeated for a prevalence-weighted WM index and 13-item index of Guio *et al.* (2016) with the same results. Therefore, the findings are robust to different prevalence weighting and index specification.

Consequences of Neglecting Distinct Zeros on Our Understanding of Material Deprivation

If zeros are distinct, the threshold of deprivation can be set at zero, and zeros should be excluded from the models of deprivation level. However, conventional models of deprivation risk use a threshold of two, and the

Table 2. Model selection between PM, NBM, HPM, and HNBM—tests

Country	Per cent of zeros	PM vs. NBM		NBM vs. HNBM			HNBM vs. HPM
		Alpha (α)	LR test of $\alpha = 0$	Vuong	Vuong AIC-corrected	Vuong BIC-corrected	LR test
Denmark	84.1	2.93	981 (pr > 0.00)	5.7	4.3	−0.5	83 (pr < 0.00)
Finland	80.1	1.89	1,433 (pr > 0.00)	8.3	7.4	4	105 (pr < 0.00)
Netherlands	78.9	1.77	1,447 (pr > 0.00)	8.7	7.8	4.5	73 (pr < 0.00)
Luxembourg	76.9	1.43	847 (pr > 0.00)	7.9	6.8	3.5	96 (pr < 0.00)
Austria	66.8	1.39	1,890 (pr > 0.00)	9.4	8.5	5.4	159 (pr < 0.00)
United Kingdom	65.4	1.34	2,188 (pr > 0.00)	12.6	11.9	9.6	157 (pr < 0.00)
Belgium	63.4	1.17	1,990 (pr > 0.00)	10.5	9.7	7	249 (pr < 0.00)
Germany	62.9	1.30	4,718 (pr > 0.00)	19.7	19.2	17.6	199 (pr < 0.00)
Ireland	59.6	0.72	734 (pr > 0.00)	8.8	7.8	4.5	177 (pr < 0.00)
France	57.6	0.84	2,384 (pr > 0.00)	14.4	13.8	11.4	282 (pr < 0.00)
Italy	55.7	0.93	5,082 (pr > 0.00)	14.5	13.9	11.6	1,426 (pr < 0.00)
Spain	49.3	0.51	1,494 (pr > 0.00)	12.5	11.8	9.1	289 (pr < 0.00)
Slovenia	49.1	0.69	1,843 (pr > 0.00)	11.9	10.9	7.7	205 (pr < 0.00)
Czech Republic	38.6	0.24	495 (pr > 0.00)	11.2	10.2	6.6	68 (pr < 0.00)
Cyprus	38.4	0.16	74 (pr > 0.00)	8.7	7.5	3.9	0 (pr < 0.99)
Estonia	34.9	0.24	288 (pr > 0.00)	7.9	6.4	1.6	51 (pr < 0.00)
Greece	34.5	0.18	423 (pr > 0.00)	12.7	11.9	9.5	37 (pr < 0.00)
Slovakia	32.6	0.27	405 (pr > 0.00)	10	8.9	5.1	75 (pr < 0.00)
Poland	28.5	0.29	1,685 (pr > 0.00)	15.3	14.6	11.9	607 (pr < 0.00)
Portugal	26.3	0.24	534 (pr > 0.00)	11.9	11.1	8.6	80 (pr < 0.00)
Lithuania	23.4	0.32	868 (pr > 0.00)	7.6	6.3	1.9	218 (pr < 0.00)
Hungary	18.9	0.21	1,004 (pr > 0.00)	15	14.3	11.9	152 (pr < 0.00)
Latvia	16.2	0.16	408 (pr > 0.00)	7.6	6.4	2.4	94 (pr < 0.00)
Romania	10.7	0.06	122 (pr > 0.00)	14.1	13.6	11.5	0 (pr < 0.99)
Bulgaria	7.6	0.002	0.25 (pr > 0.31)	11	10.3	7.9	0 (pr = 0.99)

Notes: The table presents results of fit statistics for 25 EU countries, comparing multiple count models. Alpha is a dispersion parameter. Any value bigger than 0 reflects overdispersion and preference over NBM. Vuong test (as well as its bias-corrected versions) is a maximum likelihood test for non-nested models used to choose between hurdle vs. standard models. The null hypothesis is equal fit; hence numbers higher than 1.96 shows a preference for hurdle models. In the table, the countries are ordered from highest to lowest level of zeros. There is significant overdispersion for all countries associated to the level of zeros. Hurdle models (HNBM or HPM) are the preferred model for all countries.

conventional models on deprivation level includes zeros in the analysis. In this section, I show how the results on the relationship between social class and deprivation and on the determinants of the risk and level of deprivation are distorted due to not accounting for the distinctiveness of zeros.

Social Class Variation on the Risk and the Level of Deprivation

Figure 3 shows bivariate relationship between social class and deprivation risk across four countries. The y-axes show the average predicted risk of deprivation. The solid lines show the estimates from hurdle models where the threshold for deprivation is zero (1+); the dashed lines show the estimates from conventional logit models where the threshold for deprivation is two (3+).

A strong social class gradient in the risk of deprivation can be observed for all countries when the threshold is zero. Mixed class has in average significantly higher risk of deprivation than salariat; non-manual and manual labour have in average higher risk of deprivation than both mixed and salariat. Yet, when the threshold is two, these gradients disappear in Denmark and diminish in Ireland and Portugal. Only in Hungary, the gradient is stronger when the threshold is two than zero.

