ESSAYS ON LABOUR AND HEALTH ECONOMICS

By

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ABSTRACT

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Chapter 1, titled "The Impact of Parental Job Loss on Children's Health", utilises data from the Russia Longitudinal Monitoring Survey in order to explore the extent to which the negative consequences of job loss of the household head extend to the health of the children in the family. We employ a linear model to study various health outcomes, and our estimation results indicate that children's health responds differently to female and male household head's unemployment. In particular, we find support for an adverse effect of father's unemployment on the development of chronic conditions in children and occurrence of depression, but a beneficial effect of single mother's unemployment on the kid's mental health. The paper also provides evidence of a detrimental impact of paternal job loss on the probability the kid has low height for age, while there is no corresponding impact of mother's job loss. Finally, this study indicates the possibility that children of unemployed parents are under-diagnosed in terms of chronic conditions. The latter has potential policy implications, pointing towards the need to make children health care and regular check-ups more broadly available.

Chapter 2 is titled "The Effect of Retirement on Mental Health and Social Inclusion of the Elderly". This Chapter utilises multinational data from the Survey of Health, Ageing and Retirement in Europe to investigate the effect of retirement of the elderly on their psychological well-being and social inclusion. We use an instrumental variable strategy based on plausibly exogenous variation in retirement probabilities induced by the country-level statutory and early retirement ages. The key findings of the study tell a consistent story: while labour force exit has

no significant impact on the mental health of male workers, it has a beneficial effect on women's mental health. The results also suggest a heterogeneous effect of retirement on the social connectedness of the elderly: exiting the labour force decreases the size of social networks for men but not for women; additionally, retirement enhances females' contacts with parents, but has no effect for male retirees. This heterogeneity of the retirement effect has important policy implications, as it points out the possibility that the trends in the European Union towards increasing the pensionable ages could lead to a loss of welfare for women.

The last Chapter uses data from the Programme for the International Assessment of Adult Competencies to re-examine the immigrant-non-immigrant earnings gap. We exploit the availability of cognitive skills measures in the data, such as numeracy and literacy scores, allowing us to minimize the presence of unobserved effects. Our analysis employs a modified Mincer earnings function and Oaxaca-Blinder mean log-wage decomposition (Oaxaca (1973) and Blinder (1973)); we also make use of the decomposition technique by DiNardo, Fortin and Lemieux (1996) to examine the earnings gap across the entire earnings distribution. We find that immigrants have lower returns to education than native workers, yet higher returns to literacy proficiency, which is conforming to the statistical discrimination literature. The Oaxaca-Blinder decomposition results imply that a log-wage model specified without cognitive skill measures would overestimate the unexplained part of the mean immigrant-non-immigrant gap nearly twice, while including numeracy and literacy test scores reveals lower role for discrimination. Lastly, the DiNardo-Fortin-Lemieux decomposition suggests that numeracy and literacy test scores matter almost equally throughout the entire log-wage distribution but cannot fully explain the observed immigrant-native gap, except for the bottom and the top decile.

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All remaining errors are mine.

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CHAPTER 1

THE IMPACT OF PARENTAL JOB LOSS ON CHILDREN'S HEALTH

1.1 INTRODUCTION

Up until the previous decade, the vast majority of economic literature focused on the effect of involuntary job separation on one's own socio-economic outcomes, with little or no attention being paid to families. Recent years have given rise to a number of studies examining the consequences of job loss for the entire family. For instance, Charles and Stephens (2004) and Ahituv and Robert (2005) show that spousal unemployment significantly increases the probability that the couple divorces. Moreover, Oreopoulos (2008) demonstrates the existence of important intergenerational effects of job displacement and Oreopoulos et al. (2005) find strong support for the idea that parental employment and childhood poverty have causal effects on educational outcomes. Turning to transition economies, Kertesi and Kézdi (2007) estimate a substantial causal effect of unexpected long-term unemployment of the parents on the probability their kid drops out of secondary school.

However, evidence on the effect of parental job loss on children's health outcomes remains limited. At the same time, children's health has been widely acknowledged as a major input for human capital formation (see e.g. Currie and Moretti (2007)); hence, a better understanding of the factors influencing it is of crucial importance. Indication of a significant effect of parental unemployment on their children's health may provide insight for the short and long-term well-being of the children of displaced workers, and has potentially important policy implications. Moreover, the answer to this research question may help shed light on the more general question about the causal relationship between family income and children's health.

The main question addressed in this paper is: *is there evidence of a significant effect of parental job loss on their children's health*? The question of interest is examined using household-level longitudinal data on children and parents (working age household heads). All data analysed comes from thirteen waves of the Russia Longitudinal Monitoring Survey of the University of North Carolina.

The key findings of this study can be summarised as follows. First and foremost, in line with Rege et al. (2011) and Lindo (2013) our estimation results indicate that children's health responds differently to their mother's and father's job loss, and this finding is considered the main contribution of the study. To elaborate more on this, we find an adverse effect of male household head's unemployment on the development of chronic conditions in children and mental health, but a beneficial effect of single mother's unemployment on the occurrence of child anxiety and depression. It is puzzling, however, that the opposite holds for short-term health indicators (measured as incidence of child health problems during the month before the interview), suggesting that a female household head's unemployment appears to negatively impact the children. We also provide tentative evidence of a harmful impact of paternal job loss on the likelihood that a child is in good health, as well as on the probability the kid lags behind in terms of height, and there are no such impacts of mother's job loss. Lastly, our results suggest the possibility that children of unemployed parents are under-diagnosed in terms of chronic diseases.

The remainder of this paper is organised as follows. Section 1.2 discusses the theoretical framework behind this research question and reviews the relevant literature. Section 1.3 describes the data and variable definitions employed in the study. This is followed by detailed data analysis in section 1.4. Section 1.5 develops an econometric model of children's health outcomes and discussed the estimation strategies. Finally, section 1.6 presents the estimation results, followed by a discussion of the paper's limitations.

1.2 LITERATURE REVIEW

1.2.1 Theoretical background

In the light of Grossman's 1972 seminal paper, a child's health outcome could be modelled with the help of a simple health production function approach. The first key factor playing a role in a child's health status is the child's initial stock of health capital, determined by his/her genetic endowment, and inherited from both of his/her parents. This stock establishes each child's susceptibility to certain diseases such as chronic heart disease, diabetes or learning disabilities. The second group of child's health determinants falls into the category of household-level inputs to the child's health production function, and includes monetary and time resources, such as family income and available parental time – both of which are affected by unemployment. It is important to note here that parental income and parental time have a direct effect on a child's health outcome (e.g. by offering better quality nutrition), as well as, an indirect one: they determine the parental investment in child's health care – key to sustaining and improving his/her inherent health stock.

In addition to this, various community-level factors serve as inputs to the child's health production function, and may help maintain his/her health stock, or conversely – lead to depleting it, even without any changes in the family income or time endowment. The most important example in this respect is the ease to access public health care, as well as its quality. One other channel for the effect of parental unemployment to materialise is suggested by Montgomery at al. (1998): unemployment in the family may increase the parent's stress levels, and causes them to engage in risky behaviours such as smoking and drinking. In the light of the children's health production function, this behavioural change may negatively affect the health production function itself, thus, making the production of health less efficient even if all inputs remained unchanged. Next, certain shocks, most evident of which accidents leading to trauma or injury, but also other events such as divorce or death in the family, may not only reduce the resources available to a child but may also have a direct adverse effect on his/her health due to increased level of stress (see e.g. Mauldon (1990) discussing the effects of parental divorce).

Lastly, it is worth mentioning an additional mechanism for the effect of parental job loss on children's health to arise, suggested by Becker's economic model of the family (see Becker (1993)). In particular, the model ascertains that by optimally allocating their time between home and market activities, in addition to leisure, parents aim at maximizing the total utility of all household members (which is in turn determined by leisure, consumption and child outcomes). In this context, unemployment of one of the parents in a two-parent family might enforce a suboptimal allocation of labor in the household. To elaborate more on this, paternal job loss in a family with a working mother, for instance, may induce the father to take on a bigger share of home production, and if he is less efficient in providing care for the child than the mother, then this may potentially be harmful for the kid's health.

Taking all this into consideration, the direction of the effect of parental job loss on their children's health is not clear a-priori. To elaborate more on this, economic theory suggests that a drop in household income resulting from parental job loss may make the family likely to decrease the quality and quantity of nutritional intake available to the children, as well as reduce the investment in their health. As a consequence, the children may suffer a depletion of their health stock. At the same time, however, job loss increases the amount of parental time spent with their kids, which suggests that it may have some positive impact on a children's health. In particular, more time available to a parent may lead to an increase in the investment in their kid's health; it addition, it may have a direct positive impact on the children's health status if, for example, spending more time with a parent helps reduce a child's stress levels. Since the health production function is assumed to be increasing in both types of parental inputs – income and time – the theoretical prediction of the overall impact of unemployment in the family on children's health is unclear: the direction of the effect would ultimately depend on which of the two effects prevails.

1.2.2 Empirical evidence

The empirical evidence on the effect of parental unemployment on their children's health is scarce, and draws mostly upon US data. Early work in the field indicated that poor health and infant mortality are more common among children of poor families (e.g. Mare (1982)); yet, several researchers pointed out that children's ill-health may not be driven by poverty per se but by low parental education (Edwards and Grossman (1982)). More recently Dehejia and Lleras-Muney (2004) used U.S. nation-wide birth certificate data from year 1975 onwards, and reported that babies conceived in times of high unemployment have a reduced incidence of low and very low birth weight, fewer congenital malformations, and lower post neonatal mortality. At the same time, however, Lindo (2011) utilised detailed work and fertility histories from the Panel Study of Income Dynamics to explore the extent to which the health effects of job displacement extend to the children of displaced workers, and reached the opposite conclusion – husband's job loss was found to have a significantly negative effect on infant health.

The empirical evidence is even more perplexing when it comes to the effect of maternal work status and children's health outcomes. For instance, Ruhm (2008) investigated how maternal employment is related to the outcomes of children, and reported that maternal labour supply has harmful effects on kid's cognitive development, obesity and risky behaviours such as smoking and drinking. In addition, he observed that limited maternal market work during the child's fourth through ninth year of age benefits children of low-income families. Yet, other studies found that maternity leave related non-employment has no significant effect on children's health. One example in this respect is work by Baker and Milligan (2008), who examined an increase in maternity leave mandates in Canada, and found large increases in mother's time away from work after birth, yet no effect on maternal or child health. In contrast, Liu et al. (2009) employed various parametric and non-parametric methods to study data from the US National Longitudinal Survey of Youth 79 and reported that mother's full-time employment has an adverse effect on her children's body mass index and the likelihood of becoming overweight.

There has not been much research on the effect of job loss in the family on children's health outcomes outside the US, although the topic has gained interest in the past decade. Baten and Boehm (2010) investigated the effect of parental unemployment in the East Germany area on children's anthropometric indicators, and reported that increasing unemployment is a major driving force for the decline in the average height of children. One of the few studies of the issue in developed economies was done by Liu and Zhao (2014), who utilised data from the China Health and Nutrition Survey and found that paternal job loss has a significant negative effect on children's health measured as height and weight for age, while the effect of maternal job loss appeared insignificant. Finally, Yasin et al. (2004) used data from Pakistan and concluded that family income per capita positively influenced children's vaccination uptake.

Taken as a whole, several key findings emerge from the review of the body of recent literature on the impact of parental job loss on children's health outcomes. First and foremost, the literature typically reports an adverse effect of unemployment in the family on a kid's health, although some authors find insignificant or even significant beneficial effects. Secondly, for the most part the literature focused on body weight and height indicators as the child health measure, although recent research has shed some light on the impact of parental job loss on children's behavioural outcomes, as well. Lastly, most of the empirical evidence draws upon studies of the effect of paternal unemployment, while relatively little attention has been paid to the issue of mother's unemployment.

This paper adds to the body of literature by studying how unemployment of the family head in a sample of households from the Russian Federation affects a number of child health outcomes, including both physical and psychological health indicators. Due to the rich data available, we are able to account for other parental and household-level indicators, as well as to include controls for community-level access to healthcare. In addition, we able to shed some light on a question, which has been largely overlooked by previous research: how does a kid's health response to unemployment of the household head vary depending on whether the household head is male or female?

1.3 DATA AND VARIABLES

1.3.1 Data

A major challenge of the research question addressed in this paper is to find a source of plausibly exogenous variation in the family conditions under which children are being raised. This is why a preferred methodological strategy is to look at the effect of parental unemployment on children's health using the outcomes of a natural experiment that supplies the necessary exogenous variation. Such a natural experiment is provided by the post-communist transition of many European countries that adopted large-scale subsidized employment during the communist system, but experienced fast and large job destruction once that system collapsed at the beginning of the 90s. During this period many workers (and amongst those, many parents), who had stable employment for most of their lives, lost their jobs for a prolonged period of time.

In order to explore this phenomenon, we utilize annual micro-level data from the second round of the Russia Longitudinal Monitoring Survey[1] collected in the period 1994 to 2006. The RLMS-HSE is a series of nationally representative surveys in the Russian Federation aiming at studying the effects of the reforms in on the health and economic welfare of the households. An advantage of this dataset is that, in addition to data on household income and employment, it includes a wide variety of health status variables of the household members over a period of nearly fifteen years.

As the design of RLMS-HSE is based on dwelling-units (i.e. individuals are tracked if they remain in the same dwelling unit as in the baseline year), the sample is restricted to those households who remained in the same dwelling unit between years the years 1994 and 2006. The

[1] The Russia Longitudinal Monitoring Survey, RLMS-HSE, has been organized and coordinated the Carolina Population Center at the University of North Carolina at Chapel Hill. Referred to as RLMS-HSE or RLMS henceforth.

analysis in the paper focuses on the employment status of the household head and attempts to infer on whether it has an effect on the health outcome of the children in that household. With this in mind, the sample is additionally restricted to families with working-age household heads, whose work status is either employed or unemployed. For the households in the remaining sample, head of household is assigned according to the following demographic hierarchy: (1) the oldest working-aged male in the household, (2) if no working-aged males, then the oldest working-age female. The resulting sample consists of 1,637 households and 2,163 children (individuals under age of 14) in the base year 1994.[2]

1.3.2 Variable definitions

1.3.2.1 Unemployment definition

Defining an individual's unemployment status in Russia is complicated for several reasons. A Bureau of Labour Statistics (BLS) definition of unemployment, which is available in RLMS-HSE, has the disadvantage that it only classifies as unemployed workers who have no job at present and have been actively searching for a job four weeks prior to being interviewed[3], and this may not be well-suited to reflect the fact that Russia has been through a long period of transition and economic restructuring. Faced with massive job destruction, very few employment prospects, and long joblessness experience the unemployed individuals may have entirely altering their attitudes by becoming discouraged about their prospects of obtaining a job, and thus, lowering their search efforts. Hence, a BLS definition would not account for the

[2] Due to high attrition the samples falling into the Moscow and St Petersburg regions were replaced with a new sample in year 1999.

[3] BLS defines as active job search activities including, but not limited to: having a job interview, using an employment agency, sending out resumes, filling out applications, etc. In contrast, passive job-search methods include attending a job training program, or reading about job openings that are posted in the media.

discouraged workers, and presumably, these are the ones of major interest in view of the particular research question in this paper as the effect of parental unemployment on their children's health may take longer to materialise. In addition to this, in Russia, as in most of the former communist countries, one could be working while not officially employed (i.e. has no labour contract) or even while officially unemployed (i.e. registered at a state employment office as such), or could be searching less intensively for a job as s/he is engaged in unreported activities (see e.g. Grogan and van den Berg (1999)).

Further, a registered unemployment definition is available in RLMS-HSE, as well; however, it has been reported that the unemployed in Russia often do not make use of the state employment agencies. For instance data from the Labor Force Survey showed that the true unemployment rate in the Russian Federation in the transition years was much higher than the official rate reported by the Federal Employment Service, which is limited to workers registered as unemployed at the local employment offices (Grogan and van den Berg (1999)). In this respect, employing a definition of unemployment status based on whether one is registered at an employment office is expected to severely underestimate the true unemployment rate and misclassify a significant fraction of the unemployed. Since only a small fraction of the unemployed utilize the state employment offices, whether one is registered as unemployed or not, is not taken into consideration in the unemployment definition in the paper.

Taking into account all these considerations and aiming at fully benefiting from the data available at RLMS-HSE, this paper utilises an unemployment definition based on a job holder indicator and a self report. In particular, it defines as unemployed an individual who has no job and considers him/herself unemployed, even if s/he had not been actively searching for a job in the past four weeks. Table A.1 shows a cross-tabulation of this definition and the BLS definition of unemployment. As can be seen the two definitions are identical in defining the employed persons; however, they differ in classifying one as unemployed: while the BLS definition classifies 851 persons as not in the labour force, the definition used in this paper includes them in the category of unemployed. It is also worth noting that while the correlation between the two definitions is high (0.70) it is far from 1.[4]

1.3.2.2 Health outcome variables

Another crucial variable in the study is the definition of children's health. There is no consensus in the relevant literature about the proper measurement of health, and this is even more pronounced when it comes to measurements of children's health.[5] As already mentioned the RLMS-HSE contains a wide range of health indicators such as parental evaluation of their children's health, as well as variables usually referred to in the literature as 'objective health measures' such as diagnosed health conditions (see e.g. Deschyvere (2005)). In the absence of clinical data on the children, RLMS-HSE, like nearly all surveys has to rely on parental health

[4] As Fig. 1 illustrates, the unemployment definition used in this analysis results in a pattern of the unemployment rate (among the household heads in the sample), which follows the pattern of the BLS definition and the definition based on one being registered at an employment and 9.13%); finally, the definition used in the paper is the highest (ranging from 4.93% to 16.97%). It is important to also note that all definitions show a peak of the unemployment rate in 1997, which is consistent with the findings of Earle and Brown, 2003 for a peak of job destruction rates and and 9.13%); finally, the definition used in the paper is the highest (ranging from 4.93% to 16.97%). It is important to also note that all definitions show a peak of the unemployment rate in 1997, which is consistent with the findings of Earle and Brown (2003) for a peak of job destruction rates and layoffs in Russia occurring in year 1997 (see later).

[5] A major part of the previous studies examine infant and child mortality rates as the children's health outcome (see e.g. Mare, 1982). However, child mortality rates are relatively low in the Russian Federation; in addition, the under-5 mortality rate in Russia has been consistently declining annually in the post-communist period (marking a drop from 27 children per 1,000 in 1990 to 12 in 2011 (UNICEF (2011)), contrary to the unemployment upheaval in the early years of transition. This suggests that the effect of parental job loss on their children's health may not operate via child's mortality rates; moreover, the observed number of child deaths in a sample of about 3,000 children is likely to be very low even in a period of thirteen years.

reports, which raises the concern that these may be subject to bias. One issue with the use of parental reported health evaluation is that it might suffer from measurement error since perceptions of individuals of their kid's health may vary substantially. This concern remains even when employing reports of diagnosed health conditions: e.g. Bakes at al. (2004) compared such indicators to data from adult's medical records and revealed presence of considerable reporting error. Even though the children's health status is an outcome variable in this paper, such errors in its reports are an issue of concern if the reporting error is in any way correlated to the key variable of interest.

Based on this, we look at several types of children's health measures as each of them could capture a different aspect of a child's health and could be to a different extent subject to measurement error. The first group of indicators concerns child healthcare access and utilisation, and includes variables such as whether the child has a regular physician, whether it has had preventive medical care visits in the last 3 months and in the last 12 months, and vaccinations. Further, physical health status measures are analysed, such as parental health evaluation of the kid's health status, chronic health conditions, hospitalisations, incidence of health problems in the last thirty days, and anthropometric indicators (for children below seven years). In addition to this, the kid's emotional and mental health is also considered, based on a parental report of whether the child feels any anxiety or depression. Lastly, the paper looks at various community level health care access and quality indicators, as well as child healthcare expenses.

1.4 DATA ANALYSIS

1.4.1 Child healthcare provisions in Russia

The core provisions on child healthcare in Russia are stipulated in the Fundamentals of the Russian Federation Legislation on Citizens' Health Protection Act of 1993, which establishes the existence of federal guarantees for free medical child care in all state and municipal health establishments in Russia (the 'children' category including minors below eighteen years of age).[6] In addition to the medical procedures prescribed at a federal level, the district authorities have the option to further extend the number of free medical procedures and treatments for children provided by the district hospitals and polyclinics, and to require the availability of qualified medical personnel in the nursing and child care facilities. Moreover, a Government Ordinance of June 21, 2003 prescribes that all children under the age of three have the right to free medication. Vaccination of infants and children against a number of diseases is also guaranteed by law and free of charge. Under such legislative framework, a drop in family income caused by parental job loss should have no adverse effect on the household's investment in child health care.

At the same time, however, there have been reports on breaches of the federal legislation on children healthcare. One example in this respect comes from a series of inspections conducted by the Office of the Russian Prosecutor General in 2005, which found violations of the children rights to health care in numerous regions of the Russian Federation.[7] In particular, not only did the local authorities fail to fully implement the 1993 Act on child healthcare, but they often

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[6] Law Library of Congress of the Russian Federation, 'Children's Rights: International and National Laws and Practice', 2007, available at http://www.loc.gov/law/help/child-rights/pdfs/childrensrights-russia.pdf

[7] Same as above.

intentionally decreased the number of free child health services provided in the district healthcare facilities below the federal guarantee. In addition to this, the inspection reported that no region in Russia had completely put into practice the Government Ordinance of 2003. The results from these inspections clearly show that at present the authorities in Russia fail to guarantee the implementation of the children healthcare rights stipulated in the legislation.

The RLMS-HSE data also shows evidence suggestive of the lack of full compliance with the legislation regarding the federal child healthcare guarantees. In particular, over the period 1994 to 2005 the child questionnaire asked the questions 'Did you pay the doctor for [child's last] doctor's visit?' and 'Did you pay additionally for [child's] examination or procedures?'. Table A.2 shows the sample mean responses: 14.16% of the RLMS-HSE households reported paying for the last medical appointment of their child, and 4.64% reported paying extra for medical tests and procedures.[8] It is important to note that these responses cannot be attributed to visiting private practices: 3.09% of the parents paid for the last kid's visit in regional public health clinics, and 11.79% were charged for additional medical tests in those clinics (vs. 50.22% and 69.28%, respectively for those who visited a private practice). Medicine also appears costly: 72.55% of the households reported paying for the kid's medication and 52.54% paid for medication, even though their child was less than three years old at the time. Finally, it is worth noting that 25.38% of the families incurred some travel costs to the medical facility.

All the evidence presented in the above paragraphs indicates that regardless of the favourable legislation, child healthcare in Russia involves certain costs. Therefore, households experiencing a drop in their income resulting from unemployment may be forced to reduce their healthcare investment in their children, which in turn may adversely affect their health.

[8] The cited numbers are based on stratification-adjusted means. In addition, Table 2 reports the non-adjusted means as well.

1.4.2 Sample statistics of the households

In order to test the idea that parental unemployment affects their children's health, this section of the paper compares the health outcomes of children of unemployed parents and those of employed parents. The key hypothesis of the subsequent analysis is that if parental job loss has an adverse effect on their kid's health one should be able to observe significantly worse heath outcomes in the subsample of children of unemployed parents, and vice versa. Failure to observe significant differences in the health outcomes of the two groups of children might imply that children's health outcomes are, indeed, independent of their parental employment status, or that the two opposing effects – that of decresed parental income and of increased parental time available to the kids, are offsetting each other.

Table A.3 presents the (stratification adjusted) [9] statistics of the total sample of households, and separately for the two subsamples of employed and unemployed household heads. It is evident from here that households with unemployed heads and those with employed heads differ in several important ways. First and foremost, children of unemployed household heads are roughly 25% more likely to live in poor families, and this difference is significant at the 1% level both when looking at the all-Russia poverty line and at the regional poverty indicators. Secondly, these households tend to be larger – they have more kids below six years of age, more kids in the age range seven to eighteen, and are more likely to live with a post-working age relative. Finally, such households are located in communities with significantly worse public

[9] The RLMS-HSE employed a stratified sampling based on geographical factors and level of urbanization (stratum referred to as region). Oversampling was concentrated in large urban areas, where the highest non-response rate was expected. The post-stratification adjustment weights are based on the 1989 census and 1994 micro census for rounds 5 to 12 (years 1994 to 2002), and the 2002 census starting with round 13 (year 2003 onwards). The sampling weights are utilised in this paper in order to obtain consistent estimates of the population moments. In addition, standard errors are adjusted accordingly.

health services – compared to households with employed heads they are about 15% less likely to have access to hospital and to paediatrician, and those with access to medical facilities live farther away from them.

Further, an examination of the characteristics of the parents shows that household heads who are employed and unemployed do not appear different in terms of demographics – they are of similar age and gender structure. Even though the unemployed household heads are significantly less educated by one year, the sample mean of their years of education is still very high – fifteen years, suggesting a large fraction of university graduates in this group. Somewhat unexpectedly, however, the unemployed workers in the sample appear healthier than their employed counterparts: they are 10% less likely to suffer from a diagnosed chronic condition and the difference is highly significant (the difference being driven by spinal and gastrointestinal conditions). In addition, unemployed parents do not seem to show consistent signs of increased risky behaviours compared to their employed counterparts: the difference in the frequency of monthly alcohol consumption is significant but essentially zero in magnitude, and the two subsamples do not differ in the 'drinking without eating' indicator (which may be viewed as a proxy for alcoholism). Cigarette smoking shows that unemployed parents are considerably more likely to smoke, although both sample means being very high.

Lastly, an indicator for parental time spent with the child (answer to the question: 'Has a non-household member[10] cared for the child in the last 7 days?') shows that children from families where the head is unemployed are about 9% less likely to have been cared for by a non-household member, and the difference is significant at the 1% level. This gap remains high when restricting the attention to kids of pre-school age (age below seven years), although for both

[10] The question specifies as 'non-household member' the following categories: friends, workers at a children's institution, school teachers, or relatives who live separately.

subsamples parental care for small kids appears higher. The observed differences in parental time are in line with the idea that unemployment increases the available parental time, thus increasing the time spent with the child. It should be noted, however, that this gap may, at least in part, be driven by the fact that kids with an unemployed household head tend to live in larger families.[11]

1.4.3 Sample statistics of the children

Turning to characteristics of the children of employed and unemployed household heads, the upper panel of Table A.4 suggests that children from both subsamples have similar demographics – the difference in means of kid's age and fraction of boys are not statistically significant. The table also suggests no significant differences between the two subsamples of kids in terms of immunization history – 98% of the children in both samples obtained vaccines. In order to investigate the possibility that children of unemployed parents have their immunisations delayed the analysis also presents the difference in vaccinations rates of babies aged one year or below (when most vaccinations are due). The results suggests that kids of unemployed parents might, indeed, be seeing some delay in their vaccinations – they are nearly 5% less likely to be vaccinated by the age of one, but the difference is only significant at the 10% level. Further, kids from households where the household head is unemployed have significantly lower overall healthcare utilisation – they are less likely to have had a routine medical check-up (i.e. not because of illness) in the last 3 or 12 months, and are less likely to have a regular physician, all differences being significant both in terms of magnitude and statistically. Taken as

[11] Table 1 in the Appendix presents the sample statistics of the households separately for the 1994-1998 sample and post-1998 sample. The table illustrates that while employed and unemployed household heads, and their households, appear different in both periods, the sample means are closer for the period 1994-1998.

a whole, these observations give grounds to expect that kids of unemployed parents would have worse health outcomes as their parents seem to invest less in their health.

At the same time, however, the lower panel of Table A.4 presents a somewhat unexpected picture: on average, children from families with unemployed head appear less likely to have had health problems in the last 30 days, have better parent reported health evaluation[12] and appear less likely to suffer from anxiety or depression.[13] Perhaps even more surprising is the fact that these differences arise even when looking at particular diagnosed chronic conditions as there seems to be some evidence that children of unemployed parents are less likely to suffer from gastrointestinal and spinal conditions (significant at the 1% and 5% level, respectively). As can be expected, hospitalisation rates are very low in both children samples and the difference between them is not statistically significant. Yet, one health marker on which children of unemployed parents seem to lag behind is the anthropometric indicator[14] height for age: the fraction of kids with low height for their age but normal weight for their height is 6% larger for kids of unemployed parents, while the opposite is observed for the fraction of kids with both normal height for age and weight for height. This suggests that children of unemployed parents may possibly suffer from height impairment, possibly due to worse nutrition (as suggested by the significantly lower sample mean of daily caloric intake).[15]

[12] Answer to the question 'How would you evaluate [the child's] health?'

[13] The question 'Does the child feel anxiety or depression?' was only asked in years 2005, 2006 and 2007 of the survey; hence, the variable is only available in these years. Possible answers include 'none', 'some anxiety/depression' and 'severe anxiety/depression'. The latter two are included into a single bin due to a very low fraction of observations falling into category 'severe anxiety/depression'.

[14] Anthropometric indicators are only available for kids aged 7 or below. All are computed on the full RLMS-HSE sample of children, based on a parental report for the child's height and weight.

[15] Comparison of these statistics by time period suggests that gap between the fractions of children of low height for age has been increasing in time. The sample means for the period

Figures A.2 to A.10 provide a closer look to the most important children health indicators for both subsamples by the child's age group. As can be seen from Figure A.2 the probability the child has a regular physician decreases linearly as the kids age for both groups of children. However, the fraction of kids with a registered doctor is always higher for kids of employed parents, and the gap seems to nearly double as the children get older than one year. Figures A.4 and A.5 illustrate a similar pattern in the probability that the child had a medical check-up in the last 12 and 3 months, respectively. It is evident from here that the fraction of kids who get to visit a doctor is very high (roughly 80%) for both groups of children in the first two years of their life, but considerably drops thereafter, the drop being much more pronounced for children of unemployed parents. A similar pattern can be seen in the medical check-up rates during the 3 months preceding the interview: children of employed parents are more likely to have had a doctor's visit for all age categories, and for both groups the probabilities gradually decline with the kid's age until age four, after which the lines are essentially flat.

As already mentioned, no significant differences are observed in the likelihood of a child getting a vaccination between the two groups of kids, except for babies below 1 year of age. Figure A.3 reinforces this observation and, in addition, illustrates that virtually all immunisations take place by the age of 2, regardless of parental work status. Further, Figure A.6 illustrates the child hospitalization rates in the last 3 months, confirming there are no important differences between the two groups of children: the two probabilities are not statistically different from each other for all kid's age groups.

1994-1998 are 0.090 and 0.125 (in household with employed/unemployed household head, respectively), and this difference is significant at the 5% level. However, for the post-1998 sample the corresponding fractions are 0.075 and 0.195, or nearly 12pp (significant at the 1% level). This might suggest the effect of household head's unemployment status on the kid's height (if any) takes longer time to materialise.

Next, Figure A.7 shows the probability that a child suffers from a chronic condition conditional on the kid's age. As can be seen from here, children of unemployed parents are less likely to have been diagnosed with a chronic illness for all ages above two. This may suggest an effect of parental work status, but it might as well have genetic or environmental causes, as the fraction of employed parents suffering from chronic conditions is higher than that amongst unemployed parents. The pattern of the probabilities that a kid experienced a minor health problem in the last 30 days also reveals a gap favouring children of unemployed household heads. Lastly, Figure A.10 illustrates the probability that a child shows symptoms of anxiety or depression[16], which suggests that children of unemployed parents are less likely to suffer from these conditions. The difference between the two groups is statistically significant for all kid's ages, which is in line with established facts in the medical and psychology literature typically reporting signs of anxiety first shown as early as 7–9 months of age.

1.4.4 Dynamics

This section briefly looks at the sample means of the children's health outcomes in the period right before and right after the household head loses his/her job, as well as in the period when s/he exited unemployment into employment (in case exit from unemployment occurred). The main idea of this comparison is to see if there are any changes in the kid's health indicators taking place around the time of unemployment.

The results of this analysis are presented in Tables 5. The left panel reports the sample means based on the full sample of household heads, who lost their job during the period 1994-2006. As can be seen from here, some of the child health characteristics show a considerable

[16] The analysis uses larger age groups as the number of observations for this variable is smaller due to the fact that the question was only asked in years 2005 to 2007.

variation around the period of unemployment. In particular, there is a sizeable drop in the child's mental health indicator in the period when the household head becomes unemployed (the mean declines from 0.21 to 0.16), but anxiety and depression rise back to nearly the pre-unemployment level once the household head gets reemployed (level of 0.18). In addition to this, the mean number of chronic conditions increases by nearly 0.03 (from 0.17 to 0.20) in the year when the household head gets unemployed as compared to the pre-unemployment level. The number of chronic illnesses remains at the increased level even after the family head transitions back into employment, likely due to the fact that once developed a certain chronic condition can only be treated but not cured. Equally important, the fraction of kids with low height for their age sees an increase by 4.5 percentage points in the year of parental unemployment (15.6% vs. 11.1%), and drops back once the household head gets reemployed (11.9% once reemployment occurs).

At the same time, however, other variables show little or no variation before and after the event of unemployment. For instance, the share of children who experienced some health problem in the 30 days preceding the interview marks a very slight drop when household head becomes unemployed, while the sample fraction of kids who had a minor health issue seems to be trending up. The proportion of kids in bad health (based on a parental report) also increases to some extent in the time when unemployment occurs, and this is mirrored by a minor decline in the fraction of children in good health. In contrast, the percentage of children who got vaccinated also remains essentially unchanged, regardless of the unemployment transition of the household head. Further, it is interesting to note that some variation is noticeable in the health care utilisation variables. In particular, there is a drop in the kid's yearly check-ups from 0.56 to 0.52 in the year the household head becomes unemployed, but those rise right after exit form unemployment; no such pattern is visible in the 3-month check-ups. Lastly, the dynamics of the indicator of whether the child has a regular physician seems to be reflecting a downward trend.

For completeness, the right panel of Table A.5 looks at the children's outcomes in the sample restricted to only those household heads for whom both entry and exit into unemployment were observed. To be more specific, Columns (4) and (5) now report the means of the children's health indicators conditional on the household head exiting unemployment. As can be seen from here, overall, the kid's health characteristics show a smaller variation, suggesting that unemployment might matter less in case transition into employment occurred. Taken as a whole these results suggest a change in the children's heath outcome around the time when the household head lost their job. It is important to note that the reviewed sample means may reflect a simple trend in the data and, while they do not necessarily imply that the change in kid's heath occurs as a response to the household head's unemployment, they do suggest this as a possibility.

Before concluding this section, it is also useful to look at the employment status of the spouse of the household head in the two-parent families, where the head experienced unemployment. These are shown in Table A.6. As can be seen from here, spousal employment seems to drop in periods when the household head becomes unemployed, possibly reflecting the situation at the local labour market. At the same time, the fraction of wives out of the workforce considerably declines in the period when the main earner loses his job (0.09 vs. 0.19 in the period before household head's unemployment occurred), suggesting that some secondary earners enter the labour force as a response to this adverse event. Yet, it seems from Column (2) that a large percentage of the secondary earners enter the labour force only to join the category of unemployed, rather than find a job – the fraction of spouses who are unemployed noticeably increases in the period when the household head gets unemployed, while the fraction of employed wives marks a decline. Virtually, the opposite spousal work status force transitions occur when the household head transits back into employment. The lack of an added worker effect points at the possibility that households whose head experiences unemployment fail to make up for the loss of income. The same conclusions prevail when looking at the restricted sample conditional on household head exiting unemployment.

Taken as a whole, the evidence presented in this Chapter illustrates one notable pattern: while children from families where the household head is unemployed tend to have significantly worse preventive healthcare, this does not materialise in having worse health – on the contrary, those children seem to have better health indicators. At first glance, this suggests that a parental job loss might, indeed, improve children's health outcomes due to more available parental time. However, it also raises an important question: could the observed difference be due to children of unemployed parents being under diagnosed, as these kids are less likely to have visited a physician? This possibility is also supported by the analysis of the child heath indicators around the time of unemployment. Verifying any of these possibilities would require accounting for other parental and household indicators, capturing community-level effects, as well as allowing for the effect of parental unemployment to vary based on other characteristics of the parent. The next Chapter shall attempt to model this.

1.5 ECONOMETRIC MODEL

1.5.1 Job destruction in Russia

Most studies, which analysed the job reallocation rates in the Russian Federation following the fall of the communist system, reach an agreement in identifying the time period marked by utmost job destruction. For instance, according to Earle and Brown (2003), who used survey data from a sample of industrial enterprises in the Russian Federation during the period 1990 to 1999, the end-year job destruction rate started escalating in 1994 (reaching a level of 11.79 from 7.85 during the previous year); maintained high levels through 1998, before dropping to 5.94 in 1999. An analogous pattern was observed in the worker separation rates (layoffs): they sharply increased in 1994 compared to the previous year (level of 9.10 in 1994 vs. 6.69 in 1993), continued rising in the years to follow, and peaked at 14.71 in 1997. Similarly to the job destruction rates, the worker layoff rates saw a considerable decline in 1999, while the rehiring rates remained stable throughout the entire period of data, suggesting no recalls occurred. Finally, turning to employment growth rates, those appeared negative in all analyzed years except 1999, and their pattern mimicked the pattern of involuntary job separations; in particular, the employment turndown nearly doubled in 1994 reaching a level of -9.6, remained high in the following years, before positive employment growth was marked in 1999. The general picture emerging from Earle and Brown's analysis is that job flows in the Russian Federation considerably increased in magnitude during the years 1994 to 1998, and this was especially pronounced for job destruction and involuntary separation rates.

The pattern in job destruction rates described above suggests that earlier waves of RLMS-HSE could be utilized to explore the influx of massive layoffs and plant closure in Russia in studying the effect of parental unemployment on children's health, under the assumption that those comprise a convincing case of an exogenous shock in household income. At the same time, however, the years post-1998 were marked by overall employment growth and job creation, suggesting that a different approach is required. In the latter case setting, solving the potential endogeneity of job loss becomes a major issue of concern. The main problem stems from the fact that individuals who get unemployed (either by being selected for a lay-off, or by voluntarily quitting) may have unobserved characteristics that are correlated with their children's health outcomes. Recent literature focused on a narrow category of job losses – job displacements, [17] arguing that those provide an exogenous shock to household income (see e.g. Lindo (2010)); however, data on job displacements is not available in RLMS-HSE making the approach implausible in this paper.

In a natural experiment setting, an econometric model of a child's health status as the outcome variable and a binary treatment for parental unemployment as the major variable of interest, as well as child's and family characteristics as controls, would allow consistent estimation of the causal effect of unexpected long-term parental job loss on their children's health. In the absence of a natural experiment, the central identifying assumption is that job loss provides an exogenous variation in family income, once unobserved time-invariant heterogeneity is accounted for.

1.5.2 Econometric model

Consider the following hierarchical linear model:

$$Health_{ijt} = \beta_0 + \beta_1 ParentalJobLoss_{jt} + X_{ijt}^{C}\beta_2 + X_{jt}^{H}\beta_3 + X_{jt}^{R}\beta_4 + D_t + \eta_j + c_{ij} + u_{ijt}, \qquad \textbf{(1)}$$

[17] According to the definition of the U.S. Bureau of Labor Statistics for a worker to qualify as a 'displaced worker', s/he must have lost their job due to 'plant closing'; 'insufficient demand'; or 'shift abolished'.

where the left-hand-side variable, *Health,* represents the health outcome of child i in family j at time period t, *ParentalJobLoss* is a binary variable for whether the household head in family j experienced unemployment resulting from job destruction (in the natural experiment setting of the early RLMS-HSE rounds) or any type of job loss (in the later rounds of data) at period t. X^C is a vector of characteristics of the child (age category). Vector X^H consists of parental and family-level controls including gender, education and, in some specification, health conditions of the household head, work force status of the spouse of the household head[18], as well as a household wealth indicator and number of kids in the family aged below 7 and between 7 and 18 years. Finally, X^R incorporates community-level indicators for the availability of health care (access to paediatrician), and controls for region of residence. Including regional dummies in the model is important for several reasons: first, they account for differential employment opportunities across region; secondly, they account for various environmental factors which play a role in certain health conditions; lastly, they are needed to correct for the fact the RLMS-HSE sample is stratified rather than random.[19]

[18] Category 'spouse' refers to the spouse or cohabiting partner of the household head. The work force status controls include several mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head, single male head, and living with spouse but spousal labour force status missing. The definition of spouse unemployed uses the same definition of unemployed as for the household head: the spouse of the household head is considered unemployed if they report holding no job and consider themselves unemployed.

[19] Since the stratification in RLMS-HSE is based on an observable characteristic (region), the unweighted estimation including controls for the strata is consistent, as well as the weighted estimation. Unweighted estimation with controls for the strata is preferred in this paper as weighting makes cluster-robust inference a challenging issue.
Eight main region categories are available in RLMS-HSE (those are: metropolitan areas Moscow and St. Petersburg, Northern and North Western, Central and Central Black-Earth, Volga-Vaytski and Volga Basin, North Caucasian, Ural, Western Siberian, Eastern Siberian and Far Eastern), together with sub-region location categories for every region.

Further, D_t represents time effects (both individual and household invariant). In particular, D_t includes year effects to account for changes in the overall economic and environmental conditions, as well as developments in the overall state of the health care system; in addition, month effects are included to allow for seasonal patterns in certain health conditions. Error component η_j represents time-invariant unobserved household-level heterogeneity that could affect the children's health outcomes (for instance, parental child abuse, nutritional habits of the parents or parental innate ability, all of which might be correlated with parental employment status). Error component c_{ij} stands for child's unobserved effects; the latter could be thought of as the child's inherited health stock, and includes unobserved characteristics such as the kid's predisposition to certain health problems like heart disease, diabetes, or allergies. Finally, u_{ijt} is an idiosyncratic error component which is assumed to be uncorrelated with all the right-hand-side variables.

Identification of the causal effect of parental job loss on their child's health outcome in a natural experiment setting relies on the assumption that the assignment to treatment mechanism (i.e. $ParentalJobLoss_{jt}$) is practically random from the viewpoint of the outcome variable $Health_{ijt}$ or formally: $cov(ParentalJobLoss_{ijt}, \eta_j)=0, cov(ParentalJobLoss_{ijt}, c_{ij})=0$ and $cov(ParentalJobLoss_{ijt}, u_{ijs})=0, \forall\ t, s$. If the key identifying assumptions of a natural experiment setting hold, both pooled OLS and fixed-effects estimators would consistently estimate the effect of interest.

In the absence of a natural experiment, identification hinges on the assumption that $cov(ParentalJobLoss_{ijt}, u_{ijs})=0, \forall\ t, s$. This essentially means that parental job loss is uncorrelated with the time varying unobservable characteristics of the children and their families, which could affect children's health outcomes. A major threat to validity in the absence of a natural experiment is failure of $cov(ParentalJobLoss_{ijt}, \eta_j)=0$, as household heads who lose their jobs (e.g. as a result of being fired) might be worse in their permanent unobservable charactestistics than those who remain employed. One such example arises if household heads with lower innate abilities are also the ones, who are more likely to become unemployed, i.e. $cov(ParentalJobLoss_{ijt}, \eta_j)<0$. Since parents with better abilities are likely to be better caregivers and make higher investment in their children's health, this would imply $cov(Health_{ijt}, \eta_j)>0$. The last two conditions taken together would result in a downward inconsistency of the pooled OLS estimate of the parameter on interest β_1.

In addition to this, condition $cov(ParentalJobLoss_{ijt}, c_{ij})=0$ may fail to hold as well if, for example, employers are more or less likely to fire parents of children with lower inherent health stock, or if parents of such kids are more likely to voluntarily remain unemployed longer in order to provide care for a frail child (reverse causality). The latter may not be an issue of major concern as this paper looks at household heads, who are the main earner in their family, and their employment status is less likely to be affected by the health of their children; yet, it does call for proper treatment. Lastly, $cov(ParentalJobLoss_{ijt}, c_{ij})=0$ is violated if children respond in a heterogeneous way to the unemployment of the household head, and if this response varies by unobservable characteristics of the kids.

In cases as the ones described above, where unemployment of the parents is likely to be correlated with both the unobserved child effect c_{ij} and the family effect η_j, eliminating c_{ij} along with η_j becomes an attractive estimation strategy.[20] If the key identifying assumption

[20] It is important to note that one benefit of using a linear model and fixed effects estimation is that the relationship between the unobserved heterogeneity η_j, c_{ij} and the covariates X_{iit} is unrestricted. Alternative nonlinear models, such as correlated random effects, impose additional restrictions on the distribution of the time constant unobserved heterogeneity conditional on the covariates (see Chamberlain (1980)).

$cov(ParentalJobLoss_{ijt}, u_{ijs})=0, \forall \ t, s$ holds, and the unobserved child and family effects are, indeed, time invariant, the standard fixed-effect estimation at the individual level would produce a consistent estimate of the key parameter of interest in model (1). Finally, it is important to note that since RLMS-HSE is an unbalanced panel, using fixed effects estimation leads to eliminating all observations which appear only once. This does not lead to selection bias under the assumption that selection into being observed only once is exogenous (i.e. uncorrelated with u_{ijs}), and in cases where selection into being observed only once is correlated with the unobserved heterogeneity c_{ij} or η_j, a fixed effects estimation would eliminate this source of selection bias.

The estimation results of the model described above are presented in the next section.

Another point is that, because of the nested structure of model (1), there are different fixed effects estimators available. Employing household-level fixed effects estimation eliminates the group effect η_j; however, unit specific effects c_{ij} are still part of the composite error term. Since there are reasons to suspect failure of both condition $cov(ParentalJobLoss_{ijt}, c_i)=0$ and condition $cov(ParentalJobLoss_{ijt}, \eta_j)=0$, this paper utilised individual level fixed effects estimation.

1.6 ESTIMATION RESULTS

1.6.1 Short run health indicators

Tables 5A to 5C show the estimation results from model (1) with a binary variable of whether the child had any health problems in the last 30 days as the health outcome. Due to the differential trend in the job destruction rates in Russia in the period analysed, all model specifications are estimated separately on the 1994-1998 sample, post-1998 sample and the total sample of data. The analysis shall comment on these in turn.

Column (1a) of Table A.7 presents the estimation results from the 1994-1998 sample when employing a pooled OLS estimator, and without accounting for any child or household-specific characteristics that might have affected the outcome variable. As can be seen from here, children of unemployed parents appear 5.2pp less likely to have suffered from an illness in the past 30 days, *ceteris paribus*, even after accounting for regional differences, yearly time trends and possible seasonal patterns in certain health conditions.

Further, Column (1b) reports the estimation results when including controls for the kid's age (a binary indicator for age below 7), [21] household composition and parent characteristics, as well as access to paediatrician in the community. In addition, this specification allows for the impact of parental unemployment to differ depending on whether the household head is male or female in order to capture the fact that parents of different gender may differ in their abilities to provide childcare.

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[21] As shown in the data analysis section, the probability that a child experience certain health conditions considerably increases as the kid starts school, all model specifications control for age below 7. This is preferred to estimating model (1) separately on the below and above 7 years of age subsamples due to a low number of observations for particular health outcomes. Since we find no evidence for heterogeneity of the effects by kid's gender regardless of the health outcome of interest, child's gender is omitted in the pooled OLS estimation (not significantly different from zero at the conventional levels in all specifications); as gender is time constant its inclusion in model when employing fixed estimation is of no relevance.

The coefficient on unemployment shows the partial effect of job loss for male household heads, and implies that compared to children in families with an employed male head, kids in households with an unemployed father are about 5pp less likely to have experienced health problems in the last 30 days, other factors being equal. Further, the effect of mother's unemployment on the child's short run health is obtained as the sum of the parameter estimates on unemployment and the interaction term between unemployment status and female household head. The magnitude of this effect is also negative; however, it is not statistically different from zero at the conventional levels.

Next, the specification reported in Column (1c) adds an additional covariate to the regression – total income of the household. It is important to note, that since the main channels for the effect of unemployment in the family on children's health are believed to be income and available parental time, the model does not control for the time proxy (whether a non-household member cared for the child in the last 7 days). However, looking at a specification with total income available to the household is meaningful as it consists of labour earnings and income from other sources (e.g. property rents). As can be seen from here, the model is robust to adding the log of family income (the latter appearing insignificant at the conventional levels once labour force status of the household head and his spouse are accounted for).

The results from the fixed effects estimation are presented in Columns (3a) to (3c) of Table A.7. As can be seen from here, once unobserved time-invariant child and household heterogeneity has been eliminated, the parameter estimate on parental unemployment drops somewhat in magnitude, and appears significant only at the 10% level[22] in the specification with

[22] Note that the decline in significance is also due to the fact that the fixed effects estimation is based on a lower number of observations: due to the unbalanced nature of the panel, all units which are only observed for one time period are not used in the fixed effects estimation.

no covariates. Moreover, the estimation results of the specifications with controls shown in Columns (3b) and (3c), suggest that neither the male nor the female household head's unemployment status has a significant effect on their child's probability to have experienced health problems in the last month.

Finally, Panel POLS 2 of Table A.7 estimates all model specifications on a restricted sample of children, who were observed at least twice in the period 1994-2005. These results are reported for comparison purposes as they are obtained from the same sample as the sample used in the fixed effects estimation. It is evident from here that the parameter estimates on the unemployment dummy are consistent with the results obtained by pooled OLS on the full sample; however, the coefficient on the interaction term between female household head and unemployment status now appears positive in magnitude and statistically significant.

Turning briefly to the post-1998 sample, the estimation results are presented in Table A.8. The implications of these results differ than the ones obtained on the 1994-2005 RLMS-HSE sample in an interesting way. In particular, all specifications and estimation methods point to the conclusion that, children of unemployed male household heads do not significantly differ in the probability to have suffered from a health problem in the 30 days prior to the interview. At the same time, the coefficient on the interaction term appears highly significant, positive and large in magnitude – between 0.16 and 0.18 in the different specifications and estimation methods. This implies that children in families with an unemployed female head are nearly 18pp more likely to have undergone a medical problem in the previous month and the effect is significant at the 10% level [23] (based on the results from the fixed effects estimation of specification (3c).

Finally, the model is estimated on the full sample of children in order to take advantage of the larger sample size, and the results are reported in Table A.9. In contrast to the models estimated on the two subsamples of data, the estimation results based on the total sample overall reveal an economically and statistically significant effect of parental unemployment for both mother's and father's unemployment. For instance, the fixed effects estimation results suggest that when looking at children in families with a male household head, those whose father is unemployed are about 3.5pp less likely to have suffered a health issue in the month prior to the interview, *ceteris paribus,* although the effect is only significant at the 10% level. Further, other factors equal, children in families with a single mother are more likely to experience health problems if the mother is unemployed, and the effect is both economically and statistically significant (magnitude of 0.958, significant at the 10% level in the fixed effects estimation from specification 3c).

Taken as a whole, the estimation results presented in this section tend to suggest that unemployment of the household head might be beneficial for the children's short run health outcomes if the household head is male (suggesting a two-parent household[24]). At the same time, however, there is some tentative evidence that mother's unemployment has a large adverse effect on the likelihood the child has experienced a health problem recently, if she is the household head (i.e. if the child lives in a single parent household).

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[23] The p-value of the Wald test for significance of the sum of coefficients on parental unemployment and female household head is 0.0654.

[24] Only 1.15% of the sample of households with a male head report no presence of a working-age female in the family. In contrast, all of the households with a female head report no working age male.

1.6.2 Long run health indicators

1.6.2.1 Objective health measures

1.6.2.1.1 Chronic conditions

Answers to the question ‘Does [the child] have any kind of chronic illness?’ are not available in the RLMS-HSE prior to year 1998, which is why the paper only estimates model (1) with number of chronic conditions as the child’s health outcome on the post-1998 sample of data. The estimation results are shown in Table A.10.

As before, Column (1a) reports the pooled OLS estimation results from the model with no individual and household controls. As can be seen from here, after accounting for time trends and regional heterogeneity the difference between the predicted number of chronic conditions between children of unemployed and employed parents drops to zero. This is also supported by the pooled OLS estimation on the sample restricted to units observed at least twice, shown in Column (2a). At first glance, this seems at odds with the implications from the simple data analysis which suggested that kids of unemployed parents are healthier in terms of chronic conditions. However, the regression analysis looks at this difference after accounting for regional environmental factors, as well as for the availability of medical care in the community. The fact that once health care access has been controlled, children of unemployed parents no longer appear to have less predicted chronic conditions, might imply that the lower number of observed chronic illnesses for those kids is merely because they have not been diagnosed due to worse health care access, and not because they are healthier.

At the same time, once other covariates are included and the effect of parental unemployment is allowed to vary by the gender of the parent, Column (1b) depicts a somewhat different story. The parameter estimate on the unemployment dummy in this specification appears positive in sign and significant at the conventional 5% level, suggesting that having an unemployed father negatively affects a child's health as measured by the presence of chronic conditions, *ceteris paribus*. It is important to note that since we are looking at male household heads, it is unlikely that the results are driven by reverse causality: the idea that the main earner in the family might prolong his unemployment spell in order to provide care for a frail child does not seem plausible. In contrast, the coefficient on the interaction term between female household head and unemployment status is highly insignificant, indicating that maternal unemployment plays no role in determining the number of child's chronic conditions. Those same conclusions are validated when estimating the model on the restricted sample (shown in Panel POLS 2).

Turning briefly to the results from the fixed effects estimation, the implications are consistent with those obtained by pooled OLS: male household head's unemployment is significant at the 5% level in specification (3b) and (3c) lending strong support for the idea that father's unemployment might be harmful for a child's health. To elaborate more on this, the parameter estimate on paternal unemployment is 0.052, implying that kids in households with male unemployed heads are likely to develop about 0.05 more chronic conditions, on average, holding other factors fixed. It is important to note that even though this effect seems small in magnitude, it is of high economic significance as the sample mean number of chronic conditions for the children in RLMS-HSE is 0.19. In comparison, once unobserved child and household-level time constant effects have been eliminated, female household head's work status appears insignificantly different from zero in all specifications.

Finally, although omitted from the estimation results reported in Table A.10, it is worth mentioning that the model is robust to adding a control for the household head's own number of chronic conditions (shown in Table A.3 in the Appendix). This is an important consideration if parental chronic conditions are correlated with their employment status (as suggested by the sample statistics) as medical theory predicts that children might inherit some chronic conditions from their parents. The latter is supported by the estimation results – the coefficient on household head's number of chronic conditions is positive and significant at the 1% level (magnitude of 0.064 in the fixed effects estimation). What is more relevant – the estimates on the key parameters remain essentially unchanged.

Overall, the estimation results presented in this section imply the possibility that father's unemployment increases the number of chronic conditions a child develops, *ceteris paribus*, while there is no such effect for single mother's unemployment (or employment) status. Equally important, the estimation results indicate that once health care access has been controlled, children of unemployed parents no longer appear to have a lower number of predicted chronic illnesses, suggesting their parents might be unaware of such conditions. This fits well with the medical literature pointing out that '[...] regular medical care is important for all children to increase the chance that a chronic disease is diagnosed and treated early, lessening the overall impact on the child [...]' (Torpy et al. 2010), and has potentially important policy implications.

1.6.2.1.2 Low height for age

This subsection comments on the estimation result for the probability that a child has low height for his/her age group. [25] Data availability allows estimating the model separately on the

[25] Since anthropometric indicators are only available for children below 7, the sample is only restricted to these children. All anthropometric indicators are defined based on the kid's height for age z-score. Child in low height for age is defined as a child having low height for his/her age, regardless of whether s/he has low or normal weight for age (as the two subsamples of kids of employed and unemployed parents show no significant differences in terms of kid's weight for age). The complementary (and mutually exclusive category) is defined as normal height for age (again, regardless of weight).

pre-1998 sample and on a sample from 1999 to 2003 (Table A.11 and 7B, respectively), as well as on the total sample of children (Table A.13).

Apart from the potential endogeneity of unemployment due to unobserved ability of the household head, there is another reason why the pooled OLS estimates may suffer from omitted variable bias: parental height is not controlled in the model, while at the same time it is positively correlated with child's height due to genetic hereditability. The later would bias the pooled OLS estimate on household head's unemployment if one's height is in any way correlated with their unemployment status, as suggested by some authors (see e.g. Cable and Judge (2004)). In addition, RLMS-HSE did not collect data on the respondents' race (which is related to height); yet, the Russian Federation is home to sizeable ethnic minorities, some of whom non-Caucasian. Since height of the household head is clearly time-invariant during the sample period, it is part of the unobserved heterogeneity η_j. Likewise, child's race is part of the unobserved individual effect c_{ij}; for this reason the interpretation of the results only focuses on those obtained by fixed effects.

These results for the sample 1994-1998 are shown in the rightmost panel of Table A.11. As can be seen from here, once time constant unobserved child and household-level heterogeneity have been accounted for, unemployment status of the household head has no predictive power for the probability the child has low height, and this concussion is robust to allowing for heterogeneity of the effect by the gender of the household head. It is interesting to note, however, that in model specification (3c) the fixed effects estimate on household's income is negative 0.019 and significant at the 10% level, even after controlling for the employment status of the household head and his spouse, suggesting it might not unemployment per-se which matters for children's height but rather the total income available to the family.

These observations are supported by the estimation results obtained from the 1999-2003 sample: the estimate on the log of household income is even larger in magnitude – negative 0.036, and significant at the 5% level, implying that a 10-percent raise in family income would decrease the probability that a small child in the family lags behind in terms of height by 3.6pp, *ceteris paribus*. It is also worth mentioning that the coefficient on the interaction term between female head and unemployment status appears significant at the 10% level in the specification without an income control, lending support to the idea that children of unemployed single mothers are significantly less likely to have low height for age, compared to kids of employed male household heads, holding other factors fixed. However, once income of the household is accounted for, maternal unemployment status appears irrelevant.

Lastly, Table A.13 reports the results from model (1) estimated on the full sample of data. As before, parental job loss is insignificant at conventional levels in the specification with only time and regional controls. However, the results form Column (3b) differ from those obtained separately on the two subsamples: paternal unemployment now appears a significant predictor of the probability a child has low height. In particular, kids in families headed by an unemployed male are roughly 4.5pp more likely to lag behind their peers in terms of height, *ceteris paribus*, and there is no corresponding effect for female heads.[26] Yet, once household income is controlled, the estimate on paternal unemployment drops in significance, although its magnitude remaining unchanged. Moreover, family income is statistically different from zero at the 5% level and its magnitude is nearly 2pp; compared to the RLMS-HSE sample fraction of children in low height (0.09), this is a very large effect.

[26] The p-value of the Wald test for the effect of maternal unemployment in specification (3b) estimated on the full sample of data is 0.3231. The corresponding p-values of the test from the pre-1998 and post-1998 sample estimation are 0.7128 and 0.4529, respectively.

The above paragraphs depict a somewhat unclear picture of the effect of parental job loss on their children's height: due to the non-robustness of the model to inclusion of a control for household income the estimation results lend only tentative support to the idea that father's unemployment might be harmful for the children's height. At the same time, the presented evidence unambiguously points out that the income available to the family plays an important role in the likelihood the children in the household remain of low height compared to their peers.

1.6.2.2 Subjective health measures

1.6.2.2.1 Child anxiety and depression

In years 2003 to 2005 the child RLMS-HSE asked the question 'Does [the child] feel any anxiety or depression?' as part of the child questionnaire, which makes it possible to study this metal health outcome in addition to studying the physical health of the children. One shortcoming of looking at this indicator is, however, the fact that the available sample size is relatively small, especially when employing fixed effects estimation.

The estimation results of the binary response model for child anxiety and depression are presented in Table A.14. The pooled OLS parameter estimate on unemployment in specification (1a) is -0.05, implying that after accounting for seasonal effects and environmental factors (often considered as possible causes for depression), children of unemployed parents are nearly 5pp less likely to suffer from anxiety and depression, *ceteris paribus*, and the effect is statistically significant at the 10% level.

Adding individual and group-specific controls in Column (1b) and allowing the effect on household head's unemployment status to vary based on their gender, results in the effect of paternal job loss becoming insignificant at the conventional levels. At the same time, however, the effect of maternal unemployment (obtained as the sum of the parameter estimates on the unemployment dummy and the interaction term) is negative, large in magnitude and statistically significant at the 5% level.[27] In particular, it implies that compared to children of working female household heads, kids of single mothers who are unemployed are 19.91 pp less likely to suffer from anxiety or depression, *ceteris paribus*. The model appears robust to inclusion of a household income-level indicator reported in Column (1c).

As before, all model specifications are also estimated on the restricted sample of children, who were observed at least twice in the period 2003-2005, and the results are reported in Panel POLS 2 of Table A.14. Taken as a whole, the parameter estimates somewhat drop, both in terms of magnitude and in significance, compared to the pooled OLS estimates on the entire sample. Most notably, the coefficient on the interaction term between female household head and her being unemployed is no longer significantly different from zero at the conventional levels in both specifications (2b) and (2c).

Lastly, Columns (3a) to (3c) report the estimation results when employing individual level fixed effects estimation, which has the advantage of eliminating the time invariant unobserved heterogeneity related to child depression (such as parental inclination to morbidity and child abuse). As can be seen from here, the estimate on parental job loss in the model with no covariates is similar in magnitude to the one estimated by pooled OLS, although less precisely estimated. At the same time, however, the coefficient on male household head being unemployed now appears positive and significant at the 5% level, suggesting that father's unemployment increases the likelihood the child suffers from anxiety or depression by about 10pp (obtained from the specification with a household income control). Further, the interaction term between

[27] P-value of the Wald test 0.0298.

household head being unemployed and female in Columns (3b) and (3c) also changes considerably in magnitude compared to the pooled OLS estimation, which is somewhat puzzling. Taken at face value, it implies that among families with a single mother, her unemployment reduces the probability that a child suffers from anxiety and depression by roughly 42.2pp, *ceteris paribus,* and this effect is significant at the 10% level (p-value of 0.0982).

While the story that mother's unemployment reduces the probability a child suffers from anxiety and depression does not seem implausible since mother's presence at home may reduce the kid's stress level, the implication that father's unemployment has an adverse effect on the child's mental health seems somewhat surprising. Yet, such heterogeneity of the effect of unemployment in the family is supported by recent empirical evidence. For instance, Rege at al. (2011) used Norwegian data on plant closure to investigate the effect of parental unemployment on children's school performance, and found that father's job loss has an adverse effect, while mother's job loss is associated with an insignificant increase in kid's academic outcomes. Similarly, Lindo (2013) studied the impact of economic downturns on child abuse, and established that male layoffs increase the rates of child abuse, whereas female layoffs reduce them. Moreover, a disparate effect of unemployment of fathers and mothers is in line with the psychology literature from the last decade documenting that the mental distress caused by unemployment is more severe for men than women (see e.g. McKee-Ryan et al. (2005)).

As a last remark, since chronic illness in children is often reported as a leading cause for depressive symptoms in children (see e.g. Bennett (1994)), model (1) is also estimated after accounting for presence of child chronic condition. In addition, as hospital stay and certain medical treatments may cause a distress in a child's life, leading to feeling of anxiety and depression (Miller et al. (2008) through Pinquart (2010)), a binary indicator for hospital stay in the past 3 months is included in this robustness check. The results are presented in Table A.4 in the Appendix and, overall, confirm the observations from the psychology literature – hospital stay and presence of chronic illness are significant predictors of child anxiety and depression, although the later being not statistically significant in the fixed effects estimation. Most importantly, the estimates of the parameters on the unemployment dummy and the interaction term appear robust to inclusion of these additional controls.

1.6.2.2.2 Parent evaluation of child's health

This section presents the estimation results of model (1) with the outcome variable defined as the parent's subjective evaluation of their child's health. In particular, the left-hand side variable is defined as a binary outcome for the probability that a child is in very good or good health versus average, bad or very bad health.[28]

Table A.15 presents the estimation results from the 1994-1998 sample of data. As can be seen from here, the effect on parental unemployment is not significantly different from zero in all model specifications, regardless of estimation methods employed. This holds even when allowing for the effect to vary depending on the gender of the household head. Hence, the estimation results give grounds to conclude that the unemployment status of mothers and fathers plays no role in determining the probability that their child is in good health, measured as the parent's subjective evaluation. It is worth noting, however, that when looking at two-parent families, wife of the household head being out of the labour force considerably increases the probability that the child is in good health, *ceteris paribus*, and the effect is significant at the 1%

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[28] This binning is preferred in order to address the issue that category very bad health (and to some extent category very good heath) has a low number of observations; moreover, this makes the distinction between good and bad health straightforward, and might possibly correct for reporting biases.

level in all specifications and large in magnitude (0.0613 in the pooled OLS and 0.0890 in the fixed effects estimation of specification (c).

Further, Table A.16 reports the estimation results for the 1999-2006 RLMS-HSE sample. These results appear similar with the implications of the pre-1998 sample estimation, with one important exception: the parameter on the father's unemployment now appears negative and marginally significant at the 10% level in the model specifications with covariates across all estimation methods, lending some support to the idea that paternal unemployment might have a detrimental effect on the child's health. For instance, the fixed effects estimation results imply that children in families where the household head is unemployed are about 4pp less likely to be in good health measured as a parental evaluation, other factors being equal. In contrast, the coefficient on maternal unemployment appears positive in all specifications, although not statistically different from zero at low levels.

Lastly, Table A.17 estimates the response probability model for a child being in good health based on all years of data in order to take advantage of the extended sample size. As can be seen from here, the effect of parental unemployment is essentially zero in the specification with no controls regardless of the estimation method, suggesting no link between parent's unemployment and their children's subjective health measure. This is largely supported by the specifications allowing for mother's and father's unemployment to impact their kid's health in a different way, with the exception of specification (2c) where paternal unemployment appears negative but only marginally significant. As a final remark, it is interesting to note that the pooled OLS estimate on the interaction term between female head and unemployment status is large and significant; moreover, the sum of this coefficient and the coefficient on the unemployment dummy is positive 0.07 and significant at the 10% level[29]; yet, once fixed effects estimation is employed mother's unemployment is no longer statistically different than zero.

In sum, the estimation results in this section provide evidence that mother's unemployment has no effect on the children's health measured as the parent's subjective evaluation. Yet, there is some tentative evidence suggesting that male household head's job loss might be harmful for the children in the family.

1.6.3 Tests for strict exogeneity of unemployment in the fixed effects estimation

The preceding analysis showed some evidence suggesting that unemployment of the household head has a significant effect on certain children's health outcomes and that this effect differs based on the gender of the household head. However, a major issue of concern remains even when fixed effects estimation is employed, namely: household heads, who become unemployed at a certain point of time might differ in their time-varying unobservables from those who are employed, and that it is this difference which is driving the results rather than job loss itself.

