

Poverty in Times of Crisis

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ABSTRACT

This paper evaluates the impact of a large macroeconomic shock on poverty. In particular, we use longitudinal data from the European Survey on Income and Living Conditions (EU-SILC) comprising almost two million individuals from 29 European countries in order to quantify changes in poverty transition patterns caused by the 2007 global financial crisis. Because the crisis was largely unforeseeable, it provides an appealing natural experiment allowing us to isolate the causal effect of a substantial macroeconomic shock on poverty. Employing semiparametric mixed discrete time survival analysis, we find that conditional poverty entry hazards increased temporarily by 13.4% during the crisis, while post-crisis they are estimated to be 15.7% lower than before. Not only entry hazards have decreased, also conditional exit hazards are estimated to be 31.4% lower post-crisis compared to before. *Ceteris paribus*, the crisis therefore has made it more difficult to slip into poverty, yet those who were already poor face substantially lower prospects to escape. Exploring determinants of poverty transitions, we find that being retired, having a permanent job, owning one's dwelling instead of renting it, age, marital status, and household size are the most important protective factors against poverty. Finally, we show that mostly a housing cost overburden seems to be responsible for the persistence of poverty.

JEL Classification: D31, I32

Keywords: Poverty transitions, financial crisis, entry and exit rates

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I. INTRODUCTION

Despite sustained economic growth in recent years, 23.7% of the European population are still at risk of poverty today (Eurostat 2017a). Undoubtedly, this is a matter of serious concern, for those affected directly and the society alike. In order to fight poverty effectively, detailed knowledge of underlying mechanisms which trigger transitions into and out of poverty is essential. Building on the seminal work by Bane & Ellwood (1986), the analysis of poverty transitions has received a great deal of attention in the economic literature. A common practice therein is to distinguish individual socioeconomic endowments from certain trigger events as potential determinants of poverty transitions. The former include gender, age, race, employment, and consumption which—along with life events such as becoming unemployed or physically disabled (e.g., McKernan & Ratcliffe 2005, Polin & Raitano 2014)—are typically found to explain a sizable part of the variation in individuals’ susceptibility to poverty (Jenkins 2011),¹ Large macroeconomic shocks, however, have largely been ignored in this literature, although they have indeed the potential to alter poverty patterns substantially (Jenkins et al. 2012).

In this paper we aim to fill this gap. Using microlevel longitudinal data on almost two million individuals from 29 European countries drawn from the European Survey on Income and Living Conditions (EU-SILC), we employ semiparametric mixed discrete time survival models to analyze how poverty transition patterns have changed due to the global financial crisis between 2007 and 2009. Because the crisis was largely unforeseeable, it provides an appealing natural experiment to analyze the impact of a substantial macroeconomic shock on poverty. We contribute to the literature in several important ways: Most importantly, we are the first to empirically isolate the causal effect of a large macroeconomic shock on individual poverty outcomes in a multivariate regression framework using cross-country microlevel data. Second, we introduce a variant of a mixed discrete time survival estimator to the literature which deals with unobserved heterogeneity and right-censoring in a very flexible manner. Unlike currently used econometric approaches which usually model entry and exit probabilities jointly, our estimator suits the underlying poverty duration process relatively better (see section II for more information). Third, we use a large and comprehensive dataset comprising very detailed information on socioeconomic, demographic, and health characteristics for almost two million individuals spread across Europe, which allows us to carry out a very thorough and extensive analysis of potential mechanisms underlying poverty transitions. To our knowledge, we are also

¹Most evidence on determinants of poverty transitions comes from the United States (e.g., Eller 1996, McKernan & Ratcliffe 2002, Naifeh 1998, Rank & Hirschl 1999, 2001, Ribar & Hamrick 2003). Single country analyses are available, amongst many others, for Australia (Buddelmeyer & Verick 2008), Canada (e.g., Finnie 2000), Spain (e.g., Cantó 2003), Sweden (e.g., Fritzell & Henz 2001), Turkey (Şeker & Dayıođlu 2015, Şeker & Jenkins 2015), or the United Kingdom (e.g., Jenkins et al. 2001, Jenkins & Van Kerm 2011). For developing countries, Baulch & Hoddinott (2000) provide an excellent survey on most of the earlier evidence. Cross-country analyses include Barbieri & Bozzon (2016), Callens & Croux (2009), Polin & Raitano (2014), Jenkins & Van Kerm (2011), Jenkins & Van Kerm (2014) or Van Kerm & Alperin (2013).

the first to incorporate the most recent EU-SILC wave into a poverty analysis.

The available literature considering the impact of the 2007 crisis on poverty consists almost exclusively of studies relying on aggregate data. Examples include Gábos et al. (2015), who evaluate the effect of employment on aggregate poverty measures and allow for differential employment effects achieved by interacting their employment measure with crisis dummies, Duiella & Turrini (2014) who use output, employment, social expenditures, and several other macro aggregates to explain an at-risk-of-poverty measure in multivariate linear regressions including also a crisis dummy, or Kaplanoglou & Rapanos (forthcoming) who use a more narrative approach to argue how austerity measures conducted during the crisis in Greece have altered poverty patterns. Apart from using aggregate data, none of these papers accounts for fundamental endogeneity problems associated with poverty, for example when unobserved third variables determine both poverty as well as the macroeconomic aggregate itself, or when the direction of causality is unclear.

In their influential 2012 book titled *“The Great Recession and the Distribution of Household Income,”* Jenkins, Brandolini, Micklewright & Nolan consider poverty as an important response to the financial crisis as well. Their empirical focus, however, lies more on single-country descriptive analyses rather than a comprehensive multivariate cross-country approach. Furthermore, indirect evidence for the effect of macroeconomic shocks on the poor can also be found in studies incorporating measures of GDP or aggregate employment in their analyses of poverty dynamics, both on the aggregate level (e.g. Cutler et al. 1991, Fallon & Lucas 2002) as well as on the individual level (e.g., Callens & Croux 2009, Jäntti & Jenkins 2010, McKernan & Ratcliffe 2005). Most of these studies document a positive correlation, yet causal claims are difficult to make for reasons discussed above. Another related strand of the literature we also contribute to considers state dependency of poverty (e.g., Biewen 2009, Cappellari & Jenkins 2002, 2004, 2008, Jenkins & Van Kerm 2011), since our framework allows us to look specifically at the influence of past on current poverty outcomes.

We find that poverty patterns have changed significantly due to the crisis: Before the crisis, the unconditional probability to enter poverty was comparably high at 4.4%. During the crisis, the conditional entry rate increased by around 13.4% (which corresponds to an increase from 4.4% to roughly 5% in terms of the average exit rate), while the exit rate decreased by 6.5%. After the crisis, poverty entry patterns converge back to pre-crisis figures: The conditional entry hazard eventually becomes even 15.7% lower than before the crisis. In terms of the unconditional average yearly entry rate of 3.61%, this corresponds to a rather small change by 0.6 percentage points to around 3%. A quite substantial effect, however, is found for exit rates of people entering poverty post-crisis: They are estimated to be 31.4% lower than before, which corresponds to a decrease from 30.6% to 21% in terms of the average exit rate.

Thus, the financial crisis has had a sizable impact on poverty dynamics across Europe: Al-

though fewer people become poor, it has also become increasingly difficult to escape poverty for those who indeed are poor post-crisis. Those sliding into poverty after the crisis have certain characteristics that make them seemingly less vulnerable to poverty (in terms of their socioeconomic and demographic background; they are, e.g., more likely to have a permanent job, better educated, and less likely to have physical limitations) compared to those entering pre-crisis, so the fact that besides entry hazards *also* conditional exit hazards decrease post-crisis needs further investigation. There are two possible explanations: Either the crisis caused a substantial disruption to the system which makes it relatively more difficult to exit poverty despite having more favorable socioeconomic endowments, or we capture a compositional change in the population of poor which is not covered by our arsenal of covariates. In Section V, we provide an extensive discussion why we are strongly in favor of the former explanation.

After quantifying the changes in poverty transitions induced by the financial crisis, we analyze particular demographic and socioeconomic determinants of entry and exit rates, such as gender, age, marital status, education, employment, or specific household and regional characteristics. We find that having a permanent job, having physical limitations, being widowed, having tertiary education and the number of children in the household have the biggest impact on both entry hazards (negatively) and exit hazards (positively). Finally, we use panel logit fixed effects regressions to determine potential mechanisms explaining these structural changes we detect. It turns out that the financial burden due to housing cost increased substantially during the crisis.

II. METHODOLOGY

II.1. Discrete-time survival analysis

We employ survival analysis in order to empirically analyze transitions into and out of poverty. In this section we develop a discrete time mixed proportional hazards model (Kalbfleisch & Prentice 1973, Willett & Singer 1995) which we augment by a random frailty term in order to account for unobserved heterogeneity between individuals and allow for a fully nonparametric baseline hazard (see, e.g., Scheike & Jensen 1997, Rabe-Hesketh et al. 2001, or Grilli 2005). Denote a spell (either poverty or non-poverty, depending on the question at hand) by j , and note that each individual $i = 1, \dots, N$ may have up to J_i different spells, where $J = \max_i \{J_i\}$ denotes the maximum number of spells experienced by any individual in the population. For each spell j , survival time is denoted by T_j .

Although the process underlying T_j is in fact continuous, the nature of our data requires discrete time modeling. In fact, rather than observing exact dates of poverty onset and offset, we only have yearly information on whether an individual's income was below the poverty threshold. Thus, survival times are grouped with mass points located at the respective survey dates.

Consequently, we assume that T is discrete and partitioned into $k_j = 1, \dots, K_{ji}$ disjoint periods $(0, t_{1j}], (t_{1j}, t_{2j}], \dots, (t_{k-1,j}, t_{kj}], \dots, (t_{K-1,j}, t_{Kj}]$ with $k_j = (t_{k-1,j}, t_{kj}]$ denoting the k th period of spell j , $K_j = \max_i \{K_{ji}\}$ being the maximum number of periods experienced by any individual in spell j , and $K = \max_j \{K_j\}$ being the maximum number of periods experienced by any individual in any spell. Note that period k_j begins immediately after $t_{k-1,j}$ and ends exactly at t_{kj} .

Each spell ends with the experience of a target event (either entry into or exit out of poverty, again depending on the question at hand). Define a binary random variable Y whose values $y_{kji} \in \{0, 1\}$ indicate whether individual i 's spell j ends within period k . If $y_{kji} = 0$ for all periods in spell j , the spell is right-censored. When looking at exit rates, T is in fact time in poverty, while y_{kji} takes on the value one if i exits poverty in period k . Considering entry rates, T in turn is time spent outside poverty, and y_{kji} is onset of poverty. The hazard function is generally given by

$$\lambda_{ji}(k) = \Pr(T_j = k | T_j \geq k) = \frac{S_{ji}(k-1) - S_{ji}(k)}{S_{ji}(k-1)}, \quad (1)$$

where $S_{ji} = \Pr(T_j > k)$ is the survivor function (i.e., the probability of surviving past period k in spell j). The hazard function therefore reflects the probability that individual i 's spell j is terminated in period k , conditional on surviving until the beginning of k .

We proceed by modeling the conditional hazard function by means of a generalized linear mixed model (GLMM) implementing a complementary log-log (cloglog) link and additive time-specific intercepts allowing for a fully nonparametric specification of the baseline hazard (Grilli 2005, Rabe-Hesketh et al. 2001). Formally, we can write the model as

$$\log\{-\log[1 - \lambda_{ji}(k | \mathbf{c}_k, \mathbf{x}_{kji}, \eta_i)]\} = \sum_{k=1}^K \delta_k \cdot d_k + \sum_{j=2}^J \xi_j \cdot z_j + \mathbf{c}'_k \boldsymbol{\alpha} + \mathbf{x}'_{kji} \boldsymbol{\beta} + \eta_i \quad (2)$$

with $\eta_i | \mathbf{d}, \mathbf{z}, \mathbf{c}_k, \mathbf{x}_{kji} \sim N(0, \sigma_\eta^2)$,

or, adopting a more compact notation,

$$\text{cloglog}[\lambda_{ji}(k | \mathbf{c}_k, \mathbf{x}_{kji}, \eta_i)] = \mathbf{d}' \boldsymbol{\delta} + \mathbf{z}' \boldsymbol{\xi} + \mathbf{c}'_k \boldsymbol{\alpha} + \mathbf{x}'_{kji} \boldsymbol{\beta} + \eta_i, \quad (3)$$

where $\mathbf{d} = (d_1, \dots, d_K)'$ is a K -dimensional column vector of period indicators which captures the baseline hazard, $\mathbf{z} = (z_2, \dots, z_J)'$ is a J -dimensional column vector of spell indicators shifting the baseline hazard,² \mathbf{c}_k is a vector of dummy variables indicating whether period k is measured before, during, or after the crisis (see section III for more details on the specification of our crisis dummies), \mathbf{x}_{kji} is a vector of explanatory variables (a detailed overview on all variables

²We omit the first spell of each individual.

we include is also given in section III), and η_i is a random frailty term for which we assume a normal distribution with mean zero and variance σ_η^2 . The frailty term captures unobserved heterogeneity by allowing each individual to have its own hazard function.³

The literature has identified one measure which is especially important to explain poverty dynamics, namely, considering exit rates, time already spent in poverty, or analogously, time spent outside poverty when considering entry rates. A majority of studies (see, e.g., Şeker & Dayıođlu 2015), for example, stratify spells simply in different spell length categories (e.g., already one year in poverty, already two years in poverty, etc.) and then calculate event probabilities separately for each of these categories. The problem with this approach is that it does not take into account right-censoring, so typically exit probabilities of either one or zero are assumed for right-censored observations. Consequently, this leads to an underestimation in the former or to an overestimation of exit rates in the latter case (the same notion in reverse order applies to entry rates). In our model, the vector product $\mathbf{d}'\delta$ specifically takes into account the spell duration by shifting the baseline hazard upwards or downwards depending on how long people have already been at risk before. Additionally, right-censoring is accounted for by the inherent mechanics of the duration model.

Note that the model is called ‘mixed’ because we allow for the occurrence of multiple spells per individual. Earlier contributions (notably Bane & Ellwood 1986, but also more recent papers such as Şeker & Dayıođlu 2015) ignore these cases and keep only the first spell of each individual. This approach has been criticized because neglecting people falling back into poverty within a short time-frame after escaping may lead to an underestimation of poverty persistence (Stevens 1999). In our framework, we keep multiple spells per individual and allow each further spell $J_i \geq 1$ to have its own baseline hazard (this is captured by the vector product $\mathbf{z}'\xi$).

