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TITLE OF THE DISSERTATION

ESSAYS ON THE ECONOMICS OF MIGRATION, INEQUALITIES, AND CULTURE

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ABSTRACT

The present doctoral thesis consists of three chapters of self-contained works about the economics of migration, inequalities, and culture.

In the first chapter, I introduce the outline of the thesis and shortly discuss the research questions of each chapter.

The second chapter explores the effects of mass migration on individual attitudes towards migrants. Using several data sources for the mass migration of Ukrainians in Poland between 2014-2016, this chapter is focused on how a massive exogenous increase in the stock of migrant residents and migrant co-workers affects the perception of migrants. Using both an IV methodology and a difference-in-difference analysis, I test two hypotheses: the labor market competition and contact theory, and find some evidence favoring the second. First, difference-in-difference analysis shows that Poles become more welcoming to migrants in regions with more job opportunities for migrants. Second, I find that an increase in the size of the migrant group affects attitudes towards migrants positively, inside a group of natives with similar demographic and job skills characteristics.

The third chapter explores how poverty can be explained by marital status and gender, using the RLMS-HSE household survey. This research shows that divorced women exhibit lower poverty levels than divorced men by employing longitudinal data from the Russian National Survey (RLMS-HSE) from 2004 to 2019. The result remains qualitatively invariant when considering a theoretical probability to divorce for married couples that take into account the age of the partners, labor force participation, and education. A higher probability to divorce impacts positively only men's poverty level. Investigating an inter-related dynamic model of poverty and labor market participation, we find that divorced women work more than divorced men, which is why divorce hits harder on husbands than on wives.

In the fourth chapter of the thesis, we study the effect of past exposure to communist indoctrination during early age (9-14 years) on a set of crucial attitudes in the communist ideology aiming to create the *new communist man/woman*. We focus on the indoctrination received by children during their pioneering years. School pupils automatically became pioneers when they reached 3rd or 4th grade. The purpose of the pioneer years was to educate soviet children to be loyal to the ideals of communism and the Party. We use a regression discontinuity design exploiting the discontinuity in the exposure to pioneering years due to the fall of the USSR in 1991, implying a strong association that hints to causality. We find robust evidence that has been a pioneer has long-lasting effects on interpersonal trust, life satisfaction, fertility, income, and perception of own economic rank. Overall, these results suggest that past pioneers show a higher level of optimism than non-pioneers. Finally, we look for gender differences because various forms of emulation campaigns were used to promote the desired virtues of the new communist woman. However, we find no evidence of the effect of exposure to communism on women. The indoctrination seems to have left more substantial effects on men.

Key Words: Attitudes Towards Migrants; Mass Migration; Contact Theory; Divorce; Income Poverty; Multidimensional Poverty; Labor Market; Past Exposure to Communism; Pioneering; Regression Discontinuity Design; Instrumental Variables Estimation; Difference-in-Difference; Dynamic Bivariate Estimation; RLMS-HSE household survey.

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Chapter 1

Introduction

What is culture? Social scientists use this term extensively, therefore an answer to the question would depend on a respondent's background. Economists consider *culture* as a set of beliefs, norms, and preferences specific to a given group of individuals. The effect of culture on economic outcomes is considerable and broadly studied in the economics literature of the last two decades. As discussed by Fernandez (2007), economists mostly agree that differences in beliefs are endogenous and vary across environments. However, for a long time, the effect of culture on economic outcomes was overlooked, and the differences in beliefs were explained by distinctions in institutions and policies, and the distribution of believes was taken as given. The reason behind this is that it is challenging to build a convincing identification strategy and to distinguish the effect of culture from other economic and institutional environment effects Fernández (2011). Nowadays, we face numerous research aimed at measuring the effect of culture on economic outcomes. For instance, the cross-country difference in economic performance between individuals with different marital outcomes depends on the cultural role of a woman in the society (Lapatinas et al., 2021); any past ideological propaganda inevitably affects people's self-perception and their place in the society (Voigtländer and Voth, 2015, among others); voting attitudes depend on the skill compositions of migrants (Moriconi et al., 2018).

In this doctoral thesis, I explore the effects of different types of shocks (a mass migration, the fall of the USSR) on individual attitudes and investigate inequalities across men and women, focusing on Eastern European countries such as Russia, Poland, and indirectly Ukraine. In Chapter 2, I study how the beliefs and attitudes of a native population change in response to the influx of migrants. Here I propose two empirical approaches that allow tracing a causal relation between change in culture and external demographic shock. In its turn, Chapter 3 explores gender inequalities between married and divorced individuals in Russia, where social norms regarding female labour force participation and demographic gender composition are distinct from the western societies. These cultural factors lead to the better performance of divorced females than divorced males. And finally, in Chapter 4, I study how past cultural experience of young communism indoctrination changes beliefs and economic outcomes in adulthood. Exploring the panel dimension of the data, I propose a two-stage identification strategy using a regression discontinuity to unveil whether there is a discontinuity in predicted individual outcomes and preferences, which can be explained by distinct cultural backgrounds.

How does mass migration shapes attitudes towards migrants? How does an increased physical presence of migrants shape their attitudes toward them? Is the effect homogeneous across the natives? I study these questions in the second chapter of the thesis titled "How mass migration shapes attitudes towards migrants". The main drivers of attitudes towards migrants discussed in the literature are education (Scheve and Slaughter, 2001), job skills (Ford and Mellon, 2020), welfare concerns (Crepaz and Damron, 2009), labour market competition (Mayda, 2006), racial and cultural prejudice Dustmann and Preston (2007), media exposure Hainmueller and Hopkins (2014), etc. There is a limitation that these studies share: the drivers studied are empirically challenging to measure as they are often endogenous, which does unable researchers to establish a causal link between a given driver and a change in attitudes.

To overcome this drawback and capture a casual relationship between attitudes towards migrants and change in migrant/native composition, I explore an exogenous change in Poland's migrant/native regional composition caused by a mass migration of Ukrainians to Poland during the Russian-Ukrainian war in 2014-2015. To estimate the attitudes towards migrants, I explore the data for Poland extracted from ESS, waves 6 and 8 (2012 and 2016). I test where an increased probability of meeting a migrant at a workplace or as a neighbor is associated with a change in attitudes towards migrants among natives. The difference-in-difference estimates show that in regions with more job opportunities for Ukrainian economic migrants, natives reveal significantly better attitudes to migrants overall. I interpret the result as the evidence favouring the contact theory. Notably, the Two-Stage Least Squares Model estimations point to a mechanism that is consistent with the contact theory hypothesis: the positive effect on attitudes is more pronounced among natives with a high probability of contact with Ukrainian migrants due to the personal characteristics: low-skilled, seniors (older than 49), male natives. Hence the result suggests that beliefs and cultural prejudices regarding migrants are subject to change under the external shock of the demographic composition in a given locality, and the change is more pronounced the shorter the social and physical distance between natives and migrants.

As was pointed out at the beginning of the chapter, it is hard to report robust empirical estimations of culture (beliefs, attitudes), as the question of endogeneity always arises. In Chapter 2, I tackle this issue by complementing cross-sectional data on attitudes with the data collected from the government agencies on the physical presents of migrants in regions, participation of migrants in the labour market, and regional industry specialization. Therefore, I propose two specifications: Difference-in-Difference and Instrumental variable approach, linking the variation in beliefs and exogenous demographic shock.

How does the poverty level depend on experienced marital dissolution, and if the effect is different among spouses? If there are differences in income changes associated with the place of the women in the society, gender norms, and female labour force participation? Studies in European countries and the USA have indicated that divorced women show significantly higher poverty levels than divorced men (Uunk, 2004; Andreß et al., 2006; Lundberg et al., 2016). Can these results be extended to non-western countries? Chapter 3, titled "Exploring the effects of Gender and Marital Status on Poverty: Evidence from Longitudinal data" explores the poverty of divorced men and women in Russia, using the Russian Longitudinal Monitoring Survey from 2004 to 2019.

Social and gender norms shape notably labour market composition. There are multiple works aimed to unveil the role of gender norms on female labour force participation (Antecol, 2000; Blau and Kahn, 2006; Farré and Vella, 2013; Fernández, 2013, among others) and motherhood employment (Kuziemko et al., 2018; Moriconi and Rodríguez-Planas, 2021).

Hence, it is relevant to study marital and gender income inequalities in Russia since its labour market is shaped by the country's history and background. As discussed in Goldin (1994), with the beginning of industrialization, women continued to work inside the household, and men went to the traditional labour market. Culture and gender norms dictate the following family composition: a working husband and a non-working wife. However, during the USSR period, women were pushed into the labour market, as rapid industrialization demanded extra labour resources. Therefore, gender equality was one of the main topics of communist ideology. Moreover, in USSR, unemployed individuals were not only stigmatized but were at risk of criminal prosecution for social parasitism (rus. *tuneyadstvo*). Therefore, gender norms are distinctive in post soviet states from Western countries: working females are not stigmatized but rather considered typical. In this way, Russian female employment rate is on the rise and among the highest in the world.

Notably, Russian marriage market also presents some specificities as compared to western markets. On the one hand, the marriage market is characterized by young marriages: according to Rosstat, between 2015 to 2017, the median age of first marriage for women was 25 and for men - 27. At the same time, we observe a high number of marital dissolutions. Divorce rates are the highest among OECD countries. The crude divorce rate in 2016 was 4.15 divorces per 1000 residents (Rosstat, 2016). According to the (OECD Family Database, 2018), Russia has the highest crude divorce rate among the OECD countries.

These peculiarities make Russia an appealing country to study marital and gender inequalities. We use two poverty indicators to measure these inequalities: income poverty and multidimensional poverty. Exploring the panel dimensions of the data, we study how poverty is explained by marital status and if the result varies with gender. 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. A divorced woman is 6 percentage points less likely to be in income poverty than a divorced man and 1 percentage point less likely to be multidimensional deprived. The result is distinct from the western countries, where divorced females are considered the most deprived members of society.

Further, we trace how an exogenous probability of divorce can explain poverty. We find that the higher the probability of divorce for married couples, the higher the poverty level of married men, whereas the exogenous probability of divorce does not affect the poverty levels of married women. Finally, we employ a bivariate model to unveil the possible mechanism of our main results: divorced women work more than divorced men do. When divorced women are unemployed, they are similarly poor as men are.

Chapter 4, titled "The new communist man: how exposure to communist indoctrination during early age affects individual attitudes" answers the following research question: does past exposure to communism have long-lasting effects on individuals' preferences? Precisely, we identify whether past exposure to communism indoctrination during early age has a long-lasting impact on individual outcomes and attitudes. In the USSR, children joined the Pioneer organization in elementary school and continued until adolescence Tiazhel'nikov (1973). Any child in USSR automatically became a pioneer when they reached the age threshold of 9-10 years old and stayed until 14 years old. Chapter 4 pushes forward the hypothesis that the years of pioneering marked children indelibly along individual outcomes and attitudes expressed in later years of their lives. Political systems, both dictatorships and democracies, use indoctrination to affect the outlook of children and young adults — during school years as the period of their lives during which humans are most susceptible to outside influences (Vaughan, 1964; Voigtländer and Voth, 2015; Lott, 1999; Cantoni et al., 2017; Costa-Font et al., 2020; Giuliano and Spilimbergo, 2014; Malmendier and Nagel, 2011).

To test these hypotheses, we explore the Russian Longitudinal National Survey RLMS-HSE. We apply a two-stage identification strategy. First, we estimate ancillary OLS individual fixed effects regressions to extract the predicted individual outcomes and attitudes cleaned by a cohort effect. We use these predicted outcomes in the second step, where we apply a regression discontinuity design to unveil a discontinuity in predicted individual outcomes and preferences between pioneers and non-pioneers. The collapse of communism in 1991 can be treated as a natural experiment allowing for an examination of the effects of the regime on preferences and attitudes. We find long-lasting effects of past exposure to communism on attitudes such as interpersonal trust, life satisfaction, income, fertility, perceived economic position, and a gap between actual income and perceived economic position.

When it comes to the effect of the communism on preferences and beliefs, researchers mostly explore a cross-sectional data or only one wave of longitudinal survey (Alesina and Fuchs-Schündeln, 2007; Brosig-Koch et al., 2011; Campa and Serafinelli, 2019, among others), which restricts the empirical specifications as it is not possible to explore a time variation. Moreover, these studies are mainly concentrated on exploring a case of Western and Eastern Germany and, as pointed out by Becker et al. (2020), the selection in the exposure to communism in Germany may not have been random. To overcome these drawbacks, we focus on a longitudinal database for Russia to investigate individual outcomes and attitudes in this study. Moreover, Chapter 4 unveils the effect of the communism ideology on yet overlooked relation between perceived and real economic position in the society.

The present doctoral thesis consists of three papers that can be considered independently. Each of the three chapters raises a research question, reviews the related literature, proposes an empirical strategy, and finally reports results and conclusions.

Chapter 2

How mass migration shapes attitudes towards migrants?

2.1 Introduction

The economic drivers of the attitudes to migrants discussed in the literature are labour market (Scheve and Slaughter, 2001; Mayda, 2006) and welfare concerns (Dustmann and Preston, 2007; Facchini and Mayda, 2009). The relevant sociological and political literature stresses the importance of racial and cultural prejudices, exposure to migrants, media exposure, as well as the political orientation.

The present study concentrates on the labour market competition theory, which predicts that natives express negative attitudes to migrants if they face increased labour competition from the same skilled migrants. However, an increase in the number of migrants with complementary skills predicts more welcoming attitudes (Mayda, 2006). The labour competition theory actually repeats a much older sociological hypothesis - the group threat theory - (Blalock, 1967; Key, 1984). In localities with a high concentration of migrants, natives express more hostile attitudes.

The opposing hypothesis is contact theory that predicts an increase in the pro-migrant feelings after the "contact" with a migrant (Fetzer et al., 2000). Accordingly, an increase in the number of migrants relative to the population would affect attitudes towards migrants positively. This effect would be more substantial if the group of migrants and natives are homogeneous along a series of observable characteristics (e.g. language, ethnic background, religion, etc). An increased presence of high-skilled workers would affect attitudes of the high-skilled natives negatively according to labour competition theory, but the same increase would affect high-skilled natives positively according to contact theory. The results of the division of migrants and natives by any other group characteristic: age, gender, outdoor activity - are predicted by the same logic.

This paper tests the validity of the two theories by tracing the effect of the changed migrant/native composition on attitudes. To do so, I trace exogenous shocks in the number of migrants in the labor market and the shock in the number of migrants in the neighbourhood. Further, I explore several dimensions of heterogeneity in the groups of migrants and natives to trace the relevance of these differences in attitudes. To narrow down the effect of potential "competition" or "contact", I estimate the effect at the regional instead of the country level.

Most empirical papers devoted to the topic explore the effect of the demographic composition of natives and migrants on attitudes. In most works, severe problems of endogeneity arise: preexisting attitudes could potentially shape the migrant/native composition. Therefore casual inferences between the driver and attitudes are rarely reported due to the endogeneity of demographic composition drivers. To overcome this drawback and capture a casual relational between attitudes towards migrants and change in migrant/native composition, I explore an exogenous change in Poland's migrant/native regional composition caused by a mass migration of Ukrainians to Poland after the Russian-Ukrainian war in 2014-2015. To measure individual attitudes to migrants in Poland, I explore the European Social Survey (waves 6 and 8) and the data on mass migration I collected from multiple Polish statistical services.

I apply the difference-in-difference analysis and further an instrumental approach to deal with the endogeneity and establish causal effects. Foremost, I identify the treated and control regions by dividing Poland voivodeships into more and less agriculturally oriented. For this pursuit, I employ statistics on the percentage of agricultural workers relative to the total employment in a given region. In the second part of the empirical analysis, I estimate a Two-Stage Least Squares Model, where I instrument the increase in the ratio of migrants, in a given region of Poland, by the distance to the Ukrainian border.

The main results are as follows. The difference-in-difference estimates show that in regions with more job opportunities for Ukrainian economic migrants, natives reveal significantly better attitudes to migrants overall. I interpret the result as the first evidence favouring the contact theory. Importantly, the Two-Stage Least Squares Model estimations point to mechanism that is consistent with the contact theory hypothesis: the positive effect on attitudes is more pronounced among natives with a high probability of contact with Ukrainian migrants due to the personal characteristics: low-skilled, seniors (older than 49), male natives.

Results are time persistent and there are no non-linearity effects of the main explanatory variables. I show that the benchmark results are robust to accounting for an enlarged dataset, by considering 2012 and 2016 year together. Further, I examine the data in the successive survey wave (namely wave 2018) and estimate the benchmark model to examine whether the changed demographic or labour force composition is significant several years after the mass migration. Finally, one may argue that the effect of the growth in the number of migrants relative to the native population could be non-linear (Newman, 2013; Gabszewicz and Zanaj, 2020; Joxhe et al., 2020). To check the validity of this argument, I estimate the benchmark models augmenting for nonlinear terms of the number of migrants variable.The addition of the square coefficients into the benchmark model leads to statistically insignificant results.

The paper is set out in 8 sections. In the next, I discuss the relevant literature; in the third section, I present a brief overview of the mass migration of Ukrainians into Poland between 2014-2016. Section 4 describes the data sources and main variables used in the empirical estimations; while in Section 5, I present the empirical analysis. In Section 6, I explore the mechanism of the key findings. Section 7 contains a series of robustness checks, and, finally Section 8 sums up the main findings of the paper.

2.2 Related Literature and own contribution

In the economic literature, the main drivers of individual attitudes are employment concerns and welfare concerns. A powerful predictor of anti-migrant sentiments among the native population is the threat of losing a labour income due to increased competition on the labour market (Mayda, 2006; Scheve and Slaughter, 2001). Mayda (2006) uses cross-national data and reports a significant relation between the native/migrant skill composition in a country and the immigration policy opinions: high-skilled individuals are more likely to be in favor of immigration if natives are more skilled than incoming migrants. And vice versa, if migrants are predominantly high-skilled, then high-skilled natives are less likely to support immigration. Facchini and Mayda (2009) show similar results: in countries with unskilled immigration high income is associated with less hospitality towards immigrants and skills are correlated positively with pro-migrant preferences.

Dustmann and Preston (2007) study welfare concerns, racial and cultural prejudice and labour market concerns and they measure the labour market concerns by fear of job loss, the ease of finding a job and expected future wage paths. They report welfare concerns are a more important and significant driver of attitudes than labour market concerns.Hainmueller et al. (2015) using the employees' industry survey and differentiating between skilled and unskilled migrants show that fear about labor market competition has an insignificant effect on attitudes. Moriconi et al. (2018) study the effect of skilled and unskilled immigration on voting behavior in Europe and report that natives tend to vote for less nationalistic political parties if they face a large inflow of highly educated immigrants. However, the inflow of less-educated immigrants shifts votes to more nationalistic parties. Ford and Mellon (2020) explore the cross-national European survey and suggest that natives, irrespective of their skills, are more welcoming to a skilled professional, rather than unskilled migrants. Clearly, there is no consensus in the literature regarding the effect of migrant/native skill composition and attitudes to migrants.

An important drawback of Mayda (2006), Scheve and Slaughter (2001) or Facchini and Mayda (2009) is the lack of causality: these papers report rather correlations of attitudes with the potential drivers. Another important shortcoming is the use of national-level data. In the present study I opt to estimate the labour market competition effect causally, exploring an exogenous variation in the migrant/native composition. In addition, I use regional data. In fact, a conversion of migration variables from the national to sub-national level allows us to account for spatially different proximity of migrants to the native population and distant labour market conditions.

Attitudes to migrants are also largely studied in sociology and political science. There are two competing theories, the power threat and contact theory, which are actually reflected in the economic literature.

Fetzer et al. (2000) shows that in the US natives are *more* welcoming to migrants if they live in the districts with a high ratio of the foreign-born population. The paper by Fox (2004) also presents the evidence contrary to the power threat hypothesis: the stereotypes about Latino work ethics which the native white population of the US exhibits depends positively on the increase in the size of the Latino population. Newman (2013) presents the acculturating-context hypothesis which predicts the effect of the immigration positive shock be diverse in localities with a distinct level of the preexisting immigrant population, namely an immigration growth in a locality with a high percentage of migrants would have a positive effect on attitudes and vice versa.

