FACULTY OF LAW, ECONOMICS AND FINANCE

Department of Economics and Managment

Discussion Paper

2020-16

Economics

Department of Economics and Management
University of Luxembourg

Poverty in Russia: the Role of the Marital Status and Gender

available online : https://wwwfr.uni.lu/recherche/fdef/dem/publications/discussion_papers

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Mai, 2020

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Poverty in Russia: the Role of the Marital Status and Gender *

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May 20, 2020

Abstract

Contrary to conventional thinking, this paper shows that divorced women exhibit lower levels of poverty than divorced men. We use data from the Russian Longitudinal Monitoring Survey (RLMS-HSE) for the period of 2010–2017. The result remains qualitatively invariant when considering assortative mating along education to alleviate possible endogeneity between divorce and poverty. Investigating an inter-related dynamic model of poverty and female labor market participation, we find that higher female labor participation partly explains why a divorce is harder on husbands than on wives.

Keywords: Divorce; Gender; Russia; Labor Market; Dynamic Bivariate estimation; Longitudinal Survey.

JEL classifications: I31; I32; J12; J16; J60.

1 Introduction

In this paper, we investigate the economic well-being of divorcees and married individuals in Russia, using the Russian Longitudinal Monitoring Survey for the period of 2010–2017.[1] Our purpose is to uncover what explains the differences in poverty levels between individuals who stayed married throughout the period of analysis and those who divorced before 2010 and stayed divorced throughout the entire period.

Two considerations drive our research interest. Firstly, the worldwide increase in divorce rates has brought divorce to the center of the analysis of well-being of individuals. In 2018, almost 50% of all marriages in the United States ended in divorce, with a divorce taking place every 13 seconds. It appears essential, then, to better understand whether there exist well-being differences between

*We thank Anastasia Litina and Simone Moriconi, for their insightful comments. The paper has benefited from presentation at the Gender and Economics Workshop at University of Luxembourg, 2019. Authors are grateful to their supportive partners who made research possible during the COVID-19 pandemic. The usual disclaimer applies.

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[1] Source: "Russia Longitudinal Monitoring survey, RLMS-HSE", conducted by the National Research University Higher School of Economics and OOO "Demoscope", together with the Carolina Population Center, University of North Carolina at Chapel Hill, and the Institute of Sociology of the Federal Center of Theoretical and Applied Sociology of the Russian Academy of Sciences. (RLMS-HSE websites: http://www.cpc.unc.edu/projects/rlms-hse, http://www.hse.ru/org/hse/rlms)

divorcees and married individuals. Are there any gender differences? Secondly, the country with the highest divorce rate is Russia (OECD, 2019). The crude divorce rate in 2015 in Russia was 4.2 divorces per 1000 residents (Rosstat, 2015).[2] This obviously makes the Russian case highly interesting.

The literature provides three approaches to measuring economic well-being: absolute poverty, which compares money income with subsistence level; deprivation, which measures how different individual consumption is compared to the average consumption in the reference population; and most recently, a subjective measure that explores individuals' perceptions of their economic condition. In the present paper, we use all these types of measures. In the benchmark estimation, we use income poverty as the outcome variable. We then run estimations using a multidimensional deprivation indicator that includes also subjective measures.

A crucial aspect of poverty is persistence. Prior literature has explored whether past poverty experiences determine current poverty status. For instance, poverty spells might result in depreciation of human capital that leads to low pay or longer unemployment spells, which ultimately increase poverty spells. However, the state-dependence usually observed in dynamic panel data models may also be attributed to sorting effects in the sense that the individuals who escape poverty may possess certain observed (e.g., education level) or unobserved characteristics (ability, social networks) and thus differ in a systematic way from the individuals who remain poor. To establish whether state dependence is genuine or an over-representation, we control for observed and unobserved heterogeneity, as well as the initial condition, in a dynamic model.

In our benchmark model, it is hard to claim that divorce causes poverty, despite the fact that in our data divorce has taken place years before the poverty level we are analyzing. Indeed, we cannot tell whether, a divorced individual is less poor than a married one, or whether, those who get divorced are the better economically endowed men and women. To tackle this problem, we would need exogenous variation in divorce that does not explain poverty. To the best of our knowledge, in Russia during the period under investigation, there were no changes in the divorce law that could allow proper identification. Any other IV strategy that points to individual characteristics will explain both poverty level and divorce. For this reason, we have decided to proceed differently. We estimate the probability of divorce when couples are assorted along the education level. More precisely, we proxy the quality of the match between spouses (and the thus the probability of divorce) using the level of education of the wife and the husband in married and divorce couples from 1995 to 2017. We then match married couples in the 2010–2017 sample to the probability of divorce corresponding to a specific educational assortative matching. Finally, we re-run our benchmark analysis using the probability of divorce and check how this explains poverty levels in married men and women.

Our main result can be summarized as follows. Controlling for unobserved heterogeneity and accounting for the initial conditions problem, we find that being poor is predominantly a trap, but less so for a divorced woman. Divorced women show less poverty than divorced men do during the period of 2010–2017. Considering the marginal effects, at mean values, a divorce woman is 11 percentage points less likely to be in income poverty than a divorced man and 12 percentage points less likely to be multidimensional deprived. This result holds when we consider the sample of married couples and account for the probability of divorce due to mate sorting. The higher the probability of divorce, the

[2]The US appears 6th in the world ranking.

higher the poverty level of married men, whereas the probability of divorce does not affect the poverty levels of married women.

Worldwide, women make up the majority of the poor due to the gendered division of assets, gender pay gaps, and cultural norms. As shown in our estimations, age, occupation, education level, presence of young children, urban vs. rural residency, and marital status are all key factors explaining female poverty. One would expect divorce to hit a female partner harder, which indeed appears to be the case in OECD countries. However, our analysis shows that this is not the case in Russia, where men suffer a larger loss of marriage premium than women do. Why is this the case?

An extensive body of research in economics (a seminal paper is Becker (1973)), sociology, and anthropology studies matching and sorting patterns in marriage markets. This literature has documented that marriages are not random but exhibit strong sorting patterns along various characteristics such as height, age, and above all, education level (Kalmijn, 1998). Historically in Russia, women have outnumbered men. Prolonged years of high rates of death among men in the 1990s and early 2000s further deteriorated this gender imbalance. In 2018, there were 78.8 million women and 68.1 million men in the country. The gender ratio over all ages is 1.156, whereas for the population aged over 70, this number reaches 2.38 (Rosstat, 2018). Couples marry very early, and women have a higher level of education on average. Our analysis of marital sorting for a very long period on a sample that is representative of the Russian population shows that almost 60% of divorced couples had spouses not assorted along the education level. In addition, 43.56% of divorces in the period of 1995–2017 occurred in couples where the wife had a higher education level than her husband. Only in 16.44% of the couples that divorced did the husband have more years of education than his ex-wife. Ultimately, as shown by our estimations, this means that divorce is more likely to cause harm to the husband than to the wife.

Continuing our exploration, we use a bivariate random effect estimation between poverty and status in the labor market to check whether female labor participation is the mechanism behind our result, beyond the matching pattern. Inter-related dynamics seems a natural step to take because labor market participation and poverty (and poor living conditions) are very often different faces of the same coin. Income from working crucially reduces the chance of falling under the poverty threshold. We model the two processes jointly in a discrete sequential equation model where we assume that the unemployment risk affects falling into poverty and vice versa. These bivariate estimations show that there is a strong and significant relationship between the risk of being poor and being unemployed, and this link evolves dynamically. Nevertheless, our main result remains unchanged and robust to the bivariate structure. It is true that divorced women work more than divorced men, but female labor market participation does not fully explain the difference in poverty level that remains in favor of women.

This paper is organized as follows. First, we position our paper in relation to the relevant literature. In Section 3, we uncover several characteristics of women in Russia in the labor market as well as in the marriage market. In Section 4, we describe the data we use for the estimation, providing some descriptive statistics. Section 5 is dedicated to the econometric analysis, which is followed by the exploration of the probability of divorce for married couples when taking into account the sorting of couples along education levels. In Section 6, we provide an analysis of the mechanism leading to our result using interrelated dynamic estimations. Section 7 offers some concluding remarks.

2 Related Literature

Various prior studies relate the deterioration of female economic conditions with marital disruption, both in the US (Duncan & Hoffman, 1985) and in several European countries (Uunk, 2004; Andreß *et al.*, 2006; Jarvis & Jenkins, 1999). It is argued that marriage gives support to the more socially disadvantaged partner, and it is this last who is particularly hurt by a divorce. In the overwhelming majority of cases in Western countries, the disadvantaged partner is the woman (Hogendoorn *et al.*, 2019). Sociological studies have long documented an abrupt decline in the living standards of women after divorce in Western countries. In his influential book "The Divorce Revolution", Weitzman (1985) reported a 73% decline in the living conditions of divorced women and a 42% increase in the living conditions of men in the USA. Things have changed considerably since Weltzam's book. Still, studies document women being, on average, more vulnerable to divorce in western European countries. Uunk (2004) analyzes the impact of welfare state arrangements after divorce in the European Union. He studies the change in (yearly disposable) income accompanying divorce for women in 14 EU countries for the years 1994–2000. Most women suffer economically from divorce, yet the income decline is larger in some countries than in others. Median income declines are weakest in southern European countries (Greece, Italy, Spain, and Portugal) and Scandinavian countries (Denmark and Finland) and strongest in Austria, France, Luxembourg, and the United Kingdom. Household-size and needs-corrected household income measures show a median income decline of 24% for European women from one year before marital separation to one year after marital separation. Andreß *et al.* (2006) claims that the most drastic income drop is experienced by women with children from countries with gender-specific division of labor in partnership. We bring new evidence that in Russia the exact opposite is true: it is ex-husbands who suffer more among divorcees.

