Behind a Stable Poverty Rate: Changes in the Duration of Poverty Episodes in the United States since the mid-1980s

Iryna Kyzyma*
Luxembourg Institute of Socio-economic Research, the University of Bremen and IZA Bonn

(This version as of December 2014)

Abstract

According to the U.S. Census Bureau, the poverty rate did not change much in the United States over the last 25 years: it is estimated at 15 percent in the late 2000s as in the mid-1980s. This paper aims to look 'behind' the stability of the US official poverty rate by investigating what has happened to the underlying duration of poverty episodes. It is indeed well-known that a static poverty rate hides important changes in the dynamic structure of poverty. This knowledge, however, is often neglected in the evaluation of temporal trends in cross-sectional poverty rates. I propose a methodological framework which makes it possible to estimate the entire duration distribution of poverty episodes and decompose its change over time into the contributions induced by the changes in the composition of the poor and the structure of poverty. My approach builds on the estimation of the flexible hazard function, conditional on both observed and unobserved heterogeneity, which I use to recover the entire unconditional cumulative distribution of poverty episodes by their duration.

Using monthly data from the 1984 and 2008 panels of the Survey of Income and Program Participation, I show that albeit the poverty rate was relatively stable in the US, the share of individuals with long poverty episodes has increased over time. This increase, however, was not the same for everyone. In particular, individuals living in single families, families where the head is young, black or uneducated person have experienced a disproportionally large increase in the amount of time spent below the poverty line compared to other population sub-groups. The observed changes in the duration of poverty are induced by the changes in the structure of poverty rather than the characteristics of the poor. Looking inside the structure of poverty, I find that its contribution to the upward trend in the duration of poverty is mainly driven by the increased duration dependence and the enhanced effects of unobserved heterogeneity. At the same time, changes in the effects of individual attributes have contributed to the shift in the duration distribution of poverty episodes only to a minor extent.

Keywords: poverty duration, distributional changes, decomposition.
JEL Classification: C41, D39, I32.

***** This research has been funded by the Fond National de la Recherche Luxembourg (grant agreement 2011-1). Comments and suggestions of Alessio Fusco, Sandy Jencks, Stephen Jenkins, Johannes Ludwig, Ronald Oaxaca, Martin Ravallion, Philippe Van Kerm and the participants of the ASSA 2014 Annual Meeting, Spring Meeting of Young Economists 2014, IZA Summer School in Labour Economics, and IARIW 33rd General Conference are gratefully acknowledged. I would also like to thank the Multidisciplinary Program in Inequality and Social Policy at Harvard University, where the main part of the work on this paper has been accomplished, for the hospitality and inspiring atmosphere. The usual disclaimer applies.

Correspondence to: Iryna Kyzyma, LISER, 3 avenue de la Fonte, Esch-sur-Alzette, LU-4364, Luxembourg, e-mail: iryna.kyzyma@ceps.lu

1. Introduction

Although the absolute number of people living in poverty has been on the rise in the US, the official poverty rate did not change much over the past decades. Increasing during the periods of recession and declining during the periods of economic expansion, it was at the same level of 15 percent in the late 2000s as in the mid-1980s.[1]

The temporal 'stability' of cross-sectional poverty rate does not automatically imply that the longitudinal patterns of poverty have also remained unchanged. The poverty rate does a good job in revealing the prevalence of poverty in a particular year but it tells us nothing about the composition of the poor in terms of the amount of time spent below the poverty line. In their seminal work Bane and Ellwood (1986) show that whereas some people have very short episodes of poverty, the majority of those who are poor at a particular point in time are in the middle of a long poverty spell. Hence, the same level of static poverty may be observed under completely different duration distributions of poverty episodes. This heterogeneity in the duration of poverty episodes is completely neglected in the evaluation of temporal trends in cross-sectional poverty rates.

This paper aims to look ‘behind’ the relative stability of the US poverty rate by investigating what has happened to the underlying it duration distribution of poverty episodes over the past twenty five years. In particular, I aim to identify what parts of the duration distribution of poverty episodes have been affected the most and to what extent the observed changes may be attributed to the changes in the composition of the poor and changes in the structure of poverty. Along with the aggregate analysis for the entire sample, I also estimate how the duration distribution of poverty episodes has changed for different population sub-groups.

Knowledge about what is happening with the duration distribution of poverty episodes behind the visually stable poverty rate is important, above all, from the policy-making perspective. Different policies might be needed depending on whether individuals, who are found in poverty at each moment of time, are predominantly short-term or long-term poor. Even if the aggregate estimates of poverty duration remain stable over time, different population sub-groups might be affected differently. One of the arguments in support of this thesis is that the absolute poverty rate itself evolved differently for different population sub-groups in the US. Whereas it has decreased among the elderly, female-headed families, and people with black and Hispanic origin, white individuals and working-age population have

[1] For a detailed description of the temporal fluctuations in the official US poverty rate see DeNavas-Walt et al. (2013).

become more prone to poverty over time.[2] Since individuals belonging to these groups tend to have different probabilities of exiting poverty, changes in their within-group poverty rates might imply that the duration of their poverty episodes also has changed.[3] If this is the case, a revision of social policies focusing on individuals with specific characteristics might be needed.[4]

Another explanation of why the distribution of time spent in poverty might have changed in the US lies in the recent demographic and labor market trends. There is well documented evidence that the proportion of foreign-born population has been rapidly increasing in the US which, in turn, has generated more racial and ethnical diversity. The country has also experienced substantial changes in family composition over the years manifesting themselves in the spread of single-parent and one-person families.[5] Along with demographic trends, there have also been profound labor market changes. Most of them are associated with the Federal Welfare Reform of 1996 and expansions in the earned income tax credits which served as activation policies and pushed a lot of previously economically inactive individuals back into labour force (Blank, 2009; Bollinger et al., 2009). On top of these reforms, income volatility doubled (Hardy and Ziliak, 2014) and inequality in earnings and income increased in the US between the 1980s and late 2000s affecting both the upper and bottom parts of income distribution (Daly and Valletta, 2006; Hardy and Ziliak, 2014). Finally, the expansion of the knowledge based sector of economy and advancement of technologies have resulted into profound shifts in the educational composition of the population (Goldin and Katz, 2009). People have become more educated over time.

To answer the research questions postulated above, I propose a methodological framework which makes it possible to construct and decompose the entire duration distribution of poverty episodes between two points in time. My approach builds on the estimation of the flexible hazard function, conditional on both observed and unobserved heterogeneity, which I then use to recover the entire unconditional cumulative distribution of poverty episodes by their duration. Once the model is specified, a set of counterfactual distributions can be constructed and applied to partition the overall change in the duration

[2] Trends in the poverty rate by demographic sub-groups are described in detail in DeNavas-Walt et al. (2013) and Gabe (2012).

[3] For more evidence about variation in the amount of time spent in poverty by demographic subgroups see Bane and Ellwood (1986) and Stevens (1999).

[4] The study of Card and Blank (2008) provides a good example of such a situation. Focusing on female-headed families, they find that poverty spells experienced by this specific population subgroup became shorter but more frequent between the early 1990s and the early 2000s.

[5] See Shrestha and Heisler (2011) for more details on recent trends in the US demographic profile.

distribution of poverty episodes into the parts induced by the changes in the composition of the poor and changes in the poverty structure. Along with the aggregate decomposition, I also partition the contribution of the structure of poverty into three further sub-components capturing the impact of the changes in (i) duration dependence, (ii) effects of individual observed characteristics, and (iii) effects of the unobserved heterogeneity. The analysis is based on monthly data from the 1984 and 2008 panels of the Survey of Income and Program Participation comprising up to 32 consecutive months of information about individual incomes.

The contribution of this paper to the literature is threefold. First of all, it provides new evidence about the changes in the duration distribution of poverty episodes in the US since the mid-1980s. Although there is quite extensive literature analysing temporal trends in U.S. income inequality and static poverty (e.g. Dickens and Ellwood, 2004; McKernan and Ratcliffe, 2005; Daly and Valetta, 2006; Meyer et al., 2012; Larrimore, 2013) little has been done to explore how longitudinal experiences of poverty have changed over time. Those studies which are available in the field focus either on changes in poverty dynamics (McKernan and Ratcliffe, 2005; Sandoval et al., 2009) or trends in the duration of poverty for specific population subgroups (Card and Blank, 2008). I extend this work by focusing explicitly on the duration distribution of poverty episodes for the overall adult population and development of this distribution over time.

I show that albeit the poverty rate was relatively stable, the share of people with long poverty spells has increased over time, and this increase was not the same for everyone. In particular, I find that individuals living in single parent or single person families, as well as in the families where the head is a black or uneducated person, have experienced a disproportionately large increase in the amount of time spent below the poverty line compared to other population sub-groups.

Secondly, I develop a methodological framework which makes it possible to construct and decompose the entire duration distribution of poverty episodes over time. Albeit there are studies which propose decomposition methods in order to explain changes in the probabilities of exiting poverty (unemployment) in the framework of duration analysis (Dejemeppe and Saks, 2002; Dejemeppe, 2005; Damioli, 2010), none of these methods specify how the entire duration distribution of spells can be decomposed over time. I explicitly address this issue by proposing a decomposition method for the entire duration distribution which allows to partition its change over time into components attributable to the changes in (1) the distribution of individual characteristics; (2) effects of these characteristics, (3) duration dependence, and (4) the effects of unobserved heterogeneity. Along with the poverty analysis, this decomposition framework might be useful in other settings, for example, for the analysis of the duration distribution of unemployment or welfare spells.

Finally, in the simplified version of the model (without the control for unobserved heterogeneity) I also allow the effects of covariates to vary at different values of duration in the spirit of distribution regression technique. Distribution regression has been previously applied for the analysis of distributional changes in wages and income (Fortin and Lemieux, 1998; Donald et al., 2000; Bonjour and Gerfin, 2001; Chernozhukov et al. 2013). Albeit being based on the estimation of the hazard function in most of the applications, it has not been used in the context of duration analysis where time is measured in discrete units. The main advantage of the distribution regression approach is that it allows for heterogeneous effects of covariates at different values of dependent variable which makes it possible to identify even minor changes in the duration distribution of poverty episodes over time and link them to the shifts in the distribution of covariates and their effects. I demonstrate that this flexible specification performs better than a more restricted one in predicting individual probabilities of exiting poverty and, hence, might be preferable in the settings where the control for unobserved heterogeneity is not required.

The paper is structured as follows. Section 2 presents data used for the empirical part of the paper and sample descriptive statistics. Section 3 describes modelling approach and specifies the decomposition framework. Section 4 provides the results and Section 5 concludes.

2. Data

2.1. Data and sample construction

The paper is based on data from the Survey of Income and Program Participation (SIPP). The SIPP is a multiple-panel survey which covers a nationally representative sample of US non-institutionalized households whose members are interviewed at four-month intervals during two to four consecutive years. At each interview, the respondents are asked about their demographic and labor market characteristics, family composition, sources and amounts of income, and participation in governmental programs in each of the preceding four months. The sample size in the SIPP ranges between 12000 households in the early panels and 50000 households in the most recent ones.

The main advantage of the SIPP is that it provides monthly longitudinal information on both individual attributes and income amounts. Previous research has shown that there is a lot of fluctuation in income during the year, especially among low income families. Almost half of those who fall into poverty exit it within the next four months while only few individuals remain poor for more than a year (Ruggles and Williams, 1989; Card and Blank, 2008; Anderson, 2011). These short episodes of poverty would have been missed with annual data. Another merit of the SIPP is that it measures income amounts and individual attributes at the same point in time. This is vital for correct identification of individuals' poverty status given that it depends on income of all family members and family composition. Simultaneous measurement of income and individual attributes also makes it possible to better identify the relationship between characteristics of individuals and the amount of time they spend below the poverty line.

In this study I use data from the 1984 and 2008 SIPP panels. The 1984 panel is the oldest SIPP panel which contains information collected between October 1983 and July 1986. The 2008 panel is the most recently available one with the interviews administered from September 2008 through August 2013. To make the panels comparable in length, I use up to 32 consecutive months of information from each panel and keep in the sample only those individuals who report complete data for all 32 months.[6] This restriction gives all individuals the same time frame for experiencing poverty episodes and makes it possible to correct for sample attrition by applying longitudinal weights. I also keep only adult individuals (18 years and older) in the sample because poverty status of children is directly determined by incomes of their parents.