If we consider the labour market competition theory in a view of these two theories, one could argue that the predictions of the theory are in line with the power threat hypothesis: the group which faces a high labour competition or threat (say the group of unskilled native face the threat from unskilled migrants due to the labour competition) are predicted to express more hostile attitudes towards migrants. Whereas the contact theory gives the opposite from labour competition prediction. Therefore, in the present study, I am going to test two theories: labour market competition theory versus contact theory.

2.3 Context

In this section, I briefly discuss the Polish migration landscape and the mass migration of Ukrainians into Poland between 2014-2016.

In February 2014, Russians invaded the southwest of Ukraine and Crimea starting the Russian-Ukrainian War conflict, which resulted in about 1.7 million registered internally displaced persons who were forced to run to the safe parts of Ukraine and Poland. The migration flow from Ukraine changed dramatically after 2014. Until 2013, 93,7% of Ukrainian migrants in Poland were residents of Western and Central Ukraine, whereas after 2014 the share of migrants from South-Eastern Ukraine increased from 6,3% up to 28,4% (Gulina and Poznyak, 2018).

Notably, the gender composition of migrants from Ukraine change drastically after the conflict: before 2014 there were 67% of females and 33% of males; and after the war ratios have changed to 42% and 58% respectively (Chmielewska et al., 2017). The main reason for the change is Ukraine government announced an obligatory call for military services (due to the war) and for Ukrainian men the immigration to Poland was an effective strategy to escape. This exogenous change in the gender composition predictively resulted in an increased number of contacts between Polish and Ukrainian males on the daily basis and at workplaces.[1]

Importantly, the Polish government reacted strategically to the huge inflow of Ukrainians. They massively entered Poland between 2014 and 2016 but were not recognised as refugees or internally displaced persons but as economic migrants. In fact, while in 2010-2012, 14.3% of all Ukrainian labour migrants worked in Poland, in 2015-2017 this percentage jumped to 38.9%. This phenomenon was possible because Ukraine and Poland have mutual

[1]Student migration from Ukraine also rise drastically after 2014, however, a positive trend was observed even before 2014. In the 2015-2016 academic year, there were 23,329 students from Ukraine, which amounted to 8206 more than in 2014-2015. Currently, Ukraine students constitute over 50% of all foreign students in Poland (Kapera et al., 2017). It should be noted, that among Ukrainian students, the share of females is higher than males (Gulina and Poznyak, 2018). Consequently, the effect of the presence of the Ukrainians on attitudes to migrants should be higher among individuals who are currently studying at the tertiary education institutions and the effect should be different between female and male native students.

simplified migration procedures. More specifically, to attract low-skilled workers from the neighbouring countries, in 2007 Poland introduced a simplified migration procedure. The procedure is exclusively opened for Ukraine, Russia, Georgia, Moldova, Belarus, and Armenia. If an employer in Poland intends to hire a worker from these 6 countries she/he submits a declaration (a vacancy) that she/he has the intention to mandate the temporary work (from 6 to 12 months) to a foreigner. Polish employer can directly hire a Ukrainian migrant without first place a job advertisement at the employment office. Importantly for the paper, this means that the legal context favours the labor market competition theory. A polish firm is able to open a vacancy directly for Ukrainian workers to reduce the wage bill without being obliged to first look for a polish candidate (which is the rule in other EU countries).

The statistics regarding the number of vacancies opened for Ukrainians show the predominance of agricultural, construction, and manufacturing sectors in the number of opened vacancies for Ukrainians under the simplified procedure (see Fig. 2.1). Therefore, natives working in these sectors are more likely to meet migrants at the workplace, meaning that low-skilled poles are more likely to have close contact with Ukrainians.

Figure 2.1: Number of vacancies for Ukrainians, by sector of employment, as % of the total, Source: Anacka et al. (2015)

Fig. 2.2 depicts the number of vacancies submitted for the workers from 5 countries (except Ukraine) in green and the number of vacancies for Ukrainians in blue; as the number of residents, the total number of residents is depicted in orange and the number of residents from Ukraine is in red. The share of vacancies for Ukrainians increased drastically between 2014-2016. Importantly, the rise in the number of foreign works is not correlated with the rise in unemployment or the availability of seasonal jobs (Duszczyk and Matuszczyk, 2018). As for the number of residents, we observe a rise of the Ukrainians, however not of the migrants of any other nationality.

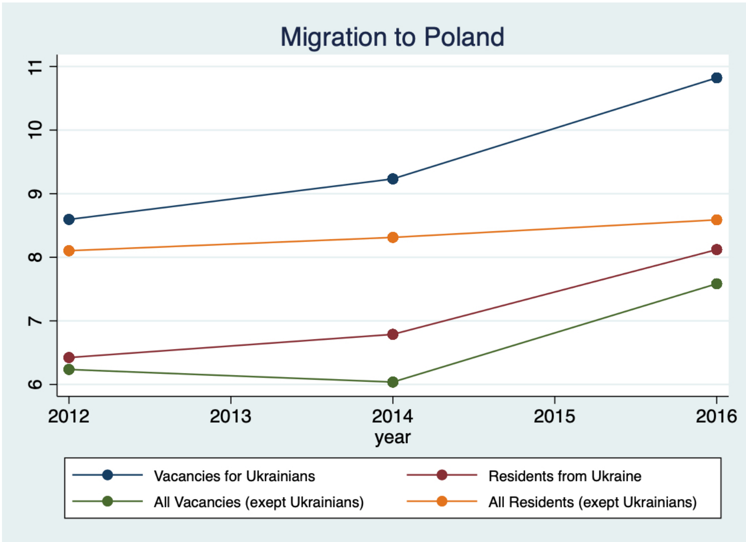


Figure 2.2: Migration to Poland

2.4 Data

To capture the effect of the migration influx in 2014-2015 years I explore the 6th and 8th wave (2012 and 2016 year respectively) of the European Social Survey (ESS) to obtain individual attitudes towards migrants and a set of individual controls in Poland.

The individual characteristics include some *demographic* variables such as age, gender, living with children, marriage, university education, studying (whether an individual is studying currently); *economic* as the skill level, *well-being*: feeling happy; *cultural* non-homophobic preferences; *political* voting attitudes (e.g. voted for PiS [2]). The sample includes 2496 individuals age 18 and older. The summary statistics on the individual controls are

[2]Prawo i Sprawiedliwość is a right-wing political party in Poland

reported in Table 2.1.

For the attitudes to immigrants at the individual level, I explore the answers given for the following three questions: *Immigration bad or good for the country's economy?*; *Country's cultural life undermined or enriched by immigrants?*; *Immigrants make a country worse or better place to live?*. As reported in Table 2.2 the answers to the questions range from 0 to 10.

To have a better understanding of these attitudes I combine the three questions using a Principal Component Analysis (PCA). Results of the PCA are reported in Tables 2.3 and 2.4. As shown in Table 2.3, Component 1 explains a substantial part of the variation (more than 70%), this allows me to use this component as the *attitudes towards immigrants index* in the analysis as the dependent variable. Component 1 ranges from -4.09 and 3.46.

To account for the differentiation between voivodeships I collect data from the Local Data Bank of Poland on mean household income at the voivodeship level - *Average Income*. This variable allows accounting for the different regional economic conditions.

2.5 Empirical Analysis

The empirical analysis consists of two parts. In the first, I compare how the mass migration of Ukrainian migrants affected attitudes to migrants in regions with broader and narrower job opportunities for Ukrainian economic migrants, applying the Difference-in-Difference analysis. This allows me to account for the uneven attractiveness of voivodships for Ukrainians. Nevertheless, some issues could result in a biased Difference-in-Difference estimator. There is no guarantee that the "treatment" i.e. the migrants' influx, was randomly assigned across the regions: Ukrainians could choose a voivodeship with broader job opportunities in agriculture based on other criteria. For instance, they could consider such factors as closeness to the Ukrainian border or the strength of the Ukrainian diaspora. Hence, I apply an IV strategy in the second part of the empirical analysis. I establish how attitudes to migrants are explained by an exogenous change in the migrants/native demographic composition and labour force composition. This specification allows me to account for the preexisting stock of Ukrainians in each voivodeship.

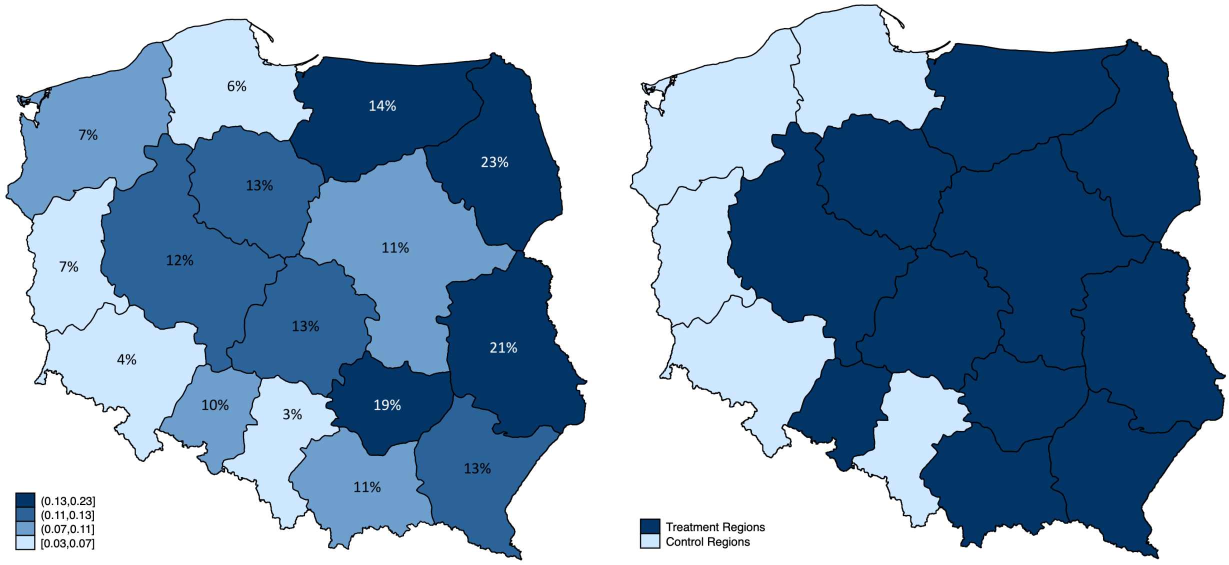
2.5.1 Difference-in-Difference Analysis

The section describes a difference-in-difference specification and reports the main results.

As presented in Figure 2.1, a primary sector of employment for Ukrainians in Poland is agriculture, as the number of open vacancies in this sector constitutes around 50% form the total number of vacancies. Therefore, natives living in agriculturally oriented regions become more exposed to Ukrainians at the workplace in 2016 than they were in 2012. Consequently, the labour market competition hypothesis suggests that natives from agricultural regions would show less welcoming behavior as they face increased job competition coming from natives. However, according to the contact hypothesis, Poles living in agricultural regions would become more tolerant to migrants.

To test these hypotheses, I employ a Difference-in-Difference analysis. To identify treated and control regions, I consider the percentage of agricultural workers relative to the total employment. Figure 2.3a shows the variation from 3% agricultural employment in Silesian Voivodeship (South of Poland) to 23% in Podlaskie Voivodeship (North-East of Poland). To form the Treatment and Control groups, we need to find an acceptable cutoff for the ratio. When we look at the country-level statistics rather than NUTS2 level statistics, the percentage of agricultural workers relative to the total employment is around 10% for Poland. Accordingly, I form the Treatment and Control group based on the above-described statistics: a region is assigned to the Treatment group if the percentage of employment in agriculture is higher than a country average - 10%, and to the Control group otherwise. Figure 2.3b depicts the geography of the Treatment and Control regions.

Using the ESS (wave 6 and 8) and Local Data Bank of Poland, Table 2.5 compares demographic using data obtained from waves 6 and 8 of ESS and Local Data Bank of Poland. Table 2.5 compares demographic and economic characteristics potentially related to the formation of attitudes to migrants among the native population. Two sample t-



(a) Employment in agriculture (% of total employment)

(b) Treatment and Control Regions

Figure 2.3: Employment in agriculture sector in Poland, *Source*: Local Data Bank of Poland

test reveals no statistical differences between two groups along the following dimensions: age, children, education, and occupation. Two groups are different with respect to gender composition. Agricultural regions have a slightly lower percentage of females (51%) than non-agricultural regions (55%) in the sample; and average income - control group shows on average higher income.

The purpose of the Difference-in-Difference analysis is to identify the effect of the increased presence of Ukrainian migrants between 2012 and 2016 on natives' attitudes to migrants. Controlling for the time, individual and regional effects, I obtain the difference-in-difference estimator estimating the following model:

$$Y_{ijt} = \gamma_j + \lambda_t + \alpha D_{jt} + \beta X_{ijt} + U_{ijt}$$

where Y_{ij} is the attitude towards migrants of individual i living in the region j at time t. γ_j dummy denotes an agricultural region: it equals to 1 if an individual lives in the region with the percentage of employment in agricultural sector from the total employment is higher than 10% and 0 otherwise. λ_t dummy denotes period: it equals to 1 if year is 2016 and 0 if year is 2012. D_{jt} is a dummy for an agricultural region after the mass migration of Ukrainians to Poland - an interaction of γ_j and λ_t. X_{ij} is a vector of demographic, economic, welling, cultural, political controls and regional control. I denote the individual specific error term by U_{ijt}.

Table 2.6 reports the basic regression results. Column (A) uses the demographic, economic, wellbeing, cultural, and political controls in the regression. Column (B) includes average income as a regional covariate. The coefficient on D_{jt} is positive and significant in both models, which serves as a piece of evidence in support of the *contact hypothesis*. Our results suggest that an influx of Ukrainian migrants significantly enhanced attitudes to migrants in agricultural-oriented regions. Contrary to conventional thinking, the enlarged presence of economic migrants has not provoked a hostility reaction in the native population.

As stated earlier in the section, this Difference-in-Difference design has some issues that could result in a biased Difference-in-Difference estimator. The treatment is only partially randomly determined, as Ukrainians could choose a voivodeship with broader job opportunities in agriculture, based not only on the economic criteria. Namely, migrants tend to go to the location with a stronger diaspora of the same nationality migrants. Notably, the treatment effect is not the same for all treated regions: employment opportunities in agricultural sectors are high but heterogeneous. To overcome these potential biases, I further introduce the IV estimation strategy.

2.5.2 Instrumental Variable Analysis

The subsection will discuss the main variables to measure migrant/native demographic composition, empirical IV strategy, and critical estimation findings.

Demographic Composition

In the earlier part of the empirical analysis, I explore ESS for 2012 and 2016. The present section explores the data only for 2016. Summary statistics of the individual and regional variables are reported in Table 2.1.

To capture the demographic composition, I collected the data from multiple sources: the Ministry of Family, Labour and Social Policy; Local Data Bank of Poland; Maps and statistics of migrants, and Polish migration services. The data is collected at the voivodeship level - NUTS2 territorial unit in Poland. In total, Poland have 16 voivodeships.

The Ministry of Family, Labour, and Social Policy provides the data on the number of vacancies opened for Ukrainians. The number of vacancies can serve as a proxy for the number of migrant workers because the actual percentage of filled vacancies by workers is high – around 60% (Duszczyk, 2015). The local Data Bank of Poland reports the demographic characteristics the of localities in Poland, namely the total population and economically active population in each voivodeship. The webpage *Maps and statistics of migrants and Polish migration services* publishes information regarding the number of foreign residents in each locality. The data is collected by Office for Foreigners (Urząd do Spraw Cudzoziemców) - a government agency responsible for providing information and assistance for immigrants coming to Poland.

To capture the mass migration of Ukrainian immigrants between 2012-2016, I create two variables which vary by region: *Growth in Resident* and *Growth in Vacancies*. The first is created by subtracting the percent of Ukrainian residents relative to the total population in 2012 from the respective percent in 2016 (Equation 2.1). The *Growth in Residents* variable captures an increased probability to meet or to live nearby a Ukrainian migrant.

$$\text{Ratio Ukrainian Residents} = \frac{\text{Ukranian Residents}}{\text{Total Population}}$$
$$\text{Growth in Residents} = \frac{\text{Ratio Ukranian Residents}_{2016} - \text{Ratio Ukranian Residents}_{2012}}{\text{Ratio Ukranian Residents}_{2012}} \tag{2.1}$$

To capture the change in working population composition I create *Growth in Vacancies* by subtracting the percent declarations submitted for Ukrainians from the economically active population in 2012 (Equation 2.2) from the respective percent in 2016. The *Growth in Vacancies* variable captures an increased likelihood to meet a Ukrainian migrant at work.

$$\text{Ratio Vacancies for Ukrainas} = \frac{\text{Vacancies for Ukrainas}}{\text{Economicaly Active Population}}$$

$$\text{Growth in Vacancies} = \frac{\text{Ratio Vacancies for Ukrainas}_{2016} - \text{Ratio Vacancies for Ukrainas}_{2012}}{\text{Ratio Vacancies for Ukrainas}_{2012}} \tag{2.2}$$

To account for attitudes to migrants in 2012, I calculate the *attitudes towards immigrants index* in 2012 and further determine a regional median of the index - *Median Regional Attitudes*. The summary statistics of regional controls are reported in Table 2.1.

2.5.3 Estimation Strategy

In this version of the analysis, I overcome the endogeneity issue by using an instrument that is correlated with both composition measures but is assumed not to directly affect the attitudes to migrants - the distance from the administrative center of a voivodeship to the Ukrainian border. The war made Ukrainians run from the country, especially from south-west Ukraine, and predictably the distance of the voivodeship from Ukraine is correlated with the preexisting stock and the flow of new coming Ukrainians. Along these lines, I address the issues of non-random probably of choosing a given voivodeship for living and/or working by a Ukrainian migrant and the nonrandom stocks of migrants before the mass migration of Ukrainians to Poland.

The results come from a series of regressions on the causal effect on individual attitudes of our two migrants/native composition growth rates. To test these hypotheses, I fit a benchmark model:

$$Y_{ij} = \beta_0 + X'_{ij}\beta_1 + Z'_j\beta_2 + \Omega'_j\beta_3 + U_{ij}$$

$$\Omega_j = \alpha_0 + X'_{ij}\alpha_1 + Z'_j\alpha_2 + W'_j\alpha_3 + V_{ij}$$

where Y_{ij} is the attitude towards immigration of individual i in living in the region j. *Growth in Residents* or *Growth in Vacancies* are denoted by Ω_j. Estimations contains a vector of demographic, economic, well-being, cultural and political controls X_{ij} and a vector of exogenous regional controls Z_j. W_j is a continuous instrument that measures the distance from the administrative center of a voivodeship to the Ukrainian border. I denote the individual specific error term by U_{ij}. The standard errors are robust and clustered at the regional level. The model is estimated using the two-stage least squares (2SLS) model.

2.5.4 Key Findings

Table 2.7 reports the benchmark results of the 2SLS model (3rd and 5th column) and the OLS model (2nd and 4th column). The OLS and IV estimated coefficients are qualitatively consistent in both specifications. The size of the coefficients is larger in the IV specification compared with OLS estimations. This indicates that IV corrects for the omitted bias in OLS. As there is only one instrument for one endogenous variable in each model, the weakness of the instrument can be tested using the first stage F statistics values in 2SLS models. F statistics in both IV specifications are high than 10 which shows that the W_j is not a weak instrument for the benchmark specification.

According to the results reported in Table 2.7, β_3 is strictly positive in both models. Hence the effect of the growth of Ukrainian workers and the growth in Ukrainian residents in the voivodeship on attitudes towards migrants is positive. These results provide evidence in support of the *contact hypothesis*: both increase in probability to live close to Ukrainian migrants or to have migrants as your coworker is associated with more hospitality among natives. The impact of age is non-linear in both specifications: the coefficient of age is positive, however, the one for its squared term is negative. The estimation results show no support towards the labour competition theory: the individuals' attitudes of works are not statistically different from not employed natives.

The size of the *Growth in Residents* coefficients is considerably higher than *Growth in Vacancies* which indicates that the change in demographic composition has a stronger effect on attitudes rather than a change in workforce composition. This difference serves as further evidence in favor of the groundlessness of the labour competition hypothesis.

However, it is worth to notice that the *High-Skilled* coefficients are significant and high in all model, which is a piece of evidence in support of the labour market competition. This result is interesting as it is at odds with the fact that the flow of Ukrainian workers are mostly unskilled, therefore previous literature predicts more pro-immigration attitudes among the more high-skilled population. To enlighten the reasons behind this result, I elaborate on the analysis of this effect deeply in Section 6.