Estimating equation (2) yields coefficients $(\hat{\delta}_1, \dots, \hat{\delta}_K)$ of the cloglog-transformed baseline hazards. Coefficients $(\hat{\xi}_2, \dots, \hat{\xi}_J)$, as mentioned above, indicate how the hazard profile is vertically offset between the first spell $j = 1$ and each subsequent spell $j = 2, \dots, J$ (Willett & Singer 1995). The variance of the frailty term σ_η^2 is a free parameter, and its estimate $\hat{\sigma}_\eta^2$ can be used to calculate the intraclass correlation coefficient

$$\hat{\rho} = \frac{\hat{\sigma}_\eta^2}{\hat{\sigma}_\eta^2 + \hat{\sigma}_\varepsilon^2}, \quad (4)$$

which is the proportion of the total variance explained by between-individual variance (Snijders & Bosker 2011). Generally we report our estimated coefficients in exponentiated form, which allows us to interpret them as hazard ratios—that is, the risk of experiencing the target event in period k conditional on not having experienced the event until the beginning of k .

Using time-specific constants for the baseline hazard, the model in equation (2) is equivalent

³To be more precise, equation (2) is a proportional hazards model, so the shape of the hazard function is assumed to be the same across individuals, but is shifted up and down by the frailty term η_i .

to the semiparametric Cox proportional hazards regression in continuous time (Kalbfleisch & Prentice 1973). We fit equation (2) via Maximum Likelihood, where the marginal log-likelihood function we seek to maximize reads

$$l(\beta) = \sum_{i=1}^n \log \left(\int \prod_{k=1}^{K_{ij}} \prod_{j=1}^{J_i} \lambda_{ji}(k)^{y_{kji}} [1 - \lambda_{ji}(k)]^{1-y_{kji}} d\eta_i, \right) \quad (5)$$

(Tutz & Schmid 2016) which is approximated using a 15-point adaptive Gaussian-Hermite quadrature as suggested by Rabe-Hesketh & Skrondal (2008). Inference is based on analytic individual-level clustered standard errors.

Note that employing discrete time survival estimators is not new in the poverty literature. A similar approach to modeling poverty transitions via a correlated-risks-type discrete time survival estimator with jointly distributed unobserved heterogeneity terms was introduced by Stevens (1999), and has frequently been used since then (e.g., Biewen 2006, Devicienti 2011, Fertig & Tamm 2010, Jenkins 2011, Kyzyma 2014). However, this estimator is only feasible for intrinsically discrete time data—in case observed survival times are grouped yet generated through a continuous time process, Jenkins (2005) shows that hazard rates cannot be identified using these methods, whereas the complementary log-log link we use in our model suits this type of data generating process especially well (Grilli 2005, Willett & Singer 1995).

II.2. Panel fixed effects logit models

In order to estimate poverty transitions in section IV.2 as well as certain binary outcome models in section IV.6, we additionally use conditional fixed effects logit models (Wooldridge 2010, pp. 621). These models have the advantage of partialling out all observable *and* unobservable time-invariant factors which may bias our estimates. This is, however, one of the reasons why we refrain from using conditional fixed effects models in our main analysis, since they do not allow us to identify effects of important time-invariant observables such as gender or education (more importantly, they do not account for right-censoring, which is an important challenge we have to deal with in our context). The conditional logit estimator can be formulated as

$$\Pr(y_{kji} = 1 \mid \mathbf{c}_k, \mathbf{x}_{kji}, \vartheta_i) = \Lambda(\mathbf{c}_k + \mathbf{x}'_{kji}\beta + \vartheta_i) \quad (6)$$

where $\Lambda(\cdot)$ is the logistic function and ϑ_i is a set of individual-level fixed effects. For details on estimation and inference we refer the reader to (Wooldridge 2010, pp. 621).

III. DATA

We use longitudinal survey data from the European Union Statistics on Income and Living Conditions (EU-SILC). Our database covers 1,992,834 individuals aged 16 or older from 793,491 private households in 29 European countries observed between 2004 to 2014. EU-SILC is designed as a four-year rotational panel, thus in each wave a new set of individuals is introduced which is then observed annually up to four years. Notable exceptions are Norway and France where individuals are observed up to 8 and 9 years, respectively. In total, we therefore have 5,592,297 observations.

Our main variable of interest is poverty status at the individual level. According to standard definitions (Aristei & Perugini 2015), we set the poverty threshold at 60% of the national median equivalized disposable household income. In order to calculate the equivalized disposable household income, we use the OECD-modified equivalence scale (OECD 2013).⁴ The reference period for income data is generally a fixed 12-month time frame which is usually the previous calendar year before the survey data collection was carried out. Exceptions include the United Kingdom and Ireland, where the income reference period is defined as the current year and the last twelve months prior to the interview, respectively.

— Table A.1 about here —

In our regressions we control for gender, binary variables indicating whether the individual has a permanent job, is retired, has a chronic disease or a physical limitation, and whether she owns her dwelling instead of renting it. On the individual level, we control additionally for age, marital status, occupation (grouped into high and low skill level white and blue collar jobs according to ISCO-88 codes), and education. On the household level, we control for equivalized household size, the number of children in the household, a binary variable indicating whether the household resides in a densely populated area, and the logarithm of imputed rent,⁵ interacted with a dummy indicating whether the individual owns the dwelling. On the country-level, we control for the logarithm of GDP and unemployment rate. Following Aristei & Perugini (2015), we additionally classify countries into six groups which ought to capture a certain degree of homogeneity with respect to socioeconomic policies and institutions (see Table A.1) and include dummy variables for each group in our estimations.

— Table A.2 about here —

⁴The OECD-modified weighting scheme assigns a weight of 1 to the first adult in the household, a weight of 0.5 to each additional adult member, and a weight of 0.3 to each child (OECD 2013).

⁵Imputed rent refers to an imputed value of rent which is available for every type of dwelling and also household that do not report a subjective rent themselves. For more information see the Eurostat operation 2013 guidelines under <http://ec.europa.eu/eurostat/publications/collections/manuals-and-guidelines>.

Summary statistics for variables measured on the individual and household-level are provided in Table A.2. Overall, individuals at risk of entering poverty post-crisis (columns 1 to 3) have less favorable characteristics compared to individuals at risk of entering before or during the crisis: They are more likely to have chronic diseases or being physically limited, they are much less likely to own their dwelling instead of renting it, and they are on average older—all these characteristics have been shown to increase poverty risk in earlier studies (Barbieri & Bozzon 2016, Buddelmeyer & Verick 2008, Callens & Croux 2009). Individuals who are poor after the crisis (columns 4 to 6), on the contrary, have more favorable characteristics compared to the pre-crisis population of poor: They are more likely to hold a permanent job, are more likely to be retired, are less likely to have a physical limitation, are on average younger and better educated. Those who actually enter poverty after the crisis also have more favorable characteristics than those entering before, while differences between those who exit before and those who exit after the crisis are largely ambiguous. In section IV.1 we elaborate on hypotheses we draw in terms of entry and exit rates given the compositional characteristics of the different subpopulations discussed here.

Besides obvious shortcomings most income surveys suffer from, such as measurement error or sample attrition,⁶ poverty analysis based on EU-SILC data is further impeded because (1) poverty status can only be assessed at an annual basis, and because (2) the four-year time frame is rather short and leads to a large number of censored poverty as well as non-poverty spells. Recall that all countries besides Norway and France have implemented a four-year rotational structure. Thus, all individuals who were poor in period k_4 have right-censored poverty spells by construction, and those non-poor in k_4 have right-censored non-poverty spells.

In section II, we mentioned that coefficients $(\hat{\delta}_1, \hat{\delta}_2, \hat{\delta}_3)$ have an interesting interpretation, because they represent the estimated cloglog-transformed baseline hazard for different spell durations (i.e., time already in the risk set). Due to right-censoring, we are only able to estimate these coefficients corresponding to periods k_1, k_2 , and k_3 . Every spell whose duration exceeds three years, $T_j \geq 3$, is right-censored by construction (except for spells of individuals residing in Norway or France, because of the different rotational structure), thus we do not have enough information to identify the hazard probabilities represented by parameters $\hat{\delta}_3, \hat{\delta}_4, \dots$ which correspond to these periods. The same notion applies to the number of spells J_i , where only j_1 and j_2 are possible to be completed in the data, and every further spell j_3, j_4, \dots is automatically right-censored with parameters $\hat{\xi}_3, \hat{\xi}_4, \dots$ being unidentifiable.

We decided to drop 826,569 observations that correspond to left-censored spells whenever we consider exit hazards in our estimations. As Iceland (1997) notes, dropping left-censored spells may lead to a selection bias when individuals who are in the midst of long-term poverty

⁶Measurement error may occur, for example, when low income households underreport social welfare benefits or do not report income earned in the informal sector at all, or when high income households are underrepresented in the survey (Eckerstorfer et al. 2016) or either underreport or refuse to give any information about their true income (Paturot et al. 2013).

spells are systematically disregarded. Because there is still no general consensus about a proper way of dealing with left-censoring, we follow Iceland's advice and compare estimates of (1) the baseline model without left-censored observations, (2) a model for the full sample where we keep left-censored observations, and (3) a model where we assume a geometric distribution of the underlying baseline hazard.⁷ Results of these exercises are discussed in section V.

According to the U.S. National Bureau of Economic Research, the last financial crisis started in December 2007 and ended in June 2009.⁸ In order to analyze how determinants of poverty dynamics changed due to the crisis, we define \mathbf{c}_k as a set of dummy variables indicating whether period k occurs before, during, or after the crisis. Let $\mathbf{1}\{\cdot\}$ denote an indicator function and let y_k denote the year which period k is measured in, then the elements of \mathbf{c}_k are defined as

$$\text{before}_k = \mathbf{1}\{y_k \leq 2007\} \quad (7)$$

$$\text{during}_k = \mathbf{1}\{y_k \in [2008, 2009]\} \quad (8)$$

$$\text{after}_k = \mathbf{1}\{y_k \geq 2010\} \quad (9)$$

Thus, the model in (2) can be written as

$$\begin{aligned} \text{cloglog}[\lambda_{ji}(k | \mathbf{x}_{kji}, \eta_i)] &= \delta_1 d_1 + \delta_2 d_2 + \delta_3 d_3 + \xi_2 z_2 + \alpha_d \cdot \text{during}_{kji} \\ &+ \alpha_a \cdot \text{after}_{kji} + \mathbf{x}'_{kji} \beta + \eta_i \end{aligned} \quad (10)$$

where before_{kji} is left out as the reference category and our main coefficients of interest (α_d, α_a) indicate the magnitude of the structural break induced by the crisis. Coefficients are reported in exponentiated form which allows interpreting them as hazard ratios with reference to the left-out pre-crisis period.

III.1. Trends in poverty, 2005–2014

Average poverty rates have been fairly stable over time, especially when compared to other macroeconomic aggregates. In Figure A.1, we contrast real GDP growth and poverty rates across different groups of countries. In terms of output, we see a remarkable dip in 2009 which was particularly pronounced for the Baltic countries. Most economies have been able to recover afterwards, yet growth rates generally seem to remain below pre-crisis levels. Poverty rates, on the other hand, are largely unaffected by fluctuations in output and employment. Even in economic upswings poverty rates are highly persistent, Vandenbroucke & Diris (2014) attribute this standstill to inefficient social protection systems in Europe: A decline in the effectiveness

⁷The geometric distribution is the discrete analogue of the exponential distribution. Assuming the baseline hazard to be geometrically distributed would solve the problem of left-censoring in theory, because the hazard rate is constant over time and does not depend on time elapsed. However, we are well aware that assuming a constant baseline hazard is rather unrealistic, as we expect the exit hazard to decrease quadratically over time.

⁸See <http://www.nber.org/cycles.html>, accessed Wednesday 1st March, 2017.

of cash transfers outweighs the pre-transfer decrease in poverty. Disaggregating poverty trends, however, reveals some heterogeneity across country groups: In social democratic countries such as Denmark, Finland, and Sweden, as well as in Mediterranean countries such as Italy or Greece, poverty has in fact increased during the crisis, and remains high ever since. Poverty in Baltic countries, on the other hand, peaked in 2008—starting with 2009, however, the trend is pointing downwards.

— Figure A.1 about here —

In the lower graph of Figure A.1, average real GDP growth rate and poverty rates are plotted on top of each other. Note that the poverty rate fluctuates much less than the graph suggests, because the vertical axis displays only the interval (0.132, 0.140). The graph suggests that poverty is moving pro-cyclical before and after the crisis, and counter-cyclically during the crisis. Moreover, the trend at the end of the observation period is pointing slightly upwards again.

IV. RESULTS

IV.1. Descriptive evidence

In Figure A.2, we provide an event study graph of average regression-adjusted poverty entry and exit rates over time, relative to the crisis period (note that $t = 0$ represents the years 2008 and 2009, rates are regression-adjusted for gender and age). Overall, we observe that entry and exit rates follow a highly similar pattern: Both decreased sharply between 2005 and 2006, and after recovering marginally in 2007, they have been decreasing steadily ever since. In Figure A.3, we plot nonparametric Kaplan Meier survival probability estimates for poor individuals (left graph) and failure probability estimates for non-poor individuals (right graph) given time already in and out of poverty, respectively. We observe that the probability of escaping poverty decreases sharply with the time the individual had already been poor before. Pre-crisis, the chances of escaping poverty for an individual who has been poor one year are roughly 60%, while they decrease to around 35% for those who have been poor for three years.

— Figure A.2 about here —

Similarly, the right graph indicates that the longer an individual has not been poor before, the lower her probability is to become poor eventually. The estimated failure probability is highest after one year out of poverty, and decreases monotonically with every further year. In terms of the crisis, we see a similar picture as before: Those being poor post-crisis are more likely to be stuck in poverty, while those who were poor during the pre-crisis period had the best chances

to escape. Individuals who have only been non-poor for a short time (right graph) have much higher chances to remain non-poor after the crisis as compared to before. Once the four year mark has been exceeded, however, individuals seldom become poor again. In the web appendix (Table B.2), we report additionally unconditional entry and exit rates for different years at risk of poverty entry or exit, split by the three periods we consider (pre-crisis, crisis, post-crisis). Similar to the Kaplan Meier graphs, we see that entry probabilities decline monotonically with every year out of poverty. After one year, the probability of becoming poor is 5.8%, while after three years it declines to 2.2%. Exit probabilities are higher the shorter an individual has been poor: After one year it is 27.4%, while it decreases sharply to 1.7% for individuals who have been poor already three years. After the crisis, escaping poverty becomes less likely even after one year, and after three years, the probability of doing so is only 1.1%.