The poverty status of each respondent is defined using the absolute measure of poverty developed by the Census Bureau. According to it, all individuals living in a family are considered to be poor if total family income falls below the officially established poverty threshold.[7] The poverty threshold is based on the minimum amount of money which is needed for a family of a given size and composition to buy food and other necessities.[8] Having been established in 1964, the thresholds for all family types are regularly adjusted by the Consumer Price Index in order to account for changes in the costs of living. Albeit this poverty measure has been heavily criticized (see, among others, Garner and Short, 2010), it remains the major eligibility criteria for many governmental programs and is the most widely used definition of poverty in the US.

---

[6] Albeit the 1984 Panel provides up to 36 month of information for some rotation groups, for other rotation groups only 32 monthly records are available.

[7] The family is defined as a group of individuals who reside together and who are related by birth, marriage or adoption. Under this definition, all family members who are not connected to each other by birth, marriage or adoption are perceived as unrelated individuals or a subfamily (U.S. Census Bureau, 2001).

[8] The corresponding poverty thresholds are provided for each family in the SIPP.

I define a spell of poverty as beginning in the first month when total family income falls below the poverty threshold and as ending in the first month it moves above the threshold. This definition of spells implies that even small fluctuations in income might result in a transition across the poverty threshold. It usually poses a problem when the duration of poverty is studied over a single period of time. In this paper, the focus is on changes in the duration distribution of poverty episodes over time. Hence, as soon as income fluctuations around the threshold remain the same in all periods, they are not expected to influence the trend in the aggregate duration of poverty.

Although I use family income to define the poverty status, the unit of analysis is individual. In this way I can follow individuals over time when they move from one household to another and analyze changes in the duration distribution of poverty episodes for different population subgroups. For each individual in the sample I delete the first spell of poverty (non-poverty) because of the unknown elapsed duration. Given that some of these spells are potentially long and the share of left-censored poverty spells has increased between the 1984 and 2008 panels, this methodological restriction might induce underestimation of the amount of time individuals spend in poverty. Because of this, all estimates presented in the paper should be considered as low bound estimates of the true changes in the duration distribution of poverty episodes.

To each spell of poverty I attach a vector of time-varying covariates capturing observed characteristics of individuals. Since the poverty status is derived from family rather than personal income, all these covariates are also defined at the family level. Among the vast majority of potential poverty correlates, I focus on those which have proved themselves as important predictors of the amount of time spent below the poverty line. The list includes age, gender, race, and education of family head, as well as type of the family an individual lives in. To control for heterogeneity of macroeconomic conditions across the US states and across the SIPP panels, I also include the monthly state unemployment rate in the vector of covariates.

The final sample of multiple poverty spells with the observed beginnings comprises 6721 individuals (44101 observations) for the 1984 panel and 11695 individuals (86869 observations) for the 2008 panel.

2.2. Sample descriptive statistics

Table 2.1 below describes the composition of the poor in the 1984 and 2008 SIPP sub-samples. Along with the mean values of the covariates in each panel, it also depicts how they change over time.

Table 2.1. Characteristics of the poor and their change over time, (%)

Covariates	1984 Panel	2008 Panel	Difference (2008 to 1984)
Age of household head			
< 25 years old	10.74	7.92	- 2.82*
25-54	60.15	67.21	+7.06***
55-64	14.54	14.77	+0.23
≥ 65	14.57	10.10	- 4.47***
Gender of household head			
Men	59.26	44.18	- 15.08***
Women	40.74	55.82	+15.08***
Race and ethnicity of household head			
Only white	70.84	63.98	-6.86***
Only black	20.08	15.84	-4.24*
Hispanic or Latino	9.08	20.18	+11.10***
Family type			
Single parent	15.43	16.03	+0.60
Single	23.43	31.69	+8.26***
Couple	51.92	42.30	-9.62***
Other	9.22	9.98	+0.76
Education			
Uncompleted high school	45.09	25.27	-19.82***
Completed high school	30.24	26.21	-4.03*
College or higher	24.67	48.52	+21.85***
Monthly state unemployment rate	7.71	9.42	+1.71***

Note: Longitudinally weighted estimates. The differences are tested for statistical significance accounting for the SIPP complex survey design.

* significant at 0.001 level, ** significant at 0.01 level, *** significant at 0.05 level.

Table 2.1 shows that the majority of the poor in the 1984 panel were living in couple-based rather than single-person or single-parent families. In addition, most of them were coming from the families where the head was of 25-54 years old, male, white and with uncompleted high school education. Towards the end of the 2000s, the composition of the poor has changed substantially. Albeit individuals living in couple-based families were still prevailing in the sample, their share substantially declined. In turn, the share of those living in single-person families has increased over time. Along with the changes in family types, there have been profound shifts in the composition of the poor with respect to the characteristics of their family heads. For example, compared to the situation twenty five years ago, a much larger portion of the poor lives nowadays in the families with a 25-54-year old head and a substantially smaller share of people live in the families headed by a white or black person.

The most remarkable change in the composition of the poor, however, can be observed in the gender and educational dimensions. Compared to the mid-1980s, when the majority of the poor were from the male-headed families, almost 56 percent of the poor were members of the female-based families in the late 2000s. Regarding education, the shares of individuals living in the families with the least educated and the most educated heads have switched over time. Whereas the vast majority of the poor were coming from the families with uneducated heads in the mid-1980s, towards the end of the 2000s the sample became composed predominantly of individuals from the families with highly educated heads.

Table A.1 in the Appendix shows that the observed changes in the composition of the poor to a large extent reflect shifts in the socio-demographic structure of the US families. In particular, there is a general decline in the shares of individuals living in the families where the head is white, male or uneducated, and a general increase in the shares of those living with a Hispanic, female, or educated family head. Similarly to Table 2.1, more and more individuals tend to live in non-couple based families nowadays than twenty five years ago. The most remarkable difference between the sample and population estimates lies in age dimension. As compared to the general population, there are more individuals from the families headed by the 35-54 years old persons and less of those who live with elderly family heads in the poverty sample. In addition, a closer inspection of the two tables shows that albeit the observed changes in the composition of the poor and population overlap in terms of the direction of changes (increase or decline), their magnitude still differs. These findings provide the first evidence that the duration distribution of poverty episodes might have changed over time.

3. Modeling the distribution of poverty duration

3.1. Specification of the unconditional duration distribution of poverty episodes

Consider a sample of *N* individuals who have just fallen into poverty and can exit it at any time. Let *T* denote the amount of time individual *i* spends poor from the moment of entry into poverty until the moment of exit. By its nature, calendar time is a continuous random variable and exit from poverty may occur at any $t \in R^+$. In practice, time is usually recorded in discrete units (e.g., in days, months, years), so that $t \in \{1, 2, ..., t_{max}\}$ and $t \equiv 0$ at the moment when the person enters poverty.

With T modeled as a discrete process, the probability that individual i, who has been poor for t-1 periods, will exit poverty at time t can be expressed as a function of his or her observed and unobserved characteristics and the amount of time uninterruptedly spent in poverty from the moment of entry:

$$h_i(t) = \Pr[T_i = t \mid T_i \geq t, X_i] = \Theta(t_i, X_i)\,, \tag{3.1}$$

where X_i is a vector of individual characteristics, that can be both observed (Z_i) and time-invariant unobserved (v_i), and Θ stands for the link function.

Equation (3.1) can be used to derive two other important probabilities: (i) the probability that individual i will stay poor for exactly t periods (Equation 3.2); and (ii) the probability that the individual will exit poverty by time t (Equation 3.3):

$$f_i(t) = \Pr[T_i = t \mid X_i] = h_i(t) \cdot \prod_{s=1}^{t-1}(1 - h_i(s))\,, \tag{3.2}$$

$$\hat{F}_i(t) = \sum_{t=1}^{t}[\hat{h}_i(t) \cdot \prod_{s=1}^{t-1}(1 - \hat{h}_i(s))] \tag{3.3}$$

Equations (3.2) and (3.3) estimated for each $t \in \{1,2,\ldots,\ t_{max}\}$ describe the probability mass function (*pmf*) and the cumulative distribution function (*cdf*) of time spent in poverty for a particular individual with a given vector of observed and unobserved characteristics. In contrast to the hazard function, which shows the probability of exiting poverty in a given period, the *pmf* documents the probability of having a poverty episode with duration T.[9] By summarizing these probabilities over the range of t, Equation (3.3) derives the cumulative probability that the duration of the poverty episode will fall below T.

Aggregation of the estimates from Equation (3.3) across all individuals with different sets of characteristics will yield the duration distribution of poverty episodes in the sample:

$$\hat{F}(t) = \Pr[T = t] = \frac{1}{N^t}\sum_{i=1}^{N^t}\hat{F}_i(t)\,, \tag{3.4}$$

[9] It comes from the following relationship between the hazard function and *pmf*: $h_i(t) = \dfrac{f_i(t)}{\prod_{s=1}^{t-1}(1 - h_i(s))}$

where N^t denotes the number of people who are at risk of exiting poverty in period *t*.

Defined for the sample of individuals, Equation (3.4) describes the fraction of people who have their poverty episodes ended prior to period *t*.

3.2. Estimation

Albeit our direct interest lies in the entire duration distribution of poverty episodes, we start calculations by estimating the conditional probability of exiting poverty defined in Equation (3.1). To do that, we use logit specification as a function linking covariates of interest to the dependent variable. The logit specification guarantees consistent parameter estimates by satisfying two vital statistical properties:

(i) it constrains hazard probabilities, $h(t)$, to fall between 0 and 1 so that $0 \leq h(t) \leq 1$; and

(ii) it ensures that the *cdf* of poverty durations is a monotonically increasing function so that $0 \leq F(T=1) \leq \ldots \leq F(T=t_{max}) \leq 1$.

Using the logit specification as a link function, we can re-write Equation (3.1) as:

$$\log h_i(t) = \lambda_{Dt} + \quad Z_i + \theta_i , \tag{3.5}$$

where λ_{Dt} denotes the baseline hazard capturing the effect of time spent below the poverty line on the probability of exiting poverty for all individuals regardless of their personal characteristics, β is a vector of coefficients associated with the vector of observed covariates X_i, and θ_i stands for the effect of time-invariant unobserved characteristics.

I specify the baseline hazard, λ_{Dt}, in the most flexible way, i.e. with a set of duration dummies D (ϵ $\{D_1, D_2, \ldots, Dt_{max}\}$) corresponding to different values of *t*.[10] This specification has proved itself as the one which better approximates the shape of the baseline hazard and captures the presence of duration dependence in the data.[11] In a similar spirit, I allow for a flexible non-parametric specification of unobserved heterogeneity following Heckman and Singer (1984). According to this specification, the sample of individuals is assumed to be composed of *k* types of individuals (*k=1, ..., K*), where each type has different chances to exit poverty determined by its unobserved characteristics. Since previous research in the field

[10] Ie set D_{tmax} for all poverty episodes lasting 13 and more months because there are very few observations left afterwards and the estimates of the duration dummies do not differ significantly between them.

[11] For comparability reasons, I have also run other specifications of the baseline hazard (as an intercept, the linear, quadratic, cubic forms) but the model fit for them was worse than for the most flexible specification with a set of dummies.

has shown that unobserved characteristics are usually better captured across multiple spells of poverty, I estimated Equation (3.5) together with the analogous equation for non-poverty spells by allowing unobserved heterogeneity terms to be correlated. The joint distribution of these terms is then approximated in a discrete way with a set of support points $\{\theta_1, \ldots, \theta_k\}$, whose combinations define the number of distinct types of individuals in the sample. I derive support points and related to them probabilities $\{p_1, \ldots, p_k\}$ together with other parameters (λ_{Di}, β) using the maximum likelihood estimator.

Once the estimates from Equation (3.5) are available, I use them to derive predicted probabilities of exiting poverty in period t for each individual i given his or her observed and unobserved characteristics (Z_i, v_i):

$$\hat{h}_i(t) = \frac{\exp(\lambda_{Dt} + \sum_{m=1}^{M} X_{itM}\beta_{tM} + v_i)}{1 + \exp(\lambda_{Dt} + \sum_{m=1}^{M} X_{itM}\beta_{tM} + v_i)}, \qquad (3.6)$$

Equation (3.6) makes it straightforward to recover the values of the *pmf* and *cdf* of T conditional on X for each observation in the sample and to aggregate them across all individuals following Equation (3.3).