As shown in Supplementary Material, similar patterns are observed for other countries. For the countries with high and medium level of zeros, differences in deprivation risk among salariat, mixed, and labour are much clearer when the threshold for deprivation is zero than two.[10] Therefore, for these countries, using a higher threshold masks the strong social class gradient in the risk of deprivation. On the other hand, for

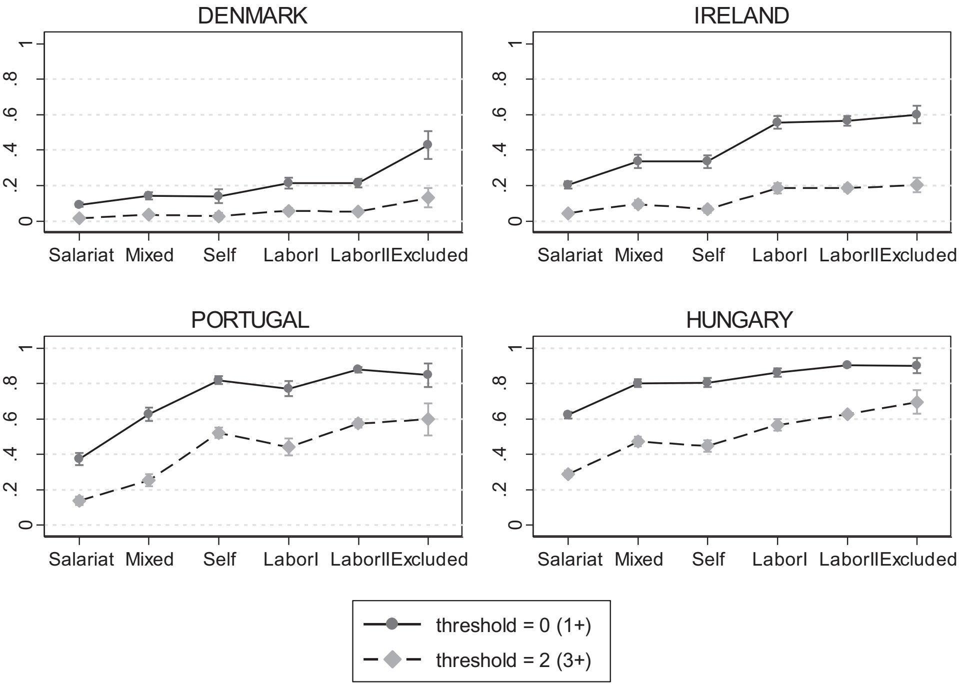

Figure 3. Social class variation on deprivation risk using different thresholds

Notes: The figure shows social class gradient in the average predicted risk of deprivation for four countries. The models do not include any control variables. The solid lines show the estimates from models where the threshold for deprivation is zero (1+), and the dashed lines show the estimates from models where the threshold for deprivation is two (3+).The figure demonstrates that social gradient in deprivation risk is much clearer when the threshold is zero except for Hungary.

countries with low level of zeros, the social class gradient is more apparent when the threshold is two than zero (mainly due to a ceiling effect).[11] Therefore, for these countries, using a zero threshold might obscure the actual social class gradient in the risk of deprivation.

Figure 4 shows the bivariate relationship between social class and deprivation level across four countries. The *y*-axes show the average predicted level of deprivation. The solid lines show the estimates from the count part of the hurdle model which does not include zeros into the analysis;[12] the dashed lines show the estimates from conventional OLS models which include zeros into the analysis.

As hypothesized, the social gradient in the level of deprivation is not strong in the hurdle models without zeros. However, when zeros are included into the analysis, a higher variation across classes exists. In the OLS with zeros compared to the hurdle model without zeros, the excluded has in average significantly higher level of deprivation than the salariat in Denmark; the gradient between all classes is more apparent in Ireland; and, the distance between salariat and other classes is wider in Portugal and Hungary. As shown in Supplementary Material, the results are similar for all other countries.[13] Therefore, including zeros into the level analysis causes some spurious social class effect on the level of deprivation.

Determinants of Risk vs. Level of Deprivation

Table 3 shows results of hurdle and conventional models on risk and level of deprivation. Between risk and level models, only statistical significance is of interest. Effect sizes are not comparable as risk models show effects on the probability of being deprived, while the level models show effects on the level of deprivation.

Based on the hurdle models, the determinants of risk and level of deprivation appear to be substantially different in Denmark, Ireland, and Portugal. As hypothesized, most of the class and life course factors significantly explain the risk of deprivation, while only some significantly explain the level of deprivation. For example, in Denmark almost all factors significantly increase the risk of deprivation, while only income, house ownership, and single parenthood significantly increase the