— Figure A.3 about here —

Summing up our descriptive results, we observe that (1) entry and exit probabilities decline substantially with the time being already at risk—which is consistent with the vast literature documenting strong and persistent state dependence in poverty (e.g., Cappellari & Jenkins 2002)—and that *both* entry and exit hazards are lower after the crisis than before. This is surprising, since we find that the population of poor after the crisis has socioeconomic characteristics which seemingly make them less vulnerable to poverty. While this explains why entry hazards are lower than before, we would expect exit rates in turn to be higher than they actually are. We will return to this question after discussing our main regression results in the next section V.

IV.2. Poverty transitions due to the crisis

Our main results are reported in Table A.3, where we estimate conditional poverty entry and exit rates before, during, and after the crisis, respectively. Pre-crisis, the unconditional probability to enter poverty was comparably high at 4.4% (see Table A.2). We find that during the crisis, entry hazards are estimated to be 13.4% larger than before the crisis (this amounts to an increase from 4.4% to roughly 5% in terms of the average entry rate), but decrease by about 12.6% to 3.8% after the crisis. Exit hazards, on the other hand, decrease from an average 30.6% before the crisis by 6.5% during the crisis, and by a massive 31.4% to an overall 21% after the crisis, *ceteris paribus*. All estimates are statistically significant at the 0.1% confidence level. Thus, even after conditioning on our arsenal of covariates, we still find that exit rates are lower after the crisis than before. In section V we will discuss whether this is an actual effect of the crisis or caused by certain unobserved factors which interfere with our crisis indicators.

— Table A.3 about here —

Another interesting result can be derived from the coefficients on our baseline hazard indicators. Again, δ_1 , δ_2 , and δ_3 give the cloglog-transformed baseline hazard for (a) people being non-poor at time t for 1, 2, and 3 years, respectively, in columns (1) and (2); and (b) people being poor at time t for 1, 2, and 3 years, respectively, in columns (3) and (4). Although these coefficients do not have a cardinal (but rather an ordinal) interpretation, we observe that the chance of slipping into poverty is almost twice as high for people who have been non-poor for only one year than for people who have been non-poor for two years. This suggests that there may be some continuous switching of individuals around the poverty threshold. Exit hazards are also highest for people who have been poor for only one year, and decrease strictly monotonically afterwards. Additionally, the coefficient on ξ_2 suggests that people who have their second poverty spell in the data have a 75.6% lower chance of exiting poverty.

— Figure A.4 about here —

In Figure A.4, we plot these predicted poverty entry and exit hazards from Table A.3 as a function of years out of poverty and already in poverty, respectively. Both entry and exit hazards decrease the longer a person was *not in* poverty (regarding entry rates), or *in* poverty (regarding exit rates). Again we observe that after the crisis, both entry and exit hazards are generally lower than before the crisis. During the crisis, conditional entry and exit hazards are similar to those observed before the crisis.

IV.3. *Heterogeneous effects by country groups*

In Table A.4, we report heterogeneous effects by country groups. It seems that results in Table A.3 are mostly driven by Continental European economies (e.g., Austria or France, see Table A.1 for an overview on the classification of countries). Liberal market economies such as the United Kingdom seem to fare reasonably well, with entry hazards being relatively low (especially post-crisis), and exit hazards being high at 127.6% compared to pre-crisis levels. In Eastern European countries, entry hazards increased by 41.8% during the crisis, and are still 18.9% higher than before after the crisis. Exit hazards, on the other hand, are 44% lower, so poverty seems to be rather persistent in these countries. In countries such as Greece or Italy which are generally believed to be struck hardest by the crisis, poverty entry has increased, *ceteris paribus*, by only by 9.8% during the crisis, yet exit rates are now 22.9% lower than before. In Northern countries (in particular Denmark, Finland, and Sweden), entry hazards also increased during the crisis, but have moved back to pre-crisis levels afterwards. On top of that, exit rates are 24.2% higher than before. Baltic countries, which were hit strong by the crisis as well but were able to recover better than other countries face both much lower entry rates (in fact, post-crisis they are estimated to be 52.6% lower than before), yet also exit rates have decreased by 48.5% compared to pre-crisis levels.

— Table A.4 about here —

IV.4. Determinants of poverty entry hazards

In Table A.5, we compare determinants of entry rates before, during, and after the financial crisis. In terms of coefficient magnitude, the most important determinants of poverty entries and exits are having a permanent job, suffering from a physical limitation, age, education, marital status and the number of children in the household, and the country of origin. Having a permanent job decreases the entry hazard, *ceteris paribus*, by over 50% before and after the crisis, and by an even higher 69.1% during the crisis. Having a physical limitation increases the entry hazard by 14.1%–25.5%. In terms of age, we find that the most vulnerable group is between 35 and 50 years old, with estimated hazard rates being lower for all other groups. Interestingly, being female does influence entry hazards only marginally post-crisis, and has no effect at all before and during the crisis.

— Table A.5 about here —

Considering marital status, it turns out that being divorced is associated with a 52.5% higher chance of sliding into poverty compared to married people, *ceteris paribus*, and this effect even increases slightly during the crisis by 4.7 percentage points. Being separated increases the hazard of becoming poor by 31.8% before the crisis, and by a massive 83.1% after the crisis. High skilled blue collar workers also have a 83% higher risk of becoming poor than high skilled white collar workers. During the crisis, the effect was even 2.5 times higher. Tertiary education reduces the chances of becoming poor by around 25.7% versus upper secondary education, and is having a university degree is slightly more protective after the crisis than before. In turn, having only pre-primary education increases chances to enter poverty by 35% before the crisis compared to individuals who have upper secondary education, and by an even higher 86.9% after the crisis. Overall, marital status, age, and education seem to be highly important determinants for the decrease in exit rates after the crisis.

On the household level, the number of children and population density are by far the most important determinants of poverty entries. Before the crisis, every additional child increases the chance to slip into poverty by 29.8%. However, this effect decreases, *ceteris paribus*, by 16 percentage points to 14% for every additional child after the crisis. Living in a densely populated area reduces chances of entering by 18.1% before the crisis, and this effect increases even more by 18 percentage points during the crisis. After the crisis, it is almost the same as before, yet roughly two percentage points higher. On the country-level, we find that unemployment rate correlates negatively with the hazard of entering poverty before the crisis, but positively during the crisis and afterwards. Here further research is necessary to analyze this switch in signs. Gross domestic product also seems to be an important control variable, yet its

coefficient is rather uninformative as it gives the change in the hazard rate for a doubling in GDP. We can conclude that the effect of GDP on the entry hazard is small but significant. In terms of country-of-origin, we find significantly higher poverty entry hazards in Mediterranean economies compared to other countries.

In Table B.4 in the web appendix, we additionally provide results from a conditional logit fixed effects model as specified in section II.2, with poverty status in binary form as the outcome variable. In general, the conclusions drawn from the panel logit model resemble those we obtain from our survival analysis reasonably well. We find that sliding into poverty was significantly more difficult after the crisis compared to before. Main determinants of poverty transitions are having a permanent job (which reduces the odds of becoming poor by over 50%), being retired, age, household size, and the number of children. Due to their greater statistical flexibility, however, we base our main conclusions on the survival models.

IV.5. Determinants of poverty exit hazards

Once stuck in poverty, it is important which socioeconomic and demographic factors facilitate exit thereof. In Table A.6, we report determinants of exit hazards for people in poverty before, during, and after the financial crisis. In terms of the baseline hazard, we generally observe a strong monotonic decrease in exit hazards the longer a person has been poor. During the crisis, however, individuals who had already been poor between one and two years had a baseline hazard insignificantly different from zero, yet it increases dramatically for individuals who had been poor three years. After the crisis, individuals who were already poor once had a 32.1% chance of becoming poor again.

— Table A.6 about here —

Before the crisis, retirees, people who owned their dwelling instead of renting it, those who have never been married, who were high skilled white collar workers, and those who lived in Continental European countries had the best chances to exit poverty. For example, being retired was associated with a 47.7% increase in the chance of leaving poverty, and being between 50 and 64 years of age caused exit hazards to be 62.5% higher, *ceteris paribus*. Interestingly, having a permanent job did not influence exit hazards, and higher education was also no protective factor in this regard, yet lower education indeed does decrease exit probabilities. During the crisis, having a job became important. Even more so, however, was being retired—retirees enjoyed a 2.3 times higher chance of escaping poverty than others. The effects of age, marital status, and occupation did not change due to the crisis as compared to before. Finally, people living in a Continental European country had a 3.5 times higher chance of escaping during the crisis than people from social democratic economies, this effect flattened out post-crisis.

IV.6. Mechanisms

In order to investigate potential mechanisms driving our results, we estimate conditional panel fixed effects logit models in Table A.7 on several outcome variables we believe are interesting intermediate outcomes. In particular, we look at (1) a dummy variable indicating whether the individual reports difficulties to make ends meet, (2) a dummy equal to unity if the individual reports that housing cost are a heavy financial burden, and (3) a dummy indicating whether repayment of debts or loans are a heavy financial burden to the individual. Note that coefficients are given as odds ratios, thus their magnitude may not be compared directly to the hazard ratios estimated in section IV.

— Table A.7 about here —

Estimates in Table A.7 suggest that both the odds of reporting difficulties to make ends meet and the odds of declaring that repayment of debts is a heavy financial burden in fact *decreased* in the aftermath of the crisis, which is an interesting result by itself but does not tell us much about potential mechanisms governing poverty persistence. The odds of reporting a burden caused by housing cost, however, are roughly 50% higher after the crisis compared to before. Generally, housing cost make up a substantial portion of individual living expenses in Europe: Around 11.9% of the total population spend more than 40% of their equivalized disposable income on housing (Eurostat 2017c), and in our sample, housing on average makes up for roughly 20% of disposable income. Thus, a housing cost overburden is likely an important determinant of poverty persistence.

V. DISCUSSION OF RESULTS AND SENSITIVITY ANALYSES

As mentioned in section IV.2, we are puzzled by the fact that exit rates are lower after the crisis compared to before, given that the population of poor has seemingly better socioeconomic characteristics from a subjective standpoint. There are two possible explanations: Either it is in fact the crisis which caused a structural change to the system making it substantially more difficult to escape poverty, despite having favorable socioeconomic endowments, or there is a compositional change in the population of poor which happened over the years and is not captured by our covariates. This is rather unlikely, however, since we control for most variables one would remotely associate with poverty. As a robustness check, we plot the average distance in Euros between an individual's income and the poverty threshold against time in Figure A.5. In case there were unobserved third variables determining poverty status which changed due to the crisis, we would expect the average distance for those at risk of exit to increase at least slightly. This is not what we see: In fact, the distance for those at risk remains remarkably

constant over time. Thus, we conclude that it is most likely a structural change induced by the crisis making it more difficult to escape poverty.

— Figure A.5 about here —

Additionally, we want to rule out the possibility that our results are driven by individuals switching around the poverty threshold (note that this would lead to an overestimation of exit rates, making the hazard rate even lower as they would be in the absence of excessive switching). As a robustness check, we therefore draw a 10% band around the poverty threshold. Entries are only considered if the drop in income exceeds this band, and likewise, exits are only considered if income increases from under 90% to at least above 110% of the poverty threshold. Results are reported in Table B.5 in the web appendix. Our estimated hazard rates are practically unchanged, in most cases they are even higher than reported in Table A.3. Excessive switching around the cutoff therefore does not influence our results.

Finally, as mentioned in section III we follow the literature and simply drop left-censored observations whenever we consider poverty exit hazards. Doing so may induce selection bias, however, if individuals who are in the midst of lengthy poverty spells (Iceland 1997). We therefore follow Iceland and compare our baseline estimates from table A.3 with two other model specifications; one where we keep all left-censored observations and one where we assume a geometric distribution of the baseline hazard.⁹ Iceland notes that, while this approach “*does not ‘solve’ the problem of censoring, it may still shed light on the issue of interest.*” Results of this exercise are reported in Table B.6 in the web appendix. If we include left-censored observations and rerun our analysis, exit rates are even slightly higher than before (column 2). If we specify a constant baseline hazard, results change neither, and again the estimated exit rate is slightly higher than in the baseline model.

VI. CONCLUSION

In this paper, we analyzed the impact of the global financial crisis between starting at the end of 2007 on poverty patterns in Europe. For our empirical analysis we used longitudinal data from the European Survey on Income and Living Conditions (EU-SILC) comprising over 1.9 million individuals from 29 countries followed over nine years. Estimating semiparametric mixed proportional hazards discrete time duration models, we find that poverty entry hazards increased temporarily during the crisis, before decreasing to 84.3% of pre-crisis levels. Not only entry hazards have decreased due to the crisis, also exit hazards declined substantially. Being only 6.5% lower during the crisis, post-crisis they have shrunk by an estimated 31.4% compared

⁹In case the underlying survival process is constant of time, assuming a geometrically distributed baseline hazard solves the problem of left-censoring (see also section III).

to before, *ceteris paribus*. Since we are likely able to identify our crisis-effects without bias caused by unobserved heterogeneities among the population or switching around the poverty threshold, we presume that the crisis caused a profound systemic disruption which has made poverty much more persistent than before.

Additionally, we examined determinants of poverty transitions. Our estimates suggest having a permanent job, having physical limitations, being widowed, having tertiary education, and the number of children in the household have the biggest impact on both entry hazards (negatively) and exit hazards (positively). Finally, we also used panel logit fixed-effects regressions to determine potential mechanisms explaining these structural changes we detect. Here it turns out that the financial burden due to housing cost increased massively during the crisis, potentially being responsible for the increase in poverty persistence.

Our results bear important implications for policy makers: We have seen that the crisis likely caused a disruption to the system making poverty more persistent, i.e., more difficult to escape. By intervening in one of the areas related to entry and exit determinants discussed above, this development can potentially be reversed. An important limitation of our study is the short observation period provided by the EU-SILC. Longer rotational panels would definitely help to further our understanding of poverty transitions (especially when it comes to state dependency of poverty) and determinants thereof. Furthermore, in order to provide more efficient policy recommendations, a more careful investigation on potential mechanisms governing the relationship between macroeconomic aggregates and poverty is necessary. This shall be subject of future research.

