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Empirical Essays on Health Inequalities

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Abstract

People's capability to flourish as human beings critically hinges on their health status. For this reason, some of the most influential scholars of our time consider health inequalities as one of the most worrying types of inequalities in our society. Although health inequalities have been a priority of many governmental and international bodies' agendas since the 1990s, they persist and the urgency of their reduction is now reiterated by the Sustainable Development Goals agenda. To reduce health inequalities, it is essential to gain a better knowledge about them, including their identification as well as their determinants and evolution. From a policy perspective, it is also fundamental to understand their aftermaths.

This doctoral thesis is a collection of three empirical essays that contribute to the understanding of drivers and consequences of health inequalities. The first essay analyzes factors that contribute to differences in physical and mental health between Italian natives and immigrants and among immigrants themselves by focusing on the entire distribution of health. The second essay presents a gender analysis of the influence of the Great Recession on the distribution of mental health in Italy. The third essay estimates the lasting effect of poor early childhood health on later educational achievements in Indonesia, shedding light on the period that matters most for child development.

Keywords: Health inequalities; immigrants; economic crisis; mental health; gender inequalities; unconditional quantile regression; decomposition analysis; Italy; child health; education; instrumental variables; financial crisis; Indonesia

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1. Introduction

'Health is among the most important conditions of human life and a critically significant constituent of human capabilities which we have reason to value' (Sen, 2002)

People's capability to prosper as human beings is critically linked to their health status. For this reason, some of the most influential scholars of our time, including the Nobel laureates Amartya Sen (2002) and James Tobin (1970), consider health inequalities – i.e. health differentials across population groups – as one of the most worrying types of inequalities in our society. Since these inequalities reflect mainly differences in constraints across groups rather than differences in their preferences, they tend to be interpreted as inequities, i.e. health differentials that are deemed unfair and avoidable (O'donnell et al., 2008). Health inequities arise when health outcomes systematically differ across population groups because of the social conditions in which people are born, grow, live, work, and age (WHO, 2008). Since they are socially triggered by circumstances largely beyond an individual's control, reducing them is primarily a matter of fairness. Yet, the reduction of health inequities also implies large economic advantages for the society as costs from illnesses decrease (Marmot, 2010).

Although health inequities have been placed at the top of many governmental and international bodies' agendas since the 1990s (DID, 1999; WHO, 1999), they persist and the urgency of their reduction is now reiterated by the Sustainable Development Goal (SDG) 3 'Ensure healthy lives and promote wellbeing for all at all ages' (UN, 2015). Identifying and monitoring inequalities in health are essential steps for addressing health inequities and reaching the SDG 3 and other health-related SDGs (Hosseinpoor et al., 2018).

Yet, studies that analyze drivers of health inequalities across population groups typically consider mean impacts. However, factors that contribute to differences in the distribution of health conditions across groups may have diverse effects across the health distribution.

This is particularly relevant when clinical concern is concentrated on the tail of the health distribution. From a policy perspective, it is therefore essential to compare the entire health distributions of different groups to identify where the main differentials are focused and which factors account for these differentials. A better understanding of factors that drive health inequalities, especially in the part of the distribution in which clinical concern is focused, is essential to prevent the widening of health inequalities.

In addition, health inequalities start to accumulate during pregnancy and early childhood. What happens in these early years (beginning in the womb) shapes people's human development in all its aspects – physical, intellectual, and psychological – exerting a lasting effect on later health and socioeconomic conditions (Marmot et al., 2012). To reduce health inequalities over the lifetime, it is therefore fundamental to analyze the factors that drive health inequalities in early childhood, including major economic and environmental events. Moreover, to enhance cost-effectiveness of policies aimed to counter these inequalities, it is essential to gain a better knowledge about which period of early childhood affects child development the most and how different aspects of human capital (e.g. health and education) relate to each other.

This dissertation contributes to the understanding of both drivers and consequences of health inequalities in three ways. Chapter 2 (co-authored by Gabriella Berloffa) tests the so-called 'healthy immigrant effect' (HIE) – i.e. at arrival in the host country, immigrants tend to be healthier than natives – and assesses its deterioration over time, focusing on the evolution of the entire health distribution. For this purpose, we use unconditional quantile regressions in combination with Oaxaca-Blinder decompositions on the most recent data from the Italian Health Condition Survey. We find a HIE for physical and mental health for both short- and long-stay immigrants, which is particularly pronounced at the lower tail of the health distributions. Yet, long-term immigrants exhibit lower levels of physical and mental health compared to short-term immigrants. Again, this holds particularly at the bottom of the distribution, which is associated with larger costs for both the individuals and the health care system.

These lower health levels are mainly due to the negative effect of some unobserved characteristics, whereas observed characteristics (such as age, gender and occupation) are associated with better health for long-stay immigrants compared to short-stay immigrants. Our findings are not compatible with explanations of long-term immigrants' lower levels of health based on the type of occupation, a 'negative acculturation', or selection effects. The only explanation compatible with our results is related to immigrants' difficulties in accessing the health care system due e.g. to a lack of knowledge, linguistic barriers, or discrimination. In any case, our findings highlight the need to improve the data collection on health determinants in order to uncover the factors behind the unobserved component.

Chapter 3 (co-authored by Gabriella Berloffa) identifies the factors that contributed to changes in the distribution of mental health of men and women during the Great Recession in Italy. By combining unconditional quantile regressions with Oaxaca-Blinder decompositions on data from the 2004/05 and 2012/13 Italian Health Condition Surveys, we find evidence of a detrimental influence of the Great Recession on Italians' mental health, with larger effects at the bottom of the health distribution for men and at the median for women. Negative shifts for men are mainly attributable to unfavorable changes in both the endowments and the 'health returns' of permanent full-time jobs and wealth as well as to the negative 'health returns' of household size. Negative shifts for women are mainly due to worse wealth endowments and negative 'health returns' of unobservable characteristics.

Yet, the economic crisis does not appear to have influenced the main determinants of the gender gap in mental health. The drivers of the gap, which is in favor of men and focuses at the lower tail of the distribution, remain men's better endowments of permanent full-time jobs and certain types of inactivity as well as their better 'health returns' in relation to both permanent full-time jobs and unobservable characteristics. Although we only provide a distributional analysis, our decomposition analysis could help policy makers to determine the most suitable set of policies to counter the influence of economic downturns on mental health and diminish the gender gap in mental health (Doorslaer and Koolman, 2004). In this perspective, our results suggest opting for a combination of mental health policies with fiscal and labor market policies, tailoring them differently according to gender. In addition, we stress again the importance to improve data collection on health determinants to identify more of the so far unobserved components.

Chapter 4 estimates the long-term effect of early childhood health on educational performance drawing on comprehensive longitudinal data from the Indonesia Family Life Survey. The endogeneity of child health is taken into account by employing an instrumental variable approach where height differentials among children are identified by using exposure in early years of life to the Asian financial crisis that hit Indonesia in late 1997. We find that poor health conditions in early childhood have a considerable impact on the likelihood to fail at least one grade in primary school. Particularly, we show that the health conditions that are critical for child development are those of the second and third year of life. Beside corroborating the idea that different health conditions in early childhood lead to different educational achievements and shedding light on the period that matters most for child development, our paper highlights the importance of considering child health and education as cooperative aims to enhance the cost-effectiveness of interventions designed to increase human capital.

2. Decomposing Immigrant Differences in Physical and Mental Health: A ‘Beyond the Mean’ Analysis*

Abstract. This paper takes a ‘beyond the mean’ perspective on physical and mental health differences between natives and immigrants and among immigrants themselves. We test the ‘healthy immigrant effect’ (HIE) and assess its deterioration over time, focusing on the evolution of the entire health distributions. Indeed, mean differences can lead to very different consequences in terms of health care costs and health inequalities, according to the underlying differences at the top and the bottom of the health distribution. Using unconditional quantile regressions combined with Oaxaca-Blinder decompositions on data from the Italian Health Condition Survey, we find a HIE for both physical and mental health, which is mainly due to large differences in the lowest quartiles. Detailed decompositions show that observed characteristics (such as age, gender, and occupation) are actually associated with better health for both natives and long-stay immigrants compared to short-stay immigrants. However, at the bottom of both the physical and mental health distributions, these gains are more than offset by the negative impact of some unobserved characteristics. Our results point toward the need of improving the data collection on health determinants, especially among immigrants, in order to uncover the drivers of the unobserved component.