Previous studies (Stewart & Swaffield 1999 or Cappellari & Jenkins 2004) document that poverty is persistent: the probability of being lowly paid depends strongly on low pay in the previous year.[3] Similarly, Finnie & Gray (2002) find that the probability of having a transition across different income quantiles is negatively correlated with the time period spent in a given quantile. Different reasons explain the poverty trap. For instance, the loss of human capital, the reduction of social and professional networks, as well as the decline in optimism or mental health are all factors that make poverty a long-lasting phenomenon.[4] In many previous studies, the feminization of poverty has been brought to the fore. The poverty trap is a larger issue for women. Nonetheless, in Russia we find that divorced women are more likely to break the persistence of poverty than divorced men. Another strand of prior literature related to our work is the one making a link between the material well-being of both partners immediately following a divorce. We clearly depart from this literature because we observe an extremely small number of marital status switchers in the benchmark sample. We rather

[3] A similar phenomenon occurs with unemployment spells. Extended periods of unemployment can lead to skill losses among workers, reducing human capital and lowering chances of exiting unemployment. However, the observed negative duration dependence in the exit rate proves to be present, but more spuriously, in unemployment studies (Cockx & Dejemeppe, 2005). Arulampalam (2001) examine unemployment dynamics for men using British data and accounting for unobserved heterogeneity. They find that there is strong state dependence, especially for older unemployed individuals. It appears evident that the individual poverty condition and the long-term unemployment risk are positively correlated.

[4] In addition, poverty can lead to low social mobility. Indeed, poor or materially deprived households are incapable of engaging in education investment for their children, raising the odds that children of poor families become poor adults.

have two large groups of people, married vs. divorced, who kept this status for the entire period.[5] It is worth reminding the reader that, in contrast to this literature, we do not focus on the reasons that lead to divorce. Our research interest is to explain the difference in well-being between married and divorced individuals while accounting for gender.

3 Women in Russia

In the following sections, we construct a picture of Russian women highlighting several aspects of the marriage market as well as female labor market participation.

3.1 The Marriage Market and Matching

Family and matrimony are institutions heavily affected by cultural norms that may be country-specific. The Russian Federation went through significant upheavals in the 20th century. Still, some features of the marriage market have remained unchanged. The age of entry into marriage by Russian females has remained young compared to US or European standards. In the United States, during the period of 1950–1960, the median age at marriage was 23 for men and 20 for women. In Western countries, a pronounced trend toward delayed marriage has emerged since the 1960s. In 2018, the median age at first marriage was almost 30 for men and almost 28 for women (U.S. Census Bureau, 2018).

According to Rosstat (2018), in Russia in the 1960s, 48.8% of women and 49% of men got married between the ages of 20 and 24 years. In the 1990s, the age distribution for women had not changed much: the mean age of women who got married for the first time was 20.8. Only in 2010 did Russia witness an increase in the median age of first marriage: the majority of marriages registered were for husbands and wives aged 25 to 29; from 2015 to 2017, the median age of first marriage for women was 25.3 and for men it was 27.4. However, despite this increase, the age of first marriage remains relatively young in contrast to Western trends.

In Europe and in the United States, a large set of factors has led to the current pattern of delayed entry into marriage. These include changing male and female employment opportunities, career-building, the growth of alternative formulas for cohabitation, and financial insecurity (Cherlin, 2004).

The age at entry into marriage has implications for the stability of marital unions. Numerous prior studies show that individuals who marry at a young age tend to be at a high risk of marital disruption (Lehrer, 1996; Teachman, 2002). The results of this literature are compatible with the very high rates of divorce in Russia.[6]

[5] Jalovaara (2003) uses matched census and administrative data from Finland and shows that Finnish women whose earnings exceeded their husbands' were significantly more likely to become divorced. Thielemans & Mortelmans (2019) studied female labor force participation after divorce using the divorce project in Flanders. The authors used a discrete-time hazard model to estimate the hazards of the first employment increase around the moment of separation. Censoring took place at the first event occurrence or after 4 years, whichever came first. Women were twice as likely to increase their employment for a short period of time after the separation. There was an increasingly negative relationship between employment intensity at the time of separation and the probability of increasing employment immediately afterwards. Observed differences between homemakers and unemployed women were likely due to compositional differences at the time of separation.

[6] Undoubtedly, divorce procedures have a great impact on divorce statistics. It is likely that liberal family laws are a

Females are more educated then men in Russia.[7] It is known that a high level of education for husbands translates into high economic resources that stabilize marriage, but whether the education level and resources of wives have a similar effect has long been debated among social scientists (see Lyngstad & Jalovaara, 2010, for a review).[8] Economists argue that female human capital can lead to divorce because it decreases returns to a gendered division of labor (Becker *et al.*, 1977). In addition, education helps reduce wives' financial dependence on their husbands. Nonetheless, it is unclear why wives' economic resources do not improve the family living standard and economic security and thus stabilize marriages. Indeed, the evidence is that educated women divorce less than women with lower levels of education in several societies today (Härkönen & Dronkers, 2006; Kalmijn, 2013; Matysiak *et al.*, 2014). This may seem to contradict the model and findings by Becker *et al.* (1977), but the two results are consistent once we consider matching in marriage. Educational assortative mating can strengthen the quality of a match, increasing the quality of the marriage (Bonke & Esping-Andersen, 2011). This is exactly what we find in the paper. In Russia, divorced women show a higher level of education than married ones, whereas divorced men reveal a lower level of education than married ones (see Table 2). This feature, together with the early age of marriage as well as the gender imbalance, suggests that the quality of matching in Russia may be a reason why divorce hits husbands harder than wives. Furthermore, as will be clarified in Section 5.2, the share of married couples in which partners have the same level of education amounts to 46.81% during the years of 1995–2017, whereas 60% of divorced couples are not assorted along education years.

3.2 Poverty and the Labor Market

The years immediately after the economic transition in Russia were accompanied by strong changes in society that clearly had repercussions on the labor market. Both males and females in Russia are employed, meaning that most of their prosperity is determined by wage earnings. Accordingly, to a large extent, wage has an effect on individuals' and households' standards of well-being and economic possibilities for investment in education. High employment in the presence of low wage floors is linked with a large number of low paid jobs. It seems that wages are a substitute for unemployment.

The presence of low-paid jobs was always large in the 90s and early 2000s, but it has declined over time. One recent study shows that the size of the low-paid group decreased from 30% of total employment in 2002 to 24% in 2016 (Gimpelson *et al.*, 2018). These rates are markedly higher than the average for EU countries (17%). The chances of being low-paid are significantly higher for workers with lower levels of education and skills and for those residing outside large cities.

The labor market in Russia has inherited several characteristics from its communist past. During the USSR period, gender equality was at the top of the political agenda. Several initiatives, not

crucial factor accounting for Russia's appalling divorce rate. These laws make divorce inexpensive (190–400 US dollars) and fast (within weeks) as compared to some EU countries such as Italy, for instance, where both the time needed to get a divorce and the costs are very high. However, one may argue that these laws are a consequence of social norms that determine the age of getting married rather than vice versa.

[7] This is documented in Table 2 for our database.

[8] Moreover, Joerg *et al.* (2016) argue that female human capital that was developed in the Polish–Lithuanian Commonwealth and other eastern European countries (including Russia) was based in a specific human capital indicator, numeracy. Their study shows that this ability had important impacts on a series of outcomes like nutrition and geography, but most importantly, on female autonomy.

only in Russia but in several eastern countries, were implemented to boost female labor participation.[9]

Since those times, Russia and other eastern European countries (Ukraine, Poland, Romania, etc.) have had comparatively high labor force participation rates among married women. Russian employment levels are above the OECD average, and the female employment rate is on the rise and amongst the highest in the world. Female employment levels in Russia exceed those of males in some European countries (e.g., in southern Europe). Such high rates hold despite the country's rather early retirement age (55 and 60 years for women and men, respectively)[10].

4 Data and Summary Statistics

In this section, we describe our data source and present summary statistics for dependent variables and relevant control covariates.

4.1 Data

Our data come from the Russian Longitudinal Monitoring Survey conducted by the Higher School of Economics (RLMS-HSE). We explicitly define all variables used in our study in Appendix 1.2 and provide summary statistics in Table 1. The RLMS-HSE collects information for a nationally representative sample of households across the Russian Federation.[11]

The survey provides micro-level data on households and individuals. The household is the unit of observation in the survey. In addition to the household questionnaire, each member of the household is asked to fill an individual questionnaire (either an adult or a child questionnaire). The survey comprises 25 rounds conducted from 1992 to now, with the target sample size of 4000 households per year.

We focus on the period of 2010 to 2017. This restriction is due to the requirement of a balanced panel for the dynamic regressions. This period allows the longest balanced panel that maximizes the number of divorced individuals followed throughout the 7 years. For the purpose of our estimation, we limit the sample individuals to those with consecutive observations in the panel (t, $t+1$, $t+2$, ...) and a one-year lagged observation ($t-1$). The latter is necessary because of the dynamic nature of the specification. Furthermore, in order to ensure a good level of representativeness at the country level, we construct a representative balanced panel starting from 2010. We take individuals who are included in the representative sample in 2010 and add observations for these individuals for the years of 2011–2017. We do not use post-stratification weights, following the suggestion of Heeringa & Arbor (1997) regarding the use of weights in multivariate analyses with fixed effects.[12]

[9]For instance, Murphy & Telhaj (2019) argue that in 1967, Albania became the first country in the world to fully ban religion. Archive documents show that the Communist Party Bureau leaders took such a decision to increase the labor participation of women, who were held back from working due to religious norms.

[10]In 2019, the retirement age was increased from 55 to 60 for females and from 60 to 64 for males in Russia

[11]The RLMS-HSE is conducted by the National Research University Higher School of Economics and OOO "Demoscope", headed by Polina Kozyreva and Mikhail Kosolapov, together with the Carolina Population Center, University of North Carolina at Chapel Hill, headed by Barry M. Popkin, and the Federal Center of Theoretical and Applied Sociology of the Russian Academy of Sciences.

[12]In RLMS data, the household characteristics that explain the greatest variation in weights are geographic region and urban/rural area, based on the administrative division in which the dwelling is located. Variation in individual weights

After dropping observations with missing crucial information, the balanced dataset comprises 1951 individuals, of whom 1536 stayed married for the 8 years and 144 stayed divorced throughout the period, for a total of 13,657 person-year observations.[13]

We measure material well-being with the individual's total income, which includes salary, pensions, bonuses, profits, benefits, material aid, odd jobs, and other cash receipts.

4.2 Poverty Indicators

We consider income poverty as well as multidimensional deprivation. An individual is defined as income-poor if his/her total reported income is less than the minimal vital income. The minimum vital income is fixed by the Russian government at the regional level and is calculated on the basis of the price of a consumer basket in each region. In order to capture the multidimensional nature of poverty, we define an individual as "multidimensionally poor" if he/she is deprived in at least one dimension: economic, material, or health.[14]

At first, to draw the poverty line, we use the official poverty threshold, i.e., a minimum vital income, issued by the Russian Statistical Office. Costs related to non-grocery-good items and utility payments are also included in the minimum vital income. If the individual's total income is less than the minimum vital income, then the individual is considered poor and acquires the right to ask for the vital income. The government defines three different thresholds for the minimum vital income: one for adults, one for children, and another for retired individuals.