Ideally, one might also be interested in allowing the observed characteristics of individuals to affect their probabilities of exiting poverty heterogeneously across different segments of t. The argument in favor of such a flexible specification is that the effects of some covariates might attenuate over the spell length whereas the effects of others, contrarily, enhance. If this is the case, holding the effects of covariates fixed over the entire range of t will produce poor predictions of the individual hazard function which, in turn, will affect the estimates of the duration distribution of poverty episodes. In the presence of unobserved heterogeneity, however, this specification becomes complicated because it tends to overparameterize the model and leads to a slow estimation process.

In order to test whether the flexibility, with which covariates are specified, substantially influences individual predictions, I have estimated a set of models without unobserved heterogeneity but with heterogeneous effects of covariates across different segments of t. To do that, I partition the entire range of t ($t \in \{1, 2, \ldots, t_{max}\}$) in equally spaced intervals, l, and allow the effects of covariates to vary across these intervals:

$$\log h_i\ (t) = \text{a}_{Dt} + \sum_{l=1}^{L} 1(\quad ^{l}, Z_i^{l}) \tag{3.7}$$

where *1(.)* is the indicator function showing whether a given observation belongs to interval *l*, X_i^l stands for the realization of the vector of covariates in period *l* and $\quad ^{l}$ captures the effects of these covariates on the logarithm of the probability of exiting poverty.

In particular, I have estimated the models with 1, 3, 4, 5, 7, and 13 equally spaced intervals *l* and compared their performance in terms of the prediction of probabilities of exiting poverty. The latter has been judged on two criteria: (1) the sums of squared prediction errors based on the same sample and on the external sample; and (2) the comparison of the empirical and fitted probabilities of exiting poverty for different population sub-groups.

Table 3.1 below provides the sums of squared prediction errors from the models with different specifications of *l*.

Table 3.1. The sums of squared prediction errors from the models with different specification of the time segments'

Dimensions	Sums of squared prediction errors					
	Fitted (1)	Fitted (2)	Fitted (3)	Fitted (4)	Fitted (5)	Fitted (6)
	Predictions based on the same sample					
Age	0.1122	0.1267	0.1390	0.1425	0.1433	0.1547
Gender	0.0613	0.0621	0.0631	0.0624	0.0622	0.0636
Race and ethnicity	0.0491	0.0550	0.0587	0.0581	0.0569	0.0593
Education	0.0558	0.0592	0.0627	0.0598	0.0598	0.0609
Family status	0.0972	0.1020	0.1084	0.1053	0.1059	0.1137
Average	0.0751	0.0810	0.0864	0.0856	0.0856	0.0905
	Predictions based on the external sample					
Age	0.2884	0.2887	0.2910	0.2950	0.2961	0.2933
Gender	0.2004	0.1997	0.1989	0.1996	0.1991	0.1956
Race and ethnicity	0.2771	0.2766	0.2780	0.2782	0.2768	0.2743
Education	0.2760	0.2734	0.2741	0.2740	0.2730	0.2840
Family status	1.1580	1.1631	1.1611	1.1637	1.1647	1.1780
Average	0.4400	0.4403	0.4406	0.4421	0.4420	0.4450

Note: Fitted (1) – the most flexible specification with 13 segments; fitted (2) – specification with 7 segments; fitted (3) – specification with 5 segments; fitted (4) – specification with 4 segments; fitted (5) – specification with 3 segments; fitted (6) – the most restricted specification with 1 segment. All estimates are based on the 2008 SIPP panel.

Since all estimates are based on the logit model, the sample average predicted probabilities equal the sample frequencies of dependent variable (Cameron and Trivedi, 2005). However, the fitted and true duration distributions still remain different for subsamples and can be compared to draw conclusions about the precision of the estimates. I have calculated the squared prediction errors for each value of *t* within each sub-sample defined by different dimensions of potential poverty correlates (age, gender, race, education, family status), sum these predictions up across all values of t and across all sub-samples belonging to the same dimension, and then derive the average across all dimensions taken together:

$$SPE = \frac{\sum_{s=1}^{S} \sum_{t=1}^{T} (\hat{h}_t^s - h_t^s)}{5}, \qquad (3.8)$$

where SPE stands for the sum of squared prediction errors, and S defines the distinct sub-samples within each dimension (e.g. male and female for gender; black, white, and Hispanic for race etc.).

The estimates presented in Table 3.1 reveal that the model with the most flexible specification of covariates (Fitted 1) yields the smallest average estimate of the sum of squared prediction errors based on both the same sample and external sample. In contrast, the model with the most restricted specification (Fitted 6) gives the largest deviations of the predicted hazard estimates from the true values. The difference gets especially large when predictions are made for the same sample, which is used for the estimation of the model, whereas the estimates based on the external sample tend to be less sensitive to the model specification.

Table A.2 in the Appendix yields further light on the performance of models with different flexibility in the specification of covariates. Similarly to Table 3.1, it shows that the predictions from more flexibly specified models are closer to the true values of the hazard function than the predictions from more restricted models. The difference becomes especially substantial for longer poverty spells. All this evidence suggests that fixing the effects of covariates to be the same across all values of t might affect predicted probabilities within sub-samples. This, in turn, might affect decomposition results which are based on the construction of counterfactual distributions (see sub-section 3.3. below). To account for this potential bias, I will present the results with both specifications – the model with the most flexible parametrization of covariates but without unobserved heterogeneity, and the model where the effects of covariates are restricted but unobserved heterogeneity is taken into account.

3.3. Decomposition methodology

The overall change in the duration distribution of poverty episodes between two periods of time, $\Delta F(t)$, can be estimated as the difference between the *cdf*s of time spent in poverty in a final period (1) and a base period (0):

$$\Delta F(t) = F^{(1)}(t) - F^{(0)}(t)\,. \tag{3.9}$$

Using the decomposability property of the cumulative distribution functions and specification of *F(t)* in Equation (3.4), this difference can be further partitioned into two components capturing (i) the contribution of the shift in the individual characteristics (composition of the poor), and (ii) the contribution of the change in the effects of these characteristics (structure of poverty):

$$\Delta F(t) = F^{(1)}(t) - F^{(0)}(t) =$$

$$= \frac{1}{N^t_{(1)}} \sum_{i \in (1)} \Lambda(\lambda^{(1)}_{Dt} + \sum_{m=1}^{M} X_{itm}\beta_{tm}^{(1)} + \theta_i^{(1)}) - \frac{1}{N^t_{(0)}} \sum_{i \in (0)} \Lambda(\lambda^{(0)}_{Dt} + \sum_{m=1}^{M} X_{itm}\beta_{tm}^{(0)} + \theta_i^{(0)}) =$$

$$= [\frac{1}{N^t_{(1)}} \sum_{i \in (1)} \Lambda(\lambda^{(1)}_{Dt} + \sum_{m=1}^{M} X_{itm}\beta_{tm}^{(1)} + \theta_i^{(1)}) - \frac{1}{N^t_{(0)}} \sum_{i \in (0)} \Lambda(\lambda^{(1)}_{Dt} + \sum_{m=1}^{M} X_{itm}\beta_{tm}^{(1)} + \theta_i^{(1)})] +$$

$$+ [\frac{1}{N^t_{(0)}} \sum_{i \in (0)} \Lambda(\lambda^{(1)}_{Dt} + \sum_{m=1}^{M} X_{itm}\beta_{tm}^{(1)} + \theta_i^{(1)}) - \frac{1}{N^t_{(0)}} \sum_{i \in (0)} \Lambda(\lambda^{(0)}_{Dt} + \sum_{m=1}^{M} X_{itm}\beta_{tm}^{(0)} + \theta_i^{(0)})] =$$

$$= \Delta C + \Delta S\ , \tag{3.10}$$

where Λ is a transformation function transforming logit estimates into probabilities.

The first term in the right-hand side of Equation (3.10), ΔC, identifies the contribution of the change in the composition of the poor to the cumulative distribution of poverty durations between periods (1) and (0). It is done by taking the difference between the actual duration distribution of poverty episodes in period (1) and the counterfactual distribution that would have prevailed in period (1) if the composition of the poor had remained the same as in period (0). The second term in the right-hand side of Equation (3.10), ΔS, captures the contribution of the structure of poverty to the overall shift in the duration distribution of poverty episodes by taking the difference between the constructed counterfactual distribution and the actual distribution in period (0).

The second term from Equation (3.10) can be further partitioned into three sub-components capturing the contributions of the changes in the duration dependence (λ_{Dt}), effects of observed characteristics (β_{tm}), and effects of unobserved characteristics (θi) of individuals:

$$\Delta S = \frac{1}{N_{(0)}^{t}} \sum_{i \pounds (0)} \Lambda(\text{a}_{Dt}^{(1)} + \sum_{m=1}^{M} X_{itm} \quad {}_{tm}^{(1)} + {}^{-}{}_{i}^{(1)}) - \frac{1}{N_{(0)}^{t}} \sum_{i \pounds (0)} \Lambda(\text{a}_{Dt}^{(0)} + \sum_{m=1}^{M} X_{itm} \quad {}_{tm}^{(0)} + {}^{-}{}_{i}^{(0)}) =$$

$$= [\frac{1}{N_{(0)}^{t}} \sum_{i \pounds (0)} \Lambda(\text{a}_{Dt}^{(1)} + \sum_{m=1}^{M} X_{itm} \quad {}_{tm}^{(1)} + {}^{-}{}_{i}^{(1)}) - \frac{1}{N_{(0)}^{t}} \sum_{i \pounds (0)} \Lambda(\text{a}_{Dt}^{(0)} + \sum_{m=1}^{M} X_{itm} \quad {}_{tm}^{(1)} + {}^{-}{}_{i}^{(1)})] +$$

$$+ [\frac{1}{N_{(0)}^{t}} \sum_{i \pounds (0)} \Lambda(\text{a}_{Dt}^{(1)} + \sum_{m=1}^{M} X_{itm} \quad {}_{tm}^{(1)} + {}^{-}{}_{i}^{(1)}) - \frac{1}{N_{(0)}^{t}} \sum_{i \pounds (0)} \Lambda(\text{a}_{Dt}^{(0)} + \sum_{m=1}^{M} X_{itm} \quad {}_{tm}^{(0)} + {}^{-}{}_{i}^{(1)})] +$$

$$+ [\frac{1}{N_{(0)}^{t}} \sum_{i \pounds (0)} \Lambda(\text{a}_{Dt}^{(0)} + \sum_{m=1}^{M} X_{itm} \quad {}_{tm}^{(0)} + {}^{-}{}_{i}^{(1)}) - \frac{1}{N_{(0)}^{t}} \sum_{i \pounds (0)} \Lambda(\text{a}_{Dt}^{(0)} + \sum_{m=1}^{M} X_{itm} \quad {}_{tm}^{(0)} + {}^{-}{}_{i}^{(0)})] =$$

$$= \Delta DP + \Delta EO + \Delta EU \qquad (3.11)$$

Since probability is a non-linear function, both Equation (3.10) and (3.11) do not allow deriving exact decomposition estimates which implies that results might depend on the order in which decomposition is performed. To test whether this is the case, I also perform a reverse order decomposition, moving from period (1) back to period (0).

4. Results

4.1. Changes in the duration distribution of poverty episodes over time

Figure 4.1 below presents the cumulative duration distributions of poverty episodes for the 1984 and 2008 SIPP panels. The horizontal line crosses the distributions at the 0.5 point helping to identify the median duration of poverty episodes.

In both panels, the majority of people who fall into poverty remain poor for a relatively short period of time. For example, in the 1984 panel 50 percent of poverty episodes ended within 2 months after the beginning, additional 40 percent ended within a year and only 10 percent of poverty spells lasted for more than twelve months. While being relatively steep in the period immediately after the start of the spell, the distribution flattens at longer durations suggesting that the probabilities of exiting poverty decline as time in the spell elapses.

Turning to the curve for the 2008 panel, we can see that the median duration of poverty episodes has increased over time and reached the point between 3 and 4 months. Remarkably, that it is not only the proportion of very short poverty spells which has declined over time, but also the proportion of poverty episodes which end within the first 12 months. The share of such spells has declined from around 90 percent in the mid-1980s to 80 percent in the 2000s. Because of the overall decline in the cumulative probabilities of exiting poverty, the share of spells, which are still in progress after 30 months, has increased from 5 percent in the 1984 panel to 10 percent in the 2008 panel.