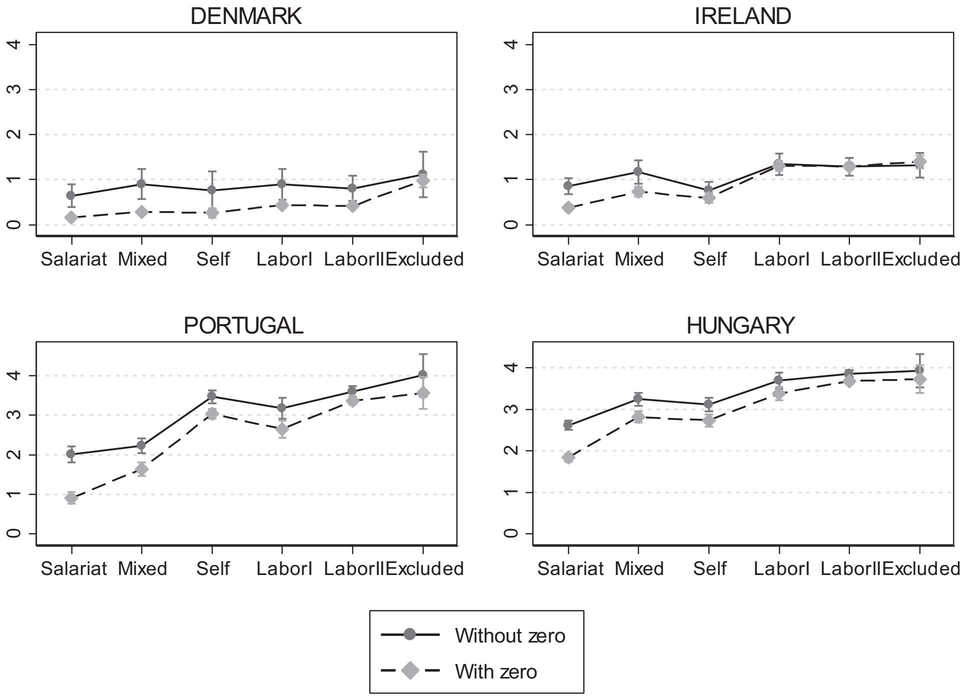

Figure 4. Social class variation on deprivation level—with and without zeros
Notes: The figure shows the average predicted level of deprivation for social classes. The models do not include any control variables. The solid lines show the estimates from zero-truncated NMBs which do not include zeros into the analysis; the dashed lines show the estimates from OLS models which include zeros into the analysis. The figure demonstrates that social gradient in deprivation level is inflated when the zero is included into the analysis.

level of deprivation; in Portugal, only lower education and single parenthood significantly increase the risk but not the level of deprivation. Thus, differences between the significant determinants of risk and level of deprivation are clearer in Denmark than in Portugal. Only in Hungary, the determinants of risk and level of deprivation are similar. As shown in Supplementary Material, this pattern also seems to be similar for other countries. In countries with high and medium level of zeros, as hypothesized, there are net effects of class and life course factors on the risk of deprivation, while for deprivation level, most of the class and life course effects are mediated through income, unemployment, health, and/or house ownership.[14] Only in countries with low level of zeros, same factors explain both the risk and the level of deprivation (and sometimes even more factors explain level).

We see, however, a different picture when the distinctiveness of zeros is neglected. Based on conventional models, the determinants of the risk and the level of deprivation are broadly similar. Consistently across countries, most of the class and life course factors explain both the risk and the level of deprivation. Therefore, in most cases, net effects of both types of variables exist for both deprivation risk and deprivation level. As shown in Supplementary Material, results are also similar for other countries without exception. Therefore, despite some variation across countries, in general, the determinants of the risk and the level of deprivation seem to be common under conventional models.

Two main reasons lie behind these differences between the hurdle and conventional models. First, in countries with high and medium level of zeros, the conventional models of deprivation risk underestimate the effects due to applying a higher non-zero threshold.[15] For example, effect sizes of income in the hurdle models are two to three times that of the corresponding effect of income in the conventional models. As a result, many factors which significantly explain the risk of deprivation in the hurdle models do not significantly explain the risk of deprivation in the conventional models. Secondly, the conventional models of deprivation level overestimate the effects due to including zeros into the analysis. For example, the effect size of unemployment