Using this poverty threshold in our sample, we have 1203 individuals classified as "never poor" during 2010–2017 and 255 who were considered poor during the whole period. Out of this, we recognize a gender poverty gap between females and males, with 27% of females and 16% of males being under the poverty income threshold, as shown in Table 1.

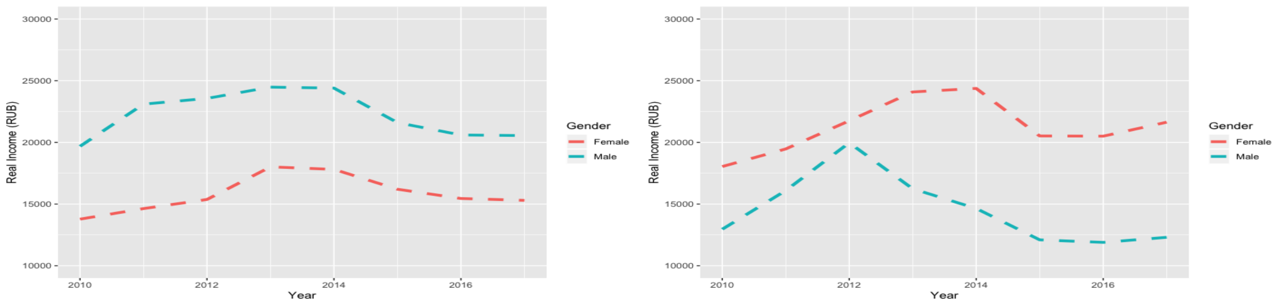
The development economics literature that focuses on poverty argues that total income is not the only indicator of poverty. Multidimensional poverty measures can be used to create a more comprehensive picture. These measures reveal not only who is poor but also how individuals are poor, showing the range of different disadvantages. A poor individual can suffer multiple disadvantages at the same time, such as poor health or malnutrition, lack of clean water or electricity, poor quality of work, or no schooling.

To capture these multidimensional aspects, we build an indicator of multidimensional poverty. The structure of this variable can be found in Appendix A1.4. To develop this index, we follow Alkire *et al.* (2014). More specifically, we use a dual-cutoff method proposed in Alkire & Foster (2011). The variables consist of 3 dimensions: economic, living conditions, and health. The economic dimension includes income poverty and work intensity. An individual is considered deprived in work intensity

will reflect geographic effects for households as well as differentials due to post-stratification of the sample by major geographic region, age, and sex.

[13] There were only 26 individuals who experienced a marital change during the years under study; therefore, we could not conduct an analysis using the switchers.

[14] We also include self-evaluation of economic conditions in the multidimensionality of the poverty indicator by considering the negative answer to the question "*Do you or your family have the opportunity, if you wish, to make a big purchase?*" and "*Are you concerned about providing yourself with the most necessary things in the next 12 months?*" Respondents were considered deprived if they answered "very concerned".



(a) All Individuals

(b) Divorced Individuals

Figure 1: Real-income dynamics by gender

if he/she works more than 8 hours per day, on average. Deprivation in living conditions is reflected by the material deprivation variable (list of variables in Table A1.3). Paying attention to what is considered vital for a Russian household, we take into account the possession of several items such as central sewerage, mobile phone, microwave, refrigerator, hot water, color TV, a dacha[15] and availability of regular meals. We also control for questions about perceived economic well-being: whether an individual has the ability to make big purchase and whether they can provide themselves with the most necessary things over the next year.

The health dimension includes 3 variables: self-evaluated health conditions, chronic disease, and the answer to the question "*Have you rejected medical help because of a lack of money in the last year?* Each of the three dimensions is equally weighted (1/3). Finally, an individual is considered multidimensionally poor if she/he is deprived in at least one dimension or the equivalent sum of the weighted deprivations.

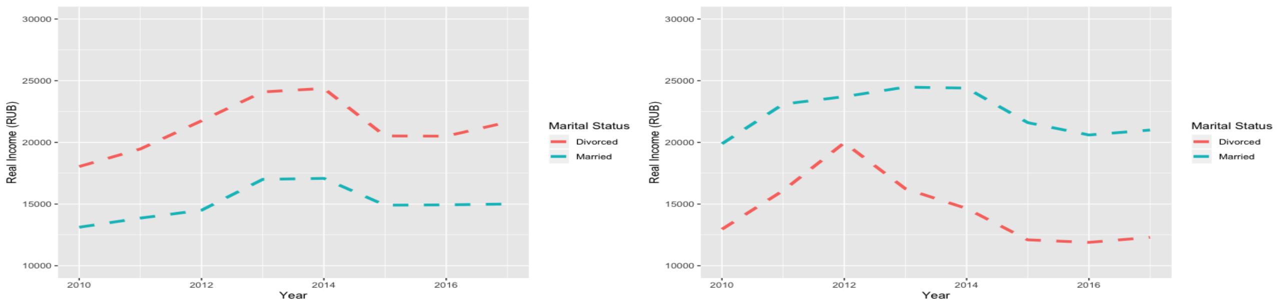
The multidimensional poverty indicator shows a different picture of well-being in Russia. When using multidimensional poverty, we have 513 individuals who were not poor, 823 individuals who were deprived for the entire period, and 370 individuals who changed status, either upward or downward. With respect to this indicator, there are no gendered differences; 59% of both males and females were multidimensionally poor, as shown in Table 1.

Finally, to highlight some relevant income differences in our database, we build the following graphs. Figure 1a and Figure 1b display, respectively, the median real income for women and men for the years of 2010–2017 and the median real income for divorced women and men. Men have almost twice as much income, but divorced women exhibit, on average, 6338 rubles more in income than divorced men. Considering men and women separately, Figure 2 shows that divorced women outperform married women, whereas divorced men do worse than married ones.

4.3 Summary Statistics

Table 1 provides summary statistics regarding our outcome and main explanatory variables. Controls include marital status, age, gender, presence of children under 18 years of age, education level, self-evaluated health status, geographical position, and income. Our sample is composed of 1119 women

[15] A dacha is sort of a country house used only during the summer period and poorly equipped.



(a) Female (b) Male

Figure 2: Real-income dynamics by marital status

and 832 men. This gender imbalance is representative of the Russian population.[16]

The first two columns display sample averages and standard deviations for females, whereas the other two report information about male participants. Divorced females are represented by a higher percentage (13%) as compared to divorced men (4%), and these shares are representative of the Russian population. In terms of average age, we observe a slightly younger female sample, whereas with respect to education level, there is clearly a gender difference. Males more often report elementary and secondary education compared to females. Instead, females represent a higher percentage of technical and higher education. These summary statistics provide insight into a positive (female) gender gap with respect to education in Russia. In addition, women are slightly more present in urban areas. There is quite a large difference between retired men (11%) and women (25%) due to the different life expectancies between genders in the Russian Federation. In terms of employment rate, females are still less employed than males and possess less working experience in years. There are no gender differences in terms of health status, especially for very good or bad health.

5 Empirical Analysis

To uncover the dynamic differences between married and divorced individuals in the Russian Federation, we estimate a random effects model applied to the period of 2010–2017 with poverty (or multidimensional poverty) as the outcome variable. Our ultimate interest is to highlight the difference between divorced and married individuals.

Our benchmark specification considers as the outcome variable different measures of poverty as defined in Section 4.2. In regards to the control variables, we include variables capturing observable characteristics of individuals (gender[17], age[18], residency, education, health[19], etc.) so as to control for the observed heterogeneity among individuals, but also time and regional dummies.

At least three main sources of endogeneity must be tackled in our endeavor to identify causal

[16]Russian National Statistics Office:https://eng.gks.ru

[17]There is a large literature that provides evidence of gendered differences in poverty levels.

[18]We control for age since the link between health and unemployment is especially relevant for older workers, seeing as health deteriorates with age.

[19]The nature of the relationship between poor health and non-employment is well established in the literature. Poor health is one of the key determinants of labor market inactivity and an important factor driving individuals out of work and reducing their probability of entry into employment (Kalwij & Vermeulen, 2008).

effects of marital status on poverty. We have an issue of reverse causality between poverty level and divorce. To tackle this problem, we make use of matching methods to determine the probability of divorce. We postpone the discussion and the analysis of this type of endogeneity until Section 5.1 of the paper. Two further econometric issues may bias our empirical specification: individual unobserved heterogeneity and the initial condition problem. Controlling for unobserved heterogeneity is a fundamental challenge in empirical research because a large set of individual characteristics are not observable and this may impact the outcomes. If these factors are correlated with the variables of interest, then without taking into account proper corrections, omitted variables bias the estimated parameters, precluding causal inference. One possible way to account for unobserved heterogeneity in a panel setting is to include individual fixed effects (Cameron & Trivedi, 2005). We account for the panel dimension of the data by using individual random effects. Given our model specification in Section 5.1, where we include lagged dependent variables, we perform a random effect estimation, assuming that unobserved heterogeneity is constant over time and is correlated with the independent variable.[20]

Furthermore, the dynamics of our dataset brings us to another econometric issue: the initial condition problem, which goes back to the seminal work of Heckman (1987). Arulampalam *et al.* (2000) stress that in order to disentangle the effect of state-dependence from unobserved heterogeneity, the initial conditions need to be modeled instead of assumed as exogenously given because the initial conditions may be correlated with the unobservables. Contextualized in our setting, initial conditions refer to the fact that those who are materially deprived or below the poverty threshold in the first year of the analysis, i.e., 2010, are not randomly selected, implying that the sample from the first year of the survey may be a non-random sample of the Russian population. The problem of initial conditions has been previously analyzed in the poverty literature, but we stress the role of marital status for both partners. To alleviate the initial condition problem, we follow Wooldridge (2005), who proposes a solution for the problem of endogeneity of the initial conditions while controlling for unobserved heterogeneity at the same time. He suggests using a joint density distribution conditional on the strictly exogenous variables and the initial condition, instead of attempting to obtain the joint distribution of all outcomes of the endogenous variables. For a binary models such as ours, the main advantage of this method is that it can be applied easily using standard random-effects software.