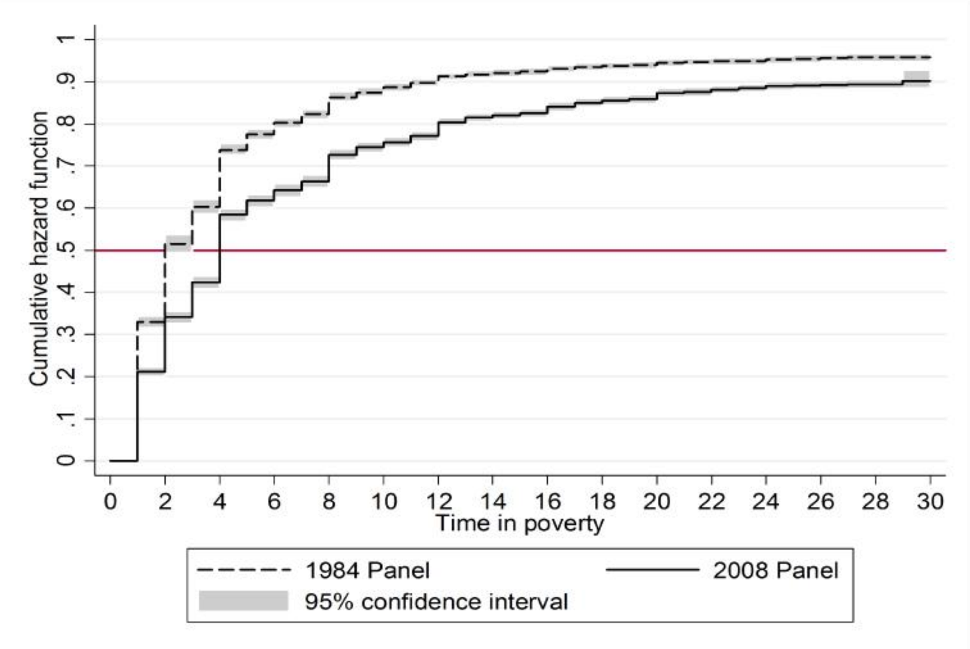


Figure 4.1. Cumulative distribution of uninterrupted poverty episodes by their duration

Note: weighted estimates. The upper limit of the CDF is not equal to one because of the small portion of spells lasting beyond 30 months. The confidence intervals are derived via the bootstrapping technique designed by Van Kerm (2013) which accounts for the complex survey design.

Figure 4.1 also shows that the duration distribution of poverty episodes for the 2008 panel lies below the distribution for the 1984 panel at all points. In addition, both distributions have very narrow and non-overlapping 95 percent confidence bounds. This findings suggest that poverty has become more persistent over time in the United States.

A closer look at Figure 4.1 reveals in which parts of the distribution the major shifts have occurred. More specifically, we can see that the largest decline took place in the lower tail of the distribution comprising spells with durations up to 3 months. For example, the probability that a poverty episode will last only one month dropped from around 33 percent in the mid-1980s to 21 percent at the end of the 2000s. The probabilities of having a spell of poverty ended within 2 and 3 months have dropped by more than 15 percentage points each. The difference in the cumulative distributions remains quite substantial up to month 12 and starts declining only at very large values of duration.

Table 4.1 below and Appendix A.3 quantify differences in the duration distribution of poverty episodes between the 2008 and 1984 SIPP panels. They provide both aggregate estimates for the entire sample and sub-group estimates for individuals with particular family characteristics.

Table 4.1. Differences in the duration distribution of uninterrupted poverty episodes between the 2008 and 1984 SIPP panels

	Mean duration	Median duration	At selected points of the cumulative hazard function			
			t=1	t=12	t=24	t=30
Total	+1.47	+1.161	-0.1178	-0.1087	-0.0619	-0.0567
Age of household head						
< 25	+1.61	+1.923	-0.1321	-0.1044	-0.0729	-0.0642
25-54 years	+1.72	+1.683	-0.1402	-0.1158	-0.0662	-0.0694
55-64 years	+1.32	+2.136	-0.0906	-0.1119	-0.0367	-0.0321
65+ years	+0.92	+0.186	-0.0061	-0.075	-0.0645	-0.0626
Sex						
Male	+1.73	+1.664	-0.1314	-0.1104	-0.0595	-0.0471
Female	+0.92	+1.146	-0.0795	-0.0833	-0.0466	-0.0468
Race						
Only white	+1.50	+1.513	-0.1160	-0.1012	-0.0553	-0.0461
Only black	+1.49	+2.223	-0.1236	-0.1654	-0.0890	-0.1029
Hispanic or Latino	+1.45	+1.470	-0.1280	-0.0936	-0.0758	-0.0731
Education						
Uncompleted high school	+1.85	+1.318	-0.0883	-0.1395	-0.0947	-0.0927
Completed high school	+1.67	+1.944	-0.1764	-0.1414	-0.0098	-0.1006
College or higher	+1.62	+1.553	-0.1265	-0.1027	-0.0464	-0.0444
Family types						
Single parent	+1.34	+1.985	-0.1425	-0.1530	-0.0932	-0.0812
Single	+1.33	+1.037	-0.0775	-0.0852	-0.0607	-0.0390
Couple	+1.72	+1.511	-0.1201	-0.0898	-0.0547	-0.0603
Other	-0.04	+1.090	-0.0842	-0.0665	-0.0101	-0.0015

Note: Longitudinally weighted estimates based on the 1984 and 2008 SIPP panels. All differences are statistically significant at 0.05 level. The significance level is defined accounting for the complex survey design. The median duration is calculated using interpolation method (see Singer and Willett, 2003).

Estimates in Table 4.1 show that the increase in the share of long poverty spells was not the same among all population sub-groups. Judging from the median duration, it was especially profound for single-parent families, for individuals living in families with the head of any age up to 65, and for members of the families headed by a black person or by a person with a completed high school education. In contrast, individuals living in single-person or other type of the families (typically multigenerational families), as well as those living in a family with the head being above 64 years old, have experienced a relatively small increase in the amount of time spent below the poverty line.

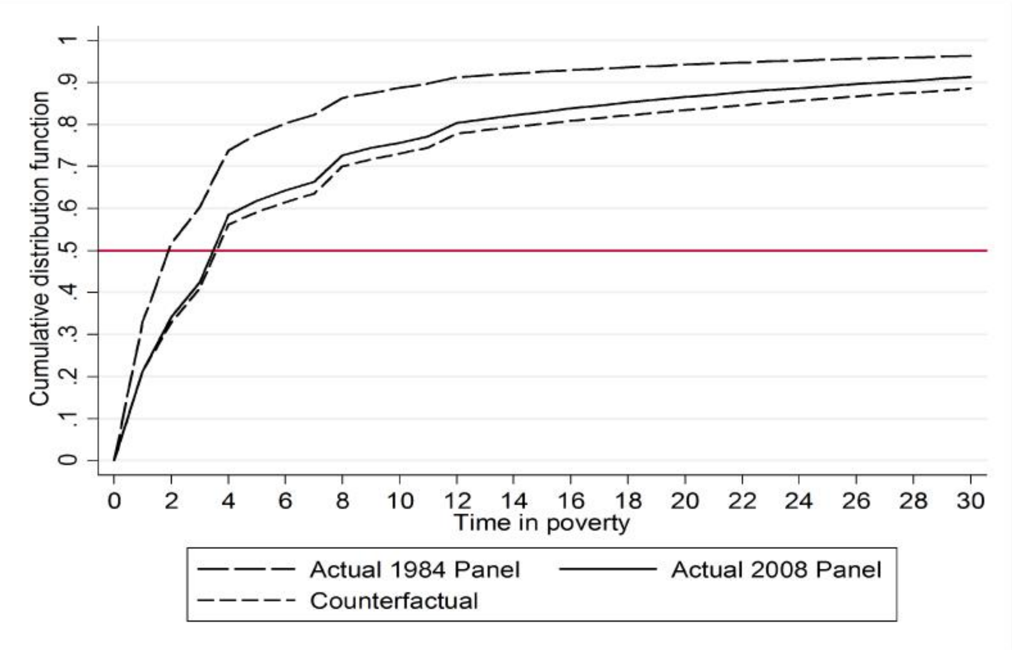
Another important finding from Table 4.1 is that for various population sub-groups changes in the duration distribution of poverty episodes are located in different parts of the distribution. For example, a disproportionally large decline in the lower tail of the distribution is observed for individuals living in single parent families, families where the head is below 55 years old, male, black or of Hispanic origin. For these subgroups the probability of experiencing a short poverty spell of 1 months dropped by 12-14 percent, as compared to the sample average of 11.7 percent. Whereas some of these sub-groups caught up with the sample average by month 12, others (like single-parent families and families headed by a black person) were still experiencing disproportionally large decline in the probabilities of having a spell completed. All in all, judging from the sub-group probabilities that a spell of poverty will end within any of the 30 months (the last column in Table 4.1), the duration of poverty has increased the most for single parent families and families where the head is black or has lower than college level of education.

4.2. Explaining the change in the distribution of poverty durations over time

In order to understand what underlies the observed changes in the duration distribution of poverty episodes, I perform further decomposition analysis aiming to partition the overall shift in the duration distribution of poverty episodes into a set of components capturing the contributions of changes in the composition of the poor and structure of poverty (returns to individual characteristics). I start this exercise by performing decomposition based on the model with the flexible specification of covariates (Equation 3.7) but without the control for unobserved heterogeneity. In the next step, I perform decomposition based on the more restricted model which, however, provides the advantage of capturing the contribution of unobserved heterogeneity (Equation 3.5).

Decomposition results: the model without unobserved heterogeneity

Figure 4.2 plots three duration distributions of poverty episodes: two actual distributions for the 1984 and 2008 panels, and one counterfactual distribution depicting how the distribution in the 2008 panel would have looked like if the composition of the poor had remained the same as in the 1984 panel. The contribution of the change in the composition of the poor to the overall shift in the duration distribution of poverty episodes can be defined as the vertical distance between the actual distribution for the 2008 panel and the counterfactual one. In line with Equation (3.10) the vertical distance between the counterfactual distribution and the actual distribution in the 1984 panel reflects the contribution of the change in the structure of poverty.



.

Figure 4.2. Aggregate decomposition of the change in the duration distribution of uninterrupted poverty episodes between the 1984 and 2008 SIPP panels

Note: Longitudinally weighted estimates based on the SIPP 1984 and 2008 panels.

Figure 4.2 shows that the change in the composition of the poor between the mid-1980s and late 2000s contributed to a decline in the proportion of long poverty spells. Had the distribution of covariates remained the same in the mid-2000s as it was in the mid-1980s, the persistence of poverty would have been even higher. The difference between the actual distribution for the 2008 panel and the counterfactual one becomes noticeable only for poverty spells lasting at least 4 months and remains stable throughout the rest of the distribution. Compared to the composition of the poor, changes in the effects of individual characteristics have induced a substantial increase in the duration of poverty. This increase is especially pronounced in the lower and middle parts of the distribution and becomes smaller in its upper part.

Figure 4.3 below quantifies the contributions of the changes in the composition of the poor and structure of poverty to the overall shift in the duration distribution of poverty episodes by depicting their magnitude at different values of duration.