Table 3. Determinants of risk and level—hurdle vs. conventional models

	Denmark				Ireland				Portugal				Hungary			
	Hurdle NBM		Conventional		Hurdle NBM		Conventional		Hurdle NBM		Conventional		Hurdle NBM		Conventional	
	Risk	Level	Risk	Level	Risk	Level	Risk	Level	Risk	Level	Risk	Level	Risk	Level	Risk	Level
Stratification variables																
HRP social class (ESEC 5)																
Mixed	0.02	0.16	0.01	0.04	0.05*	0.18	0.03*	0.10	0.09***	0.18	0.07**	0.22*	0.02	0.26**	0.05**	0.23**
Small self-employed	0.03	0.00	0.01	0.06	0.05*	−0.14	0.00	0.00	0.09***	0.83***	0.16***	0.73***	−0.02	−0.18	−0.03	−0.22*
Labour non-manual	0.04**	0.07	0.02*	0.07	0.12**	0.17	0.05**	0.30**	0.10***	0.65***	0.13***	0.57***	0.04**	0.33**	0.07***	0.37***
Labour manual	0.08**	0.02	0.02**	0.11**	0.15**	0.16	0.06**	0.31**	0.17***	1.08***	0.23***	1.13***	0.07***	0.41***	0.11***	0.54***
Excluded	0.13**	0.15	0.04**	0.50**	0.14**	0.26	0.08**	0.43**	0.10*	0.92***	0.18***	0.88***	−0.01	0.17	0.10**	0.11
HRP education																
Upper secondary	0.00	0.03	0.01	−0.00	0.01	0.03	0.01	0.04	0.06	−0.45	−0.00	−0.14	0.06***	0.44***	0.10***	0.44***
Lower secondary ≥	0.00	0.12	0.01	0.05	0.12**	0.10	0.04**	0.26**	0.11***	−0.15	0.06	0.12	0.11***	0.67***	0.15***	0.79***
HRP female	0.04**	−0.04	0.01	0.06*	0.04**	−0.02	0.00	0.05	0.05***	0.55***	0.08***	0.59***	0.06***	0.28***	0.06***	0.38***
Life course variables																
HRP divorced	0.07**	0.10	0.02*	0.19**	0.12**	0.11	0.04**	0.31**	0.04	0.18	0.04	0.23*	0.02*	0.28***	0.06***	0.33***
HRP single parent	0.14**	0.39*	0.06**	0.59**	0.19**	0.19	0.07**	0.62**	0.07*	0.19	0.09*	0.35	0.02	0.21	0.07**	0.32**
HH 3+ children	0.04	0.16	0.01	0.11	0.08**	0.08	0.04*	0.23**	0.05	0.71*	0.14**	0.82***	0.03	0.58***	0.10***	0.66***
Mediating variables																
HH Income (*log equ.*)	−0.10**	−0.30**	−0.02**	−0.23**	−0.18**	−0.28**	−0.06**	−0.38**	−0.22***	−1.00***	−0.25***	−1.29***	−0.24***	−1.38***	−0.30***	−1.76***
HRP unemployed	0.19**	0.27	0.07**	0.71**	0.25**	0.28**	0.10**	0.73**	0.10***	0.51***	0.11***	0.68***	0.08***	0.50***	0.14***	0.82***
HH chronic ill-health	0.03**	0.19	0.01*	0.10**	0.06**	0.19*	0.04**	0.22**	0.05***	0.34***	0.09***	0.39***	0.04***	0.09	0.03*	0.21***
HH disability	0.06**	0.13	0.02**	0.18**	0.10**	0.30**	0.05**	0.33**	0.05***	0.37***	0.06***	0.44***	0.06***	0.48***	0.10***	0.55***
HH tenant	0.09**	0.27**	0.04**	0.28**	0.15**	0.61**	0.11**	0.80**	0.09***	0.47***	0.11***	0.66***	0.03*	0.73***	0.13***	0.73***

Notes: $^{*}P<0.05$; $^{**}P<0.01$; $^{***}P<0.001$. The table compares the determinants of the risk and the level of deprivation for four countries (see Supplementary Material for all countries). The model also includes age as a control. The reference category for social class is salariat and for education is tertiary level. The risk of deprivation for the conventional models is estimated based on a threshold of two (3+) using logit. The level of deprivation for the conventional models is estimated using OLS. The coefficients show AMEs which is the average change in the probability of being deprived for the risk model and average change in the number of deprivations for the level model in relation to a discrete or marginal change in the variable, while all others are held at their observed values. The results show that (i) the determinants of the risk and the level of deprivation are different under the hurdle but similar under the conventional logit and OLS models (except Hungary), (ii) the conventional model of deprivation level overestimates the effects, and (iii) the conventional model of deprivation risk underestimates the effects (except Hungary).

is at least 25 per cent higher in the conventional than in the hurdle models. As a result, many factors which significantly explain the level of deprivation in the conventional models do not significantly explain the level of deprivation in the hurdle models.

The main reason why conventional models of risk and level reveal common determinants can be that both risk and level models partly reflect the differences between zeros and counts. Especially when a majority of cases in the sample are zeros, the differences between zeros and counts describe the bulk of variance and dominate the results for both risk and level. Relatedly, in countries with low level of zeros, we see the differences between conventional and hurdle models being partial. In other words, when the number of zeros is low, the consequences of ignoring their distinct nature are also limited.

Conclusion and Implications for the Measurement of Deprivation and Poverty in the EU

The study hypothesized and tested the distinctiveness of zero deprivation and examined its consequences for understanding deprivation risk and level for 25 EU countries. The exploratory data analysis and comparison of count models have revealed that, consistently across all 25 countries, zeros are qualitatively distinct; in other words, zeros and counts are determined by a distinct data-generating process; or, those who have zero deprivation has significantly different profiles to those who have at least one deprivation (from a specified list of deprivation items). These results are robust to different weighting and index specifications. Assuming the deprived can be distinguished from non-deprived based on the identified risk factors, the analysis therefore suggests that zero (1+) can be used as a conceptually and empirically valid threshold for deprivation.

The consequences of neglecting the distinctiveness of zeros are substantial for our understanding of the risk and the level of deprivation. The study focused on two substantive questions: (i) whether the risk and the level of deprivation are socially structured; and (ii) whether the determinants of the risk and the level of deprivation are common. For both questions, the findings are contrary to theoretical expectations for conventional models neglecting the distinctiveness of zeros.

Regarding the first question, there is a clear social class gradient in the risk of deprivation when zero is taken as a threshold; yet conventional models show a much narrower gradient as they underestimate the effect as a result of using a higher threshold. For the level of deprivation, when zeros are excluded from the analysis as in hurdle models, there is expectedly a rather limited class gradient in the level of deprivation (mainly between salariat and labour classes); on the other hand, conventional models show a much greater gradient (between salariat, mixed and labour classes) as they overestimate the effect as a result of including zeros into the analysis.

Regarding the second question, in the hurdle model, after controlling for variables such as income, unemployment, health, and house ownership, the net effects of class and life course risks still persist for the risk of deprivation, while they disappear for the level of deprivation. Yet the conventional models identify the same determinants for both the risk and the level of deprivation mainly because both risk and level models partly reflect the differences between zeros and counts.