5.1 Empirical Specifications

5.1.1 Baseline Estimation

Our benchmark empirical model measures the dynamic evolution of individual poverty. We run a probability random effect regression where $Y_{i,t}$ represents the poverty of individual i at time t:

$$\begin{aligned} poor_{i,t} =& \lambda poor_{i,t-1} + \gamma_1 Divorce_{i,t} + \gamma_2 Female_{i,t} + \gamma_{12} Divorce_{i,t} \times Female_{i,t} + \\ & \beta x'_{i,t} + \psi z'_i + \phi poor_{i,1} + \delta \bar{x}'_{i,t} + \alpha_r + \alpha_t + \alpha_i + u_{i,t}. \end{aligned} \tag{1}$$

The dependent variable $poor_{i,t}$ takes a value of one if individual i is below the threshold of

[20] Being aware of dynamics in poverty, we have opted for a dynamic random-effects model to control for lagged dependent variables, rather than a panel fixed-effect model. We have also run a simple logit FE model without lagged poverty, but the results hint to the same direction.

poverty in time t and zero otherwise. The variable *Divorce* captures the marital status and takes a value of one if the individual is divorced. The vector β represents time-variant parameters of interest, such as age, experience, household size, etc., and z_i is the vector of time-invariant parameters. We include individual random effects, captured by the variables α_i, as well as year dummies α_t and regional dummies α_r. To control for the initial conditions, we include the variable $poor_{i,1}$ and longitudinal means of time-variant variables $\bar{x}_{i,t}$.

The average marginal effects of the estimation are shown in Table 3.[21] Results for multidimensional poverty are in Table 4. The coefficients for the lagged poverty status and initial poverty are significant at a 99% level of confidence, implying that the effect of state dependence is present and strong. Women are 9 percentage points more likely to be poor, and poverty is state-dependent. The coefficient of divorce is not significant. Nonetheless, the marginal effect of the intersection term "Divorce × Female" is significant and predicts that a divorced female is 11 percentage points less likely to be in income poverty.

Given the nature of our research question, we report only marginal effects for the coefficient of interest, female, divorce, and the interaction between the two. Nevertheless, we can see from the output Table 3 that age, education, and living in an urban area negatively impact the probability of becoming poor. Instead, household size and having children increase the probability of becoming poor.[22]

Table 4 instead provides the results of the univariate estimation when multidimensional poverty is the outcome variable. The effect of the interaction coefficient between female and divorce variables is significant and negative, suggesting that divorced women are 12 percentage points less likely to become multidimensionally poor.

5.2 Mating and the Probability of Divorce

In our benchmark model, we cannot claim causality between divorce and poverty despite divorce having taken place in the past and looking at years of poverty after divorce. Indeed, we cannot tell whether a divorced individual is less poor than a married one or, rather, whether those who get divorced are better economically endowed men and women.

To tackle this problem, we would need exogenous variation in divorce that does not explain poverty. To the best of our knowledge, in Russia during the period under investigation, there was no change in the divorce law that could allow proper identification. Any other IV strategy that points to individual characteristics affects both poverty level and divorce. For this reason, we have decided to proceed differently and investigate the married couples in our sample. Our aim is to check how the probability of divorcing, properly defined, affects the poverty of married individuals. To be able to construct this probability, we extrapolate information about the quality of the match in married couples and divorced ones, where quality is determined by educational sorting. To do so, we estimate a probability of divorce determined by the education assortative mating of couples, using data from 1995 to 2017 to expand the number of divorcees we can trace. Then finally, we match this estimated probability of divorce to married couples in our sample from 2010–2017, using educational sorting as

[21] See Appendix A1 for the marginal effects calculation of the model.

[22] The marginal effects of control variables are available upon request.

the criterion for the match.

We describe the method in detail below. We start with the estimations of the probability of divorce, and then we present the results of our benchmark analysis using this estimated probability.

5.2.1 Probability of Divorce

Being aware of the endogeneity issue of reverse causality, we look at the quality of the marriage as an indicator of future divorce. The probability of divorce may be due to multiple reasons (observed and unobserved) but one reason is certainly the quality of the marriage. One possible way to detect the quality of a marriage is to check the mating of couples along education levels, through assortative matching as in Eika *et al.* (2019).[23] Our basic idea is to check the characteristics of divorced couples, and in particular, to sort out their level of matching along education levels. Based on this information, we then try to estimate a probability of divorce for married couples with the same matched characteristics of our divorced sample.

As a first step, we consider the whole period covered by the RLMS-HSE survey, from 1995 to 2017. The purpose is to identify individuals who stayed married or divorced and extract information about the characteristics of married couples vs. those of divorced couples. Using these enlarged data, we are able to describe the level of education of wives and husbands. Said differently, we can identify how often assortative matching occurs in this representative sample of the Russian population over a considerably long timespan. For each possible level of education in the database, we create a categorical variable: *Elementary Match*, *Secondary Match*, *Vocational Match*, and *University Match*. In Table 5, we report the full description of each variable. Variables take values from 0 to 4. Each value indicates the educational level of the individual as well as the educational level of her/his partner. As an example, the variable *Elementary Match* is equal to *1* when an individual possesses elementary education and their partner does too; *Elementary Match* equals to *2* when the individual has elementary education and his/her partner has secondary education, and so on, for each possible level of education of the partner, leading to a complete picture for couples with one partner having elementary school. We do the same complete description for all couples where one of the partners has secondary education, using the variable *Secondary Match*, as well as for couples where one partner has vocational training, and finally, university education. These four variables fully describe all possible educational combinations of married couples in the database.

In Table 6, we provide summary statistics for the education of husbands and wives in couples who stayed married and couples who got divorced. We observe 6733 couples who stayed married during the period of observation (1995–2017) and 705 divorced couples. We group them by considering the education of the wife as the benchmark category (Elementary Match–Wife, Secondary Match–Wife, Vocational Match–Wife, University Match–Wife in bold). Considering couples in which both spouses possess elementary education, 459 couples stayed married and 38 couples got divorced. However, in couples where the wife has a university degree and the husband has only finished elementary school, 107 couples stayed married and 18 divorced. The most striking differences in divorce rates occur in couples in which both partners have a university degree and in couples where the wife has a university

[23]Random matching may also occur, in particular for couples with low levels of education, but we are looking only at one particular dimension.

degree and the husband has some vocational or technical training. In both of these cases, the quality of the marriage seems superior because the match is more stable, reducing the chances of marital dissolution.

We use this enlarged sample of couples to estimate the probability of divorce separately for females and males. For females, we estimate the following probability model:

$$\begin{aligned} divorce_w = & \beta_1 Elementary_w + \beta_2 Secondary_w + \beta_3 Vocational_w + \beta_4 Higher_w + \\ & \gamma_1 Age_h + u_w, \end{aligned} \tag{2}$$

where the subscript w indicates $wife$ and h indicates *husband*. The probit model for males is easily derived by substituting the subscript w with h. We report the results in Table 9. If spouses have the same level of education, we see that the probability of divorce takes the smallest value when both partners have a university education, whereas it takes the highest value when both partners have an elementary education. An increase in the age of the partner decreases the probability of marriage dissolution. Households where the wife is working show a higher probability of divorce. As a consequence, it appears more probable that female labor participation is present in the household when marital dissolution occurs. Finally, the working status of the husband does not significantly affect the probability of getting divorced for the wife.

5.2.2 Poverty and Probability of Divorce

We are now in the condition to estimate the poverty specification by clustering errors at the individual level and using the estimated probability of divorce as a regressor. In this subsection, we focus only on married couples. Our purpose is to uncover how the probability of divorce, as estimated above, affects the poverty of married individuals. We describe the estimation of the benchmark model for the years of 2010–2017.

In the sample corresponding to the benchmark analysis, keeping only married couples for which partners filled in the questionnaire, we are left with 488 individuals observed over 8 years. We then match the predicted probabilities of getting divorced, as estimated in the previous subsection, using individual characteristics. For this, we employ the same set of variables as in Model 2: education, age of the partner, and partners' employment.

The estimates are reported in Table 10. Reassuringly, we observe that the probability of divorce for married couples still indicates that females who may get divorced have a lower probability of becoming poor. Males who face a high probability of divorce due to infelicitous marital sorting face a high probability of becoming poor. This is not true for females. The probability of divorce does not cause women to become poorer. Hence, even when we account for a counterfactual probability of divorcing, it seems that our results point to the same direction as those of the baseline specifications.

6 The Mechanism: Female Labor Participation of Divorcees

In the next step of our analysis, we aim to explore the mechanism behind our result. Why are divorced women better off than married women and divorced men. Russian women are, on average, more educated than men, and live longer, but seldom achieve positions of leadership. Of female high-school graduates, 89% are enrolled in tertiary education versus 75% of men, and women enjoy a healthy life expectancy that is almost 8 years longer than that of men. In addition, there are almost as many women as men holding a PhD (64% vs. 66%). Russian women participate in the labor force at high levels (68.9% are in the labor market). Hence, it is reasonable to believe that divorced women participate actively in the labor market. Do they participate more than divorced men? How does this impact their poverty levels? To answer these questions, we explore a bivariate relationship between poverty and labor market status to uncover the joint dynamics of the two observed characteristics. This joint inter-temporal model of poverty and labor market participation is then estimated for the period of 2010–2017.

Labor market participation and poverty (and poor living conditions) are very often faces of the same coin. Income from working crucially reduces the chances of falling under the poverty threshold. Previous research (Biewen, 2009) suggests that employment status and household composition are influenced by past poverty outcomes. Plum (2017) studies the interrelated dynamics of poverty and unemployment and shows that the risk of becoming unemployed and poor is state-dependent: it increases with the duration of unemployment and decreases with the duration of employment in Great Britain. Ayllón (2015) explores youth poverty dynamics in Europe and studies inter-relationships between poverty, employment, and residential emancipation. With individual poverty condition and long-term unemployment risk being correlated, our second main specification in this paper investigates the inter-related dynamics of poverty and labor force participation.[24]

We model the two processes jointly in a discrete sequential equation model where we assume that the unemployment risk affects falling into poverty and vice versa. To do this, we estimate a dynamic random effect bivariate model in which we explicitly account for the joint distribution of unobserved heterogeneity and control for the initial conditions as in Wooldridge (2005).