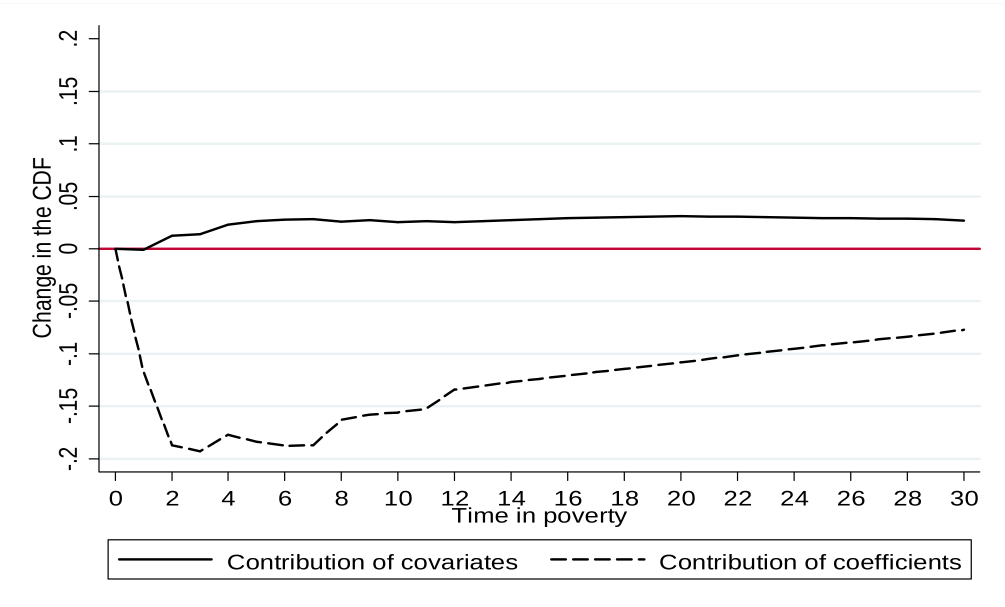


Figure 4.3. Changes in the duration distribution of poverty episodes induced by the shifts in the composition of the poor and poverty structure

Note: Longitudinally weighted estimates derived on the basis of Equation (3.10).

From Figure 4.3 follows that the change in the composition of the poor has shifted the duration distribution upwards. This implies that if the characteristics of the poor had not changed, the cumulative probabilities of exiting poverty at each duration would have been 2.5 percentage points lower in the 2008 panel than they actually was. In contrast, the contribution of the changes in the coefficients associated with these characteristics was not only negative but also substantially larger. Changes in the effects have especially affected the probabilities of having very short poverty spells lasting up to 7 months. From month 8 the size of the negative contribution started decreasing but remained at 7.5 percentage points even in the upper tail of the distribution. This implies that due to the change in the poverty structure, 7.5 percent more poverty spells were still in progress after 30 months in the 2008 panel compared to the 1984 one.

Figures A.1 - A.5 in the Appendix provide decomposition results separately for different population sub-groups, defined on the basis of each covariate. The advantage of this exercise lies in its ability (1) to capture relative differences in the changes of duration distribution of poverty episodes for various sub-groups and (2) to identify whether changes in the distribution of covariates or their effects were especially favorable / unfavorable for some of them.

In line with what has already been documented in Section 2, the largest increase in the duration of poverty is observed for individuals living in single parent families, as well as in the families where the head is 25-54 years old, black, or has only school education (completed or not). For these categories, there was an especially large decline in the probabilities of having a poverty spell with the duration below 9 months. The smallest increase, in turn, can be observed for individuals living in the couple-based families, or families with educated heads.

Regarding the contribution of the changes in the individual characteristics to the shift in the sub-group duration distributions of poverty episodes, it was favorable for all sub-groups, except of individuals living in the families with highly educated heads or where the head has completed a high school, for whom the effect is negligible in size. Similarly to the sample aggregates in Figure 4.3, the change in the coefficients is associated with an increase in the duration of poverty among all population sub-groups. Its contribution is especially large for single-person and single-parent families, and families with black or uneducated head.

Decomposition results: the model with unobserved heterogeneity

Figure 4.4 below presents the results of the aggregate decomposition based on the model with unobserved heterogeneity. The first glance at this Figure reveals that the contributions of the covariates and the structure of poverty to the overall change in the duration distribution of poverty episodes look very similar to the one in Figure 4.3. The only difference is that these contributions are slightly larger in the model where covariates are specified in the flexible way.

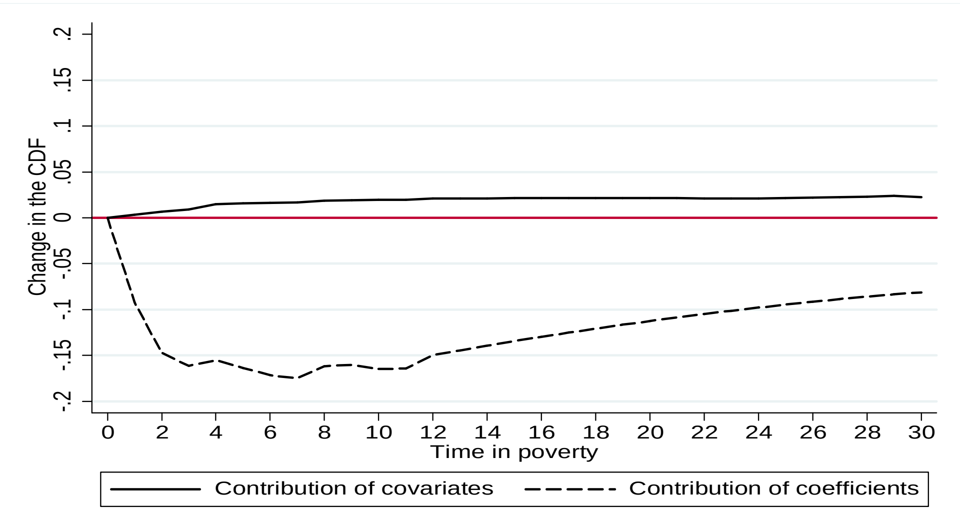


Figure 4.4. Aggregate decomposition of the changes in the duration distribution of poverty episodes based on the model with unobserved heterogeneity

Note: Longitudinally weighted estimates derived on the basis of Equation (3.10).

The main advantage of the model with the control for both observed and unobserved heterogeneity lies in its ability to partition the contribution of the structure of poverty intro three components attributable to the changes in duration dependence and changes in the effects of observed and unobserved characteristics. Figure 4.6 below provides the results of such decomposition.

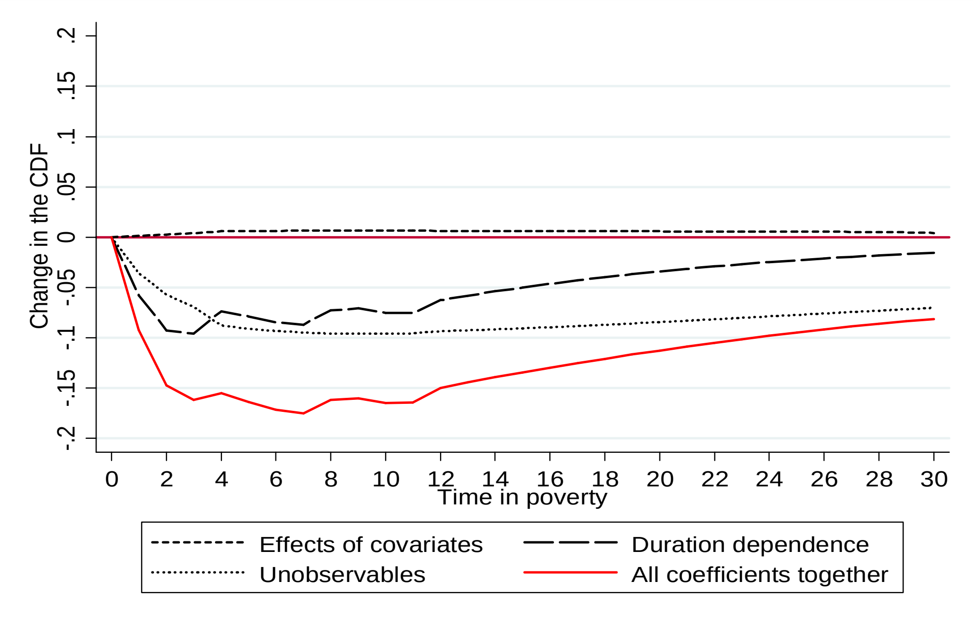


Figure 4.5. Contributions of the duration dependence, effects of observed and unobserved characteristics to the shift in the duration distribution of poverty episodes

Note: Longitudinally weighted estimates derived on the basis of Equation (3.11).

As we can see, the contribution of the change in the structure of poverty to the shift in the duration distribution of poverty episodes which we have observed so far, in fact, is driven by duration dependence and effects of unobserved characteristics. At the same time, the contribution of the effects of observed covariates is negligible in size and also positive. The increase in the duration dependence has had the largest influence on the cumulative probabilities of exiting poverty for individuals who have been poor up to one year. Those who experience long poverty spells also have been affected, but to a relatively small extent. Contrarily to duration dependence, the unfavorable change in the effects of unobserved characteristics has reflected on the duration distribution of poverty episodes more or less equally along the distribution, inducing 7 to 10 percent decline in the cumulative probabilities of exiting poverty.

4.3. Robustness checks

Figures A.6 and A.7 in the Appendix present the results of the reverse-order decomposition of the overall change in the duration distribution of poverty episodes between the 1984 and 2008 panels. In this version of decomposition, I first derive a counterfactual distribution that would have prevailed in the 1984 panel if all covariates had been distributed as in the 2008 panel. The difference between the actual distribution for the 1984 panel and the counterfactual yields the contribution of the changes in the composition of the poor to the shift in the duration of poverty whereas the difference between the counterfactual distribution and actual for 2008 defines the contribution of the change in the poverty structure.

By mirroring Figure 4.5 above, Figure A.6 shows that the reverse order decomposition does not substantially influence the results. In general, the contribution of the changes in the composition of the poor remains positive but somewhat smaller in size. Similarly, the contribution of the poverty structure remains negative with a slightly more pronounced impact on poverty spells lasting 2 to 4 month and less pronounced influence on the longer spells of poverty.

Figure A.7 in the Appendix also provides reverse-order decomposition for the detailed decomposition of the structure of poverty. Here, the general patterns remain the same as in Figure 4.6 signifying the reliability of the results.

4.4. Changes in the probabilities of poverty re-entry

Given that the poverty rate did not change much in the US between the early 1980s and late 2000s, one might expect that the increase in the duration of poverty episodes was ‘compensated’ by a decrease in their frequency. Figure A.8 in the Appendix confirms this assumption by plotting the difference between the duration distributions of non-poverty spells in the mid-1980s and late 2000s. It indeed implies that poverty has become less recurrent but more persistent in the United States over time.

5. Conclusions.

Using data from the SIPP, this paper explores how and why the duration distribution of poverty episodes has changed in the United States between the early 1980s and late 2000s. To do that, I construct the entire duration distribution of poverty episodes and decompose its change over time into the contributions induced by the changes in the composition of the poor and changes in the structure of poverty. The decomposition exercise is performed for two specifications of the model – one with the flexibly specified observed characteristics, and the other one with a more restricted specification of observed covariates but with the control for unobserved heterogeneity. For this, second, specification, I also perform a detailed decomposition. In particular, I further partition the contribution of the structure of poverty into three sub-components reflecting the contributions of duration dependence, the effects of observed individual characteristics and the effects of unobserved heterogeneity.

The results suggest that, albeit the official poverty rate was relatively stable in the US between the mid-1980s and late 2000s, poverty became more persistent. The increase in the persistence of poverty is driven by the decline in the probabilities of having very short poverty spells (1 to 3-month) with a subsequent increase in the probabilities of having longer spells, especially those lasting beyond 12 months. In addition, the increase in the duration of poverty differs by population sub-groups. I find that individuals living in single families, families where the head is young, black or uneducated person have experienced a disproportionally large increase in the amount of time spent below the poverty line compared to other population sub-groups.

The observed changes in the duration distribution of poverty episodes are induced by the changes in the structure of poverty rather than the characteristics of the poor. Looking inside the structure of poverty, I find that its contribution to the upward trend in the duration of poverty is mainly driven by the increased duration dependence and the enhanced effects of unobserved heterogeneity. At the same time, changes in the effects of individual attributes have contributed to the shift in the duration distribution of poverty episodes only to a minor extent.

Literature

Anderson, R.J. (2011). *Dynamics of economic well-being: Poverty, 2004-2006*. Current Population Reports No P70-123. Washington, D. C.: U.S. Census Bureau.

Blank, R. (2009). What we know, what we don't know, and what we need to know about welfare reform. In J. P. Ziliak (Ed.) *Welfare reform and its long-term consequences for America's poor.* Cambridge: Cambridge University Press, pp. 22-58.

Bane, M. J. and Ellwood, D. T. (1986). Slipping into and out of poverty: the dynamics of spells. *The Journal of Human Resources*, 21 (1), pp. 1-23.

Bollinger, C., Gonzalez, L., and Ziliak, J.P. (2009). Welfare reform and the level and composition of income. In J. P. Ziliak (Ed.) Welfare reform and its long-term consequences for America's poor. Cambridge: Cambridge University Press, pp. 59-103.