JEL Codes: I14, C21, J15, O15.

Keywords: Immigrants; health inequalities; unconditional quantile regression; decomposition analysis; Italy

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2.1. Introduction

The so-called 'healthy immigrant effect' (HIE), i.e. on arrival immigrants tend to be healthier than natives, is a well established finding in the literature (see e.g. Farré, 2016). Previous research also revealed the transitory nature of the HIE, providing insights into a deterioration of immigrant health over the length of stay of immigrants in the host country (for a review, see Constant, 2017). However, previous research on both these aspects focused only on mean differences. Yet, mean differences can lead to very different consequences in terms of health care costs and health-related inequalities, according to the underlying differences at the top and at the bottom of the health distribution. For example, health care costs are much more affected by changes in the lower part of the health distribution than by the rest of it. Hence, from a policy perspective, it is essential to compare the entire health distributions between natives and immigrants as well as among immigrants themselves to identify where the main differences are concentrated and which factors account for these differences. A better understanding of factors that reduce or exacerbate health inequalities and that are associated with large shifts of the left tail of the health distribution is essential to prevent the widening of health inequalities and to restrain the negative effects of the deterioration of immigrants' health (higher health care costs, lower participation to the labor market, lower tax revenues, and smaller positive externalities for the health of natives; Giuntella and Mazzonna, 2015).

In this paper, we take a 'beyond the mean' perspective on health differences between natives and immigrants as well as between short- and long-stay immigrants to shed some light on the following questions: i) at which quantiles are health differences most pronounced? ii) to what extent are these differences associated with a different endowment of observable characteristics or with different 'health returns' of these characteristics? iii) what is the contribution of different covariates to these differences?

In order to answer these questions, we combine unconditional quantile regressions with Oaxaca-Blinder decompositions at various quantiles of the health distribution. The decomposition analysis is useful to guide policy makers in choosing the most suitable policy to avoid the deterioration of immigrants' health over time, particularly in the lower part of the health distribution. Indeed, fiscal and labor market policies operate on differences in the endowment of some observable characteristics, e.g. income and occupation, while health and social policies operate on the 'health returns' of these characteristics, i.e. on the association between observable characteristics and health (Doorslaer and Koolman, 2004).

Unlike many previous studies, we take into account the multidimensionality of health by examining differences in both physical and mental health. Indeed, mental health is important because its impairment imposes substantial costs on the society (see e.g. Olesen et al., 2012). Furthermore, we use 'quasi-objective' measures of both physical and mental health, i.e. measures that are based on self-reported assessments of various health conditions, but which have been diagnosed by health professionals or concern very peculiar aspects of an individual's health. This smoothes the reporting heterogeneity bias that characterizes self-rated overall health measures (Bago d'Uva et al., 2008). Moreover, these measures are continuous and thus they allow us to carry out a 'beyond the mean' analysis.

Our empirical analysis uses the most recent wave (2012/13) of the Italian Health Condition Survey (ISTAT, 2016). By focusing on Italy, one of the leading countries harboring international migrants within the EU (UN, 2016), we add to the (still scant) literature on the HIE in Europe. We find a HIE for physical and mental health with respect to both short- and long-stay immigrants, which is particularly pronounced in the lower tail of the health distributions. Both immigrants' physical and mental health seems to deteriorate over time, again particularly at the bottom of the distribution. This deterioration is mainly due to a negative impact of some unobserved characteristics, whereas observed characteristics (such as age, gender and occupation) are actually associated with better health for both natives and long-stay immigrants compared to short-stay immigrant. Hence, our results highlight the need to improve the data collection on health determinants, especially among immigrants, in order to uncover the factors in the unobserved component.

The remainder of the paper is structured as follows. Section 2.2 summarizes the literature on the HIE and its deterioration over time. Section 2.3 illustrates the empirical strategy and

Section 2.4 presents the data and the variables used for the empirical analysis. Section 2.5 presents our estimation results and Section 2.6 concludes.

2.2. Literature Review

The HIE is a well documented regularity in developed countries, especially regarding traditional large-scale immigration countries, such as Australia, the US, and Canada (Biddle et al., 2007; Giuntella, 2017; Vang et al., 2017). Several explanations have been proposed for its existence, such as healthier diets and behaviors prior to migration (Abraido-Lanza et al., 1999), the selection of healthier individuals into migration via immigrants' choice or immigration screening processes (Jasso et al., 2004; Marmot et al., 1984; McDonald and Kennedy, 2004; Antecol and Bedard, 2006; Riosmena et al., 2013), migration policies (Constant et al., 2018), under-reporting of immigrants' health conditions on arrival (Jasso et al., 2004; McDonald and Kennedy, 2004), and the selection of unhealthy individuals into return migration (Palloni and Arias, 2004).

However, the health advantage that immigrants enjoy on arrival tends to dissipate over time (for a review, see Constant, 2017). This deterioration has been associated with several reasons, such as 'negative acculturation', i.e. a natural convergence toward the average health status of the natives (Jasso et al., 2004), riskier behaviors once more time is spent in the hosting country (Fenelon, 2013; Antecol and Bedard, 2006; Acevedo-Garcia et al., 2005), immigrants' sorting into strenuous occupations (Giuntella, 2017; Orrenius and Zavodny, 2013, 2009; Giuntella and Mazzonna, 2015), lack of knowledge of both the health care system and immigrant rights, cultural and linguistic barriers in communicating with health practitioners, and discrimination (Powles and Gifford, 1990).

Previous research has focused on physical health or self-rated overall health. For instance, Antecol and Bedard (2006) and Giuntella and Stella (2017) show that the lower Body Mass Index (BMI) that immigrants exhibit on arrival converges to the one of native Americans as the time spent in the hosting country increases. A similar pattern is found in relation to doctor-assessed disability (see e.g. Giuntella and Mazzonna, 2015 for Germany), diagnosed chronic diseases (see e.g. McDonald and Kennedy, 2004 for Canada), self-reported chronic diseases (see e.g. Biddle et al., 2007 for Australia), and self-rated health (SRH; see e.g. Hamilton et al., 2015 for the US and Constant et al., 2014 or Constant et al., 2018 for Europe). However, addressing only physical health provides an incomplete picture of health differences (with the associated health care costs) because of the multidimensional character of health. Moreover, self-assessed measures like the SRH lead to reporting heterogeneity (Lindeboom and Van Doorslaer, 2004; Etilé and Milcent, 2006; Bago d'Uva et al., 2008).

Research on mental health is scarce and, unlike physical health, often relies on self-assessed health measures. For example, Lou and Beaujot (2005) find an immigrant advantage in terms of self-assessed mental health, which assimilates to the one of Canadian natives over time. As exceptions, Janisch (2017), Rivera et al. (2016), as well as Wu and Schimmele (2005) find similar findings using 'quasi-objective' measures of mental health for Australia, Spain, and Canada, respectively. Yet, also these studies do not address the multidimensionality of health and often suffer from the reporting heterogeneity bias that characterizes self-assessed health status measures.

To the best of our knowledge, Bousmah et al. (2019) is the only study that addresses the HIE and its evolution over time with respect to both physical and mental health. Using the survey of health ageing and retirement Europe (SHARE) and five different health measures (i.e. self-assessed health, BMI, chronic conditions, physical limitations, and self-assessed mental health), the authors document an HIE for Europe and a convergence (up to a reversal of the immigrants' health advantage) over time. While this study has the merit to account for the multidimensionality of health, it considers only individuals over the age of 50 and relies on a self-assessed measure of mental health.