VII. BIBLIOGRAPHY

- Aristei, D. & Perugini, C. (2015), 'The Drivers of Income Mobility in Europe', *Economic Systems* **39**(2), 197–224.
- Bane, M. J. & Ellwood, D. T. (1986), 'Slipping Into and Out of Poverty: The Dynamics of Spells', *Journal of Human Resources* **21**(1), 1–23.
- Barbieri, P. & Bozzon, R. (2016), 'Welfare, Labour Market Deregulation and Households' Poverty Risks: An Analysis of the Risk of Entering Poverty at Childbirth in Different European Welfare Clusters', *Journal of European Social Policy* **26**(2), 99–123.
- Baulch, B. & Hoddinott, J. (2000), 'Economic Mobility and Poverty Dynamics in Developing Countries', *Journal of Development Studies* **36**(6), 1–24.
- Biewen, M. (2006), Who are the Chronic Poor? An Econometric Analysis of Chronic Poverty in Germany, in J. Creedy & G. Kalb, eds, 'Dynamics of Inequality and Poverty', Vol. 13, Emerald, pp. 31–62.
- Biewen, M. (2009), 'Measuring State Dependence in Individual Poverty Histories When There is Feedback to Employment Status and Household Composition', *Journal of Applied Econometrics* **24**(7), 1095–1116.
- Buddelmeyer, H. & Verick, S. (2008), 'Understanding the Drivers of Poverty Dynamics in Australian Households', *Economic Record* **84**(266), 310–321.

- Callens, M. & Croux, C. (2009), 'Poverty Dynamics in Europe A Multilevel Recurrent Discrete-Time Hazard Analysis', *International Sociology* **24**(3), 368–396.
- Cantó, O. (2003), 'Finding out the Routes to Escape Poverty: The Relevance of Demographic vs. Labor Market Events in Spain', *Review of Income and Wealth* **49**(4), 569–588.
- Cappellari, L. & Jenkins, S. P. (2002), 'Who Stays Poor? Who Becomes Poor? Evidence from the British Household Panel Survey', *Economic Journal* **112**(478), C60–C67.
- Cappellari, L. & Jenkins, S. P. (2004), 'Modelling Low Income Transitions', *Journal of Applied Econometrics* **19**(5), 593–610.
- Cappellari, L. & Jenkins, S. P. (2008), 'Estimating Low Pay Transition Probabilities Accounting for Endogenous Selection Mechanisms', *Journal of the Royal Statistical Society: Series C (Applied Statistics)* **57**(2), 165–186.
- Correia, S. (2015), Singletons, Cluster-Robust Standard Errors and Fixed Effects: A Bad Mix, Mimeo, Duke University.
- Cutler, D. M., Katz, L. F., Card, D. & Hall, R. E. (1991), 'Macroeconomic Performance and the Disadvantaged', *Brookings Papers on Economic Activity* **1991**(2), 1–74.
- Devicienti, F. (2011), 'Estimating Poverty Persistence in Britain', *Empirical Economics* **40**(3), 657–686.
- Duiella, M. & Turrini, A. (2014), Poverty Developments in the EU After the Crisis: A Look at Main Drivers, ECFIN Economic Brief 31, European Commission.
- Eckerstorfer, P., Halak, J., Kapeller, J., Schütz, B., Springholz, F. & Wildauer, R. (2016), 'Correcting for the Missing Rich: An Application to Wealth Survey Data', *Review of Income and Wealth* **62**(4), 605–627.
- Eller, T. J. (1996), *Dynamics of Economic Well-being: Poverty, 1992-1993: Who Stays Poor? Who Doesn't?*, US Department of Commerce, Economics and Statistics Administration, Bureau of the Census.
- Eurostat (2017a), 'Dataset: People at Risk of Poverty or Social Exclusion'. Most recent data from 2016, URL: http://ec.europa.eu/eurostat/web/products-datasets/-/t2020_50&lang=en, accessed Wednesday 1st March, 2017.
- Eurostat (2017b), 'Dataset: Real GDP Growth Rate, Volume'. Most recent data from 2016, URL: <http://ec.europa.eu/eurostat/web/products-datasets/-/tec00115&lang=en>, accessed Wednesday 1st March, 2017.
- Eurostat (2017c), 'Statistics Explained: Housing Statistics'. URL: http://ec.europa.eu/eurostat/statistics-explained/index.php/Housing_statistics, accessed Wednesday 1st March, 2017.
- Fallon, P. R. & Lucas, R. E. B. (2002), 'The Impact of Financial Crises on Labor Markets, Household Incomes, and Poverty', *World Bank Research Observer* **17**(1), 21–46.
- Fertig, M. & Tamm, M. (2010), 'Always Poor or Never Poor and Nothing in Between? Duration of Child Poverty in Germany', *German Economic Review* **11**(2), 150–168.
- Finnie, R. (2000), *Low Income (Poverty) Dynamics in Canada: Entry, Exit, Spell Durations, and Total Time*, Applied Research Branch, Strategic Policy, Human Resources Development Canada.
- Fritzell, J. & Henz, U. (2001), Household Income Dynamics: Mobility out of and into Low Income Over the Life-Course, in J. Jonsson & C. Mills, eds, 'Cradle to Grave: Life-course Change in Modern Sweden', Sociology Press, chapter 9.
- Gábos, A., Branyiczki, R., Lange, B. & Tóth, I. G. (2015), Employment and Poverty Dynamics in the EU Countries Before, During and After the Crisis, Discussion Paper 15/06, ImPRovE Poverty, Social

Policy, and Innovation.

- Grilli, L. (2005), 'The Random-Effects Proportional Hazards Model with Grouped Survival Data: A Comparison Between the Grouped Continuous and Continuation Ratio Versions', *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **168**(1), 83–94.
- Iceland, J. (1997), *The Dynamics of Poverty Spells and Issues of Left-Censoring*, Research Report 97-378, The Population Studies Center.
- Jääntti, M. & Jenkins, S. P. (2010), 'The Impact of Macroeconomic Conditions on Income Inequality', *Journal of Economic Inequality* **8**(2), 221–240.
- Jenkins, S. P. (2005), *Survival Analysis*, Unpublished Manuscript.
- Jenkins, S. P. (2011), *Changing Fortunes: Income Mobility and Poverty Dynamics in Britain*, Oxford University Press.
- Jenkins, S. P., Brandolini, A., Micklewright, J. & Nolan, B. (2012), *The Great Recession and the Distribution of Household Income*, Oxford University Press.
- Jenkins, S. P., Rigg, J. A. & Devicienti, F. (2001), *The Dynamics of Poverty in Britain*, Corporate Document Services for the Department for Work and Pensions.
- Jenkins, S. P. & Van Kerm, P. (2011), *Patterns of Persistent Poverty: Evidence from EU-SILC*, Working Paper 2011-30, Institute for Social and Economic Research.
- Jenkins, S. P. & Van Kerm, P. (2014), 'The Relationship Between EU Indicators of Persistent and Current Poverty', *Social Indicators Research* **116**(2), 611–638.
- Kalbfleisch, J. D. & Prentice, R. L. (1973), 'Marginal Likelihoods Based on Cox's Regression and Life Model', *Biometrika* **60**(2), 267–278.
- Kaplanoglou, G. & Rapanos, V. T. (forthcoming), 'Evolutions in Consumption Inequality and Poverty in Greece: The Impact of the Crisis and Austerity Policies', *Review of Income and Wealth*.
- Kyzyma, I. (2014), 'Changes in the Patterns of Poverty Duration in Germany, 1992–2009', *Review of Income and Wealth* **60**(S2), S305–S331.
- McKernan, S.-M. & Ratcliffe, C. (2005), 'Events that Trigger Poverty Entries and Exits', *Social Science Quarterly* **86**(s1), 1146–1169.
- McKernan, S.-M. & Ratcliffe, C. E. (2002), *Transition Events in the Dynamics of Poverty*, Report prepared for the U.S. Department of Health and Human Services, The Urban Institute, Washington, DC.
- Naifeh, M. (1998), *Dynamics of Economic Well-Being, Poverty, 1993-94: Trap Door? Revolving door? Or Both?*, number 63, Census Bureau.
- OECD (2013), *OECD Framework for Statistics on The Distribution of Household Income, Consumption and Wealth*, OECD Publishing.
- Paturot, D., Mellbye, K. & Brys, B. (2013), *Average Personal Income Tax Rate and Tax Wedge Progression in OECD Countries*, Working Paper 15, OECD.
- Polin, V. & Raitano, M. (2014), 'Poverty Transitions and Trigger Events across EU Groups of Countries: Evidence from EU-SILC', *Journal of Social Policy* **43**(04), 745–772.
- Rabe-Hesketh, S. & Skrondal, A. (2008), *Multilevel and Longitudinal Modeling Using Stata*, 2nd edn, Stata Press.
- Rabe-Hesketh, S., Yang, S. & Pickles, A. (2001), 'Multilevel Models for Censored and Latent Responses', *Statistical Methods in Medical Research* **10**(6), 409–427.
- Rank, M. R. & Hirschl, T. A. (1999), 'The Likelihood of Poverty across the American Adult Life Span',

- Social Work* **44**(3), 201–216.
- Rank, M. R. & Hirschl, T. A. (2001), 'Poverty across the Life Cycle: Evidence from the PSID', *Journal of Policy Analysis and Management* **20**(4), 737–755.
- Ribar, D. C. & Hamrick, K. S. (2003), *Dynamics of Poverty and Food Sufficiency*, US Department of Agriculture, Economic Research Service, Washington, DC.
- Scheike, T. H. & Jensen, T. K. (1997), 'A Discrete Survival Model with Random Effects: An Application to Time to Pregnancy', *Biometrics* **53**(1), 318–329.
- Şeker, S. D. & Dayıoğlu, M. (2015), 'Poverty Dynamics in Turkey', *Review of Income and Wealth* **61**(3), 477–493.
- Şeker, S. D. & Jenkins, S. P. (2015), 'Poverty Trends in Turkey', *Journal of Economic Inequality* **13**(3), 401–424.
- Snijders, T. A. B. & Bosker, R. J. (2011), *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*, 2nd edn, SAGE Publishing.
- Stevens, A. H. (1999), 'Climbing out of Poverty, Falling Back in: Measuring the Persistence of Poverty Over Multiple Spells', *Journal of Human Resources* **34**(3), 557–588.
- Tutz, G. & Schmid, M. (2016), *Modeling Discrete Time-to-Event Data*, Springer Series in Statistics, 1st edn, Springer International Publishing.
- Van Kerm, P. & Alperin, M. N. P. (2013), 'Inequality, Growth and Mobility: The Intertemporal Distribution of Income in European Countries 2003–2007', *Economic Modelling* **35**, 931–939.
- Vandenbroucke, F. & Diris, R. (2014), Mapping At-Risk-Of-Poverty Rates, Household Employment, and Social Spending, in B. Cantillon & F. Vandenbroucke, eds, 'Reconciling Work and Poverty Reduction – How Successful are European Welfare States?', Oxford University Press.
- Willett, J. B. & Singer, J. D. (1995), 'It's Déjà Vu All Over Again: Using Multiple-Spell Discrete-Time Survival Analysis', *Journal of Educational and Behavioral Statistics* **20**(1), 41–67.
- Wooldridge, J. M. (2010), *Econometric Analysis of Cross Section and Panel Data*, 2nd edn, The MIT Press, Cambridge, Massachusetts.

A. TABLES AND FIGURES

TABLE A.1 — Classification of countries according to *Aristei & Perugini (2015)*

Category	Abbr.^a	Countries	%^b
Liberal market economies	LibME	Iceland, Ireland, United Kingdom	7.9
Continental European economies	ContEE	Austria, Belgium, France, Norway, Netherlands	16.8
Social democratic countries	SocDC	Denmark, Finland, Sweden	9.8
Mediterranean countries	MedC	Cyprus, Greece, Spain, Italy, Malta, Portugal	27.5
Eastern European Countries	EastEC	Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Serbia, Slovenia, Slovakia	29.9
Baltic countries	BaltC	Estonia, Lithuania, Latvia	8.2

Notes: ^a Abbreviation, ^b observations belonging to this country group in % of total sample.

TABLE A.2 — Summary statistics for people at risk of entering or exiting poverty, and for people experiencing an entry or exit event.

	Individuals at risk of entering/exiting poverty						Individuals who experience entry or exit event					
	At risk of entry			At risk of exit			Individuals entering poverty			Individuals exiting poverty		
	(1) Pre	(2) Crisis	(3) Post	(4) Pre	(5) Crisis	(6) Post	(7) Pre	(8) Crisis	(9) Post	(10) Pre	(11) Crisis	(12) Post
Average survival time T	1.703	2.187	2.256	1.189	1.329	1.364	1.390	1.592	1.556	1.096	1.162	1.165
Poverty exit probability				0.306	0.269	0.197						
Poverty entry probability	0.044	0.039	0.030									
<i>Individual-level characteristics</i>												
Female	0.415	0.424	0.430	0.406	0.417	0.405	0.423	0.418	0.423	0.426	0.446	0.432
Has permanent job	0.273	0.274	0.378	0.101	0.104	0.210	0.125	0.137	0.241	0.139	0.148	0.245
Retired	0.011	0.097	0.211	0.011	0.094	0.153	0.011	0.074	0.166	0.012	0.102	0.168
Has chronic disease	0.200	0.214	0.230	0.229	0.250	0.238	0.242	0.244	0.246	0.225	0.263	0.247
Has physical limitation	0.159	0.172	0.182	0.204	0.220	0.201	0.211	0.212	0.208	0.192	0.226	0.201
Owens dwelling	0.798	0.773	0.048	0.686	0.707	0.093	0.711	0.701	0.066	0.722	0.723	0.089
<i>Age categories</i>												
Age < 25	0.116	0.113	0.105	0.122	0.117	0.126	0.129	0.134	0.131	0.142	0.125	0.135
25 ≤ age < 35	0.124	0.118	0.109	0.092	0.090	0.097	0.106	0.112	0.110	0.105	0.101	0.107
35 ≤ age < 50	0.416	0.397	0.383	0.459	0.442	0.455	0.423	0.425	0.416	0.435	0.399	0.412
50 ≤ age < 65	0.197	0.211	0.221	0.157	0.166	0.184	0.163	0.176	0.191	0.172	0.188	0.195
Age ≥ 65	0.147	0.162	0.182	0.170	0.185	0.139	0.179	0.153	0.152	0.146	0.187	0.151
<i>Marital status</i>												
Never married	0.231	0.232	0.231	0.217	0.210	0.238	0.228	0.237	0.251	0.245	0.226	0.252
Married	0.458	0.468	0.466	0.354	0.362	0.352	0.396	0.413	0.394	0.392	0.401	0.389
Separated	0.013	0.007	0.008	0.014	0.013	0.014	0.016	0.012	0.014	0.014	0.012	0.012
Widowed	0.058	0.064	0.068	0.090	0.103	0.081	0.083	0.072	0.072	0.078	0.103	0.085
Divorced	0.038	0.042	0.047	0.048	0.052	0.056	0.050	0.051	0.058	0.045	0.056	0.057
Missing	0.200	0.187	0.180	0.276	0.259	0.260	0.226	0.216	0.212	0.226	0.202	0.204
<i>Highest educational level achieved</i>												
Pre-primary	0.007	0.007	0.007	0.012	0.012	0.012	0.015	0.011	0.010	0.010	0.012	0.009
Primary	0.107	0.092	0.083	0.161	0.150	0.119	0.167	0.146	0.124	0.150	0.143	0.113
Lower secondary	0.155	0.163	0.160	0.187	0.207	0.205	0.200	0.216	0.215	0.189	0.214	0.206
Upper secondary	0.325	0.342	0.338	0.253	0.267	0.289	0.274	0.285	0.306	0.298	0.297	0.328
Post-secondary, non-tertiary	0.031	0.027	0.026	0.024	0.020	0.019	0.024	0.022	0.020	0.026	0.026	0.025
Tertiary	0.374	0.369	0.386	0.362	0.344	0.355	0.320	0.320	0.325	0.327	0.309	0.319
<i>Household-level characteristics</i>												
Equivalent household size	2.049	2.031	1.996	1.995	1.973	2.015	2.089	2.109	2.100	2.092	2.018	2.052
Number of children in the household	0.664	0.614	0.655	0.764	0.734	0.975	0.833	0.812	0.844	0.812	0.725	0.867
Densely populated area	0.361	0.349	0.349	0.335	0.315	0.318	0.328	0.316	0.320	0.322	0.333	0.331
log(imputed rent)	6.761	6.891	6.913	6.515	6.246	6.209	6.370	6.450	6.304	6.517	6.480	6.406
Observations	1,397,623	954,392	2,428,504	46,534	42,909	107,447	61,964	37,119	73,784	14,228	11,533	21,124