Bonjour, D. and Gerfin, M. (2001). The unequal distribution of unequal pay – An empirical analysis of the gender wage gap in Switzerland. *Empirical economics*, 26, pp. 407-427.

Cameron, A.C. and Trivedi, P.K. (2005). *Microeconometrics. Methods and applications.* Cambridge: Cambridge University Press.

Card, D. and Blank, R. M. (2008). The changing incidence and severity of poverty spells among female-headed families. *The American Economic Review: Papers & Proceedings*, 98 (2), pp. 387-391.

Chernozhukov, V., Fernández-Val, I. And Melly, B. (2013). Inference on counterfactual distributions. *Econometrica*, 81 (6), pp. 2205-2268.

Daly, M. C. and Valletta, R. G. (2006). Inequality and poverty in the United States: The effects of rising dispersion of men's earnings and changing family behaviour. *Economica*, 73, pp. 75-98.

Damioli, G. (2010). *How and why the dynamics of poverty differ across European countries*. Paper prepared for the 31st General Conference of the International Association for Research on Income and Wealth.

Dejemeppe, M. (2005). A complete decomposition of unemployment dynamics using longitudinal grouped duration data. *Oxford Bulletin of Economics and Statistics*, 67 (1), pp. 47-70.

Dejemeppe, M. and Saks, Y. (2005). *A new light into regional unemployment disparities in Belgium: Longitudinal analysis of grouped duration data*. IRES Discussion Paper 2002019. Universitè Catolique de Louvain.

DeNavas-Walt, C. Proctor, B. D., and Smith, J. C., U.S. Census Bureau (2013). *Income, poverty, and health insurance coverage in the United States: 2012*. Current population report No P60-245. Washington, D.C.: U.S. Government printing office.

Dickens, R. and Ellwood, D. T. (2004). Whither poverty in Great Britain and the United States? In Card, D., Blundell, R. and Freeman, R. B. (Eds.) *Seeking a premier economy: The economic effects of British economic reforms, 1980-2000*, pp. 313-369.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. *Econometrica*, 64 (5), pp. 1001-1044.

Donald, S. G., Green, D. A., and Paarsch, H. J. (2000). Differences in wage distributions between Canada and the United States: An application of a flexible estimator of distribution functions in the presence of covariates. *Review of Economic Studies*, 67, pp. 609-633.

Foresti, S. and Peracchi, F. (1995). The conditional distribution of excess returns: An empirical analysis. *Journal of the American Statistical Association*, 90 (430), pp. 451-466.

Fortin, N.M. and Lemieux, T. (1998). Rank regressions, wage distributions, and the gender gap. *The Journal of Human Resources*, 33 (3), pp. 610-643.

Gabe, T. (2012). *Poverty in the United States: 2011*. CRS Report for Congress.

Garner, T. I. and Short, K. S. (2010). Identifying the poor: Poverty measurement for the U.S. from 1996 to 2005. *The Review of Income and Wealth*, 56 (2), pp. 237-258.

Goldin, K. and Katz, L. F. (2009). *The race between education and technology*. Cambridge: The Belknap Press of Harvard University Press.

Hardy, B. and Ziliak, J. P. (2014). Decomposing trends in income volatility: the "wild ride" at the top and bottom. *Economic Inquiry*, 52 (1), pp. 459-476.

Heckman, J. and Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica*, 52, pp. 271-320.

Larrimore, J. (2013). Accounting for United States household income inequality trends: The changing importance of household structure and male and female labor earnings inequality. *Review of Income and Wealth*, 60 (4), pp. 683-701.

McKernan, S.-M. and Ratcliffe, C. (2005). Events that trigger poverty entries and exits. *Social Science Quarterly*, 86, pp. 1147-1169.

Meyer, B. D., Sullivan, J. X., Hoynes, H. W., and Hurst, E. (2012). Winning the war: poverty from the Great society to the Great Recession, *Brookings papers on Economic Activity*, pp. 133-200.

Ruggles, P. and Williams, R. (1989). Longitudinal measures of poverty: Accounting for income and assets over time. *Review of Income and Wealth*, 35 (3), pp. 225-243.

Sandoval, D. A., Rank, M. R., and Hirschl, T. A. (2009). The increasing risk of poverty across the American life course. *Demography*, 46 (4), pp. 717-737.

Singer, J.D. and Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence.* Oxford: Oxford university Press.

Shrestha, L. B. and Heisler, E. I. (2011). *The changing demographic profile of the United States.* CRP Report for Congress.

Stevens, A. H. (1999). Climbing out of poverty, falling back in: Measuring the persistence of poverty over multiple spells. *The Journal of Human Resources*, 34 (3), pp. 557-588.

U.S. Census Bureau (2001). *Survey of income and program participation users' guide*. Third edition. Washington, D.C.: U.S. Census Bureau.

Van Kerm, P. (2013). R*epeated half-sample bootstrap re-sampling.* Presentation given at 2013 London Stata Users' Meeting.

Appendix A

Table A.1. Changes in the socio-demographic structure of the US families between the mid-1980s and late 2000s, %

Individual characteristics	1984 Panel, %	2008 Panel, %	Difference 2008-1984
Age			
18-34	5.15	3.37	-1.78***
35-54	61.35	58.75	-2.60***
55-64	16.53	18.93	+2.4***
≥ 65	16.97	18.95	+1.98***
Gender			
Men	75.25	48.31	-26.94
Women	24.75	51.59	+26.94
Race and ethnicity			
Only white	83.68	76.21	-7.47***
Only black	10.39	10.99	+0.60
Hispanic or Asian origin	5.93	12.80	+6.87***
Family type			
Single parent	6.08	6.98	+0.9*
Single	14.93	22.49	+7.56***
Couple	71.87	61.04	-10.83***
Other	7.12	9.49	+2.37***
Education			
Uncompleted high school	28.56	12.30	-16.26***
Completed high school	32.38	23.46	-8.92***
College or higher	39.06	64.24	+25.18***
Monthly state unemployment rate	7.72	8.81	+1.09***

Note: Longitudinally weighted estimates based on the SIPP 1984 and 2008 panels. The differences are tested for statistical significance, accounting for the complex survey design in the SIPP.

* significant at 0.001 level, ** significant at 0.01 level, *** significant at 0.05 level.

Table A.2. Empirical and estimated poverty exit probabilities at different values of time spent in poverty

	At t=1							At t=6						
	Empirical	Fitted (1)	Fitted (2)	Fitted (3)	Fitted (4)	Fitted (5)	Fitted (6)	Empirical	Fitted (1)	Fitted (2)	Fitted (3)	Fitted (4)	Fitted (5)	Fitted (6)
Age														
< 25 years old	0.1891	0.1891	0.2009	0.2013	0.1850	0.1892	0.1997	0.801	0.0801	0.0708	0.0465	0.0647	0.0566	0.0602
25-54 years old	0.2193	0.2193	0.2202	0.2189	0.2183	0.2192	0.2177	0.0738	0.0738	0.0697	0.0633	0.0658	0.0663	0.0658
55-64 years old	0.2109	0.2109	0.2100	0.2070	0.2129	0.2106	0.2134	0.0371	0.0371	0.0551	0.0731	0.0633	0.0634	0.0643
> 65 years old	0.1664	0.1661	0.1494	0.1480	0.1749	0.1679	0.1655	0.0175	0.0175	0.0269	0.0590	0.0455	0.0489	0.0479
Gender														
Male	0.2128	0.2128	0.2133	0.2137	0.2164	0.2163	0.2193	0.0741	0.0741	0.0653	0.0664	0.0686	0.0655	0.0655
Female	0.2103	0.2103	0.2100	0.2071	0.2074	0.2074	0.2049	0.0545	0.0545	0.0618	0.0601	0.0590	0.0616	0.0607
Race														
Only white	0.2236	0.2236	0.2238	0.2200	0.2219	0.2212	0.2209	0.0635	0.0635	0.0647	0.0670	0.0665	0.0674	0.0673
Only black	0.1597	0.1597	0.1560	0.1675	0.1607	0.1599	0.1646	0.0316	0.0316	0.0445	0.0461	0.0476	0.0464	0.0478
Hispanic or Latino	0.2047	0.2047	0.2063	0.2048	0.2096	0.2123	0.2103	0.0885	0.0885	0.0744	0.0642	0.0664	0.0647	0.0637
Education														
Uncompleted school	0.1969	0.1969	0.1793	0.1792	0.1781	0.1790	0.1789	0.0602	0.0602	0.0551	0.0487	0.0539	0.0525	0.0525
Completed high school	0.1823	0.1823	0.1888	0.1860	0.1949	0.1962	0.1966	0.0628	0.0628	0.0638	0.0606	0.0609	0.0591	0.0591
College or higher	0.2313	0.2313	0.2353	0.2341	0.2329	0.2319	0.2317	0.0653	0.0653	0.0677	0.0722	0.0700	0.0718	0.0718
Family status														
Single	0.1891	0.1891	0.1954	0.1921	0.1918	0.1906	0.1912	0.0552	0.0552	0.0522	0.0523	0.0560	0.0564	0.0564
Single parent	0.1696	0.1696	0.1772	0.1783	0.1742	0.1737	0.1724	0.0483	0.0483	0.0497	0.0464	0.0448	0.0510	0.0506
Couple	0.2415	0.2415	0.2340	0.2312	0.2370	0.2367	0.2355	0.0752	0.0752	0.0729	0.0785	0.0745	0.0742	0.0737
Other	0.1916	0.1916	0.1985	0.2057	0.1984	0.2042	0.2010	0.0667	0.0667	0.0828	0.0625	0.0724	0.0624	0.0645

Note: Fitted (1) – the most flexible specification with 13 segments; fitted (2) – specification with 7 segments; fitted (3) – specification with 5 segments; fitted (4) – specification with 4 segments; fitted (5) – specification with 3 segments; fitted (6) – the most restricted specification with 1 segment. All estimates are based on the 2008 SIPP panel.

Table A.3. Changes in the duration distribution of poverty episodes between the 1984 and 2008 SIPP panels, by population sub-groups