Empirical evidence from cross-country comparative studies that use panel data confirms the existence of the HIE and its deterioration over time for both physical and mental health also for Italy (Bousmah et al., 2019; Constant et al., 2018, 2014). Yet, these studies focus only on individuals aged 50 or older, while in Italy most immigrants are notably younger (ISTAT, 2018b). The literature that analyzes health differences between immigrants and

Italians using cross-sectional data (see e.g. Moullan and Jusot, 2014; Domnich et al., 2012) also finds a health advantage for immigrants, providing support for the HIE.[1]

All the studies mentioned so far only consider mean impacts.[2] No attempt has been made to assess whether factors contributing to the differences in the distribution of health conditions between short- and long-stay immigrants have differentiated effects across the health distribution. However, this knowledge is fundamental to orient policy makers in preventing the detrimental effect of those factors that worsen especially the left tail of the health distribution, which is associated with larger costs for both the individuals and the health care system. Furthermore, previous literature does not exploit the potential of decomposition analyses that help policy makers in choosing whether to avoid a HIE deterioration through fiscal policies, which operate on differences in observables, or health and social policies, which operate on differences in 'health returns' of these observables (Doorslaer and Koolman, 2004).

In this paper, we analyze the HIE and its evolution over time in Italy, adopting a 'beyond the mean' perspective and taking advantage of 'quasi-objective' measures of both physical and mental health, which allows us to consider the multidimensional character of health and to control for reporting heterogeneity.

2.3. Empirical Strategy

Our empirical analysis is based on the unconditional quantile regression approach of Firpo et al. (2009). This method allows us to estimate the effect of various covariates on the marginal (unconditional) quantiles of the physical and the mental health distributions. Indeed, from a policy perspective, it is important to know, for instance, how an increase in

[1] These findings hold despite the fact that Italian immigrants suffer from unequal access to health care services (Giannoni, 2010; De Luca et al., 2013; Devillanova and Frattini, 2016). In support of these findings, Bruzzone and Mignolli (2018) report lower standardized hospitalization rates, standardized mortality rates, and relative mortality risks for foreign residents than for Italians. The authors also note that in Italy the deaths (hospitalizations) of foreign residents are few: about 7,000 (476,000) in 2013, equal to 0.06% (10.95%) of the total number of foreign residents.

[2] As noticed by Carrieri and Jones (2017), this shortcoming is probably due to the common unavailability of continuous health variables in standard social or health surveys as well as to the only recent development of 'beyond the mean' techniques by the econometrics literature (for a review, see Fortin et al., 2011).

the share of immigrants in a certain type of occupation modifies the overall unconditional distribution of immigrants' health and not only their health distribution conditional on other covariates. The estimation approach proposed by Firpo et al. (2009) is based on a linear approximation of the unconditional quantiles through a recentered influence function (RIF). This allows us to perform an Oaxaca-Blinder decomposition (OB; Blinder, 1973; Oaxaca, 1973) at various quantiles of the physical and mental health distributions (Firpo et al., 2018). Compared to other decomposition methods (e.g. the method proposed by Machado and Mata, 2005, based on conditional quantile regressions), the use of a linear specification for RIF-regressions allows us to apply the law of iterated expectations to the distributional statistics of interest and thus to compute approximate partial effects of single covariates on the functional form being approximated. In our setting, this method is fundamental to assess which factors determine a deterioration of the left tail of the physical and mental health distributions. More specifically, the method works as follows.

For a given health measure (H), the RIF function assigns the following value to each observation in the sample:

$$RIF_i(H;q_\tau) = q_\tau + \frac{\tau - 1\left[H_i \leq q_\tau\right]}{f_H\left(q_\tau\right)}, \tag{2.1}$$

where q_τ is the observed sample quantile of the health measure, with $0 \leq \tau \leq 1$, $1[H_i \leq q_\tau]$ is an indicator variable equal to one if the health measure for individual i is less than or equal to the observed quantile and zero otherwise, and $f_H(q_\tau)$ is the kernel density[3] of the

[3] We base our RIF estimates on a Gaussian kernel function and an 'optimal' bandwidth, which minimizes the mean integrated squared error if the true data distribution was Gaussian. In a sensitivity analysis, we also tested smaller bandwidths because, in presence of skewed dependent variables, the use of 'optimal' bandwidth might over-smooth the density. Yet, due to heaping near to our quantile values, the use of smaller bandwidths would impair the continuity assumption, which is an important consideration when computing RIF-quantiles, because of the division by $f_H\left(q_\tau\right)$. In practice, our RIF estimates change very little using alternative bandwidths and our conclusions remain unchanged. The same holds for using the Epanechnikov kernel as alternative kernel function (results available upon request).

health measure estimated at the τ_{th} quantile. For example, considering the lowest decile, we obtain:

$$RIF(H; q_{0.1}) = \begin{cases} q_{0.1} + \frac{0.1-1}{f_H(q_{0.1})} & if \quad H_i \leq q_\tau \\ q_{0.1} + \frac{0.1}{f_H(q_{0.1})} & if \quad H_i > q_\tau. \end{cases} \tag{2.2}$$

The RIF from Equation (2.1) is then used as a dependent variable in a OLS regression on the explanatory variables X, which corresponds to estimating a rescaled linear probability model. An important property of the RIF function is that its expectation yields the original value of the quantile, i.e. $E_H[RIF(H; q_\tau)] = q_\tau$. Thus, after regressing RIF on X, the unconditional quantile of the health status, q_τ, can be obtained as:

$$q_\tau = E_x \left[E \left[\widehat{RIF}(H; q_\tau) | X \right] \right], \tag{2.3}$$

where $\widehat{RIF}(H; q_\tau)|X$ is the estimated RIF conditional on covariates X (see Carrieri and Jones, 2017). Given the linear specification of the RIF regression function, we can apply the law of iterated expectations and write:

$$q_\tau = E[X]\hat{\delta}_\tau \tag{2.4}$$

where $\hat{\delta}_\tau$ is the vector of unconditional quantile regression coefficients. It is then possible to estimate the marginal effect of a change in the distribution of the explanatory variables X on the unconditional quantile of health status measured by the parameter.

A similar logic to the Oaxaca-Blinder decomposition at the mean can be applied also in the context of the RIF regression as described in Equation (2.4) (for a review, see Fortin et al., 2011). Formally, differences in estimated health levels between group 1 and group 2 at each quantile can be decomposed as follows:

$$\Delta_H^\tau = \left[\widehat{RIF}(H_1, q_{1\tau}) \right] - \left[\widehat{RIF}(H_2, q_{2\tau}) \right] \tag{2.5}$$

$$\hat{\Delta}_H^\tau = (\bar{X}_1 - \bar{X}_2)\hat{\delta}_1 + \bar{X}_2(\hat{\delta}_1 - \hat{\delta}_2), \tag{2.6}$$

where $\bar{X}_1$ and $\bar{X}_2$ are the sample means of the explanatory variables X for the two groups, and $\hat{\delta}_1$ and $\hat{\delta}_2$ denote the coefficients of the unconditional quantile regression for the two groups.

The first term in Equation (2.6) is the part of health differences that is 'explained' by different endowments of observed covariates between the two groups. This is also known as 'composition' effect. Whether to use $\hat{\delta}_1$ or $\hat{\delta}_2$ as weights to measure the 'explained' part of health differences is somewhat arbitrary. Generally, if one assumes a positive 'discrimination' of the high-outcome group, the low-outcome group's coefficients are used as weights. In our case, the HIE literature suggests health advantages for immigrants with shorter stay compared to immigrants with longer stay or natives, thus we use as weights the coefficients for natives when we decompose health differences between natives and short- or long-stay immigrants and the coefficients of long-stay immigrants when we decompose health differentials between long-stay and short-stay immigrants.

The second term in Equation (2.6) measures the part of health differences that is accounted for by differences in the coefficients associated with the covariates, i.e. different 'health returns' of the covariates in the two groups, or by differences in the constant, i.e. differences in unobservable factors. This is sometimes called 'elasticity' effect.[4] Since the first and the second term in Equation (2.6) are equal to the sum of the individual contributions of each explanatory variable, we can also derive the specific contribution of each independent variable.[5] Standard errors of the contribution of explanatory variables to the first and second part of Equation (2.6) are computed using the delta method (for a detail discussion, see Jann et al., 2008).