Interestingly, being currently in any type of education (I am referring to individuals in tertiary education, as the sample includes individuals older than 18 years old) predicts more positive attitudes. This effect can be driven by both the education effect (non-random selection into education) and the high probability to be in contact with migrants since the share of Ukrainian students increased gradually after 2014.

The wellbeing, cultural and political variables are significant predictors of the attitudes towards migrants. Happier poles are overall more likely to be in favor of immigration as well as the individuals who are more tolerant towards homosexual individuals. The feeling of safeness in the community shapes more positive attitudes towards migrants. Expectedly, poles who voted for right-wing political party PiS in the last elections are against migrants, as the rhetoric of the party is extremely intolerant against immigrants and refugees.

2.6 Mechanism

In this section, I run a series of regressions to investigate further the mechanism of how the migrant/native composition shapes attitudes. I explore heterogeneity exercises to shed light on the contact theory hypothesis. The argument is that Ukrainian migrants were mainly unskilled, men and working in agriculture. It follows that poles who are unskilled, men and working in the same sector are those who may suffer from the labor market competition but also those who were more frequently in contact with migrants. I uncover these three heterogeneity dimensions separately in the following sections.

2.6.1 Skill Differentiation

To further analyze the role of skills in attitudes towards migrants, I separate the sample into two parts. The first sub-sample includes 501 high skilled poles, the second one includes 675 low-skilled individuals. Then I replicate the benchmark model on two samples separately. The estimation results are reported in Table 2.8 and Table 2.9.

The results are consistent with the findings of the Diff-in-Diff analysis. The coefficients of both *Growth in Vacancies* and *Growth in Residents* are significant predictors of the attitudes only for the low-skilled individuals and the effect is positive. This outcome indicates the validity of the contact hypothesis: the increased presence of Ukrainians is a significant predictor of attitudes solely for natives with similar skills and occupation as Ukrainians, and the result is completely the opposite to the labour competition hypothesis: individuals who face high labour force competition due to an increased presence of same skilled migrants show more welcoming behaviour. In addition, as expected the increase of unskilled migrants does not have any effect on attitudes of high skilled poles.

2.6.2 Gender Differentiation

As was discussed earlier, the gender composition of Ukrainians in Poland changed drastically after 2014. As the further test of the contact hypothesis, I explore what if the effect of change in demographic and labour force migrant/native composition is different among women rather than men. The contact hypothesis would suggest the effect to be stronger among men rather than women, as the probability of contact with migrants changed much for men rather than women.

To capture this effect, I split the benchmark sample into two sub-samples: we observe 603 women in the first sample and 573 men in the second one. Then I replicate the benchmark model on two samples separately. The estimation results are reported in Table 2.10.

Findings show that the coefficients of both *Growth in Vacancies* and *Growth in Residents* are statistically significant only in the men sub-sample. The result again supports the contact hypothesis: the presence of Ukrainian men expanded to a greater extent than women after 2014 both as residents and as workers, consequently the change in migrant/native composition shaped attitudes towards immigrants among the male population of Poland rather than female. [3]

2.6.3 Age Differentiation

Growth in Vacancies and *Growth in Residents* are proxies of an increased probability to meet Ukrainians at work or as neighbors. Due to the demographic and occupational statistics this probability predictably varies with age: the median age of Ukrainian migrants coming to Poland is 49, therefore the closer the local pole to this age, the higher chances that she/he will make a contact with the migrant. Furthermore, it is important to note that the main sectors of employment of Ukrainians are the agricultural sector and construction. These sectors are less popular among young poles than seniors, which predicts higher exposure to migrants of the last ones compared to young individuals. But this also mean that the labor market competition by ukranian migrant must be stronger for Poles working in the same sectors of a similar age.

To explore this potential age difference, I split the sample into two sub-samples by age: the first group of individuals having ages between 18-48 and the second group with all individuals older than 48. The sample is split in the following manner as 48 is the median age at the benchmark sample. I repeat the benchmark analysis for the two sub-samples separately. The results are reported in Table 2.11.

[3] It is worth noting, the coefficients of the *Studying* variable are positive and statistically significant exclusively in the female sub-sample. That serves as extra evidence in favor of the contact hypothesis since among Ukrainian student in Poland women constitute more than half of all students, therefore female pole student has a high probability to establish a contact with a random Ukrainian student.

The results again demonstrate support of the contact theory. According to Table 2.11, both *Growth in Vacancies* and *Growth in Residents* are significant predictors with positive effects only in the senior sample. Native poles over 49 have a high probability to work with Ukrainian migrants and in terms of age are close to them, therefore individuals in the senior group are more show more positive attitudes to migrants in regions with the increased presence of migrants.

2.7 Robustness

In this section, I run a series of regressions of robustness checks.

2.7.1 Enlarged Dataset

In the second part of the empirical analysis, I explore only wave 8 (the year 2016) of the ESS survey. In this subsection, I test whether the results are robust to considering again two waves together - 2012 and 2016. As the main variables of interest reflect a relative increase of Ukrainian migrants in 2016 in comparison to 2012, I set *Growth in Vacancies* and *Growth in Residents* variables equaled to zero in 2012. After I repeat my benchmark estimations, however, I drop Median Region Attitudes from the controls and add a year fixed effect. I report the results in Table 2.12. The coefficients on both *Growth in Vacancies* and *Growth in Residents* remain statistically significant for enlarged dataset. Therefore, the benchmark results are robust to accounting for 2012 into the analysis.

2.7.2 Time Persistence

To examine the robustness of the results, I trace whether the positive effect of the growing presence of Ukrainian migrants in a given region is time persistent, as one could argue that a drastic exogenous change in demographic and labour force composition affects attitudes only temporarily. To explore this, I employ the last available wave of the ESS dataset - data of the year 2018. I repeat my benchmark estimations to evaluate whether the changes in composition from 2012-2016 are valid predictors in explaining attitudes towards migrants in 2018.

The results of the estimations are reported in Table 2.13. The coefficients on both *Growth in Vacancies* and *Growth in Residents* are statistically significant, and the magnitude of the coefficients is higher than in the estimation for 2016 (Table 2.7). These results serve as extra evidence in favor of the contact theory and an increased magnitude could be explained by the flowing confederation: as Ukrainian migrants are continuing to live at a voivodeship the potential probability of contact between natives and migrants increases with time, therefore the effect is stronger in 2018.

2.7.3 Nonlinearity of the Instrument

To examine the potential existence of a non-linear relationship with individual attitudes towards migrants, I augment the benchmark estimations in the IV analysis with the squared terms of *Growth in Vacancies* and *Growth in Residents* (see Table 2.14). This test is in line with the Newman (2013) accumulation acculturating-context hypothesis: the change in migrant/native composition exerts both positive and negative forces on attitudes, depending on the preexisting share of migrants and speed of the growth. The paper by Gabszewicz and Zanaj (2020) presents some theoretical predictions of the welfare effect of an increased labour supply in the destination country. The effect is heterogeneous, depending on the preexisting market conditions: if there is an undersupply of workers in the destination country then the welfare effect would be positive, and negative in case of the preexisting oversupply. Therefore, the migration effect depends on the size of the immigration flow, and the effect is non-linear in the situation of the undersupply of workers: first, the outcome is positive, but when this undersupply is fulfilled, the further effect is negative.

The coefficients on the main and the squared term in all models are jointly statistically insignificant. Therefore, the results show no support for the non-linear relationship between migrant/native composition growth ratios and attitudes towards migrants.

2.8 Conclusions

This paper establishes a causal link between the migrant/native composition and the individual attitudes towards migrants. Exploring ESS and several other data sources of mass migration of Ukrainians in Poland between 2014-2016, I study the effect of the changed demographic and labor force composition, along with other demographic, cultural, and political drivers. Prior literature in economics and sociology argues two contrasting theories: labour market competition and contact theory. I find that in the regions with an increased number of Ukrainian residents and economic migrants, native individuals with a high probability of being in contact with migrants: being the same age, same gender, or have the same job skills; expose more welcoming attitudes towards migrants. Accordingly, benchmark results and a series of robustness checks suggest the validity of the contact theory.

2.9 Tables

Table 2.1: Summary Statistics of Individual-Level and Regional Level Variables

	Mean	Std.Dev.	Min	Max
Demographic				
Age	47.70	16.87	18	91
Female	0.51	0.50	0	1
Children	0.50	0.50	0	1
Married	0.64	0.48	0	1
University Education	0.25	0.43	0	1
Studying	0.10	0.30	0	1
Economic				
High Skilled	0.43	0.49	0	1
Wellbeing				
Felling Happy	7.38	1.98	0	10
Cultural				
Non-Homophobic	0.58	0.49	0	1
Political				
Voted for PiS	0.23	0.42	0	1
Regional				
Average Income	7.21	0.15	6.87	7.48
Observations	2496			
Migrants				
Growth in Vacancies	9.34	5.44	2.04	21.66
Growth in Residents	4.69	1.65	2.01	8.72
Median Regional Attitudes	0.35	0.28	-0.46	0.97
Observations	1176			

Note: Age reports an individual's age in years as of the last birthday. *Female* is equal to 1 if an individual is a woman; 0, if an individual is a man. *Children* is equal to 1 if an individual lives with children; 0, if an individual lives without children. *Married* is 1 if an individual is married, and 0 otherwise. *University Education* is equal to 1 if an individual has an university degree and 0 otherwise. *High Skilled* is equal to 1 if an individual's occupation is a manager, a professional or a technical and associate professional; 0 otherwise. *Felling Happy* reports a self-estimation of happiness of an individual from 0 to 10. *Non-Homophobic* is equal to 1 if individuals express some tolerance to homosexual individuals, 0 otherwise. *Voted for PiS* 1 if an individual voted for the right-wing political party Prawo i Sprawiedliwość and 0 otherwise. *Average Income* reports average income calculated at the NUTS 2 (voivodeship) level. *Growth in Residents* is calculated by subtracting the percent of Ukrainian residents relative to the total population in 2012 from the respective percent in 2016. *Growth in Vacancies* is calculated by subtracting the percent of declarations submitted for Ukrainians from the economically active population in 2012 from the respective percent in 2016. *Median Regional Attitudes* determines a regional median of the attitudes towards immigrants index in 2012.
Source: ESS waves 6 and 8, Ministry of Family, Labour and Social Policy Data; Local Data Bank of Poland Data; Maps and statistics of migrants and Polish migration services.

Table 2.2: Questions and Summary Statistics of Attitudes Towards Immigration.

	Values	Mean	Std.Dev.
Immigrants: Are bad/good for country's economy?	0: Bad for the economy 1 to 9 10: Good for the economy	5.33	2.55
Immigrants: Undermine/Enrich country's cultural life	0: Cultural life undermined 1 to 9 10: 10: Cultural life enriched	5.73	2.10
Immigrants: Make country worse/better place to live	0: Worse place to live 1 to 9 10: Better place to live	6.21	2.43

Note: ESS (wave 6 and 8)

Table 2.3: PCA on attitudes towards migrants (ESS wave 6 and 8)

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.15092	1.69869	0.7170	0.7170
Comp2	.452226	.0553731	0.1507	0.8677
Comp3	.396853	.	0.1333	1.0000

Table 2.4: PCA eigenvectors (ESS wave 6 and 8)

Variable	Comp1	Unexplained
Migrants are good or bad for the economy	0.5730	0.2939
Migrants are good or bad for the culture	0.5864	0.2604
Migrants make Poland better or worth place to live	0.5726	0.2948

Table 2.5: Demographic Characteristics of Control and Treatment Areas

Demographic characteristics	Voivodeships with % employment in agricultural sector less than 10% (A)	Voivodeships with % employment in agricultural sector more than 10% (B)	Difference (C) = (A) - (B)
Age	47.13	46.36	0.77
	(18.39)	(18.68)	(1.15)
Female	0.55	0.51	0.04*
	(0.50)	(0.50)	(2.25)
Children	0.45	0.46	-0.01
	(0.50)	(0.50)	(-0.36)
University Education	0.20	0.22	-0.02
	(0.40)	(0.41)	(-1.44)
High Skilled	0.42	0.40	0.02
	(0.49)	(0.49)	(1.07)
Average Income	7.25	7.19	0.06***
	(0.09)	(0.17)	(11.29)
Number of regions	5	11	

Note: Columns (A) and (B) report the mean of each demographic and regional variable for voivodeships with percentage employment in agricultural sector from the total employment less then 10% and more then 10% in the sample. Column (C) reports the results of two-sample t test with equal variances. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard deviations are in parentheses.

Table 2.6: Difference-in-Difference Analysis

	(A)	(B)
Difference in Difference	0.26**	0.25**
	(0.12)	(0.12)
Individual Controls	Yes	Yes
NUTS2 Control	No	Yes
Observations	2509	2509
Adj. R^2	0.14	0.14

Note: The dependent variable is the measure of attitudes towards immigrants. Ordinary least-squares regression. Standard errors are in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level. Individual controls include: Age, Age^2, Female, Children, Married, University Education, High Skilled, Felling Happy, Non-Homophobic, Voted for PiS. Regional control is Average Income.

Table 2.7: Attitudes towards Immigrants

	OLS	IV	OLS	IV
Growth in Vacancies	0.01**	0.03***		
	(0.01)	(0.01)		
Growth in Residents			0.05**	0.08***
			(0.02)	(0.03)
Age	0.06**	0.06***	0.06**	0.06***
	(0.02)	(0.02)	(0.02)	(0.02)
Age^2	-0.01**	-0.01***	-0.01**	-0.01***
	(0.01)	(0.01)	(0.01)	(0.01)
Female	-0.04	-0.05	-0.04	-0.04
	(0.09)	(0.09)	(0.09)	(0.09)
Married	-0.06	-0.07	-0.07	-0.07
	(0.13)	(0.13)	(0.13)	(0.13)
Children	-0.16**	-0.16**	-0.16**	-0.16**
	(0.08)	(0.08)	(0.08)	(0.07)
University Education	0.21	0.22	0.22	0.23
	(0.18)	(0.17)	(0.18)	(0.17)
Studying	0.45**	0.45**	0.45**	0.44**
	(0.19)	(0.18)	(0.19)	(0.18)
High Skilled	0.32***	0.33***	0.32***	0.31***
	(0.07)	(0.07)	(0.07)	(0.07)
Felling Happy	0.11***	0.11***	0.11***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)
Non-Homophobic	0.56***	0.56***	0.56***	0.56***
	(0.11)	(0.11)	(0.11)	(0.11)
Voted for PiS	-0.30***	-0.29***	-0.29***	-0.28***
	(0.07)	(0.06)	(0.07)	(0.06)
Average Income	-0.02	0.16	-0.04	0.01
	(0.21)	(0.19)	(0.15)	(0.18)
Median Regional Attitudes	0.20	0.14	0.19*	0.16**
	(0.13)	(0.17)	(0.09)	(0.08)
Observations	1176	1176	1176	1176
Adj. R^2	0.12	0.11	0.12	0.12
K-P rk Wald F-stat		13.18		12.10

Note: The dependent variable is the measure of attitudes towards immigrants. Two-stage least-squares regression. Standard errors are in parentheses. Standard errors are clustered at NUTS2 (16 voivodeships) level and reported in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

Table 2.8: Attitudes towards Immigrants: High Skilled (Labour Force Composition Change)

	High-Skilled		**Low-Skilled**	
	OLS	IV	OLS	IV
Growth in Vacancies	0.01	0.02	0.01**	0.04***
	(0.01)	(0.01)	(0.00)	(0.01)
Individual Controls	Yes	Yes	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	501	501	675	675
Adj. R^2	0.09	0.08	0.08	0.07
K-P rk Wald F-stat		10.47		13.64

Note: The dependent variable is the measure of attitudes towards immigrants. Two-stage least-squares regression. Standard errors are in parentheses. Standard errors are clustered at NUTS2 (16 voivodeships) level and reported in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level. As individual controls Age, Age^2, Female, Children, Married, University Education, Studying, Felling Happy, Non-Homophobic, Voted for PiS are included. Regional controls are Average Income and Median Regional Attitudes

Table 2.9: Attitudes towards Immigrants: High Skilled (Demographic Composition Change)

	High-Skilled		**Low-Skilled**	
	OLS	IV	OLS	IV
Growth in Residents	0.04	0.06	0.08***	0.11***
	(0.03)	(0.05)	(0.02)	(0.03)
Individual Controls	Yes	Yes	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	501	501	675	675
Adj. R^2	0.09	0.09	0.08	0.08
K-P rk Wald F-stat		13.20		11.08

Note: The dependent variable is the measure of attitudes towards immigrants. Two-stage least-squares regression. Standard errors are in parentheses. Standard errors are clustered at NUTS2 (16 voivodeships) level and reported in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level. As individual controls Age, Age^2, Female, Children, Married, University Education, Studying, Felling Happy, Non-Homophobic, Voted for PiS are included. Regional control are Average Income and Median Regional Attitudes.

Table 2.10: Attitudes towards Immigrants: Gender Differentiation

	Female		**Male**	
	IV	IV	IV	IV
Growth in Vacancies	0.01		0.05^{***}	
	(0.02)		(0.02)	
Growth in Residents		0.01		0.16^{***}
		(0.06)		(0.05)
Individual Controls	Yes	Yes	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	603	603	573	573
Adj. R^2	0.09	0.09	0.11	0.12
K-P rk Wald F-stat	12.53	10.39	13.28	14.38

Note: The dependent variable is the measure of attitudes towards immigrants. Two-stage least-squares regression. Standard errors are in parentheses. Standard errors are clustered at NUTS2 (16 voivodeships) level and reported in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level. As individual controls Age, Age^2, Children, Married, University Education, Studying, High Skilled, Felling Happy, Non-Homophobic, Voted for PiS are included. Regional control are Average Income and Median Regional Attitudes.

Table 2.11: Attitudes towards Immigrants: Age Differentiation

	18-48		**49+**	
	IV	IV	IV	IV
Growth in Vacancies	0.01		0.04^{**}	
	(0.01)		(0.02)	
Growth in Residents		0.04		0.11^{***}
		(0.03)		(0.03)
Individual Controls	Yes	Yes	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	588	588	588	588
Adj. R^2	0.06	0.07	0.15	0.16
K-P rk Wald F-stat	11.33	11.73	14.22	11.35

Note: The dependent variable is the measure of attitudes towards immigrants. Ordinary least-squares regression. Standard errors are in parentheses. Standard errors are clustered at NUTS2 (16 voivodeships) level and reported in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level. As individual controls Female, Children, Married, University Education, Studying, High Skilled, Felling Happy, Non-Homophobic, Voted for PiS are included. Regional control are Average Income and Median Regional Attitudes.

Table 2.12: Attitudes towards Immigrants: Years 2012 - 2016

	OLS	IV	OLS	IV
Growth in Vacancies	0.01*	0.07***		
	(0.01)	(0.03)		
Growth in Residents			0.05**	0.21**
			(0.02)	(0.09)
Individual Controls	Yes	Yes	Yes	Yes
Regional Control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2496	2496	2496	2496
Adj. R^2	0.13	0.11	0.14	0.12
K-P rk Wald F-stat		10.85		11.74

Note: The dependent variable is the measure of attitudes towards immigrants. Two-stage least-squares regression. Standard errors are in parentheses. Standard errors are clustered at NUTS2 (16 voivodeships) level and reported in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level. As individual controls Female, Married, Children, University Education, Studying, High Skilled, Felling Happy, Non-Homophobic, Voted for PiS are included. Regional control is Average Income.

Table 2.13: Attitudes towards Immigrants, Year 2018

	OLS	IV	OLS	IV
Growth in Vacancies	0.02***	0.07**		
	(0.01)	(0.04)		
Growth in Residents			0.08*	0.22***
			(0.04)	(0.08)
Individual Controls	Yes	Yes	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	1056	1056	1056	1056
Adj. R^2	0.14	0.12	0.14	0.12
K-P rk Wald F-stat		10.12		11.31

Note: The dependent variable is the measure of attitudes towards immigrants. Two-stage least-squares regression. Standard errors are in parentheses. Standard errors are clustered at NUTS2 (16 voivodeships) level and reported in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level. As individual controls Female, Married, University Education, High Skilled, Studying, Felling Happy, Non-Homophobic, Voted for PiS are included. Regional control are Average Income.