These latter findings on the consequences of neglecting distinct zeros apply to all countries but to those with very low level of zeros. The evidence is much stronger for countries with high and medium level of zeros (e.g. Denmark; Ireland) than in countries with medium-low level of zeros (e.g. Portugal); in other words, the higher the level of zeros, the worse the consequences of neglecting distinct zeros.[16] However, for the countries with very low level of zeros, using a zero threshold for deprivation masks the actual social class gradient in the risk of deprivation; also, using hurdle models, more factors explain deprivation level rather than deprivation risk. This is mainly due to a ceiling effect, as in these countries, a zero threshold identifies a significant majority of the population as deprived which limits the variance to be explained.

These findings partly reflect the wide inequality among EU countries, but possibly also issues related to the reliability of deprivation items. For example, in countries with low level of zeros, deprivation rate for some items (e.g. holiday, furniture) are above 70 per cent. Such high rates raise suspicion about the reliability of these items in less affluent countries, where the problems might be related to (i) cross-cultural equivalence, as these items might not have the same meaning in all EU countries[17] (Kis *et al.*, 2015; Guio *et al.*, 2017), or (ii) reporting error due to, for example, different interpretations about what is being asked in deprivation or affordability questions (see Guio *et al.*, 2017: pp. 16–20).[18] Such item-level invariance is especially important when a zero threshold is applied. Therefore, for using deprivation scales with a zero threshold in the EU, a re-evaluation of certain deprivation items might be necessary.

Regardless of these issues, how can deprivation scales with a zero threshold be used? Three ways can be considered. The study is focused on the concept of (material) deprivation. As argued by Townsend (1987), deprivation is a useful sociological concept to study the consequences of inequality in resources on living conditions. The analysis reveals that even in the most affluent EU countries, a significant amount of people is deprived of certain necessities due to a lack of resources; and the risk of such deprivation is differentiated based on social class, and significantly higher for those with lower economic resources and needs. Therefore, deprivation scales with a zero threshold can be used to study the impact of inequality in resources on living conditions.

However, existing material deprivation scales are primarily designed as pragmatic tools to improve the identification of poverty alongside income poverty measures. For example, the EU poverty target measure defines those at-risk-of-poverty-or-social-exclusion as being in income poverty, low work intensity, or severe material deprivation. Using a zero threshold in this context would result in very high numbers even in relatively affluent countries. This might be due to aforementioned data issues or other problems related to the design of existing scales. Threshold is just one part of the design and cannot be considered independent of how the measure is structured. In that respect, the neglect of multidimensionality and limited availability of deprivation data are important matters. Existing deprivation scales collapse different types of deprivations such as food, fuel, and social activities into one scale and evaluate them together against one threshold. Rather, separating each type of deprivation (food deprivation, fuel deprivation, etc.), measuring each dimension not with one but with multiple indicators, hence creating reliable scales for each dimension might provide a solution (while also limiting the measurement error arising from the aforementioned data issues). The recently proposed version of EU's deprivation scale by Guio *et al.* (2016) includes, for example, multiple items related to social activities, but this does not solve the problem, as they are evaluated together with other types of deprivation within the same unidimensional scale. Dimensionality, in that respect, should be a key design feature to limit issues related to reliability of items. Therefore, deprivation scales can be used as poverty indicators yet with a reconsideration of their design.

If proven useful for policy purposes, a third rather more pragmatic solution can be using a consistent poverty approach as proposed by Nolan and Whelan (2011)—a target group can be defined as those who experience income poverty and at least one deprivation from a pre-specified list of deprivation items. As argued by Maître *et al.* (2013: p. 22), such consistent poverty measure can be useful primarily for 'distinguishing a subset within that [target] population which merits priority in framing anti-poverty policy'. Nevertheless, in either way, advancing the quality and extent of deprivation data are the main priorities for a better measurement.

Notes

1 Enforced lack refers to the cause of deprivation being affordability problems.

2 There are also methodological implications of the excess of zeros, as deprivation is usually examined based on OLS models, but given the excess of zeros and count nature of data, the main assumptions of constant variance, normality of residuals, and linearity of the relationship cannot be easily assumed (King, 1988).

3 The categories are 'service', 'mixed', 'small self-employed', 'labor non-manual', 'labor manual', and 'excluded'.

4 The categories are tertiary, higher secondary, and lower secondary and below. For the exploratory analysis, six-category ISCED is used.

5 Categories are 15–30, 31–45, 46–65, 65–79, and 80+.

6 Other similar mixture count models such as zero-inflated models are not appropriate for deprivation data, as they assume some structural zeros (individuals with a zero probability of deprivation) which is theoretically not possible, given that any individual might experience deprivation when they face extreme risk conditions.

7 AMEs are preferred since log-odds and odds ratio as substantive effects reflect also some unobserved heterogeneity which might vary across the applied models given their variant specifications (Mood, 2010). The marginal effects for the count part are estimated for the whole sample of the reference country.

8 Bulgaria is an exception, where the relationship follows a rather linear pattern.

9 For the BIC-corrected Vuong, Denmark, and Estonia are exceptions, where the test cannot distinguish between NBM and HNBM.

10 For Slovakia, the gradient is not different in two thresholds.

11 Due to very high prevalence of deprivation in countries with low level of zeros, the risk of deprivation for all classes except salariat is very close to 1, which limits the possibility of a gradient between lower classes.