4 In principle, considering group 2 as a treatment, the decomposition presented in Equation (2.6) might have a causal interpretation. Indeed, all the composition differences between group 1 and group 2 are captured by the explained part ($(\bar{X}_1 - \bar{X}_2)\hat{\delta}_1$). Therefore, this part might be understood as the confounding factors' selection bias for which we have to account in the program evaluation literature, while the elasticity effect ($\hat{X}_2(\hat{\delta}_1 - \hat{\delta}_2)$) might be understood as the Population Treatment Effect on the Treated (Fortin et al., 2011). However, a causal interpretation of the OB decomposition is only valid under the assumptions of common support and ignorability that guarantee the invariance of conditional distribution. In our analysis, these assumptions might be restrictive. Particularly, in the case of the ignorability assumption, unobservable determinants of the health status might be distributed unevenly across treatment status (e.g. intertemporal and risk preferences, or factors for which it is not possible to control for).

5 As suggested by Jann (2008), we transform the coefficients of all categorical variables in the model so that the results of the detailed decomposition are invariant to the choice of the base category.

2.4. Data

In this study, we use data from the most recent wave (2012/13) of the Italian Health Condition Survey (INHS) conducted by the Italian National Institute of Statistics (ISTAT, 2016). This survey is carried out starting from 1994, but only in the most recent wave it comprises information on the length of stay of immigrants, which is key to our analysis. Our sample is representative at the national level and consists of 49,811 households (119,073 individuals).[6] Eliminating all observations with missing values for at least one of the variables used in the empirical analysis, we have a final sample of 102,302 individuals (5,524 immigrants and 96,778 natives). It bears noting that our final sample only includes individuals aged 14 and older as our dependent variables are collected from the age of 14 onward. The maximum age observed in our final sample is 90 years. We identify immigrants as those individuals without Italian citizenship but with a regular residence permit, thus with a complete entitlement for national health care programs.[7] Among them, we can distinguish short- and long-stay immigrants (598 and 4,926 individuals, respectively), according to whether they have been in Italy for at least three years.

2.4.1. Measures of health status

The health measures used in our analysis are two summary indicators of physical and mental health: the physical component summary (PCS) and the mental component summary (MCS). These two indices are based on the answers to the 12 questions of the SF-12 (Short Form Health Survey) questionnaire, which investigates eight multi-item dimensions.[8] Four of these dimensions consider physical health: physical functioning, the role of limitations due to physical health, body pain, and general health. The other four dimensions relate to mental conditions: vitality, social functioning, emotional state, and mental health. According to the answers provided for each item, a total score for both physical

[6] To ensure representativeness, sample weights are applied in both descriptive statistics and estimations.
[7] Information on non-regular residents are not available in the survey.
[8] For the specific SF-12 questionnaire and a discussion on its validity for Italy, see Apolone et al. (2005).

and mental health is computed, generating a continuous variable that ranges from 0 to 100, with higher scores corresponding to better health.

The PCS and the MCS have the advantage of taking into account the multidimensional character of health and of being 'quasi-objective' health status indices, i.e. they report health problems that have been diagnosed by health professionals or very peculiar aspects of an individual's health (Lindeboom and Kerkhofs, 2009). On the one hand, 'quasi-objective' health indices smooth the reporting heterogeneity bias that characterizes self-assessed health measures (Bago d'Uva et al., 2008). On the other hand, by still relying on self-reported conditions (Ziebarth, 2010), they yield information that would not be available otherwise (Maddox and Douglass, 1973; Pfarr et al., 2012). Another important advantage of the PCS and the MCS is that they are continuous variables, thus allowing a 'beyond the mean' analysis.

2.4.2. Determinants of health status

According to the human capital model, health is a durable capital stock that depreciates with age (at an exogenous rate) and can be increased with investment (for a formal exposition, see Grossman, 1972; Cropper, 1977; Chang, 1996). An individual invests in his/her health when the opportunity cost of the investment is smaller than the expected decrease in both illness and the probability of death (Grossman, 1972). As the years of life that a person could save investing in health decrease as the person gets older, the returns on investment in health shrink over time (Grossman, 1972). Empirical evidence supports the age-related hypothesis of the human capital model by showing that older people have worse health conditions than younger people (Marmot et al., 2012). Yet, the effect of age on health is generally mediated by gender as women tend to live longer than men (Marmot et al., 2012). Accordingly, we include seven age group variables (i.e. 14-17, 18-34, 35-44, 45-54, 55-64, 65-74, 75+) for each gender.

On the contrary, investments in health increase with education as a higher level of education improves the understanding of both early signs of illness and benefits of investments in health (Grossman, 1972). Cutler and Lleras-Muney (2006) confirm this hypothesis, by detecting an education gradient for both health status and health behaviors. Therefore, we include three dummies (i.e. low education, middle education, and high education) to account for individuals' educational levels.

According to the economic theory, also wealthier individuals invest more in health (Chang, 1996). Empirical evidence generally corroborates the existence of a positive income gradient in health, by showing that an increase in income raises the likelihood of reporting good health (with a stronger effect at lower levels of income), the demand for health-related goods and services (such as nutrition or health insurance), and the adoption of healthier behaviors (for a review see Hernandez et al., 2006). Unfortunately, the INHS does not provide numeric measures of wealth or income and we therefore need to rely on some proxies. We consider a self-evaluation of the family's economic resources in the last 12 months (distinguishing between excellent wealth, appropriate wealth, poor wealth, and absolutely inadequate wealth), and a housing wealth index (because real assets are an important part of wealth and housing quality represents an important determinant of health; see Solar and Irwin, 2010).[9,10]

Furthermore, Cropper (1977) shows that the choice of occupation is a form of investment in health, as there is often a trade-off between job securty and high wages, especially in unskilled jobs. Therefore, we include five dummies (i.e. white collar job, blue collar job, self-employed, unemployed, and not participating) to control for the kind of job and, more generally, for the status in the labor market as, for instance, unemployment could have a detrimental effect on health (Krug and Eberl, 2018).[11]

9 More precisely, we calculate a one-dimensional wealth index through the Principal Component Analysis (PCA) by exploiting information regarding home ownership and typology, the number of rooms and bathrooms per person, and the presence of heating, lift, water stains, mold, and fungus. For details on the creation of an asset indicator, see (Vyas and Kumaranayake, 2006).

10 Economic theory suggests that individuals with good levels of education derive better health with less resources compared to individuals with low levels of education (Grossman and Kaestner, 1997). This is generally attributed either to the fact that individuals with good levels of education have a higher allocative efficiency (i.e. they allocate their economic resources in a manner that results in better health) or to the fact they have a higher productive efficiency (i.e. they derive a larger health advantage from any one resource or health behavior; see Grossman and Kaestner, 1997). Yet, in our analysis, the interaction between wealth and education did not turn out to be significant and for the sake of brevity, we omit it.

11 As there is some evidence in the literature that the effect of labor market status on health is mediated by both education and the economic situation (Fiori et al., 2016), we estimated a model that incorporates

Moreover, the family structure might also affect health outcomes in several ways (for a review, see Ross et al., 1990). For instance, being in a relationship might lead to the adoption of healthy lifestyles (Neimann and Schmitz, 2010) and persons from single parent families might suffer from worse mental health conditions compared to persons from mother-father families (Barrett and Turner, 2005). Therefore, we include five dummies indicating the type of households (i.e. single, single mother, single father, childless couple, and couple with one or more children).

Health behaviors also contribute to the production of health outcomes (see e.g. Cutler et al., 2009). Particularly, the behavioral risk factor that most influences mortality is smoking (Mokdad et al., 2004). Accordingly, we include three dummies to capture individuals' smoking habits (i.e. habitual smoker, occasional smoker, and non smoker).