In addition to this, as RLMS-HSE is a very unbalanced panel, attrition is worrisome even in the fixed effects estimation. One main source of attrition stems from the fact that, by design, RLMS-HSE is restricted to households which remain in the same dwelling unit. This implies that once a family or a family member change their dwelling unit, they leave the sample – a complexity resulting in attrition rates in RLMS-HSE considerably higher than those in other longitudinal datasets. Attrition becomes a particular source of concern if families tend to change location as a response to unemployment of the household head. In this respect, Table A.18

[29] P-value of the Wald test 0.0765.

presents the number of times each child and household was observed in the sample, separately for the subsamples of employed and unemployed household heads, and it does seem from here that attrition is higher in the subsample of unemployed household heads. Moreover, there is an extra complication when studying children – as children get older than 14 years they leave the children sample, in which case their health outcomes are no longer observed.[30] Lastly, an issue closely related to attrition is the fact that households might select themselves into being observed only once, and this selection may be correlated not only with the unobserved heterogeneity c_{ij} and/or η_j (in which case a fixed effects estimator would eliminate the selection bias), but also correlated with the time-varying idiosyncratic error.

In order to address these issues, this section performs a test for strict exogeneity of parental unemployment in the fixed effects estimation. Following Wooldridge (2010) a test for strict exogeneity using fixed effects consists of estimating an expanded version of model (1) from section (IV):

$$Health_{ijt} = \beta_0 + \beta_1 ParentalJobLoss_{jt} + \delta ParentalJobLoss_{jt+1} + X_{ijt}^{C}\beta_2 + X_{jt}^{H}\beta_3 + X_{jt}^{R}\beta_4 + D_t + \eta_j + c_{ij} + u_{ijt}, \qquad \textbf{(1')}$$

where $ParentalJobLoss_{jt+1}$ is the one-period lead of the dummy for unemployment status of the household head. Under strict exogeneity, δ=0; hence, a test for strict exogeneity is a tests of the null hypothesis H_0: δ=0 in equation (1') when employing a fixed effects estimation. The main idea is that if the estimation results are the capturing the effect of unobserved household or child-level heterogeneity rather than the causal effect of unemployment, then it is likely that future

[30] The reason for this is that the adult questionnaire and the child questionnaires differ considerably in the outcomes they study, including the health outcomes.
It should also be noted that there is yet another source of attrition in RLMS-HSE, namely the fact that the samples falling into the Moscow and St Petersburg regions were replaced with a new sample 1999. However, this particular type of attrition is not an issue of concern as it is random.

unemployment of the household head will have predictive power for the current health outcome of the child, even after controlling for current unemployment status (as future unemployment is correlated in a similar way to the unobserved effects).

The results from the test are reported in Table A.19. As can be seen from here, the coefficient on future unemployment status of the household head is not significantly different from zero at low levels for all health outcomes, with one notable exception. In particular, when modelling child depression/anxiety the lead of unemployment is significant at the 5% level in the specifications with controls, suggesting that that unemployment and/or household attrition is endogenous. In addition, when looking at the probability the child had any health problems in the last 30 days, the p-values of the test are comparatively low (although higher than 0.10) when the model is estimated on the pre-1998 and total samples, providing some evidence against exogeneity of parental job loss. In contrast, for the rest of the analysed health outcomes the p-values of the test are large, both when looking at the 1994-1998 and post-1998 subsamples separately, and when estimating the model on the total sample of data. For instance, when the child health outcome is number of chronic conditions, the p-value of the test ranges from 0.299 to 0.669 in the different specifications, suggesting that there is no evidence against the assumption of strict exogeneity of unemployment in the of fixed effects estimation.

It is hard to argue why the strict exogeneity assumption fails in the model for child anxiety and depression. However, one extra complication when examining this particular outcome may partly explain this, namely: since it is a subjective measure, it is possible that presence of a parent at home (due to him/her being unemployed) makes them more likely to notice symptoms of anxiety/depression their kids might experience. This might mean that child anxiety and depression in cases where both parents are employed are underreported, leading to non-classical measurement error and inconsistency of the fixed effects results. This is not likely to be the case when employing chronic conditions or even a parental report of a child's health, for example, as they are based on far more objective health indicators.

Overall, while the results presented in this section are no firm proof that the estimation of the model of parental unemployment suffers from no potential issues, they do provide somewhat of a reassurance that the fixed effects estimation results are not driven by reverse causality and potential endogeneity of parental unemployment status, at least when examining health outcomes such as number of chronic conditions, low height and parental evaluation of the kid's health.

1.7 CONCLUSIONS AND CAVEATS

This paper used longitudinal from the Russia Longitudinal Monitoring Survey to study the consequences of unemployment of the household head on the health of the children in the family. Several important conclusions can be drawn from the presented analysis. Most importantly, in line with the findings of Rege et al. (2011) and Lindo (2013), our results indicate that mother's and father's unemployment may impact their children's health in a different way, and this is considered the main contribution of the study. In terms of specific health outcomes, our analysis provides support for the existence of an adverse effect on father's unemployment on the development of chronic conditions in children, while there is no such effect for mother's employment status. Further, in line with the results of Ruhm (2008) we observes some beneficial effects of mother's unemployment on the occurrence of child anxiety and depression, while male household head's job loss appears to have an adverse effect on the kid's mental health. Somewhat unexpectedly, however, the opposite is observed for the incidence of child health problems during the month preceding the interview, suggesting that a female household head's unemployment appears to negatively impact the children. We also find some tentative evidence of a detrimental effect of male household head's unemployment on the probability that a child is in good health based on a parental report, as well as on the likelihood the child has low height for age, and there are no corresponding impacts of mother's job loss.

The implications of these findings are twofold. First, in terms of methodology, the results presented in this paper suggest that the impact of parental unemployment on their children's health needs to be investigated only when accounting for the interaction of this effect with the gender of the parent as children may respond differently to mother's and father's unemployment. Secondly, some of the findings in the study have potentially important policy implications. For instance, the fact that once access to healthcare has been accounted for, children of unemployed parents no longer appear to have a lower number of predicted chronic conditions, suggests that their parents might be unaware of such health issues and the kids might be under-diagnosed. This may be an issue of particular concern for kids aged 3 years and above as medical check-ups considerably decline after this age. In this respect, one policy suggestion might be to make children health care and regular check-ups more broadly available, e.g. by having medical offices in public schools and kindergartens – converse to the trends in the post-communist states in the past decades.

The results presented in this paper should be interpreted with care due to several important limitations. A major issue of concern remains the suspected endogeneity of parental unemployment (particularly when studying child anxiety and depression), which would invalidate the pooled OLS results and lead to questionable validity of the fixed effects estimation if the unobserved child and household-level heterogeneity is not time invariant. Another notable limitation of the analysis is the excessively high attrition rate in the RLMS-HSE sample, which is even more pronounced when studying children's outcomes. However, correcting for attrition in panel data is a challenging issue; in addition, models for attrition correction (such as Heckman's model) assume that all right-hand side variables are always observed – an assumption which in most cases fails to holds as there are missing values in virtually all explanatory variables. For this reason this paper has made no attempt at addressing the issue of attrition bias. One would hope that the importance of children's health would give rise to extensions of this type of research, which would eventually be able to account for the various econometric challenges and find the extent of the true effect of parental unemployment on their kid's health outcomes.

APPENDICES

APPENDIX A

MAIN TABLES AND FIGURES

Table A.1: Self report and job holder definition vs. BLS definition of unemployment

Definition	Bureau of Labor Supply definition			
Self report and job holder definition	**Labour force status**	**Employed**	**Unemployed**	**Not in the Labour Force**
	Employed	16,187	0	0
	Unemployed	0	892	851
	Not in LF	0	0	0

Note: the numbers reflect total person-year observations.

Figure A.1: Unemployment definitions and resulting unemployment rate

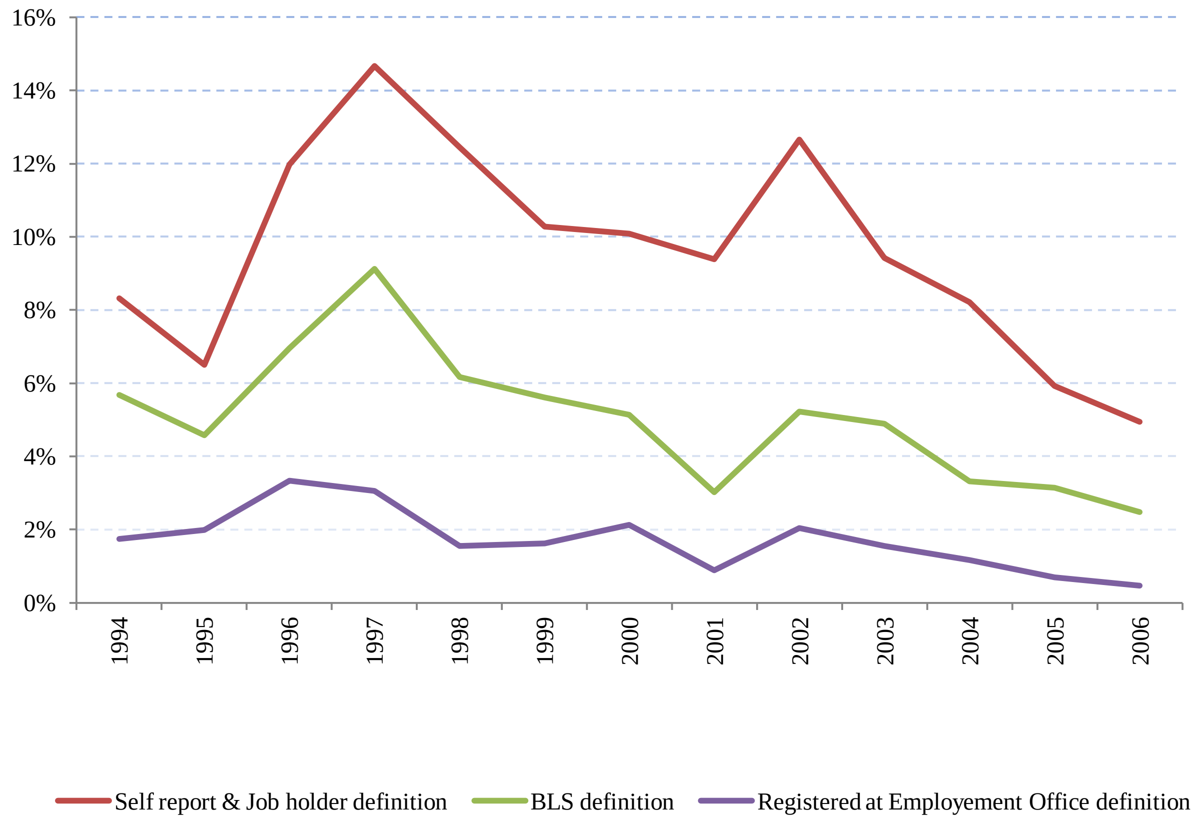


Table A.2: Child healthcare costs

Variable	Stratified sample mean	Non-stratified sample mean
Paid for medical visit	0.046	0.046*** (0.003)
Paid for child's additional tests/procedures	0.142	0.139*** (0.010)
Visited a private medical facility	0.031	0.030*** (0.004)
Paid for medical visit (district/city/village medical facility)	0.031	0.030*** (0.004)
Paid for child's additional tests/procedures (district/city/village medical facility)	0.118	0.116*** (0.012)
Paid for medical visit (private/commercial medical facility)	0.502	0.500*** (0.087)
Paid for child's additional tests/procedures (private/commercial medical facility)	0.693	0.696*** (0.056)
Paid for medicine	0.726	0.726*** (0.012)
Paid for medicine (child below 3 years of age)	0.525	0.526*** (0.040)
Any travel cost to medical facility	0.254	0.251*** (0.008)
Number of observations (children)	**3,881**	**3,881**
Number of clusters (households)	**2,129**	**2,129**

Notes:

1) All variables refer to the child's last medical visit. Variables are available for the period 1994-2005.

2) Missing stratified standard error because of stratum with a single sampling unit. Number of strata (regions) 144.

3) Test for zero population mean reported for the non-stratified sample means. *** denotes significance at the 1% level; ** denotes significance at the 5% level, and * denotes significance at the 10% level.

Table A.3: Sample statistics (households)

Characteristics	Total sample	Restricted samples		
		Employed household head	Unemployed household head	Difference (Employed – Unemployed)
Household level				
Age of household head	37.554 (0.059)	37.122 (0.061)	37.334 (0.197)	0.212 (0.206)
Years of education of household head	16.182 (0.027)	16.360 (0.028)	15.007 (0.091)	1.292*** (0.096)
Number of children aged 0-6 in the household	0.676 (0.006)	0.657 (0.006)	0.849 (0.023)	-0.192*** (0.023)
Number of children aged 7-18 in the household	1.144 (0.007)	1.127 (0.007)	1.316 (0.026)	-0.190*** (0.027)
Number of post-working age females in the household	0.216 (0.003)	0.197 (0.003)	0.333 (0.012)	-0.136*** (0.121)
Number of post-working age males in the household	0.071 (0.002)	0.065 (0.002)	0.122 (0.008)	-0.058*** (0.008)
Fraction of female household heads	0.131 (0.003)	0.128 (0.003)	0.125 (0.008)	0.003 (0.009)
Total household monthly income (real, in rubbles)	10506.58 (210.574)	10807.12 (230.490)	7257.917 (295.31)	3549.20*** (374.612)

Notes:

1) Means corrected for stratification; linearised standard errors. Number of strata (regions) 144.

2) Test for equality of means reported for the samples of employed and unemployed household heads. *** denotes significance at the 1% level; ** denotes significance at the 5% level, and * denotes significance at the 10% level.

3) Variables 'distance to paediatrician' and 'distance to hospital' refer to those with access to paediatrician/hospital; the variables are not available for year 2006. Chronic conditions are only available after 1998.

4) The total number of observations exceeds the sum of employed and unemployed as some households/children are observed in both states.

Table A.3 (cont'd)

Household below the all Russia poverty line	0.420 (0.004)	0. 390 (0.009)	0.662 (0.015)	-0.272*** (0.012)
Household below the regional poverty line	0.270 (0.003)	0.242 (0.003)	0.502 (0.012)	-0.260*** (0.013)
Frequency of monthly alcohol use (household head)	4.284 (0.011)	4.275 (0.012)	4.375 (0.037)	-0.099*** (0.039)
Drinks without eating (household head)	0.188 (0.003)	0.187 (0.004)	0.200 (0.012)	-0.014 (0.013)
Household head a smoker	0.632 (0.004)	0.627 (0.004)	0.692 (0.012)	-0.065*** (0.012)
Number of chronic conditions (household head)	0.530 (0.008)	0.525 (0.009)	0.426 (0.028)	0.099*** (0.029)
Non-household member cared for the child in the last 7 days	0.285 (0.003)	0.295 (0.004)	0.211 (0.010)	0.085*** (0.011)
Non-household member cared for the child in the last 7 days (kids below seven)	0.176 (0.004)	0.180 (0.050)	0.138 (0.128)	0.042*** (0.019)
Community level				
Fraction with access to paediatrician	0.848 (0.003)	0.858 (0.003)	0.713 (0.011)	0.146*** (0.011)
Distance to paediatrician (in kilometres)	23.169 (0.405)	22.615 (0.499)	25.535 (0.668)	-2.920*** (0.834)
Hospital in the community	0.816 (0.003)	0.829 (0.003)	0.669 (0.012)	0.159*** (0.012)
Distance to hospital (in kilometres)	19.710 (0.235)	18.622 (0.253)	24.207 (0.671)	-5.585*** (0.717)
Distance to hospital (in hours)	0.203 (0.009)	0.175 (0.010)	0.309 (0.0267)	-0.134*** (0.028)
Number of observations (children)	**6,509**	**6,203**	**1,054**	
Number of clusters (households)	**4,214**	**4,049**	**678**	

Table A.4: Sample statistics (children)

Characteristics	Total sample	Restricted samples		
		Employed household head	Unemployed household head	Difference (Employed – Unemployed)
Demographic				
Age	7.680 (0.029)	7.729 (0.032)	7.611 (0.098)	0.118 (0.103)
Fraction of boys	0.508 (0.004)	0.508 (0.004)	0.510 (0.012)	-0.002 (0.013)
Child healthcare access and utilisation				
Has a regular physician	0.581 (0.007)	0.591 (0.008)	0.457 (0.027)	0.134*** (0.028)
Had a medical check-up in the last 3 months	0.394 (0.004)	0.395 (0.004)	0.336 (0.013)	0.006*** (0 .013)
Had a medical check-up in the last 12 months	0.646 (0.006)	0.647 (0.006)	0.488 (0.022)	0.159*** (0.022)

Notes:

1) Means corrected for stratification; linearised standard errors. Number of strata (regions) 144.

2) Test for equality of means reported for the samples of employed and unemployed household heads. *** denotes significance at the 1% level; ** denotes significance at the 5% level, and * denotes significance at the 10% level.

3) Variable ‘Child has a regular physician’ and ‘Child had a medical check-up in the last 12 months’ only available for years 2003 to 2006. Variable ‘Any minor health problems in the last 30 days’ only available for years 2002 to 2006. Variable “Child feels anxiety or depression” only available for years 2003 to 2005. Anthropometric indicators only available for years 1994 to 2003.

4) The total number of observations exceeds the sum of employed and unemployed as some households/children are observed in both states.

Table A.4 (cont'd)

Ever vaccinated (all children)	0.981 (0.001)	0.980 (0.001)	0.983 (0.003)	-0.002 (0.003)
Ever vaccinated (children aged 1 year or below)	0.933 (0.007)	0.938 (0.008)	(0.891) (0.029)	0.049* (0.024)
Health conditions				
Any health problems in the last 30 days	0.388 (0.004)	0.394 (0.004)	0.311 (0.011)	0.003*** (0.012)
Minor health problems in the last 30 days	0.202 (0.005)	0.208 (0.006)	0.126 (0.015)	0.083*** (0.016)
Hospitalised in the last 3 months	0.042 (0.001)	0.042 (0.002)	0.039 (0.005)	0.003 (0.005)
Feels anxiety or depression	0.251 (0.007)	0.263 (0.008)	0.128 (0.0207)	0.135*** (0.022)
Health evaluation				
Good	0.617 (0.004)	0.608 (0.0039)	0.695 (0.011)	-0.087*** (0.012)
Average	0.357 (0.003)	0.366 (0.004)	0.278 (0.011)	0.088*** (0.012)
Bad	0.026 (0.001)	0.026 (0.001)	0.027 (0.004)	-0.001 (0.004)
Chronic heart condition	0.025 (0.001)	0.026 (0.002)	0.020 (0.005)	0.006 (0.005)
Chronic lung condition	0.021 (0.001)	0.020 (0.002)	0.014 (0.004)	0.009 (0.004)
Chronic liver condition	0.011 (0.001)	0.012 (0.001)	0.007 (0.003)	0.005 (0.003)
Chronic kidney condition	0.021 (0.001)	0.021 (0.002)	0.019 (0.005)	0.002 (0.005)
Chronic gastrointestinal condition	0.045 (0.002)	0.048 (0.002)	0.029 (0.006)	0.019*** (0.006)
Chronic spinal condition	0.030 (0.002)	0.030 (0.002)	0.020 (0.005)	0.011** (0.005)
Other chronic condition	0.090 (0.003)	0.091 (0.003)	0.0721 (0.0086)	0.019** (0.009)
Diabetes	0.003 (0.000)	0.003 (0.000)	0.0028 (0.0012)	-0.000 (0.001)
Any chronic condition	0.188 (0.004)	0.192 (0.004)	0.1327 (0.0114)	0.059*** (0.012)

Table A.4 (cont'd)

Anthropometric indicators (children aged 7 years or below)				
Height for age z-score	-0.130 (0.018)	-0.095 (0.0120)	-0.3373 (0.0673)	0.242*** (0.069)
Weight for height z-score	0.277 (0.019)	0.259 (0.021)	0.3486 (0.0683)	-0.089 (0.072)
Fraction with normal height for age and normal weight for height	0.851 (0.005)	0.860 (0.005)	0.8006 (0.0170)	0.060*** (0.016)
Fraction with normal height for age and low weight for height	0.058 (0.003)	0.057 (0.003)	0.0573 (0.0100)	-0.000 (0.011)
Fraction with low height for age and normal weight for height	0.088 (0.004)	0.080 (0.004)	0.1371 (0.0146)	-0.057*** (0 .015)
Fraction with low height for age and low weight for height	0.003 (0.001)	0.002 (0.001)	0.0049 (0.0028)	-0.003 (0.003)
Nutrition				
Total daily caloric intake	1593.821 (5.582)	1602.54 (5.907)	1519.48 (16.932)	83.05*** (18.196)
Percent calories from fat	31.359 (0.078)	31.536 (0.081)	29.852 (0.255)	1.684*** (0.253)
Percent calories from proteins	11.998 (0.025)	11.998 (0.027)	11.992 (0.077)	0.005 (0.086)
Number of observations (children)	**6,509**	**6,203**	**1,054**	
Number of clusters (households)	**4,214**	**4,049**	**678**	

Figure A.2: Probability the child has a regular physician

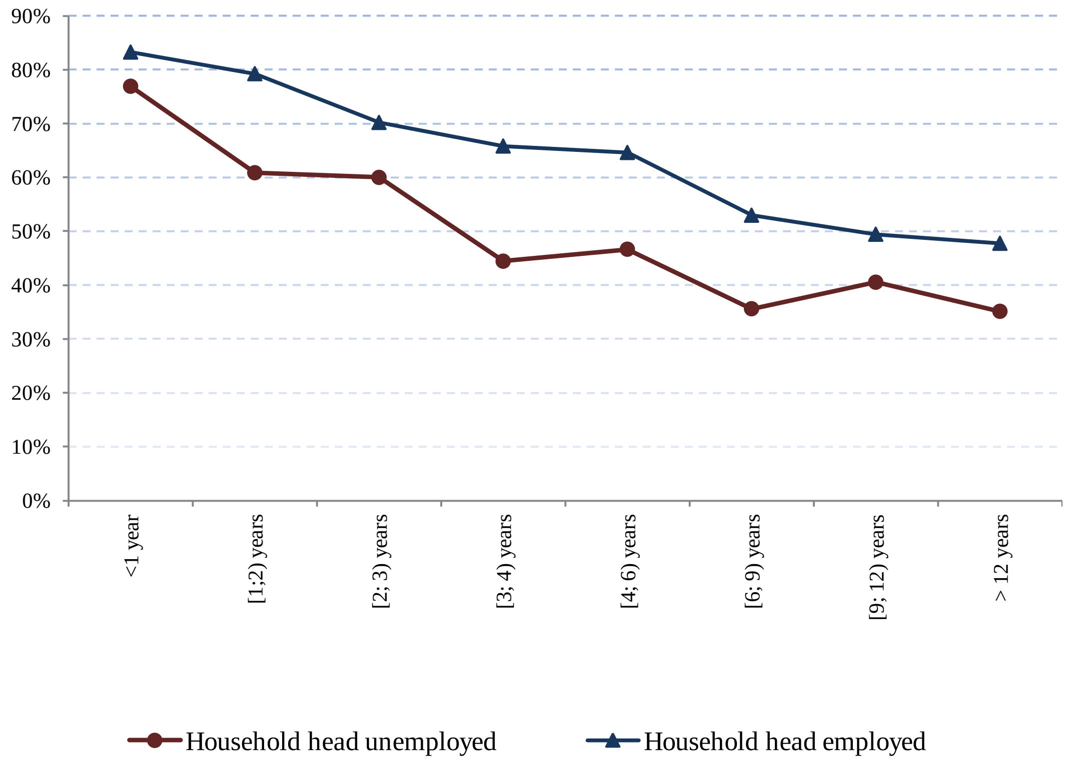


Figure A.3: Probability the child was ever vaccinated

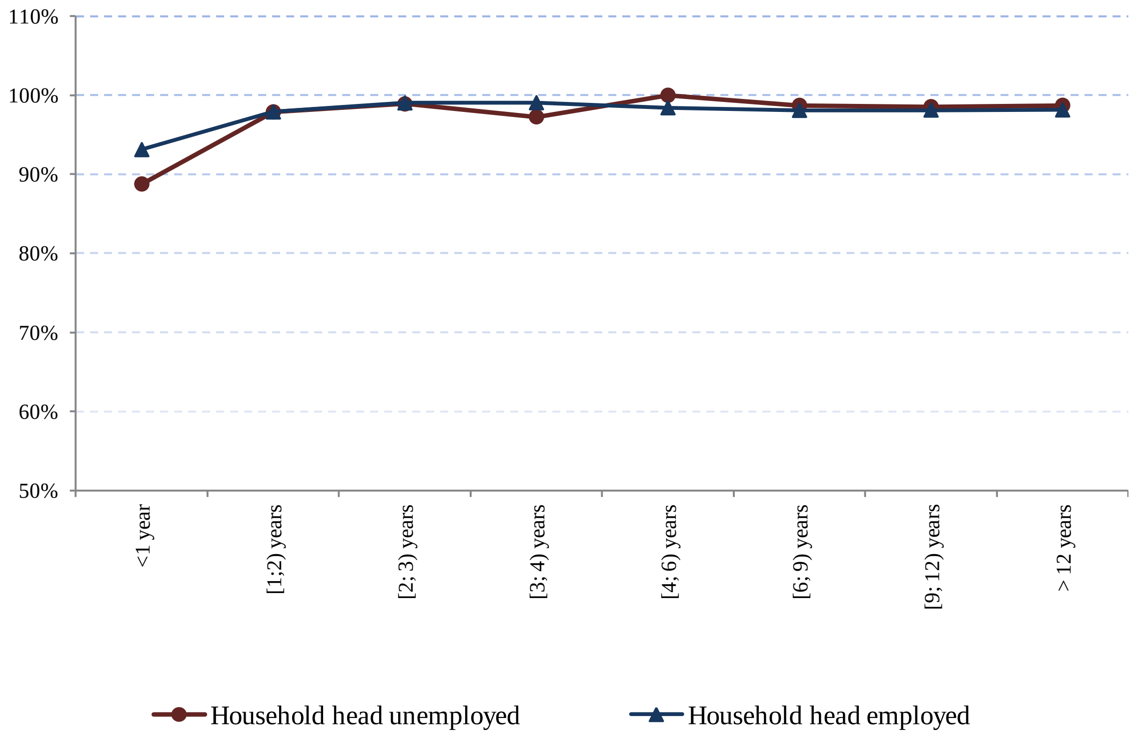


Figure A.4: Probability the child had a medical check up in the last 12 months

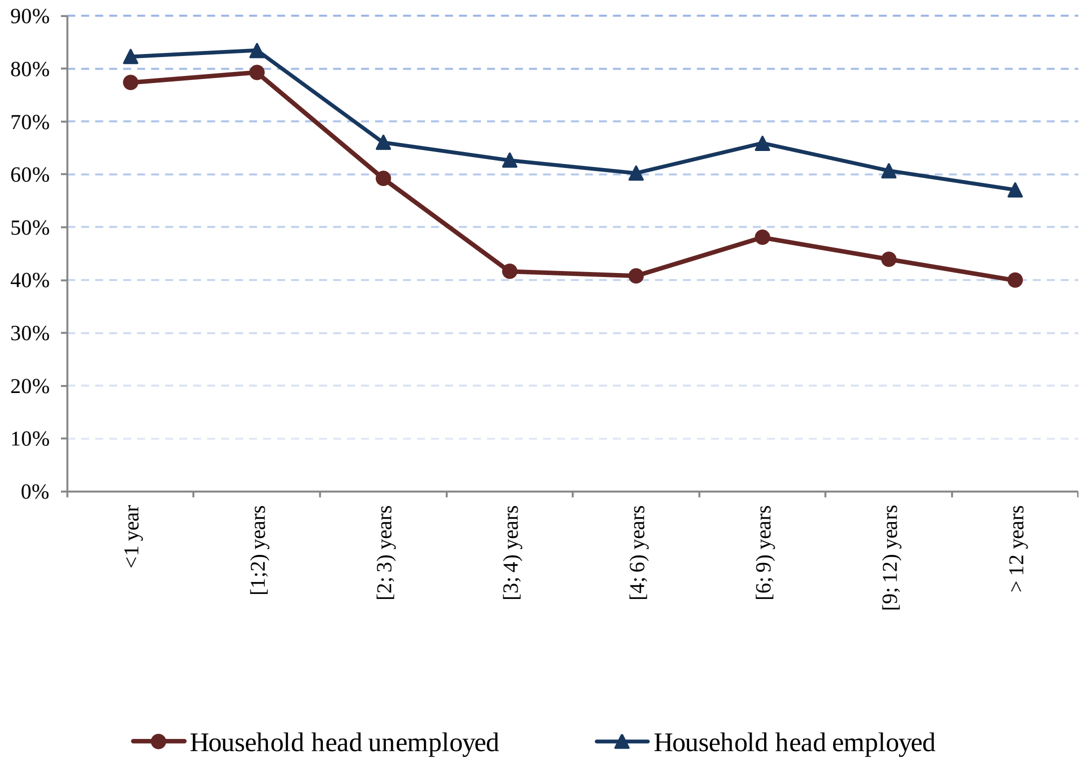


Figure A.5: Probability the child had a medical check up in the last 3 months

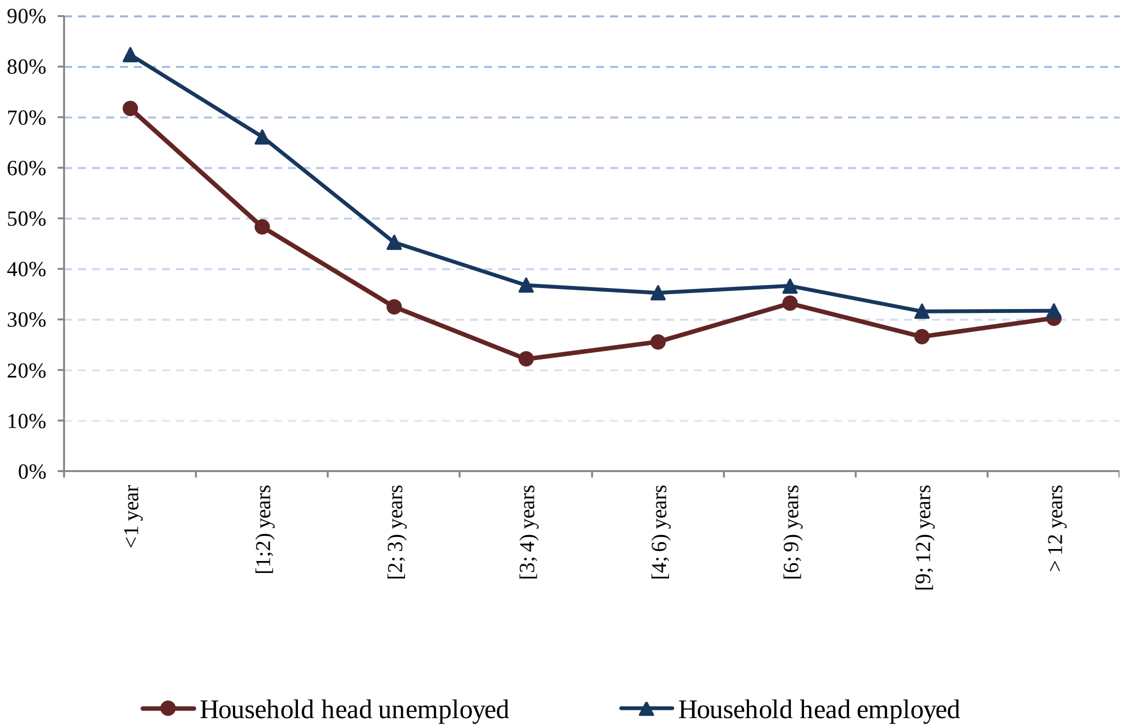


Figure A.6: Probability the child was hospitalised in the last 3 months

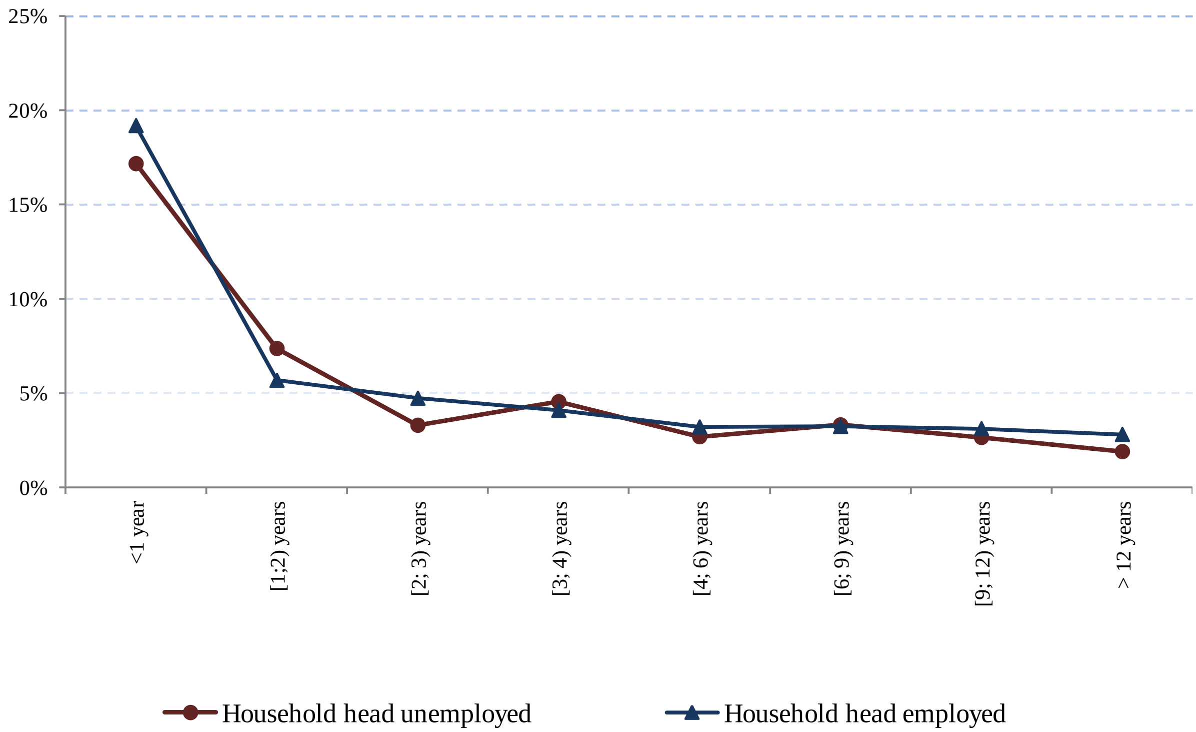


Figure A.7: Probability the child has a diagnosed chronic condition

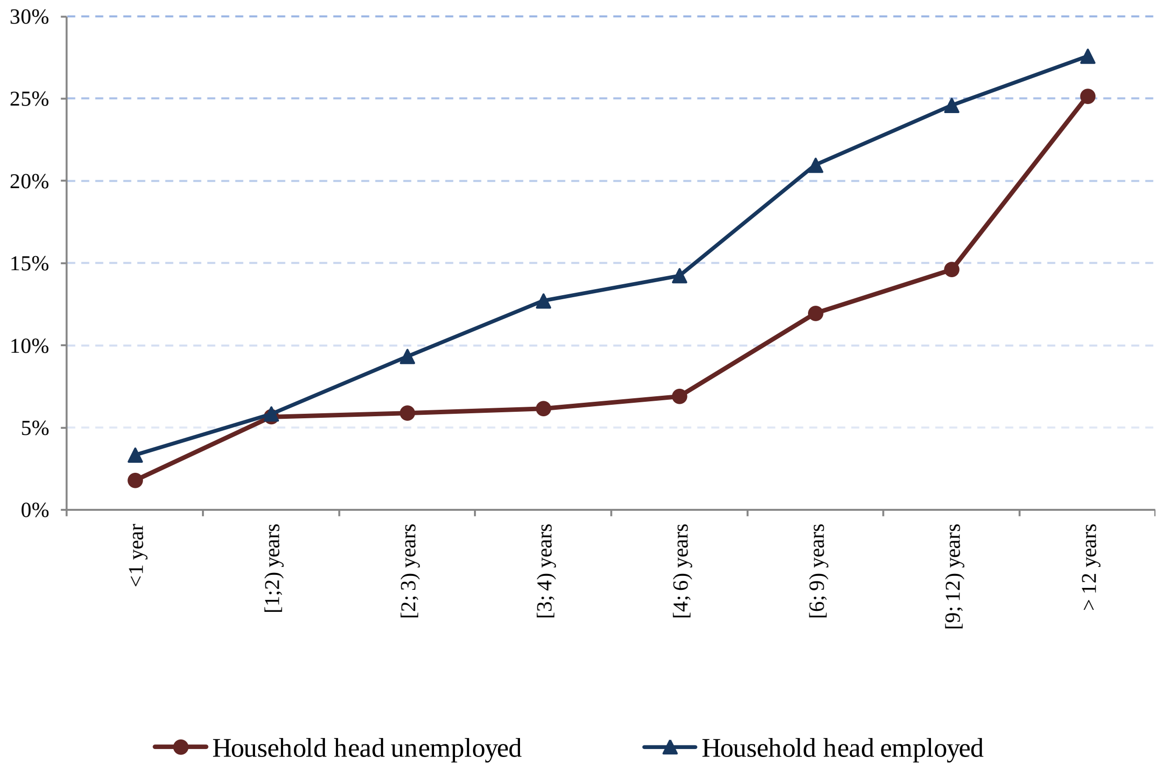


Figure A.8: Probability the child had any health problems in the last 30 days

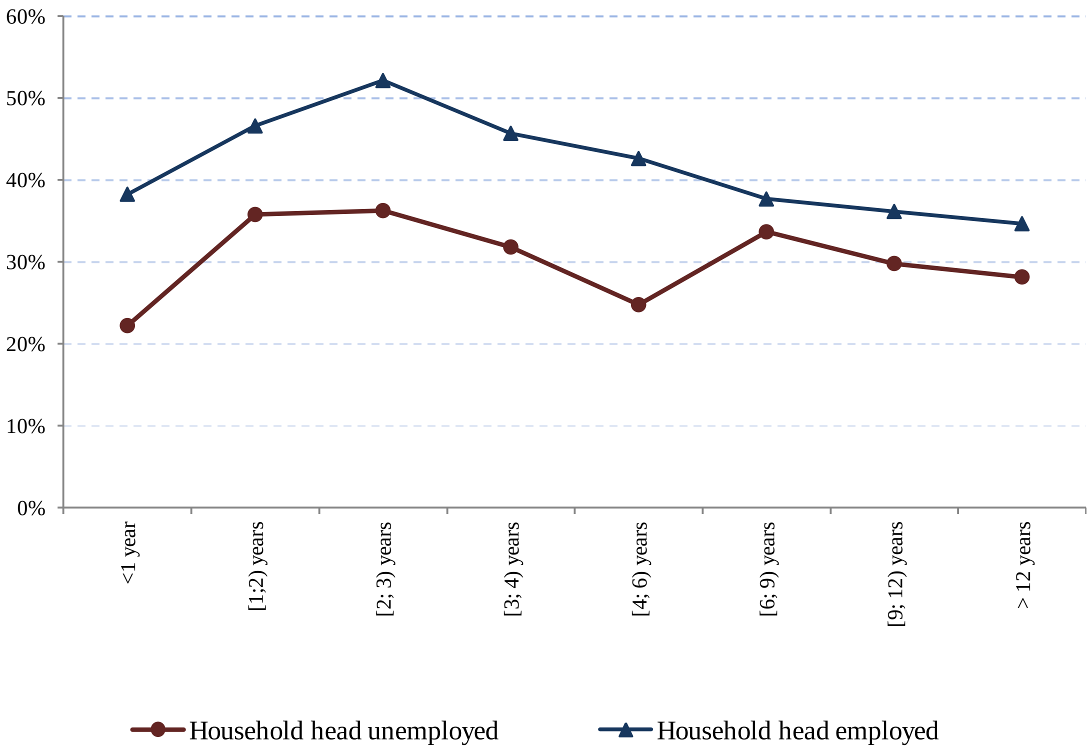
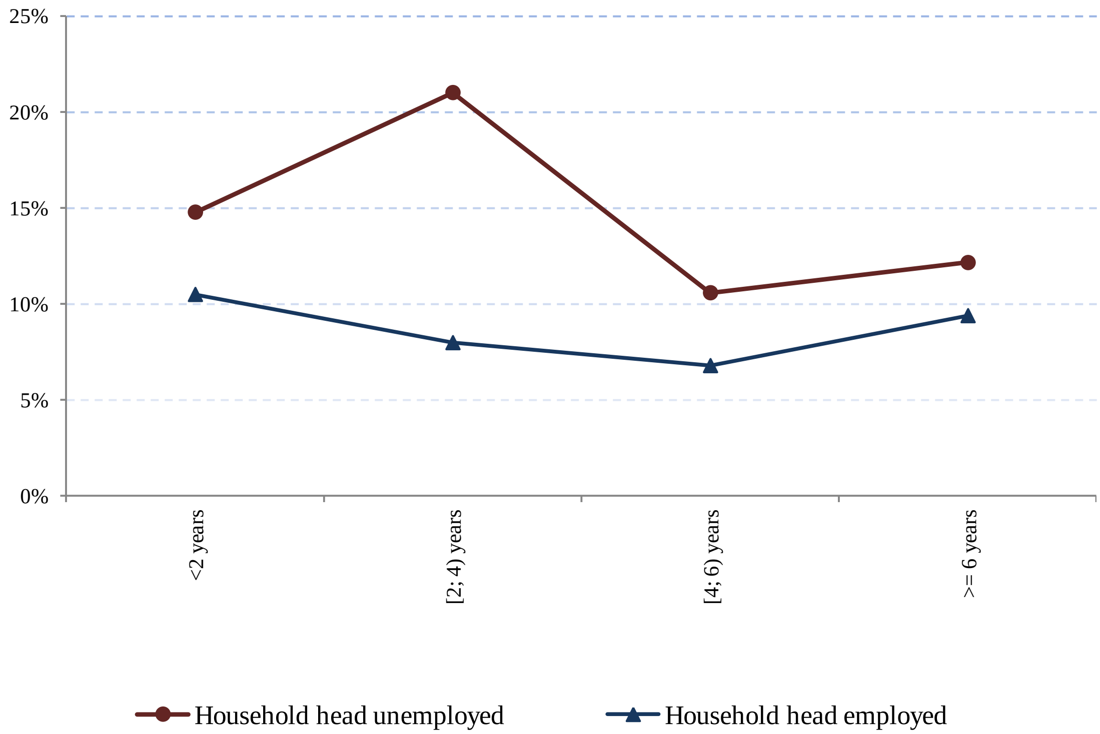
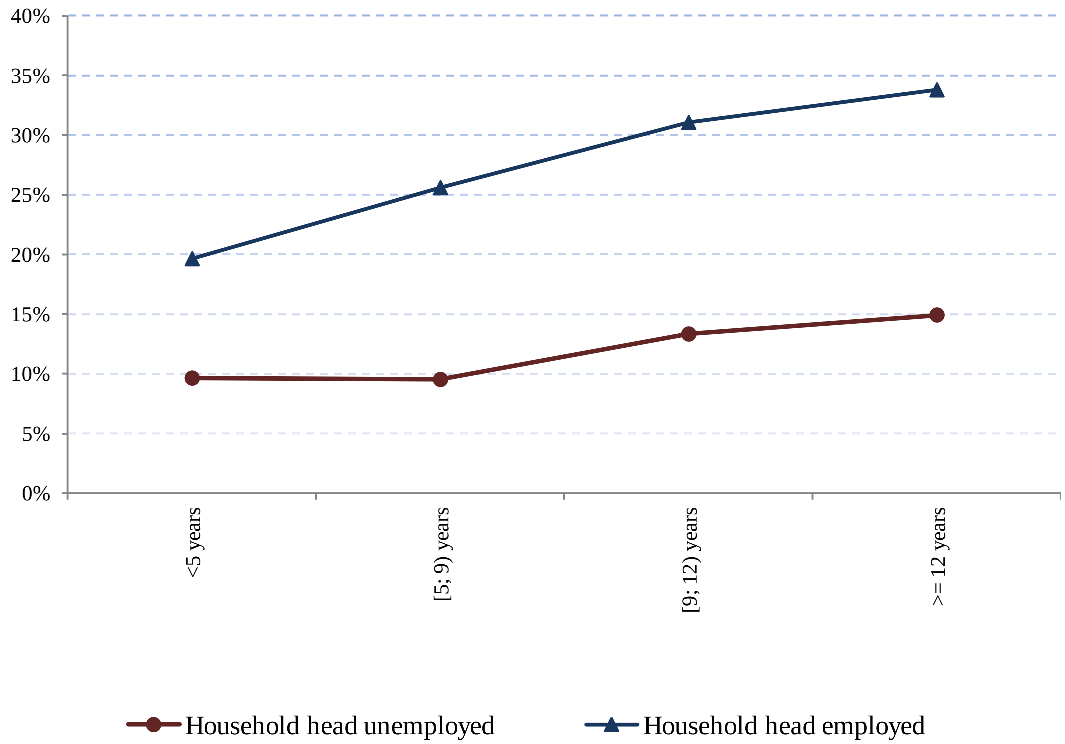


Figure A.9: Probability the child has low height for age



Note: when analysing child's low height for age child's age is binned in age categories up to 7 years as child height and weight indicators in RLMS-HSE are only available for kids aged 7 or below.

Figure A.10: Probability the child suffers from anxiety or depression



Note: For child anxiety/depression age is grouped in larger intervals compared to graphs A to G, in order to avoid having categories with less than 50 observations, as the variable is only available for years 2003-2005.

Table A.5: Variable dynamics around the time of unemployment (children)

Characteristics	Full sample			Restricted sample (both entry and exit into unemployment observed)		
	(1) Period right before becoming unemployed	(2) Period right after becoming unemployed	(3) Period right after exiting unemployment	(4) Period right before becoming unemployed conditional on exiting	(5) Period right after becoming unemployed conditional on exiting	(6) Period right after exiting unemployment
Child of the household head						
Has a regular physician	0.481	0.473	0.416	0.436	0.447	0.338
Had a medical check-up in the last 3 months	0.333	0.336	0.350	0.341	0.333	0.358
Had a medical check-up in the last 12	0.556	0.516	0.542	0.527	0.501	0.514

Notes:

1) Means corrected for stratification. Number of strata (regions) 144.

2) During the entire sampling period, there are 1,743 observations of unemployed household heads. The table reports lower numbers as in the remainder of the cases the household head's entry into unemployment is not observed (i.e. household head was unemployed when first observed or there was a gap in the panel) and/or exit from unemployment is not observed (i.e. household head was still unemployed when last observed or there was a gap in the panel). The number of such cases is 508 and 499, respectively.

Table A.5 (cont'd)

Ever vaccinated (all children)	0.986	0.987	0.988	0.985	0.987	0.994
Any health problems in the last 30 days	0.323	0.315	0.327	0.305	0.325	0.318
Minor health problems in the last 30 days	0.147	0.151	0.164	0.134	0.148	0.180
Ever vaccinated (all children)	0.986	0.987	0.988	0.985	0.987	0.994
Any health problems in the last 30 days	0.323	0.315	0.327	0.305	0.325	0.318
Minor health problems in the last 30 days	0.147	0.151	0.164	0.134	0.148	0.180
Hospitalised in the last 3 months	0.034	0.027	0.032	0.036	0.030	0.033
Feels anxiety or depression	0.208	0.156	0.184	0.138	0.159	0.202
Health evaluation						
Good health	0.687	0.668	0.674	0.685	0.683	0.675
Average health	0.297	0.305	0.306	0.299	0.298	0.314
Bad health	0.016	0.027	0.020	0.016	0.018	0.011
Number of chronic conditions	0.172	0.203	0.201	0.101	0.121	0.175
Child has low height for age	0.112	0.156	0.119	0.114	0.151	0.126
Number of observations	**661**	**664**	**633**	**437**	**437**	**437**

Table A.6: Variable dynamics around the time of unemployment (spouse)

Characteristics	Full sample			Restricted sample (both entry and exit into unemployment observed)		
	(1) Period right before becoming unemployed	(2) Period right after becoming unemployed	(3) Period right after exiting unemployment	(4) Period right before becoming unemployed conditional on exiting	(5) Period right after becoming unemployed conditional on exiting	(6) Period right after exiting unemployment
Spouse of the household head						
Spouse employed	0.557	0.266	0.532	0.543	0.267	0.563
Spouse unemployed	0.065	0.465	0.078	0.070	0.462	0.082
Spouse not in the labour force	0.1921	0.0905	0.192	0.209	0.098	0.186
Number of observations	**661**	**664**	**633**	**437**	**437**	**437**

Table A.7: Estimation results: (short run health indicators, 1994-1998 sample)

Controls	Dependent variable: child had any health problems in the last 30 days								
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Sample	**1994-1998**								
Estimation method	**POLS 1**			**POLS 2**			**FE**		
Household head unemployed	-0.051*** (0.018)	-0.053** (0.022)	-0.053** (0.023)	-0.040* (0.023)	-0.044* (0.026)	-0.065*** (0.019)	-0.045* (0.026)	-0.043 (0.030)	-0.044 (0.031)
Household head female		0.016 (0.020)	0.016 (0.021)		-0.019 (0.018)	-0.007 (0.018)		0.056 (0.045)	0.054 (0.045)
Household head unemployed & female		0.038 (0.060)	0.024 (0.060)		0.126** (0.054)	0.150*** (0.052)		0.073 (0.085)	0.055 (0.088)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.7 (cont'd)

Child's age below 7 years		-0.020 (0.023)	-0.025 (0.023)		0.063*** (0.020)	0.083*** (0.021)		0.001 (0.040)	0.005 (0.040)
Household head's years of education		-0.015 (0.010)	-0.016 (0.010)		-0.013 (0.009)	-0.014 (0.010)		-0.032* (0.0193)	-0.034* (0.020)
Household head's years of education squared		0.001* (0.000)	0.001* (0.0003)		0.001 (0.000)	0.001 (0.000)		0.001 (0.001)	0.001* (0.001)
Log of real total household income (in Rubles)			0.004 (0.006)			0.002 (0.006)			0.004 (0.008)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**4,567**	**4,412**	**4,379**	**2,240**	**2,185**	**2,166**	**2,240**	**2,185**	**2,166**
Number of clusters (households)	**3,040**	**2,928**	**2,911**	**1,530**	**1,488**	**1,479**	**1,530**	**1,488**	**1,479**
Time periods (unbalanced)	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**

Table A.8: Estimation results (short run health indicators, post-1998 sample)

Controls	Dependent variable: child had any health problems in the last 30 days								
	1a	**1b**	**1c**	**2a**	**2b**	**2c**	**3a**	**3b**	**3c**
Sample	**1999-2006**								
Estimation method	**POLS 1**			**POLS 2**			**FE**		
Household head unemployed	0.024 (0.018)	0.004 (0.023)	0.010 (0.0237)	0.033 (0.021)	0.013 (0.027)	0.022 (0.028)	0.014 (0.021)	-0.006 (0.027)	-0.003 (0.0279)
Household head female		-0.013 (0.021)	-0.010 (0.022)		-0.027 (0.026)	-0.019 (0.027)		-0.016 (0.041)	-0.019 (0.0418)
Household head unemployed & female		0.177*** (0.064)	0.173*** (0.065)		0.171** (0.080)	0.162** (0.081)		0.176** (0.082)	0.181** (0.083)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.8 (cont'd)

Child's age below 7 years		0.050** (0.021)	0.051** (0.021)		0.071*** (0.025)	0.074*** (0.025)		0.022 (0.034)	0.024 (0.034)
Household head's years of education		0.005 (0.011)	0.006 (0.011)		0.011 (0.014)	0.012 (0.014)		-0.004 (0.019)	0.001 (0.020)
Household head's years of education squared		0.000 (0.000)	0.000 (0.000)		0.000 (0.001)	-0.000 (0.000)		0.000 (0.001)	0.000 (0.001)
Log of real total household income (in Rubles)			0.009 (0.008)			0.016 (0.011)			-0.000 (0.012)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**3,054**	**2,555**	**2,547**	**2,152**	**1,813**	**1,809**	**2,152**	**1,813**	**1,809**
Number of clusters (households)	**2,190**	**1,817**	**1,813**	**1,598**	**1,338**	**1,335**	**1,598**	**1,338**	**1,335**
Time periods (unbalanced)	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**8**

Table A.9: Estimation results (short run health indicators, total sample)

Controls	Dependent variable: child had any health problems in the last 30 days								
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Sample	**1994-2006**								
Estimation method	**POLS 1**			**POLS 2**			**FE**		
Household head unemployed	-0.020 (0.013)	-0.033** (0.016)	-0.030* (0.016)	-0.003 (0.015)	-0.017 (0.019)	-0.013 (0.019)	-0.019 (0.015)	-0.038* (0.019)	-0.035* (0.019)
Household head female		0.002 (0.015)	0.002 (0.015)		-0.008 (0.018)	-0.006 (0.019)		0.010 (0.028)	0.008 (0.028)
Household head unemployed & female		0.102** (0.044)	0.091** (0.045)		0.154*** (0.053)	0.141*** (0.053)		0.136** (0.054)	0.128** (0.055)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.9 (cont'd)

Child's age below 7 years		0.009 (0.015)	0.007 (0.015)		0.048** (0.022)	0.0500** (0.022)		0.006 (0.026)	0.008 (0.025)
Household head's years of education		-0.008 (0.008)	-0.008 (0.008)		-0.006 (0.010)	-0.005 (0.010)		-0.019 (0.013)	-0.018 (0.013)
Household head's years of education squared		0.001* (0.000)	0.000* (0.000)		0.000 (0.000)	0.000 (0.000)		0.001 (0.001)	0.001 (0.001)
Log of real total household income (in Rubles)			0.005 (0.005)			0.002 (0.006)			0.009 (0.006)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**6,506**	**5,867**	**5,830**	**3,807**	**3,422**	**3,406**	**3,807**	**3,422**	**3,406**
Number of clusters (households)	**4,213**	**3,739**	**3,720**	**2,526**	**2,230**	**2,222**	**2,526**	**2,230**	**2,222**
Time periods (unbalanced)	**13**	**13**	**13**	**13**	**13**	**13**	**13**	**13**	**13**

Table A.10: Estimation results (number of chronic conditions, post-1998 sample)

Controls	Dependent variable: number of chronic conditions								
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Sample	1999-2006								
Estimation method	POLS 1			POLS 2			FE		
Household head unemployed	0.017 (0.018)	0.050** (0.021)	0.052** (0.021)	0.035 (0.022)	0.059** (0.025)	0.062** (0.025)	0.026 (0.019)	0.052** (0.021)	0.052** (0.022)
Household head female		0.071** (0.029)	0.075** (0.030)		0.097** (0.039)	0.102*** (0.039)		0.041 (0.036)	0.041 (0.037)
Household head unemployed & female		-0.062 (0.077)	-0.058 (0.078)		0.015 (0.109)	0.017 (0.113)		-0.025 (0.090)	-0.018 (0.092)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.10 (cont'd)

Child's age below 7 years		-0.095*** (0.025)	-0.095*** (0.026)		-0.085*** (0.028)	-0.084*** (0.028)		-0.028 (0.031)	-0.029 (0.031)
Household head's years of education		-0.029** (0.012)	-0.029** (0.012)		-0.044*** (0.015)	-0.044*** (0.015)		-0.035** (0.015)	-0.035** (0.015)
Household head's years of education squared		0.001** (0.000)	0.001** (0.000)		0.001*** (0.001)	0.001*** (0.001)		0.001* (0.001)	0.001* (0.001)
Log of real total household income (in Rubles)			0.007 (0.009)			0.009 (0.009)			-0.000 (0.011)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**3,039**	**2,542**	**2,534**	**2,147**	**1,808**	**1,804**	**2,147**	**1,808**	**1,804**
Number of clusters (households)	**2,184**	**1,809**	**1,805**	**1,596**	**1,334**	**1,331**	**1,596**	**1,334**	**1,331**
Time periods (unbalanced)	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**8**

Table A.11: Estimation results (low height for age, 1994-1998 sample)

Controls	**Dependent variable: child has low height for age**								
	1a	**1b**	**1c**	**2a**	**2b**	**2c**	**3a**	**3b**	**3c**
Sample	**1994-1998**								
Estimation method	**POLS 1**			**POLS 2**			**FE**		
Household head unemployed	0.021 (0.019)	0.035 (0.023)	0.027 (0.023)	0.047* (0.028)	0.072** (0.034)	0.068** (0.035)	0.026 (0.027)	0.052 (0.034)	0.050 (0.035)
Household head female		-0.003 (0.020)	-0.007 (0.021)		0.009 (0.031)	0.009 (0.032)		0.024 (0.038)	0.028 (0.036)
Household head unemployed & female		-0.053 (0.043)	-0.051 (0.045)		-0.137*** (0.052)	-0.148*** (0.053)		-0.009 (0.047)	-0.006 (0.048)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.11 (cont'd)

Child's age below 7 years		——	——		——	——		——	——
Household head's years of education		0.008 (0.010)	0.006 (0.010)		0.020 (0.015)	0.020 (0.016)		-0.017 (0.019)	-0.019 (0.019)
Household head's years of education squared		-0.000 (0.000)	-0.000 (0.000)		-0.001 (0.001)	-0.001 (0.001)		0.001 (0.001)	0.001 (0.001)
Log of real total household income (in Rubles)			-0.014* (0.007)			-0.008 (0.009)			-0.019* (0.010)
Region (time invariant)	yes	yes		yes	yes	yes	no	no	no
Number of children	**1,955**	**1,913**	**1,891**	**872**	**860**	**847**	**872**	**860**	**847**
Number of clusters (households)	**1,566**	**1,527**	**1,509**	**704**	**692**	**683**	**704**	**692**	**683**
Time periods (unbalanced)	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**

Table A.12: Estimation results (low height for age, post-1998 sample)

Controls	Dependent variable: child has low height for age								
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Sample	1999-2003								
Estimation method	POLS 1			POLS 2			FE		
Household head unemployed	0.030 (0.029)	0.061 (0.040)	0.047 (0.041)	0.048 (0.038)	0.101* (0.054)	0.095* (0.053)	0.020 (0.036)	0.052 (0.048)	0.037 (0.048)
Household head female		0.070** (0.035)	0.055 (0.035)		0.086* (0.048)	0.073 (0.048)		0.072 (0.059)	0.056 (0.059)
Household head unemployed & female		-0.189*** (0.065)	-0.183*** (0.068)		-0.229** (0.093)	-0.231** (0.097)		-0.143* (0.084)	-0.136 (0.091)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.12 (cont'd)

Child's age below 7 years		––	––		––	––		––	––
Household head's years of education		-0.030** (0.015)	-0.034** (0.014)		-0.023 (0.018)	-0.027 (0.018)		-0.011 (0.025)	-0.015 (0.024)
Household head's years of education squared		0.001* (0.001)	0.001** (0.001)		0.001 (0.001)	0.001 (0.001)		0.000 (0.001)	0.001 (0.001)
Log of real total household income (in Rubles)			-0.028** (0.013)			-0.024 (0.015)			-0.036** (0.016)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**947**	**817**	**813**	**603**	**531**	**531**	**603**	**531**	**531**
Number of clusters (households)	**798**	**691**	**688**	**532**	**469**	**469**	**532**	**469**	**469**
Time periods (unbalanced)	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**

Table A.13: Estimation results (low height for age, total sample)

Controls	Dependent variable: child has low height for age								
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Sample	**1994-2003**								
Estimation method	**POLS 1**			**POLS 2**			**FE**		
Household head unemployed	0.026* (0.016)	0.048** (0.020)	0.037* (0.020)	0.050** (0.021)	0.081*** (0.027)	0.072*** (0.027)	0.018 (0.021)	0.045* (0.027)	0.039 (0.027)
Household head female		0.014 (0.017)	0.008 (0.017)		0.020 (0.023)	0.027 (0.013)		0.022 (0.027)	0.021 (0.026)
Household head unemployed & female		-0.098*** (0.032)	-0.094*** (0.033)		-0.158*** (0.041)	-0.159*** (0.041)		-0.067 (0.045)	-0.064 (0.048)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.13 (cont'd)

Child's age below 7 years		––	––		––	––		––	––
Household head's years of education		-0.009 (0.009)	-0.012 (0.009)		-0.001 (0.017)	-0.013 (0.012)		-0.020 (0.013)	-0.024* (0.014)
Household head's years of education squared		0.000 (0.000)	0.000 (0.000)		0.000 (0.000)	0.000 (0.000)		0.001 (0.001)	0.001* (0.001)
Log of real total household income (in Rubles)			-0.018*** (0.001)			-0.018** (0.008)			-0.020** (0.008)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**2,593**	**2,429**	**2,406**	**1,406**	**1,324**	**1,312**	**1,406**	**1,324**	**1,312**
Number of clusters (households)	**2,006**	**1,865**	**1,847**	**1,108**	**1,032**	**1,025**	**1,108**	**1,032**	**1,025**
Time periods (unbalanced)	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**	**10**

Table A.14: Estimation results (anxiety or depression, 2003-2005 sample)

Controls	**Dependent variable: child suffers from anxiety or depression**								
	1a	**1b**	**1c**	**2a**	**2b**	**2c**	**3a**	**3b**	**3c**
Sample	**2003-2005**								
Estimation method	**POLS 1**			**POLS 2**			**FE**		
Household head unemployed	-0.046* (0.025)	-0.036 (0.032)	-0.034 (0.033)	-0.027 (0.031)	-0.031 (0.033)	-0.031 (0.034)	-0.047 (0.034)	0.082** (0.042)	0.101** (0.046)
Household head female		0.065* (0.037)	0.071* (0.039)		0.007 (0.042)	0.011 (0.044)		0.112 (0.168)	0.132 (0.167)
Household head unemployed & female		-0.264*** (0.096)	-0.262*** (0.096)		-0.169 (0.114)	-0.169 (0.115)		-0.557*** (0.192)	-0.555*** (0.187)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.14 (cont'd)

Child's age below 7 years		-0.088*** (0.026)	-0.087*** (0.026)		-0.071** (0.030)	-0.070** (0.030)		-0.058 (0.074)	-0.061 (0.076)
Household head's years of education		0.011 (0.018)	0.010 (0.018)		-0.006 (0.021)	-0.008 (0.021)		-0.044 (0.040)	-0.044 (0.042)
Household head's years of education squared		-0.000 (0.001)	-0.000 (0.001)		0.000 (0.001)	0.000 (0.001)		0.002 (0.001)	0.002 (0.002)
Log of real total household income (in Rubles)			0.007 (0.017)			0.003 (0.019)			0.038 (0.025)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**1,785**	**1,313**	**1,309**	**1,095**	**1,009**	**1,006**	**1,095**	**1,009**	**1,006**
Number of clusters (households)	**1,357**	**1,017**	**1,014**	**868**	**796**	**794**	**868**	**796**	**794**
Time periods (unbalanced)	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**

Table A.15: Estimation results (parental evaluation of child's health, 1994-1998 sample)

Controls	Dependent variable: child in good health (parental report)								
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Sample	1994-1998								
Estimation method	POLS 1			POLS 2			FE		
Household head unemployed	0.011 (0.018)	0.004 (0.022)	0.008 (0.022)	-0.009 (0.023)	-0.015 (0.025)	-0.014 (0.025)	-0.005 (0.023)	0.013 (0.028)	0.011 (0.029)
Household head female		0.012 (0.021)	0.020 (0.022)		0.019 (0.028)	0.025 (0.029)		-0.003 (0.045)	0.001 (0.047)
Household head unemployed & female		0.040 (0.052)	0.046 (0.053)		-0.043 (0.066)	-0.044 (0.067)		-0.057 (0.072)	-0.052 (0.075)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.15 (cont'd)

Child's age below 7 years		0.072*** (0.022)	0.073*** (0.022)		0.025 (0.039)	0.022 (0.039)		0.024 (0.038)	0.017 (0.038)
Household head's years of education		-0.003 (0.010)	-0.003 (0.010)		0.010 (0.012)	0.010 (0.013)		0.013 (0.019)	0.010 (0.020)
Household head's years of education squared		0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	-0.000 (0.0004)		-0.001 (0.001)	-0.000 (0.001)
Log of real total household income (in Rubles)			0.006 (0.006)			0.005 (0.007)			-0.008 (0.008)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**4,571**	**4,415**	**4,382**	**2,243**	**2,188**	**2,169**	**2,243**	**2,188**	**2,169**
Number of clusters (households)	**3,042**	**2,929**	**2,912**	**1,531**	**1,489**	**1,480**	**1,531**	**1,489**	**1,480**
Time periods (unbalanced)	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**	**5**

Table A.16: Estimation results (parental evaluation of child's health, post-1998 sample)

Controls	Dependent variable: child in good health (parental report)								
	1a	**1b**	**1c**	**2a**	**2b**	**2c**	**3a**	**3b**	**3c**
Sample	**1999-2006**								
Estimation method	**POLS 1**			**POLS 2**			**FE**		
Household head unemployed	-0.011 (0.017)	-0.039* (0.021)	-0.038* (0.022)	-0.025 (0.020)	-0.049** (0.025)	-0.050** (0.025)	-0.014 (0.019)	-0.038* (0.022)	-0.042* (0.023)
Household head female		-0.054** (0.022)	-0.050** (0.023)		-0.040 (0.026)	-0.040 (0.027)		-0.017 (0.035)	-0.018 (0.036)
Household head unemployed & female		0.088 (0.061)	0.090 (0.062)		0.052 (0.075)	0.062 (0.077)		0.024 (0.076)	0.031 (0.078)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.16 (cont'd)

Child's age below 7 years		0.003 (0.0215)	0.002 (0.022)		-0.009 (0.025)	-0.011 (0.025)		-0.078** (0.031)	-0.079*** (0.031)
Household head's years of education		-0.002 (0.011)	-0.004 (0.011)		0.006 (0.013)	0.003 (0.013)		0.003 (0.017)	-0.001 (0.017)
Household head's years of education squared		0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	-0.000 (0.000)		-0.000 (0.001)	0.000 (0.001)
Log of real total household income (in Rubles)			0.007 (0.008)			0.001 (0.011)			-0.001 (0.010)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**3,054**	**2,555**	**2,547**	**2,153**	**1,814**	**1,810**	**2,153**	**1,814**	**1,810**
Number of clusters (households)	**2,190**	**1,817**	**1,813**	**1,599**	**1,339**	**1,336**	**1,599**	**1,339**	**1,336**
Time periods (unbalanced)	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**8**

Table A.17: Estimation results (parental evaluation of child's health, total sample)

Controls	Dependent variable: child in good health (parental report)								
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Sample	**1994-2006**								
Estimation method	**POLS 1**			**POLS 2**			**FE**		
Household head unemployed	0.003 (0.012)	-0.010 (0.015)	-0.009 (0.015)	-0.017 (0.014)	-0.026 (0.017)	-0.031* (0.017)	-0.001 (0.014)	-0.009 (0.017)	-0.013 (0.017)
Household head female		-0.018 (0.016)	-0.013 (0.016)		-0.012 (0.025)	-0.010 (0.026)		-0.022 (0.019)	-0.022 (0.019)
Household head unemployed & female		0.075* (0.039)	0.083** (0.040)		0.009 (0.049)	0.025 (0.049)		0.020 (0.050)	0.033 (0.051)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table A.17 (cont'd)

Child's age below 7 years		0.044*** (0.015)	0.044*** (0.015)		0.015 (0.022)	0.011 (0.022)		-0.040 (0.023)	-0.041* (0.024)
Household head's years of education		-0.005 (0.007)	-0.006 (0.008)		0.000 (0.010)	-0.001 (0.010)		0.001 (0.012)	-0.001 (0.012)
Household head's years of education squared		0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	0.000 (0.000)		-0.000 (0.000)	0.000 (0.000)
Log of real total household income (in Rubles)			0.005 (0.005)			-0.004 (0.006)			-0.006 (0.006)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**6,509**	**5,869**	**5,832**	**3,809**	**3,425**	**3,409**	**3,809**	**3,425**	**3,409**
Number of clusters (households)	**4,214**	**3,740**	**3,721**	**2,527**	**2,232**	**2,224**	**2,527**	**2,232**	**2,224**
Time periods (unbalanced)	**13**	**13**	**13**	**13**	**13**	**13**	**13**	**13**	**13**

Table A.18: Child and household attrition

Number of rounds observed	Employed household head		Unemployed household head	
	Children	Households	Children	Households
1994-1998 sample				
1	53.95%	36.20%	73.96%	47.61%
2	24.43%	22.79%	19.55%	23.91%
3	13.44%	13.51%	5.21%	10.20%
4	6.58%	9.47%	1.28%	6.48%
5	1.59%	5.76%	0.00%	3.93%
Post-1998 sample				
1	37.90%	27.77%	68.10%	45.40%
2	24.65%	20.29%	20.92%	22.55%
3	16.27%	14.17%	7.86%	10.83%
4	9.27%	10.07%	3.12%	6.38%
5	6.28%	7.58%	0%	4.01%
6	3.76%	5.93%	0%	3.12%
7	1.86%	4.11%	0%	2.08%

Notes:

1) Due to high attrition the Moscow and St. Petersburg samples were completely changed in year 1998.