		Mean	Median	t=1	t=12	t=24	t=30	Survived
Total	*2008*	6.33	3.076	0.2115	0.8037	0.8904	0.9008	0.0992
	1984	4.86	1.915	0.3293	0.9124	0.9523	0.9576	0.0424
	Difference	**+1.47**	**+1.161**	**-0.1178**	**-0.1087**	**-0.0619**	**-0.0567**	**+0.0568**
Age								
<25 years	*2008*	6.41	3.842	0.1891	0.7919	0.8859	0.9049	0.0951
	1984	4.80	1.918	0.3212	0.8963	0.9588	0.9691	0.0309
	Difference	**+1.61**	**+1.923**	**-0.1321**	**-0.1044**	**-0.0729**	**-0.0642**	**+0.0642**
25-54 years	*2008*	6.22	3.378	0.2193	0.8136	0.8965	0.8999	0.1001
	1984	4.50	1.695	0.3595	0.9294	0.9627	0.9693	0.0307
	Difference	**+1.72**	**+1.683**	**-0.1402**	**-0.1158**	**-0.0662**	**-0.0694**	**+0.0694**
55-64 years	*2008*	6.03	3.496	0.2109	0.8069	0.9164	0.9210	0.0790
	1984	4.71	1.360	0.3015	0.9188	0.9531	0.9531	0.0469
	Difference	**+1.32**	**+2.136**	**-0.0906**	**-0.1119**	**-0.0367**	**-0.0321**	**+0.0321**
65+ years	*2008*	7.44	3.854	0.1661	0.7274	0.8098	0.8117	0.1883
	1984	6.52	3.668	0.1600	0.8024	0.8743	0.8743	0.1257
	Difference	**+0.92**	**+0.186**	**-0.0061**	**-0.075**	**-0.0645**	**-0.0626**	**+0.0626**
Sex								
Male	*2008*	6.05	3.414	0.2129	0.8258	0.9110	0.9289	0.0711
	1984	4.32	1.75	0.3503	0.9362	0.9705	0.9760	0.0240
	Difference	**+1.73**	**+1.664**	**-0.1314**	**-0.1104**	**-0.0595**	**-0.0471**	**+0.0471**
Female	*2008*	6.55	3.526	0.2104	0.7849	0.8726	0.8780	0.1220
	1984	5.63	2.380	0.2899	0.8682	0.9192	0.9248	0.0752
	Difference	**+0.92**	**+1.146**	**-0.0795**	**-0.0833**	**-0.0466**	**-0.0468**	**+0.0468**
Race								
Only white	*2008*	6.12	3.360	0.2236	0.8210	0.9037	0.9166	0.0834
	1984	4.62	1.847	0.3396	0.9222	0.9590	0.9627	0.0373
	Difference	**+1.50**	**+1.513**	**-0.1160**	**-0.1012**	**-0.0553**	**-0.0461**	**+0.0461**
Only black	2008	7.18	4.613	0.1597	0.7105	0.8301	0.8301	0.1699
	1984	5.69	2.390	0.2833	0.8759	0.9191	0.9330	0.0670
	Difference	**+1.49**	**+2.223**	**-0.1236**	**-0.1654**	**-0.0890**	**-0.1029**	**+0.1029**
Hispanic or Latino	*2008*	6.31	3.471	0.2047	0.8064	0.8846	0.8878	0.1122
	1984	4.86	2.001	0.3327	0.9000	0.9604	0.9609	0.0391
	Difference	**+1.45**	**+1.470**	**-0.1280**	**-0.0936**	**-0.0758**	**-0.0731**	**+0.0731**
Education								
Uncompleted high school	*2008*	7.15	3.918	0.1969	0.7434	0.8299	0.8359	0.1641
	1984	5.30	2.600	0.2852	0.8829	0.9246	0.9286	0.0714
	Difference	**+1.85**	**+1.318**	**-0.0883**	**-0.1395**	**-0.0947**	**-0.0927**	+0.0927
Completed high school	*2008*	6.31	3.644	0.1823	0.7824	0.8701	0.8701	0.1299
	1984	4.64	1.700	0.3587	0.9238	0.9681	0.9707	0.0293
	Difference	**+1.67**	**+1.944**	**-0.1764**	**-0.1414**	**-0.0098**	**-0.1006**	**+0.1006**
College or higher	*2008*	5.91	3.243	0.2313	0.8384	0.9247	0.9355	0.0645
	1984	4.29	1.690	0.3578	0.9411	0.9711	0.9799	0.0201
	Difference	**+1.62**	**+1.553**	**-0.1265**	**-0.1027**	**-0.0464**	**-0.0444**	**+0.0444**
Family types								
Single parent	*2008*	7.03	3.965	0.1696	0.7166	0.8300	0.8504	0.1496
	1984	5.69	1.980	0.3121	0.8696	0.9232	0.9316	0.0684
	Difference	**+1.34**	**+1.985**	**-0.1425**	**-0.1530**	**-0.0932**	**-0.0812**	**+0.0812**
Single	*2008*	6.65	3.704	0.1891	0.7669	0.8625	0.8887	0.1113
	1984	5.32	2.667	0.2666	0.8521	0.9232	0.9277	0.0723
	Difference	**+1.33**	**+1.037**	**-0.0775**	**-0.0852**	**-0.0607**	**-0.0390**	**+0.0390**
Couple	*2008*	5.91	3.219	0.2415	0.8499	0.9188	0.9199	0.0801
	1984	4.19	1.708	0.3616	0.9397	0.9735	0.9802	0.0198
	Difference	**+1.72**	**+1.511**	**-0.1201**	**-0.0898**	**-0.0547**	**-0.0603**	**+0.0603**
Other	*2008*	5.98	3.606	0.1916	0.8141	0.9106	0.9192	0.0808
	1984	6.02	2.516	0.2758	0.8806	0.9207	0.9207	0.0793
	ifference	**+0.04**	**-1.090**	**-0.0842**	**-0.0665**	**-0.0101**	**-0.0015**	**+0.0015**

Note: Longitudinally weighted estimates based on the 1984 and 2008 SIPP panels. All differences are statistically significant at 0.05 level. The significance level is defined accounting for the complex survey design. For some subgroups, the longest poverty spells when they were observed were up to 28-29 months.

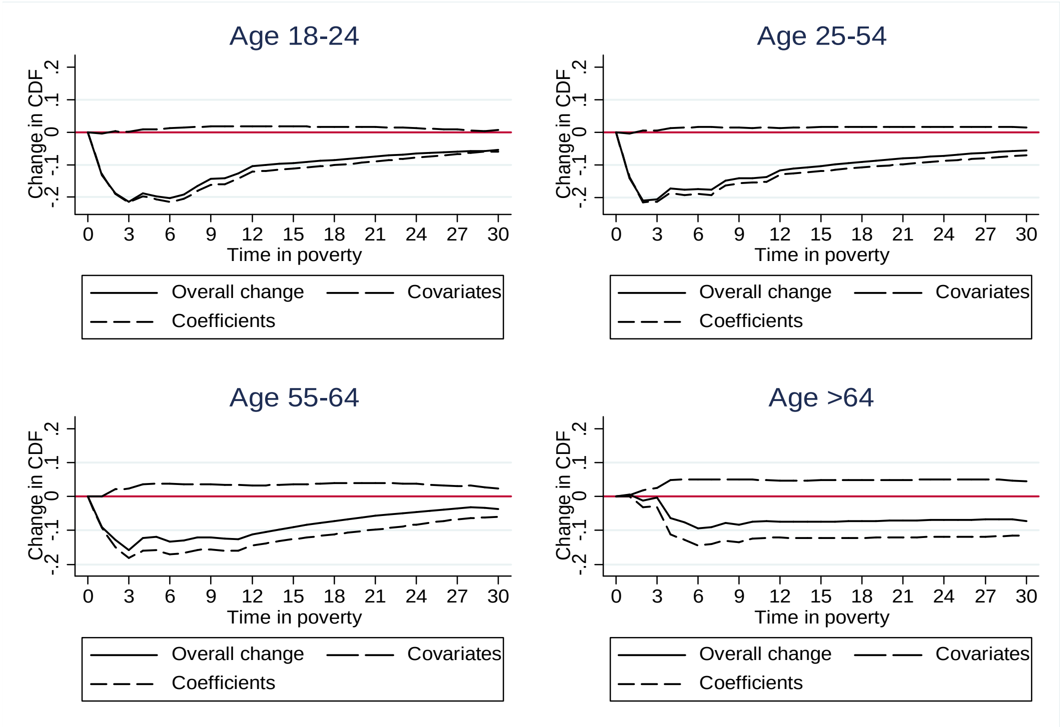


Figure A.1. Changes in the duration distribution of poverty episodes induced by the shifts in the composition of the poor and poverty structure, by age

Note: Longitudinally weighted estimates.

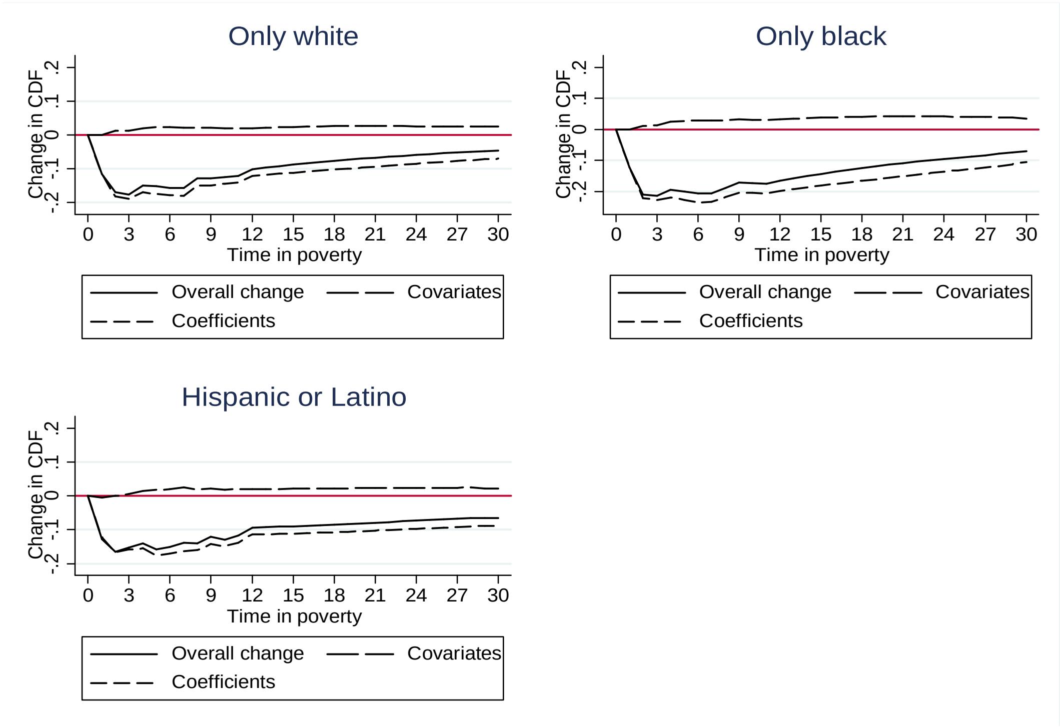


Figure A.2. Changes in the duration distribution of poverty episodes induced by the shifts in the composition of the poor and poverty structure, by race

Note: Longitudinally weighted estimates.

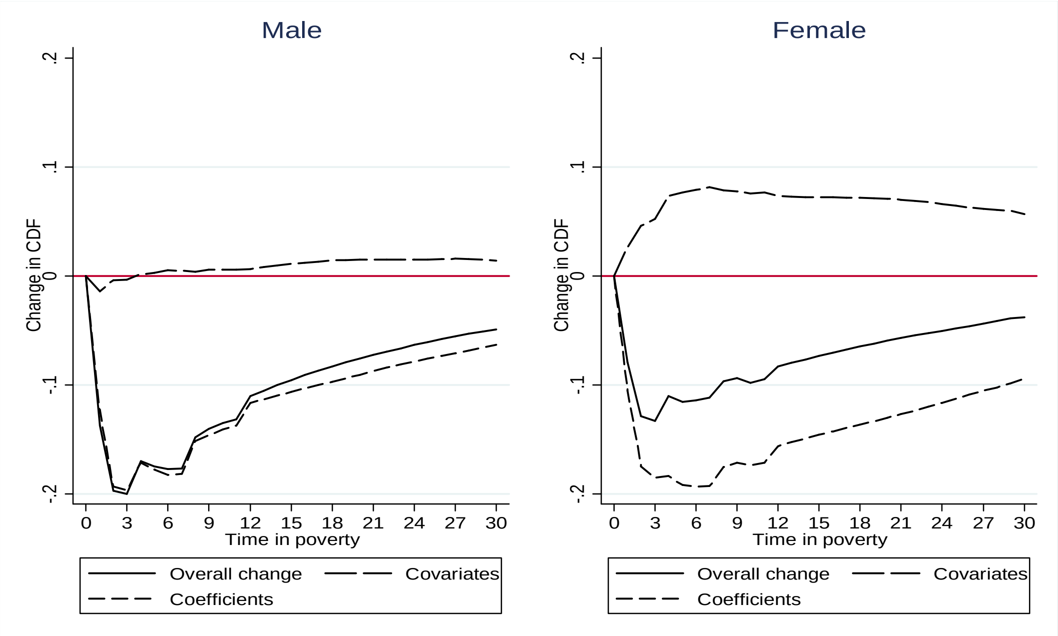


Figure A.3. Changes in the duration distribution of poverty episodes induced by the shifts in the composition of the poor and poverty structure, by gender

Note: Longitudinally weighted estimates.