In addition, health conditions might be influenced by geographical and environmental characteristics. For instance, there could be a difference in the access to and quality of health care services across regions of residence (Masseria and Giannoni, 2010). Moreover, living in cities (especially in large ones) could lead to a higher risk of mental illnesses compared to rural areas because of social risk factors, such as social isolation and discrimination (Gruebner et al., 2017). Thus, we include five dummy variables on geographical areas (i.e. North-West, North-East, Centre, South, and Islands) and four dummy variables for city size (i.e. large city, medium city, small city, and very small city). Finally, as regional variations the in pre-migration context might lead to different levels of health among immigrants (see e.g. Hamilton and Hummer, 2011), we include six dummies to control for the immigrants' area of origin (i.e. EU, Europe Non-EU, Africa, West Asia, East Asia, America).[12]

these interactions. However, our empirical results remained qualitatively unchanged and thus we omit these interactions in our final analysis.

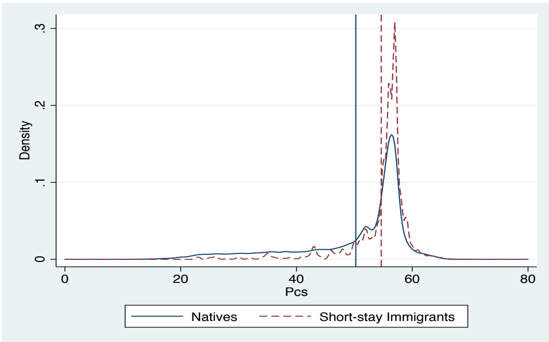
12 The INHS allows us to distinguish only by broad geographical areas of origin. We adhere to the definition of the EU in 2012/13. Since the reference period for the 2012/13 survey includes the twelve months from July 2012 to June 2013, in 2012/13 Croatia was not considered as part of the EU (it became a formal EU member starting from July 1, 2013).

2.5. Results

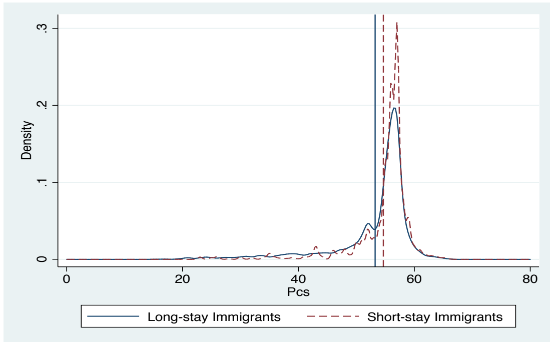
2.5.1. Descriptive Statistics

Figure 2.1 and Table 2.1 illustrate the differences in the PCS and the MCS distributions of short-stay immigrants compared to natives and to long-stay immigrants. They suggest the presence of a HIE and a deterioration of immigrants' health conditions over time in terms of both physical and mental health, although mean differences are quite small. Indeed, the average PCS of short-stay immigrants is about 4.3 points (8.5%) higher than the one of natives and about 1.5 points (2.8%) higher than the one of long-stay immigrants. Differences in mental health are smaller but go in the same direction. The average MCS of short-stay immigrants is about 2.6 points (5.3%) higher than the one of natives and about one point (2%) higher than the one of long-stay immigrants. The consideration of quantiles, however, reveals that health differences are concentrated in the lower part of the health distribution, where they are much larger compared to the mean, whereas differences are almost negligible in the upper part of the distribution. The PCS value that corresponds to the bottom decile for short-stay immigrants is 15.7 points (58.6%) higher than that of natives and 7.1 points (20.1%) higher than that of long-stay immigrants. Again, differences in mental health are less pronounced but still quite sizable: the MCS value for the bottom decile of short-stay immigrants is 8.2 points (29.9%) higher than that of natives and 3.5 points (10.9%) higher than that of long-stay immigrants.

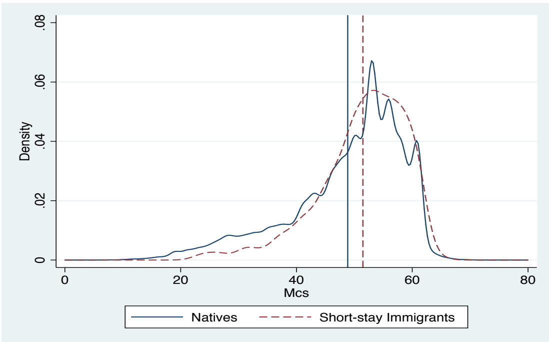
These differences could be due simply to a different age composition of the various groups (see Table A1 in Appendix A). Both short- and long-stay immigrants are younger than Italian citizens (in our sample, the mean age of the three groups is 33.6, 39.2 and 50.6 years old, respectively) and we expect that this is associated with better health conditions. Indeed, at a theoretical level, older people are expected have worse health because of both a higher depreciation rate and less investments (Grossman, 1972), and this prediction is confirmed by almost all empirical evidence (for a systematic review, see Marmot et al., 2012). However, as we describe in the following paragraphs, the distribution of other character-



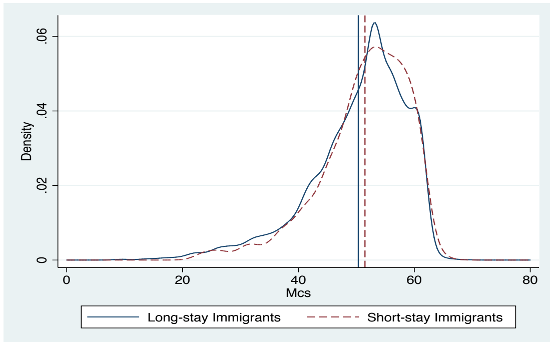
PCS, I_s and N



PCS, I_s and I_l



MCS, I_s and N



MCS, I_s and I_l

Figure 2.1.: PCS and MCS Distributions and Means of Natives, Short-stay Immigrants, and Long-stay Immigrants in Italy

istics (Table A1) is more unfavorable for immigrants, with possible negative consequences in terms of health.

First, Italian citizens and long-stay immigrants can benefit from higher educational levels compared to short-stay immigrants. The share of highly educated individuals is higher among Italians than among long- and short-stay immigrants (12.3% vs. 10.7% and 7.8%, respectively), while the share of low-educated individuals is generally lower (52.3% vs. 48.8% and 58.6%, respectively). Moreover, higher education is associated with better health from both a theoretical and an empirical point of view (Grossman, 1972; Cutler and Lleras-Muney, 2006).

Second, both short-and long-stay immigrants are more likely to be unemployed compared to Italian citizens (19.3% and 16.8% vs. 9.5%) and their occupation is prevalently in blue collar jobs (38.7% and 44.2% for short- and long-stay immigrants, respectively). In contrast, Italians are more equally split across white collar jobs (17.5%), blue collar jobs

Table 2.1.: Physical and Mental Component Summaries, Migrant Status, and Length of Stay

	Natives (N)	Short-stay Immigrants (I_s)	Long-stay Immigrants (I_l)	N-I_s	N-I_l	I_l-I_s
PCS						
Mean	50.474	54.726	53.183	-4.253***	-2.709***	-1.544***
Q10	26.791	42.465	35.340	-15.674***	-8.548***	-7.126***
Q25	41.099	53.788	49.917	-12.689***	-8.819***	-3.870***
Q50	52.688	56.000	55.208	-3.312***	-2.520***	-0.792***
Q75	56.505	57.000	57.000	-0.495***	-0.495***	0.000
Q90	58.000	58.000	58.000	0.000	0.000	0.000
MCS						
Mean	48.825	51.418	50.413	-2.593***	-1.587***	-1.005**
Q10	27.383	35.618	32.118	-8.235***	-4.735***	-3.500***
Q25	40.261	45.716	43.608	-5.455***	-3.347***	-2.108***
Q50	48.360	51.372	50.678	-3.012***	-2.318***	-0.694***
Q75	54.061	55.540	55.174	-1.478***	-1.113***	-0.366***
Q90	58.333	58.654	58.387	-0.321***	-0.054	-0.267***

*Notes: Numbers are weighted. The significance levels of the mean differences were calculated using a two-sided t-test. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

(12.6%), and self-employment (11.1%). These employment figures corroborate the idea that immigrants are more likely to work in strenuous occupations (Giuntella and Mazzonna, 2015; Grossman, 1972) and suffer from over-education (Dell'Aringa and Pagani, 2011) compared to natives with possible negative consequences in terms of health.