12 More specifically, the analysis includes zeros into the analysis but with a zero probability for deprivation.
13 Two exceptions are Italy and Bulgaria, where the two models give similar results.
14 The differences are clearer for countries with high level of zeros (e.g. Finland) than countries with medium level of zeros (e.g. the United Kingdom and Greece). One clear exception is Germany where class and life course factors significantly explain both the risk and the level of deprivation in the hurdle model.
15 Portugal and Poland are exceptions. Also, in countries with low level of zeros, hurdle models of deprivation risk underestimate the effects due to the previously mentioned ceiling effect.
16 This also shows that the empirical difference between hurdle and OLS models is mainly due to how zeros are accounted in the model and not due to the differences in functional form. Indeed, when level of deprivation is estimated using OLS without including zeros, the results are very similar to those of hurdle model.
17 While Guio *et al.* (2017) argue that cross-cultural equivalization is negligible for the proposed 13-item index, the problems identified related to deprivation data (e.g. cross-cultural equivalization and reporting error) can be much more pronounced when a zero threshold is applied.
18 For example, Guio *et al.* (2017) recently report a large decrease in deprivation rates of holiday, food, and unexpected expenses in Bulgaria between 2013 and 2014, explained by the improved interviewer training.

Supplementary Data

Supplementary data are available at *ESR* online.

Acknowledgements

The author owes thanks to Erzsébet Bukodi, Brian Nolan, Francesco Billari, Thees Spreckelsen, Caspar Kaiser, Christoph Jindra, Madeline Nightingale, and the participants of OPHI Seminars for their valuable comments on the draft of the article. The author also would like to thank the editors and four anonymous referees whose useful comments and suggestions, the author believes, improved the article significantly.

Funding

This research was made possible by Barnett Scholarship granted towards author's PhD by the Department of Social Policy and Intervention, University of Oxford.

References

Andress, H. -J. (1989). Recurrent unemployment-the West German experience: an exploratory analysis using count data models with panel data. *European Sociological Review*, **5**, 275–297.

Bárcena-Martín, E. *et al*. (2014). Country differences in material deprivation in Europe. *Review of Income and Wealth*, **60**, 802–820.

Berthoud, R. and Bryan, M. (2011). Income, deprivation and poverty: a longitudinal analysis. *Journal of Social Policy*, **40**, 135–156.

Borg, V. and Kristensen, T. S. (2000). Social class and self-rated health: can the gradient be explained by differences in life style or work environment? *Social Science and Medicine*, **51**, 1019–1030.

Cameron, A. C. and Trivedi, P. K. (2013). *Regression Analysis of Count Data*. New York: Cambridge University Press.

Deb, P. and Trivedi, P. K. (1997). Demand for medical care by the elderly: a finite mixture approach. *Journal of Applied Econometrics*, **12**, 313–336.

Desmarais, B. A. and Harden, J. J. (2013). Testing for zero inflation in count models: bias correction for the Vuong test. *The Stata Journal*, **13**, 810–835.

Dewilde, C. (2008). Individual and institutional determinants of multidimensional poverty: a European comparison. *Social Indicators Research*, **86**, 233–256.

Erikson, R. and Goldthorpe, J. H. (1992). *The Constant Flux: A Study of Class Mobility in Industrial Societies*. Oxford: Oxford University Press.

Goldthorpe, J. and McKnight, A. (2006). The economic basis of social class. In Morgan, S., Grusky, D. and Fields, G. (Eds.), *Mobility and Inequality: Frontiers of Research in Sociology and Economics*. Stanford, CA: Stanford University Press.

Goldthorpe, J. H. (2010). Analysing social inequality: a critique of two recent contributions from economics and epidemiology. *European Sociological Review*, **26**, 731–744.

Guio, A. -C. *et al*. (2016). Improving the measurement of material deprivation at the European Union level. *Journal of European Social Policy*, **26**, 219–333.

Guio, A. -C. *et al*. (2017). *Revising the EU Material Deprivation Variables: Eurostat Methodologies and Working Papers*. Luxembourg: Publications Office of the European Union. DOI: 10.2785/33408.

King, G. (1988). Statistical models for political science event counts: bias in conventional procedures and evidence for the exponential Poisson Regression model. *American Journal of Political Science*, **32**, 838–863.

Kis, A. B., Özdemir, E. and Ward, T. (2015). Micro and Macro Drivers of Material Deprivation Rates. Research Note No 7 / European Commission, Brussels.

Kuha, J. (2004). AIC and BIC: Comparisons of Assumptions and Performance. *Sociological Methods & Research*, Sage Publications: Thousand Oaks, CA, **33**, 188–229.

Kurz, K. and Blossfeld, H. -P. (2004). *Home Ownership and Social Inequality in a Comparative Perspective*. Stanford, CA: Stanford University Press.

Layte, R. *et al*. (2001). Explaining levels of deprivation in the European Union. *Acta Sociologica*, **44**, 105–121. Available from: http://journals.sagepub.com/doi/10.1177/000169930104400201 (accessed 17 February 2017).

Long, J. S. and Freese, J. (2014). *Regression Models for Categorical Dependent Variables Using Stata*. College Station, TX: Stata Press.

Maître, B., Nolan, B. and Whelan, C. (2013). *GINI DP 79: A Critical Evaluation of the EU 2020 Poverty and Social Exclusion Target: An Analysis of EU-SILC 2009*. AIAS, Amsterdam Institute for Advanced Labour Studies.

Mood, C. (2010). Logistic regression: why we cannot do what we think we can do, and what we can do about it. *European Sociological Review*, **26**, 67–82.