Table 2.14: Attitudes towards Immigrants: Non-Linearity

	IV	IV
Growth in Vacancies	0.03	
	(0.20)	
Growth in Vacancies × Growth in Vacancies	-0.01	
	(0.01)	
Growth in Residents		-0.24
		(0.80)
Growth in Residents × Growth in Residents		0.03
		(0.08)
Individual Controls	Yes	Yes
Regional Controls	Yes	Yes
Observations	1176	1176
Adj. R^2	0.16	0.11
K-P rk Wald F-stat	0.11	0.28

Note: The dependent variable is the measure of attitudes towards immigrants. Two-stage least-squares regression. Standard errors are in parentheses. Standard errors are clustered at NUTS2 (16 voivodeships) level and reported in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level. As individual controls Age, Age^2, Female, Children, Married, University Education, Studying, High Skilled, Felling Happy, Non-Homophobic, Voted for PiS are included. Regional controls is Average Income and Median Regional Income.

Chapter 3

Exploring the Effects of Gender and Marital Status on Poverty: Evidence from Longitudinal data

This paper is a joint work with Professor Dr. Skerdilajda ZANAJ and Dr. Majlinda JOXHE.

3.1 Introduction

In this paper, we explore the poverty of divorced men and women in Russia, using the Russian Longitudinal Monitoring Survey for the period of 2004–2019.[1] Our purpose is to uncover the differences in poverty levels between divorcees focusing on gender.

"The divorce revolution" (Weitzman, 1985), which reduced the cost of exiting marriage, has led to the worldwide increase in divorce rates. The size of the phenomenon has brought

[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)

divorce to the center of the analysis of poverty. In 2018, almost 50% of all marriages in the United States ended in divorce, with a divorce taking place every 13 seconds. However, Russia is the country with the highest divorce rate in the world (OECD, 2019). The crude divorce rate in 2015 in Russia was 4.2 divorces per 1000 residents (Rosstat, 2015a) It appears essential, then, to examine income inequalities and poverty levels focusing on divorcees and married individuals. In particular, are there any gender differences? Prior studies in European countries and the USA have indicated that divorced women show significant higher levels of poverty than divorced men (Uunk, 2004; Andreß et al., 2006; Lundberg et al., 2016). Can we extend these results to Russia? We show that the answer is negative.

We measure poverty using an income and multidimensional poverty indicator. Our benchmark measure is the absolute income poverty that compares total money income with a subsistence level. The multidimensional poverty indicator augments our analysis with a material deprivation measure that indicates how individual consumption and economic conditions are compared to the corresponding average levels in the reference population. Therefore, our multidimensional poverty indicator includes three dimensions: income poverty, material deprivation and health.

In the benchmark model, we employ a uni-variate specification for income poverty, controlling for a series of individual characteristics that prior literature have establish as key determinants for income poverty. These include age, occupation, education level, presence of young children, urban vs. rural residency. Our model is dynamic and includes the poverty level of the previous period, since poverty shows time persistence.[2] To establish whether poverty state dependence is genuine or an over-representation, we control for observed and unobserved heterogeneity. We investigate the issue of initial conditions in the robustness analysis.

Our main result can be summarized as follows. We find that being poor is predominantly

[2]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.

a trap, but less so for a divorced woman. Divorced women show less poverty than divorced men do, during the period of 2004–2019. Considering the average marginal effects, a divorced woman is 6 percentage points less likely to be in income poverty than a divorced man and 1 percentage points less likely to be multidimensional deprived. These results are interesting because they point exactly to the opposite direction of prior studies in Europe and the USA. In other countries, increased family instability has increased the poverty levels of women. Some of this poverty levels is due to the greater likelihood that less-educated women are divorced (Lundberg et al., 2016). Unsurprisingly, poverty rates are substantially higher for divorced women with children at all levels of education than for married women with children (Payne, 2013).

There may be obviously some other selection into divorce, for instance, more economically independent individuals may file for a divorce more easily than those depending financially on their partner. However, a priori, the more independent spouse can be either the husband or the wife and identifying who is the more vulnerable is our research interest. As mentioned, literature suggests that women have higher chances to fall into poverty after a divorce. To mitigate this selection issue, we estimate an exogenous probability of divorce for married couples using assortative mating techniques 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 2019. We then match married couples in the 2004–2019 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 results remain qualitatively unaffected. The higher the probability of divorce for married couples, the higher the poverty level of married men, whereas the exogenous 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 woman 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? A possible answer can be the labor participation of women in the labor market. Inter-related dynamics seems a natural step to investigate 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. To check whether female labor participation is the mechanism behind our result, we use a bi-variate random effect estimation between poverty and status in the labor market. 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 bi-variate estimations show that there is a very strong and significant relationship between the risk of being poor and being unemployed, and this link evolves dynamically. Our main result is due to the fact that divorced women work more than divorced men. When divorced women are unemployed, they are similarly poor as men are.

But why do divorced women work more than divorced men? Our analysis of marital sorting for a long period on a sample that is representative of the Russian population shows that almost 55% of divorced couples had spouses not assorted along the education level. In addition, 42.88% of divorces in the period of 1995–2019 occurred in couples where the wife had a higher education level than her husband. Only in 16% 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.

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 robustness analysis check, and finally in section

8 we conclude.

3.2 Related Literature

We contribute to the literature on gender and poverty focusing on the comparison between divorced men and women. Despite being the poverty literature extremely large, there are not so many empirical comparisons of divorced men's and women's poverty using individual survey data.

Prior early studies relate the deterioration of women's economic conditions with marital disruption, both in the US (Duncan and Hoffman, 1985) and in several European countries (Uunk, 2004; Andreß et al., 2006; Jarvis and 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 wife (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.

Our work is also related to a growing literature that relates divorce to economic inequality (Hogendoorn et al., 2019; Lundberg et al., 2016; McLanahan, 2004). The main idea in this literature is that that higher educated individuals marry late and form stable marriages. By contrast, lower educated individuals, marry early and divorce more. As a consequence, the inequality gap between educated and uneducated individuals has been on the rise and fuelled by divorce. Interestingly, we document that assortative mating is not so strong in Russia, as we will discus in Section 5, leading to different marriage dynamics and results in terms of poverty.

Finally, another strand of prior literature related to our work is the one making a link between divorce and labor force participation. Özcan and Breen (2012) argue that marital instability affects labor supply rather than the other way around, meaning that women increase their labour force participation in anticipation of a divorce rather then as the consequence of the divorce. Van Damme et al. (2009) uses a multiple-country setting and finds that women in Europe only modestly increase employment after separation. Among the important micro-level determinants are education, presence of young children and working experience. Thielemans and Mortelmans (2019) studied female labor force participation after divorce using the divorce project in Flanders. The authors use 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. The main finding is that women are twice as likely to increase their employment for a short period of time after the separation. Observed differences between inactive and unemployed women are likely due to compositional differences at the time of separation. Overall, these results for Flanders are consistent to those we find for Russia. We show that gender differences in employment are long-lasting and they explain differences in income among divorcees.

3.3 Context

In the following sections, for completeness, we highlight several aspects of the marriage market as well as female labor market participation in Russia. These two aspects are functional to the mechanism behind our results.

3.3.1 The Marriage Market and Matching

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).

The Russian Federation went through significant upheavals in the 20th century. Still, some features of the marriage market have remained unchanged. Couples marry very early. The age of entry into marriage by Russian women has remained young compared to US or European standards. 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(Rosstat, 2018). However, despite this increase, the age of first marriage remains relatively young in contrast to Western trends. In 2018, the median age at first marriage was almost 30 for men and almost 28 for women (U.S. Census Bureau, 2018).

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.[3]

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

Women are more educated on average then men in Russia [4]. In 2015, 339 women and 264 men in every 1000 individuals have a university education Rosstat (2015b). 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 and Jalovaara, 2010, for a review).[5]

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 and 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 and 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 3.2). 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. As shown later in the paper (in Table 3.6), the percentage of married couples in which the wife has a better education than her husband is 34,49%, whereas among the divorced the respective percentage is higher 42,88%.

[4] This is documented in Table 3.2 for our database.

[5] 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.

3.3.2 Poverty and the Labor Market

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 only in Russia but in several eastern countries, were implemented to boost female labor participation.[6]

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 among the highest in the world. Female employment levels in Russia exceed those of men 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)[7].

3.4 Data and Summary Statistics

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

3.4.1 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 3.1. The RLMS-HSE collects information for a nationally representative sample of households across the Russian Federation.[8]

[6]For instance, Murphy and 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.

[7]In 2019, the retirement age was increased from 55 to 60 for women and from 60 to 64 for men, in Russia

[8]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

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 2004-2019. For each wave of the survey, we keep only individuals included in the representative sample. Further, we restrict our analysis to the adult population of age 18-64 years old. After dropping observations with missing crucial information, the dataset comprises 14267 individuals, of whom 11682 stayed married and 1327 stayed divorced throughout the period, 1258 changed their marital status during the period under study, for a total of 71953 person-year observations.

3.4.2 Poverty Indicators

We consider two aspects of poverty: income and multidimensional poverty. An individual is considered income-poor if the total reported income is less than the minimal vital income (i.e. *prozhitochnyy minimum*). The total income includes salary, pensions, bonuses, profits, benefits, material aid, odd jobs, and other cash receipts. The minimum vital income is fixed by the Russian government at the regional level and is calculated yearly on the basis of the price of a consumer basket in each region. 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.

Using this poverty threshold, we have 7166 individuals classified as "never poor" during the entire period 2004–2019 and 1249 who were under the poverty line during the whole period. In addition, we observe a gender income poverty gap with 30% of women and 18% of men under the poverty income threshold, as shown in Table 3.1.

The development economics literature on poverty argues that total income is not the only indicator of poverty. Multidimensional poverty measures give a more comprehensive picture,

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.

revealing the way individuals are poor and 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, following Alkire et al. (2014) and Bossert et al. (2013). More specifically, we use a dual-cutoff method proposed in Alkire and Foster (2011). [9] We define an individual as "multidimensionally poor" if he/she is deprived in at least one out of three dimensions: economic, material, or health.

The *economic* dimension is measured as income poverty. The *material* dimension includes 10 material deprivation conditions (see Table A1.3). Adapting the Bossert et al. (2013) indicators of material deprivation 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[10] and availability of regular meals. If an individual is considered as "deprived" on more than 4 conditions, then he/she is deprived on the *material* dimension. The *health* dimension is measure as a self-evaluation of the individual's health. If the individual considers own health as "very bad" or "bad", we recognize him/her as deprived in *health* dimension.

Each of the three dimensions is equally weighted (1/3). Accordingly, an individual is considered multidimensionally poor if she/he is deprived in at least one dimension or the equivalent sum of the weighted deprivations. We summarize the construction of the indicator in Table A1.4.

The multidimensional poverty indicator shows a different picture as compared to the income poverty. When using the multidimensional poverty, we have 4835 individuals who were not poor, 2342 individuals who were deprived for the entire period of observation, and 7090 individuals who changed status, either upward or downward. With respect to this indicator, gendered differences are less accentuated; 45% of both women and 35% of men are multidimensionally poor, as shown in Table 3.1.

Finally, to illustrate some relevant income differences in our database, we show graph-

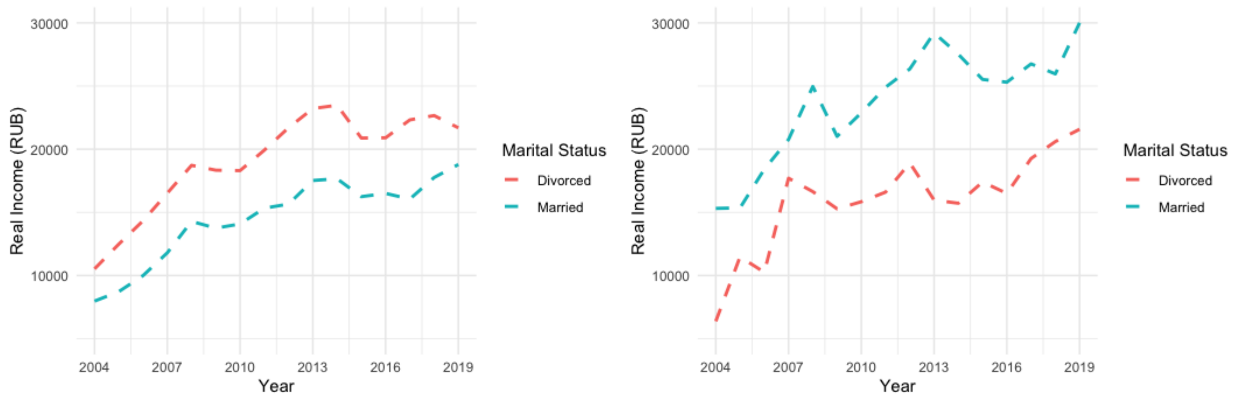
[9] Prior literature offers a large number of multidimensional poverty measures. But as shown byd'Ambrosio et al. (2011) these measures overlap in identifying an individual as multidimensional poor in 80% cases.

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

(a) All Individuals

(b) Divorced Individuals

Figure 3.1: Real-income dynamics by gender



(a) Women

(b) Men

Figure 3.2: Real-income dynamics by marital status

ically the income dynamics by gender and by marital status. Figure 3.1a and Figure 3.1b display, respectively, the median real income for women and men for the years of 2004–2019 and the median real income for divorced women and men. Men have almost twice as much income, but divorced women exhibit, on average, 3150 rubles more in real income than divorced men. Considering men and women separately, Figure 3.2a and 3.2b show that divorced women outperform married women, whereas divorced men do worse than married ones.

3.4.3 Summary Statistics

Table 3.1 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. Our sample is composed of 14267 individuals, 7738 women and 6529 men. This gender imbalance is representative of the Russian population.[11]

The first two columns display sample averages and standard deviations for women, whereas the other two report information about men. Divorced women are represented by a higher percentage (17%) as compared to divorced men (7%), and these shares are again representative of the Russian population. [12] In terms of average age, we observe a slightly younger women sample, whereas with respect to education level, there is clearly a gender difference. Men more often report elementary and secondary education compared to women. Instead, women 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 (24%) due to the different life expectancy between genders in the Russian Federation. In terms of employment rate, women are still less employed than men and possess less working experience in years. There are no gender differences in terms of health status, especially for very good or bad health.

3.5 Empirical Analysis

To uncover the dynamic differences between married and divorced individuals, as well as divorced women and men, in the Russian Federation, we estimate a random effects model applied to the period of 2004–2019 with poverty (or multidimensional poverty) as the outcome variable.

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

[12] According to the national census 2010 (Rosstat, 2010), among individuals with age between 18 and 64 year, the percentage of divorced men is 6,51% and of divorced women is 11,03% .

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[13], age[14], residency, education, health[15], etc.) so as to control for the observed heterogeneity among individuals, but also time and regional dummies.

At least three main sources of endogeneity exists in our endeavor to identify the effects of marital status on poverty of divorcees. We have an issue of selection into divorce. To tackle this problem, we make use of matching methods to determine an exogeneous probability of divorce for married couples. We postpone the discussion and this analysis until Section 5.2 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 fixed effects Cameron and 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.[16] In the robustness analysis, we also run a linear estimation model using individual fixed effects.

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

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

[15]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 and Vermeulen, 2008).

[16]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.

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., 2004, 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 initial condition problem is tackled in the robustness analysis for the period 2013-2018, using the Wooldridge (2005) approach.

3.5.1 Empirical Specifications

Baseline Estimation

Our benchmark empirical model measures the dynamic evolution of individual poverty. We run a probability random effect regression:

$$\begin{aligned} poor_{i,t} =& \lambda poor_{i,t-1} + \gamma_1 Divorce_{i,t} + \gamma_2 Female_{i,t} + \gamma_{12} Divorce_{i,t} \times Female_{i,t} + \\ & \beta x'_{i,t} + \psi z'_i + \phi poor_{i,1} + \delta \bar{x}'_{i,t} + \alpha_r + \alpha_t + \alpha_i + u_{i,t}. \end{aligned} \tag{3.1}$$

The dependent variable $poor_{i,t}$ takes a value of one if individual i is below the threshold of 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 $x_{i,t}$ represents time-variant parameters of interest, such as age, experience, number of young children, 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 calculate marginal effects of the interaction term $Divorce \times Female$ we follow Norton et al. (2004).

For the dummie variables *Female* and *Divorce* (denoted by x) we have:

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

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

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

For the interaction term $Divorce \times Female$, we:

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

Since in our case the interacted variables are both dummies, the interaction effect is expressed as the discrete double difference:

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

The average marginal effects of the estimation are shown in Table 3.3. Results for multidimensional poverty are in Table 3.4. We start by gradually introducing first the divorce and the interaction term (Column 2), the individual controls (column 3) and the year and fixed effects (Column 4). Findings in Column 4, our preferred specification, show that the lagged poverty status is significant at a 99% level of confidence, implying that the effect of state dependence is present and strong. The coefficient of gender variable shows that women on average are 10 percentage points more likely to be in income poverty as compared to men, which indicates the presence of a poverty gender gap. The coefficient of divorce is slightly significant in specification (4). Nonetheless, the marginal effect of the interaction term "Divorce $\times$ Female" is significant and predicts that a divorced woman is 6 percentage points less likely to be in income poverty.

As for the other controls, we can see from the output Table 3.3 that age, education, and living in an urban area negatively impact the probability of becoming poor. The coefficient of the employment variable has the strongest effect in term of the size. This gives us the first hint towards the mechanism of the main finding, namely the relevance of the job income in poverty formation (as we discuss in the Section 6).

Table 3.4 provides the results of the univariate estimation when multidimensional poverty is the outcome variable. As compared to the income poverty, the coefficient of the gender variable is slightly lower in size - 9 percentage points compared to 10 percentage points. This indicates that when we account for the other dimensions of deprivations the poverty gender gap is less pronounced. Therefore, unsurprisingly, the size of the interaction term "Divorce $\times$ Female" coefficient is lower compared to the one reported in Table 3.3. The effect is significant and negative, suggesting that divorced women are 1% percentage points less likely to become multidimensionally poor.

3.5.2 Mating and the Probability of Divorce

To tackle the problem of selection into divorce, we investigate the married couples in our sample. Our aim is to check how an exogenous probability of divorce 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 2019 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 2004–2019, using educational sorting as the criterion for the match, along with age and labour force participation status of the partner.

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

Probability of Divorce

We explore the quality of the marriage as an indicator of future divorce. The probability of divorce depends on multiple, observed and unobserve, factors, which are captured by the quality of the marriage. Choo and Siow (2006) in their seminal work introduce a static transferable utility model of the marriage market. They model and estimate the net gain (or matching surplus) from the marriage, using age as the only differentiation parameter between females and males. This "matching surplus" does reflect the quality of the marriage. Dupuy and Galichon (2014) have generalized this model along several dimensions. Authors determine the most relevant sorting dimensions on the marriage market and construct indices of mutual attractiveness. Besides age, they use education, height, health, BMI, and psychometric attributes as sorting dimensions. Authors demonstrate that sorting on the marriage market occurs on multiple dimensions, not on a single one.

We take a complementary approach. Rather than estimating the matching surplus, in line with our research question, we estimate the "stability" of the marriage. In particular, we statistically estimate the probability of divorce, accounting for the age of the partners, labour force participation, and education. This allows as to match a predicted probability of divorce to married individuals in the benchmark sample.

As a first step, we consider the whole period covered by the RLMS-HSE survey, from 1995 to 2019. 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 3.5, 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 the 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 the 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 3.6, we provide summary statistics for the education of husbands and wives in couples who stayed married and couples who got divorced. We observe 5949 couples who stayed married during the period of observation (1995–2019) and 625 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, 421 couples stayed married and 31 couples got divorced. However, in couples where the wife has a university degree and the husband has only finished elementary school, 21 couples stayed married and 2 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 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.

Another important sorting variable in the marriage market is age. Tables 3.10 and 3.11 reports number of divorced and married couples by different age groups. For both divorced and stayed married more than 60% wife and husband are in the same age category. However, among couples who got divorced, the percentage of couples with a wife older than the husband is 13%, whereas, for married couples, the respective percent is around 7%.