Third, immigrants have lower endowments of wealth, and this is generally associated with worse health outcomes at both a theoretical and empirical level (Chang, 1996; Hernandez et al., 2006). The majority of immigrants reports poor or absolutely inadequate wealth (about 70% for short-stay immigrants and about 62% for long-stay immigrants vs. 38% for Italian citizens) and exhibits much lower levels of the housing wealth index.

Differences between Italians and immigrants in terms of other characteristics may have more ambiguous consequences for health. For instance, both short- and long-stay immigrants are more concentrated in the Centre-North of Italy compared to natives, where health care service quality and access are better compared to the South (France et al., 2005; Masseria and Giannoni, 2010; Toth, 2014). Yet, disparities in healthcare utilization between immigrants and Italians are well documented (De Luca et al., 2013). Immigrants (especially long-term) are somewhat more concentrated in medium and large cities compared to natives, with possible negative consequences in terms of mental health (Gruebner et al., 2017). Furthermore, immigrants are more likely to be single compared to natives, but conditional on being in a couple, they are more likely to have children. While the absence of a partner is generally associated with worse health, the presence of children might have more ambiguous effects (Barrett and Turner, 2005; Ross et al., 1990). No significant differences between natives and immigrants emerge in terms of health behaviors (incidence of habitual and occasional smokers). Finally, short- and long-stay immigrants are quite homogeneously distributed across geographical areas of origin (which might lead to different levels of health; see e.g. Hamilton and Hummer, 2011).

In short, immigrants are healthier than Italian citizens, but their health conditions seem to deteriorate over time, and both these phenomena are more concentrated in the lower part of the health distribution. This could reflect the fact that immigrants are younger than natives, and they age remaining in the country. However, immigrants are also less educated, poorer, and they face more difficulties in the labor market compared to Italian citizens, and all these elements are expected to have negative consequences in terms of health. In turn, they are more concentrated in the Centre-North of Italy, where health care services are better than in the South, although they may suffer from healthcare utilization disparities with respect to natives. In the next subsections, we examine the way in which all these variables are associated with health at different quantiles of the health distribution, and their relative importance in explaining health differentials between natives and immigrants.

2.5.2. RIF Regression Results

The RIF regression results for the PCS and the MCS are shown separately for natives, short- and long-stay immigrants in Tables A2-A7. In each table, Columns 1-2 show the results of the OLS regression at the mean for comparison, while Columns 3-12 include results of the RIF regressions at the 10th, 25th, 50th, 75th, and 90th percentile of the PCS and the MCS.

The estimated associations between age, gender, wealth, and health are in line with theoretical and empirical evidence for both natives and immigrants. Physical and mental health worsen with age, and this deterioration is more pronounced among older women compared to older men. Although the entire distributions shift leftwards for older individuals, the worsening is much larger at the bottom quartiles, and for physical health than for mental health. In contrast, being wealthier is associated with better physical and mental health, especially at the bottom of the health distributions, but the estimated effects are larger for mental health than for physical health in all three groups. However, for immigrants, the estimated coefficients are smaller than for natives and often not significant. They are larger among long-stay immigrants than among short-stay immigrants, particularly in the tails of the distributions. This suggests that, for immigrants, 'wealth returns' in terms of health (especially in terms of mental health) are likely to worsen over time.

A positive education gradient emerges only for natives' physical health, again with larger effects in the lower part of the distribution. The effects of education on natives' mental health are very small in magnitude and concentrated in the central part of the distribution. Tertiary education seems to have even a harmful effect on natives' mental health in the top decile of the distribution. A similar negative association between tertiary education and mental health in the upper part of the distribution is estimated also for short-stay immigrants.

The associations between employment status, occupation, and physical health are more varied. For natives, higher shares of non-participants and of white collars are associated with a worsening of the left tail of the physical health distribution, whereas higher shares of blue-collars are associated with worse physical health in the upper part of the distribution. For short-stay immigrants, only being a white collar is significantly correlated with the distribution of physical health, but the signs of the coefficients go in the opposite direction compared to natives: a higher share of white collars, compared to blue collars, is associated with less physical health inequalities (i.e. positive effects at the bottom and negative effects at the top of the distribution). Among long-stay immigrants, no significant differences emerge between the physical health of blue collars and that of white collars or self-employed. In this group, a worsening of the left tail of the physical health distribution is mainly associated with higher shares of non-participants and/or unemployed, but not with higher shares of blue collars.

The picture changes if we consider mental health. Among natives, all occupational categories are associated with a worsening of the entire distribution, compared to blue collars, with larger effects at the bottom, and for unemployed and non-participants. This occurs also for long-stay immigrants, although the estimates are significant only for unemployment and self-employment. Among short-stay immigrants, estimates are of opposite signs: a higher share of all occupational categories is associated with better mental health compared to blue collars, but the effect is often not significant. These results suggest that, for immigrants, the 'returns' of being a blue collar in terms of mental health are likely to improve over time. Hence, we expect that employment status and occupation are not the main drivers of the worsening of immigrants' mental health distribution over time.

Family composition is significantly correlated with the distribution of health only for natives, whereas the estimated coefficients for immigrants are rarely significant. For Italians, being in a couple with children is generally correlated with better physical and mental health compared to all other family types, especially in the left tail of the distribution. Only being in a childless couple is associated slightly better mental health than being in a couple with children in the upper part of the distribution. Among short-stay immigrants, the estimated coefficients have often opposite signs, but only few of them are marginally significant. The estimated effects for long-stay immigrants are more similar to those for natives, but again only few of them are significant, mainly in the upper part of the distribution (where being a single mother is positively correlated with physical health, while being single is negatively correlated with mental health).

Natives who reside in the Centre-North of Italy enjoy, as expected, better physical health compared to those living in the South or in the Islands. Yet, they are also associated with worse mental health in the bottom part of the distribution compared to those living in the South and with worse mental health over the entire distribution compared to those living in the Islands. Similarly, living in very small cities is generally associated with worse physical health but better mental health compared to living in small, medium or large cities. In contrast, long-stay immigrants exhibit worse physical health in the Centre-North, especially in the North-East. They also have worse mental health compared to those living in the South in the lower part of the distribution (as observed for natives), but these negative effects are somehow larger. These findings might reflect difficulties in accessing health care services, self-selection of those with worse physical health towards places with better health care services, or the fact that in the North of Italy immigrants are concentrated in the industry (Gabrielli et al., 2016) and political rejection of immigrants is higher (Curran, 2004). No significant differences are associated with living in small, medium or large cities for immigrants.

2.5.3. Oaxaca-Blinder Decomposition Results

Tables 2.2-2.5 show the OB decomposition of differences between natives and immigrants as well as between long- and short-stay immigrants at various PCS and MCS quantiles. A negative (positive) difference means that a given PCS or MCS quantile is lower (higher) among natives or long-stay immigrants compared to short-stay immigrants. Panel A reports the overall composition and elasticity effects, whereas Panel B illustrates the specific composition and elasticity effects associated with some broad groups of covariates (age and gender, education, occupation, wealth, family composition, risk behavior, geography, nationality, and the constant term). In order to interpret these results, recall that we transformed the estimated coefficients of all categorical variables in the model, by expressing them as deviations from the grand mean. This ensures that results of the detailed decomposition are invariant to the choice of the base category. Hence, differences in the constant terms do not represent differences in the quantiles associated with the base category, but rather overall unexplained differences.