Notes: This table gives sample means of all variables on the individual and household level included in the regressions. A full table including also second moments can be found in the online appendix. Variables in columns (1) to (6) are measured for individuals who are *at risk* of entering [columns (1) – (3)] or exiting [columns (4) – (6)] poverty, while variables in columns (7) to (12) are measured for individuals who actually experience an entry or exit event.

TABLE A.3 — Effect of financial crisis on poverty entry and exit hazards (discrete time mixed proportional hazards models).

	Poverty entry hazard		Poverty exit hazard	
	(1)	(2)	(3)	(4)
<i>Crisis indicators (reference category: before crisis)</i>				
During crisis	1.091*** (0.01)	1.134*** (0.01)	0.944*** (0.01)	0.935*** (0.01)
After crisis	0.874*** (0.01)	0.843*** (0.01)	0.667*** (0.01)	0.686*** (0.01)
<i>Duration dependence</i>				
$\exp(\delta_1)$	0.027*** (0.00)	50.085*** (5.67)	0.406*** (0.00)	0.165*** (0.04)
$\exp(\delta_2)$	0.017*** (0.00)	28.445*** (3.25)	0.225*** (0.00)	0.091*** (0.02)
$\exp(\delta_3)$	0.013*** (0.00)	21.170*** (2.43)	0.023*** (0.00)	0.009*** (0.00)
$\exp(\xi_2)$	0.341*** (0.03)	0.862** (0.06)	0.288*** (0.01)	0.244*** (0.01)
Other covariates ^a	No	Yes	No	Yes
$\hat{\sigma}_\eta$	1.3710	0.5136	0.0005	0.0247
$\hat{\rho}$	0.5333	0.1382	0.0000	0.0004
Log-likelihood	-700,513.7	-667,924.41	242,340.05	-28,691.11
Number of observations	4,168,000	4,168,000	196,021	196,021
Number of individuals	1,817,479	1,817,479	143,444	143,444

Notes: This table reports the difference in poverty entry and exit hazard rates depending on whether the person was at risk during or after the big financial crisis, as compared to before. Coefficients are exponentiated and can be interpreted as hazard ratios, individual-level clustered standard errors are given in parentheses next to coefficients. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

^aWe control for gender, occupation, health proxies, dwelling type, age, marital status, education, household size, number of children, type of neighborhood, GDP, and unemployment rate (a detailed overview on our control variables is provided in section III). Additionally, we include missing indicator dummies for education and marital status.

TABLE A.4 — **Heterogeneous effects:** Effect of financial crisis on poverty entry and exit hazards, sample stratified by country groups (discrete time mixed proportional hazards models).

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>BaltC</i>	<i>ContEE</i>	<i>EastEC</i>	<i>LibME</i>	<i>MedC</i>	<i>SocDC</i>
Poverty entry hazard						
<i>Crisis indicators (reference category: before crisis)</i>						
During crisis	0.787*** (0.03)	1.049** (0.02)	1.418*** (0.02)	0.493*** (0.02)	1.098*** (0.01)	1.121*** (0.04)
After crisis	0.474*** (0.02)	0.635*** (0.01)	1.189*** (0.02)	0.364*** (0.01)	0.814*** (0.01)	1.018 (0.05)
Duration dependence ^a	Yes	Yes	Yes	Yes	Yes	Yes
Covariates ^b	Yes	Yes	Yes	Yes	Yes	Yes
$\hat{\sigma}_\eta$	0.0242	0.6121	0.9611	0.7144	0.0001	0.8816
$\hat{\rho}$	0.0004	0.1855	0.3596	0.2368	0.0000	0.3209
Log-likelihood	50,149.1	-89,139.9	-187,141.6	-57,421.6	1,553,834.3	-47617.16
Number of observations	341,326	678,770	1,246,317	349,332	1,105,757	446,498
Number of individuals	147,488	288,566	537,054	176,183	479,190	188,998
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>BaltC</i>	<i>ContEE</i>	<i>EastEC</i>	<i>LibME</i>	<i>MedC</i>	<i>SocDC</i>
Poverty exit hazard						
<i>Crisis indicators (reference category: before crisis)</i>						
During crisis	1.063 (0.09)	0.814*** (0.03)	0.826*** (0.03)	1.208*** (0.07)	0.977 (0.03)	0.757*** (0.07)
After crisis	0.515*** (0.08)	0.581*** (0.03)	0.560*** (0.03)	1.276*** (0.08)	0.771*** (0.02)	1.242* (0.15)
Duration dependence ^a	Yes	Yes	Yes	Yes	Yes	Yes
Covariates ^b	Yes	Yes	Yes	Yes	Yes	Yes
$\hat{\sigma}_\eta$	1.6212	0.8807	1.0103	0.0001	0.6811	1.5120
$\hat{\rho}$	0.6151	0.3204	0.3829	0.0000	0.2200	0.5816
Log-likelihood	-10,040.4	-14,952.4	-27,317.0	35,017.2	-32,564.4	-5,577.53
Number of observations	18,754	25,725	51,514	14,675	61,393	11,519
Number of individuals	14,825	18,146	40,706	12,588	47,543	9,636

Notes: In this table we stratify the sample into different country groups and report only the crisis coefficients. Essentially, we reestimate the specifications from Table A.3, columns (2) and (4) for different sets of countries in the data. A full overview on how countries are classified into groups is provided in Table A.1; “*BaltC*” refers to Baltic countries, “*ContEE*” to Continental European economies, “*EastEC*” to Eastern European countries, “*LibME*” to liberal market economies, “*MedC*” to Mediterranean countries, and “*SocDC*” refers to social democratic countries. Coefficients are exponentiated and can be interpreted as hazard ratios, individual-level clustered standard errors are given in parentheses next to coefficients. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

^a We do not report the coefficients $\widehat{\exp}(\delta_1)$, $\widehat{\exp}(\delta_2)$, $\widehat{\exp}(\delta_3)$, and $\widehat{\exp}(\xi_2)$, which indicate how entry and exit hazards change depending on the time already outside or inside poverty, respectively.

^b We control for gender, occupation, health proxies, dwelling type, age, marital status, education, household size, number of children, type of neighborhood, GDP, and unemployment rate (a detailed overview on our control variables is provided in section III). Additionally, we include missing indicator dummies for education and marital status.

TABLE A.5 — Determinants of poverty **entry** hazards before, during, and after the financial crisis (discrete time mixed proportional hazards models).

	(1) Pre-crisis		(2) Crisis			(3) Post-crisis		
	Coef.	Std. err.	Coef.	Std. err.	Diff. [†]	Coef.	Std. err.	Diff. [†]
<i>Duration dependence</i>								
exp(δ_1)	39.629***	(9.40)	0.196***	(0.08)	-39.43***	39.460***	(6.61)	-0.17
exp(δ_2)	22.871***	(5.44)	0.232***	(0.09)	-22.64***	20.217***	(3.39)	-2.65
exp(δ_3)	13.133***	(3.14)	0.227***	(0.09)	-12.91***	16.740***	(2.82)	3.61
exp(ξ_2)	0.993	(0.03)	0.883***	(0.04)	-0.11**	1.198***	(0.03)	0.20***
<i>Individual-level characteristics</i>								
Female	1.015	(0.01)	1.021	(0.02)	0.01	1.043***	(0.01)	0.03**
Has permanent job	0.466***	(0.01)	0.309***	(0.01)	-0.16***	0.494***	(0.01)	0.03***
Retired	0.907**	(0.04)	3.293***	(0.11)	2.39***	0.950***	(0.01)	0.04
Has chronic disease	1.046***	(0.02)	1.078***	(0.03)	0.03	1.093***	(0.01)	0.05**
Has physical limitation	1.141***	(0.02)	1.255***	(0.03)	0.11***	1.167***	(0.02)	0.03
Owns dwelling	1.046**	(0.02)	0.121***	(0.01)	-0.92***	0.019***	(0.00)	-1.03***
<i>Age category (reference category: 35 ≤ age < 50)</i>								
Age < 25	0.776***	(0.01)	0.733***	(0.03)	-0.04	0.842***	(0.01)	0.07***
25 ≤ age < 35	0.806***	(0.01)	0.791***	(0.02)	-0.02	0.920***	(0.01)	0.11***
50 ≤ age < 65	0.843***	(0.01)	0.697***	(0.02)	-0.15***	0.878***	(0.01)	0.03**
Age ≥ 65	0.770***	(0.01)	0.440***	(0.02)	-0.33***	0.687***	(0.01)	-0.08***
<i>Marital status (reference category: married)[‡]</i>								
Never married	1.176***	(0.02)	1.219***	(0.04)	0.04	1.133***	(0.02)	-0.04*
Separated	1.318***	(0.04)	1.675***	(0.13)	0.36**	1.831***	(0.06)	0.51***
Widowed	1.142***	(0.02)	1.170***	(0.04)	0.03	1.135***	(0.02)	-0.01
Divorced	1.525***	(0.03)	1.991***	(0.08)	0.47***	1.538***	(0.03)	0.01
<i>Occupation (reference category: high skilled white collar worker)[‡]</i>								
Low skilled white collar	1.363***	(0.03)	1.451***	(0.06)	0.09	1.422***	(0.03)	0.06
High skilled blue collar	2.122***	(0.05)	2.580***	(0.11)	0.46***	1.830***	(0.03)	-0.29***
Low skilled blue collar	1.834***	(0.04)	2.186***	(0.09)	0.35***	1.793***	(0.03)	-0.04
Armed forces	1.308***	(0.10)	2.961***	(0.27)	1.65***	1.389***	(0.05)	0.08
<i>Highest educational level achieved (reference category: upper secondary)[‡]</i>								
Pre-primary	1.350***	(0.05)	1.685***	(0.10)	0.33***	1.869***	(0.10)	0.52***
Primary	1.217***	(0.02)	1.542***	(0.05)	0.33***	1.272***	(0.02)	0.05**
Lower secondary	1.222***	(0.02)	1.646***	(0.04)	0.42***	1.282***	(0.01)	0.06***
Post secondary non-tertiary	0.883***	(0.02)	1.019	(0.06)	0.14**	0.894***	(0.02)	0.01
Tertiary	0.802***	(0.01)	0.768***	(0.02)	-0.03	0.743***	(0.01)	-0.06***
<i>Household-level characteristics</i>								
Equivalentized household size	0.915***	(0.01)	0.977	(0.01)	0.06***	1.119***	(0.01)	0.20***
Number of children in household	1.298***	(0.01)	1.432***	(0.02)	0.13***	1.140***	(0.00)	-0.16***
Densely populated area	0.819***	(0.01)	0.634***	(0.01)	-0.18***	0.840***	(0.01)	0.02**
log(imputed rent)	0.956***	(0.00)	1.036***	(0.00)	0.08***	0.950***	(0.00)	-0.01***
log(imputed rent) × owns dwelling	0.948***	(0.00)	1.187***	(0.01)	0.24***	1.404***	(0.02)	0.46***
<i>Country-level characteristics</i>								
log(GDP)	0.582***	(0.01)	0.562***	(0.02)	-0.02	0.483***	(0.01)	-0.10***
Unemployment rate	0.924***	(0.00)	1.273***	(0.00)	0.35***	1.038***	(0.00)	0.11***
<i>Country group (reference category: social democratic economy)</i>								
Baltic country	1.248***	(0.05)	1.616***	(0.10)	0.37***	0.829***	(0.02)	-0.42***
Continental European economy	1.276***	(0.02)	2.150***	(0.09)	0.87***	1.344***	(0.02)	0.07*
Eastern European economy	0.961	(0.03)	1.332***	(0.08)	0.37***	0.642***	(0.02)	-0.32***
Liberal market economy	1.254***	(0.03)	2.828***	(0.13)	1.57***	1.718***	(0.03)	0.46***
Mediterranean economy	1.960***	(0.04)	2.308***	(0.10)	0.35***	1.230***	(0.02)	-0.73***
$\hat{\sigma}_\eta$	0.0000			2.4663			0.0001	
$\hat{\rho}$	0.0000			0.7871			0.0000	
Log-likelihood	1,349,086.2		-132,633.3			3,897,881.1		
Number of observations	799,894		768,114			2,599,992		
Number of individuals	409,231		333,682			1,102,558		

Notes: This table reports the effect of several demographic and socioeconomic factors on the hazard of entering poverty for individuals whose income is above the poverty threshold. Columns (1), (2), and (3) are independent discrete time mixed proportional hazards models estimated on a sample of individuals being at risk of poverty before the crisis (1), during the crisis (2), and after the crisis (3). Coefficients are exponentiated and can be interpreted as hazard ratios, standard errors are given in parentheses next to coefficients. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[†] Difference with respect to the coefficient in column (1). The stars indicate the p -value for the z -test on the difference between coefficients.