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

$$\begin{aligned} divorce_w = &\beta_1 Elementary_w + \beta_2 Secondary_w + \beta_3 Vocational_w + \beta_4 Higher_w + \\ &\gamma_1 Age_h + \gamma_2 LFP_h + u_w, \end{aligned} \tag{3.2}$$

where the subscript w indicates $wife$ and h indicates *husband.* The probit model for men is easily derived by substituting the subscript w with h. We report the average marginal effects in Table 3.7. 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 both for wife and for husband. 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.

Poverty and Probability of Divorce

We are now in the condition to estimate the poverty specification by 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 2004–2019.

In the sample corresponding to the benchmark analysis, keeping only married couples for which partners filled in the questionnaire, we are left with 7421 individuals observed over 15 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 3.2: education, age of the partner, and partners' employment.

The estimates are reported in Table 3.12. Reassuringly, we observe that the probability of divorce for married couples still indicates that women who may get divorced in the future do not have a lower probability of becoming poor. Hence, the probability of divorce does not cause women to become poorer. Men who face a high probability of divorce due to infelicitous marital sorting face a high probability of becoming poor. 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.

3.6 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 2013–2018. 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 6 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 2013. We take individuals who are included in the representative sample in 2013 and add observations for these individuals for the years of

2013–2018. We do not use post-stratification weights, following the suggestion of Heeringa and Arbor (1997) regarding the use of weights in multivariate analyses with fixed effects.[17]

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.[18]

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).

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 and 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

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

[18] 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 over-represented in the initial period. Numerous papers show a state dependence of poverty (for instance, Cappellari and Jenkins (2002); Bigsten and Shimeles (2008); Fertig and Tamm (2010)) and persistence of unemployment (see Stewart (2007); Crépon et al. (2005); Buddelmeyer et al. (2010)).

variables in the first period into equations. Following Devicienti and 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 are used to specify his/her condition at each year t:

$$\begin{aligned}
poor_{i,t} = &\gamma_{11}Divorce_{i,t} + \gamma_{21}Female_{i,t} + \gamma_{31}Divorce_{i,t} \times Female_{i,t} + \lambda_{11}poor_{i,t-1}+\\
&\lambda_{21}lfp_{i,t-1} + \beta_1 x'_{1,i,t} + \psi_1 z'_i + \phi_{11}poor_{i,1} + \phi_{21}lfp_{i,1} + \delta_1\bar{x}'_{i,t} + \alpha_{1r} + \alpha_{1t} + \alpha_{1i} + u_{1,i,t},\\
lfp_{i,t} = &\gamma_{12}Divorce_{i,t} + \gamma_{22}Female_{i,t} + \gamma_{32}Divorce_{i,t} \times Female_{i,t} + \lambda_{12}poor_{i,t-1}+\\
&\lambda_{22}lfp_{i,t-1} + \beta_2 x'_{1,i,t} + \psi_2 z'_i + \phi_{12}poor_{i,1} + \phi_{22}lfp_{i,1} + \delta_2\bar{x}'_{i,t} + \alpha_{2r} + \alpha_{2t} + \alpha_{2i} + u_{2,i,t}.
\end{aligned} \tag{3.3}$$

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.

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. 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.

The dynamic bivariate random effect probability model is estimated using `bireprob` in `STATA` (Plum (2016)). We use the maximum simulated likelihood and consider correlation in the random-effects error terms and in the idiosyncratic shock. For more details see Appendix B.

The marginal effect for the interaction term is calculated in a similar manner as discussed for the univariate probability model (see Section 5.1.1.) but adjusting the bivariate normal distribution instead of a univariate distribution.

In Table 3.13, we report the point estimates of the bivariate estimation, whereas in Table 3.15 we show results of the bivariate regression with multidimensional poverty indicator.

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 and the interaction term in this bivariate relation, we refer the reader to Table 3.14. Similarly to the univariate estimation, when performing a bivariate estimation, women are 1 percentage point more likely than men to be poor and unemployed. The marginal effect of the interaction term $Female \times Divorce$ also exhibits a similar but stronger result to the univariate case: divorced working women are 4 percentage points less likely be in poverty and 16 percentage points more likely to be out of poverty than a divorced working men. A divorced unemployed woman is 1 percentage point less likely be in poverty but 4 percentage points more likely to be in poverty than a divorced unemployed men.

Table 3.15 and Table 3.16 present the results from our estimation of multidimensional poverty. The marginal effects of the bivariate estimates are similar to the one reported for the income poverty, with a lower magnitude. Women are 2 percentage points more likely to be poor and unemployed and 5 percentage points to work and be in poverty. However, divorced women are 2 percentage points more likely to be poor and unemployed and 14 percentage points more likely to have a job and be out of poverty. Hence, our main results remain unchanged and are even stronger when we consider a bivariate structure to account for the interdependency between unemployment and poverty.
Why is it that divorced women who work, are less poor than divorced working men? Looking at Tables 3.6 and 3.7, our analysis of marital sorting over a very long period on a sample that is representative of the Russian population shows that almost 55% of divorced couples

had spouses not assorted along the education level. In addition, 42.88% of divorces in the period of 1995–2019 occurred in couples where the wife had a higher education level than her husband. However, only in 16% of the divorced couples, 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, because the husband - as a less educated spouse, appears to be in less favorable economic position compared to a more educated spouse.

3.7 Robustness analysis

Robustness is shown with respect to (i) a sample shift to exclude the switchers, those individuals changing marital status during the period under study; (ii) the method of estimation when we use a linear model and introduce individual fixed effects rather then random effects; and finally (iii) to account for the initial conditions. These three exercises, leave our main results qualitatively intact.

3.7.1 Leaving out the switchers

In this section, we focus only individuals who remained divorced or remained married during the entire period 2004-2019. In the reduced sample we observe 11682 individuals who stayed married thought the period of observation and 1327 individuals who stayed divorced. Focusing on this sample allows to further mark away the moment of the divorce and investigate a long term effect of the marital dissolution on the poverty. We estimate the baseline probability model 3.1 and report the average marginal effects in Table 3.17. Reassuringly, the results remain unchanged. The poverty gender gap has the same exact magnitude as in the baseline specification and *Always Divorced* women are 5 percentage points less likely to fall into poverty, compared to 6 percentage points in the baseline specification.

3.7.2 Linear model with individual fixed effects

To introduce individual fixed effects, we run our benchmark estimation using an OLS specification. The results are shown in Table 3.18. As gender is a time persistent variable, we cannot estimate the coefficient of the interaction term of variables marital status and gender using the fixed effect model, therefore we split our baseline sample by gender and report the coefficient of the *Divorce* variable. The effect on income poverty for divorced women is exactly as in our benchmark estimation 6%, while the size of the coefficient for deprivation increases in size (now 3 % compared to 1 percentage point) but the sign is always pointing to the same direction - in both specifications divorced women are better off as compared to married ones, whereas the effect is not significant for a divorced man.

3.7.3 Initial conditions

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. As suggested, we use 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. To do this, we focus on the period 2013–2018 due to the restriction to use a balanced panel. Results are shown in Table 3.19. Our findings remain very stable pointing to less income poverty for divorced women as compared to divorced men.

3.8 Conclusions

In this paper, we use longitudinal data from Russia for the years 2004–2019 to explore poverty among divorcees. Our findings show that despite being the state of poverty a long-term trap, the trap seems easier to escape for divorced women. Divorced women are less poor than divorced men during the period of 2004–2019. Considering the average marginal effects, we find that a divorced woman is 6 percentage points less likely to be in income poverty. As for the multidimensional poverty divorce women and men appears quite similar with the divorced women only 1 percentage points less likely to be multidimensionally poor. Our results are confirmed when we consider the role of an exogenous probability to divorce for married couples during the period under study. The probability of divorce is associated with a higher level of poverty for men, while a future possible divorce does not impact the poverty income level of women.

We provide a possible mechanism for our findings. Using a bivariate random effect estimation, we show that divorced women work more than divorced men. Instead, when divorced women do not work, their levels of poverty are not different than those of men.

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 men and women 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. In addition, a focus on divorce is warranted for policies that aim at reducing economic inequality.

3.9 Tables

Table 3.1: Summary Statistics

	Female		Male	
	Mean	Std.Dev.	Mean	Std.Dev.
Demographics				
Age	44.41	11.48	45.33	11.04
Divorce	0.17	0.37	0.07	0.26
Retired	0.24	0.43	0.11	0.32
Urban Area	0.73	0.45	0.69	0.46
Number of Children	0.63	0.87	0.66	0.89
Education				
Elementary Education	0.09	0.28	0.15	0.36
Secondary Education	0.31	0.46	0.43	0.50
Vocational/Technical Education	0.31	0.46	0.20	0.40
University Education	0.29	0.46	0.21	0.41
Poverty and Employment				
Income Poverty	0.30	0.46	0.18	0.38
Multidimensional Poverty	0.45	0.50	0.35	0.48
Employment	0.68	0.46	0.75	0.43
Working Experience	18.95	12.44	20.08	12.56
Observations	39959		31994	

Note: Source - RLMS-HSE 2004-2019. Columns 1 and 3 report the sample averages for female and male population, 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; *Number Children* is the number of children under 18 years old.

Table 3.2: 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	0.18	0.38
Secondary Education	0.43	0.50	0.46	0.50
Vocational/Technical Education	0.20	0.40	0.19	0.40
University Education	0.21	0.41	0.16	0.37
Female				
Elementary Education	0.09	0.29	0.07	0.26
Secondary Education	0.31	0.46	0.29	0.45
Vocational/Technical Education	0.31	0.46	0.32	0.47
University Education	0.29	0.45	0.32	0.47

Note: Source: RLMS-HSE 2004-2019

Table 3.3: Income Poverty 2004-2019: Average Marginal Effects

	(1)		(2)		(3)		(4)	
	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.
Income Poverty$_{t-1}$	0.33***	0.01	0.33***	0.01	0.23***	0.01	0.20***	0.01
Female	0.09***	0.01	0.09***	0.01	0.10***	0.01	0.10***	0.01
Divorce			−0.01	0.01	−0.01*	0.01	−0.01*	0.01
Divorce× Female			−0.08***	0.01	−0.06***	0.01	−0.06***	0.01
Age					−0.01*	0.01	−0.01***	0.01
Age Sq.					0.01	0.01	0.01***	0.01
Working Experience					−0.01***	0.01	−0.01***	0.01
Secondary Educ.					−0.03***	0.01	−0.02***	0.01
Vocational Educ.					−0.05***	0.01	−0.04***	0.01
University Educ.					−0.09***	0.01	−0.07***	0.01
Employed					−0.34***	0.01	−0.34***	0.01
Num. Young Children					−0.01***	0.01	−0.02	0.01
Urban Area					−0.05***	0.01	−0.02***	0.01
Retired					−0.13***	0.01	−0.13***	0.01
Random Ind. FE	*Yes*		*Yes*		*Yes*		*Yes*	
Year FE	*No*		*No*		*No*		*Yes*	
Region FE	*No*		*No*		*No*		*Yes*	
σ_u	0.63		0.63		0.57		0.58	
ρ	0.28		0.28		0.24		0.25	
Observation	71953		7195		71953		71953	

Note: Source: Source: RLMS-HSE 2004-2019. The sample excludes all individuals who are not present in the survey throughout 2004-2019. 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.
Year FE includes 15 year dummies; *Region FE* includes 38 regional dummies; *Longitudinal Means* includes averages over 6 years of the time-varying variables Age, Age^2, Working Experience, Employed, Household Size, Number Children, Education, Health, Retired.
σ_u is the panel-level standard deviation, ρ is the proportion of the total variance contributed by the panel-level variance component.

Table 3.4: Multidimensional Poverty 2004-2019: Average Marginal Effects

	(1)		(2)		(3)		(4)	
	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.
Multidim. Poverty$_{t-1}$	0.26***	0.01	0.26***	0.01	0.21***	0.01	0.20***	0.01
Female	0.08***	0.01	0.08***	0.01	0.09***	0.01	0.09***	0.01
Divorce			0.02*	0.01	0.02***	0.01	0.02***	0.01
Divorce× Female			−0.05***	0.01	−0.02**	0.01	−0.01*	0.01
Age					−0.01**	0.01	−0.01***	0.01
Age Sq.					0.01***	0.01	0.01***	0.01
Working Experience					−0.01***	0.01	−0.01***	0.01
Secondary Educ.					−0.04***	0.01	−0.03***	0.01
Vocational Educ.					−0.07***	0.01	−0.06***	0.01
University Educ.					−0.13***	0.01	−0.12***	0.01
Employed					−0.32***	0.01	−0.32***	0.01
Num. Young Children					0.01	0.01	0.01**	0.01
Urban Area					−0.16***	0.01	−0.08***	0.01
Retired					−0.11***	0.01	−0.11***	0.01
Random Ind. FE	*Yes*		*Yes*		*Yes*		*Yes*	
Year FE	*No*		*No*		*No*		*Yes*	
Region FE	*No*		*No*		*No*		*Yes*	
σ_u	0.82		0.81		0.68		0.65	
ρ	0.40		0.40		0.31		0.29	
Observation	71953		71953		71953		71953	

Note: Source: Source: RLMS-HSE 2004-2019. The sample excludes all individuals who are not present in the survey throughout 2004-2019. The table contains the estimated average marginal effect on the probability of being multidimensionaly 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.
Year FE includes 15 year dummies; *Region FE* includes 38 regional dummies; *Longitudinal Means* includes averages over 15 years of the time-varying variables Age, Age^2, Working Experience, Employed, Household Size, Number Children, Education, Health, Retired.
σ_u is the panel-level standard deviation, ρ is the proportion of the total variance contributed by the panel-level variance component.

Table 3.5: 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 3.6: Educational Matching of Married and Divorced Couples

	Married		Divorced	
	Number	Percent	Number	Percent
Elementary Match-Wife				
Husband Education				
Elementary	421	7.08	31	4.96
Secondary	180	3.03	23	3.68
Vocational	85	1.43	8	1.28
University	21	0.35	2	0.32
Secondary Match-Wife				
Husband Education				
Elementary	269	4.52	41	6.56
Secondary	870	14.62	108	17.28
Vocational	306	5.14	29	4.64
University	163	2.74	21	3.36
Vocational Match-Wife				
Husband Education				
Elementary	243	4.08	28	4.48
Secondary	698	11.73	92	14.72
Vocational	502	8.44	61	9.76
University	389	6.54	17	2.72
University Match-Wife				
Husband Education				
Elementary	98	1.65	17	2.72
Secondary	389	6.54	51	8.16
Vocational	355	5.97	39	6.24
University	960	16.14	57	9.12
Couples	5949		625	

Note: Source: RLMS-HSE 1995-2019. 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 3.7: 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	−0.01	0.01
Vocational	−0.02	0.02	−0.01	0.01
University	0.00	0.02	−0.03	0.01
Vocational Match				
Partner's Education				
Elementary	0.01	0.02	−0.01	0.03
Secondary	0.01	0.02	−0.04***	0.01
Vocational	−0.01	0.02	−0.02	0.01
University	−0.06***	0.01	−0.03**	0.01
University Match				
Partner's Education				
Elementary	0.02	0.03	−0.01	0.07
Secondary	−0.01	0.02	−0.01	0.02
Vocational	−0.02	0.02	−0.07***	0.01
University	−0.05***	0.01	−0.07***	0.01
Age Partner	−0.01***	0.01	−0.01***	0.01
LFP Partner	−0.01	0.01	0.03***	0.01
Individuals	6574		6574	

Note: Source: RLMS-HSE 1995-2019. 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 3.8: Summary Statistics: Wife

	Married		**Before Divorce**		**After Divorce**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std.Dev.
Age	48.23	13.98	37.93	11.61	39.74	11.38
Income Poverty	0.39	0.50	0.39	0.49	0.30	0.46
Employment	0.57	0.49	0.73	0.44	0.74	0.43
Individuals	5949		625		546	

Note: Source: RLMS-HSE 1995-2019. 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 3.9: Summary Statistics: Husband

	Married		**Before Divorce**		**After Divorce**	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std.Dev.
Age	49.95	14.19	39.50	11.57	41.53	11.50
Poverty	0.24	0.43	0.26	0.44	0.36	0.48
Employment	0.67	0.47	0.79	0.41	0.72	0.45
Individuals	5949		625		351	

Note: Source: RLMS-HSE 1995-2019. 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 3.10: Married Couples by Age Categories

	Age Husband							
Age Wife	**17-25**	**26-35**	**36-45**	**46-55**	**56-65**	**66-75**	**76-85**	**86-95**
	48	40	3	0	0	0	0	0
	14	135	51	3	2	0	0	0
	2	22	107	34	3	0	0	0
	0	1	22	68	9	3	0	0
	0	0	3	15	24	5	1	0
	0	0	0	0	2	6	1	0
	0	0	0	1	0	0	0	0
	0	0	0	0	0	0	0	0
							Total	**625**

Note: Source: RLMS-HSE 1995-2019. The sample only divorced couples.

Table 3.11: Summary Statistics: Husband

Age Wife	Age Husband							
	17-25	**26-35**	**36-45**	**46-55**	**56-65**	**66-75**	**76-85**	**86-95**
	224	194	10	1	2	0	0	0
	37	691	334	13	4	0	0	0
	2	73	812	339	14	1	0	0
	0	2	86	777	287	8	1	0
	0	0	1	81	835	203	11	0
	0	0	0	6	70	422	129	1
	0	0	0	0	0	47	188	25
	0	0	0	0	0	1	5	12
							Total	**5949**

Note: Source: RLMS-HSE 1995-2019. The sample only married couples.

Table 3.12: Income Poverty using the Predicted Probability of Divorce: Average Marginal Effects

	Female		**Male**	
	Coeff	Std.Err.	Coeff	Std.Err.
Income Poverty$_{t-1}$	0.26^{***}	0.01	0.13^{***}	0.01
Pr. Divorce	-0.08	0.09	0.16^{*}	0.09
Age	-0.01^{*}	0.01	0.01^{*}	0.01
Age Sq.	0.01	0.01	-0.01	0.01
Working Experience	-0.01^{***}	0.01	-0.01^{***}	0.01
Secondary Educ.	-0.01	0.01	-0.02^{**}	0.01
Vocational Educ.	-0.02	0.02	-0.04^{***}	0.01
University Educ.	-0.07^{***}	0.02	-0.06^{***}	0.01
Employed	-0.40^{***}	0.01	-0.26^{***}	0.01
Num. Young Children	0.01	0.01	-0.01^{***}	0.01
Urban Area	-0.03^{**}	0.01	-0.06^{***}	0.01
Retired	-0.13^{***}	0.01	-0.09^{***}	0.01
Random Effects	Yes		Yes	
Year FE	Yes		Yes	
Region FE	Yes		Yes	
σ_u	0.56		0.66	
ρ	0.24		0.30	
Observations	15867		16197	

Note: Source: RLMS-HSE 2004-2019. The sample excludes all individuals who are not present in the survey for all 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 3.7 ; *Year FE* includes 6 year dummies; *Region FE* includes 38 regional dummies; *Longitudinal Means* includes averages over 6 years of the time-varying variables: Age, Age^2, Working Experience, Employed, Number Children.
σ_u is the panel-level standard deviation, ρ is the proportion of the total variance contributed by the panel-level variance component.