This is a well-known problem of initial conditions suggested by Heckman (1987) for the univariate model. He proposes replacing the equation in the first period by a static equation. Alessie *et al.* (2004) extend this approach to the bivariate case by including two static equations in the first period. The estimation of the bivariate model can be handled by maximum likelihood methods. The model is flexible; however, it is difficult to generalize to the higher-order dependence (include lags of order higher than 1), and it is computationally demanding. Devicienti & Poggi (2011) propose to account for the initial conditions problem in the bivariate model à la Wooldridge (2005) by including longitudinal averages and the values of the dependent variables in the first period into equations. Following Devicienti & Poggi (2011), in the present paper we use a dynamic random effect probit model controlling for the unobserved heterogeneity and initial conditions.

For individual i, who is working or not and who is either poor or not, the following equations

[24] A second important specificity of poverty and unemployment variables is the state dependence of both variables. Poverty traps and long-term unemployment determine state dependence, making the sample non-representative of the true population, with the unemployed or poor being overrepresented in the initial period. Numerous papers show a state dependence of poverty (for instance, Cappellari & Jenkins (2002); Bigsten & Shimeles (2008); Fertig & Tamm (2010)) and persistence of unemployment (see Stewart (2007); Crépon *et al.* (2005); Buddelmeyer *et al.* (2010)).

are used to specify his/her condition at each year t:

$$
\begin{aligned}
poor_{i,t} = &\gamma_{11} Divorce_{i,t} + \gamma_{21} Female_{i,t} + \gamma_{31} Divorce_{i,t} \times Female_{i,t} + \lambda_{11} poor_{i,t-1} + \\
&\lambda_{21} lfp_{i,t-1} + \beta_1 x'_{1,i,t} + \psi_1 z'_i + \phi_{11} poor_{i,1} + \phi_{21} lfp_{i,1} + \delta_1 \bar{x}'_{i,t} + \alpha_{1r} + \alpha_{1t} + \alpha_{1i} + u_{1,i,t}, \\
lfp_{i,t} = &\gamma_{12} Divorce_{i,t} + \gamma_{22} Female_{i,t} + \gamma_{32} Divorce_{i,t} \times Female_{i,t} + \lambda_{12} poor_{i,t-1} + \\
&\lambda_{22} lfp_{i,t-1} + \beta_2 x'_{1,i,t} + \psi_2 z'_i + \phi_{12} poor_{i,1} + \phi_{22} lfp_{i,1} + \delta_2 \bar{x}'_{i,t} + \alpha_{2r} + \alpha_{2t} + \alpha_{2i} + u_{2,i,t}.
\end{aligned}
\tag{3}
$$

The dependent variables are two dummy indicators indicating first the poverty status and second the status of participation in the labor market. Hence, as in the univariate regression, $poor_{i,t}$ takes a value one if individual i is below the threshold of poverty in time t and zero otherwise, and $lfp_{i,t}$ assumes a value of one if individual i is unemployed at time t. The vectors β_1 and β_2 are the vectors of the coefficients of the time-invariant parameters of the explanatory covariates, as in the univariate regression, and z_i is the vector of time-variant covariates. As earlier, we include individual random effects captured by the variables $\alpha_{1,i}$ and $\alpha_{2,i}$ and following a bivariate normal distribution with variances $\sigma_{\alpha,1}$ and $\sigma_{\alpha,2}$ and covariance ρ_α . The error terms $u_{1,i,t}$ and $u_{2,i,t}$ are assumed to be independent over time and to follow a bivariate normal distribution with zero means, unit variances, and cross-equation covariance ρ_u . The vectors $x_{1,i,t}$ and $x_{2,i,t}$ include a list of exogenous variables. We assume that $(\alpha_{1,i}, \alpha_{1,i})$, $(u_{1,i,t},\ u_{1,i,t})$ and $x_{i,t}$ are orthogonal.

Analogously to our benchmark estimation, Model 1, in this specification, Model 3, we include $poor_{i,1}$ and $lfp_{i,1}$ and the longitudinal means of the time-variant variables $\bar{x}'_{i,t}$: age, experience, number of children, retired, household size. Similar to Alessie *et al.* (2004), we assume sequential causality, in which the last period's unemployment is assumed to affect the current period's poverty and the last period's unemployment is assumed to affect this period's poverty.

As in the benchmark, we face the problem of initial conditions.[25] The marginal effect for the interaction term is calculated in a similar manner as discussed for the univariate probability model but adjusting the bivariate normal distribution instead of a univariate distribution.

In Table 11, we present the results of the bivariate estimation, whereas in Table 13 we show results of the bivariate regression with multidimensional poverty in place of income poverty. The significance of the coefficient of the initial period as well as the poverty and unemployment in period $t-1$ show that there is state dependence for both variables. With respect to the magnitude of divorce status and gender in this bivariate relation, we refer the reader to Table 12. Similarly to the univariate estimation, when performing a bivariate estimation, females are 2% points more likely than males to be poor and unemployed. The marginal effect of the interaction term $Female \times Divorce$ also exhibits a similar result to the univariate case: divorced females are 4% percentage points less likely be in poverty

[25] Our coefficients would be biased and inconsistent because the unobserved heterogeneity is correlated with the lagged dependent variables. To overcome this problem, we follow the solution proposed by Wooldridge (2005). More specifically, the dependent variables can be influenced by the other variables, by unobserved individual heterogeneity, and by the presence of correlated lagged endogenous variables. This approach suggests enriching the likelihood function with the reduced-form equation for the initial observation and then maximize using the full set of sample observations, allowing for cross-correlation. We follow this procedure and run our baseline estimation with simulated initial conditions. Since we control for the initial conditions problem, jointly account for unobservables in the two processes, and allow those effects to be correlated, the sequential timing circumvents the simultaneity problem and provides identification of the intertemporal effects. This identification strategy rules out that the stochastic shocks $u_{1,i,t}$ and $u_{2,i,t}$ affecting both processes are correlated over time.

and out of the labor market and almost 21% percentage points more likely to be out of poverty and in the labor market. Hence, our main result remains unchanged and robust to the bivariate structure. It is true that divorced women work more than divorced men, but female labor market participation does not fully explain the difference in poverty levels that remains in favor of women even in the bivariate estimations.

Being unemployed in $t-1$ clearly increases the odds of being poor in t, but being poor in $t-1$ also increases the chances of being unemployed in t. Hence, the causal relationship between long-term unemployment and poverty runs both ways: poverty can reinforce joblessness just like joblessness can increase poverty. While unemployment affecting poverty seems obvious, poverty affecting unemployment is less straightforward. However, poverty may make it more difficult to be active in the labor market because poverty makes it more difficult to search for a job (expenses for travel to interviews, childcare, etc.).

Table 13 and Table 14 present the results from our estimation of multidimensional poverty. Surprisingly, marginal effects do not predict females to be significantly more multidimensionally deprived than males (only a weakly significant marginal effect is found for females being 1 percentage point poorer than males). However, divorced females are shown to be 9 points more likely to be poor and unemployed and 12 percentage points more likely to have a job and be out of poverty. Interestingly, we observe a negative marginal effect for the divorce variable: divorced individuals are 6 percentage points less likely to have a job and be out of poverty. Divorced men are worse off compared to divorced women in terms of multiple deprivations.

7 Conclusions

In this paper, we use longitudinal data from Russia for the years 2010–2017 and find that being in a state of poverty is predominantly a long-term trap, but the trap seems easier to escape for divorced women. Divorced women were less poor than divorced men during the period of 2010–2017. Considering the marginal effects, we found that a divorced woman is 11 percentage points less likely to be in income poverty than a divorced man and 12 percentage points less likely to be multidimensionally poor. Prior research has shown that divorce is linked to gender economic inequality (Lundberg *et al.*, 2016) within a country. As most gender research concentrates on investigating the gap between males and females with respect to wages or education, without taking into account the effects of divorce, we try to push this area of research forward by showing the importance of considering marital status when investigating gender gaps.

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A Tables

Table 1: Summary Statistics

	Female		*Male*	
	Mean	Std.Dev.	Mean	Std.Dev.
Demographics				
Age	46.60	10.01	47.88	9.70
Divorce	0.13	0.34	0.04	0.18
Retired	0.27	0.44	0.13	0.33
Urban Area	0.63	0.48	0.60	0.49
Education				
Elementary Education	0.08	0.27	0.15	0.36
Secondary Education	0.31	0.46	0.46	0.50
Vocational/Technical Education	0.34	0.47	0.21	0.41
University Education	0.27	0.45	0.18	0.38
Poverty and Employment				
Income Poverty	0.27	0.44	0.16	0.36
Multidimensional Poverty	0.58	0.49	0.58	0.49
Employment	0.68	0.47	0.75	0.44
Working Experience	21.40	11.53	23.16	11.89
Household				
Household Size	2.85	1.50	2.95	1.56
Number of Children	0.68	0.94	0.73	0.96
Health				
Health: Very Good	0.01	0.07	0.01	0.09
Health: Good	0.28	0.45	0.35	0.48
Health: Average	0.61	0.49	0.57	0.49
Health: Bad	0.09	0.29	0.07	0.25
Health: Very Bad	0.01	0.08	0.01	0.07
Individuals	1119		832	

Note: Source - RLMS-HSE 2010-2017. The sample excludes all individuals who are not present in the survey for the 8 years. Columns 1 and 3 report the sample averages for female and male populatios, respectively. Columns 2 and 4 report standard deviations.

Divorce is coded as follows: 1, divorced; 0, not divorced; *Retired* is equal to 1 if an individual is in the retirement age; 0, if an individual is not in the retirement age; *Urban Area* is 1 if he/she lives in urban area; 0, if in rural area; *Elementary Educ.* is 1, if the highest level of education of the respondent is below secondary school; 0, if it is not below secondary school; *Secondary Educ.* is 1, if highest level of education is secondary school; 0, if highest level of education is not secondary school; *Vocational Educ.* is 1, if highest level of education is some vocational/technical training; 0, if highest level of education is not vocational/technical training; *University Educ.* is 1, if the highest level of education is university; and 0 if not. *Income Poverty* is 1, if an individual is in income poverty; 0, if an individual is not in income poverty; *Employed* is 1, if an individual is employed; 0, if an individual is not employed; *Multidim. Poverty* is 1, if an individual is multidimensionally poor; 0, if an individual is not multidimensionally poor; *Household size* is the number of household members, excluding children under 18 years old; *Number Children* is the number of children under 18 years old.