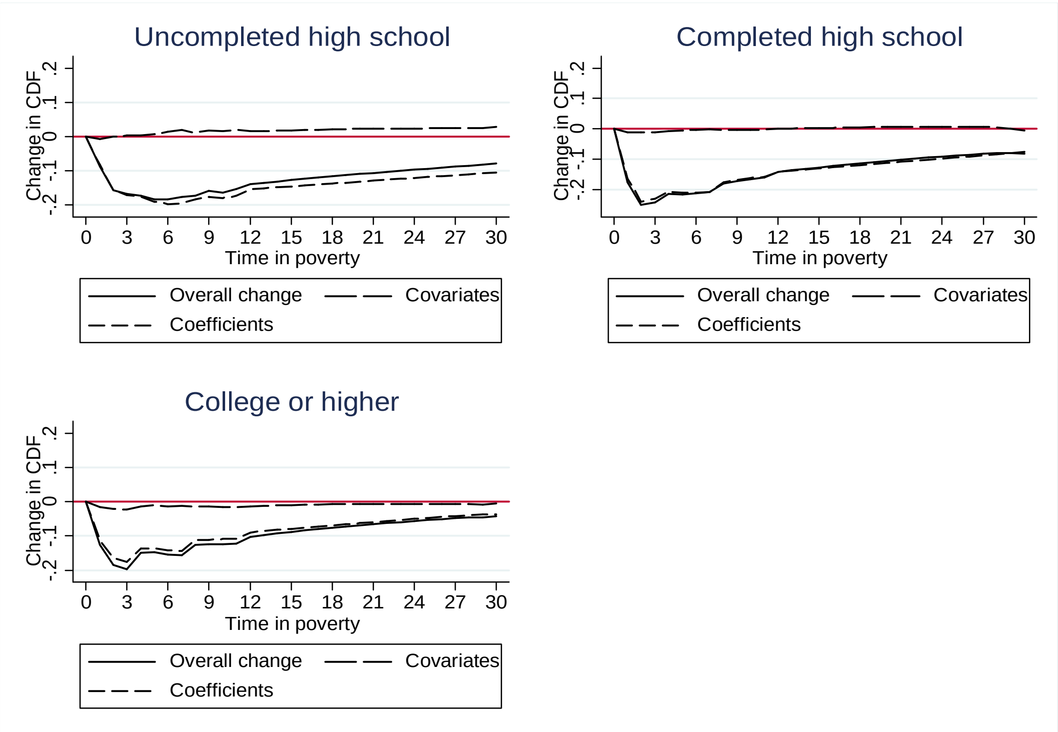


Figure A.4. Changes in the duration distribution of poverty episodes induced by the shifts in the composition of the poor and poverty structure, by education

Note: Longitudinally weighted estimates.

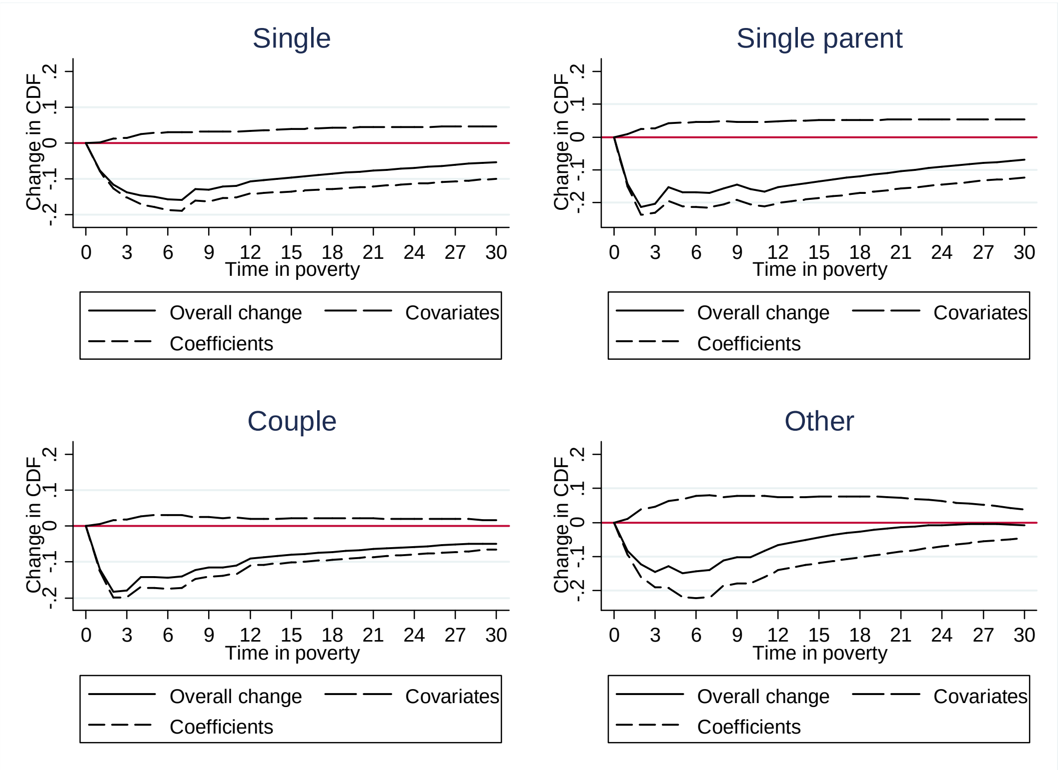


Figure A.5. Changes in the duration distribution of poverty episodes induced by the shifts in the composition of the poor and poverty structure, by family type

Note: Longitudinally weighted estimates.

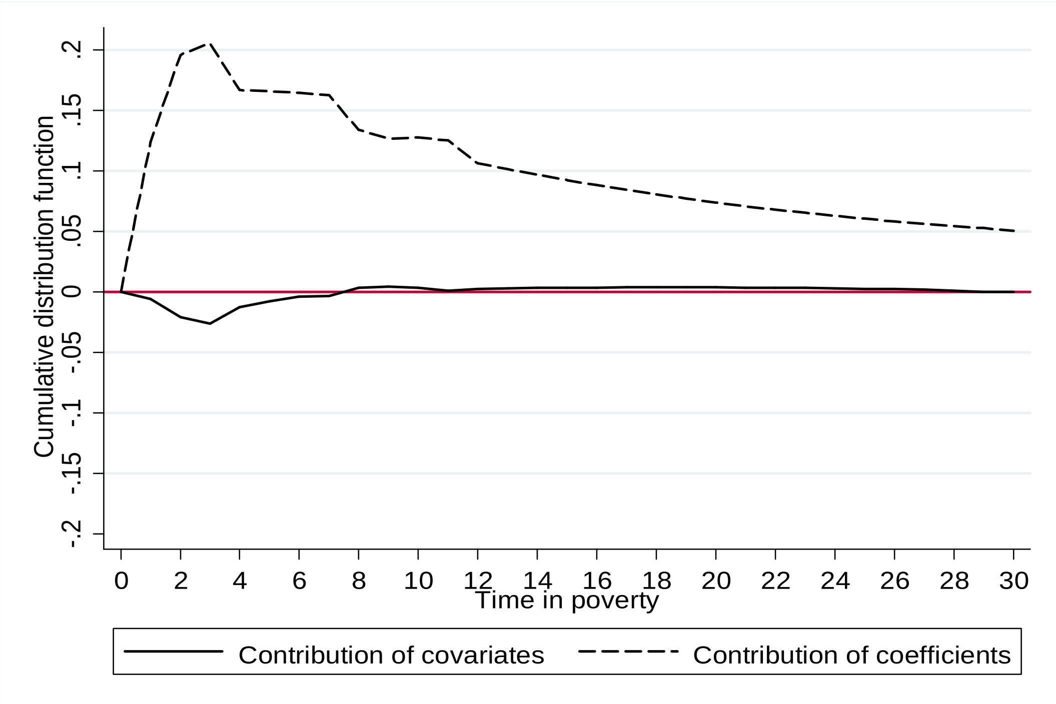


Figure A.6. Reverse order aggregate decomposition of the change in the duration distribution of poverty episodes (based on the model with unobserved heterogeneity)

Note: Longitudinally weighted estimates derived on the basis of Equation (3.10).

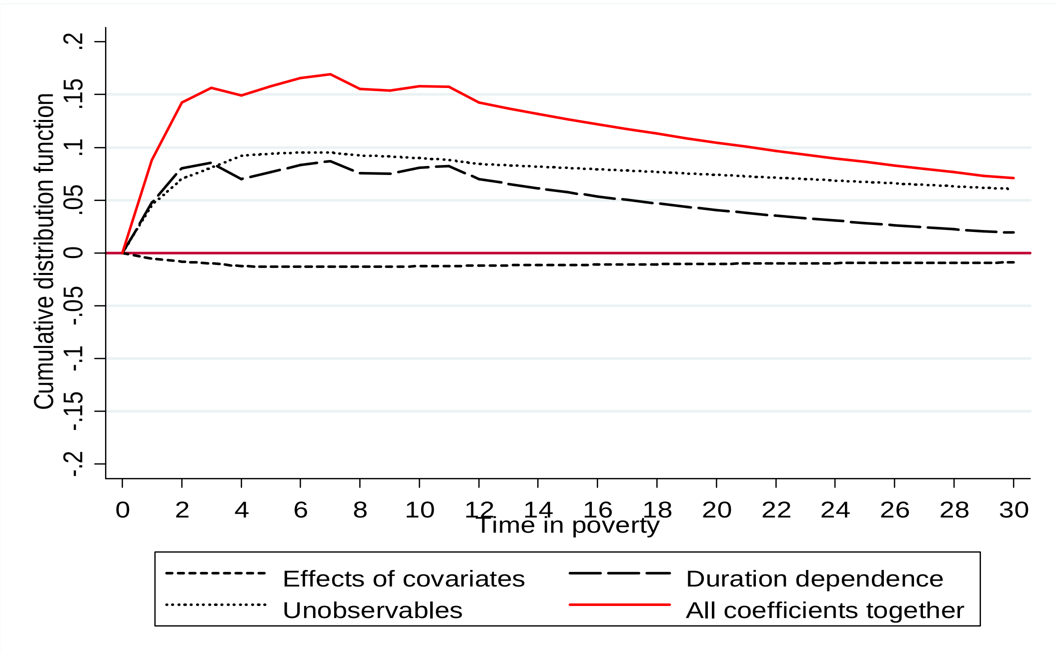


Figure A.7. Contributions of the duration dependence, effects of observed and unobserved characteristics to the shift in the duration distribution of poverty episodes (reverse order decomposition)

Note: Longitudinally weighted estimates derived on the basis of Equation (3.11).

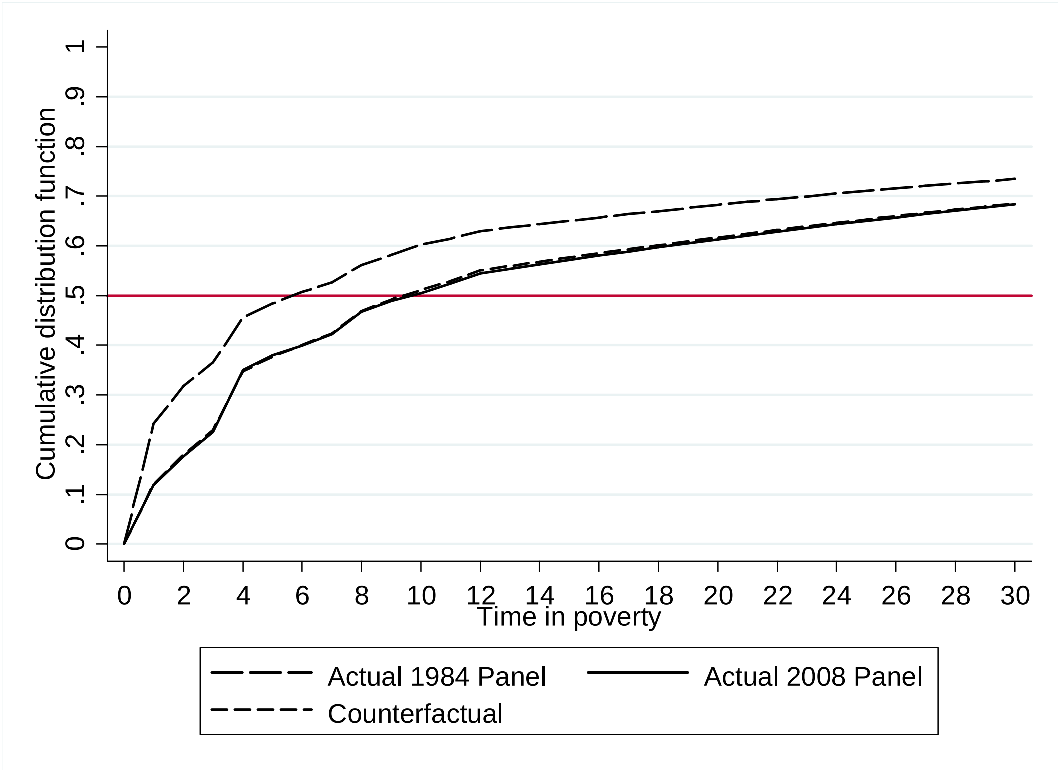


Figure A.8. Changes in the duration distribution of non-poverty spells

Note: Longitudinally weighted estimates.