Table 2.2.: Decomposition Results of Differentials between Natives and Short-stay Immigrants in Physical Component Summary

	Q10	Q25	Q50	Q75	Q90
Δ_{N-I_s}	-15.624***	-6.816***	-1.230***	-0.439***	-0.614**
	(0.754)	(0.229)	(0.125)	(0.106)	(0.271)
Panel A					
Composition Effect	-5.216***	-6.320***	-1.348***	-0.850***	-0.760
	(0.372)	(0.367)	(0.070)	(0.043)	(0.053)
Elasticity Effect	-10.408***	-0.497	0.118	0.410***	0.146
	(0.790)	(0.397)	(0.133)	(0.110)	(0.274)
due to covariates	1.124	4.237	0.346	-0.033	0.686
due to constant	-11.532	-4.733	-0.228	0.444	-0.540
Panel B: Detailed decomposition					
Composition Effect					
Age and Gender	-7.328***	-8.622***	-1.737***	-0.938***	-0.747***
	(0.206)	(0.252)	(0.058)	(0.037)	(0.033)
Education	0.142**	0.180***	0.034**	0.011**	0.010*
	(0.057)	(0.070)	(0.013)	(0.005)	(0.006)
Occupation	-1.144***	-0.626***	0.049**	0.042***	0.045*
	(0.136)	(0.114)	(0.020)	(0.016)	(0.027)
Family Composition	0.713***	0.523***	0.051***	0.002	0.021*
	(0.131)	(0.099)	(0.014)	(0.008)	(0.012)
Wealth	2.845***	2.503***	0.279***	0.016	-0.066***
	(0.230)	(0.200)	(0.028)	(0.014)	(0.026)
Risk Behavior	0.010	0.007	0.000	0.000	0.003
	(0.026)	(0.017)	(0.001)	(0.001)	(0.008)
Geography	-0.453***	-0.284***	-0.026**	0.017**	-0.026**
	(0.089)	(0.071)	(0.011)	(0.007)	(0.011)
Elasticity Effect					
Age and Gender	1.539	7.142***	0.873***	0.457***	0.434*
	(2.087)	(0.401)	(0.139)	(0.099)	(0.244)
Education	-0.134	-0.790***	-0.235**	-0.087	-0.291
	(0.531)	(0.242)	(0.119)	(0.099)	(0.214)
Occupation	1.204**	-0.305	-0.178	-0.173	-0.385*
	(0.581)	(0.370)	(0.224)	(0.130)	(0.204)
Family Composition	0.740	0.380	-0.107	0.002	0.167
	(0.598)	(0.240)	(0.147)	(0.128)	(0.348)
Wealth	-2.389**	-1.965***	-0.185	-0.155	0.387
	(1.002)	(0.402)	(0.197)	(0.271)	(0.389)
Risk Behavior	0.714	-0.511	0.087	-0.152	-0.146
	(0.676)	(0.464)	(0.243)	(0.267)	(0.878)
Geography	-0.312	0.308*	0.097	0.103	0.529**
	(0.644)	(0.177)	(0.091)	(0.078)	(0.254)
Nationality	-0.239	-0.022	-0.006	-0.027	-0.008
	(0.384)	(0.104)	(0.061)	(0.051)	(0.134)
Constant	-11.532***	-4.733***	-0.228	0.444	-0.540
	(2.721)	(0.841)	(0.457)	(0.473)	(1.243)

*Notes: Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Composition effects account for a great deal of the difference between the physical health distribution of natives and short-stay immigrants (Table 2.2), except for the bottom decile, where the elasticity effect is much larger than the composition effect. This elasticity effect at the bottom of the distribution is negative and entirely due to differences in the constant term, i.e. to unobserved factors. The detailed decomposition reveals that composition effects are mainly related to age and gender, which are in favor of short-stay immigrants, and wealth, which has the opposite sign but a much smaller effect. Indeed, immigrants are younger but less wealthy. Interestingly, the elasticity effects associated with these variables point into the opposite direction: they are positive for age and gender and negative for wealth. In other words, the 'health returns' of age and gender are in favor of Italians, but they experience larger negative consequences of (poor) wealth. The elasticity effect associated with labor market participation and the type of occupation is vey small and generally in favor of immigrants, except in the bottom decile, where it is favorable to natives. In a nutshell, most of the PCS differentials between natives and short-stay immigrants are due to differences in the shares of individuals with 'favorable' characteristics. Only differences at the bottom decile are largely associated with unobservable factors that contribute to a higher PCS of short-stay immigrants compared to natives.[13]

In Section 2.4, we have seen that short-stay immigrants exhibit also better mental health conditions compared to natives, again particularly at the bottom of the distribution. In this case, the overall composition effect is negligible (Table 2.3) because Italians' disadvantage in terms of age and gender is entirely offset by the positive composition effect associated with wealth. The 'mental health returns' of age and gender are again in favor of natives (although in this case they are insignificant) and are accompanied by generally positive 'health returns' of employment and type of occupation. However, for the lowest quartile and decile, both of them are more than offset by a large and negative difference in the constants.

[13] It is worth noting that a similar role of these unobservable factors emerges also if we restrict the sample of natives to an age group that is more similar to that of immigrants (i.e. 18-54; see Table A10 in Appendix A).

Table 2.3.: Decomposition Results of Differentials between Natives and Short-stay Immigrants in Mental Component Summary

	Q10	Q25	Q50	Q75	Q90
Δ_{N-I_s}	-8.010***	-3.827***	-1.717***	-0.684	-0.285
	(1.142)	(0.694)	(0.553)	(0.537)	(0.433)
Panel A					
Composition Effect	0.087	-0.053	-0.208	-0.242**	-0.453***
	(0.372)	(0.269)	(0.160)	(0.099)	(0.092)
Elasticity Effect	-8.097***	-3.774***	-1.509***	-0.442	0.167
	(1.174)	(0.709)	(0.564)	(0.540)	(0.441)
due to covariates	2.967	4.260	-0.517	-2.265	-2.042
due to constant	-11.064	-8.033	-0.992	1.823	2.209
Panel B: Detailed decomposition					
Composition Effect					
Age and Gender	-2.241***	-2.109***	-1.395***	-0.842***	-0.653
	(0.184)	(0.140)	(0.097)	(0.066)	(0.063)
Education	0.018	0.032*	0.020	-0.007	-0.015
	(0.022)	(0.018)	(0.013)	(0.007)	(0.008)
Occupation	-0.761***	-0.358***	-0.185***	-0.092***	-0.050
	(0.144)	(0.099)	(0.056)	(0.036)	(0.037)
Family Composition	0.351***	0.236***	0.110***	0.040*	-0.038
	(0.097)	(0.065)	(0.037)	(0.023)	(0.024)
Wealth	2.532***	2.090***	1.239***	0.675***	0.297
	(0.274)	(0.196)	(0.111)	(0.064)	(0.052)
Risk Behavior	-0.017	-0.014	-0.007	-0.004	-0.004
	(0.050)	(0.038)	(0.018)	(0.011)	(0.010)
Geography	0.204***	0.070*	0.009	-0.011	0.011
	(0.059)	(0.037)	(0.030)	(0.021)	(0.020)
Elasticity Effect					
Age and Gender	1.899	0.798	0.058	0.035	-0.378
	(1.454)	(0.763)	(0.796)	(0.591)	(0.448)
Education	-0.683	-0.649	-0.232	-0.843**	-0.339
	(1.161)	(0.673)	(0.487)	(0.385)	(0.319)
Occupation	1.937*	1.391***	0.440	0.095	-0.072
	(0.923)	(0.535)	(0.890)	(0.825)	(0.342)
Family Composition	-0.183	0.576	-0.242	-0.031	0.534
	(1.619)	(0.784)	(0.625)	(0.655)	(0.699)
Wealth	0.101	-0.150	-0.968	-0.556	-1.378
	(1.763)	(1.050)	(1.114)	(0.943)	(0.514)
Risk Behavior	0.966	2.314***	0.335	-1.234***	-0.501
	(0.941)	(0.693)	(1.178)	(0.454)	(0.381)
Geography	-0.799	0.101	0.262	0.372	0.186
	(1.080)	(0.550)	(0.417)	(0.441)	(0.394)
Nationality	-0.272	-0.121	-0.170	-0.102	-0.093
	(0.623)	(0.355)	(0.279)	(0.264)	(0.213)
Constant	-11.064***	-8.033***	-0.992	1.823	2.209
	(3.381)	(1.929)	(2.248)	(1.785)	(1.291)

*Notes: Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

The worse physical health conditions of long-stay immigrants compared to short-stay immigrants (Table 2.4), which is concentrated in the bottom quartile and decile, is partly associated with a different composition in terms of age and gender, but it is again mainly due to a negative elasticity effect, which accounts for about 70% of the differentials. The elasticity effects associated with covariates is actually positive, but it is more than offset by a large negative difference in the constants. Interestingly, the detailed decomposition reveals that, for the bottom decile, 'health returns' of age, gender, occupation (primarily blue collar jobs), as well as of family composition (mainly couple with children), are better among long-stay immigrants than among short-stay immigrants. Both composition and elasticity effects are negligible above the lowest quartile.