Nelson, K. (2012). Counteracting material deprivation: the role of social assistance in Europe. *Journal of European Social Policy*, **22**, 148–163.

Nolan, B. and Whelan, C. T. (2011). *Poverty and Deprivation in Europe. OUP Catalogue*, Oxford University Press.

Office for National Statistics (ONS). *Social Survey Division, Northern Ireland Statistics and Research Agency, Eurostat*. (2011). European Union Statistics on Income and Living Conditions, 2009. [data collection]. UK Data Service. SN: 6767, http://doi.org/10.5255/UKDA-SN-6767-1.

Özcan, B. and Breen, R. (2012). Marital instability and female labor supply. *Annual Review of Sociology*, **38**, 463–481. Available from: http://www.annualreviews.org/doi/10.1146/annurev-soc-071811-145457 (accessed 17 February 2017).

Parrado, E. A. and Morgan, S. P. (2008). Intergenerational fertility among Hispanic women: new evidence of immigrant assimilation. *Demography*, **45**, 651–671.

Pintelon, O. *et al*. (2013). The social stratification of social risks: the relevance of class for social investment strategies. *Journal of European Social Policy*, **23**, 52–67. Available from: http://esp.sagepub.com/cgi/doi/10.1177/0958928712463156 (accessed 20 October 2014).

Rose, D. and Harrison, E. (2014). *Social Class in Europe: An Introduction to the European Socio-Economic Classification*. New York, NY: Routledge.

Townsend, P. (1979). *Poverty in the United Kingdom: A Survey of Household Resources and Standards of Living*. Berkeley: University of California Press.

Townsend, P. (1987). Deprivation. *Journal of Social Policy*, **16**, 125.

Vandecasteele, L. (2011). Life course risks or cumulative disadvantage? The structuring effect of social stratification determinants and life course events on poverty transitions in Europe. *European Sociological Review*, **27**, 246–263. Available from: https://academic.oup.com/esr/article-lookup/doi/10.1093/esr/jcq005 (accessed 17 February 2017).

Whelan, C. T., Layte, R. and Maître, B. (2004). Understanding the mismatch between income poverty and deprivation: a dynamic comparative analysis. *European Sociological Review*, **20**, 287–302.

Whelan, C. T., Maître, B. and Nolan, B. (2007). *Multiple Deprivation and Multiple Disadvantage in Ireland: An Analysis of EU-SILC*. Dublin: ESRI.

Whelan, C. T. and Maître, B. (2009). Comparing poverty indicators in an enlarged European Union. *European Sociological Review*, **26**, 713–730. Available from: https://academic.oup.com/esr/article-lookup/doi/10.1093/esr/jcp047 (accessed 17 February 2017).

Whelan, C. T. and Maître, B. (2012). Understanding material deprivation: a comparative European analysis. *Research in Social Stratification and Mobility*, **30**, 489–503.

Whelan, C. T. *et al*. (2001). Income, deprivation, and economic strain: an analysis of the European Community Household Panel. *European Sociological Review*, **17**, 357–372.

Selçuk Bedük is a DPhil candidate at the University of Oxford, Department of Social Policy and Intervention. His current research interests are poverty measurement, social inequality and poverty, life course, causes and consequences of poverty, and comparative social policy.

Appendix

Deprivation items of Whelan and Maître (2012) material deprivation scale

Ability to afford

1. a meal with meat or a vegetarian alternative,
2. replacing worn-out clothes,
3. two properly fitting shoes,
4. adequate home heating,
5. spending a small amount of money each week for oneself,
6. regularly participating on a leisure activity,
7. a drink/meal with friends/relatives once a month,
8. a yearly holiday, and
9. replacing worn-out furniture.

Table A2. Per cent of missing in deprivation scale and social class for each country

Country	Deprivation scale	Social class	Education
AT	0.27	2.70	0.00
BE	0.34	0.96	0.49
BG	0.02	0.61	0.02
CY	0.00	0.00	0.00
CZ	0.00	0.54	0.00
DE	3.41	0.63	0.14
DK	0.66	2.93	1.86
EE	0.58	0.34	0.50
EL	0.14	0.00	0.14
ES	0.49	0.66	0.51
FI	0.77	0.15	1.24
FR	1.39	2.07	0.15
HU	0.13	0.05	0.00
IE	0.17	0.10	1.74
IT	1.25	0.55	1.25
LT	0.12	0.00	0.10
LU	0.54	0.09	0.21
LV	0.52	0.17	0.52
MT	4.13	0.66	0.11
NL	0.87	3.27	0.73
PL	3.53	0.06	3.55
PT	1.55	0.14	0.10
RO	0.08	0.00	0.08
SE	29.55	3.59	0.62
SI	0.00	3.11	0.00
SK	0.32	0.32	0.25
UK	7.82	1.54	5.95
Total	2.25	0.97	0.88