Table 2: Education Levels of Women and Men According to Marital Status

	Married		**Divorced**	
	Mean	Std. Dev.	Mean	Std. Dev.
Male				
Elementary Education	0.15	0.35	0.20	0.40
Secondary Education	0.47	0.50	0.43	0.50
Vocational/Technical Education	0.21	0.41	0.21	0.41
University Education	0.18	0.38	0.15	0.36
Female				
Elementary Education	0.08	0.27	0.05	0.21
Secondary Education	0.32	0.47	0.28	0.45
Vocational/Technical Education	0.34	0.47	0.32	0.47
University Education	0.26	0.44	0.35	0.48

Note: Source: RLMS-HSE 2010–2017. The sample excludes all individuals who are not present in the survey for the 8 years.

Table 3: Income Poverty: Average Marginal Effects

	(1)		(2)		(3)		(4)	
	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.
Income Poverty$_{t-1}$	0.16***	0.01	0.16***	0.01	0.12***	0.01	0.12***	0.01
Income Poverty$_{t_0}$	0.29***	0.02	0.28***	0.02	0.18***	0.01	0.17***	0.01
Female	0.05***	0.01	0.05***	0.01	0.10***	0.01	0.10***	0.01
Divorce			-0.01	0.02	0.01	0.02	0.01	0.02
Divorce$\times$ Female			-0.06***	0.02	-0.04**	0.02	-0.04**	0.02
Age					-0.02***	0.01	-0.03**	0.01
Age Sq.					0.00***	0.00	0.00***	0.00
Working Experience					0.00	0.00	0.00	0.00
Secondary Educ.					0.00	0.01	0.00	0.01
Vocational Educ.					0.01	0.02	-0.00	0.02
University Educ.					0.00	0.03	-0.01	0.03
Employed					-0.29***	0.01	-0.29***	0.01
Household Size					0.00	0.00	0.00	0.00
Num. Young Children					0.02*	0.01	0.02*	0.01
Urban Area					-0.03***	0.01	-0.01	0.01
Retired					-0.11***	0.01	-0.11***	0.01
Health FE	No		No		Yes		Yes	
Year FE	No		No		No		Yes	
Region FE	No		No		No		Yes	
Longitudinal Means	No		No		Yes		Yes	
σ_u^2	0.88		0.86		0.68		0.64	
ρ	0.47		0.46		0.40		0.39	
Individuals	1951		1951		1951		1951	

Note: Source: RLMS-HSE 2010–2017. The sample excludes all individuals who are not present in the survey throughout 2010–2017. The table contains the estimated average marginal effect on the probability of being income poor in the period t given an increase in the value of the relevant regressor. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

The estimations were performed in `STATA` using the `xtprobit` routine. It estimates random-effects and population-averaged probit models for a binary dependent variable. After, the average marginal effects are calculated.

Health FE is coded as follows: 1, very good; 2, good; 3, average; 4, bad; 5, very bad; *Year FE* includes 6 year dummies; *Region FE* includes 40 regional dummies; *Longitudinal Means* includes averages over 8 years of the time-varying variables Age, Age^2, Working Experience, Employed, Household Size, Number Children, Education, Health, Retired.

σ_u^2 are the variances of the random-effects error terms, ρ is the proportion of the total variance contributed by the panel-level variance component.

Table 4: Multidimensional Poverty: Average Marginal Effects

	(1)		(2)		(3)		(4)	
	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.
Multidim. Poverty$_{t-1}$	0.04***	0.01	0.04***	0.01	0.04***	0.01	0.03***	0.01
Multidim. Poverty$_{t_0}$	0.10***	0.01	0.10***	0.01	0.03**	0.01	0.02	0.01
Female	0.11***	0.01	0.11***	0.01	0.16***	0.01	0.15***	0.01
Divorce			-0.02	0.02	-0.01	0.02	-0.01	0.02
Divorce$\times$ Female			-0.10***	0.02	-0.06***	0.02	-0.06***	0.02
Age					-0.03***	0.01	-0.04***	0.01
Age ^{2}					0.00***	0.00	0.00***	0.00
Working Experience					-0.00	0.00	0.00	0.00
Secondary Educ.					0.00	0.01	0.01	0.01
Vocational Educ.					0.01	0.02	0.00	0.02
University Educ.					0.01	0.03	-0.00	0.03
Employed					-0.27***	0.01	-0.27***	0.01
Household Size					0.00	0.00	0.00	0.00
Num. Young Children					0.02**	0.01	0.02**	0.01
Urban Area					-0.05***	0.01	-0.02	0.02
Retired					-0.12***	0.01	-0.12***	0.01
Health FE	No		No		Yes		Yes	
Year FE	No		No		No		Yes	
Region FE	No		No		No		Yes	
Longitudinal Means	No		No		Yes		Yes	
σ_u^2	2.42		2. 34		1. 63		1. 52	
ρ	0.71		0.70		0.62		0.60	
Individuals	1951		1951		1951		1951	

Note: Source: RLMS-HSE 2010-2017. The sample excludes all individuals who are not present in the survey for the 8 years. The panel contains the estimated average marginal effect on the probability of being in income poverty in the period t given an increase in the value of the relevant regressor. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

The estimations were performed in `STATA` using the `xtprobit` routine. It estimates random-effects and population-averaged probit models for a binary dependent variable. After, the average marginal effect are calculated.

Health FE is coded as follows: 1, very good; 2, good; 3, average; 4, bad; 5, very bad; *Year FE* includes 6 year dummies; *Region FE* includes 40 regional dummies; *Longitudinal Means* includes averages over 8 years of the time-varying variables: Age, Age^2, Working Experience, Employed, Household Size, Number Children, Education, Health, Retired.

σ_u^2 is the variances of the random-effects error terms, ρ is the proportion of the total variance contributed by the panel-level variance component.

Table 5: Matching in Education: Variable Description

Variable Name	**Values**
Elementary Match	0 - education of individual is not "Elementary" 1 - education of the partner is "Elementary" 2 - education of the partner is "Secondary" 3 - education of the partner is "Vocational" 4 - education of the partner is "University"
Secondary Match	0 - education of individual is not "Secondary" 1 - education of the partner is "Elementary" 2 - education of the partner is "Secondary" 3 - education of the partner is "Vocational" 4 - education of the partner is "University"
Vocational Match	0 - education of individual is not "Vocational" 1 - education of the partner is "Elementary" 2 - education of the partner is "Secondary" 3 - education of the partner is "Vocational" 4 - education of the partner is "University"
University Match	0 - education of individual is not "University" 1 - education of the partner is "Elementary" 2 - education of the partner is "Secondary" 3 - education of the partner is "Vocational" 4 - education of the partner is "University"

Table 6: Educational Matching of Married and Divorced Couples

	Married		*Divorced*	
	Number	Percent	Number	Percent
Elementary Match-Wife				
Husband Education				
Elementary	457	6.82	37	5.34
Secondary	196	2.92	24	3.36
Vocational	95	1.42	8	1.15
University	24	0.36	3	0.43
Secondary Match-Wife				
Husband Education				
Elementary	291	4.34	44	6.35
Secondary	999	14.91	117	16.88
Vocational	326	4.86	35	5.05
University	198	2.95	22	3.17
Vocational Match-Wife				
Husband Education				
Elementary	261	3.89	30	4.33
Secondary	763	11.38	102	14.72
Vocational	559	8.34	69	9.96
University	450	6.71	22	3.17
University Match-Wife				
Husband Education				
Elementary	106	1.58	18	2.60
Secondary	447	6.67	51	7.36
Vocational	407	6.07	42	6.06
University	1123	16.76	69	9.96
Couples	6702		693	

Note: Source: RLMS-HSE 1995-2017. The sample includes couples who either stayed married during the period of observation or were married and got divorced. Columns 1 and 3 report the number of married and divorced couples, respectively, whereas columns 2 and 4 represent the percentage of couples in each educational category. Each subcategory is based upon the wife's education level: *Elementary Match-Wife*, *Secondary Match-Wife*, *Vocational Match-Wife*, *University Match-Wife*, and in each subcategory the wife's educational level does not change. In turn, each subcategory is split in four: *Elementary*, *Secondary*, *Vocational*, *University*, having as allocation key the husband's educational level.

Table 7: Summary Statistics: Wife

	Married		***Before Divorce***		***After Divorce***	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std.Dev.
Age	46.56	13.98	38.04	11.59	42.69	11.16
Income Poverty	0.43	0.50	0.49	0.50	0.26	0.44
Employment	0.61	0.49	0.71	0.46	0.79	0.41
Individuals	6702		693		570	

Note: Source: RLMS-HSE 1995-2017. The sample includes wives who either stayed married during the period of observation or were married and got divorced. Columns 1 and 2 report the mean and the standard deviation for wives who stayed married during the period of observation. Columns 3 and 4 report the mean and the standard deviation for wives before the marital split, and columns 5 and 6 report the same information for wives after the marital split. *Income Poverty* is coded as follows: 1, an individual is in income poverty; 0, an individual is not in income poverty; *Employed* is equal to 1 if an individual is employed; 0, if an individual is not employed.

Table 8: Summary Statistics: Husband

	Married		***Before Divorce***		***After Divorce***	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std.Dev.
Age	48.77	13.94	39.67	11.36	43.05	11.72
Poverty	0.26	0.44	0.34	0.47	0.40	0.49
Employment	0.69	0.46	0.76	0.43	0.64	0.48
Individuals	6702		693		309	

Note: Source: RLMS-HSE 1995-2017. The sample includes husbands who either stayed married during the period of observation or were married and got divorced. Columns 1 and 2 report the mean and the standard deviation for husbands who stayed married during the period of observation. Columns 3 and 4 report the mean and the standard deviation for husbands before the marital split, and columns 5 and 6 report the same information for husbands after the marital split. *Income Poverty* is coded as follows: 1, an individual is in income poverty; 0, an individual is not in income poverty; *Employed* is equal to 1 if an individual is employed; 0, if an individual is not employed.