2) Cases where children are observed only once do not necessarily imply attrition; these could also mean the child was born during the last round of data or that s/he was aged 13 in the first year when the household entered the survey (the latter is 1994 for all households, except for the newly-sampled Moscow and St Petersburg households in 1998).

Table A.19: Tests for strict exogeneity of unemployment in the fixed effects estimation

Dependent variable	Model specification	P-value of the test	Conclusion (5% significance level)
Child had any health problems in the last 30 days, sample 1994-1998	3a	0.221	Fail to reject the null for strict exogeneity
	3b	0.145	Fail to reject the null for strict exogeneity
	3c	0.182	Fail to reject the null for strict exogeneity
Child had any health problems in the last 30 days, sample 1999-2006	3a	0.369	Fail to reject the null for strict exogeneity
	3b	0.682	Fail to reject the null for strict exogeneity
	3c	0.748	Fail to reject the null for strict exogeneity
Child had any health problems in the last 30 days, sample 1994-2006	3a	0.167	Fail to reject the null for strict exogeneity
	3b	0.106	Fail to reject the null for strict exogeneity
	3c	0.133	Fail to reject the null for strict exogeneity
Number of chronic conditions, sample 1999-2006	3a	0.669	Fail to reject the null for strict exogeneity
	3b	0.324	Fail to reject the null for strict exogeneity
	3c	0.299	Fail to reject the null for strict exogeneity
Child has depression/anxiety, sample 2003-2005	3a	0.109	Fail to reject the null for strict exogeneity
	3b	0.032	Reject the null for strict exogeneity
	3c	0.036	Reject the null for strict exogeneity
Child in good health, sample 1994-1998	3a	0.427	Fail to reject the null for strict exogeneity
	3b	0.392	Fail to reject the null for strict exogeneity
	3c	0.351	Fail to reject the null for strict exogeneity

Table A. 19 (cont'd)

Child in good health, sample 1999-2006	3a	0.681	Fail to reject the null for strict exogeneity
	3b	0.280	Fail to reject the null for strict exogeneity
	3c	0.296	Fail to reject the null for strict exogeneity
Child in good health, sample 1994-2006	3a	0.625	Fail to reject the null for strict exogeneity
	3b	0.404	Fail to reject the null for strict exogeneity
	3c	0.437	Fail to reject the null for strict exogeneity
Child has low height for age, sample 1994-1998	3a	0.980	Fail to reject the null for strict exogeneity
	3b	0.962	Fail to reject the null for strict exogeneity
	3c	0.920	Fail to reject the null for strict exogeneity
Child has low height for age, sample 1999-2003	3a	0.706	Fail to reject the null for strict exogeneity
	3b	0.308	Fail to reject the null for strict exogeneity
	3c	0.306	Fail to reject the null for strict exogeneity
Child has low height for age, sample 1994-2003	3a	0.346	Fail to reject the null for strict exogeneity
	3b	0.722	Fail to reject the null for strict exogeneity
	3c	0.843	Fail to reject the null for strict exogeneity

APPENDIX B

SUPPLEMENTARY TABLES AND FIGURES

Table B.1: Sample statistics of the households (pre-1998 vs. post-1998)

Household characteristics	1994-1998			Post-1998		
	Employed	Unemployed	Difference	Employed	Unemployed	Difference
Age of household head	37.015	36.579	0.436	37.850	38.224	-0.374
Years of education of household head	16.248	15.054	1.193***	16.460	15.080	1.379***
Number of children aged 0-6 in the household	0.650	0.850	-0.200***	0.663	0.847	-0.183***
Number of children aged 7-18 in the household	1.210	1.344	-0.134***	1.050	1.285	-0.235***
Number of post-working age females in the household	0.175	0.286	-0.112***	0.218	0.387	-0.169***

Notes:

1) Means corrected for stratification; linearised standard errors. Number of strata (regions): 144.

2) Test for equality of means reported for the samples of employed and unemployed household heads. *** denotes significance at the 1% level; ** denotes significance at the 5% level, and * denotes significance at the 10% level.

3) Variables ‘distance to paediatrician’ and ‘distance to hospital’ refer to those with access to paediatrician/hospital; the variables are not available for year 2006. Chronic conditions are only available after 1998.

4) Total number of observations in the 1994-1998 sample: (children): 4,571; number of clusters (households): 3,042; 1999-2006 sample: (children): 3,054; number of clusters (households): 2,190. The total number of observations is below the sum of employed and unemployed as some households/children are observed in both states.

Table B.1 (cont'd)

Number of post-working age males in the household	0.058	0.101	0.042***	0.071	0.146	-0.075***
Fraction of female household heads	0.116	0.129	-0.0134	0.138	0.119	0.019
Total household monthly income (real, in rubbles)	7815.49	5933.54	1881.95***	13553.02	8766.25	4786.76***
Household below the all Russia poverty line	0.575	0.795	-0.219***	0.221	0.512	-0.291***
Household below the regional poverty line	0.362	0.618	-0.257***	0.133	0.370	-0.238***
Frequency of monthly alcohol use (household head)	4.397	4.386	0.012	4.164	4.364	-0.200***
Drinks without eating (household head)	0.142	0.170	-0.028	0.244	0.239	0.005
Household head a smoker	0.616	0.693	-0.077***	0.638	0.691	-0.052***
Number of chronic conditions (household head)	0.536	0.555	-0.019	0.523	0.400	0.123***
Non-household member cared for the child in the last 7 days	0.282	0.236	0.046***	0.308	0.182	0.126***
Non-household member cared for the child in the last 7 days (kids below seven)	0.186	0.147	0.040***	0.211	0.124	0.087***
Community level						
Fraction with access to paediatrician	0.871	0.782	0.089***	0.845	0.629	0.216***
Distance to paediatrician (in kilometres)	22.213	22.929	-0.716	23.006	27.478	-4.472***
Hospital in the community	0.835	0.721	0.114***	0.821	0.602	0.220***
Distance to hospital (in kilometres)	17.507	22.554	-5.047***	19.790	25.651	-5.861***
Distance to hospital (in hours)	0.172	0.326	-0.154***	0.178	0.294	-0.115***
Number of observations (children)	**4,306**	**696**		**2,905**	**479**	
Number of clusters (households)	**2,889**	**448**		**2,107**	**316**	

Table B.2: Sample statistics of the children (pre-1998 vs. post-1998)

Characteristics	1994-1998			Post-1998		
	Employed	**Unemployed**	**Difference**	**Employed**	**Unemployed**	**Difference**
Demographic						
Age	7.904	7.492	0.412***	7.567	7.750	-0.183
Fraction of boys	0.513	0.514	-0.002	0.504	0.504	-0.000
Child healthcare access and utilisation						
Has a regular physician	NA	NA	NA	0.591	0.457	0.134***
Had a medical check-up in the last 3 months	0.243	0.226	0.018	0.582	0.529	0.053***

Notes:

1) Means corrected for stratification; linearised standard errors. Number of strata (regions): 144.

2) Test for equality of means reported for the samples of employed and unemployed household heads. *** denotes significance at the 1% level; ** denotes significance at the 5% level, and * denotes significance at the 10% level.

3) Variables 'distance to paediatrician' and 'distance to hospital' refer to those with access to paediatrician/hospital; the variables are not available for year 2006. Chronic conditions are only available after 1998.

4) Total number of observations in the 1994-1998 sample: (children): 4,571; number of clusters (households): 3,042; 1999-2006 sample: (children): 3,054; number of clusters (households): 2,190. The total number of observations is below the sum of employed and unemployed as some households/children are observed in both states.

Table B.2 (cont'd)

Had a medical check-up in the last 12 months	NA	NA	NA	0.647	0.488	0.157***
Ever vaccinated (all children)	0.973	0.978	-0.005	0.987	0.988	-0.001
Ever vaccinated (children aged 1 year or below)	0.918	0.872	0.046	0.959	0.946	0.013
Health conditions						
Any health problems in the last 30 days	0.387	0.304	0.083***	0.400	0.319	0.081***
Minor health problems in the last 30 days	NA	NA	NA	0.208	0.126	0.083***
Hospitalised in the last 3 months	0.036	0.044	-0.009	0.048	0.034	0.014**
Feels anxiety or depression	NA	NA	NA	0.263	0.128	0.135***
Health evaluation						
Good	0.578	0.664	-0.087***	0.636	0.729	-0.094***
Average	0.390	0.297	-0.093***	0.345	0.258	0.0871***
Bad	0.033	0.039	-0.005	0.020	0.013	0.007
Chronic heart condition	0.023	0.019	0.005	0.026	0.020	0.006
Chronic lung condition	0.023	0.008	0.016*	0.020	0.015	0.005
Chronic liver condition	0.020	0.015	0.005	0.010	0.005	0.005*
Chronic kidney condition	0.019	0.040	-0.021	0.021	0.015	0.006
Chronic gastrointestinal condition	0.045	0.034	0.011	0.048	0.027	0.021***
Chronic spinal condition	0.027	0.033	-0.006	0.031	0.017	0.014***
Other chronic condition	0.084	0.099	-0.015	0.092	0.067	0.025***

Table B.2 (cont'd)

Diabetes	0.002	0.003	-0.001	0.003	0.002	0.000
Any chronic condition	0.186	0.160	0.026	0.193	0.127	0.065***
Anthropometric indicators (children aged 7 years or below)						
Height for age z-score	-0.186	-0.305	0.120	0.035	-0.390	0.425***
Weight for height z-score	0.213	0.292	-0.080	0.326	0 .458	-0.132
Fraction with normal height for age and normal weight for height	0.842	0.821	0.022	0.886	0.763	0.123***
Fraction with normal height for age and low weight for height	0.069	0.057	0.012	0.040	0.058	-0.018
Fraction with low height for age and normal weight for height	0.086	0.122	-0.036***	0.071	0.165	-0.094***
Fraction with low height for age and low weight for height	0.003	0.000	0.003***	0.002	0.014	-0.012
Number of observations (children)	**4,306**	**696**		**2,905**	**479**	
Number of clusters (households)	**2,889**	**448**		**2,107**	**316**	

Table B.3.1: Other robustness checks (number of chronic conditions, post-1998 sample)

Controls	Dependent variable: number of chronic conditions								
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Sample	1999-2006								
Estimation method	POLS 1			POLS 2			FE		
Household head unemployed	0.017 (0.018)	0.052* (0.021)	0.055** (0.022)	0.035 (0.022)	0.062** (0.025)	0.066** (0.025)	0.026 (0.019)	0.052** (0.022)	0.057** (0.022)
Household head female		0.075** (0.030)	0.050 (0.030)		0.102*** (0.039)	0.072* (0.0378)		0.041 (0.037)	0.022 (0.037)
Household head unemployed & female		-0.057 (0.078)	-0.051 (0.079)		0.017 (0.113)	0.020 (0.112)		-0.018 (0.092)	-0.013 (0.093)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table B.3.1 (cont'd)

Child's age below 7 years		-0.095*** (0.026)	-0.093*** (0.025)		-0.084*** (0.028)	-0.084*** (0.027)		-0.029 (0.031)	-0.031 (0.031)
Household head's years of education		-0.029** (0.012)	-0.026** (0.012)		-0.044*** (0.015)	-0.035*** (0.016)		-0.035** (0.015)	-0.031** (0.016)
Household head's years of education squared		0.001** (0.000)	0.001* (0.000)		0.001*** (0.001)	0.001*** (0.001)		0.001* (0.001)	0.001* (0.001)
Log of real total household income (in Rubles)		0.007 (0.0091)	0.005 (0.009)		0.009 (0.009)	0.007 (0.009)		-0.000 (0.011)	-0.002 (0.011)
Number of household head's chronic conditions			0.085*** (0.012)			0.103*** (0.014)			0.064*** (0.012)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**3,039**	**2,534**	**2,522**	**2,147**	**1,804**	**1,797**	**2,147**	**1,804**	**1,797**
Number of clusters (households)	**2,184**	**1,805**	**1,797**	**1,596**	**1,331**	**1,326**	**1,596**	**1,331**	**1,326**
Time periods (unbalanced)	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**8**	**8**

Table B.3.2: Other robustness checks (anxiety and depression, 2003-2005 sample)

Controls	Dependent variable: child suffers from anxiety or depression								
	1a	1b	1c	2a	2b	2c	3a	3b	3c
Sample	**2003-2005**								
Estimation method	**POLS 1**			**POLS 2**			**FE**		
Household head unemployed	-0.046* (0.025)	-0.034 (0.033)	-0.043 (0.032)	-0.027 (0.031)	-0.031 (0.034)	-0.054 (0.035)	-0.047 (0.034)	0.101** (0.046)	0.098** (0.045)
Household head female		0.071* (0.039)	0.062 (0.039)		0.011 (0.044)	-0.002 (0.043)		0.132 (0.167)	0.093 (0.167)
Household head unemployed & female		-0.262*** (0.096)	-0.228** (0.096)		-0.170 (0.115)	-0.209* (0.108)		-0.555*** (0.187)	-0.543*** (0.186)

Notes:

1) Standard errors clustered at household level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

2) All specifications control for: labour force status of the spouse/cohabiting partner of the household head, defined as the following mutually exclusive categories: spouse unemployed, spouse employed (omitted in the regressions), spouse not in the labour force, single female head (same category as household head female), single male head, living with spouse but spousal labour force status missing; number of children in the household aged below 7; number of children in the household aged 7 to 18; an indicator of whether the household has access to paediatrician; year and month of interview.

Table B.3.2 (cont'd)

Child's age below 7 years		-0.087*** (0.026)	-0.079*** (0.026)		-0.070** (0.030)	-0.069** (0.029)		-0.061 (0.075)	-0.051 (0.076)
Household head's years of education		0.010 (0.018)	0.013 (0.018)		-0.008 (0.021)	0.001 (0.020)		-0.044 (0.042)	-0.038 (0.041)
Household head's years of education squared		-0.000 (0.001)	-0.000 (0.001)		0.000 (0.001)	-0.000 (0.001)		0.002 (0.002)	0.002 (0.001)
Log of real total household income (in Rubles)		0.007 (0.017)	0.009 (0.016)		0.003 (0.019)	0.004 (0.018)		0.038 (0.025)	0.041 (0.024)
Child has a chronic condition			0.134*** (0.029)			0.135*** (0.036)			0.066 (0.062)
Child stayed in hospital in the last 3 months			0.110** (0.046)			0.110 (0.072)			0.158*** (0.060)
Region (time invariant)	yes	yes	yes	yes	yes	yes	no	no	no
Number of children	**1,785**	**1,309**	**1,309**	**1,095**	**1,006**	**1,006**	**1,095**	**1,006**	**1,006**
Number of clusters (households)	**1,357**	**1,014**	**1,014**	**868**	**794**	**794**	**868**	**794**	**794**
Time periods (unbalanced)	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**

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CHAPTER 2

THE EFFECT OF RETIREMENT ON MENTAL HEALTH AND SOCIAL INCLUSION OF THE ELDERLY

2.1 INTRODUCTION

Faced with the challenge of population ageing and the need to ensure the sustainability of the public health and pension systems, most countries in Europe have taken steps towards increasing retirement eligibility ages. This, in turn, makes understanding the consequences of an individual's labour force exit on their psychological well-being of considerable importance. Until the last decade, the mainstream literature in the field focused on studying the retirement of male workers, with little or no attention paid to women's retirement. At the same time, however, the increasing labour force participation rate of females, together with the fact that women's longevity outpaces that for men, have given rise to a number of studies examining the effect of work force exit on women's emotional health (see e.g. Bound and Waidmann (2007); Clark and Fawaz (2009)).

Revealing the mental health effects of retirement has important implications for the well-being of the elderly and may have significance for policy-making. To elaborate more on this, evidence of high psychic costs of labour force exit would imply that increasing the retirement ages would work towards preserving the emotional well-being of the workers. In contrast, indications of a beneficial impact of retirement might highlight a potential detrimental aspect of the present policies of encouraging continued employment of the older adults.

This paper utilizes the empirical methodology developed in a recent study by Coe and Zamarro (2011) to investigate the effect of retirement on the mental health of the elderly, and extends their analysis in several ways. First, in contrast to Coe and Zamarro (2011) who study exclusively the labour force exit of men and how it interacts with their physical and mental health, this paper examines the heterogeneity of the impact of retirement for male and female workers while restricting its attention to psychological well-being as the outcome of interest.

Secondly, while Coe and Zamarro (2011) are able to look at 11 developed economies from the first wave of the Survey of Health, Ageing and Retirement in Europe (SHARE), this study makes use of an extended version of SHARE including three waves of data on 17 countries, among which 5 post-transition economies. [31] Finally, since the last wave of SHARE enquired about the respondents' social and family networks, the analysis presented here is able to shed some light on a secondary question of interest: does retirement cause social isolation of the elderly?

The key findings of this paper can be summarised as follows. In line with the conclusions of Coe and Zamarro (2011), the analysis in this study indicates that retirement has no significant impact on men's psychological well-being. At the same time, however, the paper provides strong evidence of a favourable effect of retirement on women's mental health. To be more precise, a female's labour force exit significantly decreases the incidence of death ideation, and improves her depression score measured as a composite demotivation index and as the Euro-D depression scale. In addition, the paper finds some evidence of a heterogeneous effect of exiting work on the social contacts of the elderly – while retirement decreases the size of the social network for men, it has no effect for women; moreover, retirement appears to enhance contact with parents for female workers, but not for males. These findings on the effect of retirement on the psychological well-being and social networks of the elderly have important policy implications.

[31] This paper uses data from SHARE wave 4 release 1.1.1, as of March 28th 2013 or SHARE wave 1 and 2 release 2.5.0, as of May 24th 2011 or SHARELIFE release 1, as of November 24th 2010. The SHARE data collection has been primarily funded by the European Commission through the 5th Framework Programme (project QLK6-CT-2001-00360 in the thematic programme Quality of Life), through the 6th Framework Programme (projects SHARE-I3, RII-CT-2006-062193, COMPARE, CIT5-CT-2005-028857, and SHARELIFE, CIT4-CT-2006-028812) and through the 7th Framework Programme (SHARE-PREP, N° 211909, SHARE-LEAP, N° 227822 and SHARE M4, N° 261982). Additional funding from the U.S. National Institute on Aging (U01 AG09740-13S2, P01 AG005842, P01 AG08291, P30 AG12815, R21 AG025169, Y1-AG-4553-01, IAG BSR06-11 and OGHA 04-064) and the German Ministry of Education and Research as well as from various national sources is gratefully acknowledged (see www.share-project.org for a full list of funding institutions).

The remainder of this paper is organised as follows. Section 2.2 discusses the theoretical framework behind the main research question and reviews the relevant literature. Section 2.3 describes the data and variable definitions employed in the study, followed by detailed data analysis. Section 2.4 develops an econometric model of an individual's psychological health and discussed the identification strategy. Finally, Section 2.5 presents the estimation results, followed by concluding remarks.

2.2 LITERATURE REVIEW

2.2.1 Theoretical background

The impact of retirement on an individual's mental health is not clear a priori. On the one hand, retirement is an event involving a major lifestyle change, and the mainstream psychology literature views it as potentially stressful for the retirees (see, e.g., O. Salami (2010)). Since research suggests the existence of a causal relationship between stress and depressive episodes (Hammen (2005)), this implies that retirement can be detrimental for one's psychological well-being. In addition, a strand of the sociology literature – the so-called "role theory" (Mead (1934)) – maintains the idea that work provides a sense of identity, worth and fulfilment for the individual; hence, retirement may lead to loss of a social role, and emotional distress. Further, exiting employment often results in a drop in the income available to an individual or a family, and several studies have shown that insufficient financial resources are related to lower life satisfaction and subjective well-being (Diener et al. (1992)). Finally, some authors argue that retirement may cause a decrease in social contact and disruption of social networks, thus leading to perceived loneliness and isolation. One example in this respect is a study by Sugisawa et al. (1997), who studied retirement of male workers in Japan and found that early retirement tends to decrease the frequency of social interactions. Recently Börsch-Supan and Schuth (2014) examined data from SHARE and concluded that retirement in general, and early retirement in particular, reduces the size of one's social network and disrupts contacts with non-family members and immediate colleagues.

At the same time, however, others believe that withdrawal from work is a beneficial life change. Retirement dramatically increases the leisure time available to the retiree, which may offset the loss of income to cause a net favourable effect on psychological well-being. In addition, a job may be stressful, dissatisfying and strenuous to the individual; hence, retirement would work towards preserving emotional health. Further, a competing theory to the social role theory – the continuity theory (e.g., Atchley (1999)) – hypothesizes that the elderly will typically maintain their earlier lifestyle activities, relationships, and identity, even after exiting their jobs; hence, they need not experience any loss of self worth after retirement. Lastly, retirees often get engaged in volunteering and charity work, which has been linked to various psychological outcomes. In particular, a number of studies report that volunteering increases life satisfaction (see e.g. Meier and Stutzer (2004)), reduces depression rates (Musick and Wilson, (2003); Lum and Lightfood (2005)), and has a positive impact on subjective well-being (Morrow-Howell et al. (2003)).

2.2.2 Empirical evidence

The empirical evidence on the effect of retirement on the occurrence of depressive symptoms is largely mixed: while several studies have found support for a beneficial effect of retirement, a number of other publications reported no significant impact of workforce exit, or a detrimental effect.

One seminal paper by Charles (2004) utilised data from the Health and Retirement Study (HRS) and the National Longitudinal Survey of Mature Men (NLS-MM) to examine the effect of retirement on men's mental health, and reported that permanent exit from employment improves psychological well being. Similarly, using data from the Wisconsin Longitudinal Study, Coursolle et al. (1994) provided support for the idea that retirement is associated with fewer depressive symptoms. More recently, Bound and Waidmann (2007) examined data on morbidity from the English Longitudinal Study of Ageing and concluded that retirement has a positive, albeit small, effect on mental health for men.

Yet, the mainstream relevant literature reports a negative effect of retirement on one’s emotional well being. Early work (see, e.g., Portnoi (1983)) used cross-sectional data and concluded that retirement is strongly associated with depression; however, those results typically do not have a causal interpretation as they did not address the potential endogeneity of workforce exit. More recently, Dave et al. (2008) analysed data from the HRS and documented that full retirement caused a 6 to 9% decline in mental health. Another contemporary study by Bonsang and Klein (2012) used men’s subjective well-being measures from the German Socio-Economic Panel and indicated no significant effect of voluntary retirement, but an adverse effect when it is involuntary (i.e. resulting from employment constraints).

Finally, a number of authors have reported that retirement plays no significant role in determining one’s mental health. For instance, Beck (1982) examined data from the NLS-MM to study the effect of retirement on life satisfaction and found no impact. Clark and Fawaz (2009) used two European panels – SHARE and the British Household Panel Study – and showed that psychological well-being remains largely unchanged following labour force exit. Lastly, Coe and Zamarro (2011) utilised cross-country data on 11 European states in SHARE and found that, once endogeneity of retirement is accounted for, it appears to have no effect on occurrence of depression episodes and on a composite depression index (the “Euro-D” scale) for men.

All this research typically focused on studying the consequences of retirement on men’s mental health, with relatively little attention paid to women’s labour force exit. At the same time, however, the rising labour force participation rate of females in the developed economies in general, and in the EU in particular, has tremendously increased the scope of this research question for women. As of 2011 the females' labour force participation rate in the EU reached its highest value over the past two decades, 64.70% (compare e.g. to 56.41% as of 1990). [32] Moreover, the ratio of female-to-male labour participation in the EU has been constantly increasing as well, reaching a record high of 77.68% as of 2011.

Yet, the majority of past research generally did not study females' retirement, mainly due to concerns of sample selection and cohort effects. An important point should be made here regarding the first concern: given the research question addressed in this paper, sample selection is not an issue as the SHARE sample is representative of the population of interest – women who are in the labour force are studied as they subsequently transit into retirement, and this is the exact population one would like to study (put differently, selection is exogenous, not endogenous). The second issue, however, is potentially problematic: cohort effects are present in the EU and are particularly relevant for women, as females born in the 60s and 70s are more likely to participate in the labour force over their life-cycle. Additionally, these effects vary by country (see e.g. Balleer et al. (2009)). However, given the identification strategy employed in this study, cohort effects are a problem only if female's labour force participation does not merely vary across women's age and country of residence, but if this variation is in any way correlated to the statutory and early retirement ages – a much stronger statement.

Another reason to study the retirement of female workers is the potential presence of heterogeneous effects, and there are several reasons why labour force exit may, indeed, have a differential impact across gender. First and foremost, a consistent long-standing observation in the social epidemiology literature is the gender gap in depression, namely that depression is more prevalent amongst females than amongst males. For instance, Van de Velde et al. (2010) used

[32] Calculation based on the female population aged 15 to 64.
Source: International Labour Organization, Key Indicators of the Labour Market database.

data on 23 countries from the European Social Survey, and found higher levels of depression for women in all countries, although the gender gap exhibited a considerable cross-national variation. Moreover, some authors hypothesise the gender gap in psychological well-being is due to fact that women combine paid employment with engaging in a disproportionately larger share of the housework (see e.g. Mirowski (1996) and Lennon and Rosenfield (1992)). This direction of thought implies that exiting employment into retirement may provide an additional channel for a beneficial effect of retirement on mental health for women, but not for men.

In addition to this, a number of studies suggest that women and men who retire experience a loss in social role to a different extent. To elaborate more on this, women typically have more fragmented work histories and lower attachment to the labour market and to a particular occupation than men, while at the same time strong workplace attachment has been associated with more a painful transition into retirement (see e.g. Tibbitts (1954)). Similarly, a contemporary study conducted in the United Kingdom by Barnes and Parry (2004) found that men's more concentrated employment histories make them more likely to report a loss of social status upon retirement, compared to women.

Lastly, a number of European states still maintain different pension eligibility age for men and women, resulting in lower replacement rates for women. [33] Because economic factors have been shown to affect one's psychological well-being, this may result in a differential effect of retirement for both genders.

Taking all this into consideration, the analysis in this paper studies both men and women aiming at shedding some light on the potentially heterogeneous effect of retirement by gender.

[33] The most notable gender differential in replacement rates is observed in Italy, Poland, and Slovenia (European Commission, 2012).

2.3 DATA AND VARIABLES

2.3.1 Data and sample

The analysis in this paper utilises data from the Survey of Health, Ageing and Retirement in Europe (SHARE). SHARE is a cross-national European survey, containing micro-level data on persons aged 50 and older at the time of the first interview, and their spouses. The survey is based on probability samples in all participating countries; following the individuals from the baseline wave in 2004, subsequent interviews were conducted, on average, once in two years. [34] Since wave 3 in SHARE was entirely retrospective, the paper uses data from waves 1, 2 and 4 only. This results in a sample containing data on 17 European countries: Austria, Belgium, Czech Republic, Denmark, Estonia, France, Germany, Greece, Hungary, Italy, Netherlands, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland. [35] A detailed country representation for each wave in SHARE is shown in Table C.1.

Since SHARE collects data on the elderly for a large multinational sample over a relatively long period of time, it is particularly well suited for studying the link between retirement and health outcomes. In addition to the basic demographic and socio-economic variables, SHARE provides detailed information for the purposes of this paper – labour supply outcomes and psychological health. An important strength of the dataset is the quality of the mental health information collected: the respondents were asked series of questions on their

[34] For wave 1 interviews were conducted in year 2004 (80.8% of the sample) and 2005 (19.2%), for wave 2 – in year 2007 (75.4% of the sample) and 2006 (24.6% of the sample), and for wave 4 – predominantly in year 2011 (93.7% of the sample), and a small fraction of the respondents were interviewed in 2010 (2.8%) and 2012 (3.5%). Due to attrition, ‘refresher’ samples were drawn in later waves in most first-wave countries, aiming at keeping the national samples representative of the elderly population.

[35] Data on Ireland is also available in wave 2; however, since it does not contain key variables such as a household identifier, and income imputations, the country is excluded from the analysis.

overall emotional condition, as well as whether they experienced certain depression symptoms. Further, SHARE contains comprehensive information on variables considered key determinants of depression, such as physical health, hospital stay, and household income. Finally, wave 4 enquired about the participants' social and family networks, which allows inferring upon the effect of retirement on the social inclusion of the elderly.

Since the central research question of this paper focuses on the effect of being retired on the mental health of the elderly, attention is restricted to individuals who were aged 50 or over at the time of the first interview, and were either employed or retired at that time. [36] Persons who consider themselves unemployed, disabled or a homemaker are excluded from further analysis. In addition, individuals who never worked for pay or have not worked for pay since the age of 50, are considered out of the labour force and dropped from the sample.

2.3.2 Variable definitions

2.3.2.1 Mental health measures

This paper focuses on several measures of mental health. First, the Euro-D depression scale is an instrument developed by a number of European countries for screening the mental health of the elderly, and is available in SHARE. The scale is largely based on the Geriatric Mental State examination (Copeland et al. (1986)) and includes the following self-reported symptoms: indicators of being sad or depressed during the last month, pessimism, suicidal thoughts, feelings of guilt, trouble sleeping, loss of interest, loss of appetite, irritability, fatigue, poor concentration, enjoyment, and tearfulness. Each item is coded as a binary indicator, and the

[36] SHARE was designed for persons aged 50 or over at the time of the first interview, and their spouses; since some spouses are aged below 50, those are excluded from the sample.

Euro-D index is then composed as the summation of all indicators (on a 0 to 12 scale, where 0 stands for no depression indication and 12 for severe depression).

Further, since a number of European psychometric studies report two types of major components of mental health of the elderly – affective suffering and demotivation symptoms (see, e.g., Prince et al. (2004) and Castro-Costa et al. (2007)) – this paper defines two separate indices measuring those components. Following Castro-Costa et al. (2007) the index of demotivation symptoms is composed of dummies for pessimism, loss of interest, poor concentration and lack of enjoyment (0 to 4 scale), while the measure associated with affective suffering symptoms includes all the remaining items from the Euro-D index (0 to 8 scale).

Next, in view of the fact that death ideation is often associated with severe depression and increased suicide risk (see O'Riley et al. (2013)), the analysis examines the effect of retirement on this particular indicator. Lastly, the paper also looks at the individuals' self-report of feeling sad or depressed in the month before the interview.

2.3.2.2 Retirement definition

This paper employs the following definition of retirement. An individual is considered retired if: 1) s/he considers him/herself retired and reports supplying no work; or 2) s/he considers him/herself retired but may supply some part time work (i.e. works no more than 20 hours a week), and, in addition, 3) is not unemployed, disabled or a homemaker.[37] This definition is preferred as it captures the idea of retirement as a state of mind (i.e., one considers themselves retired although s/he might still be supplying some part-time work), while at the same time

[37] Individuals in SHARE, who report themselves a homemaker, are 97% female, and since they do not consider themselves either employed, unemployed or retired, this paper classifies them as not in labour force. Hence, they are excluded from further analysis.

reflecting the notion of retirement as a complete withdrawal from the labour force or a withdrawal from active work into the state of being retired.

The analysis models the effect of retirement on one's mental health in comparison to the alternative state of remaining employed. The latter category is composed of individuals who report themselves employed or self-employed; in addition, persons who consider themselves retired but continue supplying more than 20 hours of labour per week are also classified as working. These definitions of the retirement and employment states allow capturing the key aspect of the research question addressed in this paper, namely that work may be either draining or rewarding for the individual; thus, withdrawal from active labour versus continuation of active work may be either beneficial or harmful for their mental health.

The final sample after restrictions consists of 81,823 observations, of which 53.04% are males. The resulting retirement rate is roughly 62% in the total sample, and when looking at males and females separately (see Table C.2).

2.3.2.3 Social networks

As a secondary question of interest, the analysis looks at several measures of the social interactions of the elderly (all available only in wave 4). First, the size of one's social network is defined as the number of persons listed in the respondent's social network. [38] Since individuals who exit work are likely to have less contact with their former co-workers, we examine the number of persons in the social network with daily contact. Next, the respondents' overall satisfaction with their network is based on a self-rated measure on a 0 to 10 scale (where 0 stands for completely dissatisfied and 10 for completely satisfied). In addition, the paper studies the

[38] Based on the answer to the question "[…] Looking back over the last 12 months, who are the people with whom you most often discussed important things? […]".

effect of retirement on child-parent bonds by focusing on two binary indicators for presence of children in one's social network and presence of parents. Lastly, participation in voluntary work is investigated.

2.3.3 Sample statistics

Table C.3 presents the descriptive statistics for the full sample of observations, as well as for the male and female subsamples separately. 39 The mean age of the persons in the final sample is 65.8 years, with women being older by 0.5 years (significant at the 1% level). While the percentage of males and females who have reached early retirement age is roughly the same (67%), the fraction of women who have reached statutory retirement age is higher by 4.2 percentage points (pp); significant at the 1% level. Women are also less educated by 0.4 years and considerably more likely to be widowed – the difference in means equals 0.15; significant at low levels. Further, the mean number of children of the elderly is 2.1; the gender difference being statistically different from zero but small in magnitude. To complete the demographic representation, 9.3% of the females and 8.0% of the males report being born in a country other than their country of residence.

Next, examining the labour force outcomes of the elderly in SHARE shows that a somewhat higher fraction of females is retired, but the 1.2pp difference in means is not significant at the conventional levels. Amongst those who are still working, the highest fraction reports holding a job in the private sector (roughly 50% of the total sample of employed), followed by the public sector (30.0%) and self employed individuals (20.4%). Women are more

[39] Means and standard errors corrected for inverse probability weighted sampling; t-test for equality of means with equal variances reported.

likely to work in the public sector and significantly less likely to be self employed, and this pattern holds when looking at the last job history of the retirees, as well.

The lower panel of Table C.3 – mental health outcomes – depicts a vivid illustration of the gender gap in depression in Europe. To elaborate more on this, women are more likely to experience both the affective suffering symptoms and the demotivation symptoms of depression (the difference in means being significant at the 1% level for all indicators), resulting in a considerable gap in the composite Euro-D index of 0.95. The mental health measures exhibiting highest difference in means (relative to the female sample mean) are tearfulness (0.66), death ideation (0.47), and trouble sleeping (0.43). It is also worth noting that for both genders feeling sad or depressed in the last month appears to be the most common affective suffering symptom, while lack of hopes for the future is the most frequently reported demotivation symptom.

The two groups also differ in their physical health. In particular, women report more limitations to activities of daily living (0.23 vs. 018 for men) and mobility difficulties (1.79 vs. 1.09), as well as a higher number of chronic conditions (1.63 vs. 1.46); all differences are statistically significant at the 5% level. In addition, females in the sample are 4.0 pp more likely to evaluate their health as fair (vs. excellent or very good). Somewhat surprisingly, however, men appear worse when examining the indicator for hospital stays in the last year, although the difference is small in magnitude (0.7pp) and significant only at the 10% level.

Turning briefly to the social outcomes of the elderly suggests that, on average, women have better social and family connectedness – they have broader social networks and are more likely to keep a close relationship with children and parents. Yet, both groups seem equally satisfied with their social network – the difference in means while statistically significant is low in magnitude. Lastly, it is interesting to note men take higher participation in volunteering and charity work, although the difference in means is small in magnitude.

In sum, while the fractions of retired women and men in the sample are comparatively close, women appear older, more likely to be widowed and to suffer from ill health and, ultimately, in noticeably poorer psychological condition. This raises an interesting question: could retirement have a heterogeneous effect on the mental health of the two groups – possibly adversely affecting females and having a beneficial or no effect for males, or it is the unfavourable socio-demographic factors (such as loss of a spouse) which induce depressive suffering for women? Verifying either of the two possibilities requires that the effect of labour force exit is allowed to vary depending on one's individual characteristics, as well as on household characteristics and country-level indicators. We turn to this analysis in the next section.

2.4 ECONOMETRIC MODEL

Consider the following linear model of one's psychological well-being:

$$Y_{ict} = \beta_0 + \beta_1 Retired_{ict} + \boldsymbol{X}_{ict}^{OWN}\boldsymbol{\beta}_2 + X_{ict}^{HHD}\beta_3 + \boldsymbol{w}_c\,\boldsymbol{\beta}_4 + \boldsymbol{d}_t + (a_i + u_{ict}), \quad \textbf{(1)}$$

where Y represents the mental health outcome of individual i in country c at time t, and *Retired* is a binary indicator for whether the person is retired or still employed. $\boldsymbol{X}^{OWN}$ consist of individual characteristics considered to be important determinants of depression, such as old age, poor education and immigrant status, which have all typically been reported as drivers of mental suffering (Buber and Engelhardt (2006)).[40] In addition, since a number of studies found a protective effect of living with a partner and having children against depressive occurrences (Buber and Engelhardt (2006)), $\boldsymbol{X}^{OWN}$ includes the individual's marital status and whether s/he has any kids. Controls for physical health are also incorporated, as declining physical health is often thought of as a key factor for emotional distress (e.g. Beekman et al. (1997)). Lastly, $\boldsymbol{X}^{OWN}$ includes sector of employment at the current/last job as a measure of one's job characteristics.

Further, X^{HHD} consists of a household-level control for aggregate annual income (converted to EUR, PPP-adjusted, and where missing, imputed), and $\boldsymbol{w}_c$ incorporates a set of

[40] Based on the mainstream literature that supports the idea of a U-shaped relationship between age and depression (see e.g. Stone et al. (2010)), we specify age in quadratics in the model. However, since age is a key determinant of mental health we perform several robustness checks to the age functional form specification in Appendix A1.
Education is one of the most wide-ranging variables in Europe. Wave 1 and 2 in SHARE used the 1997 International Standard Classification of Education ISCED-97 to group the education variables into standardised levels of attained education. The latter are, however, not available in wave 4. For this reason, the analysis utilises number of years of schooling as a measure of education. Since these are only available in waves 2 and 4, the paper imputes years of education in wave 1 the following way: 1) for observations which appear both in waves 1 and 2, years of education in wave 1 is set to the report from wave 2; 2) for those appearing only in wave 1, years of education in wave 1 is set to the sample mean years of education in each ISCED-97 category (based on wave 2).

country dummies accounting for country-level heterogeneity, such as the cross-country differences in depression prevalence (Van de Velde (2010)). Next, $\boldsymbol{d}_t$ denotes year effects to control for the overall economic, public health and environmental conditions that play a role in one's mental health (see, e.g., Lavikainen et al. (2000)), as well as month-of-interview dummies as certain depressive symptoms exhibit a seasonal pattern. Next, the error component a_i represents time-invariant unobserved individual-level factors that could affect mental health outcomes. One such example is genetic predisposition, as recent research reported an association between certain genes and various anxiety and depression disorders (Donner et al. (2008)). Finally, u_{ict} is an idiosyncratic error component reflecting different shocks to one's mental health, such as stressful life events; e.g., illness or death in the family.

A long established econometric concern when studying the effect of retirement on one's mental health is the reverse causality between the two – while being retired might possibly impact one's mental health, depression may make an individual more likely to exit the labour force (Conti et al. (2008)). Following the identification strategy developed by Coe and Zamarro (2011) this paper uses the exogenous variation in the early and statutory retirement ages as instruments for the state of being retired. Since there are two potential instrumental variables available, two estimation methods could be employed: pooled instrumental variable (IV) estimator using either the statutory retirement age or the early retirement age as a single excluded instrument, and pooled two-stage least squares (2SLS) using both instruments. The later has been shown to be the most efficient IV estimator under certain assumptions (Wooldridge (2010)).

Formally, the first stage regression in the two-stage least squares (2SLS) estimation has the following form:

$$Retired_{ict} = \pi_0 + \boldsymbol{Z}_{ict}\boldsymbol{\pi}_1 + \boldsymbol{X}_{ict}^{OWN}\boldsymbol{\pi}_2 + X_{ict}^{HHD}\pi_3 + \boldsymbol{w}_c\boldsymbol{\pi}_4 + \boldsymbol{d}_t + \boldsymbol{\nu}_{ict}, \qquad \textbf{(2)}$$

where $\boldsymbol{Z}_{ict} = (Z_{1ict}, Z_{2ict})$ is the vector of excluded instruments. In particular, Z_{1ict} denotes a binary variable for whether person *i* in country *c* has reached the statutory retirement age as of time *t*, and Z_{2ict} – whether s/he has reached the early retirement age at that time. It is worth noting that both instruments vary across countries (as the pension eligibility ages vary between states in the EU), within countries (based on the individuals' ages), as well as across time (as some of the countries in SHARE changed the retirement eligibility ages during the period of the survey).

There are several identifying assumptions for consistency of the IV/2SLS estimator. Since the paper involves the use of a binary instrument and a binary instrumented variable, adopting the notation in the seminal work by Imbens and Angrist (1994) is convenient. Let $\boldsymbol{Y}_i$ denote a vector of all actual mental health outcomes of individual *i*, and $\boldsymbol{D}_i$ denote their actual retirement outcome (regarded as the treatment). Next, define $\boldsymbol{Y}_{i0}$ and $\boldsymbol{Y}_{i1}$ as the potential values of the outcome of interest when the binary treatment takes on values 0 and 1, respectively, and $\boldsymbol{D}_{i0}$ and $\boldsymbol{D}_{i1}$ as the level of the treatment received if the instrument takes on values 0 and 1. In this way e.g., when the instrument is the statutory retirement age Y_{ict0} stands for the potential mental health outcome of person *i* in country *c* at time *t* has s/he not reached full retirement age, while Y_{ict1} stands for the potential mental health of the individual has s/he reached that age. Likewise, D_{ict0} and D_{ict1} denote the potential retirement outcomes conditional on the value of the instrument in that country and time period.

Under this framework, the first key identifying assumption refers to the relevance of the instrument(s) and states that conditional on the observable covariates the probability of being retired should be a non-trivial function of the instrument:

$\mathbb{E}\ (\boldsymbol{D}_i \mid \boldsymbol{Z}_i\text{=k}, \cdot\ )$ is a non-trivial function of k, **(A1)**

where k ∈ {0;1} and · denotes a vector of all covariates from model (1).

In other words, reaching early or statutory retirement age should have an effect on the retirement propensity.

The second assumption is often referred to as independence of all potential outcomes of the instrument, or formally:

$\{Y_{itc0}, Y_{itc1}, D_{itc0}, D_{itc1}\} \perp \boldsymbol{Z}_{ict}$. **(A2)**

Statement (A2) incorporates two properties of the instrument: exogeneity and excludability. The first refers to the requirement that the instrument is essentially randomly assigned with respect to the composite error in that time period (put differently, this requires $\mathbb{E}(\mathbf{Z}_{\mathrm{ict}}' a_{\mathrm{i}})=0 \ \forall \ t$ and contemporaneous exogeneity of the instruments $\mathbb{E}(\mathbf{Z}_{\mathrm{ict}}' u_{\mathrm{ict}})=0 \ \forall \ t$). [41] Since the early and full retirement ages are decided at country level, there are no reasons to believe that they are related to the unobserved heterogeneity at individual level or the idiosyncratic error at that time. The second part of assumption (A2) captures the restriction that there is no direct link between the instrument and the outcome of interest. Put differently, the pension eligibility ages should not be related with an individual's psychological well-being other than through the state of being retired. Since the compulsory health insurance scheme in the EU covers major and

[41] For the countries in SHARE observed at least once, an alternative estimation strategy is available – fixed effects IV (FEIV). In contrast to pooled 2SLS, which assumes $\mathbb{E}(\mathbf{Z}_{\mathrm{ict}}' a_{\mathrm{i}})=0 \ \forall \ t$ and contemporaneous exogeneity of the instruments $\mathbb{E}(\mathbf{Z}_{\mathrm{ict}}' u_{\mathrm{ict}})=0 \ \forall \ t$, FEIV allows $\mathbb{E}(\mathbf{Z}_{\mathrm{ict}}' a_{\mathrm{i}})\neq 0$ but imposes the stronger restriction $\mathbb{E}(\mathbf{Z}_{\mathrm{icr}}' u_{\mathrm{ict}})=0, \ \forall \ r, t$ (strict exogeneity, see e.g. Wooldridge (2010)). Since the statutory and early retirement ages are decided at country level, the value of the instruments in each time period only depends on the pensionable ages in a given country and on the individual's age at that time period; hence, there is no reason to believe that $\mathbb{E}(\mathbf{Z}_{\mathrm{ict}}' a_{\mathrm{i}})=0$ would fail to hold as a_{i} only varies at individual level. It is more worrisome, however, to assume that $\mathbb{E}(\mathbf{Z}_{\mathrm{icr}}' u_{\mathrm{ict}})=0, \ \forall \ r, t$ as it would rule out the possibility that the retirement ages were changed at country level as a response to shocks in the past, which may have also affected the persons' mental health. For this reason, pooled 2SLS is the preferred estimation strategy in the paper. In addition, Appendix 3 reports the main results when model (1) is estimated under less restrictive assumptions than the ones imposed by FEIV, namely, fixed effects estimation (see Appendix A3).

minor risks for all employees and retirees, and this coverage does not discontinuously change when reaching a certain age, be that early or full retirement age,[42] one would not expect the instruments to have a direct effect on a person's mental health.[43]

The last assumption requires that the retirement probability is monotonic in the instruments:

Either $\boldsymbol{D}_{i1} \geq \boldsymbol{D}_{i0}\ \forall i$, or $\boldsymbol{D}_{i0} \geq \boldsymbol{D}_{i1}\ \forall\ i$. **(A3)**

In other words, while reaching early or statutory retirement age may have no effect on some individuals' retirement probability, all of those who are affected by the instrument should be affected in the same direction (also referred to the assumption of "no defiers"). Condition (A3) is likely to hold; in particular, it is credible that $\boldsymbol{D}_{i1} \geq \boldsymbol{D}_{i0}$ for all i, as there is no reason to believe any person would be more likely to retire while being below pensionable age but less likely thereafter.

Under assumptions (A1) through (A3), the IV estimand captures the local average treatment effect (LATE), i.e., it identifies the average treatment effect of retirement on mental health for the subpopulation of retirees whose retirement was induced by the instrument. Several important notes can be made here. First, the effect of retirement need not be the same when employing the early and statutory retirement age as an instrument since the groups affected by

[42] *Source:* Healthcare Systems in the EU: a Comparative Study, European Parliament (2010)

[43] Given that all countries in the EU set retirement ages to '[...] fundamentally follow life expectancy [...] trends' (European Commission Social Protection Committee Pension Adequacy Report 2010-2050), the statutory and early retirement ages are expected to be linked to the country-average physical health of the elderly. One might worry, then, that this implies a correlation between an individual's physical health status and the country pensionable ages as SHARE is a nationally representative survey and the national-average physical health depends on each individual's health status. However, even if excludability is an issue of concern when the outcome is individual's physical health, it is not likely to be the case when studying the effect of retirement on depression of outpatients (mental illness has been shown to lower life expectancy for inpatients due to the detrimental physical health effect of antipsychotic medication; see e.g. Crystal et al. (2009)).

each of these instruments are different. Secondly, given that the retirement eligibility ages would most likely affect planned voluntary retirement rather than involuntary retirement, the implications of the analysis are most relevant for the former. Lastly, it is worth mentioning that a usual criticism of LATE is that it often identifies an effect which is not important from a policy perspective; however, in our paper, LATE is of particular interest as it identifies an effect caused by the exact variables that could be targeted by policy-makers – the early and statutory retirement ages.

2.5 ESTIMATION RESULTS

2.5.1 First stage

2.5.1.1 Statutory and early retirement ages, and actual retirement ages in SHARE

Table C.4 shows the statutory, early and actual mean retirement ages in SHARE for each country in the sample, separately for waves 1-2 and wave 4.[44] Several observations are worth noting at this point. First, even though there has been some convergence of the statutory retirement ages towards age 65 and the early retirement ages towards age 60, some cross-country variation in those ages still exists. Secondly, on average, the post transition economies provide access to early and full retirement considerably earlier than the EU-15 and Switzerland; in addition, the new EU members are more likely to maintain different pensionable ages for women and men.

Furthermore, although not a perfect predictor of the actual ages of retirement, statutory and early retirement ages do have "bite". For instance, the country with highest statutory retirement age in Europe is Sweden, setting the full retirement age at 67 as of 2010, and it is also the country with highest actual retirement ages for men and one of the highest for women. Next, an increase of the statutory retirement age appears to result in an increase of the actual age of retirement: e.g., Italy increased this age for women from 60 to 65 years following wave 2, and saw an increase of the mean female's retirement age in the sample from 57 to 58.1 years – considerably higher than the increase for men (0.5 years). Finally, while women tend to retire earlier in all countries, the gender differential in the mean retirement ages is lower for countries

[44] The question about year of retirement was asked in waves 2 and 4 only. Year of retirement imputed for the retired individuals in wave 1 based on the report from wave 2. Retirement age derived as the difference between year of retirement and year of birth.
Waves 1 and 2 are grouped together as the main sources of information for the early and statutory retirement ages in years 2004 and 2007 report no changes in those in the period.

with equal treatment of women and men; for instance, for wave 4, this differential was 2.7 years in Poland but only 0.1 years in Sweden.

To further illustrate the link between the legislative provisions for retirement and the actual ages of retirement, it is also useful to examine the entire histogram of the ages of labour force exit. Figure C.1 to C.4 show these histograms for four of the countries in the SHARE sample – Sweden and Switzerland selected amongst the states with high statutory and early retirement ages, and the Czech Republic and Poland amongst those with low eligibility ages. It is apparent that the largest fractions of women and men in Sweden, which has equal treatment for both genders, retire at the pre-2010 statutory retirement age, and the two histograms exhibit very similar patterns (Figure C.1). Males in Switzerland also appear most likely to exit from labour when reaching full retirement age (65 years), while the largest fraction of females stops working at the early retirement age (62 years), followed by relatively equal shares of retirees at age 63 and the full retirement age, 64 (Figure C.2). Turning to the post-transition countries, Figure C.3 shows the retirement probabilities in Poland display a clear peak at the (pre-2009) early retirement age for both genders, followed by a secondary peak at the respective statutory retirement ages. Lastly, while most men in the Czech sample exit the labour force at the single early retirement age, 60, the retirement probabilities for females are high, albeit declining, for all ages 55 through 59, likely due to the linkage of retirement eligibility to number of children (Figure C.4). Overall, these examples strongly confirm that the early and statutory retirement ages strongly influence the distribution of retirement ages.

2.5.1.2 Estimation results

Tables C.6 and C.7 report the first stage estimation results separately for the male and female subsamples. Column (1a) reports estimates from Model (2) using the statutory retirement age as a single excluded instrument, column (1b) uses the early retirement age only, and column (1c) uses both instruments. Columns (2a-2c) repeat the specifications but add a binary indicator for being in bad health; this measure is potentially endogenous to mental health, but we include it to assess its effect on the estimated treatment effect of interest.

As can be seen from the table, the statutory and the early retirement ages are strong predictors of retirement for both genders. For instance, column (1a) of Table C.6 implies that having reached statutory retirement age on average increases the probability that a male has retired by 23.8 pp, *ceteris paribus*, and the effect is highly significant. The corresponding specification from Table C.7 states that reaching full retirement age would make a female 28.8 pp more likely to exit the labour force, other factors being equal. The early retirement age is also estimated to induce retirement with a high probability for both men and women (magnitudes of 0.25 and 0.28, respectively), and the effects are statistically different than zero at low levels. Essentially the same conclusions prevail when both instruments are employed, and the models are robust to the exclusion of the bad health indicator. It is also interesting to note that age appears a significant predictor of exiting work, even after accounting for reaching full and early retirement age.

Lastly, it is useful to examine the first stage F-statistic and the F-statistic on the excluded instruments as suggested by several studies (see, e.g., Stock and Yogo (2005)). In particular, a number of authors reported a correspondence between the first stage F-statistic and the bias of the IV estimator relative to the bias of the OLS estimator, and some proposed rules of thumb for evaluating the relevance of the instruments. For instance, Staiger and Stock (1997) suggested an F-statistic on the excluded instruments of at least 10. The lower panel of Tables C6 and C7 reports the non-robust and the cluster-robust F-statistic of the regression – they are considerably higher than 10 in all specifications.[45]

2.5.2 Second stage

2.5.2.1 Mental health by age distance to statutory and early retirement

Figures C.5 to C.8 illustrates the pattern of the mental health indicators[46] for men and women by age distance to statutory retirement age; in addition, a histogram of the distance between the actual and statutory retirement ages in each age group are presented. The graphs for women (depicted on the left-hand-side panels) show that the most sizeable peak in the females' retirement occurs five years prior to reaching statutory retirement age (nearly 30 percent of the actual retirement ages are in this group). In addition, a large fraction of women exit from work the year when reaching full retirement age. For men (right-hand side graphs), the majority of retirements occur at statutory age (30% of the actual retirement ages), followed by a peak five years prior this age.

Panels A and B of Figure C.5 show the mean death ideation by age category for women and men, respectively. Focusing on the changes that occur around the statutory retirement age

[45] The critical values and rules of thumb for the F-statistic on the excluded instruments are based on the assumption of i.i.d. errors. Since SHARE collects household-level country data, heteroskedasticity and serial correlation are likely to be present; for this reason, the tables also report the cluster-robust F-statistic on the excluded instruments. The related theoretical results do not extend to proposing critical values for the robust F-statistic but a recent study by Bun and De Haan (2010) used simulations and showed that a decrease in the robust F-statistic is enough to offset the increase in the IV bias relative to OLS; in other words, even values lower than 10 would suffice.

[46] The graphs do not look at the indicator for feeling sad or depressed during the month preceding the interview as this measure is particularly likely to exhibit seasonal patterns.

reveals a large improvement in this indicator for women in the years before reaching statutory retirement age when females' retirement marks a sizeable increase. Death ideation starts declining two years before the cut-off, and its mean remains at a lower level two years after full retirement age, before gradually increasing thereafter. For men, suicidal wishing is characterised by a large jump at the cut-off and no drop prior to it; in addition, the decline in this measure following full retirement age is mirrored by an almost equally sized increase the year after. Next, Figure C.6 illustrates the patterns of the demotivation measure: while this index sees a sizeable drop for females a year before reaching statutory retirement, the index for men shows a sharp increase at the cut-off. Turning to the affective suffering index (Figure C.7) shows a large decline in this measure in the years around the cut-off for women, while the improvement for men is not as striking. Lastly, the patterns in the Euro-D scale (Panels G and H on Figure C.8), point towards a substantial decline for women around the statutory retirement age, while suggesting only a minor favourable development for men following the year after reaching statutory retirement age. It is also worth noting that for women very few retirements occur two years past statutory retirement age, after which virtually all mental health indicators increase in a nearly linear fashion. The later suggests that in the absence of retirement, the drop of all depressive symptoms around statutory retirement age may not have occurred, and that, instead, mental health would have deteriorated linearly with age. A similar conclusion can be drawn for men, as well, although the improvement in emotional well-being for males being concentrated only the year after reaching statutory retirement age.

Figures C.9 to C.12 illustrates the analogous graphs for both genders by distance to early retirement age (restricting attention to 12 years around that age). The largest proportions of women and men tend to retire when they are first eligible for early retirement (the retirement age histograms reaching nearly 0.2 for women at the cut-off, and about 0.25 for men). The pattern of the mean death ideation for women (Panel A, Figure C.9) depicts an improvement when early retirement age is reached and the year after, and only a minor increase during the following six years. There is a parallel drop in this mental health measure for men, as well (Panel B, Figure C.9), occurring at early retirement age – the age when most male workers retire; however, this is followed by sharp increase thereafter. Examining the demotivation index (Panels C and D, , Figure C.10) also suggests an improvement for both genders at the time when the elderly are most likely to retire, with this improvement being more pronounced for females. The patterns of the affective suffering index and the Euro-D scale are essentially the identical at the cut-off: a large and sustained decline for women and only a temporary drop for men; the male indices also improve two years after reaching early retirement. Overall, for females all mental health measures exhibit a nearly linear upward trend starting about five years after early retirement eligibility age, after which very few retirements are observed. This implies that, in the absence of retirement, the sizeable improvement in women's emotional health around the cut-off may possibly not have occurred. A similar conclusion can be drawn for men, as well, although the mental health patterns being not as clear for this subsample.

2.5.2.2 Estimation results

2.5.2.2.1 Mental health

As shown in the previous section, both instruments – the statutory and the early retirement age – are strong predictors of retirement. In the absence of weak instrument concerns the 2SLS estimator combining both IVs provides efficiency gains; for this reason, the main part of the subsequent analysis focuses on the estimation results when using both instruments, but we will also examine second stage results based on each instrument separately.

Table C.8 to C.15 report these results for men and women, respectively, when the mental health outcome of interest is whether the person had suicidal thoughts. Table C.8 shows the pooled OLS estimates for the male sample when model (1) includes controls for age, time and country dummies only (specification (1a), as well as when employing all covariates (specification (1b). Due to suspected endogeneity of the binary indicator for being in bad health, column (1c) reports the estimation results when omitting this variable. As can be seen from here, the pooled OLS estimates suggest a statistically significant detrimental impact of a male's retirement on death ideation, *ceteris paribus*. In contrast, panels (2) to (4) of Tables C.9 to C. 11 report the parameter estimates when employing an instrumental variable estimation on the same specifications as in Panel (1). The key implication from this set of results is that once endogeneity of retirement is accounted for, a male's labour force exit does not play an important role in the occurrence of suicidal thoughts – the coefficient on retirement appears negative in sign but insignificantly different from zero in all but one specification. The only exception is the 2SLS estimate from column (4a) when both instruments are employed – it is negative 0.018 and marginally significant, but it drops in magnitude and significance once covariates are included in specifications (4b) and (4c).

Tables C.12 to C.15 reports the corresponding estimation results for the female sample. As before, the pooled OLS estimates on retirement exhibit an upward bias, although the coefficients are somewhat smaller in magnitude and significance than the ones obtained on the male sample (refer to Table C.12). Columns (2a) to (2c) of Table C.13 report the results when employing the statutory retirement age as an instrument for retirement, and the parameters on retirement have the interpretation of an average treatment effect for the female subpopulation of compliers with the full retirement age. These results imply that for women whose labour force exit is induced by the statutory retirement age, retirement reduces the occurrence of suicidal thoughts by nearly 4pp, *ceteris paribus*, and the effect is statistically significant at the 5% level. Next, specifications (3a) to (3c) of Table C.14 report the estimation results on the female subsample when the early retirement age is employed as the single excluded instrument. In these specifications, the parameters on retirement are still negative in sign but lower in magnitude and less precisely estimated, implying no important effect of labour force exit on death ideation for the women whose retirement is induced by the early retirement age. Further, Table C.15 reports the 2SLS results when both instruments are used; the average treatment effect of retirement for both groups of compliers is roughly negative 0.03, implying a beneficial effect of labour force exit on suicidal thoughts for these women (also note the considerably lower standard errors on the estimates illustrating the efficiency gain of pooled 2SLS compared to pooled IV). Lastly, it is worth noting that compared to the female sample mean of the death ideation indicator, 0.087, the estimated magnitude of the effect of retirement of 0.03 is very large.

Taken as a whole, the estimation results examined so far suggest a large and significant beneficial effect of retirement on death ideation for women but no corresponding effect for men. In addition, although this impact is significant when looking at both groups of compliers as shown by the 2SLS results, it does seem stronger for the compliers with the statutory retirement age. The next sections shall focus on the 2SLS estimation results in order to make use of the efficiency gain when employing both instruments and aiming at reporting an average treatment effect for both groups of compliers.

Tables C.16 and C.17 show the estimation results on the parameter of interest for all the remaining mental health measures. When the outcome is the composite demotivation index (the later ranges from 0 to 4, where higher values imply worse psychological well-being), the pooled OLS estimates on retirement for men (reported in Panel A of Table C.16) are positive and highly significant in all specifications. However, once retirement is instrumented by the statutory and early retirement ages, the key parameter of interest appears negative in sign and not statistically different from zero in all specifications. Turning to panel B of Table C.17, the pooled OLS estimates overall imply a detrimental effect of retirement on the composite demotivation index for women; yet, once a 2SLS estimator is employed, the impact of retirement for the females complying with the instruments appears negative in sign and statistically significant at low levels across all specifications. For instance, the estimate from column (2b), obtained when including all covariates, is -0.187, implies that, other factors equal, labour force exit has a beneficial effect on the demotivation index for women (interpreted as a local average treatment effect). Moreover, the magnitude of this effect is very large – roughly one-third of the female sample mean for this mental health indicator.

The next section of Tables C.16 and C.17 reports the second stage results for the effect of retirement on the affective suffering index (scale ranging from 0 to 8). As can be seen from here, both sets of estimation results tell a similar story – while the pooled OLS estimator implies that retirement increases the occurrence of affective suffering symptoms both for women and for men, the pooled 2SLS estimator suggests that labour force exit has no important impact on this composite mental health index for either gender.

Tables C.16 and C.17 also illustrates the estimation results when the outcome of interest is the Euro-D index. As before, the pooled OLS estimates on retirement are positive and significant for both genders, meaning that exiting the workforce worsens one's psychological well-being, *ceteris paribus*. 2SLS leads to entirely different conclusions, namely that retirement plays no significant role in determining the Euro-D index for men, but it has a favourable effect for women. The magnitude of this effect is non-negligible (0.24, based on the specification with covariates), compared to the female sample mean of the Euro-D scale, 2.78.

Lastly, we examine the results when the mental health outcome variable is a dummy for feeling sad or depressed in the month preceding the interview (reported in the lowest section of each Table C.16 and C.17). In short, while the pooled OLS estimator suggests a detrimental effect of retirement, the 2SLS estimates imply that retirement is not a significant predictor of the occurrence of sadness and depression episodes, either for women or for men. [47]

2.5.2.2.2 Social networks

This subsection of the paper uses the last wave in SHARE to estimate model (1) when the dependent variable represents a social outcome of interest rather than mental health. In particular, Y_{it} represents the size and satisfaction with one's social network; number of persons in the network with daily contact; a binary indicator for children and parents present in the network, as well as participation in voluntary work. All covariates are the same as before, except that vector X^{OWN} includes number of children rather than a dummy for having kids in all

[47] The same identification strategy could be employed to investigate the presence of spousal retirement cross-effects amongst the couple households in SHARE (21,528 couple observations). Treating spousal retirement as endogenous and instrumenting both own and spousal retirement (the later by whether spouse has reached full and early retirement age, and controlling for spousal age) reveals that, conditional on own retirement, spousal retirement has no significant impact on one's own mental health. It is also important to note that the gender heterogeneity in the effect of retirement holds when restricting the attention to couple household only – retirement significantly reduces women's death ideation (magnitude of the effect negative 0.37 in the specification with covariates) and demotivation index (magnitude negative 0.135 in the specification with covariates), while having no effect for men.

specifications but the one for volunteering, and an additional control for number of living parents when the dependent variable is presence of a parent in the respondent's social network. The model is estimated using the identification strategy described in section III in order to account for the reverse causality between retirement and social outcomes. To elaborate more on this, prior studies report that labour force exit reduces social contacts and induces social isolation (Sugisawa et al. (1997)), while at the same time social networks and interactions have been found to be significant determinants of a worker's retirement decision (Duflo and Saez (2003)). Since both the statutory and the early retirement ages are likely exogenous in a model of social outcomes and affect those outcomes only through retirement, employing them as instruments for retirement becomes an attractive estimation strategy.

The top section of Table C.18 and C.19 (panels A and B for men and women, respectively) report the estimation results when the outcome of interest is the number of persons in a respondent's immediate social network. As can be seen from here, once reverse causality between the size of one's social network and the decision to exit the labour force is accounted for, retirement decreases the number of persons in a male retiree's network by roughly 0.20 (compared to a sample mean of 2.28), while there is no analogous effect for females. A somewhat similar suggestion of an adverse effect of retirement on social contacts for men can be drawn based on the next section of Table C.18. Specifically, the 2SLS results from column (2a) imply that exiting work lessens the number of persons with daily contact amongst a male's social network, *ceteris paribus*, although, this effect is not different from zero at low significance levels once other covariates are included. Again, there is no corresponding effect for women (panel B, Table C.19). At the same time, Tables C.18 and C.19 also suggest that retirement has no significant impact on the overall satisfaction of the elderly with their social network – the parameter on retirement is low in magnitude and significance for both genders.