[‡] Observations with missing values on this variable are flagged using a missing indicator dummy and included in the regression.

TABLE A.6 — Determinants of poverty exit hazards before, during, and after the financial crisis (discrete time mixed proportional hazards models).

	(1) Pre-crisis		(2) Crisis			(3) Post-crisis		
	Coef.	Std. err.	Coef.	Std. err.	Diff. [†]	Coef.	Std. err.	Diff. [†]
<i>Duration dependence</i>								
exp(δ_1)	38.822***	(49.08)	0.674	(0.55)	-38.15	0.049***	(0.02)	-38.77
exp(δ_2)	51.934***	(66.26)	0.762	(0.63)	-51.17	0.028***	(0.01)	-51.91
exp(δ_3)	11.851*	(15.28)	0.085***	(0.07)	-11.77	0.002***	(0.00)	-11.85
exp(ξ_2)	0.007***	(0.00)	0.070***	(0.01)	0.06***	0.321***	(0.02)	0.31***
<i>Individual-level characteristics</i>								
Female	1.089*	(0.05)	1.123***	(0.05)	0.03	1.016	(0.02)	-0.07
Has permanent job	1.106	(0.07)	1.337***	(0.09)	0.23*	0.973	(0.02)	-0.13*
Retired	1.477***	(0.22)	2.263***	(0.16)	0.79***	1.110***	(0.03)	-0.37
Has chronic disease	1.135**	(0.06)	1.135**	(0.06)	0.00	1.001	(0.02)	-0.13*
Has physical limitation	0.928	(0.05)	0.888**	(0.05)	-0.04	0.938**	(0.02)	0.01
Owens dwelling	1.513***	(0.13)	0.552***	(0.06)	-0.96***	0.047***	(0.01)	-1.47***
<i>Age category (reference category: 35 ≤ age < 50)</i>								
Age < 25	1.217**	(0.10)	1.277***	(0.10)	0.06	1.095***	(0.03)	-0.12
25 ≤ age < 35	1.031	(0.07)	1.112	(0.08)	0.08	1.059**	(0.03)	0.03
50 ≤ age < 65	1.625***	(0.11)	1.528***	(0.10)	-0.10	1.039	(0.02)	-0.59***
Age ≥ 65	1.421***	(0.11)	1.438***	(0.11)	0.02	1.101***	(0.04)	-0.32***
<i>Marital status (reference category: married)[‡]</i>								
Never married	1.265***	(0.08)	1.114*	(0.07)	-0.15	0.966	(0.02)	-0.30***
Separated	1.280*	(0.19)	0.927	(0.14)	-0.35	0.812***	(0.05)	-0.47**
Widowed	1.095	(0.08)	0.995	(0.07)	-0.10	1.075**	(0.03)	-0.02
Divorced	0.950	(0.08)	0.942	(0.08)	-0.01	0.948*	(0.03)	0.00
<i>Occupation (reference category: high skilled white collar worker)[‡]</i>								
Low skilled white collar	0.833*	(0.09)	0.829*	(0.08)	0.00	0.856***	(0.03)	0.02
High skilled blue collar	0.715***	(0.07)	0.719***	(0.07)	0.00	0.816***	(0.03)	0.10
Low skilled blue collar	0.786**	(0.08)	0.714***	(0.07)	-0.07	0.887***	(0.03)	0.10
<i>Highest educational level achieved (reference category: upper secondary)[‡]</i>								
Pre-primary	0.577***	(0.10)	1.030	(0.17)	0.45**	0.596***	(0.05)	0.02
Primary	0.689***	(0.04)	0.747***	(0.05)	0.06	0.882***	(0.02)	0.19***
Lower secondary	0.786***	(0.04)	0.951	(0.05)	0.17**	0.880***	(0.02)	0.09**
Post secondary non-tertiary	0.910	(0.10)	1.246*	(0.14)	0.34*	1.078	(0.05)	0.17
Tertiary	0.961	(0.07)	1.042	(0.07)	0.08	0.982	(0.02)	0.02
<i>Household-level characteristics</i>								
Equivalized household size	1.562***	(0.06)	1.348***	(0.05)	-0.21***	1.199***	(0.01)	-0.36***
Number of children in household	1.111***	(0.02)	1.074***	(0.02)	-0.04	0.932***	(0.01)	-0.18***
Densely populated area	0.976	(0.04)	1.060	(0.04)	0.08	1.022	(0.02)	0.05
log(imputed rent)	0.964***	(0.01)	1.035***	(0.01)	0.07***	1.022***	(0.00)	0.06***
log(imputed rent) × owns dwelling	1.007	(0.01)	1.083***	(0.02)	0.08***	1.381***	(0.04)	0.37***
<i>Country-level characteristics</i>								
log(GDP)	0.636***	(0.07)	0.776***	(0.06)	0.14	1.145***	(0.03)	0.51***
Unemployment rate	0.892***	(0.01)	1.099***	(0.01)	0.21***	1.010***	(0.00)	0.12***
<i>Country group (reference category: social democratic economy)</i>								
Baltic country	0.379***	(0.07)	0.932	(0.12)	0.55***	1.255***	(0.06)	0.88***
Continental European economy	2.988***	(0.27)	3.467***	(0.41)	0.48	1.475***	(0.05)	-1.51***
Eastern European economy	0.823	(0.13)	1.024	(0.14)	0.20	1.133**	(0.06)	0.31**
Liberal market economy	0.365***	(0.04)	1.306***	(0.13)	0.94***	1.306***	(0.05)	0.94***
Mediterranean economy	1.146	(0.10)	0.988	(0.09)	-0.16	0.943	(0.04)	-0.20*
$\hat{\sigma}_\eta$		2.2279		1.9568			0.0001	
$\hat{\rho}$		0.7511		0.6995			0.0000	
Log-likelihood		-24,249.33		-22,206.51			244,932.89	
Number of observations		40,145		40,984			114,892	
Number of individuals		33,311		30,319			82,316	

Notes: This table reports the effect of several demographic and socioeconomic factors on the hazard of exiting poverty for individuals who are poor. Columns (1), (2), and (3) are independent discrete time mixed proportional hazards models estimated on a sample of individuals being poor before the crisis (1), during the crisis (2), and after the crisis (3). Coefficients are exponentiated and can be interpreted as hazard ratios, standard errors are given in parentheses next to coefficients. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[†] Difference with respect to the coefficient in column (1). The stars indicate the p -value for the z -test on the difference between coefficients.

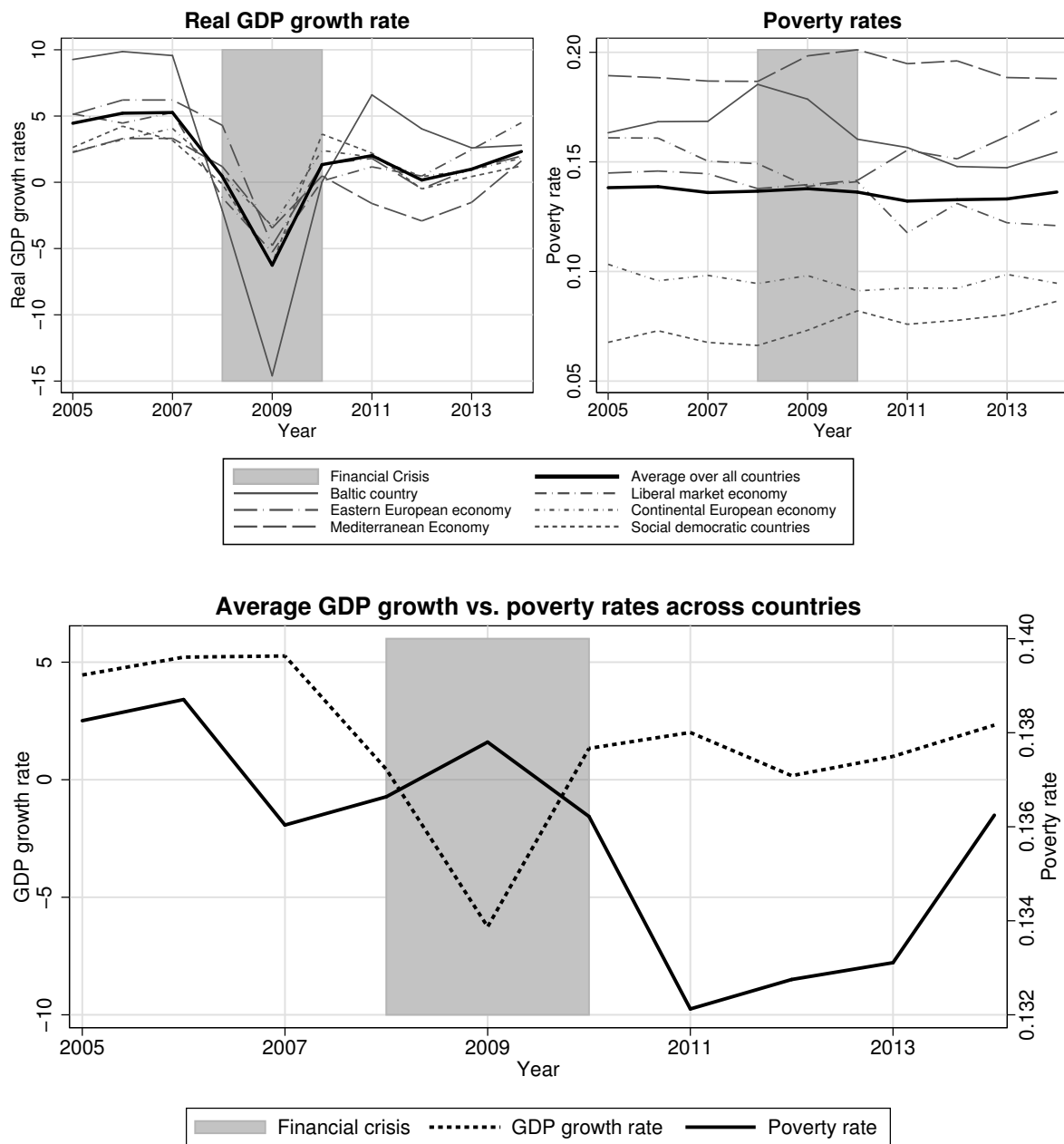
[‡] Observations with missing values on this variable are flagged using a missing indicator dummy and included in the regression.

TABLE A.7 — Effect of financial crisis on different other outcomes possibly related to poverty (fixed-effects panel logit model).

	(1)	(2)	(3)
	Difficulties to make ends meet	Housing cost are heavy fin. burden	Repayment of debts is heavy fin. burden
<i>Crisis indicators (reference category: before crisis)</i>			
During crisis	0.738*** (0.03)	1.139*** (0.05)	0.836** (0.06)
After crisis	0.858*** (0.04)	1.501*** (0.08)	0.505*** (0.04)
<i>Individual-level characteristics</i>			
Has permanent job	0.835*** (0.01)	0.854*** (0.01)	0.935*** (0.01)
Retired	0.950*** (0.01)	0.904*** (0.01)	0.882*** (0.02)
Has chronic disease	1.061*** (0.01)	1.163*** (0.01)	1.219*** (0.01)
Has physical limitation	1.217*** (0.01)	1.157*** (0.01)	1.152*** (0.01)
Owns dwelling	0.903*** (0.02)	0.754*** (0.01)	1.079*** (0.03)
<i>Age category (reference category: 35 ≤ age < 50)</i>			
Age < 25	1.125*** (0.02)	1.102*** (0.02)	0.995 (0.02)
25 ≤ age < 35	1.004 (0.02)	1.047*** (0.01)	1.022 (0.02)
50 ≤ age < 65	0.876*** (0.01)	0.920*** (0.01)	0.954** (0.02)
Age ≥ 65	0.832*** (0.02)	0.853*** (0.02)	0.827*** (0.03)
<i>Marital status (reference category: married)[‡]</i>			
Never married	1.142*** (0.02)	1.145*** (0.02)	1.025 (0.02)
Separated	1.460*** (0.05)	1.272*** (0.04)	1.127*** (0.04)
Widowed	1.193*** (0.03)	1.250*** (0.03)	1.048 (0.04)
Divorced	1.231*** (0.03)	1.236*** (0.03)	1.084*** (0.03)
<i>Occupation (reference category: high skilled white collar worker)[‡]</i>			
Low skilled white collar	1.117*** (0.01)	1.038*** (0.01)	1.078*** (0.02)
High skilled blue collar	1.136*** (0.02)	1.005 (0.01)	1.080*** (0.02)
Low skilled blue collar	1.125*** (0.02)	1.011 (0.01)	1.116*** (0.02)
<i>Household-level characteristics</i>			
Equalized household size	1.025** (0.01)	1.009 (0.01)	1.319*** (0.01)
Number of children in household	1.004 (0.00)	1.023*** (0.00)	1.024*** (0.00)
Densely populated area	1.048*** (0.02)	1.037** (0.01)	0.941*** (0.02)
log(imputed rent)	0.984*** (0.00)	0.979*** (0.00)	1.008*** (0.00)
log(imputed rent) × owns dwelling	1.015*** (0.00)	1.029*** (0.00)	0.978*** (0.00)
<i>Country-level characteristics</i>			
log(GDP)	0.804*** (0.03)	0.677*** (0.03)	0.383*** (0.02)
Unemployment rate	1.055*** (0.00)	1.031*** (0.00)	1.017*** (0.00)
Year fixed-effects	Yes	Yes	Yes
Log-likelihood	-550,525.18	-694,507.72	-331,465.57
Number of observations	1,498,458	1,879,931	905,891
Number of individuals	436,758	554,571	268,814

Notes: In this table we estimate the impact of the financial crisis on outcomes other than poverty. We use conditional logit models incorporating individual-level fixed effects (Wooldridge 2010). Following Correia (2015), we drop observations for whom the value of the respective outcome variable never changes during the observation period prior to performing the estimation in order to improve computational efficiency. Coefficients are exponentiated and can be interpreted as odds ratios, individual-level clustered standard errors are given in parentheses next to coefficients. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

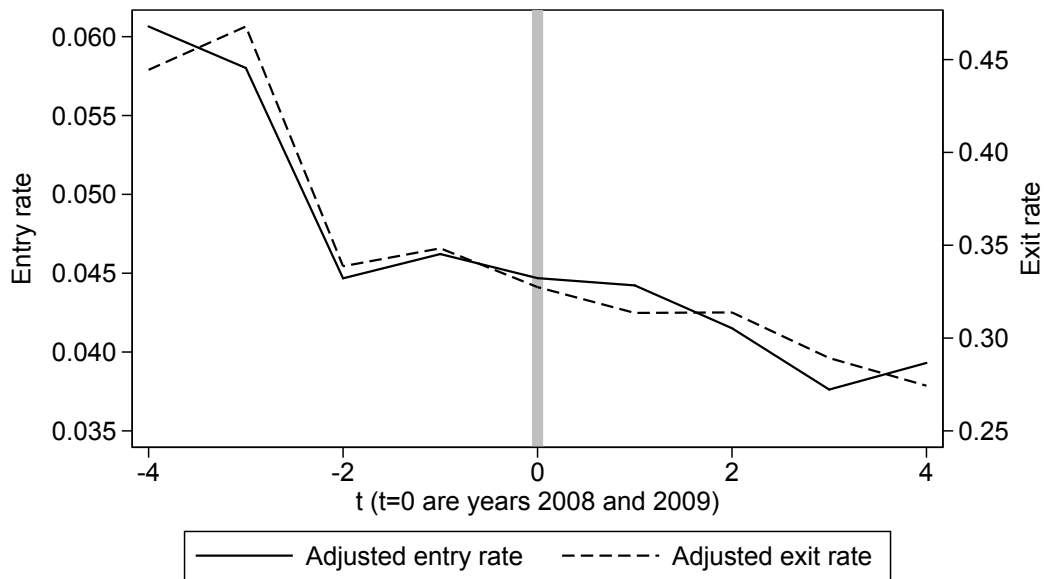
FIGURE A.1 — Real GDP growth and poverty rates for different groups of countries in the data.