Table 9: Probability of Divorce: Average Marginal Effects

	Wife		***Husband***	
	Coeff	Std.Err.	Coeff	Std.Err.
Secondary Match				
Partner's Education				
Elementary	0.02	0.02	-0.01	0.02
Secondary	-0.01	0.01	-0.02**	0.01
Vocational	-0.02	0.02	-0.01	0.01
University	-0.01	0.02	-0.03***	0.01
Vocational Match				
Partner's Education				
Elementary	0.01	0.02	-0.03	0.03
Secondary	0.00	0.01	-0.03**	0.01
Vocational	-0.01	0.01	-0.02	0.01
University	-0.06***	0.01	-0.04***	0.01
University Match				
Partner's Education				
Elementary	0.02	0.03	0.03	0.07
Secondary	-0.03*	0.02	-0.03	0.02
Vocational	-0.03**	0.02	-0.07***	0.01
University	-0.06***	0.01	-0.06***	0.01
Age Partner	-0.01***	0.01	-0.01***	0.01
Individuals	7395		7395	

Note: Source: RLMS-HSE 1995-2017. The sample includes couples who either stayed married during the period of observation or were married and got divorced. The panel contains the estimated average marginal effect on the probability of getting divorced given an increase in the value of the relevant regressor, reported in columns 1 and 3. The standard errors are reported in columns 2 and 4. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.
Results are reported separately for wives and husbands: columns 1 and 2, columns 3 and 4, respectively. Each subcategory of education is based upon the individual's education level: *Secondary Match*, *Vocational Match*, *University Match*, and in each subcategory the individual's educational level does not change. In turn, each subcategory is split in four: *Elementary*, *Secondary*, *Vocational*, *University*, having as allocation key the partner's educational level.

Table 10: Income Poverty using the Predicted Probability of Divorce: Average Marginal Effects

	Female		***Male***	
	Coeff	Std.Err.	Coeff	Std.Err.
Income Poverty$_{t-1}$	0.15***	0.02	0.10***	0.02
Income Poverty$_{t_0}$	0.13***	0.02	0.17***	0.03
Pr. Divorce	-0.14	0.29	0.93**	0.41
Age	-0.05*	0.03	0.01	0.02
Age Sq.	0.00**	0.00	-0.00	0.00
Working Experience	-0.00	0.00	0.00	0.00
Secondary Educ.	0.00	0.04	-0.01	0.02
Vocational Educ.	-0.05	0.06	-0.01	0.04
University Educ.	-0.14**	0.07	0.04	0.07
Employed	-0.32***	0.03	-0.23***	0.03
Household Size	0.01	0.02	0.00	0.01
Num. Young Children	0.00	0.02	0.01	0.02
Urban Area	-0.04	0.03	-0.04	0.02
Retired	-0.15***	0.03	-0.11***	0.02
Health FE	Yes		Yes	
Year FE	Yes		Yes	
Region FE	Yes		Yes	
Longitudinal Means	Yes		Yes	
σ_u^2	0.47		0.53	
ρ	0.32		0.35	
Individuals	488		456	

Note: Source: RLMS-HSE 2010–2017. The sample excludes all individuals who are not present in the survey for the 8 years and who are not married. The panel contains the estimated average marginal effect on the probability of being in income poverty in the period t given an increase in the value of the relevant regressor. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.
The estimations were performed in `STATA` using the `xtprobit` routine. It estimates random-effects and population-averaged probit models for a binary dependent variable. After, the average marginal effect are calculated.
Pr. Divorce is the estimated probability of getting divorced, based on the characteristics reported in Table 9 ; *Health FE* is coded as follows: 1, very good; 2, good; 3, average; 4, bad; 5, very bad; *Year FE* includes 6 year dummies; *Region FE* includes 40 regional dummies; *Longitudinal Means* includes averages over 8 years of the time-varying variables: Age, Age^2, Working Experience, Employed, Household Size, Number Children, Education, Health, Retired.
σ_u^2 is the variances of the random-effects error terms, ρ is the proportion of the total variance contributed by the panel-level variance component.

Table 11: Income Poverty Estimates of the Bivariate Probability Random Effects Model

	Poverty		LFP	
	Coeff	Std.Err.	Coeff	Std.Err.
Income Poverty$_{t-1}$	0.79***	0.05	0.05	0.07
Employed$_{t-1}$	−0.21**	0.07	1.53***	0.06
Income Poverty$_{t_0}$	0.8***	0.07	-0.14*	0.07
Employed$_{t_0}$	−0.03	0.07	0.7***	0.09
Female	0.49***	0.06	-0.13***	0.06
Divorce	0.37*	0.17	-0.23	0.18
Female × Divorce	−0.61**	0.19	0.43*	0.21
Age	−0.26***	0.08	0.27 *	0.09
Age^2	0.01***	0.01	-0.01***	0.01
Working Experience	0.01	0.01	-0.01	0.01
Secondary Educ.	−0.07	0.07	0.08	0.08
Vocational Educ.	−0.28***	0.08	0.26**	0.08
University Educ.	−0.47***	0.09	0.49***	0.09
Household Size	0.12*	0.03	-0.06	0.03
Number Children	0.04	0.05	-0.09	0.06
Urban Area	−0.07	0.08	0.1	0.09
Retired	−0.67***	0.08	-0.71***	0.09
Health FE	Yes		Yes	
Year FE	Yes		Yes	
Region FE	Yes		Yes	
Longitudinal Means	Yes		Yes	
$\sigma^2_{\alpha_1}$	0.52***		0.06	
$\sigma^2_{\alpha_2}$	0.55***		0.08	
ρ_α	−0.51***		0.10	
ρ_u	−0.64***		0.04	
Individuals	1951			

Note: Source: RLMS-HSE 2010-2017. The sample excludes all individuals who are not present in the survey for the 8 years. The first column contains the point estimates on the probability of being income poor in the period t, the third column contains the point estimates on the probability of being employed in the period t. Standard errors are reported in columns 2 and 4. Coefficients are statistically significantly different from the true value at the * 0.10 level; ** at the 0.05 level; *** at the 0.01 level. The estimations were performed in `STATA` using the `bireprob` routine. It estimates two nonlinear regressions and accounts for the correlation in the time-specific and individual-specific error terms (Plum, 2016).

Health FE is equal to 1 if health is very good; 2 if good; 3 if average; 4 if bad; and 5 if very bad; *Year FE* includes 6 year dummies; *Region FE* includes 40 regional dummies; *Longitudinal Means* includes averages over 8 years of the time-varying variables Age, Age^2, Working Experience, Household Size, Number Children, Education, Health, Retired.

$\sigma^2_{\alpha_1}$ and $\sigma^2_{\alpha_2}$ are the variances of the random-effects error terms, ρ_α is the correlation of the random-effects error terms, ρ_u is the correlation of the idiosyncratic shock.

Table 12: Marginal Effects: Income Poverty (at mean values)

	$Poor = 1, LFP = 1$		$Poor = 1, LFP = 0$		$Poor = 0, LFP = 1$		$Poor = 0, LFP = 0$	
	Coeff	Std.Err.	Coeff	Std.Err.	Coeff	Std.Err.	Coeff	Std.Err.
Female	0.049***	0.01	0.02***	0.01	-0.19***	0.02	-0.01	0.02
Divorce	0.01	0.01	0.01	0.01	0.01	0.03	0.01	0.02
Divorce × Female	-0.04***	0.01	-0.1***	0.01	0.21***	0.01	-0.03***	0.01
Individuals	1951							

Note: Source: RLMS-HSE 2010-2017. The sample excludes all individuals who are not present in the survey for the 8 years. The first column contains the estimated marginal effect on the probability of being *in income poverty and employed*; the third column contains the estimated marginal effect on the probability of being *in income poverty and unemployed*; the fifth column contains the estimated marginal effect on the probability of being *not in income poverty and employed*; the seventh column contains the estimated marginal effect on the probability of being *not in income poverty and unemployed*; given an increase in the value of the relevant regressor, holding all other regressors at their mean values. Standard errors are reported in columns 2, 4, 6, 8. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level. *Female* is equal to 1 if female and 0 if male; *Divorce* is equal to 1 if divorced and 0 if not divorced; *Divorce* × *Female* is an interaction term of the variables *Divorce* and *Female*.

Table 13: Multidimensional Poverty Estimates of the Bivariate Probability Random Effects Model

	Poverty		**LFP**	
	Coeff	Std.Err.	Coeff	Std.Err.
Multidim. Poverty$_{t-1}$	0.67***	0.04	-0.11*	0.06
Employed$_{t-1}$	−0.02	0.05	1.45***	0.06
Multidim. Poverty$_{t_0}$	0.77***	0.05	-0.01	0.07
Employed$_{t_0}$	−0.03	0.06	0.86***	0.09
Female	0.08	0.05	-0.12*	0.06
Divorce	0.46**	0.16	-0.24	0.18
Female × Divorce	−0.38*	0.17	0.40	0.2
Age	0.07	0.07	0.23**	0.09
Age^2	−0.01	0.01	-0.01***	0.01
Working Experience	−0.01	0.01	-0.01	0.01
Secondary Educ.	−0.01	0.06	0.04	0.08
Vocational Educ.	−0.09	0.07	0.26**	0.09
University Educ.	−0.24**	0.07	0.46***	0.10
Household Size	0.01	0.02	-0.06*	0.03
Number Children	0.03	0.05	-0.08	0.06
Urban Area	−0.47***	0.07	0.20*	0.10
Retired	−0.22**	0.07	-0.75**	0.09***
Health FE	Yes		Yes	
Year FE	Yes		Yes	
Region FE	Yes		Yes	
Longitudinal Means	Yes		Yes	
$\sigma^2_{\alpha_1}$	0.44***		0.05	
$\sigma^2_{\alpha_2}$	0.67**		0.07	
ρ_α	0.064		0.06	
ρ_u	−0.017		0.03	
Individuals	1951			

Note: Source: RLMS-HSE 2010–2017. The sample excludes all individuals who are not present in the survey for the 8 years. The first column contains the point estimates on the probability of being multidimensionally poor in the period t, the third column contains the point estimates on the probability of being employed in the period t. Standard errors are reported in columns 2 and 4. Coefficients are statistically significantly different from the true value at the * 0.10 level; ** at the 0.05 level; *** at the 0.01 level. The estimations were performed in `STATA` using the `bireprob` routine. It estimates two nonlinear regressions and accounts for the correlation in the time-specific and individual-specific error terms (Plum, 2016).

Health FE is coded as follows: 1, very good; 2, good; 3, average; 4, bad; 5, very bad; *Year FE* includes 6 year dummies; *Region FE* includes 40 regional dummies; *Longitudinal Means* includes averages over 8 years of the time-varying variables Age, Age^2, Working Experience, Household Size, Number Children, Education, Health, Retired.

$\sigma^2_{\alpha_1}$ and $\sigma^2_{\alpha_2}$ are the variances of the random-effects error terms, ρ_α is the correlation of the random-effects error terms, ρ_u is the correlation of the idiosyncratic shock.