Table 3.13: Income Poverty Estimates of the Bivariate Probability Random Effects Model

	Poverty		**LFP**	
	Coeff	Std.Err.	Coeff	Std.Err.
Income Poverty$_{t-1}$	0.87^{***}	0.06	0.23^{***}	0.06
Employed$_{t-1}$	-0.13^{**}	0.07	1.65^{***}	0.07
Income Poverty$_{t_0}$	0.81^{***}	0.07	-0.21^{***}	0.07
Employed$_{t_0}$	-0.08	0.07	0.87^{***}	0.10
Female	0.58^{***}	0.05	-0.22^{***}	0.05
Divorce	0.20	0.13	-0.28^{**}	0.14
Female × Divorce	-0.46^{***}	0.15	0.37^{**}	0.16
Age	-0.03	0.09	0.25^{**}	0.10
Age^2	0.01	0.01	-0.01^{***}	0.01
Working Experience	0.01	0.01	0.01	0.01
Secondary Educ.	-0.20^{***}	0.07	0.13^{*}	0.07
Vocational Educ.	-0.32^{***}	0.07	0.32^{***}	0.08
University Educ.	-0.54^{***}	0.08	0.57^{***}	0.08
Number Children	0.12^{**}	0.06	-0.05	0.06
Urban Area	-0.10	0.07	0.17^{**}	0.08
Retired	-0.52^{***}	0.08	-0.64^{***}	0.09
Random Ind. FE	Yes		Yes	
Year FE	Yes		Yes	
Region FE	Yes		Yes	
Longitudinal Means	Yes		Yes	
$\sigma^2_{\alpha_1}$	0.41^{***}		0.06	
$\sigma^2_{\alpha_2}$	0.41^{***}		0.08	
ρ_α	-0.98^{***}		0.03	
ρ_u	-0.57^{***}		0.02	
Observations	13115			

Note: Source: RLMS-HSE 2013-2018. The sample excludes all individuals who are not present in the survey for the 6 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).
Year FE includes 4 year dummies; *Region FE* includes 37 regional dummies; *Longitudinal Means* includes averages over 6 years of the time-varying variables Age, Age^2, Working Experience, Number Children, 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 3.14: 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	0.05^{***}	0.01	0.01^{***}	0.01	-0.13^{***}	0.02	-0.01	0.01
Divorce	-0.01	0.01	0.01	0.01	-0.01	0.03	0.02	0.03
Divorce × Female	-0.04^{***}	0.01	-0.01^{***}	0.01	0.16^{***}	0.01	-0.04^{***}	0.01
Observations	13115							

Note: Source: RLMS-HSE 2013-2018. The sample excludes all individuals who are not present in the survey for the 6 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 3.15: Multidimensional Poverty Estimates of the Bivariate Probability Random Effects Model

	Mult. Poverty		LFP	
	Coeff	Std.Err.	Coeff	Std.Err.
Multidim. Poverty$_{t-1}$	0.57***	0.05	0.06	0.06
Employed$_{t-1}$	−0.25	0.07	1.67***	0.07
Multidim. Poverty$_{t_0}$	1.00***	0.06	−0.17***	0.06
Employed$_{t_0}$	0.02	0.08	0.79***	0.09
Female	0.30***	0.05	−0.16***	0.05
Divorce	0.18	0.15	−0.24*	0.12
Female × Divorce	−0.31**	0.15	0.32**	0.15
Age	0.01	0.08	0.20**	0.10
Age^2	0.01	0.01	−0.01***	0.01
Working Experience	0.01	0.01	0.01	0.01
Secondary Educ.	−0.17***	0.08	0.13**	0.07
Vocational Educ.	−0.23***	0.08	0.34***	0.08
University Educ.	−0.56***	0.08	0.58***	0.09
Number Children	0.02	0.05	−0.03	0.06
Urban Area	−0.26***	0.07	0.18**	0.07
Retired	−0.26***	0.07	−0.61***	0.08
Year FE	Yes		Yes	
Region FE	Yes		Yes	
Longitudinal Means	Yes		Yes	
$\sigma^2_{\alpha_1}$	0.79		0.05	
$\sigma^2_{\alpha_2}$	0.89		0.11	
ρ_α	−0.63		0.13	
ρ_u	−0.50		0.04	
Observations	13115			

Note: Source: RLMS-HSE 2013-2018. 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).

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 3.16: Marginal Effects: Multidimensional Poverty (at mean values)

	Mult. Poor=1, LFP=1		**Mult. Poor=1, LFP=0**		**Mult. Poor=0, LFP=1**		**Mult. Poor=0, LFP=0**	
	Coeff	Std.Err.	Coeff	Std.Err.	Coeff	Std.Err.	Coeff	Std.Err.
Female	0.05^{***}	0.01	0.02^{***}	0.01	-0.09^{***}	0.02	-0.01	0.01
Divorce	-0.01	0.02	0.01	0.01	-0.01	0.03	0.01	0.01
Divorce × Female	-0.03^{***}	0.01	-0.04^{***}	0.01	0.14^{***}	0.01	-0.02^{***}	0.01
Observations	13115							

Note: Source: RLMS-HSE 2013-2018. The sample excludes all individuals who are not present in the survey for the 6 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*.

Table 3.17: Income Poverty 2004-2019, Switchers' Sample: Average Marginal Effects

	Income Poverty	
	Coeff	Std. Err.
Income Poverty$_{t-1}$	0.20^{***}	0.01
Female	0.10^{***}	0.01
Always Divorced	-0.01	0.01
Always Divorced$\times$ Female	-0.05^{***}	0.01
Age	-0.01^{***}	0.01
Age sq.	0.01^{**}	0.01
Working Experience	-0.01^{***}	0.01
Secondary Educ.	-0.02^{***}	0.01
Vocational Educ.	-0.04^{***}	0.01
University Educ.	-0.07^{***}	0.01
Employed	-0.33^{***}	0.01
Num. Young Children	-0.01	0.01
Urban Area	-0.02^{***}	0.01
Retired	-0.13^{***}	0.01
Random Ind. FE	Yes	
Year FE	Yes	
Region FE	Yes	
σ_u	0.59	
ρ	0.26	
Observations	64068	

Note: Source: Source: RLMS-HSE 2004-2019. The sample includes only individuals who did not change the marital status through the period of observation: they either stayed married or stayed divorced in each period t. 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.
Year FE includes 15 year dummies; *Region FE* includes 38 regional dummies; *Longitudinal Means* includes averages over 6 years of the time-varying variables Age, Age^2, Working Experience, Employed, Household Size, Number Children, Education, Health, Retired.
σ_u is the panel-level standard deviation, ρ is the proportion of the total variance contributed by the panel-level variance component.

Table 3.18: Income and Multidimensional Poverty: OLS with Fixed Effects

	Income Poverty				**Mult. Poverty**			
	Female		*Male*		*Female*		*Male*	
	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.	Coeff	Std. Err.
Income Poverty $_{t-1}$	0.07***	0.01	0.02**	0.01				
Multidim. Poverty$_{t-1}$					0.03***	0.01	−0.01	0.01
Divorce	−0.06***	0.01	0.02	0.02	−0.03*	0.02	−0.01	0.02
Age	0.01	0.01	0.01**	0.01	−0.01	0.01	0.02**	0.01
Age sq.	−0.01	0.01	−0.01***	0.01	0.01	0.01	−0.01***	0.01
Working Experience	0.01	0.01	0.01	0.01	−0.01	0.01	−0.01	0.01
Secondary Educ.	0.01	0.02	−0.01	0.01	−0.02	0.02	0.01	0.01
Vocational Educ.	−0.02	0.02	−0.01	0.02	−0.03*	0.02	−0.01	0.02
University Educ.	−0.04	0.02	−0.01	0.02	−0.04	0.03	−0.01	0.03
Employed	−0.38***	0.01	−0.30***	0.01	−0.31***	0.01	−0.26***	0.01
Num. Young Children	0.01*	0.01	−0.02***	0.01	0.02***	0.01	−0.01	0.01
Urban Area	−0.04	0.10	0.02	0.07	−0.01	0.08	0.09	0.06
Retired	−0.09***	0.01	−0.15***	0.01	−0.07***	0.01	−0.09***	0.02
Individual FE	*Yes*		*Yes*		*Yes*		*Yes*	
Year FE	*Yes*		*Yes*		*Yes*		*Yes*	
σ_u	0.29		0.25		0.35		0.36	
σ_e	0.32		0.28		0.36		0.34	
ρ	0.45		0.45		0.49		0.53	
Observations	39959		31994		39959		31994	

Note: Source: Source: RLMS-HSE 2004-2019. The sample includes individuals who have change the marital status from married to divorce during the observation window. We observe each individual last year married and first year divorced. The table contains the estimated average marginal effect on the probability of being income poor in the period t (Columns 2 and 3) and being multidimensionaly poor in the period t (Columns 4 and 5) 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 `xtreg` routine with fixed effects. It estimates fixed-effects linear models. *Year FE* includes 15 year dummies. σ_u is the panel-level standard deviation, σ_e is the standard deviation of the time-variant error term, ρ is the fraction of total variance due to the individual term.

Table 3.19: Income Poverty 2013-2018: Average Marginal Effects

	(1) Coeff	(1) Std. Err.	(2) Coeff	(2) Std. Err.	(3) Coeff	(3) Std. Err.	(4) Coeff	(4) Std. Err.
Income Poverty$_{t-1}$	0.18***	0.02	0.18***	0.02	0.15***	0.02	0.13***	0.01
Income Poverty$_{t_0}$	0.23***	0.02	0.23***	0.01	0.14***	0.01	0.13***	0.01
Female	0.06***	0.01	0.06***	0.01	0.08***	0.01	0.09***	0.01
Divorce			−0.03*	0.01	−0.02	0.01	−0.02	0.02
Divorce× Female			−0.07***	0.02	−0.05***	0.02	−0.05***	0.01
Age					−0.01***	0.01	0.01	0.01
Age Sq.					0.01**	0.01	−0.01	0.01
Working Experience					−0.01	0.01	0.01	0.01
Secondary Educ.					−0.05***	0.01	−0.04***	0.01
Vocational Educ.					−0.05***	0.01	−0.05***	0.01
University Educ.					−0.08***	0.02	−0.07***	0.01
Employed					−0.29***	0.01	−0.32***	0.02
Num. Young Children					−0.01	0.01	0.02**	0.01
Urban Area					−0.03***	0.01	−0.01	0.01
Retired					−0.13***	0.01	−0.12***	0.01
Year FE	*No*		*No*		*No*		*Yes*	
Region FE	*No*		*No*		*No*		*Yes*	
Longitudinal Means	*Yes*		*Yes*		*Yes*		*Yes*	
σ_u	0.81		0.80		0.73		0.73	
ρ	0.40		0.39		0.35		0.35	
Observation	13115		13115		13115		13115	

Note: Source: Source: RLMS-HSE 2013-2018. The sample excludes all individuals who are not present in the survey throughout 2013-2018. 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.
Year FE includes 6 year dummies; *Region FE* includes 38 regional dummies; *Longitudinal Means* includes averages over 6 years of the time-varying variables Age, Age^2, Working Experience, Employed, Household Size, Number Children, Education, Health, Retired.
σ_u is the panel-level standard deviation, ρ is the proportion of the total variance contributed by the panel-level variance component.

3.10 Appendix B

3.10.1 Appendix B1: Variable definitions and sources

Tables B1.1: 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 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 B1.2: 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 square at *t*	age_sq = age^2
Divorce	1 – an individual is divorce 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 higher 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 estimate his health as "very good" *2* – an individual estimate his health as "good" *3* – an individual estimate his health as "average" 4 – an individual estimate his health as "bad" 5 – an individual estimate 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 B1.3: 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

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 opportunity, if you wish, to buy big purchase?	*1* - Yes *0* - No	J721633
Do you concern to provide 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 B1.4: 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 an if he/she is depraved 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	
Did you reject a medical help because of lack of money in 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 disease	1 - Yes 0 - No	chron_disease = 1 if M20_6* = 1 chron_disease = 0 otherwise	1/9

3.10.2 Appendix B2: The structure of the dynamic bivariate model

The sample likelihood of the Dynamic Bivariate Model 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 $\rho_\alpha \sigma_{\alpha,1} \sigma_{\alpha,2}$.

The 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).

Chapter 4

"The new communist man": how exposure to communist indoctrination during early age affects individual attitudes

This paper is a joint work with Professor Dr. Simone MORICONI and Professor Dr. Skerdilajda ZANAJ

> "Communism is a total revolution aiming to establish a new society, a new way of life. A new society presupposes new men with *new minds, new ideas, new emotions, and new attitudes*." Hsi-en Chen, 1969.

4.1 Introduction

In this study, we are interested in identifying whether past exposure to communism indoctrination during early age (9-14 years) has long-lasting effects on individual outcomes and attitudes. The term communism refers to the political system established in Russia from 1917 to 1991. We focus on two sets of individual variables: a series of individual outcomes such as marital status, level of education, opinion on having or not children, number of young children, labor force participation and finally unemployment status, and income; and secondly on a set of attitudes about religion, interpersonal trust, life satisfaction, and perceived own economic rank. These individual outcomes and attitudes were at the center of the communist ideology. They constituted the main blocks of the indoctrination campaigns aimed to build a new man/woman, family-oriented, hard-working, educated, no religious, trusting and life-satisfied. Hence if communism affected Russians, the outcome and preferences we investigate in this paper shall be impacted.

The first systematic impact of the communist indoctrination at the individual level was the pioneering years. The pioneer movement was an organization for children operated by the communist party. Typically children entered into the organization in elementary school and continued until adolescence (Tiazhel'nikov, 1973). Becoming a pioneer was not a choice. Any child in USSR automatically became a pioneer when they reached the age threshold of 9-10 years old (3rd and 4th grade).

In 1922 all Scout organizations were banned and replaced by the Young Pioneer organization of the Soviet Union. This organization would resemble the Scout movement but adequately educate children with Communist teachings. The Communist Party controlled the Pioneer movement and used it as a powerful indoctrination. Pioneers were promoted as models of a genuine socialist future generation of youth determined to help bring the USSR towards the total victory of communism at home in all sectors of society. Nadezhda Krupskaya, Vladimir Lenin's wife, was one of the main contributors to the cause of the Pioneer movement.

We advance the hypothesis that the years of pioneering marked children indelibly along individual outcomes and attitudes expressed in later years of their lives. The idea is that children are highly susceptible to being influenced, and this impact may affect them for the rest of their lives (Krosnick and Alwin, 1989). Literature in different fields, from psychology to economics (Bisin and Verdier, 2001), has documented that schools, parents, and media outlets teach and transmit values, lifestyles, attitudes, and beliefs. Political systems, both dictatorships and democracies, use indoctrination to affect the outlook of children and young adults — during school years as the period of their lives during which humans are most susceptible to outside influences (Vaughan, 1964; Voigtländer and Voth, 2015; Lott, 1999; Cantoni et al., 2017; Costa-Font et al., 2020; Giuliano and Spilimbergo, 2014; Malmendier and Nagel, 2011). The efficiency of such policies or actions is very disputed Schein (1956); Bowles and Gintis (1976).

To test our hypothesis, we explore the Russian Longitudinal National Survey RLMS-HSE [1] for the period 2015-2019. To identify pioneers and non-pioneers, we consider two cohorts: the cohort of individuals born during 1977 - 1981, which includes individuals who become pioneers and gave the solemn promise to the Communist Party to become the new man/woman. These individuals make our treated group. The second cohort includes individuals born in the years 1983 - 1987. They were of age from 4 to 8 years old in 1991, so they were born in communism but too young to be pioneers. This group constitutes the control group. Our analysis rolls out into two steps. First, we estimate ancillary OLS individual fixed effects regressions controlling for age, age squared and "regional by time" fixed effects to extract the predicted individual outcomes and attitudes cleaned by a cohort effect. We use these predicted outcomes in the second step regression discontinuity to unveil whether there is a discontinuity in predicted individual outcomes and preferences between pioneers and non-pioneers. In particular, we use a regression-discontinuity design because being pioneer changes discontinuously if an individual is born before 1991 but too young to be a pioneer because the pioneer movement was shut down in 1990 with the fall of soviet communism. Thus this can produce "near" experimental causal estimates of the effect of having been a pioneer. The collapse of communism can be treated as natural experiment allowing for an examination of the effects of the regime on preferences and attitudes. Accordingly, since the switch from communism towards a new political system can be considered exogenous to the individual level, only the first cohort could be a pioneer is exogenous.

We find long-lasting effects of past exposure to communism on fertility (number of children) and on attitudes such as interpersonal trust, life satisfaction, income, perceived

[1] Source: "Russia Longitudinal Monitoring Survey, RLMS-HSE», conducted by National Research University "Higher School of Economics" and OOO "Demoscope" together with Carolina Population Center, the 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 web sites: https://rlms-hse.cpc.unc.edu, https://www.hse.ru/org/hse/rlms)

economic position, income and the gap between real and perceived income. This last result resonates with findings by Senik (2004), who uses the same data RLMS-HSE but for years 1994 to 2000 and shows that for Russians, variables reflecting income distribution do not influence satisfaction through social comparisons; individuals instead seem to use their informational content in order to form their expectations. We shed light on Senik results by looking at this topic through the lenses of pioneering years. Taken altogether, our findings suggest that past exposure to communism at an early age has impacted deep-seated attitudes related to the optimism expressed in trust, fertility, satisfaction and perceptions about own economic position.

Various forms of emulation campaigns were used to promote the desired virtues of the new man/woman. Not only schoolchildren were led to strive to become "good pupils of the age of Communism". Girls and women were encouraged to become "good daughters of the Communist party". We explore gender in heterogeneous exercises, and indeed we find gender differences.

We check the robustness of our results along with several arguments. We test whether there is a discontinuity in outcomes that should not be affected by communism indoctrination: alcohol consumption and internet use. We find no statistically significant discontinuity. We also run all our regressions using a different cutoff value for the discontinuity. These extensions do not vary our findings.

The paper is organized as follows. Section 2 locates the paper in the literature. Section 3 gives some context and explains what it meant to be a pioneer—section 4 details the database and the main variables of the analysis. The empirical investigation and identification strategy are laid out in Section 5. The placebo test for robustness are presented in Section 6. Finally, Section 7 concludes the paper.

4.2 Related Literature

Our paper contributes to the literature that examines the effects of institutions on preferences (Alesina and Giuliano, 2015; Lapatinas et al., 2021, among others), focusing on the exposure to soviet communism. Most of the prior economic literature has exploited the German separation and later reunification to investigate whether political regimes shape attitudes (Alesina and Fuchs-Schündeln, 2007; Bursztyn and Cantoni, 2016; Lippmann et al., 2020, among others). Papers have mainly studied the effects of living in a communist regime on preferences for redistribution, trust and gender norms for exploiting the quasi-experiment of the division and the reunification of East and West Germany. Overall, the results of prior literature show that the communism doctrine has been quite effective in affecting individuals' attitudes for redistribution, gender and trust.

Alesina and Fuchs-Schündeln (2007) and Brosig-Koch et al. (2011) study preference for redistribution using Eastern versus Western Germany evidence. Alesina and Fuchs-Schündeln (2007) find that East Germans preferred public social policies that entail redistribution to Germans born in the western part of the country. In particular, Alesina and Fuchs-Schündeln (2007) estimated that the preferences for redistribution expressed by average East and West Germans would converge 20 to 40 years after the reunification of Germany. Brosig-Koch et al. (2011) use laboratory experiments and find that East Germans show consistently less solidarity than West Germans, and there has been no convergence in the 20 years after the reunification.

Rainer and Siedler (2009) provide evidence of the erosion of social and institutional interpersonal trust in Eastern Germany after communism. Similarly, Aghion et al. (2010) documented a negative correlation between government regulation, typical communist countries, and trust.

Bauernschuster and Rainer (2012) study attitudes about appropriate roles for women in the family and the labour market. Authors show that East Germans are significantly more likely to hold egalitarian sex-role attitudes than West Germans. During the divided years, East German institutions encouraged female employment, while the West German system deterred women, in particular mothers, from full-time employment.

We know little about the effect of communism beyond the German case study. Documenting the effect of communism in other countries is relevant for two reasons. First, it will confirm or not the findings of East and West Germany comparison. Second, as pointed out by Becker et al. (2020), the selection in the exposure to communism in Germany may not have been random. Motivated by these two reasons, we focus on a rich longitudinal database for Russia to investigate individual outcomes and attitudes in this study.

Economic studies like Booth et al. (2018), Nikolova et al. (2022) and Costa-Font et al. (2020) about the effect of communism in China and Russia are few and very recent. Booth and coauthors focus on trust and find adverse effects on trust in China. For soviet communism, Nikolova et al. (2022) document a link between worse trust and the proximity to a gulag in Russia. Costa-Font et al. (2020) study Central and East European and Russia and focus on family values and family as an insurance institution.

We take a broader view and examine various individual outcomes and attitudes to exploit longitudinal variation and use a regression discontinuity to capture the effects of communist indoctrination at an early age. We observe pioneers and non-pioneers outcomes and attitudes many years after the fall of communism when pioneers are of age 34-42 years and non-pioneers 28-36. We find persisting effects that have signed pioneers for a lifetime.

There have already been several studies that have focused on life satisfaction in Russia for the period of transition, e.g. Ravallion and Lokshin (2001), Schyns (2001) and Senik (2004) or Frijters et al. (2006). This literature uses significant exogenous changes in real income to investigate the causal effect of income changes on life satisfaction. As for religion, communist governments suppressed religious activities, and some brought the campaign against religion to extreme levels. For instance, in 1967, Albania became the first country to ban religion entirely. Telhaj and Murphy worked on secret archives of the time that the Communist Party Bureau leaders decided to increase the labor participation of women, who were held back from working due to religious norms.