Notes: This graph displays real GDP growth rates as well as poverty rates for different country groups in the EU-SILC data. We group countries according to [Aristei & Perugini \(2015\)](#), see [Table A.1](#) for a detailed overview on the classification. Real GDP growth rate is calculated as the percentage change of real GDP with respect to the previous year, poverty rates is the fraction of people in each year whose disposable household income is below 60% of the median equivalized disposable household income in the respective year. The shaded areas indicate the big financial crisis spanning the years 2008 and 2009.

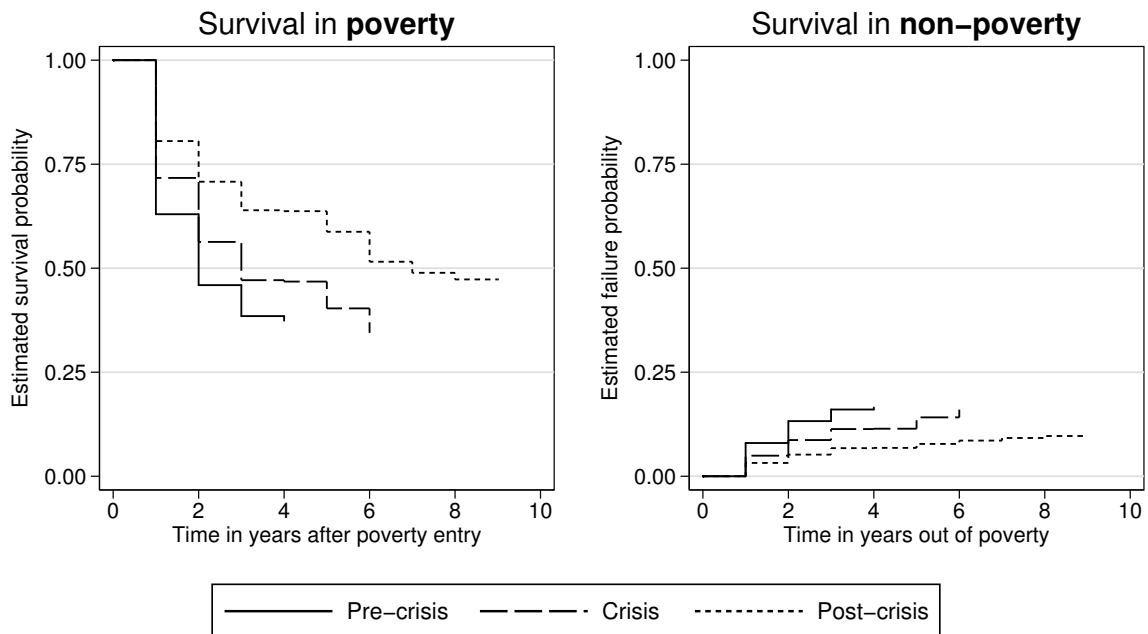
Source: Real GDP growth data are retrieved from [Eurostat \(2017b\)](#), poverty rates are our own calculations based on EU-SILC data.

FIGURE A.2 — Average adjusted poverty entry and exit rates over time relative to the crisis.



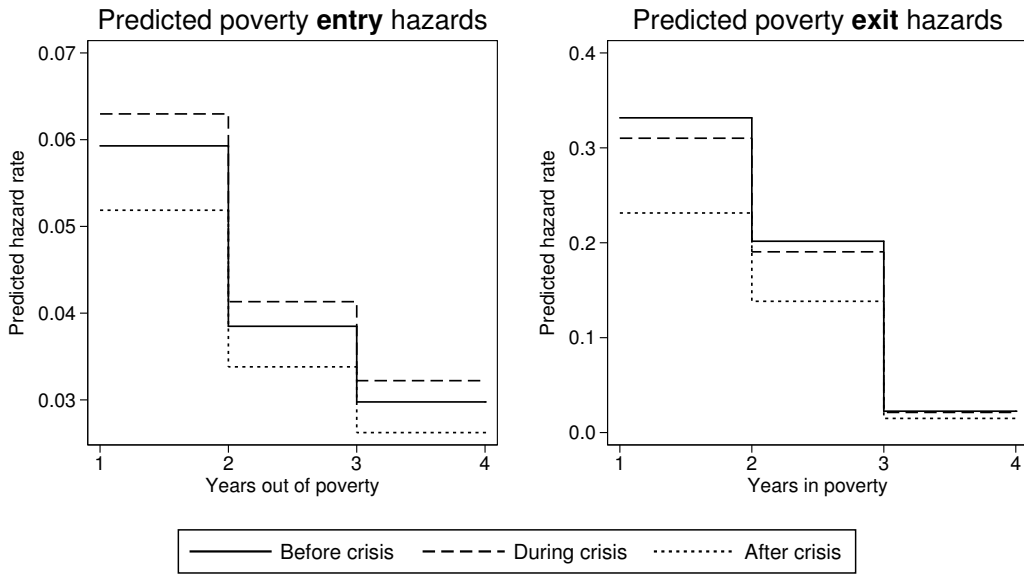
Notes: This graph depicts average entry rates (left axis) and exit rates (right axis) which are regression-adjusted for age and gender against time, relative to the years of the crisis ($t = 0$ are the years 2008 and 2009).

FIGURE A.3 — Kaplan Meier estimates of survival and failure probability.



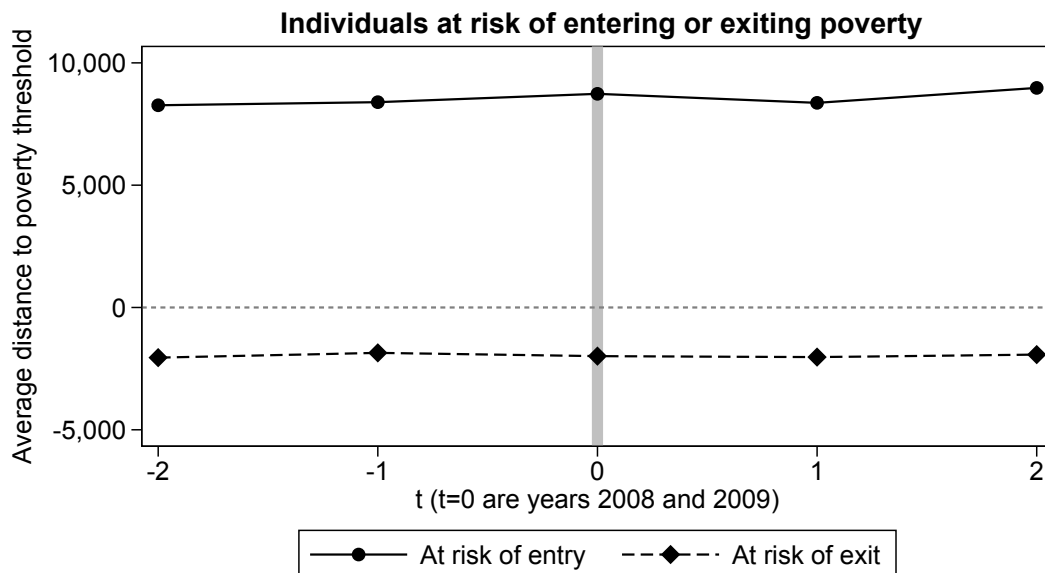
Notes: These graphs display Kaplan Meier survival estimates for individuals who are currently in a *poverty spell* (left graph) and failure estimates for individuals currently in a *non-poverty spell* (right graph). On the horizontal axis is time in years, either after poverty entry (left graph) or in non-poverty (right graph).

FIGURE A.4 — Predicted conditional poverty entry and exit hazard rates.



Notes: This graph displays the predicted cloglog-transformed conditional poverty entry and exit hazard rate for each period $k = \{1, 2, 3\}$ in non-poverty and poverty, respectively. Predictions are based on models 1 and 3 in Table A.3 which do not include control variables. In case an individual has multiple spells $J > 1$ in the data, we use the average hazard rate for each period k over its J_i spells.

FIGURE A.5 — Average adjusted difference of people entering and exiting poverty over time relative to the crisis.



Notes: This graph plots the average distance between total equivalized household income and the poverty threshold at 60% of the median equivalized household income in Euros for individuals that are *at risk* of entering or exiting poverty against time, relative to the years of the crisis ($t = 0$ are the years 2008 and 2009).

B. WEB APPENDIX

This *Web Appendix* (not for publication) provides additional material discussed in the unpublished manuscript ‘Poverty in Times of Crisis’ by Alexander Ahammer and Stefan Kranzinger.

TABLE B.1 — Average equivalized disposable household incomes.

	Individuals at risk of poverty entry or exit					
	<i>At risk of entry</i>			<i>At risk of exit</i>		
	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.
Pre-crisis	1,397,621	31,804.64	(35,567.1)	46,499	10,086.69	(18,142.0)
Crisis	954,392	32,599.70	(30,876.9)	42,904	9,504.18	(21,729.9)
Post-crisis	2,428,504	33,154.61	(30,905.0)	107,447	10,141.66	(10,478.7)
	Individuals experiencing entry or exit event					
	<i>Entry event</i>			<i>Exit event</i>		
	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.
Pre-crisis	61,964	21,123.02	(55,989.3)	14,216	10,689.90	(28,522.6)
Crisis	37,119	21,751.41	(31,190.6)	11,528	10,845.66	(12,808.1)
Post-crisis	73,784	21,394.32	(21,598.4)	21,124	11,387.42	(12,438.2)

Notes: This table summarizes averages of total equivalized disposable household income (equivalized using the OECD-modified weighting scheme) by crisis period (pre-crisis, during crisis, post-crisis) for individuals that are either *at risk* of experiencing a target event (entry or exit), and individuals who *in fact* experience a target event.

TABLE B.2 — Unconditional entry and exit rates.

Spell length	Entry probabilities			Exit probabilities		
	At risk	Prob.	Std. err.	At risk	Prob.	Std. err.
<i>Overall</i>						
1	1,868,558	0.058	(0.23)	147,899	0.274	(0.45)
2	1,396,886	0.031	(0.17)	37,238	0.162	(0.37)
3	903,195	0.022	(0.15)	10,990	0.017	(0.13)
<i>Pre-crisis</i>						
1	720,456	0.059	(0.24)	38,714	0.333	(0.47)
2	422,605	0.035	(0.18)	6,825	0.188	(0.39)
3	203,309	0.021	(0.14)	995	0.043	(0.20)
<i>Crisis</i>						
1	343,834	0.062	(0.24)	31,749	0.308	(0.46)
2	263,156	0.038	(0.19)	8,420	0.197	(0.40)
3	195,396	0.028	(0.16)	2,573	0.024	(0.15)
<i>Post-crisis</i>						
1	804,268	0.056	(0.23)	77,436	0.231	(0.42)
2	711,125	0.026	(0.16)	21,993	0.140	(0.35)
3	504,490	0.019	(0.14)	7,422	0.011	(0.10)

Notes: Estimates of unconditional entry and exit hazard rates for different non-poverty and poverty spell lengths. In panels '*Pre-crisis*', '*Crisis*', and '*Post-crisis*' the sample is stratified to spells that end before, during, or after the big financial crisis, respectively.

TABLE B.3 — Summary statistics for people at risk of entering or exiting poverty.