The next two sets of regressions look at the effect of labour force exit on child-parent bonding. In particular, Tables C.18 and C.19 reports the results from estimating model (1) on a restricted sample of elderly with at least one living child, when the outcome of interest is a binary indicator for presence of children in one's social network. The estimates imply that being a retired parent is not an important predictor of keeping a relationship with one's kids, either for women or for men. Further, Tables C.18 and C.19 show the estimation results when the dependent variable is a dummy for presence of a parent in the social network (based on the subsample of respondents with at least one living parent). Those results reveal that retirement significantly increases the probability that a female keeps contact with a parent by roughly 19pp, *ceteris paribus*. There is also some tentative evidence that men are more likely to have a parent in their social network once they exit work (column (2a) of Table C.18), but this effect drops in magnitude and significance once controls are included.

Lastly, we examine the effect of retirement on an important social activity of the elderly – volunteering. The central implication from Tables C.18 and C.19 is that labour force exit significantly increases the probability of involvement with voluntary or charitable work for both genders, *ceteris paribus*. The magnitude of this effect is 0.08 for males and 0.11 for females (based on the specifications will all covariates). This comprises large effects compared to the sample means of voluntary work (0.18 for men and 0.16 for women, respectively).

2.5.3 More on the gender heterogeneity and mechanism of the effect

In order to complete the discussion on the gender heterogeneity of the effect of retirement

Tables C.20 presents a test for equality of the parameter on retirement in model (1) by gender; in other words, they report the results from testing the hypothesis H_0: $\beta_1^{\text{Female}} = \beta_1^{\text{Male}}$. As can be seen from here, the effect of retirement on one's demotivation index is significantly different for men and women: the bootstrap estimates of this difference are large in magnitude and statistically significant (significance at the 1% level in the model with no controls, and at the 5% level in the specifications with covariates). At the same time, however, the test cannot reject the null that the coefficient on retirement is the equal for both genders when the outcome of interest is any other psychological well-being measure, or a measure of the social connectedness of the elderly (in the later case the comparison is further complicated by the reduced sample size and lower estimation precision). Overall, this provides further support for the idea of gender heterogeneity of the effect of labour force exit on mental health measured by the composite demotivation index.

Before concluding, the paper addresses an issue which has been largely overlooked by previous research: does the mechanism of the effect of retirement on one's mental health go through their social network? This may be the case as retirement was shown to affect the social connectedness of the elderly – it narrows down a male retiree's social network, while having no effect for females, which may potentially explain why labour force exit appears beneficial for women's mental health but not for men's. In addition, females in the sample have better social connectedness overall, and better relations with children in particular, both of which have been hypothesised to lower depression rates. Lastly, exiting work was revealed to increase volunteering of the elderly, which has in turn been linked to lower depression rates (Lum and Lightfood (2005)). We proceed by estimating model (1) from section III on the last wave of data and include a number of social inclusion measures, such as size of the social network, children in the network and volunteering. We then examine the resulting change in the estimated effect of retirement, compared to the model with no controls for social networks.

The results are reported in Tables C.20 to C.26. It is evident that the model is robust to inclusion of social network size and presence of children in the network for both genders. However, the parameter on women's retirement drops both in magnitude and in significance when volunteering is included in the regressions for the demotivation and Euro-D measures (columns (2d) of Table C.22 column and (3d) of Table C.23), but not in the model for death ideation. For the male sample, the effect of labour force exit on the death ideation and demotivation index also changes in significance once volunteering is controlled (column (2d) of Table C.22); yet, the magnitude of these changes is essentially zero.

Based on the above results, this paper fails to find any evidence that the effect of workforce exit on a person's mental health goes through altering their social network; however, the analysis suggests that, at least in part, the beneficial effect of retirement on the composite Euro-D and demotivation indices for women is explained by the increase in volunteering following their labour force exit.

2.6 CONCLUDING REMARKS

This study utilised household-level multinational data from 17 countries in Europe to explore the effects of labour force exit on the mental health of the elderly. Following the identification strategy developed by Coe and Zamarro (2011) the paper explored the exogenous variation in the retirement propensity of the older workers, induced by the national statutory and early retirement ages. Consistent with the findings of Coe and Zamarro (2011) the analysis presented here provides support for the idea that retirement has no significant impact on men's psychological well-being, other factors being equal. At the same time, however, this study finds evidence for a beneficial effect of retirement on women's emotional health, which is an important contribution to the literature. In particular, exiting the workforce is predicted to decrease the likelihood that a female has suicidal thoughts by about 3pp, *ceteris paribus*, and to improve her mental health as measured by the composite demotivation and Euro-D depression scores. The magnitude of this effect is large for the death ideation and demotivation indicators, while relatively low for the Euro-D index. Lastly, there is no evidence that retirement plays an important role on the occurrence of a recent depressive episode and on the composite affective depression measure for either gender.

The central estimates also uncover a role for retirement on the social contacts of older adults. In particular, the analysis presented evidence that exiting work decreases the size of the immediate social network for male retirees (in agreement with the findings of Sugisawa et al. (1997)) with no corresponding effect for women. Moreover, retirement significantly increases the probability of a parent present in the social network for females, but not for males. Lastly, the paper found no evidence that retirement induces self-perceived social isolation – exit from work has no significant impact on one's overall satisfaction with their social network, and has a beneficial effect on volunteering for both genders.

The implications of these findings are twofold. First, the finding retirement affects the mental health of men and women differently, is in line with contemporary theories in the psychology literature suggesting a differential impact of employment on a female's and a male's emotional well-being. Secondly, the results in this paper have potentially important policy implications. Specifically, the lack of an important impact of labour force exit on men's psychological health implies that the recent trends in the EU towards increasing the statutory and early ages of retirement would lead to no detrimental consequences for their mental health, and may have a favourable impact on their social connectedness. At the same time, however, the existence of a beneficial effect of retirement on women's psychological well-being and relationship with parents, cannot rule out the possibility that increasing the pensionable ages – as well as equalizing those ages across gender – would lead to a loss of social welfare for women.

APPENDICES

APPENDIX C

MAIN TABLES AND FIGURES

Table C.1: Country representation

Country	Fraction of total sample		
	wave 1	wave 2	wave 4
Austria	0.068	0.037	0.092
Germany	0.117	0.082	0.026
Sweden	0.141	0.106	0.037
Netherlands	0.088	0.068	0.039
Spain	0.062	0.049	0.041
Italy	0.081	0.079	0.052
France	0.117	0.093	0.100
Denmark	0.071	0.093	0.044
Greece	0.090	0.083	NA
Switzerland	0.040	0.048	0.070
Belgium	0.124	0.084	0.080
Czech Republic	NA	0.108	0.125
Poland	NA	0.070	0.024
Hungary	NA	NA	0.053
Portugal	NA	NA	0.034
Slovenia	NA	NA	0.047
Estonia	NA	NA	0.136
Total	**18,632**	**22,257**	**40,934**

Table C.2: Labour force status by gender

Labour force status	Number of observations			Employment / retirement rate		
	Males	Females	Total	Males	Females	Total
Employed	16,372	14,610	30,982	37.7%	38.0%	37.9%
Retired	27,028	23,813	50,841	62.3%	62.0%	62.1%
Total	**43,400**	**38,423**	**81,823**	**100.00%**	**100.0%**	**100.0%**

Note: sample restricted to individuals for whom the main variables of interest are not missing.

Table C.3: Sample statistics

Characteristic	Total sample	Male subsample	Female subsample
Demographic			
Age	65.790 (0.070)	65.574 (0 .092)	66.053 (0.108)
Male	0.530 (0.499)	1.000	0.000
Has reached statutory retirement age	0.540 (0.003)	0.521 (0.004)	0.563 (0.005)
Has reached early retirement age	0.672 (0.003)	0.671 (0.004)	0.673 (0.005)
Education (in years)	10.832 (0.027)	11.021 (0 .039)	10.603 (0.039)
Marital status			
Married /partnered	0.719 (0.449)	0.819 (0.384)	0.605 (0.488)
Divorced / separated	0.092 (0.289)	0.068 (0.251)	0.119 (0.324)
Widowed	0.133 (0.339)	0.063 (0.244)	0.212 (0.408)
Never married	0.056 (0.229)	0.049 (0.216)	0.063 (0.243)
Number of children	2.075 (0.010)	2.128 (0.013)	2.010 (0.015)
Foreign country of birth	0.087 (0.001)	0.080 (0.002)	0.093 (0.003)
Labour force status and employment history			
Retired (vs. still employed)	0.618 (0.003)	0.611 (0.004)	0.627 (0.004)
Current job in the public sector (conditional on being employed)	0.299 (0.005)	0.256 (0.006)	0.353 (0.007)
Current job in the private sector (conditional on being employed)	0.497 (0.005)	0.503 (0.008)	0.489 (0.008)

Notes: 1) Means corrected for inverse probability weighed sampling; linearised standard errors reported in parentheses. **2)** Social networks available for wave 4 only. Number of observations: 21,394 men and 21,416 women.

Table C.3 (cont'd)

Current job as self employed (conditional on being employed)	0.204 (0.004)	0.240 (0.006)	0.157 (0.006)
Last job in the public sector (conditional on being retired)	0.314 (0.003)	0.290 (0.004)	0.343 (0.005)
Last job in the private sector (conditional on being retired)	0.519 (0.004)	0.545 (0.005)	0.489 (0.006)
Last job as self employed (conditional on being retired)	0.166 (0.002)	0.165 (0.003)	0.168 (0.004)
Mental health			
Affective suffering symptoms			
Felt sad or depressed last month	0.378 (0.003)	0.287 (0.004)	0.489 (0.004)
Felt would rather be dead	0.065 (0.001)	0.046 (0.001)	0.087 (0.002)
Tearfulness	0.221 (0.002)	0.117 (0.003)	0.348 (0.004)
Feelings of guilt	0.211 (0.002)	0.173 (0.003)	0.258 (0.004)
Trouble sleeping	0.314 (0.003)	0.234 (0.003)	0.411 (0.004)
Loss of appetite	0.074 (0.001)	0.060 (0.002)	0.091 (0.002)
Irritability	0.277 (0.003)	0.263 (0.004)	0.294 (0.004)
Fatigue	0.316 (0.003)	0.266 (0.004)	0.377 (0.004)
Affective suffering symptoms index (0 to 8)	1.731 (0.012)	1.343 (0.013)	2.202 (0.019)
Demotivation symptoms			
Pessimism (no hopes for the future)	0.157 (0.002)	0.148 (0.003)	0.169 (0.003)
Loss of interest	0.076 (0.001)	0.065 (0.002)	0.090 (0.002)
Poor concentration (reading)	0.143 (0.002)	0.131 (0.002)	0.158 (0.003)
Feels no enjoyment	0.132 (0.002)	0.125 (0.002)	0.142 (0.003)
Demotivation symptoms index (0 to 4)	0.488 (0.005)	0.451 (0.007)	0.534 (0.008)

Table C.3 (cont'd)

Euro-D depression index (0 to 12)	2.262 (0.014)	1.832 (0.017)	2.784 (0.023)
Physical health			
Number of limitations to activities of daily living (0 to 6)	0.205 (0.005)	0.183 (0.006)	0.231 (0.008)
Number of chronic conditions (0 to 12)	1.539 (0.009)	1.462 (0.012)	1.633 (0.014)
Bad health (self report of less than very good health)	0.755 (0.003)	0.734 (0.004)	0.774 (0.004)
Mobility, arm function and fine motor limitations (0 to 10)	1.407 (0.014)	1.091 (0.016)	1.791 (0.024)
Hospital stay in the last 12 months	0.144 (0.002)	0.147 (0.003)	0.140 (0.003)
Social networks			
Size of the immediate social network (number of persons)	2.506 (0.019)	2.346 (0.027)	2.688 (0.027)
Number of persons in the social network with daily contact	1.208 (0.012)	1.231 (0.016)	1.182 (0.018
Social network satisfaction (0 to 10)	8.757 (0.018)	8.723 (0.024)	8.796 (0.027)
Children in the social network (conditional on having a living child)	0.597 (0.006)	0.532 (0.009)	0.670 (0.008)
Parents in the social network (conditional on having a living parent)	0.321 (0.016)	0.309 (0.026)	0.332 (0.019)
Done voluntary or charity work (last year)	0.173 (0.004)	0.184 (0.007)	0.161 (0.006)
No. observations	**81,823**	**43,400**	**38,423**

Table C.4: Statutory, early and actual retirement ages by country and gender (wave 1 & 2)

Country	Wave 1 & 2 (interview year 2004 & 2007)					
	Early retirement age		Statutory retirement age		Actual mean retirement age	
	Male	Female	Male	Female	Male	Female
Austria [48]	60	57	65	60	58.4	56.7
Belgium	60	60	65	64	60.1	58.7
Czech Rep [49]	60	59	61y 10m	60	59.4	55.9
Denmark [50]	65	65	65	65	62.8	62.5
Estonia	NA	NA	NA	NA	NA	NA
France [51]	56	56	60	60	59.2	59.4
Germany [52]	63	63	65	65	61.0	60.0
Greece [53]	55	55	65	60	60.3	60.4
Hungary [54]	NA	NA	NA	NA	NA	NA
Italy	57	57	65	60	58.1	57.0
Netherlands	60	60	65	65	61.1	60.4
Poland [55]	60	55	65	60	59.6	57.3
Portugal	NA	NA	NA	NA	NA	NA
Slovenia	NA	NA	NA	NA	NA	NA
Sweden	61	61	65	65	62.3	61.6
Switzerland	63	62	65	64	63.1	61.7
Spain	60	60	65	65	61.3	61.4
No. observations (retired individuals)					**13,207**	**9,984**

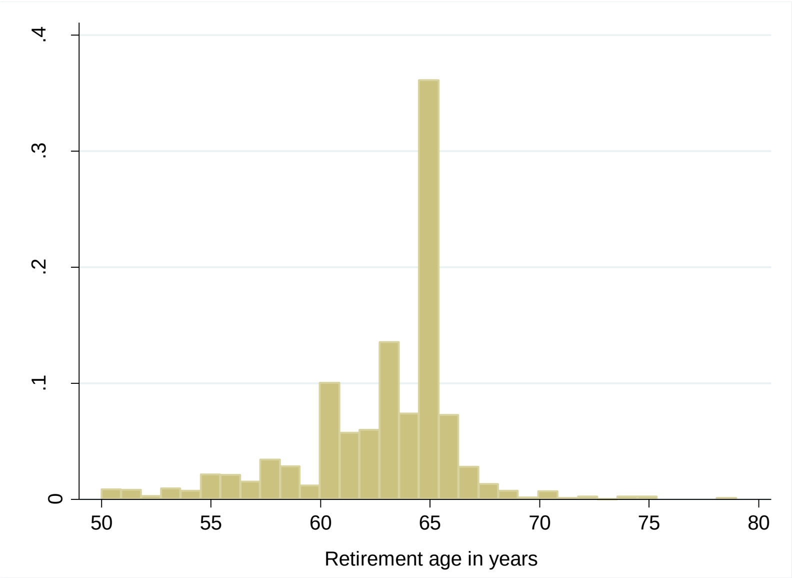
[48] Statutory retirement age 61.5 years in the public sector; values 65 and 60 are assigned to all men/women in the sample regardless of sector.
[49] Statutory and early retirement age reduced by one year for women for each child up to the 4th; value of 60 and 59 for the statutory/early retirement age assigned to all women in the sample.
[50] No option for early retirement provided in Denmark; value of the early retirement age set to equal the statutory retirement age.
[51] Early retirement age linked to the number of years of contribution; value of 56 assigned to the entire sample.
[52] Statutory retirement age increased to 65 years, 1 month as of Jan 1, 2012; gradual increase by one month every year planned until reaching age 67.
[53] Early retirement age linked to the number of years of contribution; value of 56 assigned to the entire sample.
[54] Early retirement age reduced by one year for each additional five-year period (men) or four-year period (women) of hazardous or unhealthy work. Age 60 assigned to the entire sample.
[55] Access to early retirement abolished after 2008; value of the early retirement age in wave 4 set to equal the statutory retirement age.

Table C.5: Statutory, early and actual retirement ages by country and gender (wave 4)

Country	Wave 4 (interview year 2011)					
	Early retirement age		Statutory retirement age		Actual mean retirement age	
	Male	Female	Male	Female	Male	Female
Austria	62	60	65	60	59.1	57.7
Belgium	60	60	65	65	60.2	59.2
Czech Rep	60	59	61y 10m	60	59.9	56.2
Denmark	65	65	65	65	62.8	62.3
Estonia	60	57y 6 m	63	60y 6m	62.5	60.0
France	56	56	62	62	59.1	59.5
Germany	63	63	65	65	61.2	60.7
Greece	NA	NA	NA	NA	NA	NA
Hungary	60	60	62	62	58.2	56.2
Italy	57	57	65	65	58.7	58.1
Netherlands	60	60	65	65	61.5	61.1
Poland	65	60	65	60	59.5	56.8
Portugal	55	55	65	65	60.4	60.4
Slovenia	58	58	63	61	58.5	55.5
Sweden	61	61	67	67	62.6	62.5
Switzerland	63	62	65	64	63.2	61.8
Spain	60	60	65	65	61.9	61.5
No. observations (retired individuals)					**13,821**	**13,829**

Figure C.1: Retirement age histograms (Sweden)

Men



Women

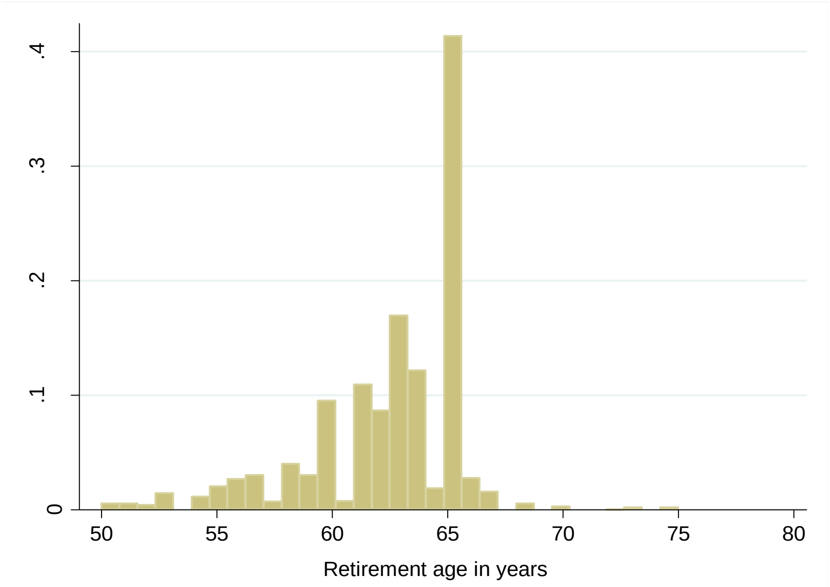
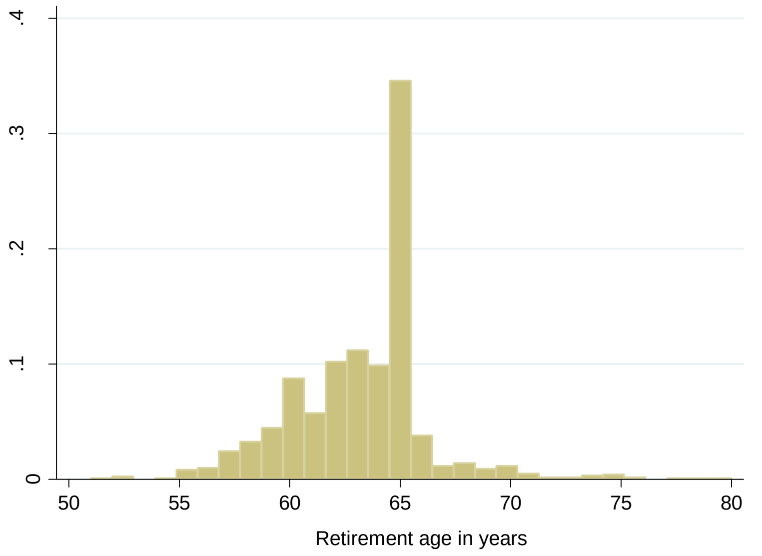


Figure C.2: Retirement age histograms (Switzerland)

Men



Women

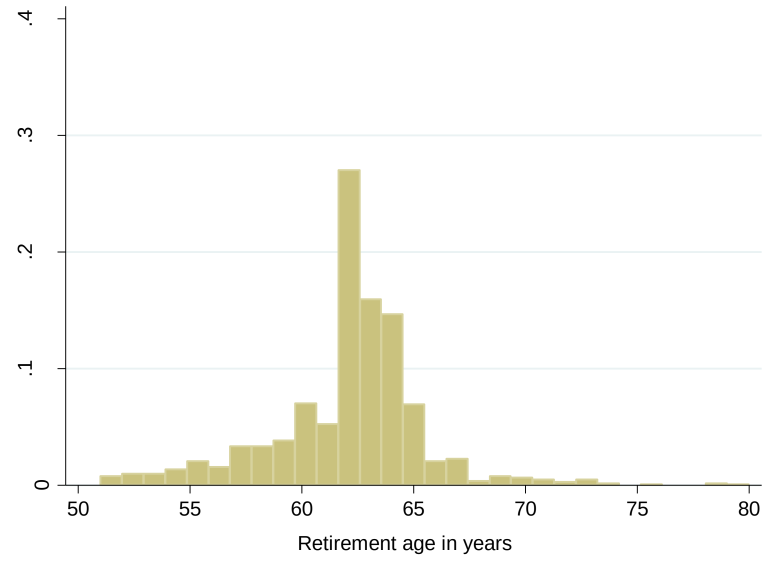
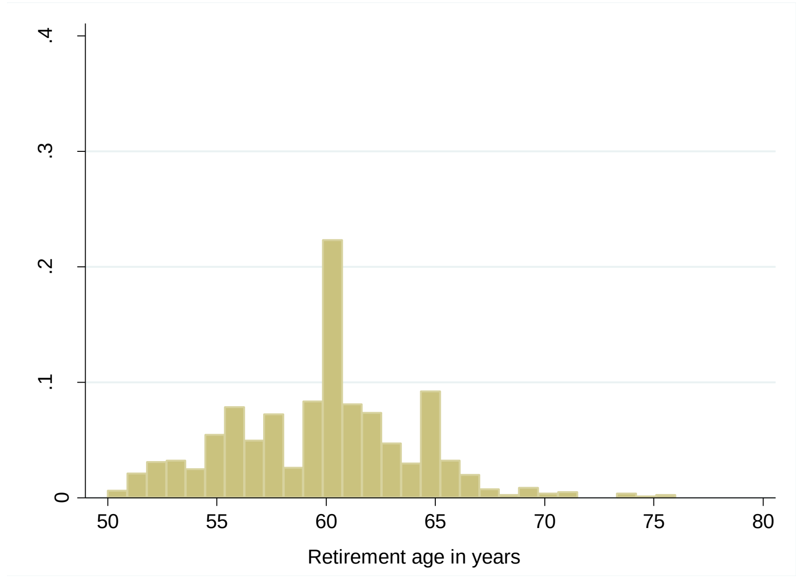


Figure C.3: Retirement age histograms (Poland)

Men



Women

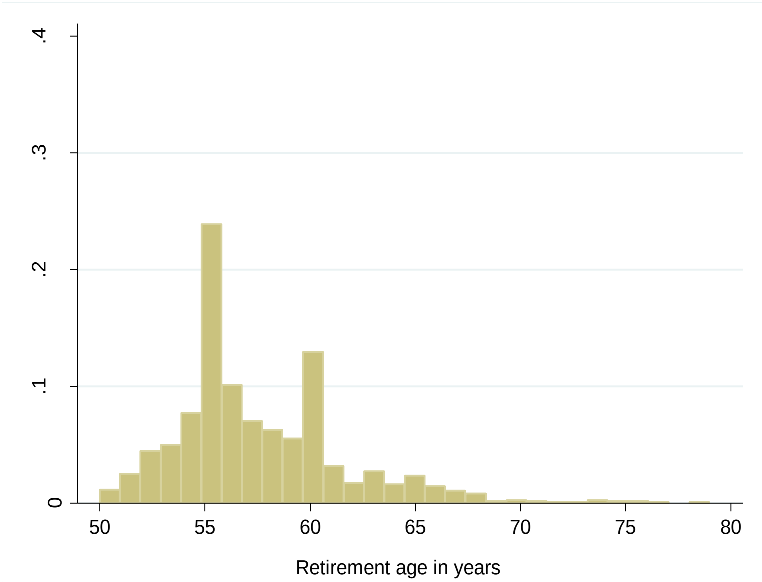
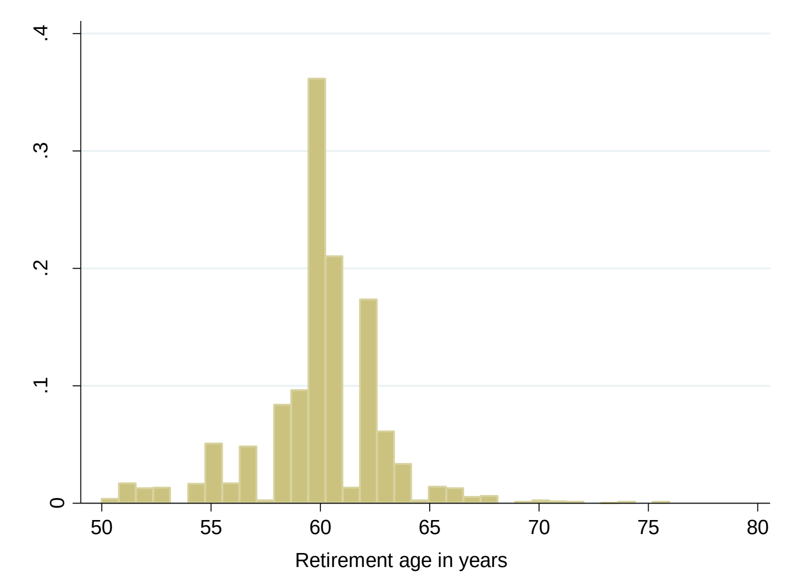


Figure C.4: Retirement age histograms (Czech Republic)

Men



Women

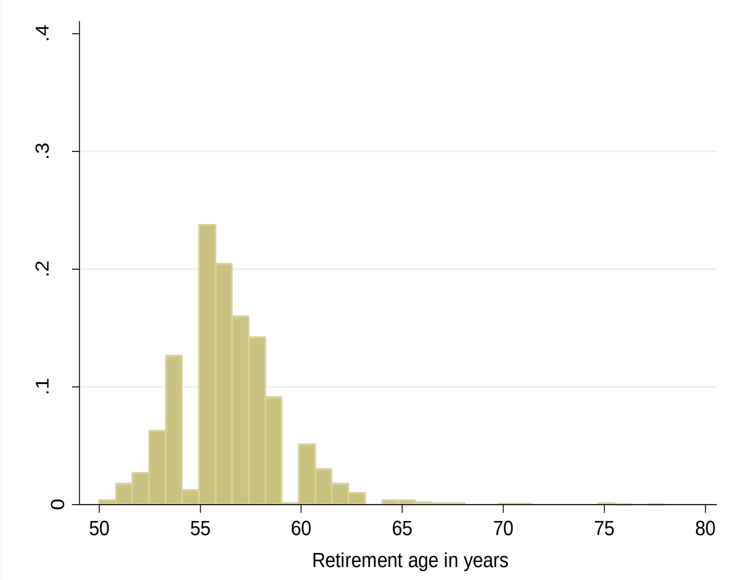


Table C.6: First stage estimation results (men)

Outcome: retired (vs. still employed)	Sample restricted to men					
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Has reached statutory retirement age	0.238*** (0.016)		0.215*** (0.015)	0.238*** (0.016)		0.215*** (0.015)
Has reached early retirement age		0.249*** (0.019)	0.224*** (0.017)		0.249*** (0.019)	0.224*** (0.018)
Age (in years)	0.178*** (0.005)	0.155*** (0.006)	0.119*** (0.006)	0.178*** (0.005)	0.155*** (0.006)	0.120*** (0.006)
Age (in years), squared	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Education (in years)	0.003** (0.001)	0.000 (0.001)	0.001 (0.001)	0.002* (0.001)	0.000 (0.001)	0.001 (0.001)
Education (in years), squared	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)

Notes:

1) All specifications control for: year, month and country dummies, and aggregate household income. Models estimated by pooled OLS.

2) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

3) Omitted category for variable marital status: separated/divorced; omitted category for variable current/last sector of employment: self employed.

Table C.6 (cont'd)

Married/partnered	0.023*** (0.006)	0.022*** (0.006)	0.023*** (0.006)	0.023*** (0.006)	0.022*** (0.006)	0.023*** (0.006)
Never married	0.011 (0.009)	0.010 (0.009)	0.009 (0.009)	0.012 (0.009)	0.011 (0.009)	0.010 (0.009)
Widowed	0.020*** (0.007)	0.012 (0.008)	0.017** (0.007)	0.020*** (0.007)	0.012 (0.008)	0.017** (0.007)
Has bad health	0.029*** (0.004)	0.029*** (0.004)	0.029*** (0.004)			
Has any kids	0.004 (0.006)	0.002 (0.006)	0.001 (0.006)	0.004 (0.006)	0.002 (0.006)	0.001 (0.006)
Hospital stay (last 12 months)	0.017*** (0.004)	0.018*** (0.004)	0.017*** (0.004)	0.021*** (0.004)	0.022*** (0.004)	0.021*** (0.004)
Foreign born	0.001 (0.006)	0.003 (0.006)	0.000 (0.006)	0.002 (0.006)	0.004 (0.006)	0.001 (0.006)
Public sector of employment (last / current job)	0.128*** (0.006)	0.125*** (0.006)	0.125*** (0.005)	0.129*** (0.006)	0.126*** (0.006)	0.126*** (0.005)
Private sector of employment (last / current job)	0.107*** (0.005)	0.106*** (0.005)	0.105*** (0.005)	0.108*** (0.005)	0.107*** (0.005)	0.106*** (0.005)
Intercept	-6.275*** (0.192)	-5.650*** (0.213)	-4.296*** (0.205)	-6.279*** (0.191)	-5.652*** (0.213)	-4.301*** (0.205)
First stage F statistic (cluster-robust)	**515.84**	**539.92**	**800.36**	**525.81**	**548.18**	**808.58**
F statistic on the excluded instruments (cluster-robust)	**211.09**	**177.71**	**279.95**	**210.39**	**177.51**	**278.17**
F statistic on the excluded instruments (non-robust)	**1,963.76**	**1,861.05**	**1,787.45**	**1,951.89**	**1,856.55**	**1,779.37**
No. observations	**43,291**	**43,291**	**43,291**	**43,315**	**43,315**	**43,315**
R-squared	**0.65**	**0.65**	**0.66**	**0.65**	**0.65**	**0.66**

Table C.7: First stage estimation results (women)

Outcome: retired (vs. still employed)	Sample restricted to women					
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Has reached statutory retirement age	0.288*** (0.021)		0.231*** (0.022)	0.289*** (0.021)		0.231*** (0.022)
Has reached early retirement age		0.278*** (0.022)	0.208*** (0.023)		0.277*** (0.022)	0.207*** (0.023)
Age (in years)	0.162*** (0.006)	0.150*** (0.007)	0.118*** (0.007)	0.162*** (0.006)	0.151*** (0.007)	0.119*** (0.007)
Age (in years), squared	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Education (in years)	0.004*** (0.002)	0.002 (0.002)	0.003* (0.001)	0.004*** (0.002)	0.002 (0.002)	0.002* (0.001)
Education (in years), squared	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)

Notes:

1) All specifications control for: year, month and country dummies, and aggregate household income. Models estimated by pooled OLS.

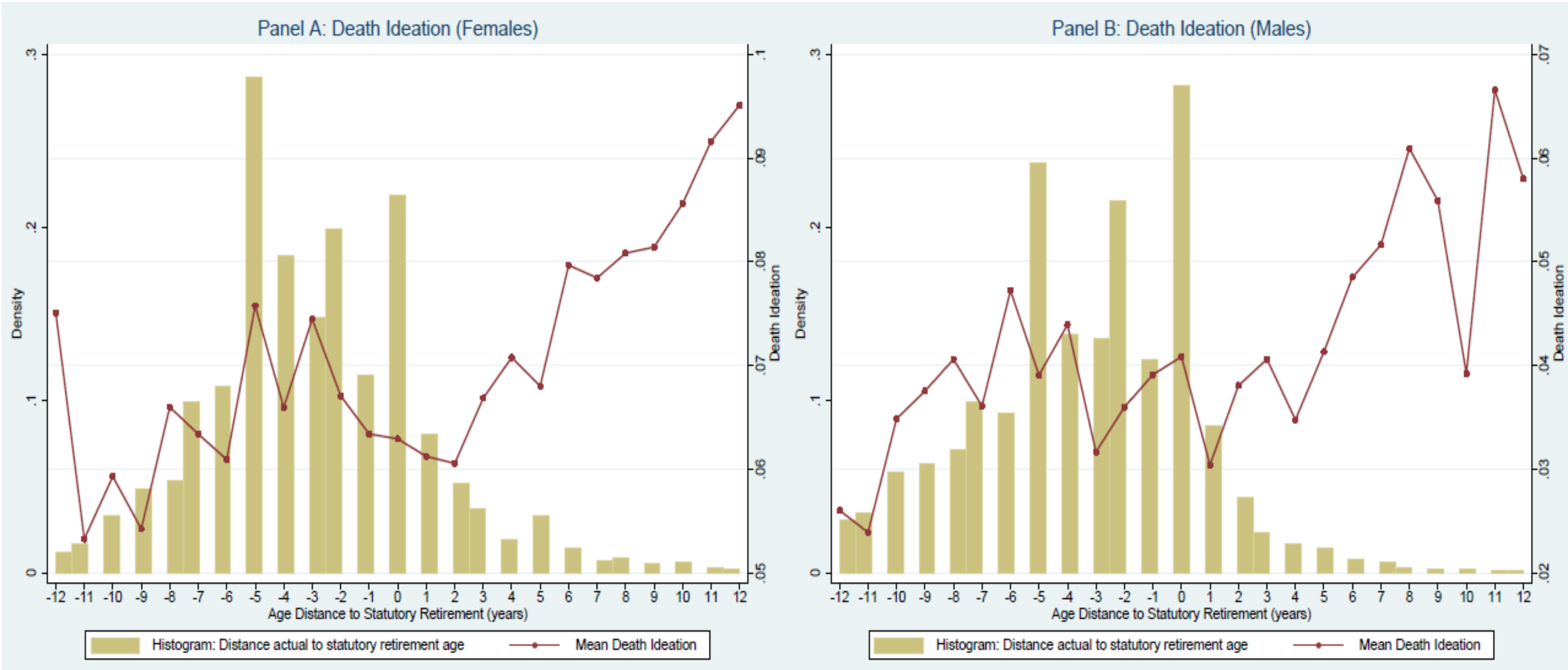
2) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

3) Omitted category for variable marital status: separated/divorced; omitted category for variable current/last sector of employment: self employed.

Table C.7 (cont'd)

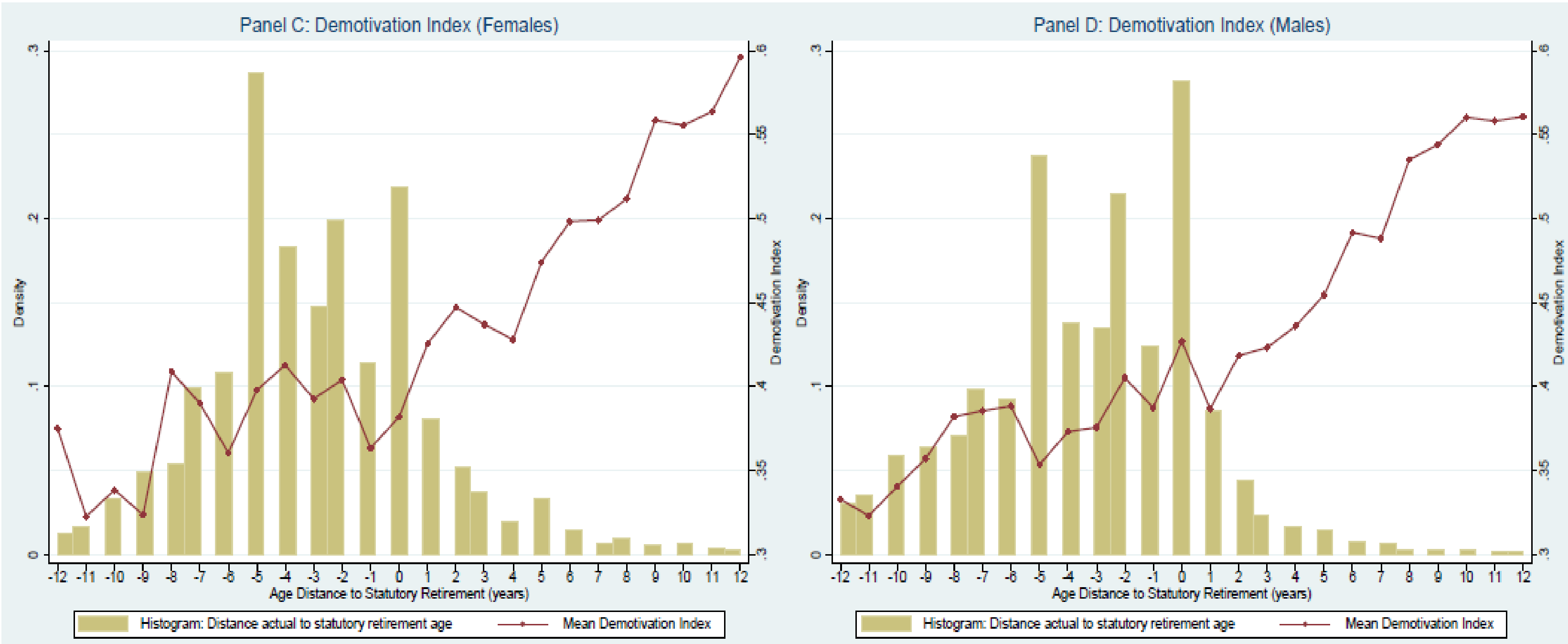
Married/partnered	0.032*** (0.005)	0.031*** (0.005)	0.031*** (0.005)	0.032*** (0.005)	0.031*** (0.005)	0.031*** (0.005)
Never married	0.008 (0.008)	0.007 (0.009)	0.006 (0.008)	0.007 (0.008)	0.007 (0.009)	0.006 (0.008)
Widowed	0.010* (0.005)	0.010* (0.006)	0.011** (0.005)	0.010* (0.005)	0.009* (0.006)	0.011* (0.006)
Has bad health	0.031*** (0.004)	0.032*** (0.004)	0.031*** (0.004)			
Has any kids	-0.005 (0.005)	-0.007 (0.005)	-0.007 (0.005)	-0.005 (0.005)	-0.007 (0.005)	-0.007 (0.005)
Hospital stay (last 12 months)	0.014*** (0.004)	0.014*** (0.004)	0.015*** (0.004)	0.018*** (0.004)	0.018*** (0.004)	0.019*** (0.004)
Foreign born	-0.006 (0.006)	-0.005 (0.006)	-0.005 (0.006)	-0.005 (0.006)	-0.004 (0.006)	-0.004 (0.006)
Married/partnered	0.081*** (0.006)	0.076*** (0.006)	0.078*** (0.006)	0.081*** (0.006)	0.076*** (0.006)	0.078*** (0.006)
Never married	0.071*** (0.005)	0.069*** (0.006)	0.068*** (0.005)	0.072*** (0.005)	0.069*** (0.006)	0.069*** (0.005)
Intercept	-5.582*** (0.218)	-5.274*** (0.233)	-4.082*** (0.227)	-5.750*** (0.229)	-5.460*** (0.238)	-4.263*** (0.230)
First stage F statistic (cluster-robust)	**467.93**	**435.22**	**598.15**	**477.91**	**444.90**	**609.45**
F statistic on the excluded instruments (cluster-robust)	**188.91**	**153.34**	**186.46**	**189.76**	**153.21**	**187.40**
F statistic on the excluded instruments (cluster-robust)	**2,639.01**	**2,215.51**	**1,953.00**	**2,639.40**	**2,207.36**	**1,950.08**
No. observations	**38,085**	**38,085**	**38,085**	**38,105**	**38,105**	**38,105**
R-squared	**0.68**	**0.68**	**0.69**	**0.68**	**0.68**	**0.69**

Figure C.5: Mental health by age distance to statutory retirement age (death ideation)



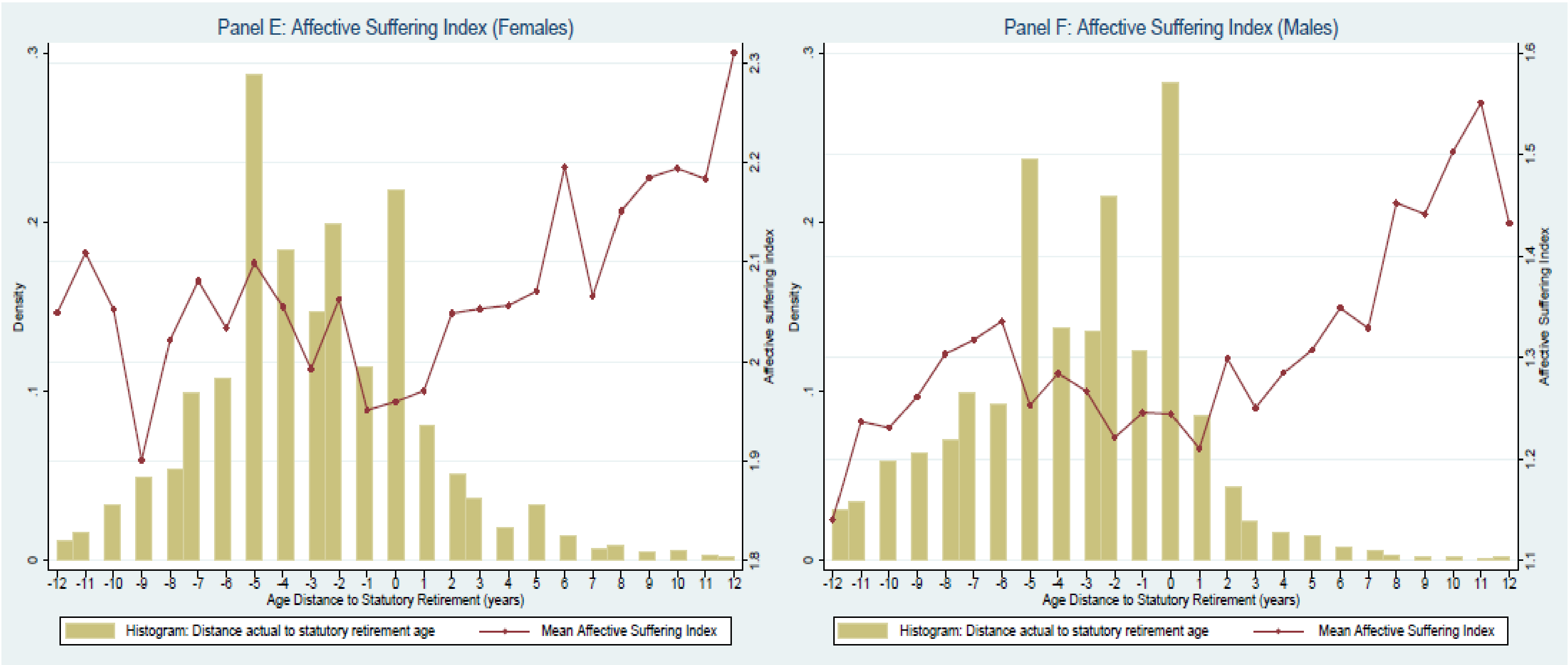
Note: Distance to statutory retirement age computed as the difference between the person’s age and the statutory retirement age in his/her country of residence, and rounded to integer.

Figure C.6: Mental health by age distance to statutory retirement age (demotivation index)



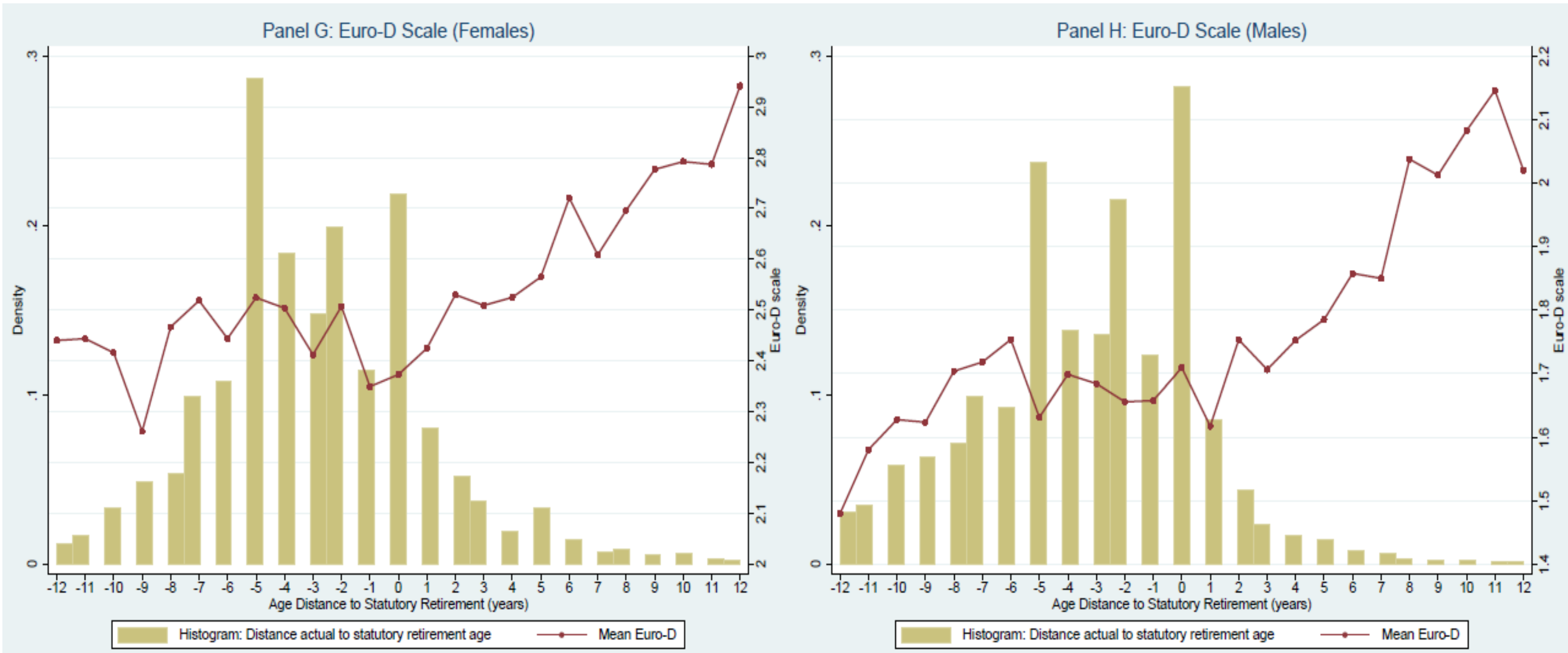
Note: Distance to statutory retirement age computed as the difference between the person's age and the statutory retirement age in his/her country of residence, and rounded to integer.

Figure C.7: Mental health by age distance to statutory retirement age (affective suffering index)



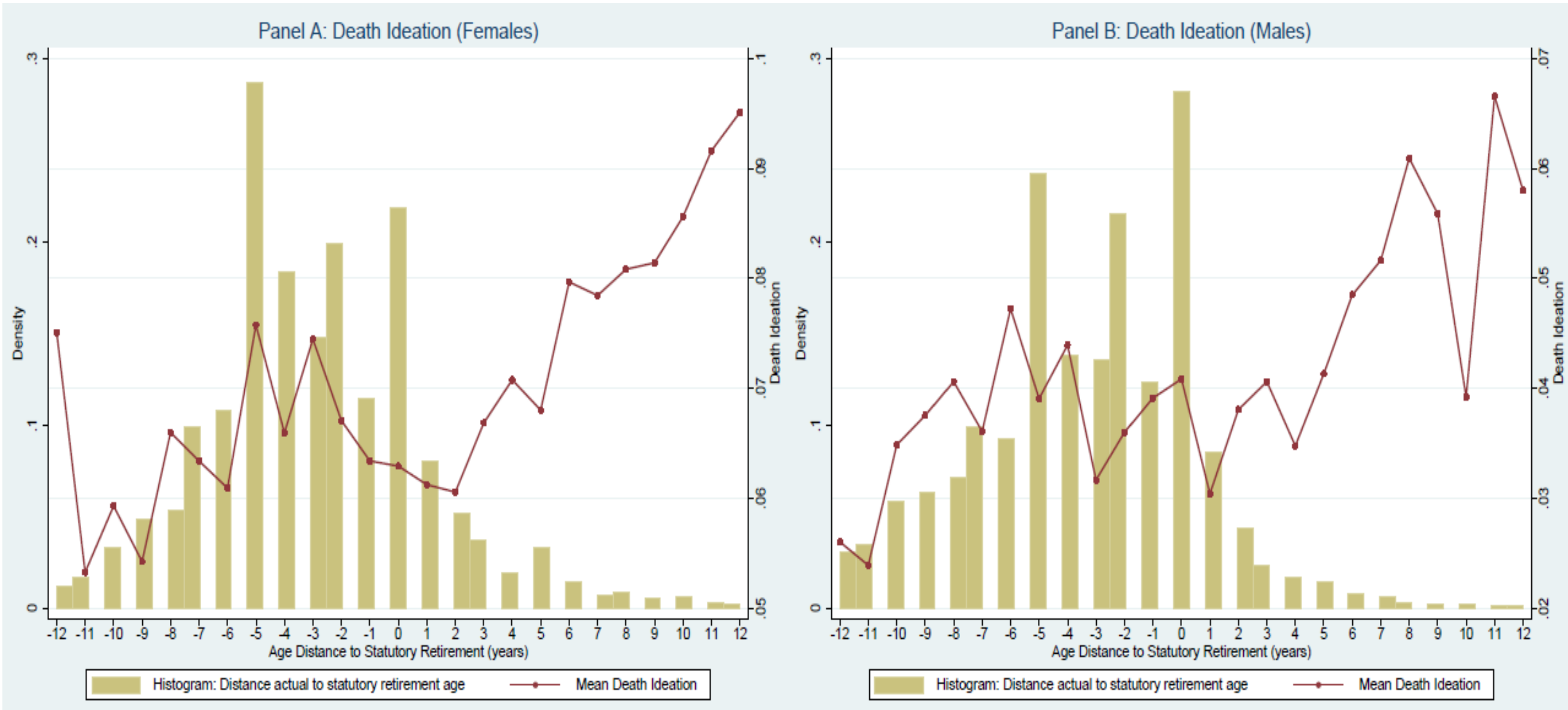
Note: Distance to statutory retirement age computed as the difference between the person's age and the statutory retirement age in his/her country of residence, and rounded to integer.

Figure C.8: Mental health by age distance to statutory retirement age (Euro-D scale)



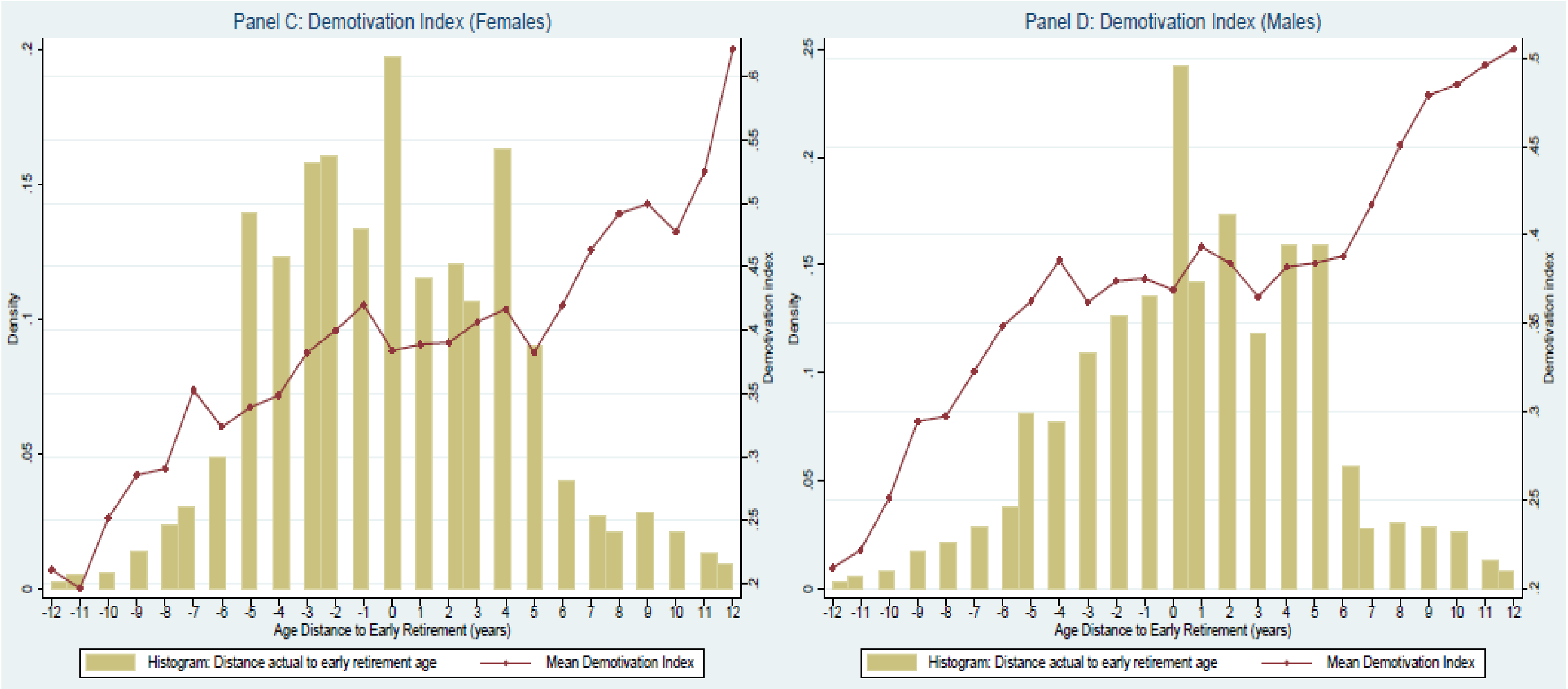
Note: Distance to statutory retirement age computed as the difference between the person's age and the statutory retirement age in his/her country of residence, and rounded to integer.

Figure C.9: Mental health by age distance to early retirement age (death ideation)



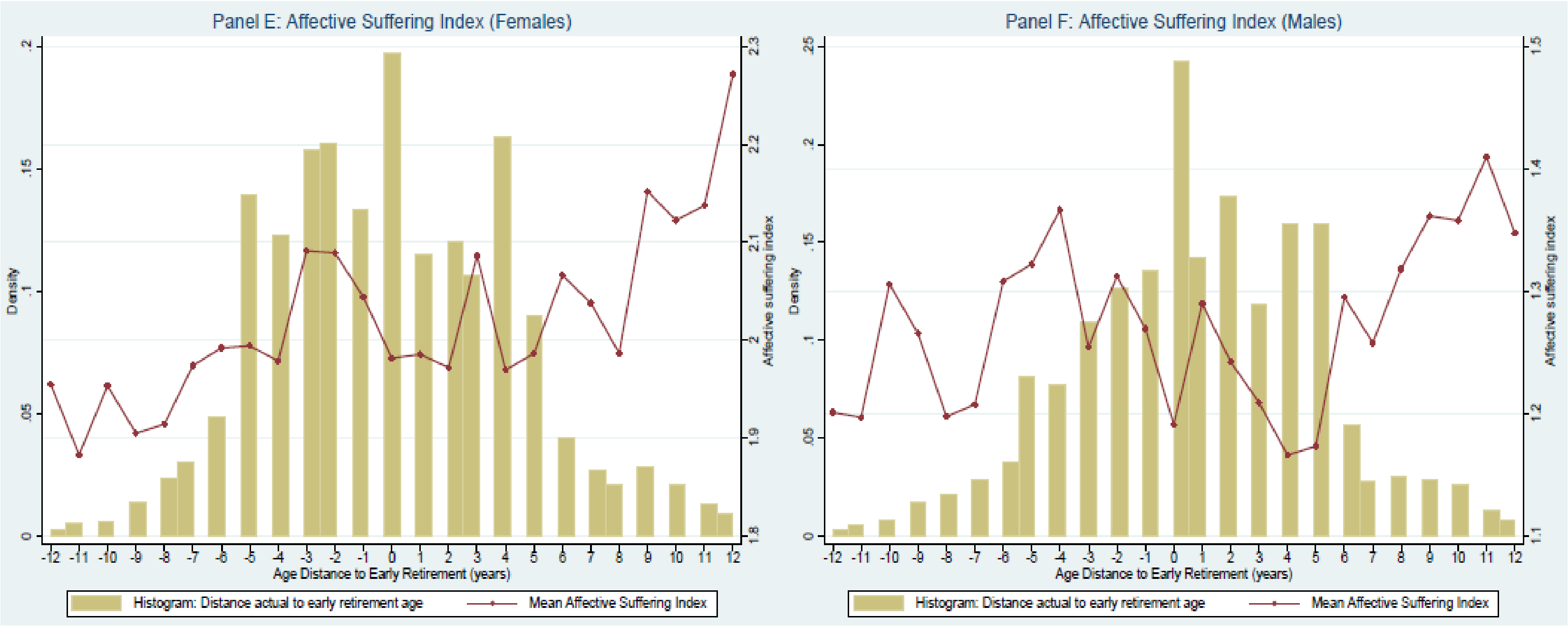
Note: Distance to early retirement age computed as the difference between the person's age and the early retirement age in his/her country of residence, and rounded to integer.

Figure C.10: Mental health by age distance to early retirement age (demotivation index)



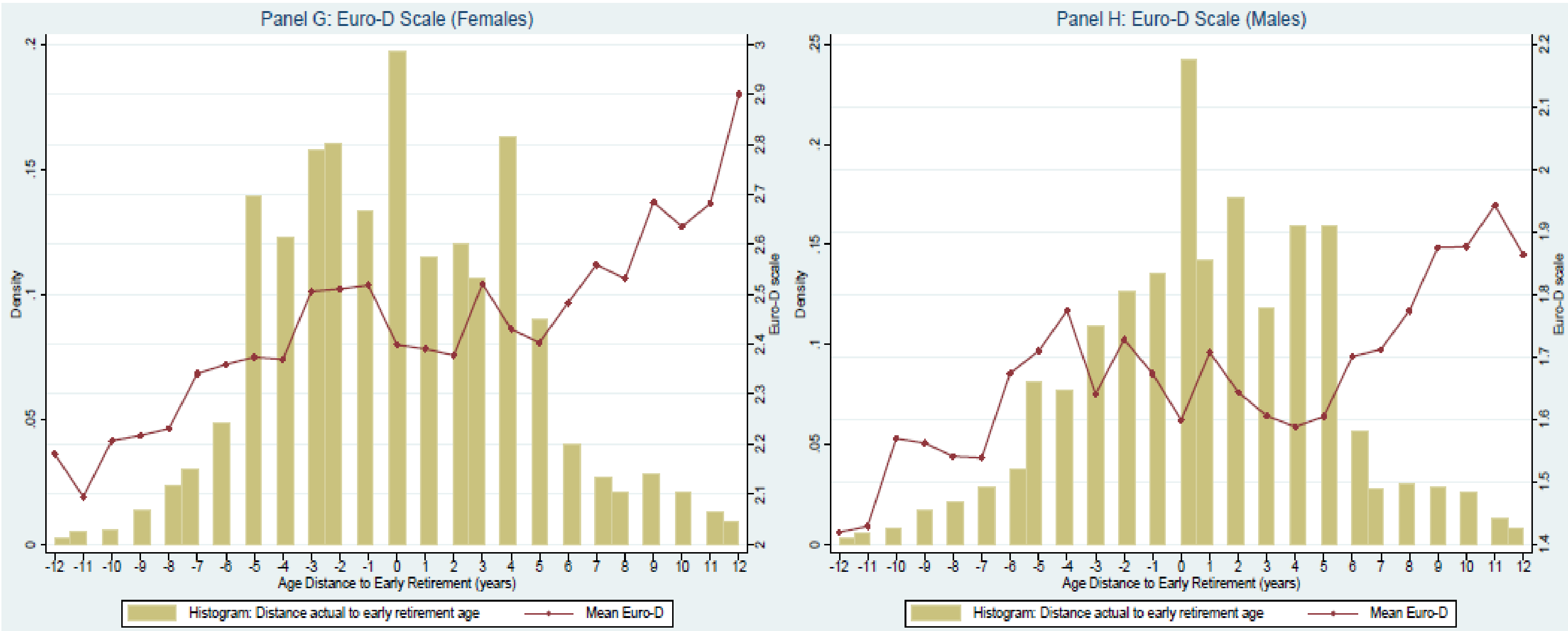
Note: Distance to early retirement age computed as the difference between the person's age and the early retirement age in his/her country of residence, and rounded to integer.

Figure C.11: Mental health by age distance to early retirement age (affective suffering index)



Note: Distance to early retirement age computed as the difference between the person's age and the early retirement age in his/her country of residence, and rounded to integer.

Figure C.12: Mental health by age distance to early retirement age (Euro-D scale)



Note: Distance to early retirement age computed as the difference between the person's age and the early retirement age in his/her country of residence, and rounded to integer.