4.3 Vladimir Lenin Pioneer Organization

Vladimir Lenin Pioneer Organization was a mass youth organization of the USSR for children and adolescents aged 9–15 between 1922 and 1991. In 1922, the All-Russian Congresses of the Russian Union of the Communist Youth (Komsomol) decided to eradicate the Scout movement in Russia and create an organization of the communist type that would take Soviet children and adolescents under its umbrella. This organization would resemble the Scout movement but adequately educate children with Communist teachings. The movement took the name of Lenin and Nadezhda Krupskaya. Vladimir Lenin's wife was one of the main contributors to the cause of the Pioneer movement. Similar to the Scouting organizations of the Western Bloc, pioneers learned social cooperation skills and attended publicly funded summer camps. Pioneers were one of the most iconic symbols of the USSR. Being a pioneer was an essential milestone in the life of every soviet child. The movement did an effective job of uniting and educating children and instilling a communist ideology (Kasvin and Savina, 1968).

Typically children entered into the organization in elementary school and continued until adolescence. Becoming a pioneer was not a choice. Any child in USSR became a pioneer when they reached the age threshold of 9-10 years old (3rd and 4th grade). The Communist Party closely controlled the movement, and it was a powerful form of indoctrination. Pioneers were promoted as models of a genuine socialist future generation of youth determined to help bring the USSR towards the total victory of communism at home in all sectors of society. Many adult Russians still remember that spine-tingling day when a red tie was placed around their neck. The Pioneer tie was always bright red and served as the sacred symbol of the whole movement. Red in Soviet symbolism represents the blood spilt for the sake of the revolution. Each corner of the triangular shape of the tie denoted one of three generations: Communists, Komsomol members, and Pioneers. Hence, for the children, being a pioneer was the first step towards membership to communist ideals and the communist party, irrespectively whether membership ever arrived in adulthood.

Pioneer activities included outdoor exercise camping but also socially valuable activities.

For instance, children took part in *subbotniks* (community workdays, usually on Saturday), collected waste paper and scrap metal, assisted older adults, helped fellow schoolmates falling behind in class, and formed part of volunteer fire brigades. They also followed indoctrination activities where Soviet ideals about society and a young person's role Schlesinger (1967).

Their solemn promise when becoming a pioneer was:

> *" I, (last name, first name), joining the ranks of the V. I. Lenin All-Union Pioneer Organization, in the presence of my comrades solemnly promise: to love and cherish my Motherland passionately, to live as the great Lenin bade us, as the Communist Party teaches us, and as required by the laws of the Young Pioneers of the Soviet Union."*

The pioneering experience was extended in all ex-communist countries and not only USSR, but each country has specific elements in its organisation.[2]

4.4 Data and Summary Statistics

The main source for the data is the Russian Longitudinal Monitoring Survey conducted by the Higher School of Economics (RLMS-HSE). The RLMS-HSE collects information for a nationally representative sample of households across the Russian Federation.[3] 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).

Table 4.1 reports descriptive statistics of our variables of interest by cohort. The first cohort represents pioneers and the second non-pioneers. We have two sets of variables: the

[2]An author of this paper, experienced the Albanian version of the pioneering years from age 8 to 12 years.

[3]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.

demographics and the attitudes. Our analysis is focused on the period from 2015 to 2019 to maximize the sample size for our variables of interest. This means we observe individuals many years later from the pioneering years. The set of individual outcomes includes marital status, level of education, opinion on having or not children, number of young children, labor force participation and finally unemployment status and income. This last is defined as the per capital household income that is calculated simply as the ratio total household income divided by household size.

The second set of dependent variables captures several individual attitudes such as interpersonal trust, life satisfaction, religion, perception of own economic position, per capital household income, and finally the gap between the perceived economic position and real income. Own perception of economic position is defined as follows. Each individual is asked to place himself in a scale from 1 to 9. Hence, this variable is a proxy of the perceived income position of the individual. The gap between the real income and perceived economic position is measured as follows. First, we construct an Income Group by year and PSU (primary sampling unit) that ranges from 1 to 9. Then, the gap is defined as the distance between the actual Income Group and perception about income position. The lowest value of the gap, equal to 1, corresponds to an individual with an Income Group equals to "9", and Perceived Economic Position equals to "1", and "17" correspondents to an individual with Income Group equals to "1", and Perceived Economic Position equals to "9".

Our main explanatory variable used as the running variable in the RDD estimation is *Communism Ratio*. We construct this variable to have a continuous running variable. The variable measures past exposure to communism:

$$\textit{Communism Ratio} = \frac{1991 - \text{birth year}}{\text{year} - \text{birth year}}$$

We consider two cohorts over *2015 - 2019* period:

1. *Pioneers – Cohort 1977 - 1981*: includes individuals who were of age from 10 to 14 years old in 1991. These individuals were pioneers and gave the solemn promise to the Communist Party.

2. *Non-Pioneers – Cohort 1983 - 1987*: includes individuals who were of age from 4 to 8 years old in 1991, so individuals born in communism but too young to be pioneers.

After dropping observations with missing crucial information, the dataset comprises 8771 observations of 2611 individuals over 5 years.

From Table 4.1, it is worth mentioning two clear differences between pioneers and non-pioneers that are closely related. Pioneers are older by construction since this is the cohort that was old enough to enroll as pioneer before 1991, whereas the other cohort despite being born in communism was too young to be a pioneer. This leads to differences in the Communism ratio variable. As will be clarified later, we have build our empirical strategy to net out this cohort effect by first running OLS individual fixed effects estimation controlling for age and aged squared.

The validity of the regression discontinuity design hinges on two assumptions: absence of manipulation of the pioneering enrollment and continuity of potential confounders at the cutoff. While the absence of manipulations is easy to argument our setting since individuals answering the RLMS-HSE could not have manipulated the fall of communism in 1991, attention is required for the second condition. In our setting, we cannot proceed as usual and investigate how different are the two categories along the the control variables presented in Table 4.1, because we do not observe these individuals in 1991. We observe them only many years later in 2015. Even more problematically, the communist indoctrination that magnified the importance of family-orientation, comradeship, fertility, gender equality, and so, may have impacted the demographic characteristics as much as the attitudes (except for age and gender). For this reason, we consider both the two sets as outcome variables and run RDD for the demographics as well as attitude variables.

Table 4.1: Summary Statistics

	Cohort 1977-1981				*Cohort 1983-1987*			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Demographics								
Communism Ratio	0.32	0.03	0.26	0.37	0.19	0.04	0.12	0.25
Female	0.53	0.50	0	1	0.53	0.50	0	1
Age	37.81	2.04	33	42	31.87	2.03	27	36
Children	0.84	0.37	0	1	0.70	0.46	0	1
Number of Small Children	1.29	1.02	0	7	1.12	0.99	0	9
Married	0.64	0.48	0	1	0.58	0.49	0	1
University Educ.	0.35	0.48	0	1	0.41	0.49	0	1
LFP	0.88	0.32	0	1	0.87	0.33	0	1
Attitudes								
Trust	0.15	0.36	0	1	0.15	0.36	0	1
Life Satisfaction	2.32	0.81	1	3	2.35	0.79	1	3
Perc. Econ. Position	4.08	1.47	1	9	4.10	1.42	1	9
Log PC Household Income	9.59	0.64	5.56	13.81	9.62	0.61	5.35	12.79
Real - Perceived Income Gap	8.79	2.65	1	17	8.64	2.69	1	16
N	4106				4665			

Children became pioneer starting from age 9, not at once but in several rounds. To ensure that a given individual was a pioneer, we need to take those who were at least 10 years old in 1991 (i.e. born in 1981). We can be almost sure that all children were pioneers in the cohort 1977 - 1981. We exclude individuals born in 1982 (9 years old in 1991) because we can not be sure if they were pioneers already. But robustness checks show that their inclusion does not alter our analysis.

4.5 Empirical Analysis and Identification Strategy

The empirical analysis is designed to test our main hypotheses in two layers. In the first step, we run ancillary OLS individual fixed effects regressions controlling for age, age squared, "region by year" fixed effect to estimate the predicted individual fixed effects outcome and attitudes cleaned from a possible cohort effect. Then, we use a regression discontinuity design exploiting a discontinuity in the access to pioneer years due to the fall of communism in 1991. In particular, we use predicted individual fixed effects of the pioneer cohort 1977

- 1981 and non pioneer cohort 1983 - 1987, both born under communism, to identify the effect of pioneer years.

4.5.1 Ancillary OLS Fixed Effects Regressions

We estimate the following regression:

$$y_{irt} = \alpha_0 + \alpha_1 X_{it} + \alpha_2 Y_{rt} + \delta_i + \epsilon_{irt} \tag{4.1}$$

where, y_{irt} is the variable capturing demographic outcomes and attitudes of individual i in psu (primary sampling unit) r and year t. We take into account the cohort differences applying the appropriate controls X_{it} such as age and age squared at time t. Y_{rt} is a vector of region-by-year fixed effects aimed to capture time-varying regional factors that could affect individual responses. δ_i is the individual fixed effect while ϵ_{irt} is the error term. We estimate robust standard errors, clustered at the regional level.

Results are reported in Appendix in Tables 4.8 and 4.9. From this ancillary regression (4.1) we estimate the predicted individual fixed effects $\widehat{\delta_i}$ for both specifications, cleaned by cohort, regional and time differences.

4.5.2 Regression discontinuity analysis

We use the predicted outcomes of the ancillary regressions to check whether there is a discontinuity in predicted individual outcomes and attitudes between cohort 1977 - 1981 and cohort 1983 - 1987. We run sharp RD estimates using local polynomial regression of order 1 and 2, with $\widehat{\delta_i}$ as an outcome variable.

In the "sharp" regression-discontinuity design, treatment status is a deterministic function of some underlying continuous variable, that is,

$$T_{it} = T(x_{it}) = 1 \bullet [x_{it} > \bar{x}]$$

where $1[\bullet]$ is an indicator function and x_i is a continuous variable or an assignment variable, and i is a treatment threshold separating the units into two mutually exclusive groups: those units receiving treatment ($T = 1$) and those which do not ($T = 0$). The idea is to compare the outcomes for units whose value of the underlying targeting variable is "just below" and "just above" the treatment threshold $\bar{x}$ because they on average will have similar characteristics except for the treatment. In other words, those units slightly below the threshold will provide the counterfactual outcome for those units slightly above because the treatment status will be randomized in a neighborhood of treatment threshold. In our context being at the age of having just finished pioneering is the assignment variable that assigns individuals in one group or the other and where the treatment threshold is being old enough to finish pioneering before the fall of USSR in 1991.

The simplest possible approach of the RDD analysis is to just compare average outcomes in a small neighborhood on either side of the treatment threshold. This approach is feasible and gives good measures of the treatment effect because we have large sample size for the regression-discontinuity method not be subject to a large degree of sampling variability.

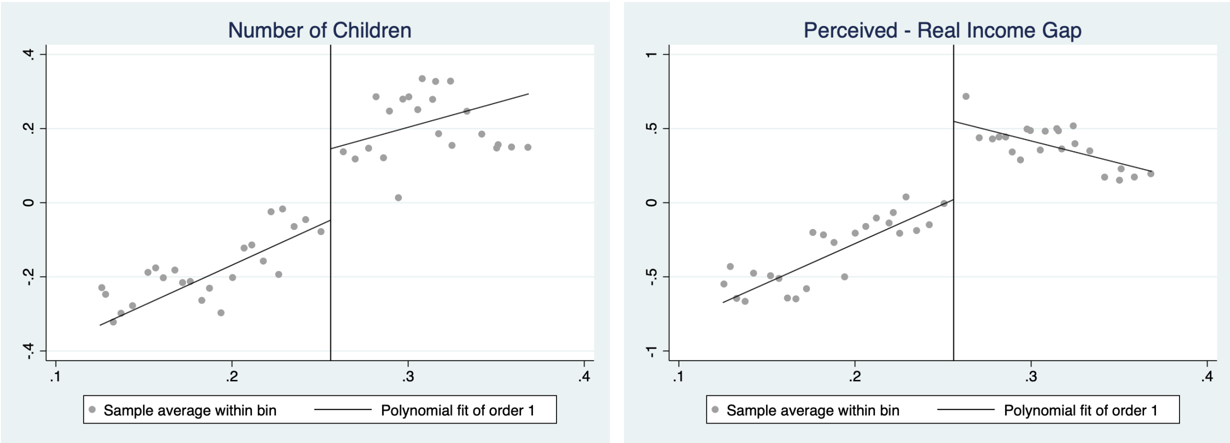
Empirically, the running variable is the *Communism Ratio*. If cofounders behave continuously around the threshold and in addition, knowing that individuals in the RLMS-HSE cannot manipulate their pioneer membership, this strategy causally identifies the impact of pioneering years. Formally, the RDD specification is:

$$\widehat{\delta_i} = \alpha + \beta T(x_{it}) + \gamma f(T(x_{it})) + \epsilon_{it} \tag{4.2}$$

Where i is the subscript for the individual, t for year. $\widehat{\delta_i}$ is the individual fixed effect predicted predicted by the OLS individual fixed effects estimations, x_{it} is the running variable. We also add $f(T(x_{it})$ which is a polynomial of degree two interacted with treatment. In fact, throughout our analysis we report results for a linear and a quadratic specification of the RDD specification. This equation is estimated on a narrow margin around the cutting threshold. The reference bandwidth is selected to carefully divide the pioneers from non pioneers. In addition, we run robustness checks for the cutting threshold. In particular, for the cohort 1977 - 1981, the running variables varies from 0,26 to 0,37 whereas for the cohort 1983 - 1987 the range of values is [0,12; 0,25]. In the benchmark specification of the RDD design, we use *Communism Ratio* equals to 0,256 as a cut-off.

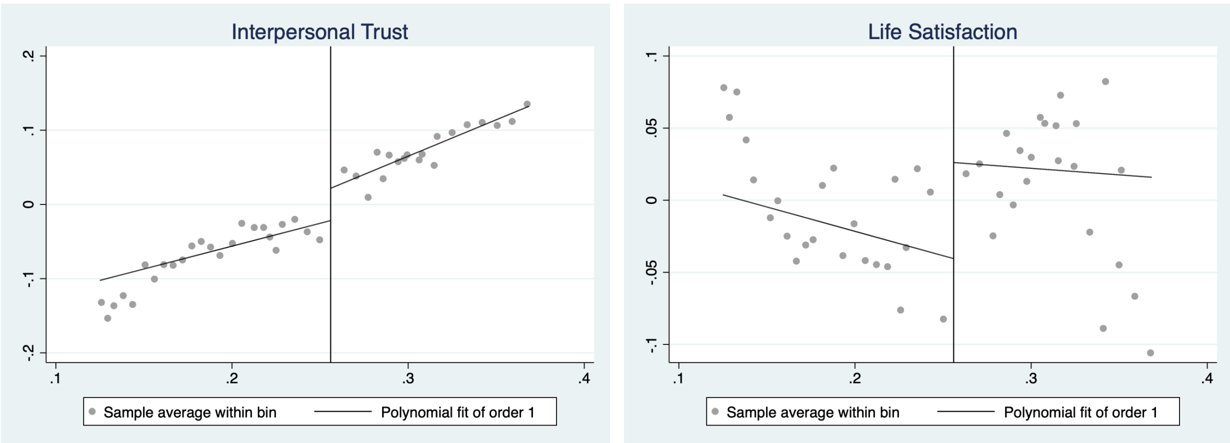
We start with a graphical presentations which provide a powerful visual answer to the question of whether or not there is evidence of a discontinuity (or "jump") in the outcome at the cut-off point. The graphs concerning the individual outcomes, namely marital status, level of education, having or not children, labor force participation and finally unemployment status show no discontinuity at the cut-off level (they are reported in Appendix C1). The only outcome where there is a jump is the number of young children (Figure 4.1a). The two groups seems not different in any of these characteristics but the fertility level – number of children. These findings suggest the intensive family and work-oriented indoctrination does not not seem to have had large effects on demographic characteristics of individuals.

Importantly, these results are useful for the second set of outcome variables that are attitudes. In fact, one could interpret these results as a test for the continuity assumption of potential confounders. Since none of these demographic features, apart from fertility, is discontinues at the cutoff point, we have an internal validity test for our analysis. In particular, there is no evidence that the results on individual attitudes are driven by any other characteristic. Hence, we are able to include these controls in robustness checks (not reported for space) in the RDD specifications of individual attitudes.



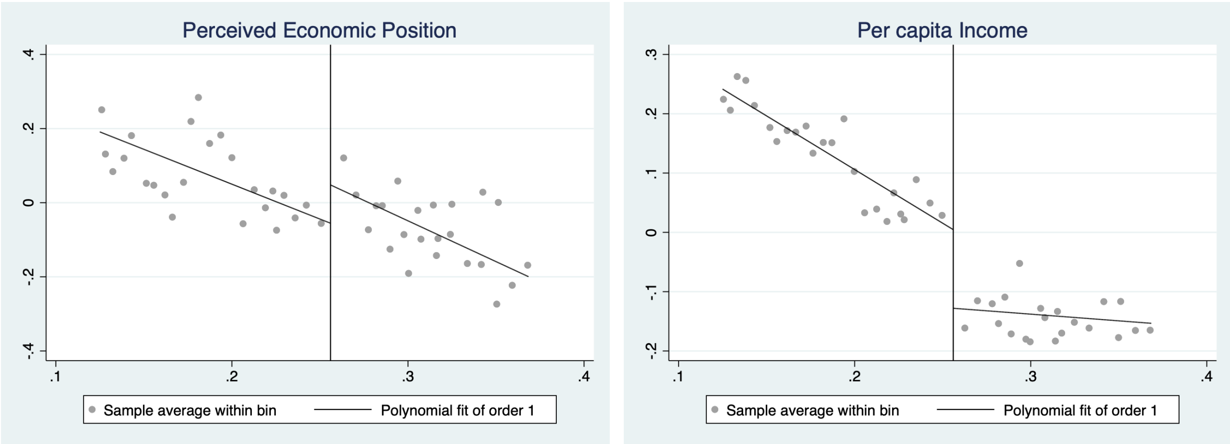
(a) (b)

Figure 4.1: Regression Discontinuity Design Graphs for Number of Children and Gap between Real Income and Perceived Economic Position



(a) (b)

Figure 4.2: Regression Discontinuity Design Graphs for Interpersonal Trust and Life Satisfaction



(a) (b)

Figure 4.3: Regression Discontinuity Design Graphs for Interpersonal Perceived Economic Position and Per capita Household Income

The following graphs represent the possible jumps in our attitude variables about interpersonal trust, life satisfaction, perceived economic position, per capita household income, real - perceived income gap.

Differently from the individual outcomes, several attitudes present discontinuities. Figures 4.1 - 4.3 suggest that there are jumps for interpersonal trust, life satisfaction, perceived economic position, per capita household income, real - perceived income gap. However, we do not observe a discontinuity for religion: pioneers are not less religious than non-pioneers (the graph is reported in Appendix C1).

The econometric results of our analysis are shown in Tables 4.2 and 4.3. In Table 4.2, we group the individual outcomes, whereas in the following Table 4.3, we group attitudes such as interpersonal trust, life satisfaction, perceived economic position, per capita household income, real - perceived income gap and religion. In line with graphical representation, pioneers are more trustful, more life-satisfied, perceive a high own economic position, they own a lower level of per capita income, a higher gap between perceived own economic position and real per capital income. However, they do not marry more often, are not less religious, are not more educated, are not more often childless, do not participate more in the labor market and are not more or less unemployed. Taken as whole, our findings suggest that communist indoctrination during early age has made individuals on average more optimistic as they do more children, trust people more, are more satisfied with their life and interestingly show a high level of economic optimism about their economic position.

To conclude on our main results, in line with the Soviet doctrine of state atheism, the «Young Pioneer Leader's Handbook» stated that "Every Pioneer would set up an atheist's corner at home with anti-religious pictures, poems, and sayings". Actually, our findings suggest that among attitudes considered religiosity is unaffected by the indoctrination. However, past communism has affected pioneers indelibly along other individual attitudes. Taken altogether, our findings on attitudes suggest that pioneers are more optimistic than non-pioneers along several dimensions such as trust, life satisfaction, perception about own economic position, income, and the gap between real income and perceived economic position.