Table 14: Marginal Effects: Multidimensional Poverty (at mean values)

	$Poor = 1, LFP = 1$		$Poor = 1, LFP = 0$		$Poor = 0, LFP = 1$		$Poor = 0, LFP = 0$	
	Coeff	Std.Err.	Coeff	Std.Err.	Coeff	Std.Err.	Coeff	Std.Err.
Female	-0.01	0.01	0.01*	0.01	-0.02	0.01	0.01	0.01
Divorce	0.06**	0.02	0.02	0.02	-0.06***	0.02	-0.02*	0.01
Divorce × Female	-0.03***	0.01	-0.09***	0.01	0.12***	0.01	-0.01***	0.01
Individuals	1951							

Note: Source: RLMS-HSE 2010-2017. The sample excludes all individuals who are not present in the survey for the 8 years. The first column contains the estimated marginal effect on the probability of being *multidimensionally poor and employed*; the third column contains the estimated marginal effect on the probability of being *multidimensionally poor and unemployed*; the fifth column contains the estimated marginal effect on the probability of being *not multidimensionally poor and employed*; the seventh column contains the estimated marginal effect on the probability of being *not multidimensionally poor and unemployed*; given an increase in the value of the relevant regressor, holding all other regressors at their mean values. Standard errors are reported in columns 2, 4, 6, and 8. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

Female is coded as follows: 1, female; 0, male; *Divorce* is 1 if divorced; 0 if not divorced; *Divorce* × *Female* is an interaction term of the variables *Divorce* and *Female*.

B Variable Definitions and Sources

Tables A1.1: Dependent Variables

NAME	DESCRIPTION	DATA
Income Poverty	Dummy variable: *1* – an individual is in poverty at time *t* 0 – an individual is in poverty at time *t*	$poor_{itj}$ = 1 if J60 < $living\_wage_{jt}$ $poor_{itj}$ = 0 if J60 **>=** $living\_wage_{jt}$
Labor Force Participation	Dummy variable: *1* – an individual is working or is on non-paid or paid leave, including maternity leave or leave to care for a child under 3 year old at time *t* *0* – an individual is not employed at time *t*	lfp_{itj} = 1 if J77 = 1 lfp_{itj} = 0 if J77 = 2
Multidimensional Poverty	Dummy variable: *1* – an individual is multidimensionally poor at time *t* *0* – an individual is multidimensionally poor at time *t*	$poor\_mult_{itj}$ = 1 if mult_poverty >= 1/3 $poor\_mult_{itj}$ = 0 if mult_poverty **<** 1/3

Tables A1.2: Control Variables

NAME	DESCRIPTION	DATA
Lag of Poverty	*1* – an individual is in poverty at time *t-1* *0* – an individual is in poverty at time *t-1*	l_poor_{itj}
Lag of Labor Force Participation	*1* – an individual is employed at time *t-1* *0* – an individual is not employed at time *t-1*	l_lfp_{itj}
Poverty in First Period	*1* – an individual is in poverty at time *t=1* *0* – an individual is in poverty at time *t=1*	$poor0_{itj}$
Labor Force Participation in the First Period	*1* – an individual is employed at time *t=1* *0* – an individual is not employed at time *t=1*	$lfp0_{itj}$
Age	Age at time *t*	age
Age^2	Age squared at *t*	age_sq = age^2
Divorce	*1* – an individual is divorced at time *t=1* *0* – an individual is married at time *t=1*	divorce = 1 if marst = 4 or marst = 6 divorce = 0 if marst = 2 or marst = 3 or marst = 7
Experience	Years of employment	J161_3Y
Education	*1* – an individual has an elementary education *2* – an individual has a secondary education *3* – an individual has a vocational (technical) education *4* – an individual has a university education	diplom_1= 1 if diplom ==1 | diplom ==2 | diplom == 3 diplom_1 = 2 if diplom == 4 diplom_1 = 3 if diplom == 5 diplom_1 = 4 if diplom == 6
Number of Young Children	Number of young children in the household	J72_173
Household Size	Number of household members (except young children)	household_size_1 = nfm - J72_173
Retired	*1* – an individual is at the retirement age at time *t* *0* – an individual is at the retirement age at time *t*	retired=1 if age > 54 & female = 1 retired=1 if age > 59 & male = 1
Health	*1* – an individual estimates his health as “very good” *2* – an individual estimates his health as “good” *3* – an individual estimates his health as “average” 4 – an individual estimates his health as “bad” 5 – an individual estimates his health as “very bad”	M3
Urban Area	*1* – an individual lives in an urban area *0* – an individual lives in a rural area	urban = 1 if status = 3
Year	Year of the survey	INT_Y
Region	*1 – 38* indicates region and the city/village where an individual lives	region

Tables A1.3: Material Deprivation

NAME	DESCRIPTION	DATA
Material Deprivation	Dummy variable: *1* – an individual lives in a materially deprived household at time *t* *0* – an individual lives in a non-materially deprived household at time *t*	$p\_living\_con_{itj}$ = 1 if $conditions_{jt} > 0.4$ $p\_living\_con_{itj}$ = 0 otherwise

$\textbf{Conditions}_{it}$

Flat colour TV	*1* - No 0 - Yes	C9_5_1A
Central sewerage	*1* - No 0 - Yes	C7_5
Dacha (country house)	*1* - No *0* - Yes	C9_101A
Manage to have meal regularly?	1 - No *0* - Yes	M152
Hot water	*1* - No *0* - Yes	C7_3
Do you or your family have the means, if you wish, to make a big purchase?	*1* - Yes *0* - No	J721633
Are you concerned about providing yourself with the most necessary things in the next 12 months?	*1* – Very Concerned *0* – Otherwise	J66
Mobile phone	*1* - No *0* - Yes	J184
Microwave	*1* - No *0* - Yes	C9_3_1A
Refrigerator	*1* - No *0* - Yes	C9_1_1A

Tables A1.4: Multidimensional Poverty

NAME	DESCRIPTION	DATA
Multidimensional Poverty	Dummy variable: *1* – an individual is multidimensionally poor at time *t* *0* – an individual is multidimensionally poor at time *t* An individual is multidimensionally poor if he/she is deprived in at least one dimension (or the equivalent sum of the weighted deprivations).	$poor\_mult_{itj}$ = 1 if mult_poverty >= 1/3 $poor\_mult_{itj}$ = 0 if mult_poverty < 1/3

Poverty Dimensions

NAME	DESCRIPTION	DATA	WEIGHTS
	Dimension 1 – ECONOMIC		
Income Poverty	*1* – an individual is in poverty at time *t* *0* – an individual is in poverty at time *t*	$poor_{itj}$ = 1 if J60 < $living\_wage_{jt}$ $poor_{itj}$ = 0 if J60 >= $living\_wage_{jt}$	1/6
Work Intensity	*1* - an individual works more then 8 hours per day *0* - an individual works less then 8 hours per day	dep_work = 1 if hours_work > 8 dep_work = 0 if hours_work <= 8	1/6
	Dimension 2 – LIVING CONDITIONS		
Material Deprivation	*1* – an individual lives in a materially deprived household at time *t* *0* – an individual lives in a non-materially deprived household at time *t*	$p\_living\_con_{itj}$ = 1 if $conditions_{jt}$ > 0.4 $p\_living\_con_{itj}$ = 0 otherwise	1/3
	Dimension 3 - HEALTH		
Have you rejected medical help because of lack of money in the last 12 months?	*1* - Yes *0* - No	no_money_med =1 if F16_1=1 no_money_med = 0 otherwise	1/9
Self-health evaluation	*1* – an individual's self-evaluation health is lower than fair at time *t* *0* – an individual's self-evaluation health is higher than fair at time *t*	dep_health = 1 if health_e = 5 or health_e = 4 dep_health = 0 if health_e = 1 or health_e = 2 or health_e = 3	1/9
Do you have any chronic diseases?	*1* - Yes *0* - No	chron_disease = 1 if M20_6* = 1 chron_disease = 0 otherwise	1/9

C Marginal Effects Calculation for Univariate Probability Model

We calculate marginal effects following Norton *et al.* (2004). For the dummies Female and Divorce (x):

$$E[y|x, X] = \Phi(\gamma_1 x + \beta X) = \Phi(u)$$

where Φ is the standard normal cumulative distribution. If F is the probability that $y = 1$, then the marginal effect of dummy x is the discreet difference:

$$\frac{\Delta F}{\Delta x} = F(\gamma_1 + \beta X) - F(\beta X)$$

Instead, the marginal effect of of the interaction term of $Divorce \times Female$ is derived as follows:

$$E[y|x_1, x_2, X] = \Phi(\gamma_1 x_1 + \gamma_2 x_2 + \gamma_{12} x_1 * x_2 + \beta X) = \Phi(u)$$

When the interacted variables are both dummy variables, the interaction effect is the discrete double difference:

$$\frac{\Delta F}{\Delta x_1 \Delta x_2} = F(\gamma_1 + \gamma_2 + \gamma_{12} + \beta X) - F(\gamma_1 + \beta X) - F(\gamma_2 + \beta X) + F(\beta X)$$

D The Structure of the Dynamic Bivariate Model

The sample likelihood is the following (Stewart, 2006; Plum, 2016)

$$L = \prod_{i=1}^{N} \int_{\alpha_1} \int_{\alpha_2} \prod_{t=2}^{T} [P_{it}(\alpha_1, \alpha_2)]\, f_2(\alpha_1, \alpha_2, \rho_\alpha \sigma_{\alpha,1} \sigma_{\alpha,2}) d\alpha_1 d\alpha_2,$$

where $P_{it}(.)$ is the joint probability of the observed binary sequence for individual i, $f_2(.)$ is the joint density of (α_1, α_2), with the covariance of the random-effects error terms $\rho_\alpha \sigma_{\alpha,1} \sigma_{\alpha,2}$.

Our estimation method allows for correlated unobserved heterogeneity and accounts for the initial conditions of the two processes. To estimate a bivariate random effects model, we use the command `bireprob`, written by Plum (2016). This command uses the maximum simulated likelihood and considers correlation in the random-effects error terms and in the idiosyncratic shock. Random effects are simulated using 10 Halton draws.

The variance of the composite errors are not normally distributed ($\sigma^2_{\alpha,j} \neq 1$), therefore, the predicted probabilities need to be corrected for $\sqrt{\frac{1}{\sigma^2_{\alpha,j}}}$ (Plum, 2016).