	Persons at risk to enter/exit poverty												Persons who experience entry or exit event											
	Persons entering poverty						Persons exiting poverty						Persons entering poverty						Persons exiting poverty					
	(1) Before	(2) During	(3) After	(4) Before	(5) During	(6) After	(7) Before	(8) During	(9) After	(10) Before	(11) During	(12) After	(7) Before	(8) During	(9) After	(10) Before	(11) During	(12) After						
<i>T</i>	1.70	(0.85)	2.19	(1.14)	2.26	(1.20)	1.19	(0.44)	1.33	(0.61)	1.36	(0.66)	1.39	(0.64)	1.59	(0.79)	1.56	(0.81)	1.10	(0.30)	1.16	(0.40)	1.16	(0.42)
Exit probability							0.31	(0.46)	0.27	(0.44)	0.20	(0.40)												
Entry probability	0.04	(0.21)	0.04	(0.19)	0.03	(0.17)																		
<i>Individual-level characteristics</i>																								
Female	0.42	(0.49)	0.42	(0.49)	0.43	(0.50)	0.41	(0.49)	0.42	(0.49)	0.40	(0.49)	0.42	(0.49)	0.42	(0.49)	0.42	(0.49)	0.43	(0.49)	0.45	(0.50)	0.43	(0.50)
Has permanent job	0.27	(0.45)	0.27	(0.45)	0.38	(0.48)	0.10	(0.30)	0.10	(0.31)	0.21	(0.41)	0.13	(0.33)	0.14	(0.34)	0.24	(0.43)	0.14	(0.35)	0.15	(0.36)	0.24	(0.43)
Retired	0.01	(0.10)	0.10	(0.30)	0.21	(0.41)	0.01	(0.10)	0.09	(0.29)	0.15	(0.36)	0.01	(0.10)	0.07	(0.26)	0.17	(0.37)	0.01	(0.11)	0.10	(0.30)	0.17	(0.37)
Has chronic disease	0.20	(0.40)	0.21	(0.41)	0.23	(0.42)	0.23	(0.42)	0.25	(0.43)	0.24	(0.43)	0.24	(0.43)	0.24	(0.43)	0.25	(0.43)	0.22	(0.42)	0.26	(0.44)	0.25	(0.43)
Has physical limitation	0.16	(0.37)	0.17	(0.38)	0.18	(0.39)	0.20	(0.40)	0.22	(0.41)	0.20	(0.40)	0.21	(0.41)	0.21	(0.41)	0.21	(0.41)	0.19	(0.39)	0.23	(0.42)	0.20	(0.40)
Owns dwelling	0.80	(0.40)	0.77	(0.42)	0.05	(0.21)	0.69	(0.46)	0.71	(0.46)	0.09	(0.29)	0.71	(0.45)	0.70	(0.46)	0.07	(0.25)	0.72	(0.45)	0.72	(0.45)	0.09	(0.28)
<i>Age categories</i>																								
Age < 25	0.12	(0.32)	0.11	(0.32)	0.10	(0.31)	0.12	(0.33)	0.12	(0.32)	0.13	(0.33)	0.13	(0.34)	0.13	(0.34)	0.13	(0.34)	0.14	(0.35)	0.12	(0.33)	0.14	(0.34)
25 ≤ age < 35	0.12	(0.33)	0.12	(0.32)	0.11	(0.31)	0.09	(0.29)	0.09	(0.29)	0.10	(0.30)	0.11	(0.31)	0.11	(0.31)	0.11	(0.31)	0.11	(0.31)	0.10	(0.30)	0.11	(0.31)
35 ≤ age < 50	0.42	(0.49)	0.40	(0.49)	0.38	(0.49)	0.46	(0.50)	0.44	(0.50)	0.45	(0.50)	0.42	(0.49)	0.43	(0.49)	0.42	(0.49)	0.43	(0.50)	0.40	(0.49)	0.41	(0.49)
50 ≤ age < 65	0.20	(0.40)	0.21	(0.41)	0.22	(0.41)	0.16	(0.36)	0.17	(0.37)	0.18	(0.39)	0.16	(0.37)	0.18	(0.38)	0.19	(0.39)	0.17	(0.38)	0.19	(0.39)	0.19	(0.40)
Age ≥ 65	0.15	(0.35)	0.16	(0.37)	0.18	(0.39)	0.17	(0.38)	0.19	(0.39)	0.14	(0.35)	0.18	(0.38)	0.15	(0.36)	0.15	(0.36)	0.15	(0.35)	0.19	(0.39)	0.15	(0.36)
<i>Marital status</i>																								
Never married	0.23	(0.42)	0.23	(0.42)	0.23	(0.42)	0.22	(0.41)	0.21	(0.41)	0.24	(0.43)	0.23	(0.42)	0.24	(0.43)	0.25	(0.43)	0.24	(0.43)	0.23	(0.42)	0.25	(0.43)
Married	0.46	(0.50)	0.47	(0.50)	0.47	(0.50)	0.35	(0.48)	0.36	(0.48)	0.35	(0.48)	0.40	(0.49)	0.41	(0.49)	0.39	(0.49)	0.39	(0.49)	0.40	(0.49)	0.39	(0.49)
Separated	0.01	(0.11)	0.01	(0.09)	0.01	(0.09)	0.01	(0.12)	0.01	(0.11)	0.01	(0.12)	0.02	(0.13)	0.01	(0.11)	0.01	(0.12)	0.01	(0.12)	0.01	(0.11)	0.01	(0.11)
Widowed	0.06	(0.23)	0.06	(0.24)	0.07	(0.25)	0.09	(0.29)	0.10	(0.30)	0.08	(0.27)	0.08	(0.28)	0.07	(0.26)	0.07	(0.26)	0.08	(0.27)	0.10	(0.30)	0.08	(0.28)
Divorced	0.04	(0.19)	0.04	(0.20)	0.05	(0.21)	0.05	(0.21)	0.05	(0.22)	0.06	(0.23)	0.05	(0.22)	0.05	(0.22)	0.06	(0.23)	0.04	(0.21)	0.06	(0.23)	0.06	(0.23)
Missing	0.20	(0.40)	0.19	(0.39)	0.18	(0.38)	0.28	(0.45)	0.26	(0.44)	0.26	(0.44)	0.23	(0.42)	0.22	(0.41)	0.21	(0.41)	0.23	(0.42)	0.20	(0.40)	0.20	(0.40)
<i>Highest educational level achieved</i>																								
Pre-primary	0.01	(0.08)	0.01	(0.08)	0.01	(0.08)	0.01	(0.11)	0.01	(0.11)	0.01	(0.11)	0.01	(0.12)	0.01	(0.10)	0.01	(0.10)	0.01	(0.10)	0.01	(0.11)	0.01	(0.09)
Primary	0.11	(0.31)	0.09	(0.29)	0.08	(0.28)	0.16	(0.37)	0.15	(0.36)	0.12	(0.32)	0.17	(0.37)	0.15	(0.35)	0.12	(0.33)	0.15	(0.36)	0.14	(0.35)	0.11	(0.32)
Lower secondary	0.16	(0.36)	0.16	(0.37)	0.16	(0.37)	0.19	(0.39)	0.21	(0.41)	0.20	(0.40)	0.20	(0.40)	0.22	(0.41)	0.21	(0.41)	0.19	(0.39)	0.21	(0.41)	0.21	(0.40)
Upper secondary	0.33	(0.47)	0.34	(0.47)	0.34	(0.47)	0.25	(0.43)	0.27	(0.44)	0.29	(0.45)	0.27	(0.45)	0.29	(0.45)	0.31	(0.46)	0.30	(0.46)	0.30	(0.46)	0.33	(0.47)
Post-secondary	0.03	(0.17)	0.03	(0.16)	0.03	(0.16)	0.02	(0.15)	0.02	(0.14)	0.02	(0.14)	0.02	(0.15)	0.02	(0.15)	0.02	(0.14)	0.03	(0.16)	0.03	(0.16)	0.02	(0.15)
Tertiary	0.37	(0.48)	0.37	(0.48)	0.39	(0.49)	0.36	(0.48)	0.34	(0.47)	0.36	(0.48)	0.32	(0.47)	0.32	(0.47)	0.32	(0.47)	0.33	(0.47)	0.31	(0.46)	0.32	(0.47)
<i>Household-level characteristics</i>																								
Equiv. household size	2.05	(0.63)	2.03	(0.63)	2.00	(0.63)	1.99	(0.75)	1.97	(0.76)	2.02	(0.75)	2.09	(0.73)	2.11	(0.72)	2.10	(0.73)	2.09	(0.72)	2.02	(0.74)	2.05	(0.71)
Number of children	0.66	(0.97)	0.61	(0.94)	0.65	(1.06)	0.76	(1.13)	0.73	(1.11)	0.98	(1.54)	0.83	(1.15)	0.81	(1.13)	0.84	(1.22)	0.81	(1.10)	0.72	(1.05)	0.87	(1.27)
Densely pop. area	0.36	(0.48)	0.35	(0.48)	0.35	(0.48)	0.34	(0.47)	0.32	(0.46)	0.32	(0.47)	0.33	(0.47)	0.32	(0.46)	0.32	(0.47)	0.32	(0.47)	0.33	(0.47)	0.33	(0.47)
log(imputed rend)	6.76	(3.00)	6.89	(2.75)	6.91	(2.70)	6.52	(3.09)	6.25	(2.99)	6.21	(3.02)	6.37	(3.19)	6.45	(2.95)	6.30	(2.98)	6.52	(3.12)	6.48	(2.91)	6.41	(2.94)
Observations	1397623		954392		2428504		46534		42909		107447		61964		37119		73784		14228		11533		21124	

Notes: This table displays sample means of all variables included in the regressions.

TABLE B.4 — Effect of financial crisis on poverty transitions (fixed-effects panel logit model).

	Poverty transitions	
	(1)	(2)
<i>Crisis indicators (reference category: before crisis)</i>		
During crisis	0.789*** (0.04)	0.615*** (0.04)
After crisis	0.668*** (0.04)	0.386*** (0.02)
<i>Individual-level characteristics</i>		
Has permanent job		0.493*** (0.01)
Retired		0.795*** (0.01)
Has chronic disease		0.978** (0.01)
Has physical limitation		1.014 (0.01)
Owns dwelling		0.953** (0.02)
<i>Age category (reference category: 35 ≤ age < 50)</i>		
Age < 25		1.406*** (0.03)
25 ≤ age < 35		0.971 (0.02)
50 ≤ age < 65		0.741*** (0.01)
Age ≥ 65		0.494*** (0.01)
<i>Marital status (reference category: married)[‡]</i>		
Never married		1.376*** (0.03)
Separated		1.515*** (0.05)
Widowed		1.953*** (0.05)
Divorced		1.408*** (0.04)
<i>Household-level characteristics</i>		
Equivalized household size		0.558*** (0.01)
Number of children in household		0.994 (0.00)
Densely populated area		1.041* (0.02)
log(imputed rent)		0.977*** (0.00)
log(imputed rent) × owns dwelling		0.991*** (0.00)
<i>Country-level characteristics</i>		
log(GDP)		2.010*** (0.11)
Unemployment rate		1.030*** (0.00)
Individual fixed-effects	Yes	Yes
Year fixed-effects	Yes	Yes
Log-likelihood	-334,110.9	-325,415.9
Number of observations	905,123	905,123
Number of individuals	268,813	268,813

Notes: In this table we report results obtained from performing a conditional logit fixed effects estimation (Wooldridge 2010) with poverty as the outcome variable. Following Correia (2015), we drop observations for whom the value of the respective outcome variable never changes during the observation period prior to performing the estimation in order to improve computational efficiency. Observations who never change their poverty status have been dropped before the regression. Coefficients are exponentiated and can be interpreted as odds ratios, individual-level clustered standard errors are given in parentheses next to coefficients. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B.5 — **Robustness check:** Effect of financial crisis on poverty entry and exit hazards, including a 10% band around the poverty threshold (discrete time mixed proportional hazards models).

	Poverty entry hazard				Poverty exit hazard			
	(1)		(2)		(3)		(4)	
<i>Crisis indicators (reference category: before crisis)</i>								
During crisis	1.119***	(0.01)	1.167***	(0.01)	0.878***	(0.01)	0.872***	(0.01)
After crisis	0.889***	(0.01)	0.881***	(0.01)	0.647***	(0.01)	0.696***	(0.01)
<i>Duration dependence</i>								
$\exp(\delta_1)$	0.035***	(0.00)	46.462***	(6.53)	0.294***	(0.00)	0.146***	(0.04)
$\exp(\delta_2)$	0.018***	(0.00)	25.278***	(3.56)	0.154***	(0.00)	0.075***	(0.02)
$\exp(\delta_3)$	0.013***	(0.00)	18.909***	(2.67)	0.013***	(0.00)	0.006***	(0.00)
$\exp(\xi_2)$	1.150***	(0.03)	0.931**	(0.03)	0.216***	(0.01)	0.201***	(0.02)
Other covariates ^a	No		Yes		No		Yes	
$\hat{\sigma}_\eta$	0.4880		0.5156		0.4384		0.3360	
$\hat{\rho}$	0.1265		0.4726		0.1046		0.0642	
Log-likelihood	-495,783.7		-474,342.1		-89,582.4		-87,321.71	
Number of observations	4,168,000		4,168,000		196,021		196,021	
Number of individuals	1,817,479		1,817,479		143,444		143,444	

Notes: This table reports the difference in poverty entry and exit hazard rates depending on whether the person was at risk during or after the big financial crisis, as compared to before. Poverty entries are only considered as such if post-entry income is below a 10% band around the poverty threshold. Likewise, exits are only considered as such if post-exit income is above a 10% band around the threshold. Coefficients are exponentiated and can be interpreted as hazard ratios, individual-level clustered standard errors are given in parentheses next to coefficients. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

^a We control for gender, occupation, health proxies, dwelling type, age, marital status, education, household size, number of children, type of neighborhood, GDP, and unemployment rate (a detailed overview on our control variables is provided in section III). Additionally, we include missing indicator dummies for education and marital status.

TABLE B.6 — Robustness check: Effect of financial crisis on poverty exit hazards, including left-censored observations and using a geometric distribution of the baseline hazard (discrete time mixed proportional hazards models).

	(1)	(2)	(3)
	Baseline	Full sample	Geometric BH
<i>Crisis indicators (reference category: before crisis)</i>			
During crisis	0.935*** (0.01)	0.943*** (0.01)	0.946*** (0.01)
After crisis	0.686*** (0.01)	0.734*** (0.01)	0.740*** (0.01)
<i>Duration dependence</i>			
$\exp(\delta_1)$	0.165*** (0.04)	0.325*** (0.04)	
$\exp(\delta_2)$	0.091*** (0.02)	0.187*** (0.02)	
$\exp(\delta_3)$	0.009*** (0.00)	0.135*** (0.02)	
$\exp(\xi_2)$	0.244*** (0.01)	0.450*** (0.01)	0.430*** (0.01)
T			0.622*** (0.00)
Other covariates ^a	Yes	Yes	Yes
$\hat{\sigma}_\eta$	0.0247	0.0002	0.1063
$\hat{\rho}$	0.0004	0.0000	0.0068
Log-likelihood	-28,691.1	876,290.4	-390,583.6
Number of observations	196,021	768,772	768,772
Number of individuals	143,444	444,168	444,168

Notes: This table presents results of reestimating the model in Table A.3, column (4), on different samples and with a different specification of the baseline hazard, for the purpose of analyzing the extent to which our estimates change when we use different methods to account for left-censoring (Iceland 1997). Column (1) gives again the baseline estimates for comparison, in column (2) we keep left-censored observations instead of dropping them as done for our main exit hazard estimations, and in column (3) we assume that the baseline hazard is constant over time. Coefficients are exponentiated and can be interpreted as hazard ratios, individual-level clustered standard errors are given in parentheses next to coefficients. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

^aWe control for gender, occupation, health proxies, dwelling type, age, marital status, education, household size, number of children, type of neighborhood, GDP, and unemployment rate (a detailed overview on our control variables is provided in section III). Additionally, we include missing indicator dummies for education, occupation, and marital status.