Table C.8: Second stage estimation results, Pooled OLS (death ideation, men)

Outcome: death ideation	**Pooled OLS**		
	(1a)	(1b)	(1c)
Retired	0.020*** (0.003)	0.016*** (0.003)	0.017*** (0.003)
Age (in years)	-0.015*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.002*** (0.001)	-0.003*** (0.001)
Education (in years), squared		0.000** (0.000)	0.000* (0.000)
Married/ partnered		-0.016*** (0.004)	-0.016*** (0.004)
Never married		-0.019*** (0.007)	-0.019*** (0.007)
Widowed		0.029*** (0.007)	0.029*** (0.007)
Has bad health		0.023*** (0.002)	
Has any kids		-0.013*** (0.005)	-0.013*** (0.005)
Hospital stay (last 12 months)		0.033*** (0.004)	0.037*** (0.004)
Foreign born		0.003 (0.004)	0.004 (0.004)
No. observations	**44,104**	**42,680**	**42,691**
R-squared	**0.02**	**0.03**	**0.03**

Note: All specifications control for year, month and country dummies, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table C.9: Second stage estimation results, Pooled IV (statutory retirement age) (death ideation, men)

Outcome: death ideation	Pooled IV (statutory retirement age)		
	(2a)	(2b)	(2c)
Retired	-0.013 (0.013)	-0.009 (0.014)	-0.010 (0.014)
Age (in years)	-0.007** (0.003)	-0.007** (0.003)	-0.006* (0.003)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.002*** (0.001)	-0.003*** (0.001)
Education (in years), squared		0.000* (0.000)	0.000 (0.000)
Married/ partnered		-0.016*** (0.004)	-0.016*** (0.004)
Never married		-0.019*** (0.007)	-0.018*** (0.007)
Widowed		0.029*** (0.007)	0.029*** (0.007)
Has bad health		0.024*** (0.002)	
Has any kids		-0.013*** (0.005)	-0.013*** (0.005)
Hospital stay (last 12 months)		0.033*** (0.004)	0.037*** (0.004)
Foreign born		0.003 (0.004)	0.004 (0.004)
No. observations	**44,104**	**42,680**	**42,691**
R-squared	**0.02**	**0.03**	**0.03**

Note: All specifications control for year, month and country dummies, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table C.10: Second stage estimation results, Pooled IV (early retirement age) (death ideation, men)

Outcome: death ideation	Pooled IV (early retirement age)		
	(3a)	(3b)	(3c)
Retired	-0.023 (0.015)	-0.022 (0.015)	-0.023 (0.015)
Age (in years)	-0.005 (0.004)	-0.004 (0.004)	-0.003 (0.004)
Age (in years), squared	0.000** (0.000)	0.000* (0.000)	0.000 (0.000)
Education (in years)		-0.002*** (0.001)	-0.002*** (0.001)
Education (in years), squared		0.000 (0.000)	0.000 (0.000)
Married/ partnered		-0.015*** (0.004)	-0.015*** (0.004)
Never married		-0.019*** (0.007)	-0.018*** (0.007)
Widowed		0.029*** (0.007)	0.029*** (0.007)
Has bad health		0.024*** (0.002)	
Has any kids		-0.013*** (0.005)	-0.013*** (0.005)
Hospital stay (last 12 months)		0.034*** (0.004)	0.038*** (0.004)
Foreign born		0.003 (0.004)	0.004 (0.004)
No. observations	**44,104**	**42,680**	**42,691**
R-squared	**0.02**	**0.03**	**0.02**

Note: All specifications control for year, month and country dummies, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table C.11: Second stage estimation results, Pooled 2SLS (death ideation, men)

Outcome: death ideation	Pooled 2SLS (both instruments)		
	(4a)	(4b)	(4c)
Retired	-0.018* (0.010)	-0.015 (0.011)	-0.016 (0.011)
Age (in years)	-0.006** (0.003)	-0.005* (0.003)	-0.005* (0.003)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.002*** (0.001)	-0.002*** (0.001)
Education (in years), squared		0.000* (0.000)	0.000 (0.000)
Married/ partnered		-0.016*** (0.004)	-0.015*** (0.004)
Never married		-0.019*** (0.007)	-0.018*** (0.007)
Widowed		0.029*** (0.007)	0.029*** (0.007)
Has bad health		0.024*** (0.002)	
Has any kids		-0.013*** (0.005)	-0.013*** (0.005)
Hospital stay (last 12 months)		0.034*** (0.004)	0.037*** (0.004)
Foreign born		0.003 (0.004)	0.004 (0.004)
No. observations	**44,104**	**42,680**	**42,691**
R-squared	**0.02**	**0.03**	**0.03**

Note: All specifications control for year, month and country dummies, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table C.12: Second stage estimation results, Pooled OLS (death ideation, women)

Outcome: death ideation	Pooled OLS		
	(1a)	(1b)	(1c)
Retired	0.010** (0.004)	0.005 (0.004)	0.008* (0.004)
Age (in years)	-0.015*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.008*** (0.001)	-0.008*** (0.001)
Education (in years), squared		0.000*** (0.000)	0.000*** (0.000)
Married/ partnered		-0.040*** (0.005)	-0.039*** (0.005)
Never married		-0.038*** (0.008)	-0.038*** (0.008)
Widowed		0.006 (0.006)	0.006 (0.006)
Has bad health		0.040*** (0.003)	
Has any kids		-0.015*** (0.006)	-0.015*** (0.006)
Hospital stay (last 12 months)		0.039*** (0.005)	0.043*** (0.005)
Foreign born		0.023*** (0.005)	0.024*** (0.005)
No. observations	**39,138**	**37,760**	**37,769**
R-squared	**0.03**	**0.05**	**0.04**

Note: All specifications control for year, month and country dummies, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table C.13: Second stage estimation results, Pooled IV (statutory retirement age) (death ideation, women)

Outcome: death ideation	**Pooled IV (statutory retirement age)**		
	(2a)	(2b)	(2c)
Retired	-0.038** (0.016)	-0.039** (0.017)	-0.039** (0.017)
Age (in years)	-0.004 (0.004)	-0.005 (0.004)	-0.004 (0.004)
Age (in years), squared	0.000** (0.000)	0.000** (0.000)	0.000* (0.000)
Education (in years)		-0.007*** (0.001)	-0.008*** (0.001)
Education (in years), squared		0.000*** (0.000)	0.000** (0.000)
Married/ partnered		-0.038*** (0.005)	-0.038*** (0.005)
Never married		-0.037*** (0.008)	-0.037*** (0.008)
Widowed		0.006 (0.006)	0.006 (0.006)
Has bad health		0.042*** (0.003)	
Has any kids		-0.015*** (0.006)	-0.015*** (0.006)
Hospital stay (last 12 months)		0.039*** (0.005)	0.044*** (0.005)
Foreign born		0.023*** (0.005)	0.024*** (0.005)
No. observations	**39,138**	**37,760**	**37,769**
R-squared	**0.03**	**0.05**	**0.04**

Note: All specifications control for year, month and country dummies, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table C.14: Second stage estimation results, Pooled IV (early retirement age) (death ideation, women)

Outcome: death ideation	Pooled IV (early retirement age)		
	(3a)	(3b)	(3c)
Retired	-0.029 (0.019)	-0.020 (0.019)	-0.020 (0.019)
Age (in years)	-0.006 (0.005)	-0.009* (0.005)	-0.008* (0.005)
Age (in years), squared	0.000** (0.000)	0.000*** (0.000)	0.000** (0.000)
Education (in years)		-0.008*** (0.001)	-0.008*** (0.001)
Education (in years), squared		0.000*** (0.000)	0.000*** (0.000)
Married/ partnered		-0.039*** (0.005)	-0.038*** (0.005)
Never married		-0.037*** (0.008)	-0.037*** (0.008)
Widowed		0.006 (0.006)	0.006 (0.006)
Has bad health		0.041*** (0.003)	
Has any kids		-0.015*** (0.006)	-0.015*** (0.006)
Hospital stay (last 12 months)		0.039*** (0.005)	0.044*** (0.005)
Foreign born		0.023*** (0.005)	0.024*** (0.005)
No. observations	**39,138**	**37,760**	**37,769**
R-squared	**0.03**	**0.05**	**0.04**

Note: All specifications control for year, month and country dummies, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table C.15: Second stage estimation results, Pooled 2SLS (death ideation, women)

Outcome: death ideation	Pooled 2SLS (both instruments)		
	(4a)	(4b)	(4c)
Retired	-0.034** (0.014)	-0.031** (0.014)	-0.031** (0.014)
Age (in years)	-0.005 (0.004)	-0.007* (0.004)	-0.006 (0.004)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)
Education (in years)		-0.007*** (0.001)	-0.008*** (0.001)
Education (in years), squared		0.000*** (0.000)	0.000*** (0.000)
Married/ partnered		-0.038*** (0.005)	-0.038*** (0.005)
Never married		-0.037*** (0.008)	-0.037*** (0.008)
Widowed		0.006 (0.006)	0.006 (0.006)
Has bad health		0.041*** (0.003)	
Has any kids		-0.015*** (0.006)	-0.015*** (0.006)
Hospital stay (last 12 months)		0.039*** (0.005)	0.044*** (0.005)
Foreign born		0.023*** (0.005)	0.024*** (0.005)
No. observations	**39,138**	**37,760**	**37,769**
R-squared	**0.03**	**0.05**	**0.04**

Note: All specifications control for year, month and country dummies, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table C.16: Second stage estimation results (mental health, men)

	Pooled OLS			Pooled 2SLS		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Panel A: men						
Outcome: demotivation index (0 to 4)						
Retired	0.088*** (0.011)	0.051*** (0.011)	0.059*** (0.011)	-0.059 (0.042)	-0.059 (0.041)	-0.065 (0.042)
No. observations	**42,454**	**41,101**	**41,110**	**42,454**	**41,101**	**41,110**
R-squared	**0.08**	**0.11**	**0.11**	**0.08**	**0.11**	**0.10**
Outcome: affective suffering index (0 to 8)						
Retired	0.128*** (0.024)	0.063*** (0.023)	0.094*** (0.023)	-0.047 (0.090)	-0.057 (0.087)	-0.080 (0.090)
No. observations	**42,280**	**40,940**	**40,947**	**42,280**	**40,940**	**40,947**
R-squared	**0.04**	**0.10**	**0.07**	**0.04**	**0.10**	**0.07**
Outcome: Euro-D index (0 to 12)						
Retired	0.225*** (0.030)	0.122*** (0.029)	0.164*** (0.029)	-0.116 (0.109)	-0.128 (0.104)	-0.153 (0.107)
No. observations	**43,695**	**42,302**	**42,309**	**43,695**	**42,302**	**42,309**
R-squared	**0.08**	**0.14**	**0.11**	**0.07**	**0.14**	**0.11**

Notes:

1) Specifications (1a) and (2a) control for year, month and country dummies. Specifications (1b) and (2b) control for control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, and aggregate household income. Specifications (1c) and (2c) are the same as (1b) and (2b) with the exception of dropping the bad heath indicator.

2) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. (Refer to Appendix 2 reporting a robustness check to different levels of clustering).

Table C.16 (cont'd)

Outcome: sad or depressed last month						
Retired	0.016** (0.007)	0.009 (0.007)	0.016** (0.007)	0.011 (0.026)	0.011 (0.026)	0.007 (0.027)
No. observations	**44,197**	**42,765**	**42,776**	**44,197**	**42,765**	**42,776**
R-squared	**0.02**	**0.05**	**0.04**	**0.02**	**0.05**	**0.04**

Table C.17: Second stage estimation results (mental health, women)

	Pooled OLS			Pooled 2SLS		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Panel B: women						
Outcome: demotivation index (0 to 4)						
Retired	0.049***	0.020	0.030**	-0.208***	-0.187***	-0.188***
	(0.013)	(0.013)	(0.013)	(0.045)	(0.046)	(0.045)
No. observations	**37,703**	**36,382**	**36,391**	**37,703**	**36,382**	**36,391**
R-squared	**0.11**	**0.14**	**0.13**	**0.10**	**0.13**	**0.13**
Outcome: affective suffering index (0 to 8)						
Retired	0.173***	0.077**	0.129***	-0.032	0.003	-0.002
	(0.034)	(0.033)	(0.034)	(0.106)	(0.104)	(0.108)
No. observations	**37,539**	**36,230**	**36,239**	**37,539**	**36,230**	**36,239**
R-squared	**0.05**	**0.11**	**0.08**	**0.05**	**0.11**	**0.08**
Outcome: Euro-D index (0 to 12)						
Retired	0.211***	0.090**	0.152***	-0.304**	-0.244*	-0.245*
	(0.042)	(0.040)	(0.042)	(0.129)	(0.127)	(0.130)
No. observations	**38,795**	**37,430**	**37,439**	**38,795**	**37,430**	**37,439**
R-squared	**0.09**	**0.15**	**0.12**	**0.08**	**0.15**	**0.11**

Notes:

1) Specifications (1a) and (2a) control for year, month and country dummies. Specifications (1b) and (2b) control for control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, and aggregate household income. Specifications (1c) and (2c) are the same as (1b) and (2b) with the exception of dropping the bad heath indicator.

2) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table C.17 (cont'd)

Outcome: sad or depressed last month						
Retired	0.027*** (0.009)	0.016* (0.009)	0.025*** (0.009)	-0.005 (0.029)	0.007 (0.030)	0.006 (0.030)
No. observations	**39,197**	**37,794**	**37,803**	**39,197**	**37,794**	**37,803**
R-squared	**0.03**	**0.06**	**0.04**	**0.03**	**0.06**	**0.04**

Table C.18: Second stage estimation results (men, social networks)

	Pooled OLS			Pooled 2SLS		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Panel A: men						
Outcome: size of the social network (number of persons)						
Retired	-0.035 (0.035)	0.009 (0.037)	0.007 (0.037)	-0.157 (0.126)	-0.201 (0.123)	-0.205* (0.123)
No. observations	**21,394**	**20,306**	**20,322**	**21,394**	**20,306**	**20,322**
R-squared	**0.04**	**0.05**	**0.05**	**0.04**	**0.05**	**0.05**

Notes:

1) Samples restricted to individuals with at least one living child in the model with outcome variable “children in the social network”. Samples restricted to individuals with at least one living parent in the model with outcome variable “parents in the social network”.

2) Specifications (1a) and (2a) of control for year, month and country dummies. Specifications (1b) and (2b) control for control for year, month and country dummies; age and education (in quadratics); marital status, number of children (dummy for having children in Table C.16); bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, aggregate household income, and number of living parents in the model with outcome variable “parents in the social network”. Specifications (1c) and (2c) are the same as (1b) and (2b) with the exception of dropping the bad heath indicator.

3) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table C.18 (cont'd)

Outcome: number of persons in social network with daily contact						
Retired	-0.044** (0.019)	-0.029 (0.020)	-0.028 (0.020)	-0.119* (0.070)	-0.111 (0.071)	-0.112 (0.071)
No. observations	**20,809**	**19,755**	**19,770**	**20,809**	**19,755**	**19,770**
R-squared	**0.07**	**0.13**	**0.13**	**0.07**	**0.13**	**0.13**
Outcome: social network satisfaction (0 to 10)						
Retired	-0.040 (0.031)	-0.019 (0.032)	-0.032 (0.032)	0.096 (0.116)	0.051 (0.115)	0.061 (0.116)
No. observations	**20,901**	**19,889**	**19,894**	**20,901**	**19,889**	**19,894**
R-squared	**0.02**	**0.04**	**0.03**	**0.02**	**0.04**	**0.03**
Outcome: children in the social network						
Retired	0.001 (0.012)	0.005 (0.013)	0.004 (0.013)	-0.069 (0.046)	-0.073 (0.047)	-0.074 (0.047)
No. observations	**18,515**	**17,601**	**17,606**	**18,515**	**17,601**	**17,606**
R-squared	**0.05**	**0.06**	**0.06**	**0.05**	**0.06**	**0.06**
Outcome: parents in the social network						
Retired	-0.007 (0.025)	-0.015 (0.025)	-0.013 (0.025)	0.161* (0.094)	0.129 (0.097)	0.131 (0.096)
No. observations	**3,395**	**3,218**	**3,218**	**3,395**	**3,218**	**3,218**
R-squared	**0.08**	**0.17**	**0.17**	**0.06**	**0.16**	**0.16**
Outcome: done voluntary/charity work in the last 12 months						
Retired	0.021** (0.010)	0.044*** (0.010)	0.041*** (0.010)	0.069** (0.033)	0.076** (0.032)	0.076** (0.032)
No. observations	**21,269**	**20,208**	**20,220**	**21,269**	**20,208**	**20,220**
R-squared	**0.09**	**0.10**	**0.10**	**0.08**	**0.10**	**0.10**

Table C.19: Second stage estimation results (women, social networks)

	Pooled OLS			Pooled 2SLS		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Panel B: women						
Outcome: size of the social network (number of persons)						
Retired	-0.083*	-0.039	-0.040	-0.148	-0.113	-0.112
	(0.042)	(0.043)	(0.043)	(0.148)	(0.147)	(0.147)
No. observations	**21,416**	**20,399**	**20,418**	**21,416**	**20,399**	**20,418**
R-squared	**0.07**	**0.09**	**0.09**	**0.07**	**0.09**	**0.09**

Notes:

1) Samples restricted to individuals with at least one living child in the model with outcome variable “children in the social network”. Samples restricted to individuals with at least one living parent in the model with outcome variable “parents in the social network”.

2) Specifications (1a) and (2a) of control for year, month and country dummies. Specifications (1b) and (2b) control for control for year, month and country dummies; age and education (in quadratics); marital status, number of children (dummy for having children in Table C.16); bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, aggregate household income, and number of living parents in the model with outcome variable “parents in the social network”. Specifications (1c) and (2c) are the same as (1b) and (2b) with the exception of dropping the bad heath indicator.

3) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table C.19 (cont'd)

Outcome: number of persons in social network with daily contact						
Retired	-0.037 (0.023)	-0.066*** (0.023)	-0.064*** (0.023)	0.022 (0.082)	-0.001 (0.080)	-0.001 (0.080)
No. observations	**20,803**	**19,818**	**19,837**	**20,803**	**19,818**	**19,837**
R-squared	**0.10**	**0.15**	**0.15**	**0.10**	**0.15**	**0.15**
Outcome: social network satisfaction (0 to 10)						
Retired	-0.016 (0.032)	-0.010 (0.033)	-0.024 (0.033)	-0.004 (0.112)	-0.032 (0.113)	-0.037 (0.113)
No. observations	**21,122**	**20,168**	**20,178**	**21,122**	**20,168**	**20,178**
R-squared	**0.02**	**0.03**	**0.03**	**0.02**	**0.03**	**0.03**
Outcome: children in the social network						
Retired	-0.010 (0.012)	-0.006 (0.013)	-0.006 (0.013)	-0.024 (0.042)	-0.034 (0.044)	-0.034 (0.044)
No. observations	**18,748**	**17,889**	**17,897**	**18,748**	**17,889**	**17,897**
R-squared	**0.04**	**0.06**	**0.06**	**0.04**	**0.06**	**0.06**
Outcome: parents in the social network						
Retired	0.021 (0.025)	0.017 (0.025)	0.016 (0.025)	0.231*** (0.088)	0.191** (0.086)	0.190** (0.086)
No. observations	**4,134**	**3,892**	**3,893**	**4,134**	**3,892**	**3,893**
R-squared	**0.08**	**0.17**	**0.17**	**0.06**	**0.16**	**0.16**
Outcome: done voluntary/charity work in the last 12 months						
Retired	0.033*** (0.010)	0.052*** (0.010)	0.050*** (0.010)	0.087*** (0.033)	0.112*** (0.035)	0.112*** (0.035)
No. observations	**21,324**	**20,339**	**20,353**	**21,324**	**20,339**	**20,353**
R-squared	**0.07**	**0.09**	**0.08**	**0.07**	**0.08**	**0.08**

Table C.20: Tests for equality of the effect of retirement by gender

Dependent variable	Instrument list	Model specification	Difference $\hat{\beta}_1^{\text{Female}} - \hat{\beta}_1^{\text{Male}}$	P-value for the test $\mathbf{H_0}$: $\beta_1^{\text{Female}} = \beta_1^{\text{Male}}$
Mental health				
Death ideation	Statutory retirement age	No controls	-0.025	0.214
		All controls	-0.030	0.145
		All controls, bad health omitted	-0.029	0.148
	Early retirement age	No controls	-0.005	0.821
		All controls	0.002	0.933
		All controls, bad health omitted	0.003	0.920
	Statutory & early retirement age	No controls	-0.015	0.355
		All controls	0.016	0.326
		All controls, bad health omitted	-0.014	0.420
Demotivation index	Statutory & early retirement age	No controls	-0.154***	0.005
		All controls	-0.141**	0.013
		All controls, bad health omitted	-0.123**	0.018
Affective suffering index	Statutory & early retirement age	No controls	0.015	0.906
		All controls	-0.052	0.749
		All controls, bad health omitted	0.078	0.565
Euro-D index	Statutory & early retirement age	No controls	-0.188	0.200
		All controls	-0.116	0.509
		All controls, bad health omitted	-0.092	0.566
Sad or depressed last month	Statutory & early retirement age	No controls	-0.016	0.683
		All controls	0.003	0.974
		All controls, bad health omitted	-0.001	0.988

Note: Test for parameter equality based on bootstrap estimates, 500 replications.

Table C.20 (cont'd)

Dependent variable	Instrument list	Model specification	Difference $\hat{\beta}_1^{\text{Female}} - \hat{\beta}_1^{\text{Male}}$	P-value for the test $\mathbf{H_0}$: $\beta_1^{\text{Female}} = \beta_1^{\text{Male}}$
Social networks				
Size of the social network	Statutory & early retirement age	No controls	0.009	0.959
		All controls	0.045	0.798
		All controls, bad health omitted	0.093	0.655
Social network satisfaction	Statutory & early retirement age	No controls	-0.100	0.554
		All controls	-0.114	0.515
		All controls, bad health omitted	-0.101	0.570
Children in the social network	Statutory & early retirement age	No controls	0.044	0.500
		All controls	0.046	0.465
		All controls, bad health omitted	-0.005	0.918
Parents in the social network	Statutory & early retirement age	No controls	0.070	0.542
		All controls	0.037	0.805
		All controls, bad health omitted	0.058	0.593
# persons in social network with daily contact	Statutory & early retirement age	No controls	0.141	0.132
		All controls	0.168	0.111
		All controls, bad health omitted	0.111	0.277
Volunteering	Statutory & early retirement age	No controls	0.018	0.659
		All controls	0.008	0.872
		All controls, bad health omitted	0.036	0.399

Table C.21: Mechanism of the effect (men, death ideation)

Characteristics	Death ideation			
	(1a)	(1b)	(1c)	(1d)
Retired	-0.006 (0.015)	-0.007 (0.015)	-0.005 (0.016)	-0.006 (0.015)
Other covariates (including bad health)	yes	yes	yes	yes
Size of the social network	–	-0.004*** (0.001)	–	–
Children in the social network	–	–	-0.008*** (0.003)	–
Volunteering	–	–	–	-0.010** (0.003)
Test for equality with β_1 from specification (a): difference & p-value	NA	0.001 0.336	0.001 0.111	-0.000** 0.045
No. observations	**19,944**	**19,944**	**17,468**	**19,930**
R-squared	**0.03**	**0.03**	**0.03**	**0.03**

Notes:

1) All models estimated on data from wave 4 only. Samples in specification (1c) restricted to individuals with at least one living child.

2) All specifications control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy, and aggregate household income. Omitted category for variable marital status: separated/divorced.

3) Test for parameter equality based on bootstrap estimates, 500 replications.

Table C.22: Mechanism of the effect (men, demotivation index)

Characteristics	Demotivation index			
	(2a)	(2b)	(2c)	(2d)
Retired	-0.068 (0.062)	-0.074 (0.062)	-0.070 (0.062)	-0.065 (0.062)
Other covariates (including bad health)	yes	yes	yes	yes
Size of the social network	–	-0.041*** (0.003)	–	–
Children in the social network	–	–	-0.053*** (0.012)	–
Volunteering	–	–	–	-0.080*** (0.012)
Test for equality with $\boldsymbol{\beta}_1$ from specification (a): difference & p-value	NA	0.009 0.106	0.005 0.190	-0.006** 0.020
No. observations	**19,208**	**19,208**	**16,837**	**19,197**
R-squared	**0.11**	**0.12**	**0.11**	**0.11**

Notes:

1) All models estimated on data from wave 4 only. Samples in specification (1c) restricted to individuals with at least one living child.

2) All specifications control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy, and aggregate household income. Omitted category for variable marital status: separated/divorced.

3) Test for parameter equality based on bootstrap estimates, 500 replications.

Table C.23: Mechanism of the effect (men, Euro-D scale)

Characteristics	Euro-D scale			
	(3a)	(3b)	(3c)	(3d)
Retired	-0.232 (0.150)	-0.235 (0.151)	-0.228 (0.155)	-0.230 (0.151)
Other covariates (including bad health)	yes	yes	yes	yes
Size of the social network	–	-0.012 (0.009)	–	–
Children in the social network	–	–	-0.060*** (0.029)	–
Volunteering	–	–		-0.070*** (0.037)
Test for equality with $\boldsymbol{\beta}_1$ from specification (a): difference & p-value	NA	0.001 0.824	0.005 0.170	-0.006 0.208
No. observations	**19,749**	**19,749**	**17,316**	**19,737**
R-squared	**0.13**	**0.13**	**0.13**	**0.13**

Notes:

1) All models estimated on data from wave 4 only. Samples in specification (1c) restricted to individuals with at least one living child.

2) All specifications control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy, and aggregate household income. Omitted category for variable marital status: separated/divorced.

3) Test for parameter equality based on bootstrap estimates, 500 replications.

Table C.24: Mechanism of the effect (women, death ideation)

Characteristics	Death ideation			
	(1a)	**(1b)**	**(1c)**	**(1d)**
Retired	-0.054** (0.022)	-0.054** (0.022)	-0.055** (0.024)	-0.053** (0.022)
Other covariates (including bad health)	yes	yes	yes	yes
Size of the social network	–	-0.003** (0.001)	–	–
Children in the social network	–	–	-0.012** (0.005)	–
Volunteering	–	–	–	-0.001 (0.005)
Test for equality with β_1 from specification (a): difference & p-value	NA	0.000 0.484	0.000 0.554	0.000 0.709
No. observations	**20,234**	**20,234**	**17,817**	**20,216**
R-squared	**0.05**	**0.05**	**0.04**	**0.05**

Notes:

1) All models estimated on data from wave 4 only. Samples in specification (1c) restricted to individuals with at least one living child.

2) All specifications control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy, and aggregate household income. Omitted category for variable marital status: separated/divorced.

3) Test for parameter equality based on bootstrap estimates, 500 replications.

Table C.25: Mechanism of the effect (women, demotivation index)

Characteristics	Demotivation index			
	(2a)	(2b)	(2c)	(2d)
Retired	-0.239*** (0.067)	-0.244*** (0.067)	-0.277*** (0.073)	-0.227*** (0.068)
Other covariates (including bad health)	yes	yes	yes	yes
Size of the social network	–	-0.048*** (0.004)	–	–
Children in the social network	–	–	-0.073*** (0.014)	–
Volunteering	–	–	–	-0.099*** (0.014)
Test for equality with $\boldsymbol{\beta}_1$ from specification (a): difference & p-value	NA	0.001 0.928	0.003 0.460	-0.011*** 0.001
No. observations	**19,507**	**19,507**	**17,212**	**19,492**
R-squared	**0.12**	**0.13**	**0.12**	**0.12**

Notes:

1) All models estimated on data from wave 4 only. Samples in specification (1c) restricted to individuals with at least one living child.

2) All specifications control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy, and aggregate household income. Omitted category for variable marital status: separated/divorced.

3) Test for parameter equality based on bootstrap estimates, 500 replications.

Table C.26: Mechanism of the effect (women, Euro-D scale)

Characteristics	Euro-D scale			
	(3a)	**(3b)**	**(3c)**	**(3d)**
Retired	-0.494** (0.184)	-0.493** (0.184)	-0.486** (0.195)	-0.477** (0.187)
Other covariates (including bad health)	yes	yes	yes	yes
Size of the social network	–	0.005 (0.011)	–	–
Children in the social network	–	–	-0.039 (0.038)	–
Volunteering	–	–		-0.131*** (0.041)
Test for equality with $\boldsymbol{\beta}_1$ from specification (a): difference & p-value	NA	-0.000 0.925	-0.001 0.275	-0.014** 0.044
No. observations	**20,050**	**20,050**	**17,660**	**20,034**
R-squared	**0.14**	**0.14**	**0.13**	**0.19**

Notes:

1) All models estimated on data from wave 4 only. Samples in specification (1c) restricted to individuals with at least one living child.

2) All specifications control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy, and aggregate household income. Omitted category for variable marital status: separated/divorced.

3) Test for parameter equality based on bootstrap estimates, 500 replications.

APPENDIX D

SUPPLEMENTARY TABLES AND FIGURES

Appendix D.1: Allowing for a more flexible age specification

The mainstream literature agrees that the relationship between age and psychological well-being is U-shaped once covariates have been accounted for (see e.g. Stone et al. (2010)). In addition, most authors who studied this relationship for the elderly adults reported a linear relationship between age and mental health after a certain age (e.g. Wu et al. (2014) observed a linear increase in depressive symptoms after age 65) – a finding largely supported by this paper (refer to section 4B.1 in the main text).

However, since age is a key driver of depression, we explicitly address the concern that a quadratic in age might not be flexible enough, and double-check that the key results from the paper still hold and are not due to misspecification. In this section, we show the results of estimating model (1) from the main text when allowing for a cubic specification in age. As can be seen from Table A1 on the next page, the model is robust to including a cubic in age, and the key implications for a beneficial effect of retirement on female's mental health continue to hold – the parameter estimates for females are unchanged up to 3 decimals places. Moreover, in the female models with death ideation and demotivation index as the mental health outcome, the linear, quadratic and cubic terms age are not jointly significant (see columns (1b) and (2b)). Since the quadratic terms are always jointly significant across all outcomes and since all models are robust to changing the age specification, our preferred specification is a quadratic in age. It is also worth noting the results are robust to including a 4th order polynomial in age, and that higher order polynomials or age dummies (for every year of age) show signs of severe multicollinearity.

Table D.1: Age specification robustness checks

ariable	Outcome: death ideation		Outcome: demotivation index		Outcome: Euro-D index	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Panel A: men						
Retired	-0.015 (0.011)	-0.017 (0.011)	-0.063 (0.040)	-0.049 (0.042)	-0.134 (0.045)	-0.172 (0.105)
Age	-0.005* (0.003)	-0.014 (0.014)	-0.012 (0.012)	0.032 (0.052)	-0.128*** (0.027)	-0.385*** (0.120)
Age squared	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	-0.000 (0.000)	0.001*** (0.000)	0.005*** (0.02)
Age cubic		-0.000 (0.000)		0.000 (0.000)		-0.000** (0.000)
Test for joint significance	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age}{}^2$= =0 **P-value 0.0000**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age}{}^2$ $=\boldsymbol{\beta}_{age}{}^3$=0 **P-value 0.2475**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age}{}^2$ =0 **P-value .0000**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age}{}^2$ $=\boldsymbol{\beta}_{age}{}^3$=0 **P-value 0.0295**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age}{}^2$ =0 **P-value 0.0000**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age}{}^2$ $=\boldsymbol{\beta}_{age}{}^3$=0 **P-value 0.0000**
No. observations	**42,680**		**41,101**		**42,302**	

Notes:

1) All specifications control for year, month and country dummies; marital status, a dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, aggregate household income.

2) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table D.1 (cont'd)

Panel B: women						
Retired	-0.031** (0.014)	-0.031** (0.014)	-0.187*** (0.046)	-0.186*** (0.046)	-0.244*** (0127)	-0.244** (0.126)
Age	-0.007** (0.004)	0.022 (0.017)	-0.014 (0.012)	-0.021 (0.054)	-0.077** (0.033)	-0.375*** (0.141)
Age squared	0.000*** (0.000)	-0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.001*** (0.000)	0.005** (0.002)
Age cubic		0.000 (0.000)		-0.000 (0.000)		-0.000** (0.000)
Test for joint significance	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age^2} = 0$ **P-value 0.0497**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age^2} = \boldsymbol{\beta}_{age^3} = 0$ **P-value 0.2658**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age^2} = 0$ **P-value 0.0000**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age^2} = \boldsymbol{\beta}_{age^3} = 0$ **P-value 0.9002**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age^2} = 0$ **P-value 0.0000**	H_0: $\boldsymbol{\beta}_{age} = \boldsymbol{\beta}_{age^2} = \boldsymbol{\beta}_{age^3} = 0$ **P-value 0.0184**
No. observations		**37,760**		**36,382**		**37,430**

Appendix D.2: Robustness to different levels of standard error clustering

Table D.2: Standard error clustering robustness checks

	Men			**Women**		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Outcome: death ideation						
Retired	-0.018 (0.010)* [0.010] {0.013}	-0.015 (0.011) [0.011] {0.014}	-0.016 (0.011) [0.011] {0.014}	-0.034 (0.014)** [0.017]* {0.017}*	-0.031 (0.014)** [0.017]* {0.018}*	-0.031 (0.014)** [0.017]* {0.017}*
No. observations	**44,104**	**42,680**	**42,691**	**39,138**	**37,760**	**37,769**
R-squared	**0.02**	**0.03**	**0.03**	**0.03**	**0.05**	**0.04**
Outcome: demotivation index (0 to 4)						
Retired	-0.059 (0.042) [0.036] {0.050}	-0.059 (0.041) [0.039] {0.050}	-0.065 (0.042) [0.036] {0.059}	-0.208 (0.045)*** [0.046]*** {0.050}***	-0.187 (0.046)*** [0.043]*** {0.048}***	-0.188 (0.045)*** [0.041]*** {0.044}***

Notes:

1) Standard errors clustered at age-country-year level shown in “( )”parentheses.

2) Standard errors clustered at country- year level shown in “[ ]”parentheses.

3) Standard errors clustered at country level shown in “{ }”parentheses.

4) Specifications (1a) and (2a) control for year, month and country dummies. Specifications (1b) and (2b) control for control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, and aggregate household income. Specifications (1c) and (2c) are the same as (1b) and (2b) with the exception of dropping the bad heath indicator.

Table D.2 (cont'd)

No. observations	**42,454**	**41,101**	**41,110**	**37,703**	**36,382**	**36,391**
R-squared	**0.08**	**0.11**	**0.10**	**0.10**	**0.13**	**0.13**
Outcome: affective suffering index (0 to 8)						
Retired	-0.047 (0.090) [0.090] {0.108}	-0.057 (0.087) [0.087] {0.101}	-0.080 (0.090) [0.090] {0.105}	-0.032 (0.106) [0.138] {0.172}	0.003 (0.104) [0.125] {0.165}	-0.002 (0.108) [0.121] {0.158}
No. observations	**42,280**	**40,940**	**40,947**	**37,539**	**36,230**	**36,239**
R-squared	**0.04**	**0.10**	**0.07**	**0.05**	**0.11**	**0.08**
Outcome: Euro-D index (0 to 12)						
Retired	-0.116 (0.109) [0.100] {0.118}	-0.128 (0.104) [0.099] {0.106}	-0.153 (0.107) [0.103] {0.112}	-0.304 (0.129)** [0.158]* {0.206}	-0.244 (0.127)* [0.141]* {0.198}	-0.245 (0.130)* [0.135]* {0.185}
No. observations	**43,695**	**42,302**	**42,309**	**38,795**	**37,430**	**37,439**
R-squared	**0.07**	**0.14**	**0.11**	**0.08**	**0.15**	**0.11**
Outcome: sad or depressed last month						
Retired	0.011 (0.026) [0.029] {0.035}	0.011 (0.026) [0.030] {0.035}	0.007 (0.027) [0.031] {0.036}	-0.005 (0.029) [0.043] {0.056}	0.007 (0.030) [0.042] {0.057}	0.006 (0.030) [0.042] {0.056}
No. observations	**44,197**	**42,765**	**42,776**	**39,197**	**37,794**	**37,803**
R-squared	**0.02**	**0.05**	**0.04**	**0.03**	**0.06**	**0.04**

Appendix D.3: Fixed Effects Estimation

Consider again model (1) in the text:

$$Y_{ict} = \beta_0 + \beta_1 Retired_{ict} + \boldsymbol{X}_{ict}^{OWN}\boldsymbol{\beta}_2 + X_{ict}^{HHD}\beta_3 + \boldsymbol{w}_c\,\boldsymbol{\beta}_4 + \boldsymbol{d}_t + (a_i + u_{ict}). \quad \textbf{(1)}$$

For the countries in the sample observed for at least two waves, an alternative identification strategy is available, namely: fixed effects estimation at individual level.[56] Fixed effects (FE) estimation allows for identifying the parameters on the time varying repressors only; for this reason the model is estimated with the following controls: vector $\boldsymbol{X}_{ict}^{OWN}$ includes age (in quadratics), marital status, a binary indicator for being in bad health, and a dummy for hospital stay; vector X_{ict}^{HHD} includes household income; as before, $\boldsymbol{d}_t$ stands for year and month dummies.

Identification of the causal effect of interest by FE relies on the assumption that retirement is uncorrelated with the time varying unobservable characteristics of the elderly, which could affect their mental health outcome Y_{ict}, or formally: $cov(Retired_{ict}, u_{ics})=0, \ \forall \ t, s$. This condition rules out the possibility that the elderly exit the labour force as a response to shocks affecting their mental health. In addition, since SHARE is unbalanced panel, FE estimation leads to eliminating all observations which appear in one wave only.[57] This does not lead to attrition bias under the assumption that selection into being observed only once is exogenous (i.e. uncorrelated with u_{ics}). Under the assumptions stated above FE estimation consistently identifies the average treatment effect (ATE) of retirement on one's mental health.

We check whether the key findings of the paper continue to hold when a FE estimator is employed, and present the FE estimation results for death ideation, motivation index and Euro-D scale in the rightmost panel of Table D3. The leftmost panel of the table reports the pooled 2SLS

[56] Countries in SHARE observed once are: Hungary, Portugal, Slovenia and Estonia (all observed in wave 4 only).

[57] This, together with the above restriction, results in dropping 54.06% of the total male sample and 51.01% of the total female sample in the FE estimation.

estimation results based on the full sample of countries; in contrast, the centre panel reports the 2SLS estimation results based on the same sample as the one used in the FE estimation (i.e. a sample restricted to countries observed at least twice, and persons in those countries observed at least twice). As can be seen from here, the FE estimation results suggest no significant effect of labour force exit on a male worker's mental health across all specifications and outcomes of interest; in addition, the parameter on retirement is not significantly different from zero for women when the outcome of interest is death ideation (see Table A2, panel B).

At the same time, however, the FE estimates reported in Tables A2 point to a beneficial effect of exiting work on the motivation index and Euro-D scale for women, although this effect is lower both in terms of magnitude and in significance compared to the 2SLS estimates on the full sample. In particular, the FE estimate of the retirement effect on the motivation index from specification (3b) of is of magnitude -0.042 compared to -0.156 based on the 2SLS estimation; likewise, the FE estimate of the effect on the Euro-D scale is of magnitude negative 0.106 compared to 0.247 based on the 2SLS estimation (see column (1b)). One reason for this may be the fact that the FE estimation identifies an ATE for all retirees, while the 2SLS estimation identifies a LATE for the two groups of women complying with the statutory and early retirement ages, and the effect for the later group may be stronger. Another potential explanation is that the FE estimates are obtained on a different set of countries in SHARE, namely – the countries that participated in the survey for at least two waves. To address the later, it is worth examining the 2SLS estimation results on the restricted 'fixed effects' sample (central panel): this leads to estimates generally lower in magnitude and in significance compared to the full sample of observations in SHARE, suggesting the effect of beneficial effect of retirement on women's mental health may be less pronounced in this set of countries.

Table D.3: Fixed effects estimation results

	Pooled 2SLS (full sample)			Pooled 2SLS (restricted sample)			Fixed effects (restricted sample)		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**	**(3b)**	**(3b)**	**(3c)**
Panel A: men									
Outcome: death ideation									
Retired	-0.018*	-0.010	-0.016	-0.020	-0.010	-0.017	0.006	0.006	0.006
	(0.010)	(0.010)	(0.011)	(0.014)	(0.014)	(0.014)	(0.005)	(0.005)	(0.005)
No. observations	**44,104**	**42,680**	**42,691**	**23,881**	**23,800**	**23,819**	**23,881**	**23,800**	**23,819**
R-squared	**0.02**	**0.04**	**0.03**	**0.02**	**0.03**	**0.02**	**0.00**	**0.01**	**0.01**

Notes:

1) Specifications (1a-c) and (2a-c) are analogous to specifications (2a-c) in Table 7. Specification (3a) controls for year, month and country dummies, and age (in quadratics). Specification (3b) controls for year, month and country dummies, age (in quadratics), marital status, a binary indicator for being in bad health, and a dummy for hospital stay. Specification (3c) is the same as (3b) with the exception of dropping the bad heath indicator.

2) Standard errors clustered at age-country-year level in the pooled 2SLS estimation and at household level in the FE estimation. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

3) Restricted sample includes only observations from countries observed at least twice.

Table D.3 (cont'd)

Outcome: demotivation index (0 to 4)									
Retired	-0.059 (0.041)	-0.034 (0.040)	-0.065 (0.041)	-0.050 (0.052)	-0.010 (0.051)	-0.045 (0.052)	-0.012 (0.020)	-0.013 (0.020)	-0.015 (0.020)
No. observations	**42,454**	**41,101**	**41,110**	**22,706**	**22,633**	**22,633**	**22,706**	**22,633**	**22,633**
R-squared	**0.08**	**0.14**	**0.10**	**0.07**	**0.12**	**0.09**	**0.01**	**0.02**	**0.02**
Outcome: Euro-D index (0 to12)									
Retired	-0.116 (0.109)	-0.027 (0.099)	-0.153 (0.107)	-0.137 (0.139)	-0.006 (0.128)	-0.156 (0.139)	-0.055 (0.046)	-0.051 (0.046)	-0.060 (0.046)
No. observations	**43,695**	**42,302**	**42,309**	**23,601**	**23,528**	**23,541**	**23,601**	**23,528**	**23,541**
R-squared	**0.07**	**0.19**	**0.11**	**0.06**	**0.17**	**0.09**	**0.02**	**0.06**	**0.03**
Panel B: women									
Outcome: death ideation									
Retired	-0.033** (0.014)	-0.023* (0.014)	-0.031** (0.014)	-0.020 (0.016)	-0.007 (0.017)	-0.016 (0.017)	-0.008 0.008	-0.008 0.008	-0.008 0.008
No. observations	**39,150**	**37,760**	**37,769**	**18,801**	**18,765**	**18,776**	**18,801**	**18,765**	**18,776**
R-squared	**0.03**	**0.06**	**0.04**	**0.03**	**0.06**	**0.04**	**0.00**	**0.01**	**0.00**
Outcome: demotivation index (0 to 4)									
Retired	-0.208*** (0.045)	-0.156*** (0.044)	-0.188*** (0.045)	-0.137** (0.055)	-0.093* (0.056)	-0.099* (0.055)	-0.042* (0.024)	-0.042* (0.024)	-0.041* (0.024)
No. observations	**37,703**	**36,382**	**36,391**	**17,840**	**17,804**	**17,815**	**17,840**	**17,804**	**17,815**
R-squared	**0.10**	**0.15**	**0.13**	**0.10**	**0.15**	**0.12**	**0.01**	**0.02**	**0.01**
Outcome: Euro-D index (0 to 12)									
Retired	-0.304** (0.129)	-0.247* (0.127)	-0.245* (0.130)	-0.143 (0.158)	-0.082 (0.154)	-0.104 (0.158)	-0.115* (0.066)	-0.106* (0.064)	-0.114* (0.065)
No. observations	**38,795**	**37,430**	**37,439**	**18,605**	**18,569**	**18,580**	**18,605**	**18,569**	**18,580**
R-squared	**0.08**	**0.19**	**0.11**	**0.08**	**0.18**	**0.10**	**0.01**	**0.05**	**0.02**

Appendix D.4: New EU member states

In this section we assess whether heterogeneity across country exists by estimating model (1) separately on the sample of new EU member-states in SHARE (Czech Republic, Poland, Hungary, Slovenia and Estonia). The main motivation for this is that previous research has generally not studied the effect of retirement on mental health in the post-communist states, while at the same time there may be reasons why the effect differs in those countries.

Tables D4.1 and D4.2 show the pooled-IV estimation results obtained from a sample of 8,561 men and 11,145 women in those countries. The model is robust to the inclusion of a dummy for being in bad health; hence, the paper omits reporting the specifications when this dummy is not controlled. Since for both genders all mental health measures have considerably higher sample means in the post-communist countries than in all countries in SHARE, the estimated magnitudes are not directly comparable to the estimates obtained on the full sample. In order to allow inference on the parameter magnitudes, Tables D4.1 and D4.2 also report the sample means for the post-communist economies.

As can be seen from Table D4.1, labour force exit does not impact a male worker's death ideation, demotivation index and the probability of feeling sad or depressed, ceteris paribus. However, in contrast to the results obtained on the full sample of countries, the results reported in panels (3) and (4) suggest a statistically significant beneficial effect of retirement on the affective suffering index and Euro-D scale for men. The effect is of economic importance, as well – its magnitude is roughly a third of the mean for the affective suffering measure, and 25% of the mean for the Euro-D scale. Turing briefly to the results for women, Table D4.2 implies a very strong favourable impact of retirement on women's emotional well-being in the new EU members: the parameter on retirement is negative and highly significant for all mental health measures, except for the demotivation index in specification (2b). The magnitude of the effect is also very large: ranging from a third of the mean for the Euro-D index to just above half of the mean for suicide wishing.

Taken together, these results suggest a somewhat stronger favourable effect of retirement on women's psychological well-being in the post-communist states than in the entire female SHARE sample, and a favourable effect on some depression measures for men in those countries. It is worth noting here that all the new EU member-states in SHARE are reasonably similar to the old EU members in terms of retiree's living standards: retirees have replacement ratios similar to the mean EU-27, and with the exception of Poland and Slovenia the at-risk-of-poverty rate (at 60% of median income) for retirement age persons in those countries is lower that the mean EU-27 (European Commission (2012)). However, in contrast to the old EU member-states where most retirement transitions occur around statutory retirement age, the vast majority of women and men in the post-communist economies retire when first eligible – at the early retirement age (see e.g. Figure E.1 in the body of the paper), and it may be that this difference in retirement patterns is driving the results.

Table D.4.1: Second stage estimation results (New EU-member states, men)

Characteristics	Death ideation		Demotivation index		Affective suffering index	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Retired	-0.033 (0.024)	-0.037 (0.024)	-0.019 (0.098)	-0.060 (0.097)	-0.593*** (0.203)	-0.550*** (0.195)
Other covariates (including bad health)	no	yes	no	yes	no	yes
Sample mean outcome (weighted)	0.063 (0.005)		0.650 (0.020)		1.577 (0.037)	
No. observations	**8,544**	**8,399**	**8,177**	**8,043**	**8,122**	**7,990**
R-squared	**0.01**	**0.02**	**0.09**	**0.13**	**0.04**	**0.11**

Notes:

1) Sample restricted to Czech Republic, Poland, Hungary, Slovenia and Estonia.

2) Sample means corrected for inverse probability weighed sampling; linearised standard errors reported in parentheses.

3) Specifications (a) control for year, month and country dummies, and age (in quadratics). Specifications (b) control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy, and aggregate household income. Omitted category for variable marital status: separated/divorced.

4) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table D.4.1 (cont'd)

Characteristics	Euro-D scale		Sad/depressed last month	
	(4a)	(4b)	(5a)	(5b)
Retired	-0.550** (0.226)	-0.567** (0.226)	-0.087 (0.062)	-0.075 (0.060)
Other covariates (including bad health)	no	yes	no	yes
Sample mean outcome (weighted)	2.293 (0.048)		0.368 (0.011)	
No. observations	**8,434**	**8,294**	**8,561**	**8,415**
R-squared	**0.09**	**0.15**	**0.03**	**0.06**

Table D.4.2: Second stage estimation results (New EU-member states, women)

Characteristics	Death ideation		Demotivation index		Affective suffering index	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Retired	-0.084** (0.041)	-0.068* (0.040)	-0.243** (0.123)	-0.148 (0.111)	-0.799*** (0.243)	-0.648*** (0.240)
Other covariates (including bad health)	no	yes	no	yes	no	yes
Sample mean outcome (weighted)	0.124 (0.007)		0.792 (0.021)		2.543 (0.042)	
No. observations	**11,139**	**10,968**	**10,636**	**10,478**	**10,567**	**10,410**
R-squared	**0.02**	**0.05**	**0.10**	**0.15**	**0.05**	**0.12**

Notes:

1) Sample restricted to Czech Republic, Poland, Hungary, Slovenia and Estonia.

2) Sample means corrected for inverse probability weighed sampling; linearised standard errors reported in parentheses.

3) Specifications (a) control for year, month and country dummies, and age (in quadratics). Specifications (b) control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy, and aggregate household income. Omitted category for variable marital status: separated/divorced.

4) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table D.4.2 (cont'd)

Characteristics	Euro-D scale		Sad/depressed last month	
	(4a)	**(4b)**	**(5a)**	**(5b)**
Retired	-1.145*** (0.320)	-0.881*** (0.308)	-0.218*** (0.068)	-0.202*** (0.067)
Other covariates (including bad health)	no	yes	no	yes
Sample mean outcome (weighted)	3.392 (0.051)		0.543 (0.010)	
No. observations	**11,000**	**10,835**	**11,145**	**10,973**
R-squared	**0.08**	**0.17**	**0.02**	**0.06**

Appendix D.5: Allowing for country-specific trends

The subsequent section presents the estimation results when adding country-specific trends in model (1) allowing for the trends in psychological well-being and social networks to vary by country:

$$Y_{ict} = \beta_0 + \beta_1 Retired_{ict} + \boldsymbol{X}_{ict}^{OWN}\boldsymbol{\beta}_2 + X_{ict}^{HHD}\beta_3 + \boldsymbol{w}_c\,\boldsymbol{\beta}_4 + \boldsymbol{d}_t + \boldsymbol{w}_c'\boldsymbol{d}_t\boldsymbol{\beta}_5 + (a_i + u_{ict}), \qquad \textbf{(1')}$$

where $\boldsymbol{w}_c'\boldsymbol{d}_t$ denotes the interaction terms between year and country dummies.

As can be seen from Tables D4.1 through D4.6, both the first and the second stage of the model are robust to inclusion of country-specific trends and the key implications from the estimation results remain unchanged. Given this, the specification without country-specific trends is preferred in order to avoid introducing high collinearity in the model.

Table D.5.1: First stage estimation results (men)

Outcome: retired (vs. still employed)	Sample restricted to men					
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Has reached statutory retirement age	0.238*** (0.016)		0.215*** (0.015)	0.238*** (0.016)		0.215*** (0.015)
Has reached early retirement age		0.249*** (0.019)	0.224*** (0.017)		0.249*** (0.019)	0.224*** (0.017)
Age (in years)	0.177*** (0.005)	0.155*** (0.006)	0.119*** (0.006)	0.178*** (0.005)	0.155*** (0.006)	0.120*** (0.006)
Age (in years), squared	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Education (in years)	0.003** (0.001)	0.001 (0.001)	0.001 (0.001)	0.003** (0.001)	0.001 (0.001)	0.001 (0.001)
Education (in years), squared	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)

Notes:

1) All specifications control for: year, month and country dummies, country specific trends, and aggregate household income. Models estimated by pooled OLS.

2) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

3) Omitted category for variable marital status: separated/divorced; omitted category for variable current/last sector of employment: self employed.

Table D.5.1 (cont'd)

Married/partnered	0.025*** (0.006)	0.025*** (0.006)	0.025*** (0.006)	0.025*** (0.006)	0.025*** (0.006)	0.025*** (0.006)
Never married	0.012 (0.009)	0.011 (0.009)	0.009 (0.009)	0.013 (0.009)	0.012 (0.009)	0.01 (0.009)
Widowed	0.022*** (0.007)	0.013* (0.008)	0.019** (0.007)	0.022*** (0.007)	0.014* (0.008)	0.019*** (0.007)
Has bad health	0.028*** (0.004)	0.029*** (0.004)	0.029*** (0.004)			
Has any kids	0.004 (0.006)	0.002 (0.006)	0.001 (0.006)	0.004 (0.006)	0.002 (0.006)	0.001 (0.006)
Hospital stay (last 12 months)	0.017*** (0.004)	0.018*** (0.004)	0.017*** (0.004)	0.021*** (0.004)	0.022*** (0.004)	0.021*** (0.004)
Foreign born	0.001 (0.006)	0.003 (0.006)	0.000 (0.006)	0.002 (0.006)	0.004 (0.006)	0.000 (0.006)
Public sector of employment (last / current job)	0.127*** (0.005)	0.125*** (0.006)	0.125*** (0.005)	0.128*** (0.006)	0.126*** (0.006)	0.126*** (0.005)
Private sector of employment (last / current job)	0.107*** (0.005)	0.106*** (0.005)	0.105*** (0.005)	0.108*** (0.005)	0.107*** (0.005)	0.106*** (0.005)
First stage F statistic (robust)	**625.80**	**644.11**	**868.06**	**640.93**	**658.96**	**972.51**
F statistic on the excluded instruments (robust)	**215.46**	**180.92**	**293.67**	**215.64**	**180.16**	**292.41**
F statistic on the excluded instruments (non-robust)	**1,958.44**	**1,867.45**	**1,786.61**	**1,953.12**	**1,859.39**	**1,780.11**
No. observations	**43,291**	**43,291**	**43,291**	**43,315**	**43,315**	**43,315**
R-squared	**0.65**	**0.65**	**0.66**	**0.65**	**0.65**	**0.66**

Table D.5.2: First stage estimation results (women)

Outcome: retired (vs. still employed)	Sample restricted to women					
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Has reached statutory retirement age	0.290*** (0.021)		0.232*** (0.022)	0.290*** (0.021)		0.232*** (0.022)
Has reached early retirement age		0.278*** (0.022)	0.208*** (0.023)		0.278*** (0.022)	0.208*** (0.022)
Age (in years)	0.161*** (0.006)	0.150*** (0.007)	0.118*** (0.006)	0.162*** (0.006)	0.151*** (0.007)	0.119*** (0.006)
Age (in years), squared	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Education (in years)	0.004*** (0.001)	0.002 (0.001)	0.002* (0.001)	0.004*** (0.001)	0.002 (0.001)	0.002* (0.001)
Education (in years), squared	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)

Notes:

1) All specifications control for: year, month and country dummies, country specific trends, and aggregate household income. Models estimated by pooled OLS.

2) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

3) Omitted category for variable marital status: separated/divorced; omitted category for variable current/last sector of employment: self employed.

Table D.5.2 (cont'd)

Married/partnered	0.034*** (0.005)	0.032*** (0.005)	0.032*** (0.005)	0.034*** (0.005)	0.033*** (0.005)	0.033*** (0.005)
Never married	0.008 (0.008)	0.008 (0.009)	0.006 (0.008)	0.008 (0.008)	0.008 (0.009)	0.006 (0.008)
Widowed	0.010* (0.005)	0.010* (0.006)	0.011** (0.006)	0.010* (0.006)	0.010* (0.006)	0.011* (0.006)
Has bad health	0.031*** (0.004)	0.031*** (0.004)	0.031*** (0.004)			
Has any kids	-0.005 (0.005)	-0.007 (0.005)	-0.007 (0.005)	-0.005 (0.005)	-0.007 (0.005)	-0.007 (0.005)
Hospital stay (last 12 months)	0.014*** (0.004)	0.015*** (0.004)	0.016*** (0.004)	0.018*** (0.004)	0.019*** (0.004)	0.019*** (0.004)
Foreign born	-0.005 (0.006)	-0.005 (0.006)	-0.004 (0.006)	-0.004 (0.006)	-0.004 (0.006)	-0.003 (0.006)
Married/partnered	0.080*** (0.006)	0.075*** (0.006)	0.078*** (0.006)	0.081*** (0.006)	0.076*** (0.006)	0.078*** (0.006)
Never married	0.071*** (0.005)	0.069*** (0.006)	0.069*** (0.005)	0.071*** (0.005)	0.069*** (0.006)	0.069*** (0.005)
First stage F statistic (robust)	**505.09**	**515.95**	**660.93**	**479.58**	**503.04**	**709.23**
F statistic on the excluded instruments (robust)	**198.44**	**154.35**	**192.08**	**199.20**	**154.76**	**193.00**
F statistic on the excluded instruments (non-robust)	**2,654.12**	**2,227.93**	**1,959.65**	**1,740.41**	**2,221.65**	**1,955.28**
No. observations	**38,085**	**38,085**	**38,085**	**38,105**	**38,105**	**38,105**
R-squared	**0.68**	**0.68**	**0.69**	**0.68**	**0.68**	**0.69**

Table D.5.3: Second stage estimation results, Pooled OLS (death ideation, men)

Outcome: death ideation	Pooled OLS		
	(1a)	(1b)	(1c)
Retired	0.019*** (0.003)	0.015*** (0.003)	0.017*** (0.003)
Age (in years)	-0.015*** (0.002)	-0.012*** (0.002)	-0.012*** (0.002)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.003*** (0.001)	-0.003*** (0.001)
Education (in years), squared		0.000** (0.000)	0.000** (0.000)
Married/ partnered		-0.016*** (0.004)	-0.016*** (0.004)
Never married		-0.020*** (0.007)	-0.019*** (0.007)
Widowed		0.028*** (0.007)	0.029*** (0.007)
Has bad health		0.023*** (0.002)	
Has any kids		-0.013*** (0.005)	-0.013*** (0.005)
Hospital stay (last 12 months)		0.033*** (0.004)	0.036*** (0.004)
Foreign born		0.003 (0.004)	0.004 (0.004)
No. observations	**44,104**	**42,680**	**42,691**
R-squared	**0.02**	**0.03**	**0.03**

Note: All specifications control for year, month and country dummies, country specific trends, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table D.5.4: Second stage estimation results, Pooled IV (statutory retirement age) (death ideation, men)

Outcome: death ideation	Pooled IV (statutory retirement age)		
	(2a)	(2b)	(2c)
Retired	-0.003 (0.013)	0.004 (0.014)	0.004 (0.014)
Age (in years)	-0.009*** (0.003)	-0.010*** (0.003)	-0.009*** (0.003)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.002*** (0.001)	-0.002*** (0.001)
Education (in years), squared		0.000* (0.000)	0.000 (0.000)
Married/ partnered		-0.016*** (0.004)	-0.016*** (0.004)
Never married		-0.019*** (0.007)	-0.018*** (0.007)
Widowed		0.029*** (0.007)	0.029*** (0.007)
Has bad health		0.024*** (0.002)	
Has any kids		-0.013*** (0.005)	-0.013*** (0.005)
Hospital stay (last 12 months)		0.033*** (0.004)	0.037*** (0.004)
Foreign born		0.003 (0.004)	0.003 (0.004)
No. observations	**44,104**	**42,680**	**42,691**
R-squared	**0.02**	**0.03**	**0.03**

Note: All specifications control for year, month and country dummies, country specific trends, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table D.5.5: Second stage estimation results, Pooled IV (early retirement age) (death ideation, men)

Outcome: death ideation	Pooled IV (early retirement age)		
	(3a)	(3b)	(3c)
Retired	-0.016 (0.015)	-0.011 (0.015)	-0.011 (0.015)
Age (in years)	-0.006 (0.004)	-0.006* (0.004)	-0.006 (0.004)
Age (in years), squared	0.000*** (0.000)	0.000** (0.000)	0.000** (0.000)
Education (in years)		-0.002*** (0.001)	-0.002*** (0.001)
Education (in years), squared		0.000* (0.000)	0.000 (0.000)
Married/ partnered		-0.016*** (0.004)	-0.016*** (0.004)
Never married		-0.019*** (0.007)	-0.018*** (0.007)
Widowed		0.029*** (0.007)	0.029*** (0.007)
Has bad health		0.024*** (0.002)	
Has any kids		-0.013*** (0.005)	-0.013*** (0.005)
Hospital stay (last 12 months)		0.033*** (0.004)	0.037*** (0.004)
Foreign born		0.003 (0.004)	0.003 (0.004)
No. observations	**44,104**	**42,680**	**42,691**
R-squared	**0.02**	**0.03**	**0.03**

Note: All specifications control for year, month and country dummies, country specific trends, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table D.5.6: Second stage estimation results, Pooled 2SLS (death ideation, men)

Outcome: death ideation	Pooled 2SLS (both instruments)		
	(4a)	(4b)	(4c)
Retired	-0.015 (0.011)	-0.008 (0.011)	-0.009 (0.011)
Age (in years)	-0.007** (0.003)	-0.007** (0.003)	-0.006** (0.003)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.002*** (0.001)	-0.002*** (0.001)
Education (in years), squared		0.000* (0.000)	0.000 (0.000)
Married/ partnered		-0.016*** (0.004)	-0.016*** (0.004)
Never married		-0.019*** (0.007)	-0.018*** (0.007)
Widowed		0.029*** (0.007)	0.029*** (0.007)
Has bad health		0.024*** (0.002)	
Has any kids		-0.013*** (0.005)	-0.013*** (0.005)
Hospital stay (last 12 months)		0.033*** (0.004)	0.037*** (0.004)
Foreign born		0.003 (0.004)	0.003 (0.004)
No. observations	**44,104**	**42,680**	**42,691**
R-squared	**0.02**	**0.03**	**0.03**

Note: All specifications control for year, month and country dummies, country specific trends, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table D.5.7: Second stage estimation results, Pooled OLS (death ideation, women)

Outcome: death ideation	**Pooled OLS**		
	(1a)	(1b)	(1c)
Retired	0.010** (0.004)	0.005 (0.004)	0.008* (0.004)
Age (in years)	-0.015*** (0.002)	-0.015*** (0.002)	-0.015*** (0.002)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.008*** (0.001)	-0.008*** (0.001)
Education (in years), squared		0.000*** (0.000)	0.000*** (0.000)
Married/ partnered		-0.040*** (0.005)	-0.039*** (0.005)
Never married		-0.038*** (0.008)	-0.038*** (0.008)
Widowed		0.006 (0.006)	0.006 (0.006)
Has bad health		0.040*** (0.003)	
Has any kids		-0.015*** (0.006)	-0.015*** (0.006)
Hospital stay (last 12 months)		0.039*** (0.005)	0.043*** (0.005)
Foreign born		0.023*** (0.005)	0.024*** (0.005)
No. observations	**39,138**	**37,760**	**37,769**
R-squared	**0.03**	**0.05**	**0.04**

Note: All specifications control for year, month and country dummies, country specific trends, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table D.5.8: Second stage estimation results, Pooled IV (statutory retirement age) (death ideation, women)

Outcome: death ideation	Pooled IV (statutory retirement age)		
	(2a)	(2b)	(2c)
Retired	-0.038** (0.016)	-0.036** (0.016)	-0.036** (0.016)
Age (in years)	-0.004 (0.004)	-0.006 (0.004)	-0.005 (0.004)
Age (in years), squared	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)
Education (in years)		-0.008*** (0.001)	-0.008*** (0.001)
Education (in years), squared		0.000*** (0.000)	0.000** (0.000)
Married/ partnered		-0.038*** (0.005)	-0.038*** (0.005)
Never married		-0.037*** (0.008)	-0.037*** (0.008)
Widowed		0.006 (0.006)	0.006 (0.006)
Has bad health		0.042*** (0.003)	
Has any kids		-0.015*** (0.006)	-0.015*** (0.006)
Hospital stay (last 12 months)		0.039*** (0.005)	0.044*** (0.005)
Foreign born		0.023*** (0.005)	0.024*** (0.005)
No. observations	**39,138**	**37,760**	**37,769**
R-squared	**0.03**	**0.05**	**0.04**

Note: All specifications control for year, month and country dummies, country specific trends, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table D.5.9: Second stage estimation results, Pooled IV (early retirement age) (death ideation, women)

Outcome: death ideation	Pooled IV (early retirement age)		
	(3a)	(3b)	(3c)
Retired	-0.023 (0.018)	-0.011 (0.020)	-0.014 (0.019)
Age (in years)	-0.008 (0.005)	-0.012** (0.005)	-0.010** (0.005)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.008*** (0.001)	-0.008*** (0.001)
Education (in years), squared		0.000*** (0.000)	0.000*** (0.000)
Married/ partnered		-0.039*** (0.005)	-0.039*** (0.005)
Never married		-0.037*** (0.008)	-0.038*** (0.008)
Widowed		0.006 (0.006)	0.006 (0.006)
Has bad health		0.041*** (0.003)	
Has any kids		-0.015*** (0.006)	-0.015*** (0.006)
Hospital stay (last 12 months)		0.039*** (0.005)	0.044*** (0.005)
Foreign born		0.023*** (0.005)	0.024*** (0.005)
No. observations	**39,138**	**37,760**	**37,769**
R-squared	**0.03**	**0.05**	**0.04**

Note: All specifications control for year, month and country dummies, country specific trends, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table D.5.10: Second stage estimation results, Pooled 2SLS (death ideation, women)

Outcome: death ideation	**Pooled 2SLS (both instruments)**		
	(4a)	(4b)	(4c)
Retired	-0.033** (0.014)	-0.030** (0.014)	-0.029** (0.014)
Age (in years)	-0.005 (0.004)	-0.007* (0.004)	-0.006* (0.004)
Age (in years), squared	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Education (in years)		-0.007*** (0.001)	-0.008*** (0.001)
Education (in years), squared		0.000*** (0.000)	0.000*** (0.000)
Married/ partnered		-0.039*** (0.005)	-0.038*** (0.005)
Never married		-0.037*** (0.008)	-0.037*** (0.008)
Widowed		0.006 (0.006)	0.006 (0.006)
Has bad health		0.041*** (0.003)	
Has any kids		-0.015*** (0.006)	-0.015*** (0.006)
Hospital stay (last 12 months)		0.039*** (0.005)	0.044*** (0.005)
Foreign born		0.023*** (0.005)	0.024*** (0.005)
No. observations	**39,138**	**37,760**	**37,769**
R-squared	**0.03**	**0.05**	**0.04**

Note: All specifications control for year, month and country dummies, country specific trends, aggregate household income and sector of employment. Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level. Omitted category for variable marital status: separated/divorced.

Table D.5.11: Second stage estimation results (mental health, men)

	Pooled OLS			Pooled 2SLS		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Panel A: men						
Outcome: demotivation index (0 to 4)						
Retired	0.089***	0.052***	0.060***	-0.053	-0.063	-0.069*
	(0.011)	(0.011)	(0.011)	(0.041)	(0.040)	(0.041)
No. observations	**42,454**	**41,101**	**41,110**	**42,454**	**41,101**	**41,110**
R-squared	**0.09**	**0.11**	**0.11**	**0.08**	**0.11**	**0.10**
Outcome: affective suffering index (0 to 8)						
Retired	0.125***	0.060***	0.092***	0.005	-0.063	-0.086
	(0.024)	(0.023)	(0.023)	(0.089)	(0.086)	(0.088)
No. observations	**42,280**	**40,940**	**40,947**	**42,280**	**40,940**	**40,947**
R-squared	**0.05**	**0.10**	**0.07**	**0.04**	**0.10**	**0.07**
Outcome: Euro-D index (0 to 12)						
Retired	0.222***	0.120***	0.163***	-0.120	-0.134	-0.162
	(0.030)	(0.029)	(0.029)	(0.106)	(0.103)	(0.106)
No. observations	**43,695**	**42,302**	**42,309**	**43,695**	**42,302**	**42,309**
R-squared	**0.08**	**0.14**	**0.11**	**0.07**	**0.14**	**0.11**

Notes:

1) Specifications (1a) and (2a) control for year, month and country dummies, and country specific trends. Specifications (1b) and (2b) control for control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, and aggregate household income. Specifications (1c) and (2c) are the same as (1b) and (2b) with the exception of dropping the bad heath indicator. 2) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table D.5.11 (cont'd)

Outcome: sad or depressed last month						
Retired	0.015** (0.007)	0.008 (0.007)	0.015** (0.007)	0.010 (0.026)	0.009 (0.026)	0.005 (0.027)
No. observations	**44,197**	**42,765**	**42,776**	**44,197**	**42,765**	**42,776**
R-squared	**0.02**	**0.05**	**0.04**	**0.02**	**0.05**	**0.04**

Table D.5.12: Second stage estimation results (mental health, women)

	Pooled OLS			Pooled 2SLS		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Panel B: women						
Outcome: demotivation index (0 to 4)						
Retired	0.048***	0.020	0.030**	-0.211***	-0.183***	-0.183***
	(0.013)	(0.013)	(0.013)	(0.045)	(0.045)	(0.044)
No. observations	**37,703**	**36,382**	**36,391**	**37,703**	**36,382**	**36,391**
R-squared	**0.11**	**0.14**	**0.13**	**0.11**	**0.13**	**0.13**
Outcome: affective suffering index (0 to 8)						
Retired	0.174***	0.078**	0.129***	-0.041	0.002	-0.005
	(0.034)	(0.033)	(0.034)	(0.105)	(0.104)	(0.107)
No. observations	**37,539**	**36,230**	**36,239**	**37,539**	**36,230**	**36,239**
R-squared	**0.05**	**0.11**	**0.08**	**0.05**	**0.11**	**0.08**
Outcome: Euro-D index (0 to 12)						
Retired	0.213***	0.091**	0.153***	-0.312**	-0.252**	-0.256**
	(0.042)	(0.040)	(0.042)	(0.129)	(0.126)	(0.129)
No. observations	**38,795**	**37,430**	**37,439**	**38,795**	**37,430**	**37,439**
R-squared	**0.09**	**0.15**	**0.12**	**0.08**	**0.15**	**0.11**

Notes:

1) Specifications (1a) and (2a) control for year, month and country dummies, and country specific trends. Specifications (1b) and (2b) control for control for year, month and country dummies; age and education (in quadratics); marital status, dummy for having children; bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, and aggregate household income. Specifications (1c) and (2c) are the same as (1b) and (2b) with the exception of dropping the bad heath indicator. 2) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table D.5.12 (cont'd)

Outcome: sad or depressed last month						
Retired	0.028***	0.016*	0.025***	-0.007	0.003	0.003
	(0.009)	(0.009)	(0.009)	(0.029)	(0.030)	(0.030)
No. observations	**39,197**	**37,794**	**37,803**	**39,197**	**37,794**	**37,803**
R-squared	**0.03**	**0.06**	**0.05**	**0.03**	**0.06**	**0.04**

Table D.5.13: Second stage estimation results (men, social networks)

	Pooled OLS			Pooled 2SLS		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Panel A: men						
Outcome: size of the social network (number of persons)						
Retired	-0.037	0.009	0.004	-0.147	-0.240*	-0.194
	(0.035)	(0.037)	(0.037)	(0.126)	(0.124)	(0.123)
No. observations	**21,394**	**20,306**	**20,322**	**21,394**	**20,306**	**20,322**
R-squared	**0.04**	**0.05**	**0.05**	**0.04**	**0.05**	**0.05**

Notes:

1) Samples restricted to individuals with at least one living child in the model with outcome variable "children in the social network". Samples restricted to individuals with at least one living parent in the model with outcome variable "parents in the social network".

2) Specifications (1a) and (2a) of control for year, month and country dummies, and country-specific trends. Specifications (1b) and (2b) control for control for year, month and country dummies; age and education (in quadratics); marital status, number of children (dummy for having children in Table E.16); bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, aggregate household income, and number of living parents in the model with outcome variable "parents in the social network". Specifications (1c) and (2c) are the same as (1b) and (2b) with the exception of dropping the bad heath indicator.

3) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table D.5.13 (cont'd)

Outcome: number of persons in social network with daily contact						
Retired	-0.041 (0.031)	-0.019 (0.032)	-0.033 (0.032)	0.096 (0.116)	0.051 (0.115)	0.062 (0.117)
No. observations	**20,809**	**19,755**	**19,770**	**20,809**	**19,755**	**19,770**
R-squared	**0.02**	**0.04**	**0.03**	**0.02**	**0.04**	**0.03**
Outcome: social network satisfaction (0 to 10)						
Retired	-0.045** (0.019)	-0.029 (0.020)	-0.030 (0.020)	-0.116* (0.070)	-0.113 (0.071)	-0.109 (0.071)
No. observations	**20,901**	**19,889**	**19,894**	**20,901**	**19,889**	**19,894**
R-squared	**0.07**	**0.13**	**0.13**	**0.07**	**0.13**	**0.13**
Outcome: children in the social network						
Retired	0.001 (0.012)	0.005 (0.013)	0.004 (0.013)	-0.069 (0.046)	-0.074 (0.047)	-0.073 (0.047)
No. observations	**18,515**	**17,601**	**17,606**	**18,515**	**17,601**	**17,606**
R-squared	**0.05**	**0.06**	**0.06**	**0.05**	**0.06**	**0.06**
Outcome: parents in the social network						
Retired	-0.007 (0.025)	-0.015 (0.025)	-0.013 (0.025)	0.161* (0.094)	0.129 (0.097)	0.131 (0.096)
No. observations	**3,395**	**3,218**	**3,218**	**3,395**	**3,218**	**3,218**
R-squared	**0.08**	**0.17**	**0.17**	**0.06**	**0.16**	**0.16**
Outcome: done voluntary/charity work in the last 12 months						
Retired	0.021** (0.010)	0.044*** (0.010)	0.041*** (0.010)	0.073** (0.033)	0.076** (0.032)	0.078** (0.032)
No. observations	**21,269**	**20,208**	**20,220**	**21,269**	**20,208**	**20,220**
R-squared	**0.09**	**0.10**	**0.10**	**0.08**	**0.10**	**0.10**

Table D.5.14: Second stage estimation results (women, social networks)

	Pooled OLS			Pooled 2SLS		
	(1a)	**(1b)**	**(1c)**	**(2a)**	**(2b)**	**(2c)**
Panel B: women						
Outcome: size of the social network (number of persons)						
Retired	-0.084**	-0.039	-0.042	-0.139	-0.110	-0.111
	(0.043)	(0.043)	(0.043)	(0.148)	(0.147)	(0.147)
No. observations	**21,416**	**20,399**	**20,418**	**21,416**	**20,399**	**20,418**
R-squared	**0.07**	**0.09**	**0.09**	**0.07**	**0.09**	**0.09**

Notes:

1) Samples restricted to individuals with at least one living child in the model with outcome variable "children in the social network". Samples restricted to individuals with at least one living parent in the model with outcome variable "parents in the social network".

2) Specifications (1a) and (2a) of control for year, month and country dummies, and country-specific trends. Specifications (1b) and (2b) control for control for year, month and country dummies; age and education (in quadratics); marital status, number of children (dummy for having children in Table E.16); bad health and hospital stay in the last 12 months; foreign born dummy; sector of employment, aggregate household income, and number of living parents in the model with outcome variable "parents in the social network". Specifications (1c) and (2c) are the same as (1b) and (2b) with the exception of dropping the bad heath indicator.

3) Standard errors clustered at age-country-year level and shown in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table D.5.14 (cont'd)

Outcome: number of persons in social network with daily contact						
Retired	-0.016 (0.032)	-0.01 (0.033)	-0.024 (0.033)	-0.008 (0.112)	-0.034 (0.113)	-0.040 (0.113)
No. observations	**20,803**	**19,818**	**19,837**	**20,803**	**19,818**	**19,837**
R-squared	**0.02**	**0.03**	**0.03**	**0.02**	**0.03**	**0.03**
Outcome: social network satisfaction (0 to 10)						
Retired	-0.037* (0.023)	-0.066*** (0.023)	-0.054*** (0.020)	0.025 (0.082)	0.029 (0.073)	0.030 (0.073)
No. observations	**21,122**	**20,168**	**20,178**	**21,122**	**20,168**	**20,178**
R-squared	**0.10**	**0.15**	**0.31**	**0.10**	**0.15**	**0.31**
Outcome: children in the social network						
Retired	-0.010 (0.012)	-0.006 (0.013)	-0.005 (0.013)	-0.022 (0.042)	-0.034 (0.044)	-0.031 (0.043)
No. observations	**18,748**	**17,889**	**17,897**	**18,748**	**17,889**	**17,897**
R-squared	**0.04**	**0.06**	**0.06**	**0.04**	**0.06**	**0.06**
Outcome: parents in the social network						
Retired	0.022 (0.025)	0.017 (0.025)	0.016 (0.025)	0.231*** (0.088)	0.188** (0.086)	0.200** (0.087)
No. observations	**4,134**	**3,892**	**3,893**	**4,134**	**3,892**	**3,893**
R-squared	**0.08**	**0.17**	**0.17**	**0.06**	**0.16**	**0.16**
Outcome: done voluntary/charity work in the last 12 months						
Retired	0.032*** (0.010)	0.053*** (0.010)	0.050*** (0.010)	0.086** (0.033)	0.112*** (0.035)	0.112*** (0.035)
No. observations	**21,324**	**20,339**	**20,353**	**21,324**	**20,339**	**20,353**
R-squared	**0.07**	**0.09**	**0.08**	**0.07**	**0.08**	**0.08**

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CHAPTER 3

THE IMMIGRANT-NON-IMMIGRANT WAGE GAP REVISITED: EVIDENCE FROM THE PROGRAMME FOR THE INTERNATIONAL ASSESSMENT OF ADULT COMPETENCIES

3.1 INTRODUCTION

Immigrants comprise a large and growing fraction of the population worldwide. Over the past two decades the international migrant stock nearly doubled from 154.2 million persons in 1990 to 231.5 in 2013.[58] A large number of those immigrants reside in countries in the Organisation for Economic Co-operation and Development (OECD) and comprise a significant proportion of the total population in these states. For instance, in 2013 the U.S. hosted nearly 46 million immigrants – more than any other country in the world – with immigrants accounting for about 20% of its total population. The number of foreign-born residents of Germany is at present close to 10 million, while the number of immigrants in the United Kingdom, France and Canada overpasses 7 million.[59] Even countries like Japan and Korea, which were traditionally highly homogeneous societies, have seen a steady increase in their immigrant inflows since year 2000.

At the same time, there is ample evidence in the economic literature that immigrants in all countries earn less than the native-born workers, and are typically hit harder by a worsening of the economic conditions (see e.g. Chiswick (1978), Borjas (1985), and OECD and DESA-UN Report (2013)). Understanding the source of this immigrant-non-immigrant earnings gap has potentially important policy implications. To elaborate more on this, evidence of presence of labour market discrimination might put forward the need for stronger anti-discrimination legislative provisions, and for the implementation of government financial assistance programs targeting the immigrant population. Conversely, evidence that the gap originates from lower workplace skills of the immigrant workers might call for the development of education and qualification programs aimed at increasing the immigrants' competences and, hence, speeding up the convergence of their earnings to those of native-born workers.

[58] Source: DESA, UN. "Trends in international migrant stock: The 2013 revision." (2013).
[59] Source: OECD and DESA-UN. "World Migration in Figures." (2013).

The primary objective of this study is to examine the immigrant-native earnings gap using a cross-section of 21 countries from the 2011/2012 Programme for the International Assessment of Adult Competencies, [60] and to make inferences on the extent of labour market discrimination against the immigrant workers. To this end, we employ a modified Mincerian earnings function and a standard Oaxaca-Blinder mean wage decomposition (Oaxaca (1973) and Blinder (1973)). In addition to this, we extend our analysis to include the decomposition technique by DiNardo, Fortin and Lemieux (1996), aiming at capturing the differences in the earnings of immigrant and natives across the entire wage distribution. Last but not least, we seek to establish the particular way in which the labour market returns for immigrants and natives differ, and to evaluate these in the light of the labour market discrimination theories of the past decades.

Our contribution to the literature in the field is twofold. First, in contrast to previous studies which typically focused on a single country, we examine the immigrant-non-immigrant wage gap in a large pool of countries from PIAAC. As a consequence, we are able to make cross-country comparisons due to the same data structure and methodology applied. Secondly, we make use of the advantages of PIAAC for examining our main question of interest, in particular – the fact that the dataset contains a number of measures of the workers' cognitive skills and competences (e.g. numeracy and literacy test scores). This allows us to minimize the presence of unobserved effects such as ability bias, and ultimately – to have more credible results.

The key findings of the paper can be summarized as follows. First, we find evidence that immigrants in PIAAC have lower returns to education than native workers but enjoy higher

[60] PIAAC henceforth

returns to cognitive skills, and the latter is especially pronounced for literacy test score. This observation is line with the statistical discrimination theory suggesting that employers may view educational attainment as a less reliable productivity signal for immigrants, and that in the absence of other reliable productivity signals they place higher weight on immigrants' language proficiency. Secondly, the Oaxaca-Blinder decomposition of the immigrant-native mean earnings gap in the PIAAC sample suggests that a log-wage model specified with the controls usually employed by previous literature would overestimate the unexplained part of the gap nearly two times. In contrast, including measures for numeracy and literacy proficiency reveals a much lower role of the labour market discrimination component – just below 7 percent, while the composition effect is twice more important. Lastly, the DiNardo, Fortin and Lemieux (1996) results reveal that numeracy and literacy proficiency matter in the same way throughout the entire distribution of log-wages. Yet, even after controlling for these test scores, the differences in observables cannot fully account for the differences in the log-earning distributions between native and immigrant workers, except for the bottom 10 and the top 10 percentile earners. Hence, much like the Oaxaca-Blinder results, the DiNardo, Fortin and Lemieux results imply presence of labour market discrimination against the non-native workers, but suggest the magnitude of this discrimination is lower than that implied without controls for numeracy and literacy proficiency.

The remainder of this study is organised as follows. Section 3.2 reviews the main findings of the literature in the field. Section 3.3 discusses the data and defines the key variable employed in the study; this is followed by detailed data analysis. Section 3.4 proceeds by describing the methodology employed in the study for the immigrant-non-immigrant gap decomposition. Section 3.5 presents the key results, followed by concluding remarks.

3.2 LITERATURE REVIEW

Most of the literature on the immigrant-native wage gap draws upon data from the U.S. and Canada – countries which have often been referred to as "traditional" migration destinations (see e.g. Borjas (1994)). One of the earliest works in the field was done by Chiswick (1978), who analyzed the earnings of foreign-born and native men in the U.S., and observed that immigrants earned less than natives at the beginning of their working lives but enjoyed higher wage gains with the increase of their working experience and accumulation of skills, so that 10 to 15 years later their earnings surpassed those of non-immigrant workers. This study gave rise to what is known as the "assimilation" strand of the literature in the field, focusing on identifying whether and at what speed do immigrant earnings converge to those of native workers.

Another early study employing the assimilation approach was done by Tandon (1978), who used data from the 1971 Canadian census to study the immigrant-native wage gap, and reached a similar yet different conclusion for Canada, as compared to the findings by Chiswick (1978). In particular, the author reported that immigrants in Canada earn less than natives when they enter the labour market and have steeper wage-experience profiles than natives; however, in contrast to the U.S., the wage gap between immigrant and native workers in Canada only narrowed over time but remained substantial. During the last decade several authors have taken advantage of the availability of long panels to re-evaluate the early findings in the field. One example in this respect is a study by Lubotsky (2000), who used longitudinal data from the U.S. Social Security records and reported that the immigrant-non-immigrant wage gap closed by 10–15 percent during the first 20 years of immigration, or nearly twice slower compared to the typical estimates based on cross-sectional data.

A number of important studies in the field focused on analyzing the role of the changing composition of immigrant flows to the U.S. on their labour market performance and on the speed of convergence of their earnings to those of native workers. For instance, Borjas (1984) used the 1970 and 1980 censuses to study the earnings growth of various immigrant cohorts during that period. The key finding of that study was that for most immigrant groups the within-cohort growth was considerably smaller than the one predicted by cross-section regressions, which the author interpreted as evidence of the declining immigrant “quality”. In contrast, LaLonde and Topel (1991) used the 1970 and 1980 censuses, as well, but found that Asian and Mexican immigrants saw an earnings increase of roughly 20 percent in the first 10 years in the U.S., which did not lend strong support for the idea of declining immigrant quality. The issue of “immigrant quality” received little attention in the Canadian literature, although a recent study by Aydemir and Skuterud (2005) attempted to explore it. In particular, the authors analyzed data from five Canadian Censuses between 1981 and 2001 to explore the reasons for the declining entry earnings of immigrant men and women, and reported that nearly a third of this decline is explained by compositional shifts in the language proficiency of the immigrants. At the same time, the authors found evidence of a decline in the returns to foreign labour market experience but no evidence of a decline in the returns to foreign education.

The past decades gave rise to several European studies in the field. A large fraction of these studies employed the assimilation approach, yet several authors used a methodology borrowed from the “discrimination” literature and first suggested by Oaxaca (1973). This second approach allows for decomposing the mean immigrant-non-immigrant earnings gap to a part due to differences in observables and a part due to discrimination. An early assimilation study by Pischke (1992) analyzed data from the German Socioeconomic Panel from the 1980s and reported a sizeable native-immigrant earnings gap of roughly 20 to 25 percent; in addition, the author found little evidence that the earnings of foreign-born workers catch up with those of Germans – a finding he attributed to the fact immigrants were concentrated in unskilled and low-skilled jobs. Another study by Kee (1993) examined the employment likelihood of native Dutch men in the 80s, on the one hand, and four groups of immigrants, on the other: Antilleans, Surinamese, Turks and Moroccans. The key findings of this study suggested that while Moroccans and Antilleans would have enjoyed the same employment probabilities had they had the same characteristics as native workers, for Surinamese and Turk employees at least part of the gap was due to discrimination (25% and 60%, respectively). Further, Le Grand and Szulkin (2002) employed the decomposition approach to analyze a large sample of Swedish workers in 1995 and found that immigrants from countries other than those in Western Europe earn considerably less than native workers – 5.5 percent for male workers and 2.8 percent for females, and that a large part of the observed gap could be attributed to discrimination. A recent study by Coppola et al. (2013) used a nationally-representative data from Italy to examine the labour market outcomes of immigrants and non-immigrants in the country, and found a considerable wage differential between immigrants and natives which increases along the wage distribution.

Most of the empirical studies in the field focused on a single country rather than on a broader cross-country analysis. One of the few comprehensive analyses was one by Adsera and Chiswick (2004), who used the 1994-2000 waves of the European Community Household Panel to analyze of the earnings of native and immigrant workers, and reported a significant negative effect of immigrant status on one's earnings, although this effect varied considerably across countries. In particular, immigrants in Germany and Portugal enjoyed highest earnings relative to those of native workers, while immigrants in countries such as Sweden, Denmark, Spain and

Luxembourg were paid lowest relative to native workers. The authors also reported some gender and country-of-origin heterogeneity in the immigrant wage levels with Asian, Latin-American and Eastern European men, and Latin-American and Eastern European women being at the bottom of the male and female wage distributions.

To sum up the review of the relevant literature, most research on the immigrant-native earnings gap is country-specific with only few cross-country studies. While this has the benefit of large country samples and the potential to develop models that are better fitted to a specific labour market, it also has the disadvantage that clear cross-country comparisons are unfeasible due to the fact that the data structure as well as the approach to measure the native-immigrant earnings gap generally differ between studies. This paper aims at extending the current decomposition literature in that it intends to revisit the previous findings on the immigrant-native wage gap based on a large cross-country snapshot from the 2011/2012 PIAAC. Even though some PIAAC country-immigrant samples are small making estimation for that particular country unfeasible, using a single pooled dataset has the advantage that it allows for the application of a unified research approach in the 20 members-states of OECD, and Russia, and makes it possible to draw country-level conclusions, as well as conclusions for the entire area.

In addition to this, we aim at adding to the previous findings by employing better measures of the worker skills. To elaborate more on this, prior research typically estimated Mincer-type earnings functions with years of formal schooling and labour market experience as the key human capital measures. In addition, some authors included other observable characteristics such as gender and ethnic background; type of education; skill-based occupational category and industry of employment (see e.g. Reitz (2001)), and only few studies had access to measures of workers' skills such as language proficiency (see e.g. Aydemir and Skuterud (2005) and Coppola et al. (2013)). All this has the drawback that presence of unobserved effects, and most notably ability bias, cannot be ruled out as a potential threat to the validity of the results. We take advantage of a unique feature of PIAAC, which makes the dataset particularly well-suited for our key question of interest, namely: the fact PIAAC contains various measures of the respondents' cognitive skills. This allows us to not only study the immigrant and native workers returns on education and experience, as the vast body of literature did, but to also examine the returns of the two groups of workers to workplace competences, and ultimately – to make better inference on the presence of labour market discrimination against immigrant workers, and on its importance.

3.3 DATA AND DESCRIPTIVE STATISTICS

3.3.1 Data and sample

This paper uses data from the Programme for the International Assessment of Adult Competencies. PIAAC is an international survey, implemented in 24 countries and targeted at adults aged between 16 and 65 years. Data was collected in 2011 and 2012. Data on Australia not yet available; in addition, we exclude Sweden due to the fact wage data in this country is restricted in PIAAC and could not be imputed from other publicly available sources (see below). The final sample consists of data from 21 countries: Austria, Belgium (Flanders only), Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, United Kingdom, and the United States.

In order to obtain a sample of workers with comparable labour force attachment, we focus our attention to all prime-age individuals in PIAAC, who are full-time employed at the time of the survey. We employ the OECD definition of prime age, i.e. persons aged 25 to 54 years. In turn, full-time employment is defined as working at least 30 hours a week. [61] In addition to this, following the mainstream literature, we drop the lowest and the highest wage percentile in each country in order to limit the influence of outliers and observations with implausible hourly wage values. All persons with missing wage are also dropped from the sample.

The final sample consists of 45,697 observations on full-time employed prime age individuals.

[61] There is a considerable variation in the full-time working week duration by country. E.g. the Affordable Care Act in the U.S. defines a full-time week 30 hours or more; countries in Europe have typically a definition between 30 and 40 hours a week (e.g. 37 hours in Denmark; 38 in Belgium; 35-40 hours in the Netherlands and Germany; 40 hours in Poland, etc). For this reason this paper adopts a definition of a minimum of 30 hours a week.

3.3.2 Variables definitions

3.3.2.1 Wage and immigrant status

The wage measure employed is gross hourly earnings in USD and PPP-adjusted. For Austria, Canada, Germany, Sweden, and the United States the public use PIAAC files only contain wage data as deciles in the hourly wage distribution. For this reason, for all these countries except Sweden we impute the hourly wage as the mean wage for full-time employed workers in each decile in the corresponding country. [62]

We focus our analysis on measuring the wage gap between first generation immigrants and non-immigrants. In turn, immigrants are defined as persons who are foreign-born, and have at least one foreign-born parent.

3.3.2.2 Skill measures

The unique feature of PIAAC is that apart from providing demographic and socio-economic information, the respondents answered a series of questions aimed at measuring their cognitive and workplace skills and competences. The main skill measures in PIAAC are divided into three domains:

1. Numeracy skills: PIAAC defines numeracy as the ability to use and interpret mathematical information, and it encompasses solving a problem in mathematical content.

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[62] All calculations are based on OECD data on the mean wages by deciles and country for full-time employed persons in 2009 (in USD and PPP-adjusted). OECD values are reported annually for Austria, weekly for Canada and the U.S., and monthly for Germany. All values were converted to hourly equivalents assuming the following work-interval durations: 8 hours per day, 40hours per week, 173 hours per month and 2,080 hours per year. The same week/month/year durations are used by PIAAC. In turn, all the resulting weekly values were CPI adjusted to 2011 values based on the 2011-2009 CPI (source: http://www.inflation.eu/inflation-rates/historic-cpi-inflation.aspx). Data for Sweden is only reported for deciles 10, 50 and 90, making the wage imputation implausible; for this reason the country is excluded from the analysis.

2. Literacy proficiency: literacy is defined as the ability to understand written text, and it includes skills such as text decoding, as well as comprehension and interpretation. In each countries in PIAAC the literacy score reflects the respondents' proficiency in the main language of that country. This implies that for foreign-language immigrants the literacy test serves as a measure of their proficiency in the language of the receiving country (rather than their native language), making the test of particular importance in our analysis.

3. Problem solving in technology-rich environment: this domain is defined as the ability to use information technology to obtain, assess and communicate information.

The design of the skill testing in PIAAC was based on matrix sampling where each respondent answered only a subset of questions from the total question pool. Item response theory scaling was then applied in order to obtain cognitive test scores for the entire PIAAC sample in terms of a common scale. In order to increase the accuracy of these measurements, multiple imputation procedure was used to obtain a set of plausible values of each respondent's score. For each skill domain, ten plausible score values were computed; we use the first plausible value in each domain. [63] All test scores are measured on a scale ranging from 0 to 500.

Various working environment skill measures, such as cooperation, communication, and time organizing are also available.

[63] No plausible value is better than either of the others; in principle, we could have used all 10 plausible values. However, this has the disadvantage that computing standard errors with 10 plausible values and 80 replicates for each country would require computing 800 statistics (80 replicates times 10 plausible vales), and 10 more statistics using the whole sample and final sample weight, i.e. a total of 810 computations of statistic of interests. For this reason we focus on using the first plausible value only, i.e. the first test score imputation for every respondent in the sample.

3.3.2.3 Other covariates

Demographic characteristics such as age, gender, education, marital status, number of children and parental education level are also available in PIAAC. In addition, education and labour force characteristics, such as actual working experience (years of paid work during lifetime), job tenure, and skill-based occupational category are also available. However, the public data files do not contain the raw variables in some countries. For instance, age in years is not available for Austria, Canada, Germany and the US. For this reason, we employ a categorical age definition based on 5-year age intervals, which are available for all countries. Likewise, working experience in PIAAC was top-coded at 47 years for Austria, Canada, Germany and the US. Given that we focus on workers age between 25 and 54, the top coding could not lead to censoring in our sample, so we opt for using experience as a continuous variable. Lastly, various education measures are available in PIAAC: highest level of education grouped in ISCED categories, years of education (not available for Germany, but imputed), and education categorized as below high school, high school and above high school (not available for Austria, but imputed). [64]

3.3.3 Sample statistics

Table E.1 presents the key sample statistics in the total pooled sample, and by country. Several things are worth noting here. First and foremost, countries with higher than the pooled

[64] Variable "years of education" is not available for Germany. We impute this variable for each respondent based on their education by ISCED category, and the typical duration for each ISCED educational category in Germany. Education categorized as below high school, high school and above high school is not available for Austria. We impute this variable based on the available education by ISCED categories for Austria.
Source: Classifying Educational Programmes: Manual for ISCED-97 Implementation in OECD Countries. OECD 1999, available at http://www.oecd.org/edu/skills-beyond-school/1962350.pdf

sample mean wages also have a higher fraction of immigrants, on average. E.g. Canada and the U.S. are the countries with highest mean wages in the PIAAC sample, and the share of immigrant population in these countries is much above the OECD average. This is in line with the theoretical literature which lists the economic conditions in the country of destination amongst the key pull factors of migration. Turning briefly to demographics, the prime age full-time employed in Ireland and Poland appear significantly younger than average, with the fraction of workers in the 25-34 age range of above 40 percent. Lastly, there is a large country variation in the share of women in the full-time prime age employed population: the Netherlands, Germany, Italy, Korea and Japan have particularly low fraction of females, while Finland, Denmark, post-communist Europe, and the US have relatively high fractions of females amongst the full-time employed prime age workers.

Turning to the education and skill-levels in the country samples, it appears from Table E.1 that the full-time employed prime age workers in Ireland and Norway are particularly well educated (sample mean years of schooling of roughly 16 and 15 years, respectively). Four other European countries – Italy, France, Spain and Austria – are on the other end of the spectrum with mean years of education of just between 11.5 and 12.5 years. The mean years of actual labour market experience by country naturally follows the age structure and educational attainment of the employees. Last but not least, workers in Japan, Finland, Netherlands and Norway appear to score highest across all cognitive skill measures; those countries also have below average to average fraction of immigrant population. In contrast, Italy, Spain, the U.S, Poland and France have lowest across in the PIAAC sample across most skill domains; all countries in this group, except Poland, have a large immigrant population amongst the full-time employed prime age individuals.

A glance at the labour market characteristics of the two subsamples reveals that non-immigrants appear significantly better qualified in terms of education – both measured as years of schooling, and as highest degree obtained (Table E.2). It is also worth mentioning that nearly 19% of the respondents in the immigrant sample are high-school drop-outs versus only 9% in the non-immigrant sample. In addition to this, immigrants have nearly 2.5 years less of working experience during their lifetime. Further, non-immigrants are employed in better occupations: they have higher number years of formal education required to obtain the current job they hold (13.1 years vs. 12.3 for immigrants), and are nearly 10% more likely to be employed at skilled occupations. Related to this, non-immigrants are about 10% more likely to have undergone on-the-job training during the year preceding the interview. The two groups also differ by sector of employment with non-immigrants being considerably more likely to be employed in the public sector (28% of all versus 18% for non-immigrants).

Turning to cognitive competences, non-immigrants perform significantly better in all skill domains. The gap between the two groups is particularly pronounced for the numeracy test scores – nearly 40 points, or roughly 0.8 standard deviations. Immigrants also score lower on the literacy test (difference in means of just over 30 points, or 0.65 standard deviations); this is expected as nearly 75% of all immigrants have a foreign-language background. In addition, those workers also demonstrate worse problem solving skills (gap of about 20 points, or 0.4 standard deviations). Moreover, native workers appear more likely to use numeracy, reading and writing skills at work, and have a higher index of learning and readiness to learn at work.

All the above observations strongly point towards immigrants in the PIAAC sample having, on average, worse labour market characteristics and cognitive abilities. It is somewhat puzzling then, at first, that immigrants earn slightly higher wages, on average ($18.62 vs.

$18.05); however, this is merely a reflection of the fact that countries with higher wages have larger immigrant-populations. This suggests that in order to get the complete picture of the earnings differences between the two groups, we need to examine those outcomes when controlling for country-specific heterogeneity. We present this analysis in the next paragraphs.

Figures E.1 to E.7 depict the mean wage gap between native and immigrant workers conditional on observable covariates, and after accounting for country-level heterogeneity. Figures E.1 to E.4 present the differences in mean wages conditional on educational attainment, labour market experience, sector of employment and occupation. These graphs reveal an interesting pattern: a sizeable and statistically significant earnings gap, even within each category. For instance, the mean wages of native workers are considerably larger than those of immigrants conditional on educational attainment, and this gap remains stable across all education categories. The existence of such a gap might imply presence of labour market discrimination against immigrant workers, but there is an alternative plausible explanation, as well, namely: there might be considerable heterogeneity in education quality between immigrant and native workers within each educational attainment group. Virtually the same observation prevails when examining the immigrant and non-immigrant mean earnings by labour market experience and sector of employment (Figures E.2 and E.3), although the gap in the public sector appears somewhat smaller than the gap observed in the private and non-profit sectors. Figure E.4 also reveals earnings differences within a skill-based occupational category, although those differences are smaller than the ones observed within each education and experience group; moreover, the gap is lower for high skill occupations than for elementary, semi-skilled white collar and semi-skilled blue collar ones.

All these observations lend support for idea that at least some of the immigrant-non-immigrant wage gap observed within each educational, experience, sector of employment and occupational groups, might be due to differences in skills. This explanation is further reinforced when examining the mean wages of native and immigrant workers conditional on numeracy, literacy and problem solving scores (standardized to have a mean of zero and a standard deviation of 1), presented on Figures E.5, E.6 and E.7. As can be seen from here, in all skill domains the mean wage gap within a given bin is considerably lower than the gap conditional on the conventional observable characteristics, such as education and working experience. In addition to this, the mean earnings gap between native and foreign born workers decreases with the increase of test scores, and is not statistically different from zero in the top score ranges. This is particularly well pronounced for numeracy and literacy proficiency, and to a lesser extent – for problem solving test score. Lastly, it is worth noting the steep increase of both immigrants' and natives' earnings with the increase of literacy and numeracy skills, and the flatter earnings increase with problem solving test score. This is consistent with the findings of a recent paper by Hanushek et al., 2013 who used data from PIAAC and reported considerably larger labour market returns to numeracy and literacy test skills than for problem solving skills.

3.4 IDENTIFICATION STRATEGY

3.4.1 Mean wage gap decomposition

Following the mainstream literature, we start with a standard linear model written explicitly with an intercept, relating log-wages and covariates, defined for two mutually exclusive groups of interest:

$$Y_{gi} = \beta_{g0} + \boldsymbol{X}_i \boldsymbol{\beta}_{\boldsymbol{g}} + u_{ig},\ g \in \{I, N\}, \qquad \textbf{(1)}$$

where I stands for immigrants, and N – for non-immigrants; Y denotes log-earnings, $\boldsymbol{X}$ is a vector of observable covariates and u_{ig} – the idiosyncratic error term.

It is well established in the economic literature that the raw wage gap (defined as the difference in the mean outcomes for the two groups, $\widehat{\Delta}_0^{\mu} = \overline{\mathrm{Y}}_{\mathrm{I}} - \overline{\mathrm{Y}}_{\mathrm{N}}$) can be represented as:

$$\widehat{\Delta}_0^{\mu} = [(\hat{\beta}_{I0} - \hat{\beta}_{N0}) + \overline{\boldsymbol{X}}_{\boldsymbol{I}}(\widehat{\boldsymbol{\beta}}_{\boldsymbol{I}} - \widehat{\boldsymbol{\beta}}_{\boldsymbol{N}})] + (\overline{\boldsymbol{X}}_{\boldsymbol{I}} - \overline{\boldsymbol{X}}_{\boldsymbol{N}})\,\widehat{\boldsymbol{\beta}}_{\boldsymbol{N}}$$

where $\hat{\beta}_{g0}$ and $\hat{\beta}_{g}$, $g \in \{I, N\}$, are the estimates of the intercept and slope parameters from model (1), for group I and N, respectively. This representation is known as the Oaxaca-Blinder decomposition (Oaxaca (1973) and Blinder (1973)).

The first term in the decomposition, $\widehat{\Delta}_S^{\mu} = [(\hat{\beta}_{I0} - \hat{\beta}_{N0}) + \overline{\boldsymbol{X}}_{\boldsymbol{I}}(\widehat{\boldsymbol{\beta}}_{\boldsymbol{I}} - \widehat{\boldsymbol{\beta}}_{\boldsymbol{N}})]$, is often referred to as the "unexplained effect", the "wage structure effect", or the "effect of returns to skills", or simply as "discrimination". The second component, $\widehat{\Delta}_X^{\mu} = (\overline{\boldsymbol{X}}_{\boldsymbol{I}} - \overline{\boldsymbol{X}}_{\boldsymbol{N}})\,\widehat{\boldsymbol{\beta}}_{\boldsymbol{N}}$, is the so called "composition effect", or the "explained effect" as it arises from differences in the covariates. It is worth noting that $(\hat{\beta}_{I0} - \hat{\beta}_{N0})$ is the returns to skills effect for the baseline group, and it will generally depend on which group is chosen as a baseline (see e.g. Oaxaca and Ransom (1999)).

In order to illustrate the decomposition more formally, it is convenient to adopt the framework developed by Fortin, Lemieux and Firpo (2011), according to which the wage structure effect can be interpreted as a treatment effect. To elaborate more on this, immigrant status can be viewed as a binary treatment D_i, taking a value of 1 if the person is an immigrant, and 0 otherwise; in this way, the treatment identifies two distinct and mutually exclusive groups, *I* and *N*. Next, define Yi_N and Yi_I as the potential values of the outcome of interest for worker *i* when the binary treatment takes on values 0 and 1, respectively, and D_{iN} and D_{iI} as the potential treatment, i.e. moving from group *I* to group *N*, and vice versa.

Of course, the main difficulty of the analysis stems from the fact that the counterfactual outcomes are not observed; we only observe the actual earnings Y_i of worker *i*, which can be expresses as Y_i=$D_{gi}Y_{gi}$, $g \in \{I, N\}$. Hence, we could only compare the actual mean wages of the two groups, $\mathbb{E}(Y_{iI} \mid D_{iI} = 1)and\mathbb{E}(Y_{iN} \mid D_{iN} = 1)$. However, using a program evaluation approach we can represent the mean wage gap the following way:

$$
\begin{aligned}
\Delta_0^{\mu} = {} & \mathbb{E}(Y_I) - \mathbb{E}(Y_N) \\
& = \mathbb{E}(Y_I \mid D_I = 1) - \mathbb{E}(Y_N \mid D_N = 1) \\
& = \mathbb{E}\{\mathbb{E}[(Y_I \mid \boldsymbol{X}, D_I = 1) \mid D_I = 1]\} - \mathbb{E}\{\mathbb{E}[(Y_N \mid \boldsymbol{X}, D_N = 1) \mid D_N = 1]\} \\
& = [\beta_{IO} + \mathbb{E}(\boldsymbol{X} \mid D_I = 1)\boldsymbol{\beta_I} + \mathbb{E}(u_I \mid D_I = 1)] \\
& -[\beta_{NO} + \mathbb{E}(\boldsymbol{X} \mid D_N = 1)\boldsymbol{\beta_N} + \mathbb{E}(u_N \mid D_I = 1)] \\
& = (\beta_{IO} - \beta_{NO}) + \mathbb{E}(\boldsymbol{X} \mid D_I = 1)\boldsymbol{\beta_I} - \mathbb{E}(\boldsymbol{X} \mid D_N = 1)\boldsymbol{\beta_N} \\
& = \{(\beta_{IO} - \beta_{NO}) + [\mathbb{E}(\boldsymbol{X} \mid D_I = 1)\boldsymbol{\beta_I} - \mathbb{E}(\boldsymbol{X} \mid D_I = 1)\boldsymbol{\beta_N}]\} \\
& + [\mathbb{E}(\boldsymbol{X} \mid D_I = 1)\boldsymbol{\beta_N} - \mathbb{E}(\boldsymbol{X} \mid D_N = 1)\boldsymbol{\beta_N}] \\
& = [(\beta_{IO} - \beta_{NO}) + \mathbb{E}(\boldsymbol{X} \mid D_I = 1)(\boldsymbol{\beta_I} - \boldsymbol{\beta_N})] + [\mathbb{E}(\boldsymbol{X} \mid D_I = 1) - \mathbb{E}(\boldsymbol{X} \mid D_N = 1)]\boldsymbol{\beta_N} \\
& = \Delta_S^{\mu} + \Delta_X^{\mu}
\end{aligned}
$$

(where we have applied the Law of Iterated Expectations, and used the assumption that $\mathbb{E}(u_g \mid D_g = 1) = 0$).

Here the first term $[(\beta_{IO} - \beta_{NO}) + \mathbb{E}(\boldsymbol{X} \mid D_I = 1)(\boldsymbol{\beta_I} - \boldsymbol{\beta_N})]$ equals Δ_S^{μ}, and represents the average treatment effect of the treated (ATT), or more intuitively – the difference between the actual mean wages of immigrants, and the potential wages of immigrants had they been rewarded according to the wage structure of natives.[65] The second term in the mean wage gap, $[\mathbb{E}(\boldsymbol{X} \mid D_I = 1) - \mathbb{E}(\boldsymbol{X} \mid D_N = 1)]\boldsymbol{\beta_N}$, represents the difference between the potential earnings of non-immigrants if they had the same observable characteristics as immigrants and the actual mean non-immigrant wages.

Given this set-up, the wage decomposition problem could be restated the following way: what would the wages of non-immigrants be if they had the same returns to skills as immigrant workers, or, in other words – consistently estimating ATT (or ATUT, respectively). This representation is useful as it allows applying well-known results from the program evaluation literature – consistent estimation of ATT requires that two key assumptions are satisfied:

A1) overlapping support

Stated in simple terms, the overlap assumption requires that $\forall \boldsymbol{X}$ in its support $\boldsymbol{\chi}$,

$$0 < P(D = 1|\boldsymbol{X} = \boldsymbol{x}) < 1$$ (see e.g. Wooldridge (2010)).

Intuitively, this rules out cases where the factors affecting the log-earnings may differ across the two groups of interest. In the literature of wage decomposition, this assumption often fails to hold (see e.g. Fortin, Lemieux and Firpo (2011)). Studies of the immigrant-non-

[65] The choice of a reference group is arbitrary; an alternative representation would be:
$\Delta_0^{\mu} = [(\beta_{NO} - \beta_{IO}) + \mathbb{E}(\boldsymbol{X} \mid D_N = 1)(\boldsymbol{\beta_N} - \boldsymbol{\beta_I})] + [\mathbb{E}(\boldsymbol{X} \mid D_N = 1) - \mathbb{E}(\boldsymbol{X} \mid D_I = 1)]\boldsymbol{\beta_I} =$
$= \Delta_S^{\mu} + \Delta_X^{\mu}$.
In this case, the first term represents the average treatment effect of the untreated (ATUT).

immigrant wage gap also face a potential fail of the overlap assumption, if e.g. factors such as age and country of immigration are important determinants of immigrant wages as these factors do not affect wages of native workers and would, hence, serve to unambiguously identify group *I*. In order to ensure $0 < P(D = 1|\boldsymbol{X} = \boldsymbol{x}) < 1$ holds, we impose the same dimension of the two vectors of covariates X_I and X_{N}.

A2) unconfoundedness (also known as "ignorability of treatment")

This assumption states that a sufficient condition for consistent estimation of ATT, is that conditional on the observable covariates $\boldsymbol{X}_{ig}$, the distribution of the unobservables u_{ig} is the same in the two groups:

$$D(u_i|\, \boldsymbol{X}_i, \text{D=1}) = D(u_i|\, \boldsymbol{X}_i, \text{D=0}) \text{ (Wooldridge (2010)).}$$

As a corollary, the consistent estimation of ATT is possible, even though e.g. unobserved innate ability and educational attainment are correlated, as long as once the observable characteristics (such as age, labour market experience, cognitive skills test scores, etc.) in vector $\boldsymbol{X}$ have been accounted for, the dependence structure between ability and education is the same in groups *I* and *N*.

3.4.2 DiNardo-Fortin-Lemieux decomposition

Numerous authors have proposed further extensions of the Oaxaca-Blinder decomposition framework to allow for decomposing the differences in the entire log-wage distribution, rather than merely focusing on the mean-wage gap. We follow one commonly used approach in the literature, proposed by DiNardo, Fortin and Lemieux (1996) (referred to as "DFL" henceforth). In particular, this methodology involves the use of propensity score weights to construct counterfactual wage distributions, and can be summarized as follows.

Adapting the notation from DiNardo, Fortin and Lemieux (1996) and DiNardo (2002) to the notation of this paper, let $f^N(Y)$ be the actually observed distribution of log-wages for natives, and $f^I(Y)$ – the actual distribution of log-wages for immigrants. DFL represent the actual distribution for the native and immigrant workers, $f^N(y)$ and $f^I(y)$, respectively as a conditional distribution of log-wages on individual attributes, [66] integrated over the distribution of individual attributes, or formally:

$$f^N(y) = \int f^N(y)dy = \int f^N(y|\boldsymbol{x}, g = N)\, h(\boldsymbol{x}|g = N)dx$$

$$f^I(y) = \int f^I(y)dy = \int f^I(y|\boldsymbol{x}, g = I)\, h(\boldsymbol{x}|g = I)dx,$$

where $h(\boldsymbol{x}|\cdot)$ is the distribution of covariates is each group.

Further, consider the counterfactual density for native workers $f^N_{CF}(y)$, i.e. the density that would have been observed if native workers had the distribution of individual covariates of immigrant workers, and were paid according to the natives' wage structure:

$$f^N_{CF}(y) = \int f^N(y|\boldsymbol{x}, g = N)\, h(\boldsymbol{x}|g = I)dx.$$

The counterfactual density for immigrants is composed analogously as:

$$f^I_{CF}(y) = \int f^I(y|\boldsymbol{x}, g = I)\, h(\boldsymbol{x}|g = N)dx.$$

Then difference between the actual density for native workers and the counterfactual density for those workers can be expressed as:

$$f^N(y) - f^N_{CF}(y) =$$

$$\int f^N(y|\boldsymbol{x}, g = N)\, h(\boldsymbol{x}|g = N)dx - \int f^N(y|\boldsymbol{x}, g = N)\, h(\boldsymbol{x}|g = I)dx,$$

[66] This follows from representing $f^N(y)$ as a joint distribution of wages $f^N(y, \boldsymbol{x}\,|g = N)$, integrated over the distribution of individual attributes, and then applying Law of Iterated Expectation.

and reveals the part of the wage gap, which is due to differences in the distribution of covariates between native and immigrant workers. The part due to discrimination is given by the difference between the counterfactual density for natives and the actual density for immigrants:

$f_{CF}^{N}(y) - f^{I}(y) =$

$$\int f^{N}(y|\boldsymbol{x}, g = N)\, h(\boldsymbol{x}|g = I)dx - \int f^{I}(y|\boldsymbol{x}, g = I)\, h(\boldsymbol{x}|g = I)dx.$$

However, since generally $h(\boldsymbol{x}|\cdot)$ includes several explanatory variables, integrating over multiple dimensions of covariates may be unfeasible. In order to avoid a potentially unsolvable problem, DFL suggest representing the counterfactual density for natives as a reweighted actual density for natives:

$f_{CF}^{N}(y) =$

$$\int f^{N}(y|\boldsymbol{x}, g = N)\, h(\boldsymbol{x}|g = I)dx =$$

$$\int f^{N}(y|\boldsymbol{x}, g = N)\, h(\boldsymbol{x}|g = N)\frac{h(\boldsymbol{x}|g = I)}{h(\boldsymbol{x}|g = N)}\, dx \equiv$$

$$\int f^{N}(y|\boldsymbol{x}, g = N)\, h(\boldsymbol{x}|g = N)\omega(\boldsymbol{x})\, dx,$$

where $\omega(\boldsymbol{x})$ is the weight applied to the actual density of natives.[67]

In turn, applying Bayes' rule allows representing the conditional distribution of covariates $h(\boldsymbol{x}|\cdot)$ for natives and immigrants as:

$$h(\boldsymbol{x}|g = N) = \frac{P(g = N|\boldsymbol{x})f(\boldsymbol{x})}{P(g = N)}$$

$$h(\boldsymbol{x}|g = I) = \frac{P(g = I|\boldsymbol{x})f(\boldsymbol{x})}{P(g = I)},$$

[67] Similarly, the counterfactual density for immigrants can be represented as:
$f_{CF}^{I}(y) = \int f^{I}(y|\boldsymbol{x}, g = I)\, h(\boldsymbol{x}|g = I)\frac{h(x|g=N)}{h(x|g=I)}\, dx \equiv \int f^{I}(y|\boldsymbol{x}, g = I)\, h(\boldsymbol{x}|g = I)[\omega(\boldsymbol{x})]^{-1}dx.$

where $f(\boldsymbol{x})$ is unconditional distribution of covariates in the total population. Plugging in the expressions for $h(\boldsymbol{x}|g = N)$ and $h(\boldsymbol{x}|g = I)$ in the definition of $\omega(\boldsymbol{x})$ yields:

$$\omega(\boldsymbol{x}) = \frac{P(g = N|\boldsymbol{x})f(\boldsymbol{x})}{P(g = N)} : \frac{P(g = I|\boldsymbol{x})f(\boldsymbol{x})}{P(g = I)} = \frac{P(g = N|\boldsymbol{x})}{P(g = I|\boldsymbol{x})} \cdot \frac{P(g = I)}{P(g = N)}.$$

The advantage of this representation of ω(x) is that it replaces the conditional distribution of covariates $h(\boldsymbol{x}|\cdot)$ with the conditional probabilities $P(g = I|\boldsymbol{x})$ and $P(g = N|\boldsymbol{x})$, which are analogous to standard binary response models. $P(g = I|\boldsymbol{x})$ and $P(g = N|\boldsymbol{x})$ are often referred to as the "propensity scores" and can be interpreted as the probability that a given worker belongs to group g, $g \in \{I, N\}$ respectively, given the set of his/her observable characteristics. Alternatively, employing the treatment approach from the previous section and viewing immigrant status as the treatment, $P(g = I|\boldsymbol{x})$ is the probability a given worker would have been exposed to treatment conditional on the set of his/her observable covariates. The unconditional probabilities $P(g = I)$ and $P(g = N)$ are simply the fractions of immigrants and natives in the total population.

Given this set-up, estimating the reweighting function $\omega(\boldsymbol{x})$ boils down to estimating the propensity score; the later can be done by the following steps:

1. Define a binary treatment variable *D*, such that D_i =1 if worker *i* is an immigrant, and 0 otherwise.

2. Run a logit or probit of the treatment indicator D on the set of observable covariates $\boldsymbol{X}$.

3. Obtain the predicted probability $P(\widehat{D = 1}|\boldsymbol{x}) \equiv P(\widehat{g = I}|\boldsymbol{x})$.

The unconditional probabilities in expression above, $P(g = \mathrm{I})$ and $P(g = \mathrm{N})$, can be estimated simply as the fraction of immigrants and the fraction of non-immigrants in the pooled sample, and do not vary by observation. In practice, these terms can be ignored in the estimation of $\omega(\boldsymbol{x})$ since the statistical packages apply a subsequent normalization to the weighting variable such that it sums up to 1 (see e.g. DiNardo (2002)).

It is important to note an additional step for data with sampling weights, such as PIAAC: the final re-weighting factor, $\widehat{\omega(\boldsymbol{x})}$ in such cases is composed as the product of $\widehat{\omega(\boldsymbol{x})}$ and the final sampling weight (see DiNardo (2002)). Once the weighting factor $\widehat{\omega(\boldsymbol{x})}$ has been obtained, the counterfactual density for native workers can be obtained via a non-parametric kernel density estimation, [68] where their actual log-earnings density is reweighted by $\widehat{\omega(\boldsymbol{x})}$.

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[68] A general kernel density estimator has the form: $\widehat{f(\boldsymbol{y})} = \frac{1}{Nh}\sum_{\mathrm{i=1}}^{\mathrm{N}} k \, \frac{(y_i - y)}{h}$, where h> 0 is the so-called bandwidth and $k(\cdot)$ is the kernel function. It can be shown that under weak conditions, if $h \to 0$ and $Nh \to \infty$, $\widehat{f(\boldsymbol{y})} \xrightarrow{p} f(y)$ (see Wooldridge (2010)). We use a commonly used kernel–Epanechnikov which has the form $k(u)$ = $\frac{3}{4}$ (1-u^2), -1<u<1, and the default 'rule-of-thumb' bandwidth incorporated in the quantitative software package STATA.

3.5 ESTIMATION RESULTS

3.5.1 Mean wage gap decomposition

3.5.1.1 OLS results

Before we get to the mean wage gap computation and decomposition, it is useful to examine the OLS estimation results from model (1) from the previous section. This model is estimated separately on the pooled PIAAC immigrant and non-immigrant subsamples, and with a different set of controls (see Tables 3 and 4). In particular, specification (A) of Table E.3 reports the results from estimating a Mincer-type equation including education, labour market experience and experience squared in the vector of covariates $\boldsymbol{X}$; in addition, the model is specified with country dummies in order to account for country-level heterogeneity. Specification (B) adds gender dummies and controls for sector of employment (parameterized as public, private and non-governmental sector) in the list of covariates. [69] Next, columns (C) to (G) in both tables take advantage of the novelty of PIAAC in that it contains a wide range of measures of cognitive skills and competences. To be more specific, specifications (C) to (E) include separate skill measures for the numeracy, literacy and problem solving in technology-rich environment domains; specification (F) controls for numeracy and literacy test scores, and specification (G) controls for all these measures jointly. [70]

As can be seen from column (A) of Table E.3, foreign-born workers appear to have lower return to education than natives (difference of 1.5 percentage points; significant at the 1% level),

[69] Other relevant variables, such as job tenure, on-the-job training, or skill-based occupational category are available in PIAAC. However, these have the disadvantage that they have a high non-response rate (e.g. on-the-job training), or are not available in the public data-files for part of the countries in PIAAC. We opt for omitting them in the regression in order to avoid further lowering the sample size.

[70] Note that France, Italy and Spain did not take part in the survey of the problem solving in technology-rich environment skills, which results in a lower number of observations in the specification where this test score is controlled.

although slightly higher return to experience. The results from specification (B) confirm this observation. Once cognitive skill measures have been accounted for in columns (C) to (E), the gap between the return to education for immigrants and natives further deepens. At the same time, however, immigrants appear to have higher returns to cognitive abilities, although the difference between the two groups is not always statistically significant. The later holds across all skill domains, and is particularly well pronounced in the literacy and problem solving test domain – both in terms of magnitude and in terms of statistical significance. For instance, the estimation results in specification (D) imply that a one standard deviation increase in literacy solving test score increases immigrants earnings by 9.2% vs. 8.0% for non-immigrants, *ceteris paribus*, while specification (E) of Table E.4 implies that the wage gain associated with a one standard deviation increase in problem solving test score is 9.2% for foreign-born workers vs. 7.6% for non-immigrants, *ceteris paribus*. Lastly, when all test scores are included in the regression (column (G) of Table E.4), the native workers' returns on literacy proficiency appear nearly three times lower than those of immigrants, and the difference is statistically significant at the 5% level. It is also worth noting that the difference in the return to education between the two groups is statistically significant at the conventional levels across all specifications.

Tables F.1A to F.11B in Appendix F present the analogous results estimated at a country-level for the countries in PIAAC with average and above-average share of immigrants (as compared to the total sample mean). [71] Since the country-level immigrant subsamples are small, we omit reporting the results for the specification jointly controlling for all test scores due to

[71] The country results are reported in decreasing order of the fraction of immigrant population.

high collinearity between these scores. [72] Overall, the country-level results are in line with the implication from the pooled analysis – immigrants tend to have lower returns to education but considerably higher returns to numeracy, literacy and problem solving proficiency, although the differences are not always statistically significant (the latter is expected due to the small country samples). The immigrant-non-immigrant gap in returns to cognitive skills is particularly marked in Canada, Norway, Belgium, the UK, and Estonia. At the same time, however, it is worth noting that several of the PIAAC countries foreign-born workers have worse returns to both education and cognitive skills; such examples are France, Spain, the U.S., and Austria (although, in the last two countries the returns to education of both groups are virtually the same, once cognitive skills have been accounted for).

Taken as a whole, the estimation results of model (1) suggest that immigrants have lower returns to schooling than non-immigrants, but enjoy higher returns to cognitive skills. This is line with the theory of statistical discrimination suggesting that employers are likely to view educational attainment as a less reliable signal of productivity for an immigrant than for a non-immigrant worker. In addition to this, it is interesting that in some model specifications the relative earnings gain associated with literacy test score is two-to-three times larger for immigrants than for non-immigrants. This might suggest that in the absence of other reliable signals for an immigrant worker's productivity, employers are likely to place much higher weight on language proficiency than they do for a native-born worker. The later makes sense also because nearly 100% of the natives report the primary language of their country of residence as their mother tongue vs. only a quarter of the immigrants; hence, for a foreign-born worker to

[72] The sample correlation between numeracy and literacy test score is 0.83; 0.79 between problem solving test and literacy test score, and 0.74 between numeracy and problem solving test score.

have acquired a certain level of proficiency in the language of the receiving country would reveal more about their productivity than it would for a native speaker.

3.5.1.2 Oaxaca-Blinder decomposition

Table E.5 presents the results from the immigrant-non-immigrant wage gap estimation and the Oaxaca-Blinder decomposition of this gap based on model (1). In turn, model (1) includes the same set of controls as specifications (A) to (G) from the previous subsection, and adds a baseline specification, denoted as (0). Specifications (0), and (A) to (E) illustrate the results based on the entire PIAAC sample, while specifications (F) and (G) are only estimated on the sample of countries which administered the problem solving test score. Column (1) reports the estimated raw wage gap between the immigrant and native workers, and columns (2) and (3) report the Oaxaca-Blinder decomposition for each specification. In particular, Column (2) illustrates the difference in earnings between immigrants and natives due to differences in their observable characteristics (as already noted previously, we shall refer to this part as the "explained" or "composition effect"). Column (3) reports the second part of the gap, namely: the difference between immigrant and native workers' wages that arises due to differences in the returns to skills (we shall refer to this part as the "wage structure effect", "unexplained" or as "discrimination").

The baseline specification (0) reports the results when no observable covariates are included in the log-wage regressions for both groups, other than country dummies. Column (1) states that the raw mean wage gap between the immigrant and native workers estimated on the total sample of 45,697 prime age full time workers in OECD and Russia is 0.065, and this gap is statistically significant at the 5% level. While the sign of the mean gap may appear surprising at first, it is merely a reflection of the fact that, on average, countries with higher wages are also countries with higher shares of immigrants. The later can also be illustrated by looking at the composition effect reported in Column (2): this effect is positive in sign, implying that on average, immigrants have better observables, i.e. they are more concentrated in countries with higher wages. Or, more intuitively, the potential earnings of the natives if they had the same country distribution as immigrants would have surpassed their actual earnings. The magnitude of the explained part of the gap is 0.25 meaning that immigrants enjoy a 25 percent earnings gain compared to native workers due differences the in country-distribution.

At the same time, however, a large fraction of the mean wage gap remains unexplained – negative 0.185 (Column (3)), implying that immigrants earn, on average, roughly 19 percent less than non-immigrant workers after accounting for country-level heterogeneity. Alternatively, a program evaluation interpretation would imply that the gap between the actual mean wages of immigrant workers and the potential mean wages those workers had they been awarded according to the wage structure of natives, is 19 percent.

We proceed by examining the Oaxaca-Blinder decomposition results from the specifications that include both country indicators, as well as various individual characteristics. Specification (A) depicts these results when including education and labour market experience as measures of workers' competences. [73] Column (2) reports the wage gap that would have arisen due to differences in covariates; this part is still positive in sign but lower in magnitude compared to the baseline specification (0.193 vs. 0.25) – the drop being a reflection of the fact that, on average, immigrants have lower educational attainment and working experience

[73] The raw mean gap now appears significant only at the 10% level, likely due to the slight drop in sample size because of missing values for variables education and/or experience for 426 observations (1% of the sample).

compared to native workers. The part due to discrimination drops in magnitude, as well (Column (3)) suggesting better average returns to schooling and experience for immigrants, yet remains negative and substantial, -0.127. As expected, with the inclusion of individual covariates the relative importance of the composition effect in the total observed wage gap increases. Including controls for gender and sector of employment in specification (B) leaves the results essentially unchanged.

Next, we turn to specifications (C) to (E), which include numeracy and literacy cognitive skill measures. Once numeracy test score is controlled in specification (C) shows that, the results look noticeably different; in particular, the composition effects drops further to 0.137 reflecting the fact that, on average, immigrant workers score lower on the numeracy test. Equally important, the unexplained part of the gap is now nearly twice lower in magnitude compared to specification (B) – just -0.071, further lending support to the idea suggested in the previous section that immigrants enjoy higher returns to test scores, and numeracy skills in particular. As expected, the relative importance of the observable characteristics in the total mean wage gap additionally increases – the explained part of the gap is now nearly twice as important as the unexplained. The implications from controlling for literacy test score (specification (D)) are virtually the same. To complete the analysis specification (E) includes controls for both literacy and numeracy skills. This results in a further drop of the magnitude of the unexplained gap to negative 0.067, implying that immigrants enjoy better joint returns to both sets of cognitive skills, even though the discrimination component remains statistically significant at the conventional 5% level and large in magnitude.

The remaining specifications (F) and (G) add problem solving test score in the vector of covariates for a subsample of countries excluding France, Italy and Spain, which did not administer this test. For comparison purposes we also report the results from specification (B) estimated on this smaller set of countries. The estimated raw wage gap is 0.118, of which 0.221 is explained and -0.103 is unexplained (the relative importance of composition being roughly twice larger than that of discrimination). Controlling for the measure of problem solving skills in specification (F), results in the unexplained part of the gap decreasing in magnitude by nearly 40% to -0.06, while the explained part correspondingly shifts to 0.178. Put differently, the results now imply a much higher relative importance of endowments than the part due to discrimination. Lastly, controlling for all test scores jointly (specification (G)) further reinforces the idea that the composition effect plays a key role in the observed immigrant-non-immigrant gap – roughly 17 percent, while discrimination plays a much smaller part – only 5 percent.

To sum up, the results obtained by model (1) specified with the observable covariates typically included by the mainstream literature would have lead us to incorrectly conclude that the unexplained part of the mean immigrant-non-immigrant wage gap obtained from the entire PIAAC sample is roughly 13 percent. In contrast, including controls for numeracy and literacy skills reveals that the role of discrimination is nearly twice lower – 6.7 percent; yet, the wage structure effects remains statistically significant at the conventional 5% level and considerable in magnitude, implying that the actual mean wages of immigrants are nearly 7 percent lower than what they would have been, had immigrants enjoyed the same returns as natives. Lastly, our analysis suggests that the key reason behind the observed immigrant-native gap in the analyzed countries is the fact that immigrants have, on average, worse workplace skills and competences – the part of the wage gap due to endowments is roughly twice larger than the part due to discrimination.

3.5.2 DiNardo-Fortin-Lemieux decomposition

Figures E.8 through E.10 depict the estimated actual log-earnings kernel density for both groups of workers, and the counterfactual kernel density for non-immigrants. The latter comprises the hypothetical earnings distribution of native workers that would have prevailed if those workers had the same observable characteristics distribution as immigrants, and enjoyed returns according to the native wage structure. Figure E.11 shows the estimated actual difference between the densities of the two groups plotted against the unexplained part of this difference, obtained when employing a different set of controls.

Figure E.8 shows the actual log-wage densities for immigrant and natives (the solid blue and dark red line, respectively), together with the corresponding 95% confidence intervals. As can be seen from here, the density for native workers appears somewhat skewed to the right, while that of immigrants is more symmetric. In addition to this, the natives' probability density is substantially to the left of the immigrants' density in the lower tail of the distribution (roughly 1st to 20th percentile), implying a sizeable wage gap in favour of immigrant workers in this range. This is mirrored by a correspondingly lower share of native earners in the range between the 20th and 50th percentile. At the same time, however, natives are more densely concentrated in the above-mean range (65th-90th percentile), although the raw gap between the two densities being relatively small. Lastly, there is a noticeably higher share of immigrants above the 90th percentile of the log-earnings range, implying a larger fraction of top-earners amongst immigrants. The solid red line in Figure E.11 depicts the difference in the actual densities between immigrant and non-immigrant workers and confirms the implication from Figure E.8, namely: immigrants enjoy higher earnings – a reflection of the fact they are more prevalent in countries with higher wages.

Next, Figure E.9 plots the actual wage density for immigrants (solid blue line) and the counterfactual densities for natives, together with the corresponding 95% confidence intervals (shown by the dashed lines). In turn, the counterfactual densities are obtained when using three different sets of propensity score weights: 1) only accounting for the differences in the country distribution between immigrants and natives (solid black line); 2) accounting for the differences in the country distribution and the distribution of observable covariates typically included in the log-earnings function regressions, as listed in specification B from the previous section (solid green line); 3) accounting for the differences in literacy and numeracy proficiency, in addition to the controls included in 2 (solid orange line). [74] Comparison between the actual density for immigrant workers and the counterfactual densities for native workers would reveal the contribution of each of these sets of observable covariates to the raw wage gap across the entire wage distribution. The difference between these densities is depicted on Figure E.11 using the same colour coding as the one used on Figure E.9; in addition, Figure E.11 illustrates the gap between the actual immigrant and native log-wage densities (red line). We examine the counterfactual densities in turn.

The black line on Figure E.9 displays the counterfactual density of log-wages that would have been observed if native workers had the same country distribution as immigrants but were paid according to their own wage structure. As can be seen from here, this line is shifted considerably to the right of the blue line for most of the earnings distribution range, and the 95% confidence intervals of the two densities show virtually no overlap. This is particularly

[74] We do not plot the results for all specifications (0) to (G) as described in Table E.5 from the previous section on the same graph for the purposes of better visibility; those are presented on separate graphs in Appendix F, Figures F.1 to F.6. In addition, we opt not to include a control for problem solving test score due to the fact this score is not available for the entire sample. Appendix F, Figures F.7 to F.15 presents the complete analysis on the set of countries that administered this test.

pronounced for the above mean earners where the gap between the actual immigrants' density and the counterfactual natives' density is substantial; the lines only converge for values of the log-wage of roughly 3.7 and above, or the 95th percentile. The difference between the two densities is depicted by the black line on Figure E.11, which confirms these findings; in addition, it provides a vivid illustration of the fact that a large fraction of the gap between the wage densities of immigrants and natives remains unexplained when only accounting for country of residence. Taken as whole, this comparison indicates that native workers would have enjoyed higher earnings than immigrants at nearly the entire range of the wage distribution if they had the advantage of being concentrated in higher-earning countries.

Turning to the green line on Figure E.9 reveals what the distribution of natives' earnings would have been if they had the same country, education, labour market experience, gender and employment sector distribution as immigrant workers, but retained their own returns. Compared to the black line, the green line is considerably closer to the actual immigrants' wage distribution in the entire earnings range, and the 95% confidence intervals of the two counterfactual densities do not overlap for most of this range. Taken together, these imply that immigrants' disadvantages in terms of the labour market characteristics listed above play an important role in the distribution of the observed earnings gap. At the same time, however, the distance between the green and the blue lines remains substantial and would imply presence of considerable discrimination virtually in the entire log-earnings range. One other important observation is that the distance between the black and the green lines is roughly the same between the 5th and the 95th percentile suggesting that the included observable characteristics matter equally across most the earnings distribution. This interpretation is further reinforced by examining the green line of Figure E.11.

Lastly, the orange line on Figure E.9 depicts the native workers' counterfactual earnings distribution obtained after accounting for differences in the country distribution, and the distribution of all other observable covariates, including literacy and numeracy test scores. Several important observations can be made here. First, the orange line is much closer to the blue line than the green line is, and this holds over the entire range of the wage distribution, although the 95% confidence intervals show some overlap below the 65th percentile. This suggests that literacy and numeracy proficiency play an important role in the observed wage distribution in the entire earnings range. What is more, the density depicted by the orange line appears much like a leftward shift of the density depicted by the green line, suggesting that numeracy and literacy test scores matter practically equally throughout the whole distribution of log-earnings.

It is also worth examining particular ranges of the wage distribution in more detail. At the very bottom of the earnings distribution (log-wages or roughly below 2, corresponding to 1st to 15th percentile) the orange and blue lines nearly coincide and the 95% confidence interval of the actual immigrants' density does not exclude that of the counterfactual natives' density, suggesting that differences in observables almost entirely explain the wage gap between natives and immigrants in this range. This can also be seen from Figure E.11, showing that the unexplained part of the gap is essentially zero below value of log-earnings below roughly 2, corresponding to the 15th percentile. A similar observation can be made for the top 5 percentile earners, as well. At the same time, however, for all earners in the range of roughly between the 15th and the 95th percentile the counterfactual density for natives is shifted to the right of the actual density for immigrants, and their confidence intervals show no overlap. This suggests that even if native workers had the observable characteristics of immigrants, but were paid according to the natives' wage structure, they would have enjoyed a more favourable wage distribution. To elaborate more on this, focusing on the 15th-65th percentile range reveals that the non-immigrant workers would have had a lower concentration in this earnings range than immigrants, even if they had the immigrants' observables. This is mirrored by a significant departure between the actual immigrant density and the counterfactual native density based of the fullest set of controls in earning percentiles 65th to 95th.

These observations are of considerable importance as they reveal that differences in the observable covariates cannot fully account for the differences in the log-earning distributions between natives and immigrants, even after controlling for numeracy and literacy proficiency. This, in turn, implies presence of considerable labour market discrimination against the non-native workers especially in the above-mean earnings range. Yet, the magnitude of this discrimination is considerably lower than the magnitude implied based on the counterfactual density constructed without controlling for numeracy and literacy proficiency.

Turning briefly to Figure E.10, it is interesting to compare the actual log-wage density of native workers (dark red line) and the counterfactual log-wage density of these workers obtained with the fullest set of controls (orange line). Perhaps the most interesting observation here is that for values of log-earnings of roughly above the 75th percentile, these lines nearly coincide and the 95% confidence interval of the counterfactual density includes the actual density. Taken together, these imply that for this earnings range, even if native workers had the characteristics of immigrants they would have still earned the same as their actual wages as long as they were paid according to the natives' earnings structure. Put differently, this implies that above the 75th log-earnings percentile, the explained component of the observed wage gap is very small and that the main part of the raw gap is due to discrimination. The same conclusion prevails after examining the orange line on Figure E.11, depicting the difference between the actual wage distribution for immigrant workers and the counterfactual distribution for native workers obtained after controlling for all observable covariates. In particular, it is evident that beyond values of log-wage of about 3.15, corresponding to the 75th percentile, the orange line overlaps with the red line, suggesting that in this earnings range practically the entire raw earnings gap remains unexplained.

Table E.6 allows examining the DFL results from a somewhat different perspective, namely, it reports the decomposition into an explained part and wage structure effect for selected quanitles in the log-wage distribution for all specifications (0) to (E) as described in the previous section. Even though the implications from this representation of the results are largely the same as the ones that follow from the DFL graphical analysis, several interesting observations can be made.

First, as a fuller set of controls is added, the contribution of the observable characteristics in the raw gap increases, overall, and this is particularly well-pronounced in the low percentiles. For instance, specification (B) reports the DFL decomposition results obtained when accounting for differences in the country distribution, as well as education, labour market experience, gender and employment sector. Focusing on the 10th percentile, the results from this specification indicate that the explained part of the wage gap for the low earners in PIAAC is 0.437, implying that the potential earnings of native workers if they had the immigrants’ characteristics would surpass their actual earnings by roughly 44 percent. The part of the 10th percentile gap due to discrimination is negative 0.150, meaning that a 15 percent wage gap between immigrants and natives in this quantile originates from differences in the returns to skills. In contrast, the DFL decomposition results from specification (E), adding controls for numeracy and literacy test scores, indicate an explained effect of 0.331 and only -0.044 unexplained, leading to the conclusion that for low earners composition plays considerably larger role in the observed gap than discrimination does. A similar conclusion prevails for all earners below the 50th percentile.

Turning to the above-median earners, including literacy and numeracy test scores causes the unexplained part of the wage gap in each percentile to drop by roughly half, suggesting a noticeably lower role for discrimination than what is implied by specification (B). At the same time, however, the explained part of the gap drops correspondingly, as well (as expected since immigrants score lower on those tests), implying a lower role for the composition effect relative to the unexplained. To elaborate more on this, when looking at e.g. the 80th percentile of the earnings distribution, specification (E) suggests that immigrants earn 7.2 percent lower wages due to differences in returns to skills, while specification (B) would have attributed a nearly twice larger share to discrimination – 13.6 percent. Yet, the relative importance of composition is lower in the model with test scores, suggesting that labour market discrimination may be stronger for earners close to the right tail of the log-wage distribution. Nevertheless, the magnitude of this discrimination appears nearly uniform across the entire range of the wage distribution, except for the bottom 10 percent and the top 10 percent of the workers. These are essentially the same observation that prevailed from the graphical analysis.