Table 4.2: RD Results: Demographics

	Married	University Degree	Children	Number of Children	Labour Force Participation	Unemployment
Local Linear Regression	0.04	-0.04	0.03	0.23	0.05	0.01
	(0.07)	(0.07)	(0.06)	(0.14)	(0.04)	(0.04)
Local Quadratic Regression	0.07	-0.07	0.08	0.31**	0.06	0.01
	(0.08)	(0.08)	(0.07)	(0.14)	(0.04)	0.04
N	8213	8213	8213	8209	7937	8213

Note: Local polynomial regression-discontinuity point estimation. Standard errors are in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

Table 4.3: RD Results: Attitudes

	Interpersonal Trust	Life Satisfaction	Perceived Econ. Posit.	Per Capita Income	Real - Perceived Income Gap	Religion
Linear Reg.	0.09**	0.16	0.31*	-0.18**	0.87***	-0.19
	(0.04)	(0.10)	(0.16)	(0.08)	(0.32)	(0.03)
Quadratic Reg.	0.15***	0.27**	0.42**	-0.21***	0.92**	-0.01
	(0.05)	(0.11)	(0.19)	(0.08)	(0.36)	(0.036)
N	8135	8189	8213	8207	8213	8213

Note: Local polynomial regression-discontinuity point estimation. Standard errors are in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

4.6 Gender Differences: Smiling Women and Fighting Men?

In this section, we explore whether our findings are gendered. Combining economic and ideological considerations, communist regimes massively encouraged women's paid employment, and spread new female representations, including those of the female laborer, tractor conductor and later engineer. At the same time, official discourse, which was passed on by considerable iconography, dramatized men in roles such as laborers, soldiers and managers, while women personified mothers and peasants. Shall we expect different effects on boys and girls pioneers? Prior literature on the effect of communism has unveiled differences in gender. For instance, Lippmann et al. (2020) study the case of Germany and find that a woman can earn more than her husband without putting their marriage at risk because GDR had designed institutions that were much more gender equalizing than their counterpart in the former FRG. Lippmann and Senik (2018) study the effect of the socialist episode in East Germany on gender norms focusing on the performance in mathematics. Authors show that the under performance of girls in math is sharply reduced in the regions of the former GDR, in contrast with those of the former FRG.

To examine this hypothesis, we run our RDD specifications for men and women separately. The results are gathered in Tables 4.4 and 4.5, where we report RDD results for the benchmark specification but separately for male and female samples. Very interestingly we find that pioneering years affected men more often than women. Pioneer men are more trustful than non-pioneering men, while pioneering and non-pioneering women do not hold difference in trust levels. Men pioneer have a lower income than men non-pioneer but however, pioneer men have a higher perception of their economic position irrespective of their lower income. Whereas women pioneer do not differ from non-pioneer women. In addition, pioneer men have are also driving our effects on fertility. The only outcome that seems to have been affected by pioneering years for women is marital status. Women pioneer get more often married than non-pioneer ones. These results are different from those of the gender literature on socialism and communism. There are at least two explanation about this. The first in favor of our analysis. Differently from previous papers that use pooled cross-sectional data, we use longitudinal data that allow us to control for individual fixed effects. Hence, from this perspective our analysis is more robust than prior literature on attenuating omitted variable bias. The second possible explanation is that communism did affect Russian women more than we find but these effects did not occur during pioneer years but later in their life time. This is a interesting questions that we want to investigate in future research.

Table 4.4: RD of Demographic Variables: Gender Differentiation

	Married		University		Children		Num. of Child.		LFP	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Local Linear Regression	0.01	0.15*	−0.03	0.01	0.13	0.00	0.44**	0.15	−0.04	0.11*
	(0.11)	(0.08)	(0.10)	(0.09)	(0.10)	(0.06)	(0.21)	(0.18)	(0.05)	(0.06)
Local Quadratic Regression	−0.02	0.21**	−0.05	−0.00	0.13	0.07	0.63***	0.21	−0.04	0.09
	(0.12)	(0.09)	(0.11)	(0.11)	(0.11)	(0.08)	(0.22)	(0.17)	(0.06)	(0.06)
N	3857	4356	3857	4356	3857	4356	3854	4355	3689	4248

Note: Local polynomial regression-discontinuity point estimation. Standard errors are in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

Table 4.5: RD of Attitudes: Gender Differentiation

	Interper. Trust		Life Satisf.		Perc. Econ. Posit.		Per Capita Income		Perc.- Real Gap	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Local Linear Regression	0.19***	−0.06	0.12	0.21	0.40	−0.04	−0.28**	−0.04	1.40**	0.73*
	(0.06)	(0.06)	(0.15)	(0.13)	(0.27)	(0.21)	(0.12)	(0.10)	(0.56)	(0.41)
Local Quadratic Regression	0.25***	−0.02	0.22	0.28*	0.57	−0.07	−0.27**	−0.09	2.00***	0.93*
	(0.07)	(0.06)	(0.18)	(0.16)	(0.37)	(0.22)	(0.14)	(0.12)	(0.62)	(0.55)
N	3826	4309	3844	4345	3857	4356	3853	4354	3857	4356

Note: Local polynomial regression-discontinuity point estimation. Standard errors are in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

4.6.1 Robustness Checks and Placebo Analysis

We check the robustness of our analysis along two relevant lines. First, we check how robust are the results for different cutoff values for the discontinuity. These estimations shall not yield significant results as the discontinuity point must the one that sharply divides pioneers from non pioneers. The results reported in Table 4.6 are reassuring. We do not see significant cutoffs in most of the cases.

Table 4.6: Placebo Test (Local Linear Regression)

	Interpersonal Trust	Life Satisfaction	Perceived Econ. Posit.	Per Capita Income	Real-Perceived Income Gap
Cutoff 0,200	0.03	0.05	-0.17	-0.14**	0.55*
	(0.03)	(0.07)	(0.16)	(0.06)	(0.29)
Cutoff 0,210	-0.03	-0.02	0.20	0.05	-0.05
	(0.04)	(0.07)	(0.15)	(0.07)	(0.26)
Cutoff 0,220	-0.02	0.01	-0.00	0.02	0.00
	(0.03)	(0.06)	(0.12)	(0.05)	(0.23)
Cutoff 0,290	0.01	-0.01	0.17	0.22**	-0.01
	(0.03)	(0.07)	(0.14)	(0.09)	(0.21)
Cutoff 0,300	-0.01	-0.01	-0.13	-0.04	0.06
	(0.03)	(0.06)	(0.11)	(0.05)	(0.21)
Cutoff 0,310	-0.01	0.01	0.04	-0.02	0.02
	(0.03)	(0.06)	(0.11)	(0.06)	(0.22)
N	8674	8736	8622	8320	8213

Note: Local polynomial regression-discontinuity point estimation. Standard errors are in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

As a final analysis assessing the validity of our results, we perform a placebo analysis using two other variables as the outcome variable. We propose alcohol use and internet use as placebo outcomes because we argue in none of these individual outcomes we would expect an effect of pioneering years. As for the alcohol use, we believe this is a good placebo test because alcohol was not a topic in the agenda of pioneers and importantly, prior studies in sociology argue that communism did not really put on top of the propaganda the reduction of alcohol use (Treml, 1997). Russian, on average, consumed alcohol before, during and after communist years (Treml, 1997). As for the internet use, we use this a Placebo because it is difficult to imagine a first order impact of pioneering years occurring in the 80s on a technological phenomenon of many years later. Only in 2010, 40 percent of Russian were using internet (Statista, 2020).

If the placebo analysis returned significant coefficients we would have a discontinuity on alcohol use and internet use between pioneers and non-pioneers, we might have concerns that some confounding variable is actually driving our result. The result of the placebo are reported in Table 4.7. Coefficients of are insignificant, suggesting that there is no a discontinuity and thus a difference in the use of alcohol or internet between pioneers and non-pioneers. All in all, this strengthens further our main findings.

Table 4.7: RD Results: Placebo

	Consume Alcohol	Use Internet
Local Linear Regression	-0.05	-0.05
	(0.05)	(0.03)
Local Quadratic Regression	-0.02	-0.05
	(0.05)	(0.04)
N	8721	8760

Note: Local polynomial regression-discontinuity point estimation. Standard errors are in parentheses. Coefficients are statistically significantly different from the true value at the * 10% level; ** at the 5% level; *** at the 1% level.

4.7 Conclusion

Efforts at modifying public perceptions and attitudes are various and range from advertising to schooling and their effectiveness is highly contentious. We demonstrate that communist indoctrination—among children of young age—was highly effective. Russians who grew up with no pioneering experience are less trustful, less life satisfied, make fewer children and are less economically optimistic than Russians who experienced pioneering years. These findings demonstrate that beliefs can be modified massively through policy intervention and by institutions. Similarly, to prior papers in the literature (Vaughan, 1964, Lott, 1999, Voigtländer and Voth 2015, Cantoni et al 2014, Costa-Font et al, 2020) affecting children at the school age seems an effective way to change peoples attitudes. We also show that for deep-seated values in a society (e.g. religion), the indoctrination was not successful.

In particular, in this paper, we study the effect of past exposure to communist indoctrination during early age (9-14 years) on a set of crucial attitudes in the communist ideology aiming to create the *new communist man/woman*. We focus on the indoctrination received by children during pioneering years. School pupils automatically became pioneers when they reached 3rd or 4th grade. The purpose of pioneer years was to educate soviet children to be loyal to the ideals of communism and to the 'Mother Party", as expressed in their motto: *"Pioneer, be ready to fight for the cause of the Communist Party"*. We use a regression discontinuity design exploiting the discontinuity in the exposure to pioneering years due to the fall of the USSR in 1991. We find robust evidence that having been a pioneer has long-lasting effects on interpersonal trust, life satisfaction, fertility, income, and perception of own economic rank. Overall, these results suggest that past pioneers show a higher level of optimism than non-pioneers. Finally, we look for gender differences because various forms of emulation campaigns were used to promote the desired virtues of the new communist woman. However, we find no evidence of the effect of exposure to communism on women. The indoctrination seems to have left more substantial effects on men.

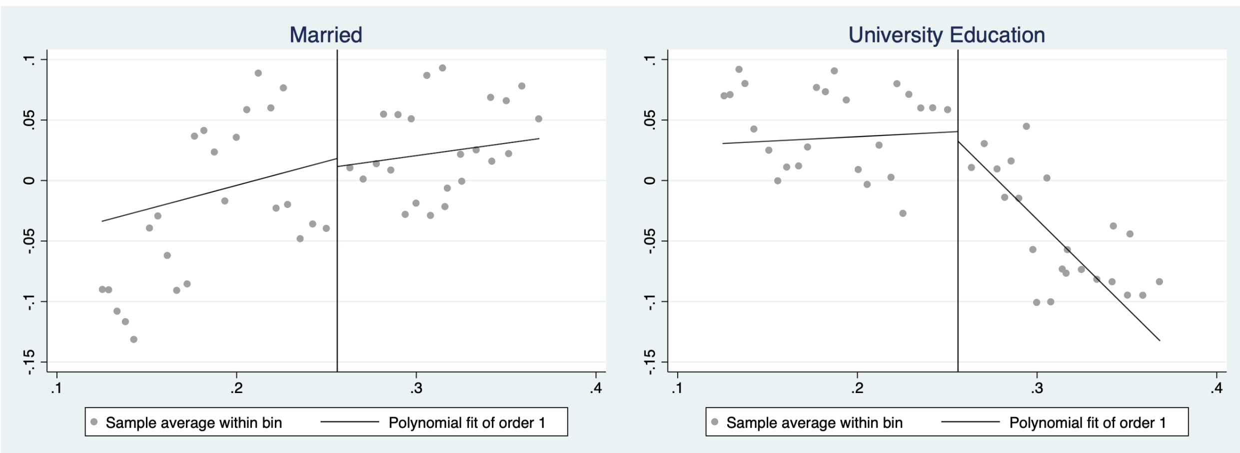
Beyond the new hypothesis that we push forward, we contribute to prior literature because we use longitudinal and RDD design that allows for an identification strategy cleared from the cohort effect.

Our results demonstrate the effectiveness of communism propaganda: children who were indoctrinated with the socialist ideals of humbleness tend to overestimate their economic position in adulthood. As a result, the population has lower living standards and economic potential.

Well-known results in the literature concern redistribution preferences and gender norms. Authors argue that individuals with past experiences in communist countries (East Germany for redistribution preferences and Russia for gender norms) are strongly affected by communism. We cannot test neither of these two interesting individual outcomes because none of related questions in asked in the window 2015-2019. It would be interesting to analyze these two individual outcomes with our method. We leave this for future research.

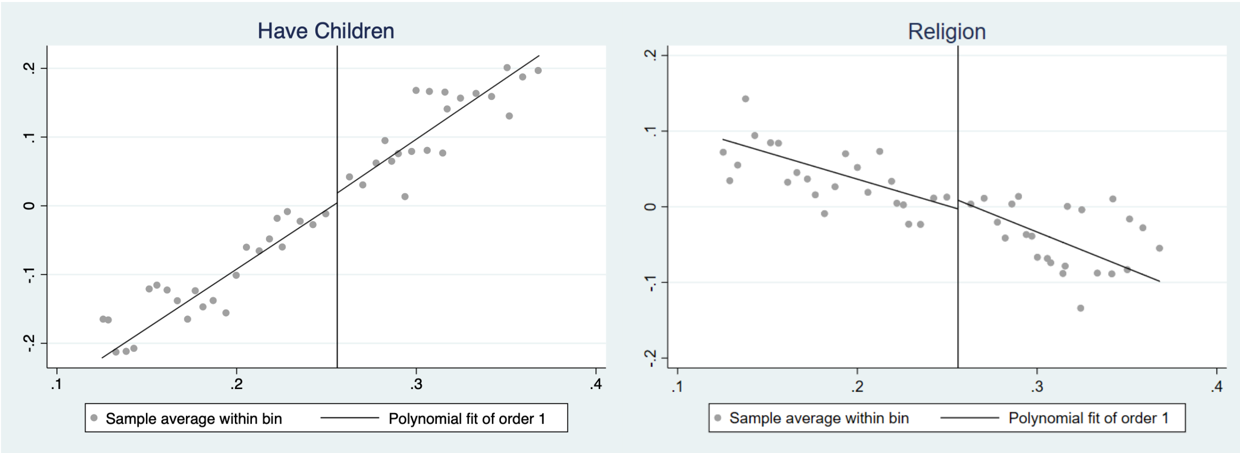
4.8 Appendix C

4.8.1 Appendix C1. Regression Discontinuity Design graphs



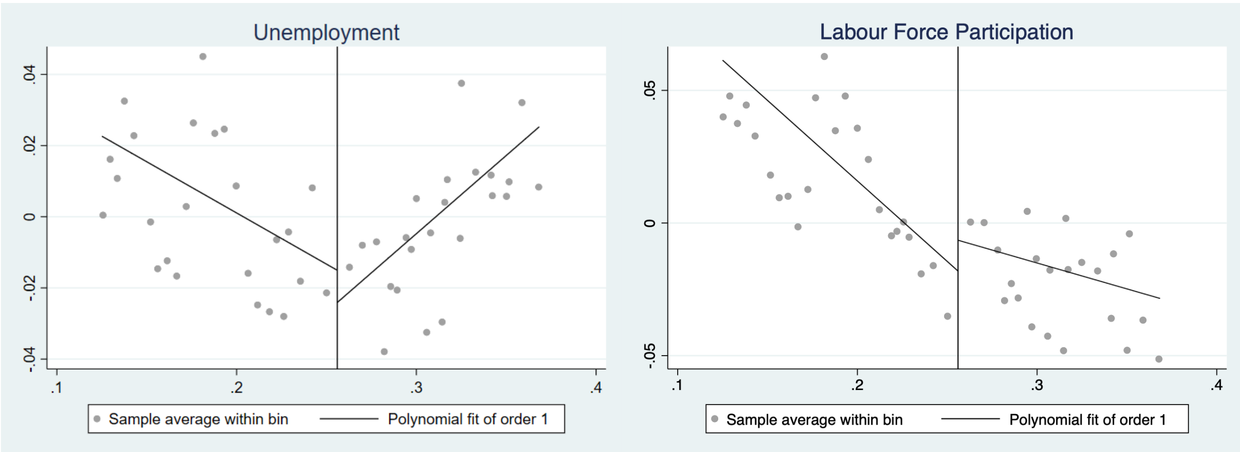
(a) (b)

Figure 4.4: Regression Discontinuity Design Graphs for Marriage and University Degree



(a) (b)

Figure 4.5: Regression Discontinuity Design Graphs for Having Children and Atheism



(a) (b)

Figure 4.6: Regression Discontinuity Design Graphs for Unemployment and Labour Force Participation

4.8.2 Appendix C2. Ancillary OLS FE regressions results

Table 4.8: Ancillary Regression Results: Demographics

	Married	University Degree	Children	Number of Child.	LFP	Unemployment
Age	0.03	0.03^{**}	0.04	0.46^{***}	-0.01	0.01
	(0.02)	(0.01)	(0.02)	(0.06)	(0.03)	(0.03)
Age^2	-0.01	-0.01^{*}	-0.01^{***}	-0.01^{***}	0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Year × PSU FE	Yes	Yes	Yes	Yes	Yes	Yes
σ_u	0.48	0.48	0.43	0.96	0.27	0.33
σ_e	0.16	0.12	0.13	0.33	0.20	0.24
ρ	0.90	0.94	0.92	0.89	0.63	0.65
N	8771	8771	8771	8767	8444	8444

Note: OLS FE regression. Standard errors in parentheses and clustered at the PSU (primary sampling unit) level. * $p < .1$, ** $p < .05$, *** $p < .01$

Table 4.9: Ancillary Regression Results: Attitudes

	Trust	Life Satisf.	Perceived Econ. Posit.	Per Capita Income	Real - Perceived Gap	Religion
Age	-0.06	-0.01	0.04	0.04	-0.24	0.01
	(0.04)	(0.06)	(0.11)	(0.06)	(0.25)	(0.03)
Age^2	0.01	0.01	-0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Year × PSU FE	Yes	Yes	Yes	Yes	Yes	Yes
σ_u	0.30	0.67	1.23	0.59	2.40	0.25
σ_e	0.29	0.60	0.99	0.34	1.75	0.21
ρ	0.52	0.56	0.61	0.75	0.65	0.59
N	8674	8736	8622	8320	8213	8770

Note: OLS FE regression. Standard errors in parentheses and clustered at the PSU (primary sampling unit) level. * $p < .1$, ** $p < .05$, *** $p < .01$

4.8.3 Appendix C3. Variables description

Table 4.10: Variables Description: RLMS-HSE

	Description	Source Name
Communism	Portion of an individual's age he/she lived under the communism	$\frac{1991 - \text{birth year}}{\text{year} - \text{birth year}}$
Demographics		
Age	Age	*age*
Age^2	Squared age	$age\_sq = age^2$
Married	*What is your marital status?* 1 - Married 0 - Not Married	*J*322
University	*What is your educational level?* 1 - University Education 0 - No University Education	DIPLOM
Children	*Do you have children?* 1 - Has Children 0 - No Children	*J*72.171
Number of Small Children	*How many children younger than 18 year old do you have?*	*J*72.173
LFP	*Are you active in the labour force?* 1 - Active in thee labour force 0 - Not active in the labour force	*J*90
Unemployment	*Are you currently employed?* 1 - Employed 0 - Unemployed	*J*90
Attitudes		
Religion	*Individual's religion*: 1 - An atheist 0 - A religious person	*J*72_19

Trust	*Could people be trusted?* 1 - Can be trusted 0 - Should be careful OR Depends on a person	$J206$
Life Satisfaction	*Are you satisfied with life at present?* 1 - Satisfied 2 - Both yes and no 3 - Not Satisfied	$J65$
Perceived Economic Position	What is your economic position on 9 - step ladder?	J62
Per capita Income	Log of the household income divided by number of household members	$\frac{F14}{NFM}$
Number of Household Members	How many household member in your household?	NFM
Income Group	Calculated income group in a given PSU and year from 1 to 9	
Real-Perceived Income Gap	Difference between Income Group and Perceived Economic Position	
Fixed Effects		
Year	Year of the survey	INT_Y
PSU	1 – 38 indicates region and the city/village where an individual lives	psu

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