Table A1. Missing data for variables of interest in the whole sample

Variables	# of missing cases	Per cent of missing cases	Mean	SD	Minimum	Maximum	Sample size
Deprivation scale	4,887	2.25	1.54	2.10	0	9	217,170
MDholiday	261	0.12	0.39	0.49	0	1	217,170
MDmeat	114	0.05	0.11	0.31	0	1	217,170
MDwarm	133	0.06	0.10	0.31	0	1	217,170
MDrefurnish	2,504	1.15	0.32	0.47	0	1	217,170
MDcloth	3,595	1.66	0.12	0.33	0	1	217,170
MDshoes	3,585	1.65	0.03	0.16	0	1	217,170
MDg_out	3,593	1.65	0.14	0.34	0	1	217,170
MDleisure	3,585	1.65	0.17	0.37	0	1	217,170
MDsmoney	3,689	1.70	0.16	0.36	0	1	217,170
Social class (ESEC 5)	2,105	0.97	3.05	1.72	1	6	217,170
Education (ISCED 3)	1,918	0.88	2.12	0.74	1	3	217,170
Income (*equivalized disposable*)	0	0.00	16,717	16,124	−589,401	747,474	217,170
Female	0	0.00	0.40	0.49	0	1	217,170
Unemployment	1,010	0.47	0.05	0.21	0	1	217,170
Single parenthood	66	0.03	0.04	0.19	0	1	217,170
Divorced	929	0.43	0.11	0.31	0	1	217,170
Chronic health problem in HH	783	0.36	0.46	0.50	0	1	217,170
Disability problem in HH	873	0.40	0.39	0.49	0	1	217,170
Having three children	0	0.00	0.03	0.18	0	1	217,170
Renter	36	0.02	0.19	0.39	0	1	217,170

Table A3. Model selection between PM, NBM, HPM, and HNBM—AIC, BIC

		PM	NBM	HPM	HNBM	OLS	Preferred
Denmark	AIC	7,466	6,487	6,462	6,385	13,545	HNBM
	BIC	7,604	6,632	6,701	6,629	13,684	HNBM
Finland	AIC	14,720	13,289	13,090	12,997	25,505	HNBM
	BIC	14,871	13,447	13,357	13,270	25,656	HNBM
Netherlands	AIC	14,764	13,319	13,064	13,003	25,424	HNBM
	BIC	14,913	13,476	13,331	13,276	25,574	HNBM
Luxembourg	AIC	7,340	6,495	6,364	6,273	13,221	HNBM
	BIC	7,473	6,635	6,600	6,514	13,354	HNBM
Austria	AIC	14,211	12,323	12,126	11,974	19,896	HNBM
	BIC	14,351	12,469	12,382	12,235	20,036	HNBM
United Kingdom	AIC	19,317	17,131	16,620	16,482	26,632	HNBM
	BIC	19,463	17,284	16,889	16,757	26,778	HNBM
Belgium	AIC	15,979	13,990	13,759	13,526	21,903	HNBM
	BIC	16,120	14,138	14,019	13,792	22,044	HNBM
Germany	AIC	35,500	30,784	29,390	29,197	46,098	HNBM
	BIC	35,657	30,948	29,682	29,495	46,254	HNBM
Ireland	AIC	12,192	11,460	11,331	11,166	16,584	HNBM
	BIC	12,329	11,604	11,586	11,427	16,721	HNBM
France	AIC	28,196	25,814	25,304	25,047	37,274	HNBM
	BIC	28,348	25,973	25,590	25,338	37,426	HNBM
Italy	AIC	56,598	51,518	52,020	50,621	72,659	HNBM
	BIC	56,764	51,692	52,336	50,944	72,825	HNBM
Spain	AIC	36,075	34,584	34,269	33,982	44,668	HNBM
	BIC	36,232	34,748	34,568	34,289	44,825	HNBM
Slovenia	AIC	27,864	26,023	25,731	25,527	33,544	HNBM
	BIC	28,013	26,179	26,015	25,818	33,693	HNBM
Czech Republic	AIC	29,561	29,068	28,710	28,644	34,394	HNBM
	BIC	29,712	29,226	29,002	28,943	34,545	HNBM
Cyprus	AIC	9,443	9,371	9,180	12,729	10,873	HPM
	BIC	9,570	9,504	9,425	12,989	11,000	HPM
Estonia	AIC	15,312	15,024	14,893	14,843	17,372	HNBM
	BIC	15,449	15,167	15,157	15,113	17,508	HNBM
Greece	AIC	21,837	21,416	20,833	20,802	25,061	HNBM
	BIC	21,981	21,567	21,111	21,087	25,204	HNBM
Slovakia	AIC	17,502	17,099	16,851	16,777	19,517	HNBM
	BIC	17,640	17,243	17,118	17,050	19,655	HNBM
Poland	AIC	47,276	45,593	45,332	44,727	52,077	HNBM
	BIC	47,433	45,757	45,638	45,040	52,234	HNBM
Portugal	AIC	19,046	18,514	18,064	17,987	20,438	HNBM
	BIC	19,183	18,657	18,330	18,260	20,574	HNBM
Lithuania	AIC	20,767	19,901	19,922	19,706	21,678	HNBM
	BIC	20,904	20,044	20,190	19,980	21,815	HNBM
Hungary	AIC	40,543	39,540	38,790	38,640	41,306	HNBM
	BIC	40,693	39,698	39,087	38,944	41,457	HNBM
Latvia	AIC	23,683	23,278	23,148	23,056	24,341	HNBM
	BIC	23,823	23,424	23,423	23,338	24,481	HNBM
Romania	AIC	33,378	33,258	32,312	32,314	33,217	HPM
	BIC	33,524	33,411	32,601	32,610	33,363	HPM
Bulgaria	AIC	24,558	24,560	23,962	23,964	23,880	OLS
	BIC	24,697	24,705	24,238	24,247	24,019	OLS

Notes: Lower values of information criteria (AIC, BIC) show better fit. The results show a strong preference for HNBM.