3.6 CONCLUDING REMARKS

This study utilised a large cross-section of 21 countries from the 2011/2012 Programme for the International Assessment of Adult Competencies in order to evaluate the earnings gap between immigrant and native workers in these countries. Following the mainstream literature in the field, we employ a decomposition methodology, in particular – a modified Mincer regression and Oaxaca-Blinder mean log-wage decomposition (Oaxaca (1973) and Blinder (1973)), as well as the decomposition technique developed by DiNardo, Fortin and Lemieux (1996).

Consistent with the findings of several authors for the U.S. (e.g. Bratsberg and Terrell (2002), Betts and Lofstrom (2000)), we find that immigrants have lower returns to education than native workers, yet higher returns to cognitive abilities, especially in the literacy domain. Moreover, we observe this same pattern in most countries in PIAAC, as well as in the pool of data. This is consistent with the main idea of the statistical discrimination theory that employers may view educational attainment as a less reliable productivity signal for immigrants, and that in the absence of other reliable productivity signals, they place substantial weight on language proficiency for foreign-born workers. Next, a central finding of the Oaxaca-Blinder decomposition is that a log-wage regression specified without controls for cognitive skills would greatly overestimate the unexplained part of the mean immigrant-native wage gap, while including numeracy and literacy test scores reveals a much lower role of discrimination. Finally, the DiNardo-Fortin-Lemieux results show that numeracy and literacy test scores matter considerably and almost equally throughout the entire log-wage distribution, yet differences in numeracy and literacy proficiency between natives and immigrants cannot fully explain the observed earnings gap, except for the bottom and the top deciles.

The implications of these findings are twofold. First, in terms of methodology, our results suggests that measuring the true earnings gap between immigrant and native workers is not feasible without accounting for the differences in cognitive competences between the two groups, as this leads to a severe overestimation of the unexplained component of the wage gap. Secondly, the results of this study have important policy implications. In particular, the fact that immigrants have lower literacy and numeracy proficiency than native-born workers, combined with the finding that differences in these skills explain a considerable part of the earnings gap, calls for the development and implementation of education and qualification programmes for the immigrant population. Such programmes would increase the cognitive competences of the foreign-born workers, which in turn would facilitate the convergence of their earnings towards those of natives. At the same time, however, the existence of a significant earnings gap even after accounting for cognitive abilities implies that presence of labour market discrimination cannot be ruled out, which puts forward the need for stronger legislative provisions against discrimination based on immigration status.

APPENDICES

APPENDIX E

MAIN TABLES AND FIGURES

Table E.1: Descriptive statistics (total sample)

Country	Austria	Belgium (Flanders)	Canada	Czech Republic	Denmark	Estonia	Finland	France
Hourly wage (in USD, PPP)	21.931 (0.189)	22.145 (0.197)	27.811 (0.188)	8.892 (0.124)	25.267 (0.142)	10.056 (0.130)	20.047 (0.121)	15.820 (0.100)
Female	0.401 (0.010)	0.417 (0.007)	0.447 (0.005)	0.458 (0.012)	0.469 (0.008)	0.531 (0.008)	0.488 (0.008)	0.440 (0.007)
Immigrant	0.187 (0.010)	0.061 (0.006)	0.277 (0.007)	0.051 (0.010)	0.101 (0.003)	0.103 (0.007)	0.043 (0.005)	0.109 (0.005)
Age 25-34	0.310 (0.009)	0.330 (0.008)	0.316 (0.006)	0.339 (0.011)	0.278 (0.007)	0.349 (0.009)	0.308 (0.007)	0.322 (0.007)
Age 35-54	0.690 (0.008)	0.670 (0.008)	0.684 (0.006)	0.661 (0.011)	0.722 (0.007)	0.651 (0.009)	0.692 (0.007)	0.678 (0.007)
Education (years)	12.503 (0.049)	13.226 (0.062)	14.009 (0.042)	13.470 (0.068)	13.460 (0.044)	12.682 (0.052)	13.531 (0.048)	12.198 (0.059)
Experience (years)	20.075 (0.196)	18.304 (0.146)	19.572 (0.131)	17.826 (0.242)	20.639 (0.169)	17.392 (0.168)	16.955 (0.166)	18.016 (0.157)
Numeracy score (0-500)	282.236 (1.250)	294.355 (1.176)	275.880 (0.952)	280.420 (1.390)	291.143 (1.148)	281.001 (0.880)	298.422 (1.060)	267.384 (1.040)
Literacy score (0-500)	275.626 (1.153)	287.860 (1.077)	282.357 (0.910)	278.379 (1.433)	281.788 (1.027)	282.616 (0.856)	303.052 (0.987)	271.045 (0.774)
Problem solving score (0-500)	287.423 (1.134)	288.392 (1.081)	286.636 (0.778)	284.180 (1.687)	290.717 (1.062)	278.516 (0.956)	297.886 (0.908)	-
No. observations	**1,690**	**1,736**	**9,280**	**1,622**	**2,375**	**2,221**	**2,106**	**2,272**

Notes:

1) Means corrected for inverse probability weighted sampling; jack-knife standard errors based on replicate weights (80 replications).

Unweighted number of observations reported.

2) France, Italy and Spain did not participate in the survey of problem solving skills in technology-rich environment.

Table E.1 (cont'd)

Country	Germany	Ireland	Italy	Japan	Korea	Nether-lands	Norway	Poland
Hourly wage (in USD, PPP)	19.278 (0.178)	22.937 (0.404)	15.591 (0.234)	16.895 (0.211)	15.758 (0.191)	23.752 (0.212)	25.979 (0.190)	8.866 (0.139)
Female	0.372 (0.011)	0.445 (0.012)	0.369 (0.014)	0.359 (0.009)	0.390 (0.009)	0.304 (0.010)	0.441 (0.008)	0.455 (0.009)
Immigrant	0.146 (0.010)	0.236 (0.013)	0.095 (0.015)	0.001 (0.001)	0.016 (0.003)	0.130 (0.008)	0.143 (0.008)	0.001 (0.001)
Age 25-34	0.315 (0.010)	0.438 (0.011)	0.277 (0.013)	0.327 (0.008)	0.348 (0.008)	0.340 (0.011)	0.308 (0.008)	0.415 (0.011)
Age 35-54	0.685 (0.010)	0.562 (0.011)	0.723 (0.013)	0.672 (0.008)	0.652 (0.008)	0.660 (0.011)	0.692 (0.008)	0.585 (0.011)
Education (years)	13.815 (0.070)	16.054 (0.069)	11.489 (0.128)	13.687 (0.046)	13.816 (0.057)	14.145 (0.066)	14.918 (0.047)	13.673 (0.075)
Experience (years)	18.513 (0.208)	16.743 (0.244)	17.502 (0.269)	17.161 (0.189)	12.697 (0.169)	18.461 (0.209)	18.216 (0.143)	14.963 (0.233)
Numeracy score (0-500)	282.117 (1.566)	272.592 (1.407)	258.671 (1.759)	300.901 (1.039)	270.574 (0.866)	295.847 (1.358)	294.219 (1.248)	266.092 (1.305)
Literacy score (0-500)	277.274 (1.430)	279.979 (1.418)	257.664 (1.672)	307.503 (0.777)	278.290 (0.791)	297.875 (1.261)	291.693 (0.988)	272.342 (1.210)
Problem solving score (0-500)	286.392 (1.429)	285.190 (1.436)	-	304.649 (1.253)	285.945 (0.945)	297.112 (1.076)	294.446 (0.908)	273.782 (1.685)
No. observations	**1,669**	**1,610**	**1,226**	**1,877**	**2,134**	**1,387**	**2,073**	**1,890**

Table E.1 (cont'd)

Country	Russia	Slovakia	Spain	UK	USA	Total OECD[75]	Total Sample
Hourly wage (in USD, PPP)	4.765 (0.110)	8.960 (0.161)	14.889 (0.179)	20.669 (0.363)	28.735 (0.524)	18.714 (0.195)	18.050 (0.192)
Female	0.483 (0.012)	0.484 (0.010)	0.423 (0.011)	0.389 (0.009)	0.471 (0.010)	0.428 (0.004)	0.431 (0.004)
Immigrant	0.036 (0.010)	0.014 (0.003)	0.120 (0.007)	0.151 (0.011)	0.174 (0.011)	0.108 (0.004)	0.104 (0.004)
Age 25-34	0.367 (0.013)	0.338 (0.009)	0.324 (0.009)	0.346 (0.007)	0.350 (0.008)	0.333 (0.003)	0.336 (0.003)
Age 35-54	0.633 (0.011)	0.662 (0.008)	0.676 (0.009)	0.654 (0.008)	0.650 (0.008)	0.667 (0.003)	0.664 (0.003)
Education (years)	14.034 (0.080)	13.799 (0.074)	12.516 (0.070)	13.419 (0.053)	14.044 (0.062)	13.518 (0.023)	13.543 (0.023)
Experience (years)	17.046 (0.368)	17.423 (0.199)	16.548 (0.208)	19.555 (0.194)	19.350 (0.241)	17.800 (0.096)	17.765 (0.091)
Numeracy score (0-500)	274.352 (2.462)	286.337 (1.077)	260.488 (1.111)	277.705 (1.500)	263.070 (1.387)	279.973 (0.534)	279.706 (0.465)
Literacy score (0-500)	277.505 (2.056)	281.494 (1.011)	264.737 (1.183)	285.191 (1.408)	276.610 (1.320)	281.669 (0.505)	281.471 (0.473)
Problem solving score (0-500)	280.269 (4.218)	284.146 (1.207)	-	285.191 (1.408)	283.359 (1.360)	288.500 (0.608)	288.109 (0.639)
No. observations	**929**	**1,671**	**1,695**	**2,557**	**1,677**	**44,768**	**45,697**

[75] Excluding the Russian Federation as it is not a member-state.

Table E.2: Descriptive statistics (immigrant/non-immigrant subsamples)

Characteristic	Immigrant subsample	Non-immigrant subsample
Demographic		
Age below 35		
25-34	0.369 (0.011)	0.332 (0.003)
35-54	0.631 (0.011)	0.668 (0.003)
Female	0.427 (0.015)	0.431 (0.004)
Education in years	13.425 (0.129)	13.562 (0 .025)
Education (highest level of schooling)		
Less than high school	0.190 (0.015)	0.099 (0.002)
High school	0.339 (0.014)	0.417 (0.004)
Above high school	0.471 (0.016)	0.484 (0.004)
Married /partnered	0.818 (0.013)	0.803 (0.005)
Has any children	0.707 (0.014)	0.683 (0.006)
Immigrant	1.000	0.000
Age at immigration	23.778 (0.361)	NA
Native language speaker	0.239 (0.019)	0.979 (0.002)
Employment history		
Actual working experience (years of paid work during lifetime)	15.492 (0.330	18.008 (0.084)
Sector of employment (current job)		
Private sector	0.793 (0.015)	0.694 (0.007)

Note: Means corrected for inverse probability weighted sampling; jack-knife standard errors based on replicate weights (80 replications). Unweighted number of observations reported.

Table E.2 (cont'd)

Public sector	0.184 (0.012)	0.283 (0.007)
Non-profit organization	0.022 (0.008)	0.023 (0.002)
Occupation (current job)		
Skilled	0.369 (0.017)	0.472 (0.004)
Semi-skilled white-collar	0.245 (0.017)	0.248 (0.004)
Semi-skilled blue-collar	0.251 (0.015)	0.223 (0.004)
Elementary	0.135 (0.013)	0.057 (0.003)
Years of formal education required to obtain current job	12.293 (0.147)	13.147 (0.032)
On-the-job training	0.376 (0.018)	0.467 (0.005)
Hourly wage (in USD, PPD adjusted)	18.622 (0.717)	18.047 (0.207)
Skills and competences		
Skill test score		
Numeracy skills score (0-500)	249.275 (2.774)	283.247 (0.531)
Literacy skills score (0-500)	252.652 (2.229)	284.876 (0.521)
Problem solving in technology-rich environment (0-500)	271.178 (2.313)	289.9012 (0.648)
Skill use at work (current job)		
Index of use of information and communications technology (ICT) skills at work	2.180 (0.054)	2.133 (0.014)
Index of use of numeracy skills at work	2.096 (0.035)	2.101 (0.011)
Index of use of reading skills at work	1.908 (0.047)	2.105 (0.010)
Index of use of writing skills at work	2.103 (0.010)	2.190 (0.011)
Index of use of task discretion at work	1.728 (0.039)	1.899 (0.008)
Index of readiness to learn at work	2.120 (0.042)	2.051 (0.012)

Table E.2 (cont'd)

Index of learning at work	2.067 (0.039)	2.006 (0.013)
Health self evaluation		
Excellent	0.189 (0.016)	0.167 (0.005)
Very good	0.345 (0.017)	0.333 (0.006)
Good	0.344 (0.021)	0.358 (0.006)
Fair	0.358 (0.006)	0.126 (0.003)
Bad	0.126 (0.003)	0.015 (0.003)

Figure E.1: Mean wage conditional on education

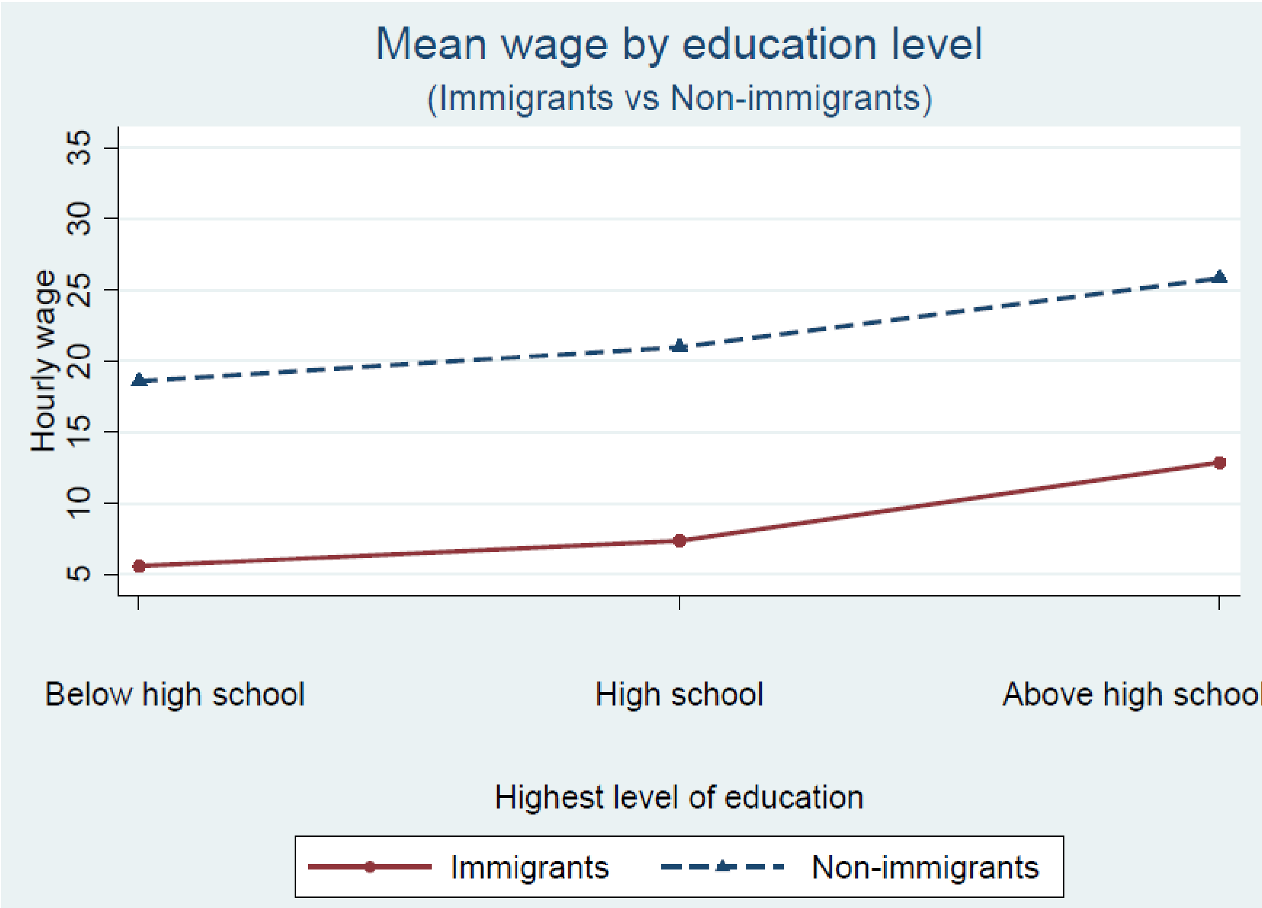


Figure E.2: Mean wage conditional on labour market experience

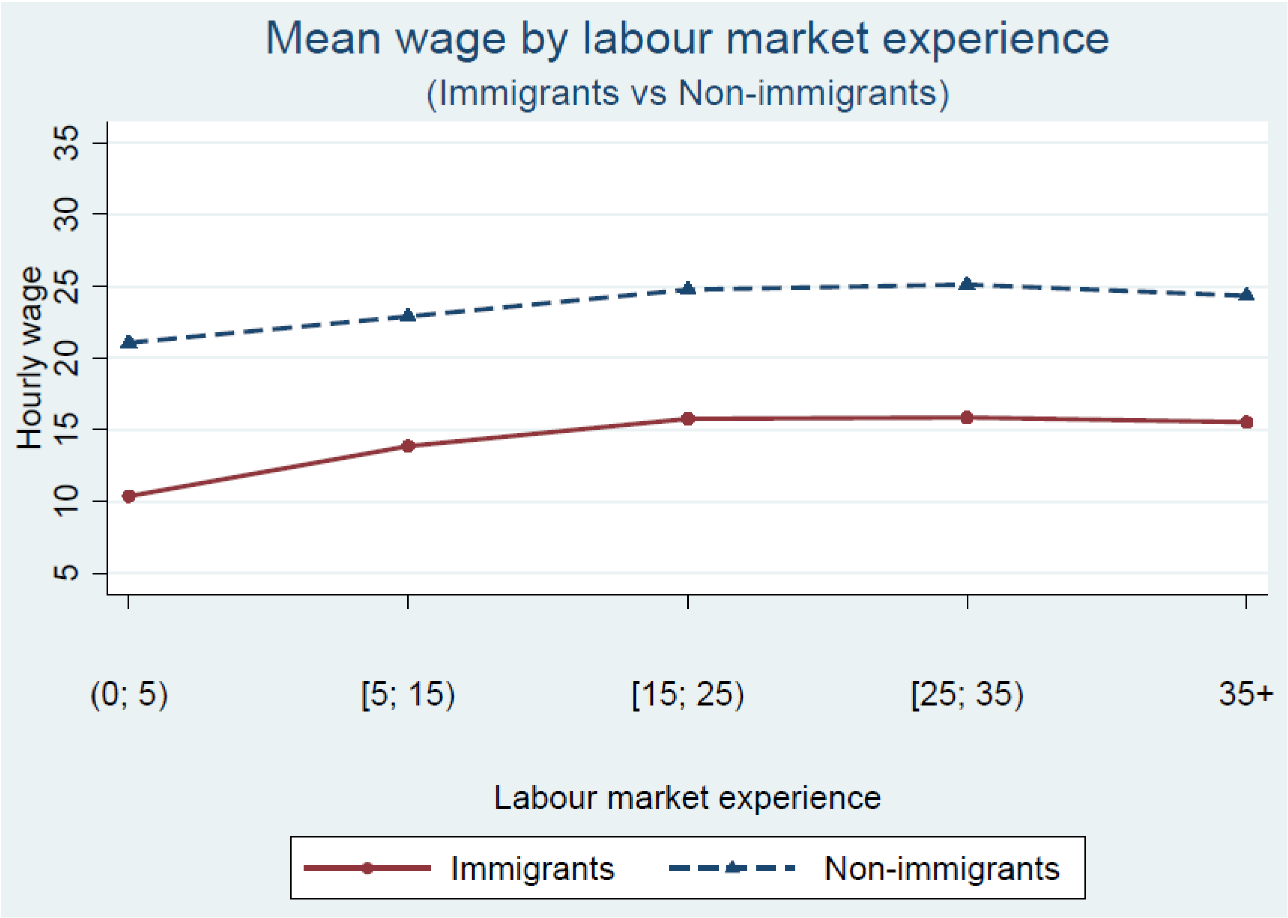


Figure E.3: Mean wage conditional on sector of employment

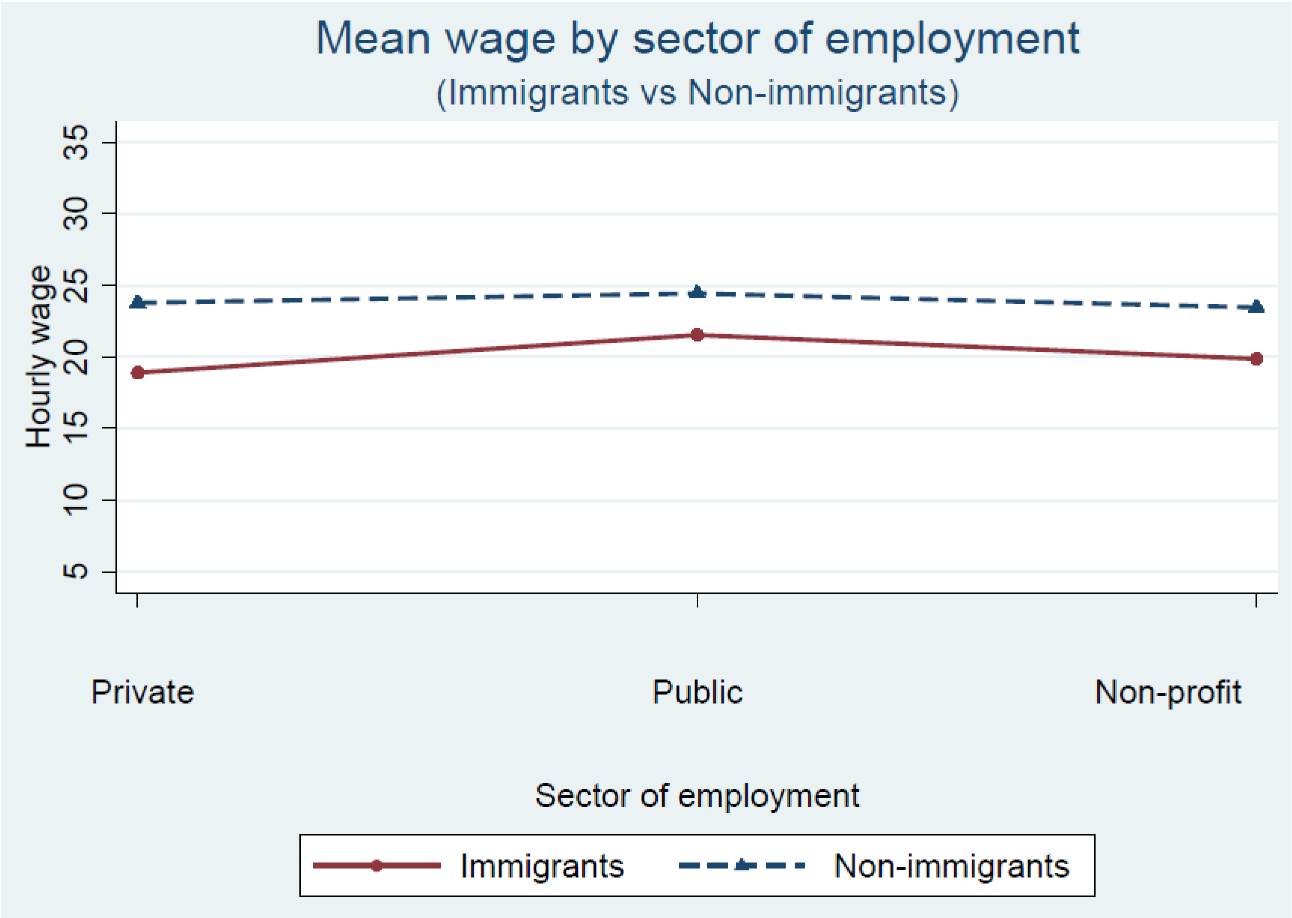


Figure E.4: Mean wage conditional on skill-based occupational category

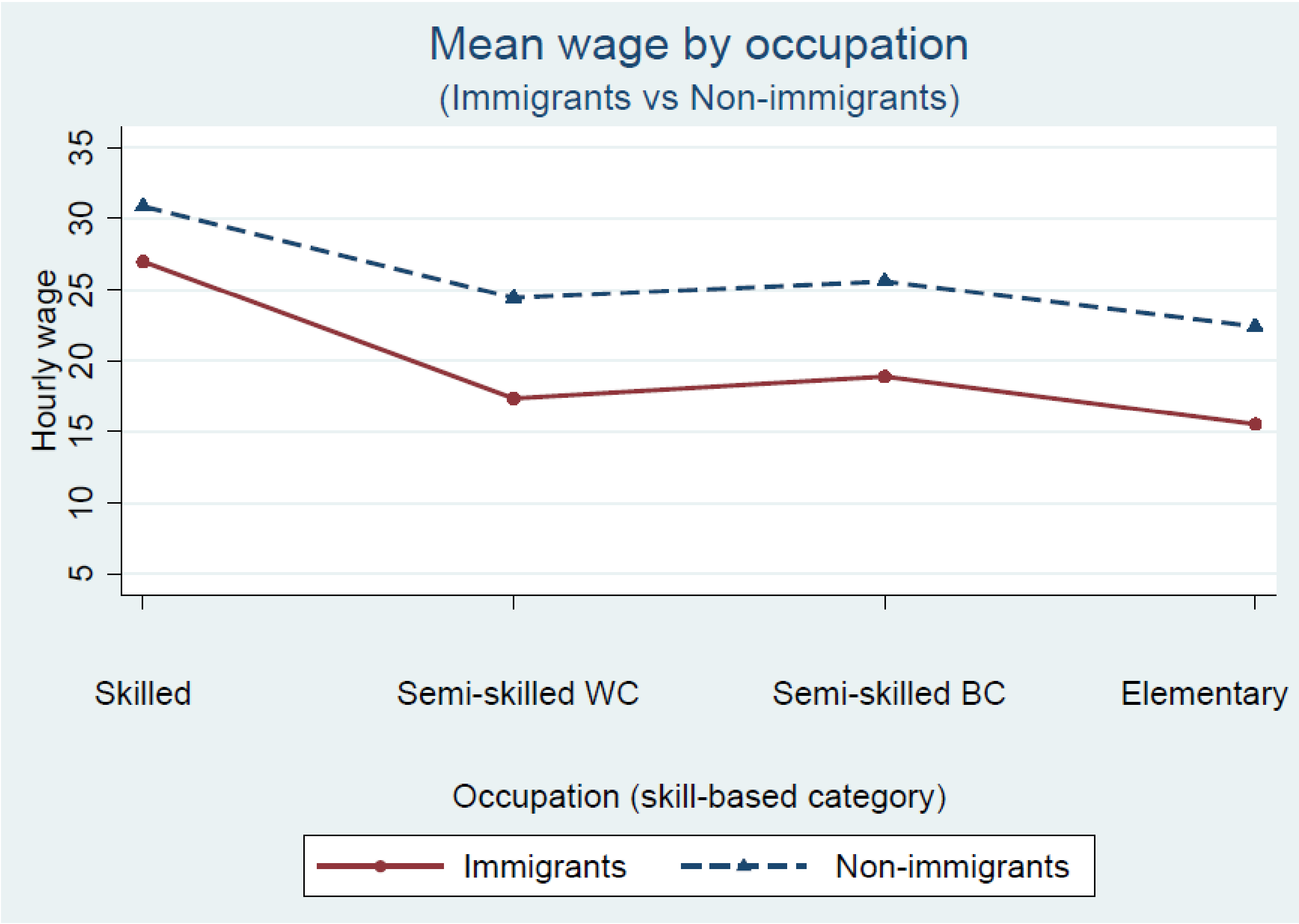


Figure E.5: Mean wage conditional on numeracy test score

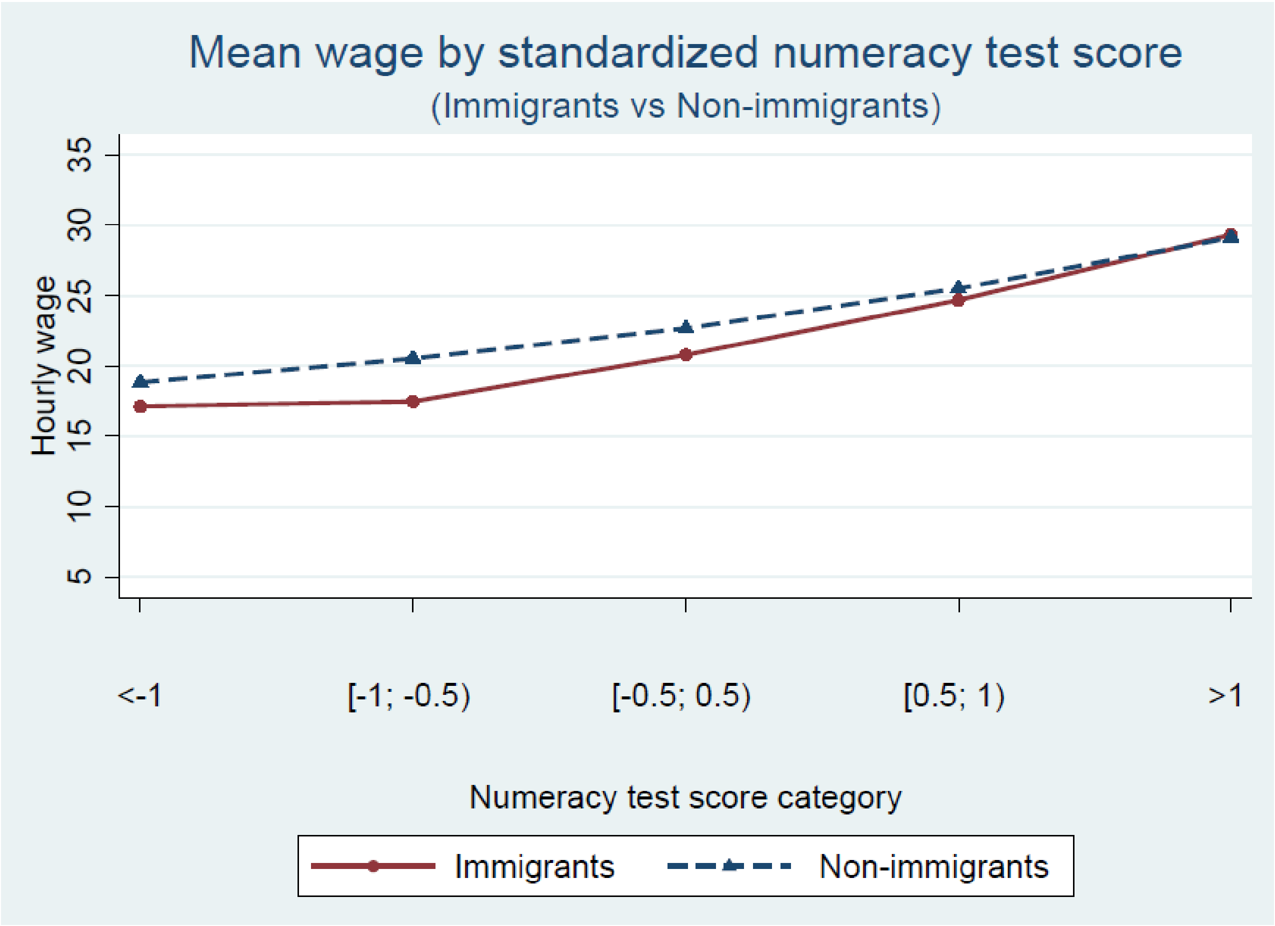


Figure E.6: Mean wage conditional on literacy test score

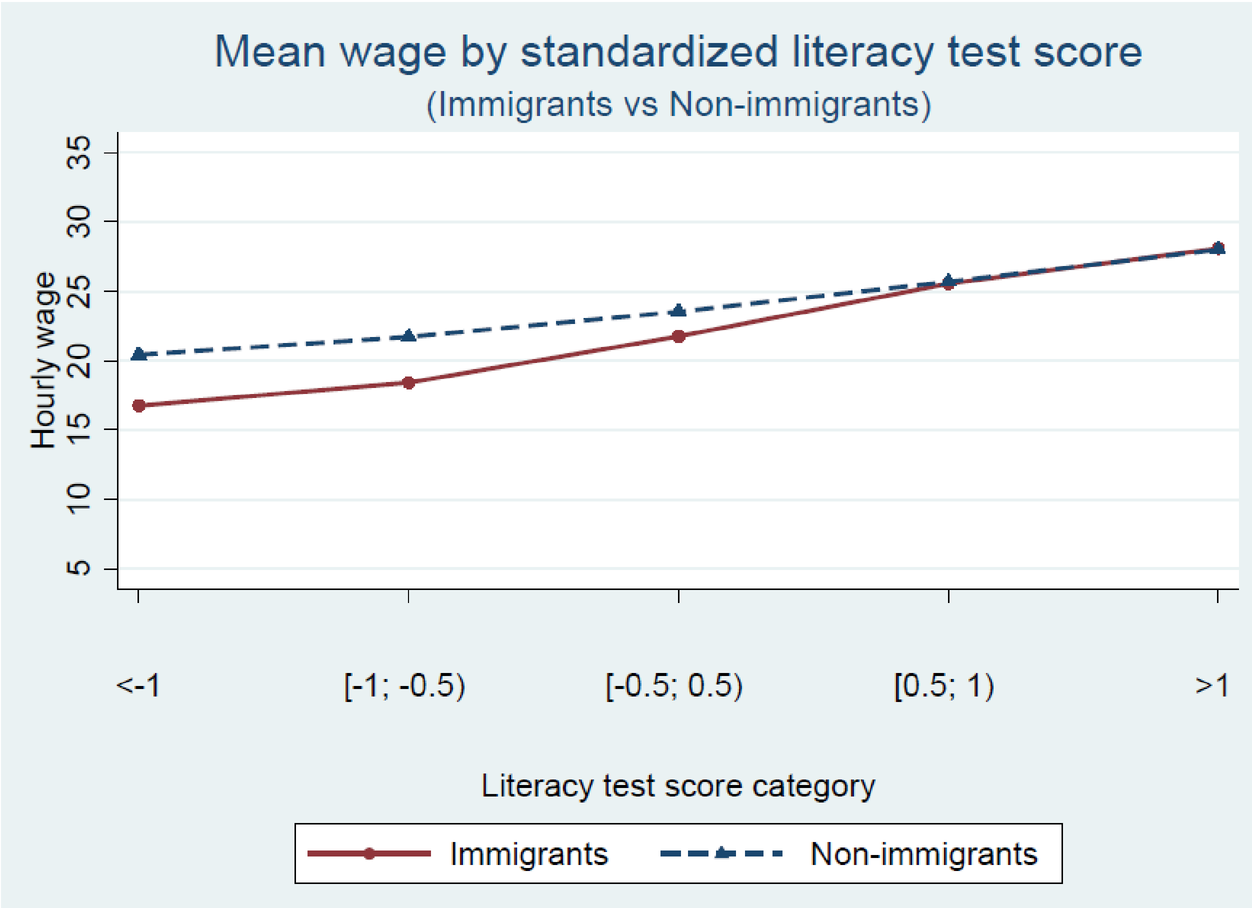


Figure E.7: Mean wage conditional on problem solving test score

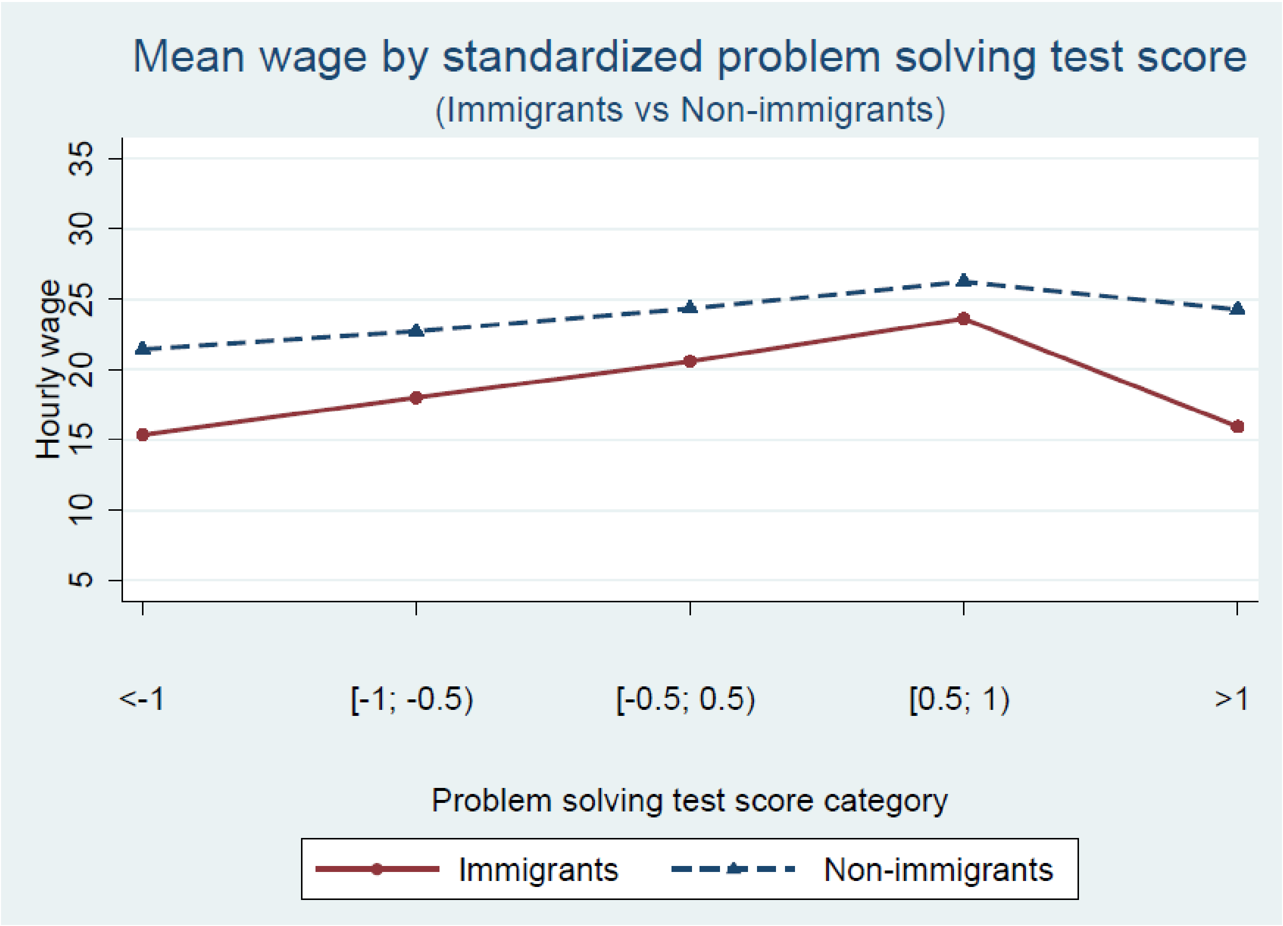


Table E.3: OLS results (pooled total sample)

Controls	(A)		(B)		(C)		(D)	
	Immigrant	***Non-immigrant***	***Immigrant***	***Non-immigrant***	***Immigrant***	***Non-immigrant***	***Immigrant***	***Non-immigrant***
Education (years)	0.050*** (0.004)	0.065*** (0.001)	0.050*** (0.004)	0.069*** (0.001)	0.035*** (0.003)	0.056*** (0.001)	0.035*** (0.002)	0.058*** (0.001)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000	
Experience (years)	0.029*** (0.004)	0.025*** (0.012)	0.026*** (0.004)	0.025*** (0.001)	0.023*** (0.003)	0.024*** (0.001)	0.024*** (0.003)	0.025*** (0.001)
Experience squared	-0.001*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Female	-	-	-0.161*** (0.044)	-0.185*** (0.005)	-0.141*** (0.013)	-0.163*** (0.005)	-0.158*** (0.015)	-0.180*** (0.005)

Notes:

1) All specifications include country dummies; in addition, specifications (5) to (7) control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

4) Japan dropped from the pooled sample since the low number of immigrant-observations in the country leads to insufficient degrees of freedom to estimate the immigrant model with country effects.

Table E.3 (cont'd)

Numeracy score (standardized)	-	-	-	-	0.092*** (0.011)	0.089*** (0.005)	-	-
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.9918			
Literacy score (standardized)	-	-	-	-	-	-	0.092*** (0.008)	0.080*** (0.003)
							p-value for H_0: $\beta_j^I = \beta_j^N$ 0.1246	
Problem solving score (standardized)	-	-	-	-	-	-	-	-
Intercept	1.564*** (0.072)	2.009*** (0.025)	1.564*** (0.118)	2.005*** (0.030)	1.470*** (0.137)	2.229*** (0.028)	1.452*** (0.130)	2.186*** (0.028)
No. observations	**5,127**	**38,226**	**5,127**	**38,226**	**5,126**	**38,225**	**5,126**	**38,225**

Table E.4: OLS results (pooled restricted sample)

Controls	(A)		(E)		(F)		(G)	
	Immigrant	***Non-immigrant***	***Immigrant***	***Non-immigrant***	***Immigrant***	***Non-immigrant***	***Immigrant***	***Non-immigrant***
Education (years)	0.050*** (0.003)	0.065*** (0.001)	0.044*** (0.006)	0.059*** (0.001)	0.034*** (0.003)	0.056*** (0.001)	0.038*** (0.006)	0.055*** (0.002)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000	
Experience (years)	0.029*** (0.004)	0.025*** (0.012)	0.028*** (0.007)	0.028*** (0.002)	0.023*** (0.005)	0.024*** (0.011)	0.026*** (0.007)	0.027*** (0.002)
Experience squared	-0.001*** (0.000)	-0.000*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Female	-	-	-0.138*** (0.029)	-0.167*** (0.011)	-0.148*** (0.036)	-0.167*** (0.010)	-0.134*** (0.024)	-0.160*** (0.011)

Notes:

1) All specifications include country dummies; in addition, specifications (5) to (7) control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

4) Japan dropped from the pooled sample since the low number of immigrant-observations in the country leads to insufficient degrees of freedom to estimate the immigrant model with country effects.

5) Specifications (A) to (G) estimated on the restricted sample of countries which administered the problem solving test.

Table E.4 (cont'd)

Numeracy score (standardized)	-	-	-	-	0.052*** (0.030)	0.068*** (0.005)	0.046*** (0.042)	0.042*** (0.008)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.1469		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.9725	
Literacy score (standardized)	-	-	-	-	0.048*** (0.022)	0.027*** (0.005)	0.074*** (0.037)	0.026** (0.011)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0846		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0111	
Problem solving score (standardized)	-	-	0.092*** (0.013)	0.076*** (0.006)	-	-	0.010 (0.029)	0.033*** (0.008)
			p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0710				p-value for H_0: $\beta_j^I = \beta_j^N$ 0.1322	

Table E.5: Oaxaca-Blinder decomposition

Controls	(1) Raw mean gap	(2) Explained (Composition effect)	(3) Unexplained (Wage structure effect)	(4) No. observations
(0) Country dummies only	0.065** (0.033)	0.250*** (0.021)	-0.185*** (0.022)	**45,697**
(A) Education, and Experience (quadratic)	0.065* (0.034)	0.193*** (0.024)	-0.127*** (0.022)	**45,271**
(B) A + Gender, and Sector of employment	0.065* (0.034)	0.194*** (0.024)	-0.129*** (0.022)	**45,226**
(C) B + Numeracy test score	0.065* (0.034)	0.137*** (0.026)	-0.071*** (0.021)	**45,224**
(D) B + Literacy test score	0.065* (0.034)	0.139*** (0.024)	-0.073*** 0.022)	**45,224**
(E) B + Numeracy and Literacy test scores	0.065* (0.034)	0.132*** (0.025)	-0.067*** (0.026)	**45,224**
(B) A + Gender, and Sector of employment (restricted sample)	0.118** (0.045)	0.217*** (0.034)	-0.099*** (0.026)	**33,889**
(F) B + Problem solving test score	0.118** (0.045)	0.178*** (0.034)	-0.060** (0.023)	**33,889**
(G) B + Numeracy, Literacy, Problem solving test scores	0.118** (0.045)	0.169*** (0.035)	-0.051** (0.022)	**33,889**

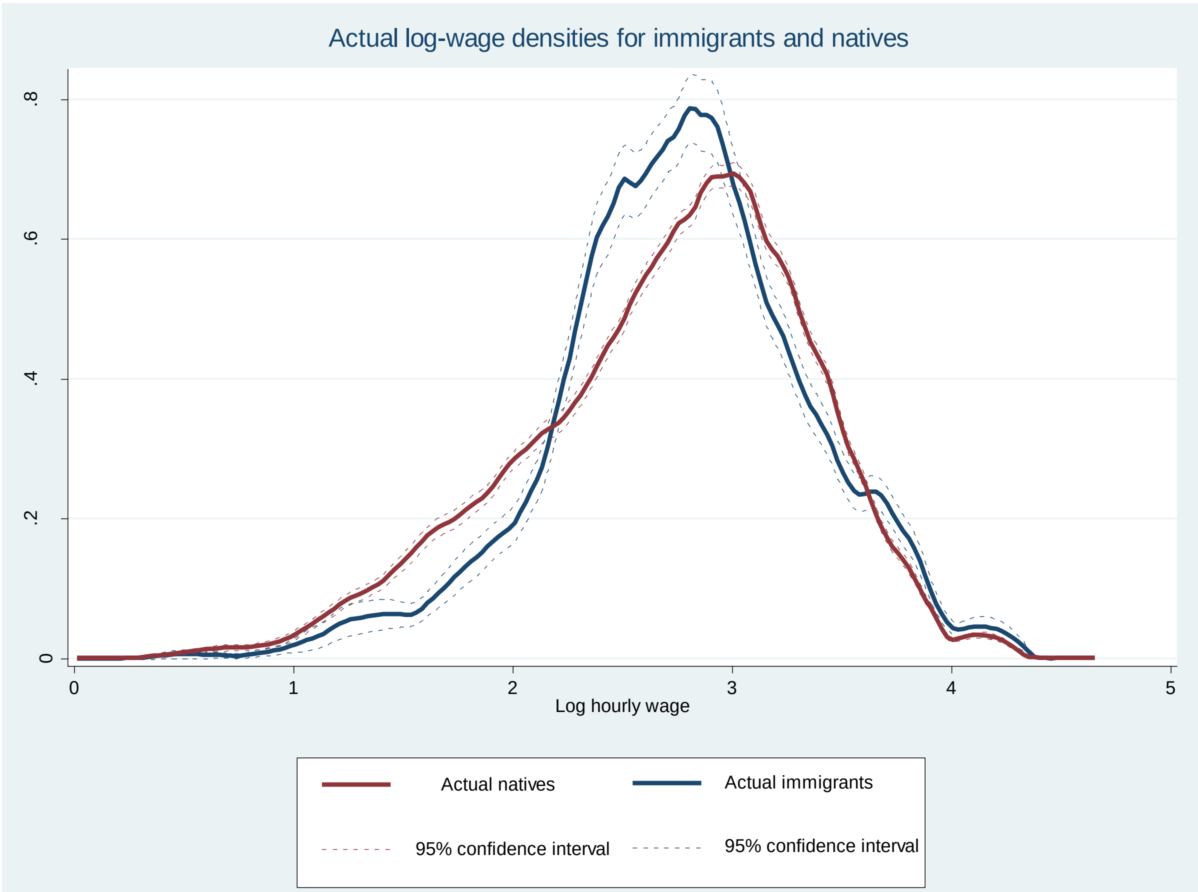
Note:

1) Reference group: native workers.

2) All specifications (A) to (H) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling. Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Figure E.8: Estimated densities of log-earnings (actual)

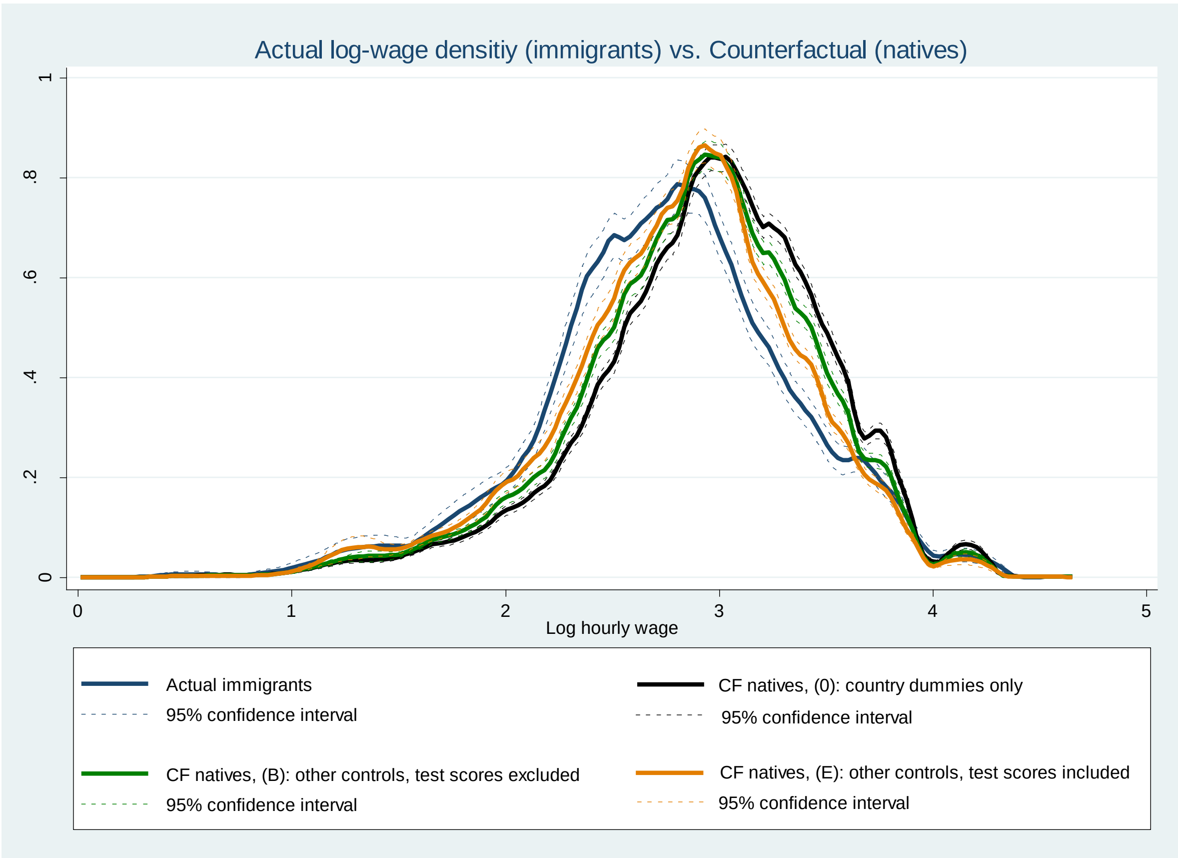


Notes:

1) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

2) 95% pointwise confidence intervals obtained via bootstrapping.

Figure E.9: Estimated densities of log-earnings (actual immigrants vs. counterfactual natives)



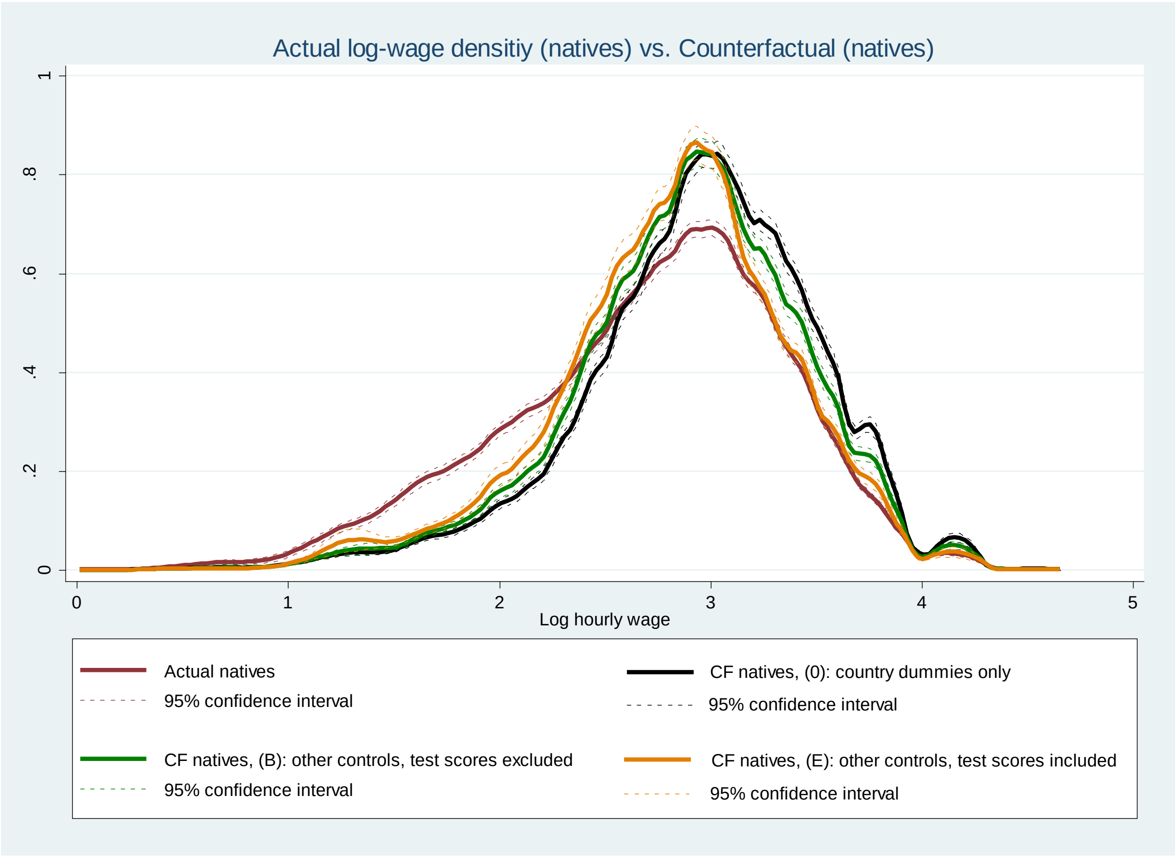
Notes:

1) Specification (0) includes country dummies only. Specification (B) controls for education, labour market experience (in quadratics), gender and sector of employment. Specification (E) adds numeracy test and literacy test scores. Both specifications (B) and (E) include country dummies.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) 95% pointwise confidence intervals obtained via bootstrapping.

Figure E.10: Estimated densities of log-earnings (actual natives vs. counterfactual natives)



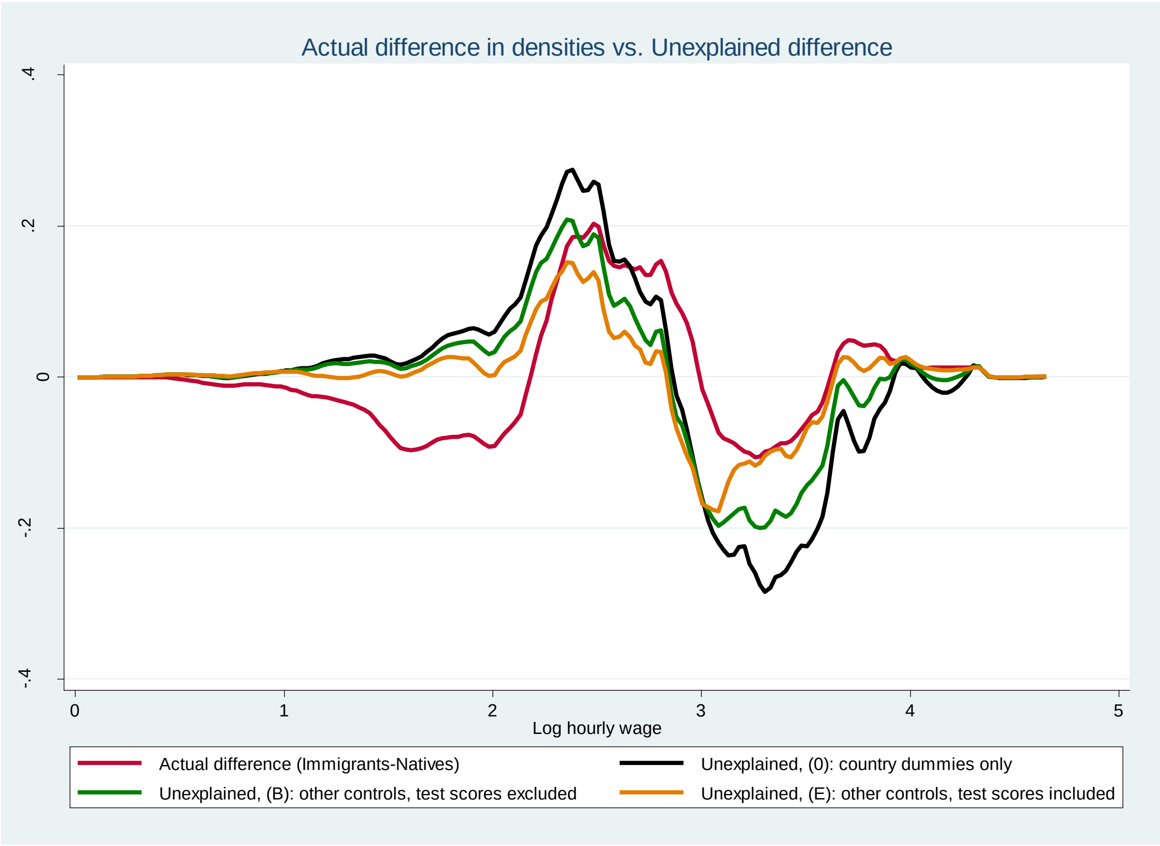
Notes:

1) Specification (0) includes country dummies only. Specification (B) controls for education, labour market experience (in quadratics), gender and sector of employment. Specification (E) adds numeracy test and literacy test scores. Both specifications (B) and (E) include country dummies.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) 95% pointwise confidence intervals obtained via bootstrapping.

Figure E.11: Estimated log-earnings gap (actual vs. unexplained)



Notes:

1) Specification (0) includes country dummies only. Specification (B) controls for education, labour market experience (in quadratics), gender and sector of employment. Specification (E) adds numeracy test and literacy test scores. Both specifications (B) and (E) include country dummies.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) 95% pointwise confidence intervals obtained via bootstrapping.

Table E.6: DFL decomposition results for selected quantiles

Quantile	Raw Gap	(0) Country dummies only		(A) Education, and Experience (quadratic)		(B) A + Gender, and Sector of employment	
		(1) Explained (Composition effect)	(2) Unexplained (Wage structure effect)	(1) Explained (Composition effect)	(2) Unexplained (Wage structure effect)	(1) Explained (Composition effect)	(2) Unexplained (Wage structure effect)
10th	0.287	0.488	-0.201	0.437	-0.150	0.437	-0.150
20th	0.193	0.389	-0.196	0.328	-0.135	0.327	-0.134
30th	0.067	0.305	-0.238	0.237	-0.170	0.236	-0.168
40th	0.025	0.240	-0.215	0.177	-0.152	0.177	-0.152
50th	-0.009	0.201	-0.210	0.152	-0.161	0.152	-0.161
60th	-0.041	0.179	-0.220	0.112	-0.153	0.109	-0.150
70th	-0.046	0.161	-0.207	0.089	-0.136	0.089	-0.135
80th	-0.043	0.140	-0.183	0.093	-0.136	0.093	-0.136
90th	0.040	0.098	-0.058	0.054	-0.014	0.059	-0.019
mean	0.065	0.250	-0.185	0.193	-0.127	0.194	-0.129

Notes:

1) Reference group: native workers.

2) All specifications (C) to (E) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling.

Table E.6 (cont'd)

Quantile	Raw Gap	(C) B + Numeracy test score		(D) B + Literacy test score		(E) B + Numeracy and Literacy test scores	
		(1) Explained (Composition effect)	(2) Unexplained (Wage structure effect)	(1) Explained (Composition effect)	(2) Unexplained (Wage structure effect)	(1) Explained (Composition effect)	(2) Unexplained (Wage structure effect)
10th	0.287	0.345	-0.058	0.332	-0.044	0.331	-0.044
20th	0.193	0.267	-0.074	0.258	-0.065	0.253	-0.060
30th	0.067	0.187	-0.120	0.185	-0.118	0.176	-0.108
40th	0.025	0.123	-0.099	0.129	-0.104	0.117	-0.092
50th	-0.009	0.083	-0.092	0.090	-0.099	0.082	-0.091
60th	-0.041	0.043	-0.084	0.047	-0.088	0.036	-0.077
70th	-0.046	0.033	-0.080	0.036	-0.083	0.025	-0.071
80th	-0.043	0.040	-0.083	0.040	-0.083	0.029	-0.072
90th	0.040	0.019	0.021	0.019	0.021	0.019	0.021
mean	0.065	0.137	-0.071	0.139	-0.073	0.132	-0.067

APPENDIX F

SUPPLEMENTARY TABLES AND FIGURES

Table F.1A: Country-level OLS results, test scores excluded (Canada)

Controls	Country sample: Canada (share of immigrants 27.7%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.055*** (0.005)	0.066*** (0.003)	0.048*** (0.005)	0.065*** (0.003)
	p-value for H0: $\beta_j^I = \beta_j^N$ 0.0062		p-value for H0: $\beta_j^I = \beta_j^N$ 0.0023	
Experience (years)	0.032*** (0.005)	0.022*** (0.003)	0.027*** (0.005)	0.022*** (0.003)
Experience squared	-0.001*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Female	-	-	-0.161*** (0.024)	-0.157*** (0.013)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	2.026*** (0.082)	2.090*** (0.052)	2.239*** (0.112)	2.063*** (0.073)
No. observations	**1,852**	**7,392**	**1,850**	**7,381**
R-squared	**0.19**	**0.20**	**0.26**	**0.26**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.1B: Country-level OLS results, test scores included (Canada)

Controls	Country sample: Canada (share of immigrants 27.7%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.026*** (0.005)	0.049*** (0.003)	0.026*** (0.006)	0.050*** (0.003)	0.033*** (0.007)	0.054*** (0.003)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0001		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0030	
Experience (years)	0.023*** (0.005)	0.022*** (0.003)	0.022*** (0.005)	0.023*** (0.003)	0.023*** (0.006)	0.025*** (0.004)
Experience squared	-0.000** (0.000)	-0.000*** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000* (0.000)	-0.000*** (0.000)
Female	-0.117*** (0.023)	-0.133*** (0.013)	-0.144*** (0.022)	-0.151*** (0.014)	-0.124*** (0.027)	-0.153*** (0.015)
Numeracy score (standardized)	0.122*** (0.010)	0.075*** (0.008)	-	-	-	-
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0005					
Literacy score (standardized)	-	-	0.120*** (0.011)	0.065*** (0.008)	-	-
			p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000			
Problem solving score (standardized)	-	-	-	-	0.098*** (0.013)	0.053*** (0.007)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0017	
Intercept	2.599*** (0.114)	2.260*** (0.075)	2.591*** (0.115)	2.227*** (0.074)	2.455*** (0.123)	2.172* (0.078
No.	**1,850**	**7,381**	**1,850**	**7,381**	**1,520**	**6,434**
R-squared	**0.35**	**0.29**	**0.34**	**0.28**	**0.30**	**0.27**

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.2A: Country-level OLS results, test scores excluded (Ireland)

Controls	Country sample: Ireland (share of immigrants 23.6%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.081** (0.010)	0.083*** (0.006)	0.077*** (0.010)	0.080*** (0.006)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.7493		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.7576	
Experience (years)	0.059*** (0.009)	0.043*** (0.008)	0.051*** (0.009	0.045*** (0.003)
Experience squared	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Female	-	-	-0.049*** (0.069)	-0.070*** (0.025)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	1.070*** (0.1631)	1.215*** (0.131)	1.410*** (0.167)	1.322*** (0.142)
No. observations	**347**	**1,263**	**347**	**1,263**
R-squared	**0.30**	**0.25**	**0.34**	**0.26**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.2B: Country-level OLS results, test scores included (Ireland)

<table>
<tr><th rowspan="3">Controls</th><th colspan="6">Country sample: Ireland (share of immigrants 23.6%)</th></tr>
<tr><th colspan="2">(3)</th><th colspan="2">(4)</th><th colspan="2">(5)</th></tr>
<tr><th>I</th><th>N</th><th>I</th><th>N</th><th>I</th><th>N</th></tr>
<tr><td rowspan="2">Education (years)</td><td>0.063** (0.010)</td><td>0.058*** (0.006)</td><td>0.064** (0.009)</td><td>0.061*** (0.006)</td><td>0.063** (0.013)</td><td>0.070*** (0.008)</td></tr>
<tr><td colspan="2">p-value for H_0: $\beta_j^I = \beta_j^N$ 0.6301</td><td colspan="2">p-value for H_0: $\beta_j^I = \beta_j^N$ 0.8496</td><td colspan="2">p-value for H_0: $\beta_j^I = \beta_j^N$ 0.6108</td></tr>
<tr><td>Experience (years)</td><td>0.042*** (0.009)</td><td>0.043*** (0.007)</td><td>0.040 (0.010)</td><td>0.043*** (0.002)</td><td>0.057*** (0.010)</td><td>0.049*** (0.008)</td></tr>
<tr><td>Experience squared</td><td>-0.001**** (0.000)</td><td>-0.001*** (0.000)</td><td>-0.001 (0.000)</td><td>-0.001*** (0.000)</td><td>-0.001*** (0.000)</td><td>-0.001*** (0.000)</td></tr>
<tr><td>Female</td><td>-0.045*** (0.036)</td><td>-0.029 (0.024)</td><td>-0.063*** (0.038)</td><td>-0.051** (0.024)</td><td>-0.026 (0.040)</td><td>-0.067** (0.026)</td></tr>
<tr><td rowspan="2">Numeracy score (standardized)</td><td>0.098** (0.031)</td><td>0.125*** (0.017)</td><td rowspan="2">-</td><td rowspan="2">-</td><td rowspan="2">-</td><td rowspan="2">-</td></tr>
<tr><td colspan="2">p-value for H_0: $\beta_j^I = \beta_j^N$ 0.2851</td></tr>
<tr><td rowspan="2">Literacy score (standardized)</td><td rowspan="2">-</td><td rowspan="2">-</td><td>0.097*** (0.021)</td><td>0.107*** (0.018)</td><td rowspan="2">-</td><td rowspan="2">-</td></tr>
<tr><td colspan="2">p-value for H_0: $\beta_j^I = \beta_j^N$ 0.7159</td></tr>
<tr><td rowspan="2">Problem solving score (standardized)</td><td rowspan="2">-</td><td rowspan="2">-</td><td rowspan="2">-</td><td rowspan="2">-</td><td>0.105*** (0.027)</td><td>0.081*** (0.015)</td></tr>
<tr><td colspan="2">p-value for H_0: $\beta_j^I = \beta_j^N$ 0.4635</td></tr>
<tr><td>Intercept</td><td>1.706*** (0.172)</td><td>1.665*** (0.148)</td><td>1.768*** (0.178)</td><td>1.580*** (0.138)</td><td>1.580*** (0.228)</td><td>1.410*** (0.181</td></tr>
<tr><td>No.</td><td>347</td><td>1,263</td><td>347</td><td>1,263</td><td>253</td><td>1,074</td></tr>
<tr><td>R-squared</td><td>0.39</td><td>0.31</td><td>0.38</td><td>0.30</td><td>0.37</td><td>0.29</td></tr>
</table>

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.3A: Country-level OLS results, test scores excluded (Austria)

Controls	Country sample: Austria (share of immigrants 18.7%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.065*** (0.006)	0.070*** (0.003)	0.063*** (0.007)	0.069*** (0.003)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.3716		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.4473	
Experience (years)	0.026*** (0.009)	0.023*** (0.004)	0.021** (0.009)	0.022*** (0.004)
Experience squared	-0.001** (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)
Female	-	-	-0.124*** (0.045)	-0.110*** (0.017)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	1.811*** (0.105)	1.870*** (0.050)	1.965*** (0.157)	1.898*** (0.083)
No. observations	**259**	**1,431**	**258**	**1,427**
R-squared	**0.31**	**0.24**	**0.34**	**0.26**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.3B: Country-level OLS results, test scores included (Austria)

Controls	Country sample: Austria (share of immigrants 18.7%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.047*** (0.007)	0.054*** (0.003)	0.045*** (0.007)	0.055*** (0.003)	0.054*** (0.012)	0.056*** (0.004)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.4020		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.2248		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.8051	
Experience (years)	0.020** (0.009)	0.022*** (0.004)	0.024** (0.009)	0.023*** (0.003)	0.028* (0.014)	0.023*** (0.004)
Experience squared	0.000 (0.000)	-0.000*** (0.000)	-0.000* (0.000)	-0.000*** (0.000)	-0.001 (0.000)	-0.000** (0.000)
Female	-0.125*** (0.039)	-0.088*** (0.017)	-0.142*** (0.041)	-0.105*** (0.017)	-0.078 (0.059)	-0.092*** (0.019)
Numeracy score (standardized)	0.080*** (0.012)	0.103*** (0.009)	-	-	-	-
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.2516					
Literacy score (standardized)	-	-	0.089*** (0.017)	0.106*** (0.009)	-	-
			p-value for H_0: $\beta_j^I = \beta_j^N$ 0.3934			
Problem solving score (standardized)	-	-	-	-	0.108*** (0.032)	0.085*** (0.011)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.4374	
Intercept	2.236*** (0.152)	2.033*** (0.078)	2.228*** (0.159)	2.019*** (0.081)	2.077*** (0.272)	2.030*** (0.085)
No.	**258**	**1,427**	**258**	**1,427**	**168**	**1,229**
R-squared	**0.39**	**0.32**	**0.39**	**0.32**	**0.37**	**0.30**

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.4A: Country-level OLS results, test scores excluded (United States)

Controls	Country sample: United States (share of immigrants 17.4%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.083*** (0.006)	0.103*** (0.007)	0.089*** (0.006)	0.109*** (0.007)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0587		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0340	
Experience (years)	0.037*** (0.011)	0.044*** (0.007)	0.035*** (0.011)	0.045*** (0.007)
Experience squared	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Female	-	-	-0.233** (0.094)	-0.192*** (0.028)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	1.591*** (0.111)	1.273*** (0.105)	1.595*** (0.234)	1.267*** (0.126)
No. observations	**227**	**1,258**	**227**	**1,258**
R-squared	**0.38**	**0.28**	**0.43**	**0.31**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.4B: Country-level OLS results, test scores included (United States)

Controls	Country sample: United States (share of immigrants 17.4%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.081***	0.082***	0.076***	0.085***	0.078***	0.083***
	(0.010)	(0.007)	(0.008)	(0.007)	(0.015)	(0.007)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.9415		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.4651		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.7303	
Experience (years)	0.034***	0.044***	0.034***	0.045***	0.024	0.041***
	(0.012)	(0.007)	(0.011)	(0.006)	(0.017)	(0.006)
Experience squared	-0.001***	-0.001***	-0.001***	-0.001***	0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.221**	-0.146***	-0.231**	-0.177***	-0.310***	-0.183***
	(0.085)	(0.029)	(0.093)	(0.028)	(0.062)	(0.028)
Numeracy score (standardized)	0.033	0.111***	-	-	-	-
	(0.045)	(0.020)				
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.1370					
Literacy score (standardized)	-	-	0.062*	0.113***	-	-
			(0.036)	(0.019)		
			p-value for H_0: $\beta_j^I = \beta_j^N$ 0.2899			
Problem solving score (standardized)	-	-	-	-	0.087**	0.118***
					(0.044)	(0.017)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.5177	
Intercept	1.751***	1.640***	1.868***	1.579***	1.970***	1.615***
	(0.368)	(0.126)	(0.321)	(0.118)	(0.391)	(0.125)
No.	**227**	**1,258**	**227**	**1,258**	**151**	**1,163**
R-squared	**0.43**	**0.34**	**0.44**	**0.34**	**0.36**	**0.35**

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.5A: Country-level OLS results, test scores excluded (United Kingdom)

Controls	Country sample: United Kingdom (share of immigrants 15.1%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.084*** (0.015)	0.082*** (0.005)	0.085*** (0.015)	0.084*** (0.005)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.9607		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.9813	
Experience (years)	0.047*** (0.012)	0.034*** (0.006)	0.044*** (0.013)	0.036*** (0.006)
Experience squared	-0.001*** 0.000	-0.001*** 0.000	-0.001*** 0.000	-0.001*** 0.000
Female	-	-	-0.104 (0.063)	-0.149*** (0.020)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	1.265*** (0.229)	1.453*** (0.081)	1.187*** (0.264)	1.420*** (0.116)
No. observations	**284**	**2,153**	**284**	**2,150**
R-squared	**0.20**	**0.17**	**0.21**	**0.20**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.5B: Country-level OLS results, test scores included (United Kingdom)

Controls	Country sample: United Kingdom (share of immigrants 15.1%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.053*** (0.014)	0.064*** (0.005)	0.056*** (0.014)	0.065*** (0.005)	0.062*** (0.017)	0.062*** (0.006)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.4988		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.5685		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.9974	
Experience (years)	0.038*** (0.010)	0.032*** (0.006)	0.033*** (0.011)	0.033*** (0.006)	0.048*** (0.014)	0.035*** (0.006)
Experience squared	-0.001*** (0.000)	-0.001*** (0.000)	-0.001** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Female	-0.012 (0.055)	-0.106*** (0.020)	-0.089 (0.063)	-0.137*** (0.019)	-0.025 (0.072)	-0.107*** (0.019)
Numeracy score (standardized)	0.232*** (0.028)	0.139*** (0.014)	-	-	-	-
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0046					
Literacy score (standardized)	-	-	0.187*** (0.029)	0.140*** (0.013)	-	-
			p-value for H_0: $\beta_j^I = \beta_j^N$ 0.1648			
Problem solving score (standardized)	-	-	-	-	0.177*** (0.035)	0.142*** (0.017)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.3343	
Intercept	1.611*** (0.232)	1.682*** (0.121)	1.639*** (0.232)	1.656*** (0.120)	1.549*** (0.287)	1.677*** (0.121)
No.	**284**	**2,150**	**284**	**2,150**	**249**	**2,030**
R-squared	**0.40**	**0.27**	**0.35**	**0.27**	**0.32**	**0.27**

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.6A: Country-level OLS results, test scores excluded (Germany)

Controls	Country sample: Germany (share of immigrants 14.6%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.038*** (0.007)	0.057*** (0.004)	0.039*** (0.007)	0.057*** (0.004)
	p-value for H0: $\beta_j^I = \beta_j^N$ 0.0111		p-value for H0: $\beta_j^I = \beta_j^N$ 0.0159	
Experience (years)	0.020 (0.014)	0.022*** (0.004)	0.018 (0.015)	0.022*** (0.004)
Experience squared	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)
Female	-	-	-0.149*** (0.054)	-0.109*** (0.016)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	2.046*** (0.153)	1.867*** (0.071)	2.096*** (0.313)	1.780*** (0.091)
No. observations	**190**	**1,459**	**190**	**1,459**
R-squared	**0.23**	**0.24**	**0.26**	**0.27**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.6B: Country-level OLS results, test scores included (Germany)

Controls	Country sample: Germany (share of immigrants 14.6%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.019** (0.009)	0.038*** (0.004)	0.021** (0.009)	0.041*** (0.004)	0.039*** (0.011)	0.046*** (0.003)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0280		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0173		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.4727	
Experience (years)	0.017 (0.014)	0.021*** (0.004)	0.019 (0.015)	0.021*** (0.004)	0.030* (0.016)	0.024*** (0.004)
Experience squared	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)
Female	-0.106* (0.057)	-0.087*** (0.016)	-0.122** (0.057)	-0.109*** (0.016)	-0.147** (0.064)	-0.110*** (0.016)
Numeracy score (standardized)	0.112*** (0.025)	0.104*** (0.011)	-	-	-	-
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.7567					
Literacy score (standardized)	-	-	0.114*** (0.027)	0.093*** (0.011)	-	-
			p-value for H_0: $\beta_j^I = \beta_j^N$ 0.4585			
Problem solving score (standardized)	-	-	-	-	0.053* (0.028)	0.077*** (0.010)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.3871	
Intercept	2.374*** (0.255)	2.025*** (0.085)	2.321*** (0.290)	2.004*** (0.092)	2.025*** (0.287)	1.908*** (0.076)
No.	**190**	**1,459**	**190**	**1,459**	**152**	**1,335**
R-squared	**0.34**	**0.32**	**0.34**	**0.31**	**0.36**	**0.31**

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.7A: Country-level OLS results, test scores excluded (Norway)

Controls	Country sample: Norway (share of immigrants 14.3%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.046*** (0.007)	0.052*** (0.003)	0.048*** (0.007)	0.065*** (0.003)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0314		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0172	
Experience (years)	0.023*** (0.008)	0.029*** (0.003)	0.022*** (0.008)	0.028*** (0.003)
Experience squared	-0.000* (0.000)	-0.001*** (0.000)	-0.000* (0.000)	-0.001*** (0.000)
Female	-	-	-0.062* (0.036)	-0.145*** (0.013)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	2.139*** (0.124)	2.146*** (0.057)	2.252*** (0.181)	1.907*** (0.074)
No. observations	**275**	**1,796**	**275**	**1,796**
R-squared	**0.25**	**0.17**	**0.27**	**0.29**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.7B: Country-level OLS results, test scores included (Norway)

Controls	Country sample: Norway (share of immigrants 14.3%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.035*** (0.007)	0.055*** (0.003)	0.037*** (0.007)	0.058*** (0.003)	0.042*** (0.009)	0.056*** (0.003)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0102		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0052		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.1107	
Experience (years)	0.017** (0.007)	0.027*** (0.003)	0.019*** (0.007)	0.028*** (0.003)	0.019** (0.008)	0.030*** (0.003)
Experience squared	0.000 (0.000)	-0.001*** (0.000)	0.000 (0.000)	-0.001*** (0.000)	0.000 (0.000)	-0.001*** (0.000)
Female	-0.054 (0.035)	-0.127*** (0.013)	-0.073** (0.036)	-0.140*** (0.013)	-0.043 (0.039)	-0.138*** (0.013)
Numeracy score (standardized)	0.073*** (0.013)	0.057*** (0.008)	-	-	-	-
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.2906					
Literacy score (standardized)	-	-	0.072*** (0.013)	0.049*** (0.009)	-	-
			p-value for H_0: $\beta_j^I = \beta_j^N$ 0.1440			
Problem solving score (standardized)	-	-	-	-	0.080*** (0.018)	0.056*** (0.009)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.2168	
Intercept	2.525*** (0.174)	2.021*** (0.074)	2.475*** (0.164)	1.965*** (0.075)	2.395*** (0.209)	1.988*** (0.077)
No.	**275**	**1,796**	**275**	**1,796**	**210**	**1,717**
R-squared	**0.35**	**0.31**	**0.34**	**0.31**	**0.36**	**0.31**

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.8A: Country-level OLS results, test scores excluded (Netherlands)

Controls	Country sample: Netherlands (share of immigrants 13.0%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.047*** (0.008)	0.085*** (0.004)	0.044*** (0.007)	0.086*** (0.004)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000	
Experience (years)	0.025** (0.010)	0.039*** (0.004)	0.024*** (0.009)	0.038*** (0.004)
Experience squared	0.000 (0.000)	-0.001*** (0.000)	0.000 (0.000)	-0.001*** (0.000)
Female	-	-	-0.128** (0.055)	-0.062*** (0.018)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	1.991*** (0.133)	1.454*** (0.081)	2.263*** (0.162)	1.453*** (0.085)
No. observations	**124**	**1,263**	**123**	**1,261**
R-squared	**0.25**	**0.28**	**0.30**	**0.29**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.8B: Country-level OLS results, test scores included (Netherlands)

Controls	Country sample: Netherlands (share of immigrants 13.0%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.025*** (0.009)	0.073*** (0.005)	0.026*** (0.009)	0.072*** (0.005)	0.030*** (0.009)	0.074*** (0.005)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0002	
Experience (years)	0.030*** (0.009)	0.037*** (0.004)	0.027*** (0.009)	0.036*** (0.004)	0.036*** (0.010)	0.037*** (0.004)
Experience squared	-0.000** (0.000)	-0.001*** (0.000)	-0.000* (0.000)	-0.001*** (0.000)	-0.001** (0.000)	-0.001*** (0.000)
Female	-0.085 (0.056)	-0.042** (0.018)	-0.118** (0.058)	-0.056*** (0.018)	-0.032 (0.059)	-0.059*** (0.019)
Numeracy score (standardized)	0.116*** (0.027)	0.076*** (0.013)	-	-	-	-
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.1820					
Literacy score (standardized)	-	-	0.100*** (0.026)	0.083*** (0.012)	-	-
			p-value for H_0: $\beta_j^I = \beta_j^N$ 0.5642			
Problem solving score (standardized)	-	-	-	-	0.098*** (0.026)	0.071*** (0.012)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.3227	
Intercept	2.506*** (0.178)	1.608*** (0.087)	2.498*** (0.183)	1.621*** (0.089)	2.267*** (0.210)	1.596*** (0.094)
No.	**123**	**1,261**	**123**	**1,261**	**100**	**1,210**
R-squared	**0.39**	**0.31**	**0.38**	**0.32**	**0.36**	**0.31**

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.9A: Country-level OLS results, test scores excluded (Spain)

Controls	Country sample: Spain (share of immigrants 12.0%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.027** (0.012)	0.076*** (0.002)	0.030** (0.012)	0.072*** (0.003)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0002		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0006	
Experience (years)	0.023* (0.011)	0.031*** (0.005)	0.018 (0.011)	0.029*** (0.004)
Experience squared	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)
Female	-	-	-0.220*** (0.065)	-0.169*** (0.019)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	1.725*** (0.150)	1.310*** (0.050)	1.702*** (0.457)	1.370*** (0.093)
No. observations	**200**	**1,494**	**200**	**1,494**
R-squared	**0.11**	**0.34**	**0.18**	**0.39**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.9B: Country-level OLS results, test scores included (Spain)

Controls	Country sample: Spain (share of immigrants 12.0%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.024* (0.014)	0.063*** (0.003)	0.027** (0.013)	0.064*** (0.003)	NA	NA
	p-value for H$_0$: $\beta_j^I = \beta_j^N$ 0.0043		p-value for H$_0$: $\beta_j^I = \beta_j^N$ 0.0051			
Experience (years)	0.018* (0.010)	0.027*** (0.004)	0.018 (0.011)	0.028*** (0.004)		
Experience squared	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)		
Female	-0.207*** (0.072)	-0.142*** (0.019)	-0.216*** (0.069)	-0.154*** (0.020)		
Numeracy score (standardized)	0.049 (0.045)	0.076*** (0.014)	-	-		
	p-value for H$_0$: $\beta_j^I = \beta_j^N$ 0.5404					
Literacy score (standardized)	-	-	0.029 (0.040)	0.060*** (0.012)		
			p-value for H$_0$: $\beta_j^I = \beta_j^N$ 0.4565			
Problem solving score (standardized)	-	-	-	-		
Intercept	1.908*** (0.518)	1.502*** (0.092)	1.810*** (0.482)	1.469*** (0.092)		
No.	**200**	**1,494**	**200**	**1,494**		
R-squared	**0.19**	**0.40**	**0.18**	**0.40**		

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

4) Spain did not administer the problem solving test.

Table F.10A: Country-level OLS results, test scores excluded (France)

Controls	Country sample: France (share of immigrants 10.9%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.034*** (0.004)	0.058*** (0.002)	0.036*** (0.004)	0.060*** (0.002)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0000	
Experience (years)	0.014** (0.006)	0.021*** (0.003)	0.013** (0.006)	0.021*** (0.003)
Experience squared	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)
Female	-	-	-0.080** (0.039)	-0.119*** (0.013)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	1.962*** (0.065)	1.699*** (0.040)	1.842*** (0.095)	1.652*** (0.053)
No. observations	**210**	**2,044**	**210**	**2,043**
R-squared	**0.31**	**0.26**	**0.32**	**0.30**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.10B: Country-level OLS results, test scores included (France)

Controls	Country sample: France (share of immigrants 10.9%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.026*** (0.004)	0.045*** (0.002)	0.029*** (0.004)	0.050*** (0.003)	NA	NA
	p-value for H0: $\beta_j^I = \beta_j^N$ 0.0004		p-value for H0: $\beta_j^I = \beta_j^N$ 0.0001			
Experience (years)	0.013** (0.006)	0.022*** (0.003)	0.013* (0.006)	0.022*** (0.003)		
Experience squared	0.000 (0.000)	-0.000*** (0.000)	0.000 (0.000)	-0.000*** (0.000)		
Female	-0.068* (0.039)	-0.097*** (0.013)	-0.082** (0.039)	-0.116*** (0.013)		
Numeracy score (standardized)	0.068*** (0.020)	0.085*** (0.007)	-	-		
	p-value for H0: $\beta_j^I = \beta_j^N$ 0.3978					
Literacy score (standardized)	-	-	0.057*** (0.019)	0.072*** (0.007)		
			p-value for H0: $\beta_j^I = \beta_j^N$ 0.4594			
Problem solving score (standardized)	-	-	-	-		
Intercept	2.063*** (0.080)	1.824*** (0.051)	1.995*** (0.088)	1.762*** (0.053)		
No.	**209**	**2,042**	**209**	**2,042**		
R-squared	**0.36**	**0.34**	**0.35**	**0.33**		

Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

4) France did not administer the problem solving test.

Table F.11A: Country-level OLS results, test scores excluded (Estonia)

Controls	Country sample: Estonia (share of immigrants 10.3%)			
	(1)		(2)	
	I	N	I	N
Education (years)	0.026* (0.014)	0.058*** (0.004)	0.025* (0.014)	0.077*** (0.004)
	p-value for H$_0$: $\beta_j^I = \beta_j^N$ 0.0138		p-value for H$_0$: $\beta_j^I = \beta_j^N$ 0.0004	
Experience (years)	0.005 (0.015)	0.035*** (0.005)	0.01 (0.014)	0.030*** (0.005)
Experience squared	0.000 (0.000)	-0.001*** (0.000)	0.000 (0.000)	-0.001*** (0.000)
Female	-	-	-0.527*** (0.073)	-0.433*** (0.021)
Numeracy score (standardized)	-	-	-	-
Literacy score (standardized)	-	-	-	-
Problem solving score (standardized)	-	-	-	-
Intercept	1.716*** (0.231)	1.239*** (0.071)	1.810** (0.720)	1.112*** (0.115)
No. observations	**199**	**2,019**	**198**	**2,014**
R-squared	**0.04**	**0.11**	**0.27**	**0.28**

Notes:

1) Specifications (2) controls for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Table F.11B: Country-level OLS results, test scores included (Estonia)

Controls	Country sample: Estonia (share of immigrants 10.3%)					
	(3)		(4)		(5)	
	I	N	I	N	I	N
Education (years)	0.006 (0.015)	0.060*** (0.005)	0.017 (0.015)	0.068*** (0.004)	0.014 (0.020)	0.058*** (0.005)
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0005		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0010		p-value for H_0: $\beta_j^I = \beta_j^N$ 0.0292	
Experience (years)	0.016 (0.014)	0.029*** (0.005)	0.016 (0.014)	0.030*** (0.005)	0.002 (0.019)	0.040*** (0.005)
Experience squared	0.000 (0.000)	-0.001*** (0.000)	0.000 (0.000)	-0.001*** (0.000)	0.000 (0.000)	-0.001*** (0.000)
Female	-0.487*** (0.069)	-0.402*** (0.022)	-0.522*** (0.071)	-0.428*** (0.021)	-0.555*** (0.078)	-0.419*** (0.025)
Numeracy score (standardized)	0.175*** (0.042)	0.118*** (0.014)	-	-	-	-
	p-value for H_0: $\beta_j^I = \beta_j^N$ 0.2512					
Literacy score (standardized)	-	-	0.094** (0.040)	0.068*** (0.013)	-	-
			p-value for H_0: $\beta_j^I = \beta_j^N$ 0.5429			
Problem solving score (standardized)	-	-	-	-	0.076 (0.048)	0.093*** (0.014)
					p-value for H_0: $\beta_j^I = \beta_j^N$ 0.7399	
Intercept	1.905*** (0.600)	1.312*** (0.114)	1.867*** (0.623)	1.203*** (0.116)	1.578*** (0.385)	1.235*** (0.126)
No.	**198**	**2,014**	**198**	**2,014**	**145**	**1,574**
R-squared	**0.32**	**0.30**	**0.29**	**0.29**	**0.30**	**0.29**

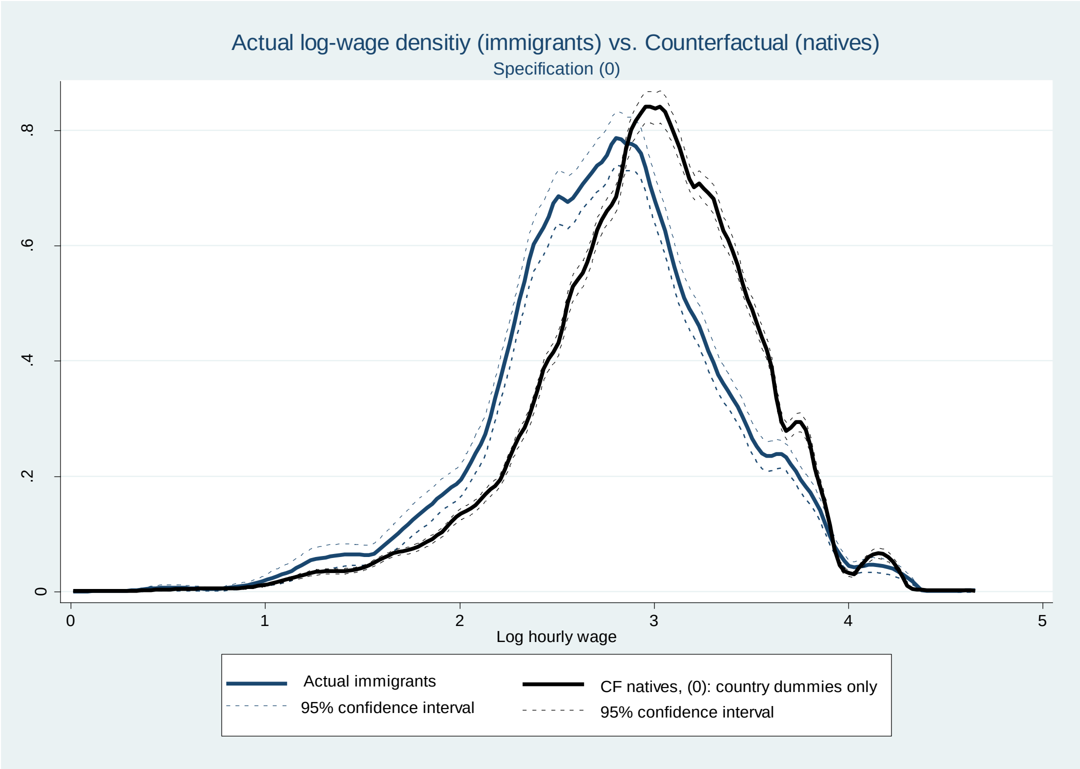
Notes:

1) All specifications control for sector of employment.

2) Final sample weight used to correct for inverse probability weighted sampling.

3) Jack-knife standard errors based on replicate weights reported in parentheses (80 replications).

Figure F.1: Total sample DFL results: specification (0)



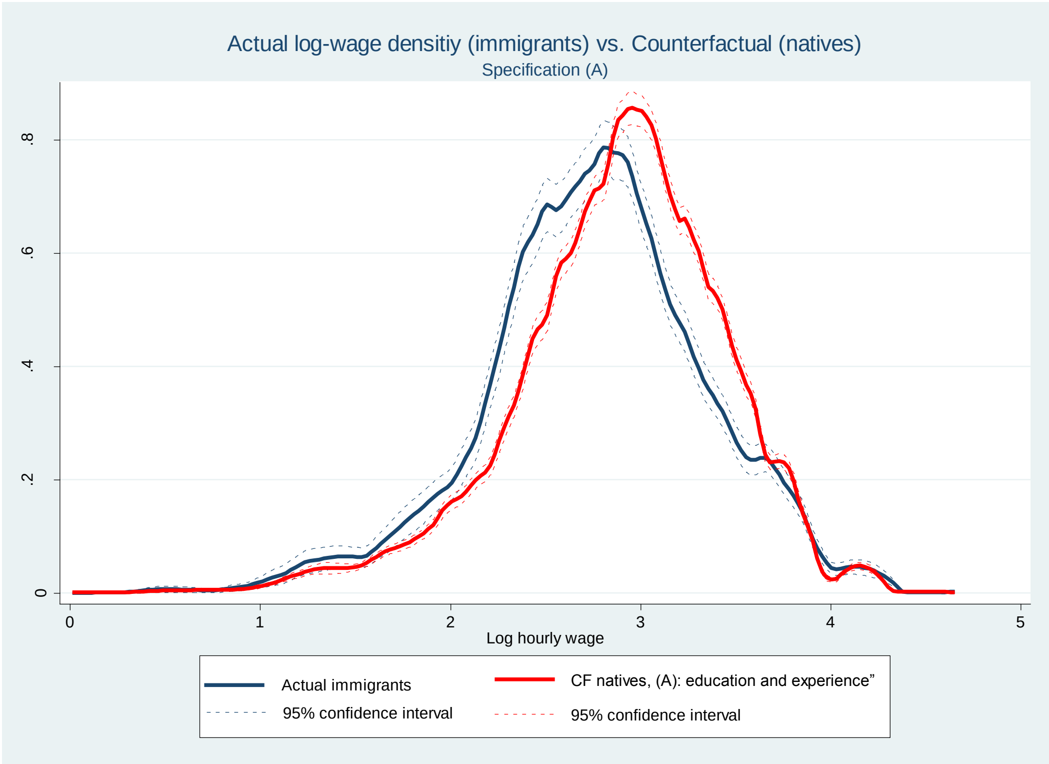
Notes:

1) Specification (0) includes country dummies only. Specification (A) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (C) adds numeracy test score to the list of covariates in specification (B); specification (D) adds literacy test score to that list, while specification (E) adds both literacy and numeracy test scores. All specifications (A) to (E) include country dummies.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.2: Total sample DFL results: specification (A)



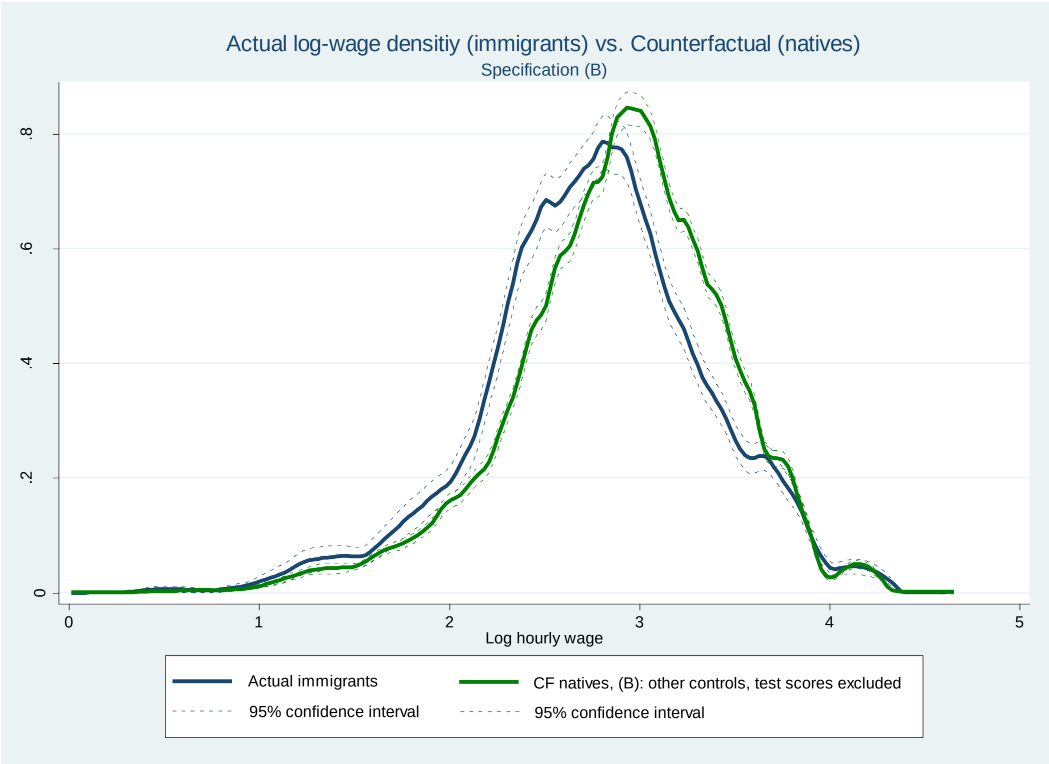
Notes:

1) Specification (0) includes country dummies only. Specification (A) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (C) adds numeracy test score to the list of covariates in specification (B); specification (D) adds literacy test score to that list, while specification (E) adds both literacy and numeracy test scores. All specifications (A) to (E) include country dummies.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.3: Total sample DFL results: specification (B)



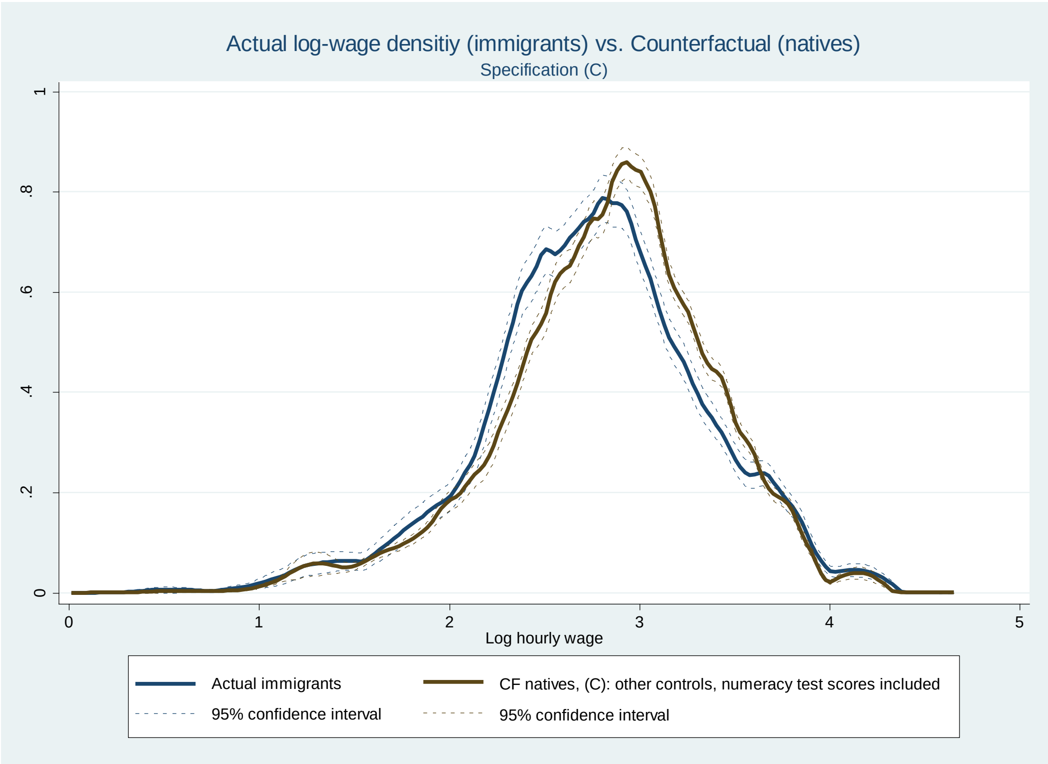
Notes:

1) Specification (0) includes country dummies only. Specification (A) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (C) adds numeracy test score to the list of covariates in specification (B); specification (D) adds literacy test score to that list, while specification (E) adds both literacy and numeracy test scores. All specifications (A) to (E) include country dummies.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.4: Total sample DFL results: specification (C)



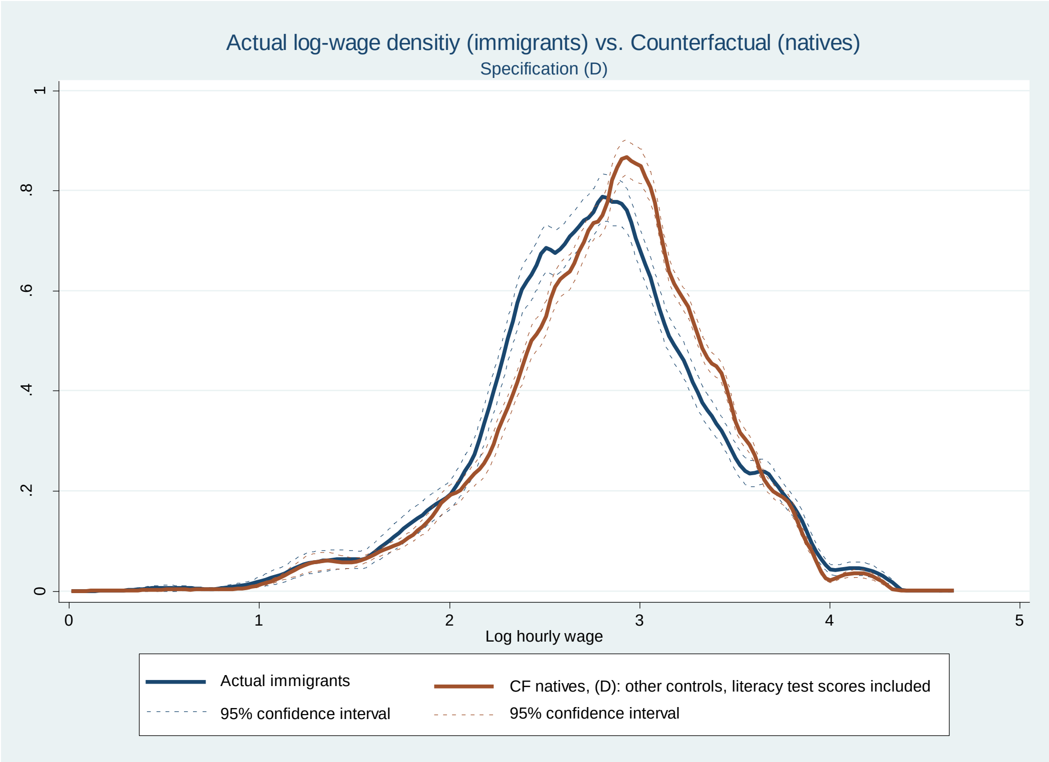
Notes:

1) Specification (0) includes country dummies only. Specification (A) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (C) adds numeracy test score to the list of covariates in specification (B); specification (D) adds literacy test score to that list, while specification (E) adds both literacy and numeracy test scores. All specifications (A) to (E) include country dummies.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.5: Total sample DFL results: specification (D)



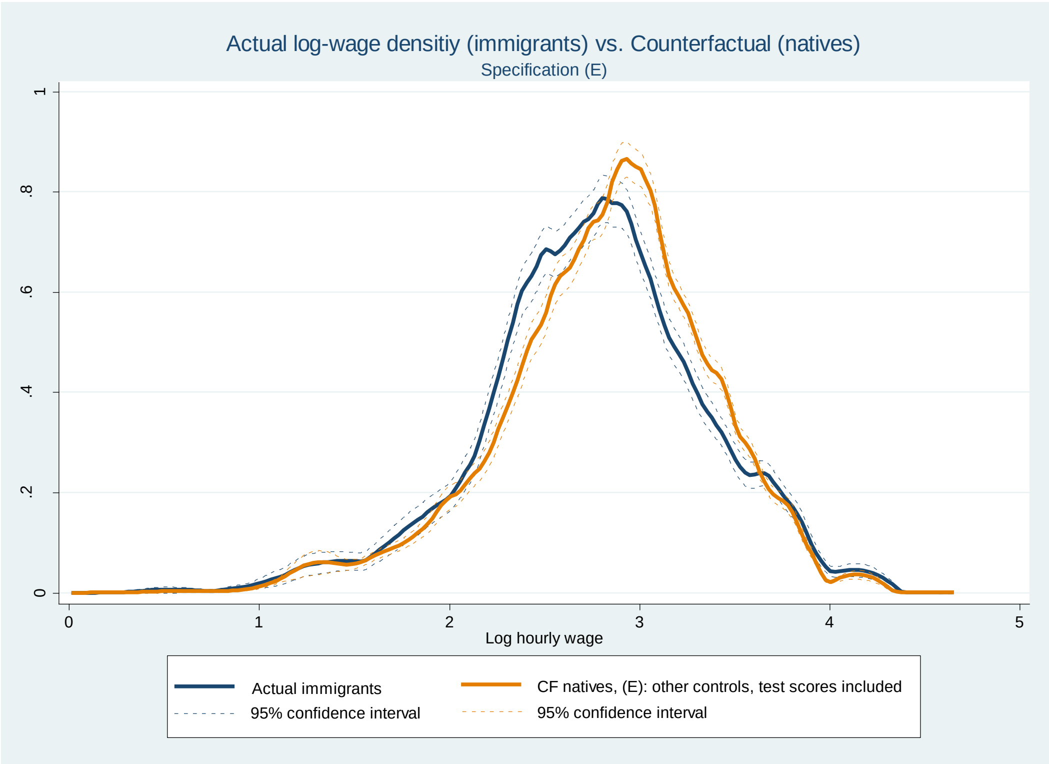
Notes:

1) Specification (0) includes country dummies only. Specification (A) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (C) adds numeracy test score to the list of covariates in specification (B); specification (D) adds literacy test score to that list, while specification (E) adds both literacy and numeracy test scores. All specifications (A) to (E) include country dummies.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.6: Total sample DFL results: specification (E)



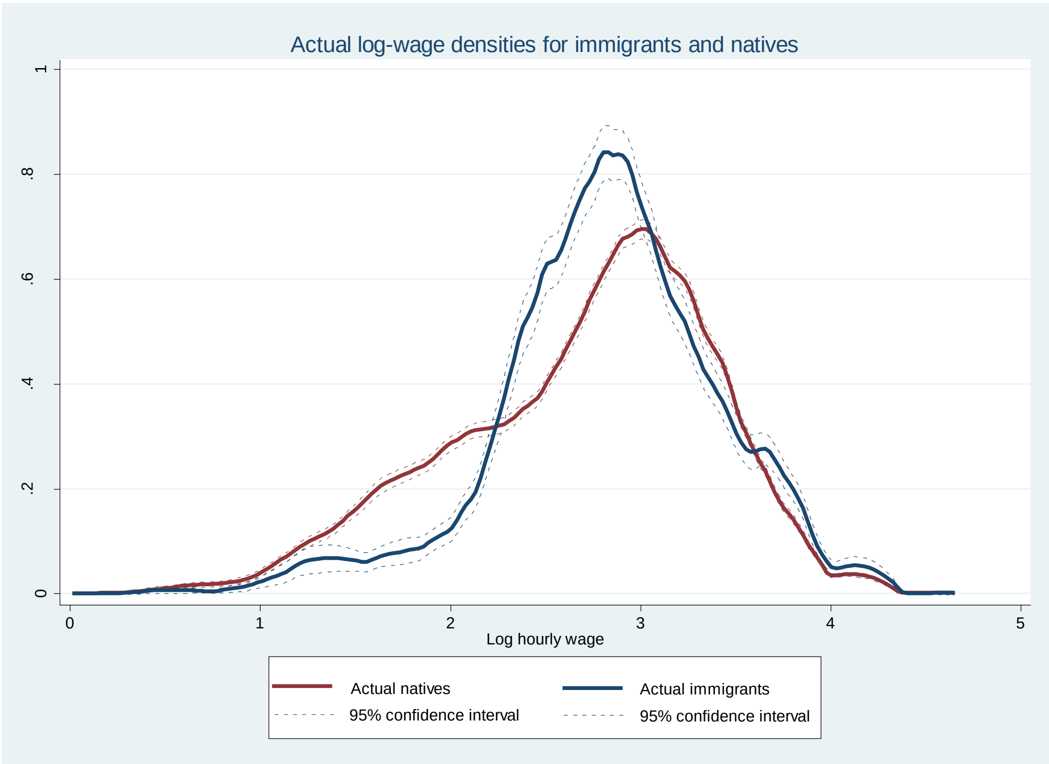
Notes:

1) Specification (0) includes country dummies only. Specification (A) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (C) adds numeracy test score to the list of covariates in specification (B); specification (D) adds literacy test score to that list, while specification (E) adds both literacy and numeracy test scores. All specifications (A) to (E) include country dummies.

2) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

3) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.7: Restricted sample DFL results: estimated densities of log-earnings (actual)



Notes:

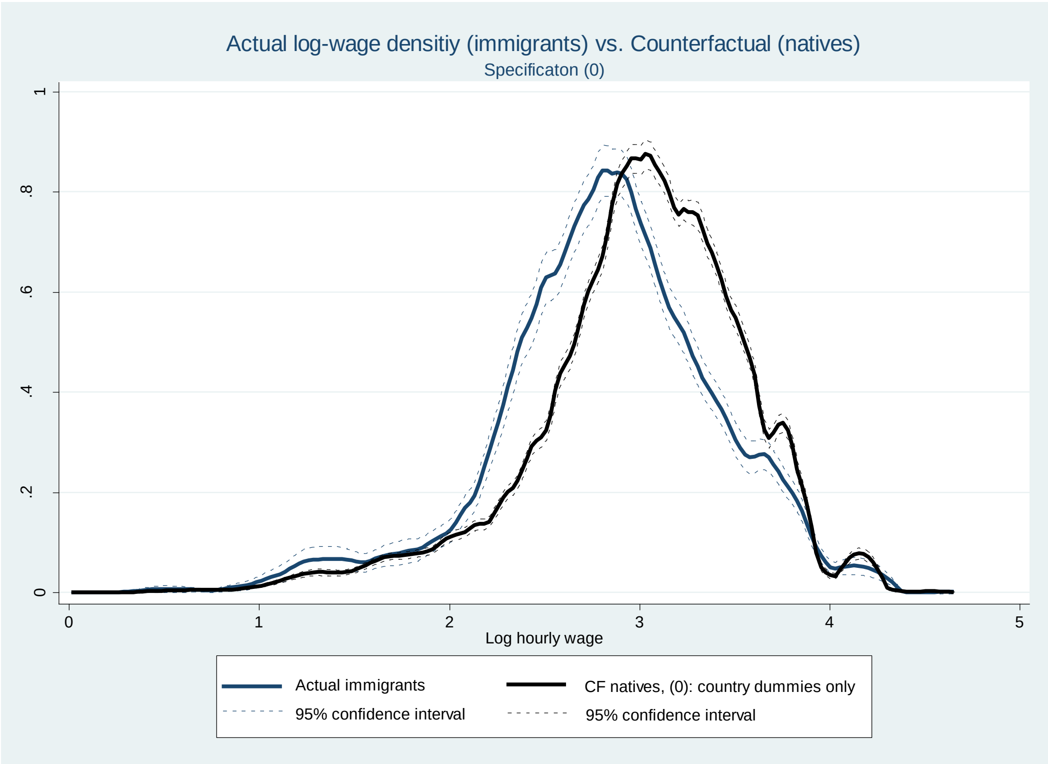
1) Sample restricted to countries in PIAAC which administered all test scores. France, Italy and Spain excluded.

2) Specification (0) includes country dummies only. Specification (B) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (G) adds numeracy, literacy and problem solving test score to the list of covariates in specification (B). Both specifications (B) and (G) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

4) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.8: Restricted sample DFL results: specification (0)



Notes:

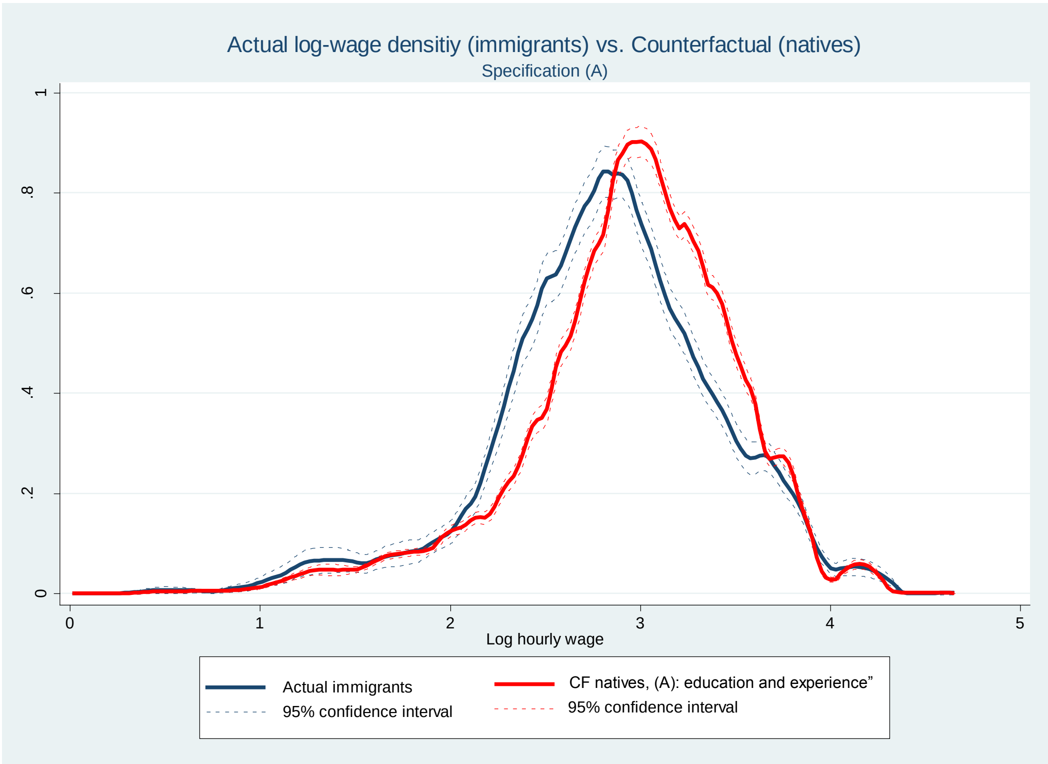
1) Sample restricted to countries in PIAAC which administered all test scores. France, Italy and Spain excluded.

2) Specification (0) includes country dummies only. Specification (B) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (G) adds numeracy, literacy and problem solving test score to the list of covariates in specification (B). Both specifications (B) and (G) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

4) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.9: Restricted sample DFL results: specification (A)



Notes:

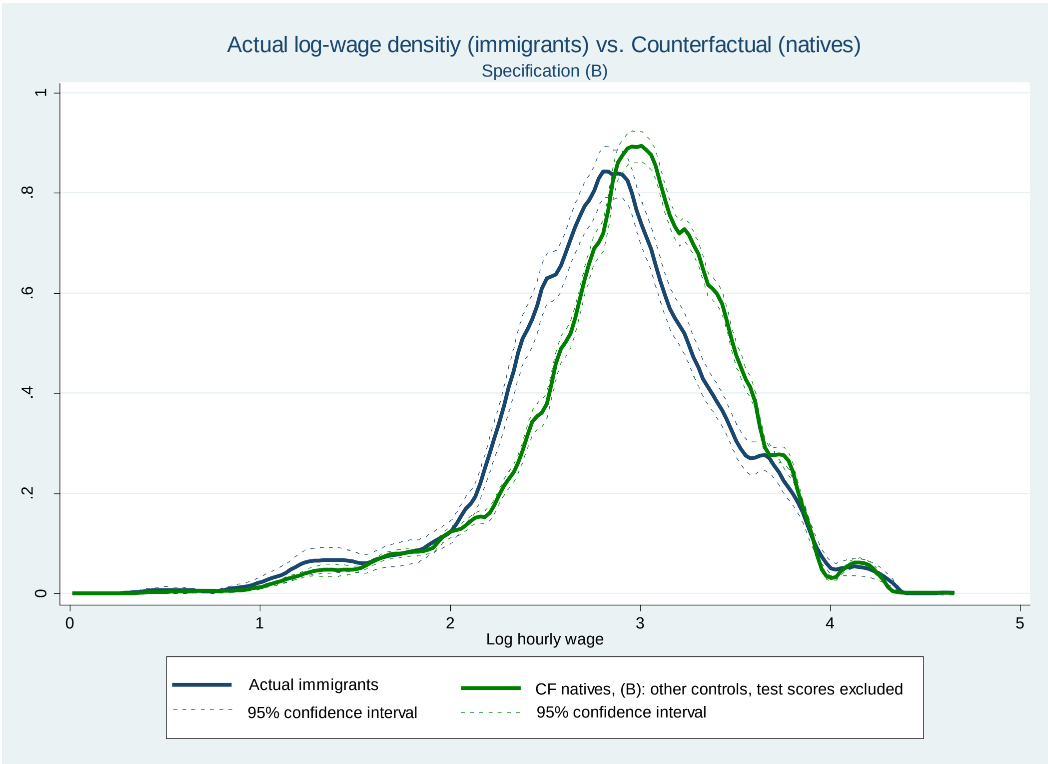
1) Sample restricted to countries in PIAAC which administered all test scores. France, Italy and Spain excluded.

2) Specification (0) includes country dummies only. Specification (B) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (G) adds numeracy, literacy and problem solving test score to the list of covariates in specification (B). Both specifications (B) and (G) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

4) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.10: Restricted sample DFL results: specification (B)



Notes:

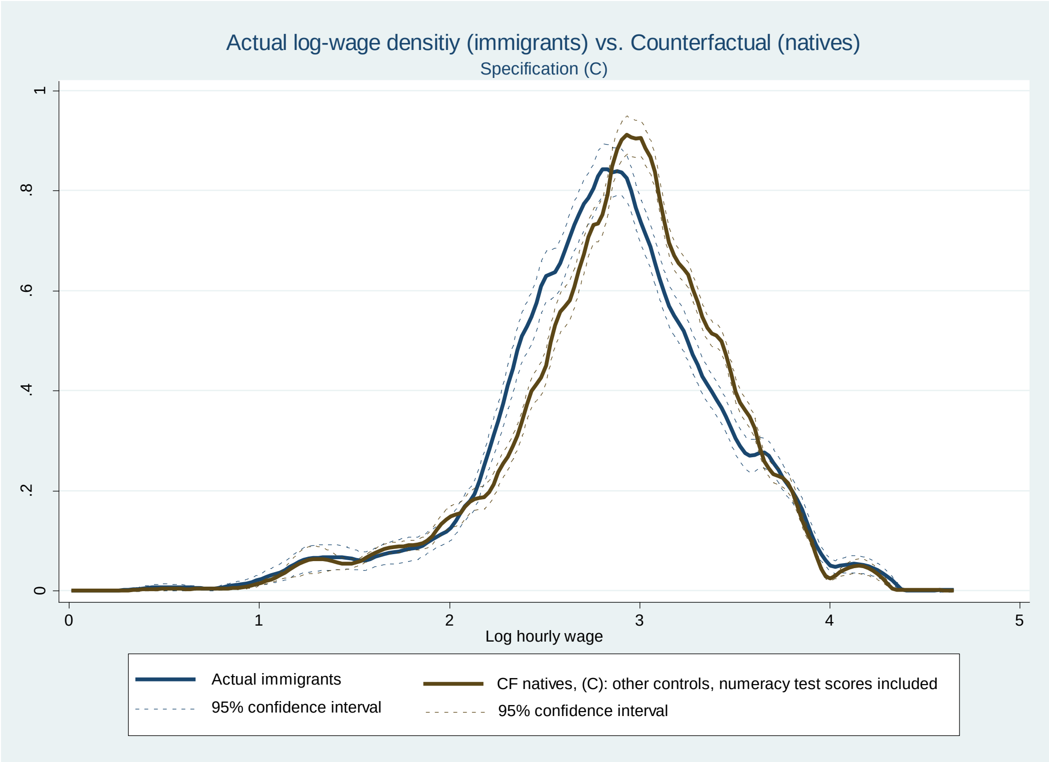
1) Sample restricted to countries in PIAAC which administered all test scores. France, Italy and Spain excluded.

2) Specification (0) includes country dummies only. Specification (B) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (G) adds numeracy, literacy and problem solving test score to the list of covariates in specification (B). Both specifications (B) and (G) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

4) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.11: Restricted sample DFL results: specification (C)



Notes:

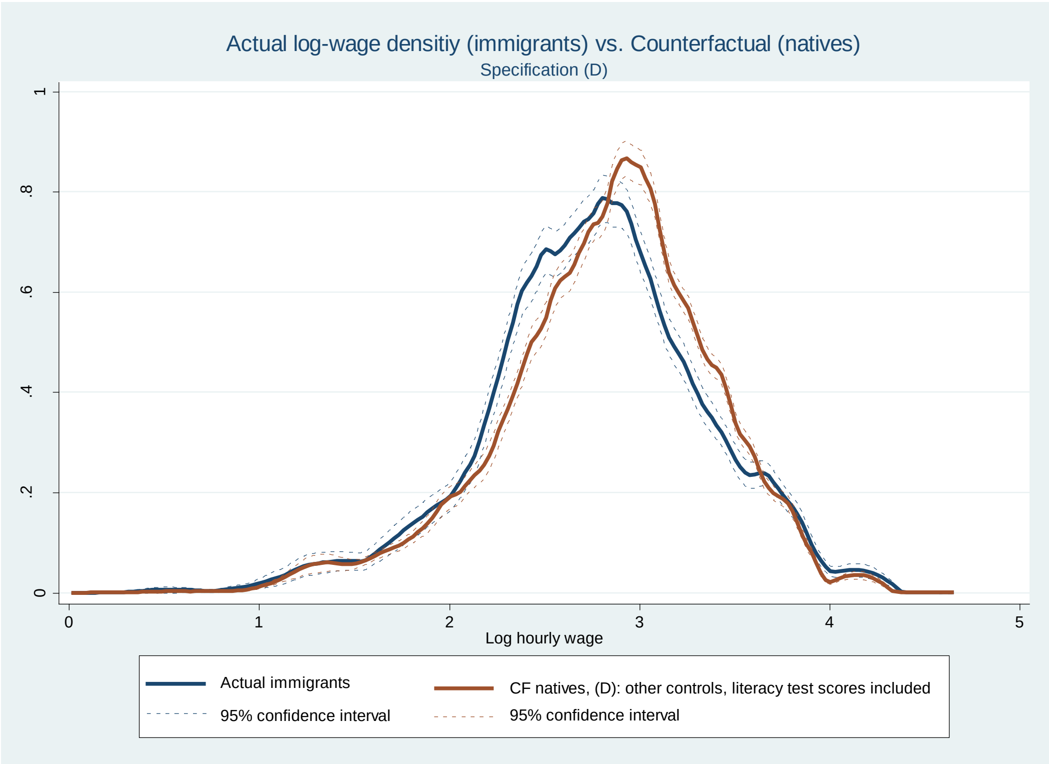
1) Sample restricted to countries in PIAAC which administered all test scores. France, Italy and Spain excluded.

2) Specification (0) includes country dummies only. Specification (B) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (G) adds numeracy, literacy and problem solving test score to the list of covariates in specification (B). Both specifications (B) and (G) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

4) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.12: Restricted sample DFL results: specification (D)



Notes:

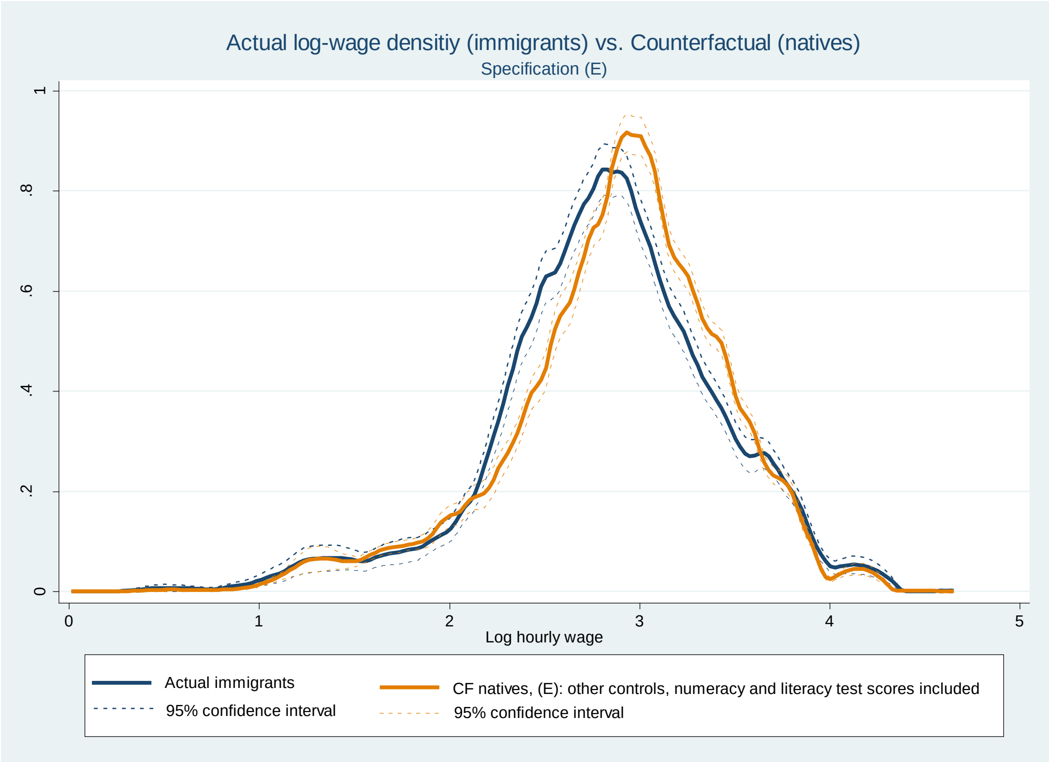
1) Sample restricted to countries in PIAAC which administered all test scores. France, Italy and Spain excluded.

2) Specification (0) includes country dummies only. Specification (B) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (G) adds numeracy, literacy and problem solving test score to the list of covariates in specification (B). Both specifications (B) and (G) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

4) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.13: Restricted sample DFL results: specification (E)



Notes:

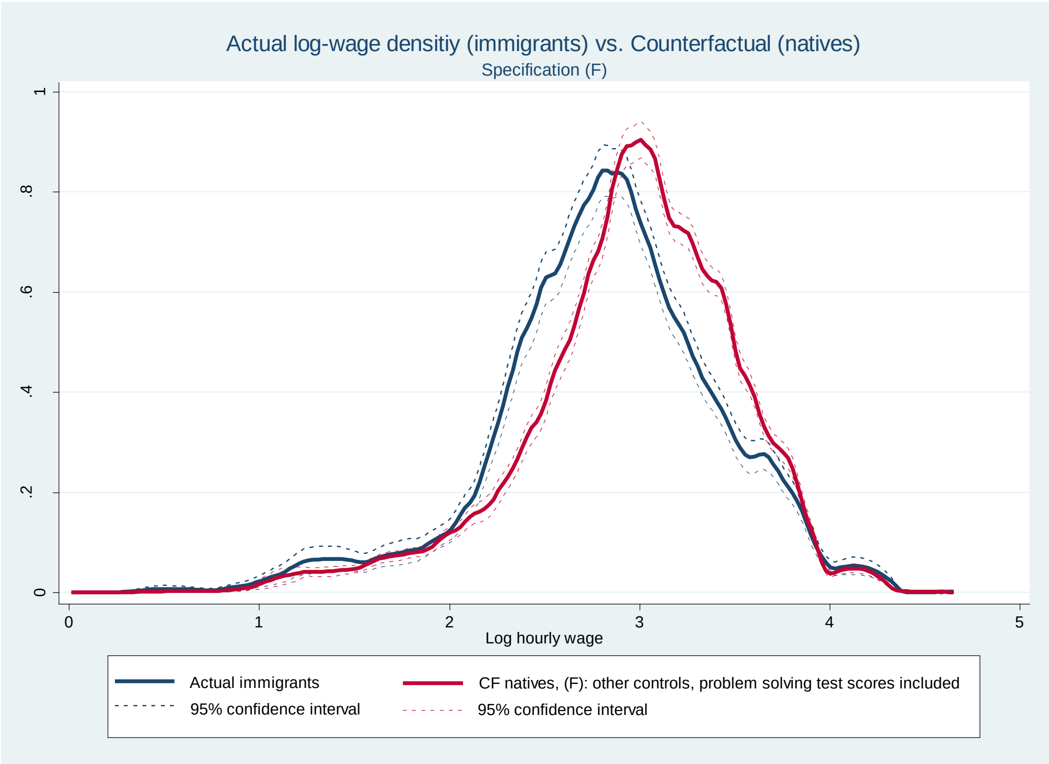
1) Sample restricted to countries in PIAAC which administered all test scores. France, Italy and Spain excluded.

2) Specification (0) includes country dummies only. Specification (B) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (G) adds numeracy, literacy and problem solving test score to the list of covariates in specification (B). Both specifications (B) and (G) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

4) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.14: Restricted sample DFL results: specification (F)



Notes:

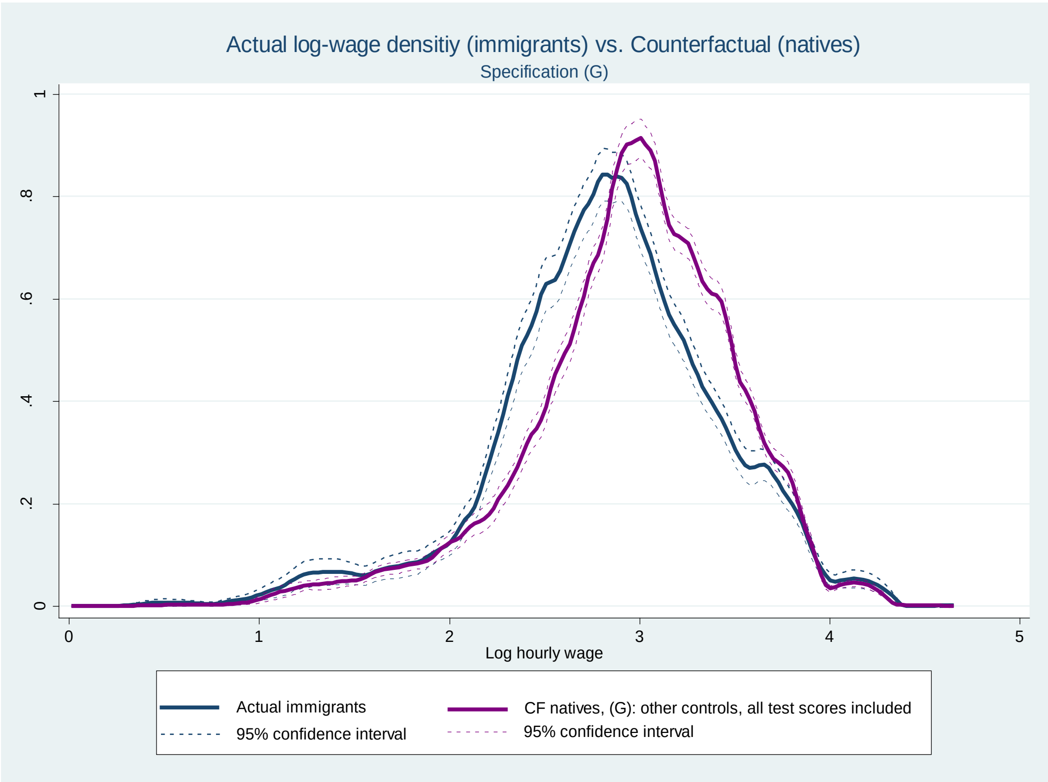
1) Sample restricted to countries in PIAAC which administered all test scores. France, Italy and Spain excluded.

2) Specification (0) includes country dummies only. Specification (B) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (G) adds numeracy, literacy and problem solving test score to the list of covariates in specification (B). Both specifications (B) and (G) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

4) 95% pointwise confidence intervals obtained via bootstrapping.

Figure F.15: Restricted sample DFL results: specification (G)



Notes:

1) Sample restricted to countries in PIAAC which administered all test scores. France, Italy and Spain excluded.

2) Specification (0) includes country dummies only. Specification (B) controls for education and labour market experience (in quadratic); Specification (B) adds controls for gender and sector of employment. Specification (G) adds numeracy, literacy and problem solving test score to the list of covariates in specification (B). Both specifications (B) and (G) include country dummies.

3) Final sample weight used to correct for inverse probability weighted sampling; equal weight is placed on each country.

4) 95% pointwise confidence intervals obtained via bootstrapping.

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