Table 2.4.: Decomposition Results of Differentials between Long-stay Immigrants and Short-stay Immigrants in Physical Component Summary

	Q10	Q25	Q50	Q75	Q90
$\Delta_{I_l - I_s}$	-5.743***	-2.250***	-0.431***	-0.108	-0.389*
	(0.863)	(0.228)	(0.109)	(0.092)	(0.216)
Panel A					
Composition Effect	-1.645**	-0.700***	-0.207***	-0.224***	-0.205***
	(0.681)	(0.172)	(0.052)	(0.048)	(0.074)
Elasticity Effect	-4.098***	-1.549***	-0.224**	0.117	-0.183
	(0.996)	(0.253)	(0.113)	(0.100)	(0.225)
due to covariates	7.449	1.714	0.230	-0.050	0.793
due to constant	-11.546	-3.263	-0.454	0.167	-0.977
Panel B: Detailed decomposition					
Composition Effect					
Age and Gender	-2.162***	-0.718***	-0.225***	-0.197	-0.178
	(0.475)	(0.124)	(0.040)	(0.036)	(0.044)
Education	-0.047	-0.012	0.005	0.005	0.019
	(0.130)	(0.032)	(0.010)	(0.009)	(0.015)
Occupation	0.454*	0.060	0.010	-0.005	-0.004
	(0.247)	(0.044)	(0.012)	(0.011)	(0.019)
Family Composition	0.437	0.041	0.028	-0.003	-0.052
	(0.291)	(0.081)	(0.027)	(0.023)	(0.037)
Wealth	0.202	0.067	0.015	0.006	-0.004
	(0.255)	(0.066)	(0.013)	(0.010)	(0.022)
Risk Behavior	0.056	-0.002	-0.004	-0.001	0.004
	(0.063)	(0.007)	(0.005)	(0.002)	(0.007)
Geography	-0.448**	-0.125**	-0.039**	-0.027	-0.018
	(0.215)	(0.062)	(0.017)	(0.015)	(0.020)
Nationality	-0.137	-0.012	0.003	-0.004	0.027
	(0.135)	(0.036)	(0.012)	(0.011)	(0.019)
Elasticity Effect					
Age and Gender	7.534***	2.195***	0.049	0.186	0.176
	(2.412)	(0.399)	(0.119)	(0.092)	(0.202)
Education	0.410	-0.130	-0.148	-0.062	-0.265
	(0.665)	(0.205)	(0.099)	(0.083)	(0.171)
Occupation	1.283	0.006	-0.051	-0.130	-0.319
	(0.815)	(0.314)	(0.177)	(0.109)	(0.169)
Family Composition	1.825*	0.657**	0.017	0.041	0.182
	(1.049)	(0.293)	(0.138)	(0.113)	(0.289)
Wealth	-1.177	-0.649*	-0.037	-0.102	0.598
	(1.478)	(0.373)	(0.170)	(0.214)	(0.322)
Risk Behavior	-0.929	-0.043	0.332	-0.090	-0.219
	(0.848)	(0.431)	(0.204)	(0.219)	(0.682)
Geography	-1.158*	-0.274*	0.044	0.094	0.547
	(0.687)	(0.163)	(0.079)	(0.070)	(0.196)
Nationality	-0.340	-0.048	0.024	0.012	0.093
	(0.441)	(0.115)	(0.054)	(0.045)	(0.105)
Constant	-11.546***	-3.263***	-0.454	0.167	-0.977
	(3.354)	(0.842)	(0.387)	(0.390)	(0.978)

*Notes: Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

In short, a higher share of long-stay immigrants exhibits extremely poor physical health (compared to short-stay immigrants), but this is not due neither to demographics (long-stay immigrants are older but with better health at older age), nor to labor market related phenomena (long-stay immigrants are more likely to be employed, with better health associated with their type of occupation).

Hence, explanations of immigrants' health deterioration over time based on the type of occupation or on a 'negative acculturation'[14] do not appear to be consistent with our findings. Furthermore, our results are not consistent with selection effects either. Indeed, if unhealthy immigrants were more likely to return home, the left tail of immigrants' health distribution would shift rightward over time, and the elasticity effect associated with the constant would be positive in the bottom part of the distribution (ceteris paribus).[15]

On the other hand, if immigrants with better health were more likely to move to other destinations, the upper tail of the distribution would shift leftward, and we would observe a negative elasticity effect of the constant in the upper part of the distribution. The only explanation for the deterioration of immigrants health over time that is consistent with our findings is related to difficulties in accessing the health care system (lack of knowledge, linguistic barriers, discrimination, etc.). Indeed, these difficulties become important when the need to access health care services is stronger, i.e. when health is particularly bad. If immigrants with more critical health conditions do not receive adequate health services, their health is likely to worsen faster over time and this could explain the large unobserved component at the bottom of the distribution highlighted by the decompositions.[16]

14 The hypothesis of a natural convergence toward the average health status of natives should lead to smaller elasticity effects associated with covariates when we consider differences between natives and long-stay immigrants, than when we consider differences between natives and short-stay immigrants. But this is not the case. If we compare the PCS distribution of natives and long-stay immigrants, the elasticity effects associated with covariates are negative and particularly large for age and gender, whereas the opposite occurs when we compare natives and short-stay immigrants (cfr. Table 2.2 with Table A8).

15 According to Burgio et al. (2016), the return migration bias in Italy can be considered negligible due to the increasing level of stability of the foreign population, the good quality of health facilities, and the professional competence of health personnel.

16 Unfortunately, the INHS does not allow us to control for factors, such as lack of knowledge, linguistic barriers, and discrimination. However, previous research corroborates this explanation by providing evidence of an unequal access to health care services for immigrants compared to natives (Giannoni, 2010; De Luca et al., 2013; Devillanova and Frattini, 2016).

A similar pattern emerges also for mental health (Table 2.5). Differences in the MCS distributions between long-stay and short-stay immigrants are entirely driven by elasticity effects. Again, in the bottom part of the distribution, elasticity effects associated with age, gender, and occupation (again mainly blue collar jobs) are positive, but they are more than offset by the negative effect associated with the constant. Interestingly, in the case of mental health, the opposite occurs at the top of the distribution: the elasticity effects associated with covariates is negative (in particular due to education and wealth), whereas that associated with the constant is positive.[17] Again, it is difficult to explain these results in terms of labor market conditions and selection effects. Difficulties in accessing health care services are again consistent with our results for the bottom part of the distribution, but they cannot explain our findings for the upper part of the mental health distribution.

[17] A similar pattern emerges if we restrict the sample of natives to the 18-54 age group (Table A11), with the only difference that, in the bottom part of the distribution, the elasticity effects associated with age and gender become negligible, while that associated with employment and type of occupation remains positive and quite large.

Table 2.5.: Decomposition Results of Differentials between Long-stay Immigrants and Short-stay Immigrants in Mental Component Summary

	Q10	Q25	Q50	Q75	Q90
$\Delta_{I_l - I_s}$	-2.261**	-1.296**	-0.571	-0.201	-0.007
	(0.963)	(0.575)	(0.444)	(0.439)	(0.361)
Panel A					
Composition Effect	-0.463	-0.314	-0.057	-0.119	-0.095
	(0.463)	(0.245)	(0.152)	(0.173)	(0.146)
Elasticity Effect	-1.798*	-0.982*	-0.515	-0.082	0.087
	(1.028)	(0.581)	(0.455)	(0.457)	(0.384)
due to covariates	6.303	4.502	-0.497	-2.661	-3.012
due to constant	-8.101	-5.483	-0.017	2.579	3.099
Panel B: Detailed decomposition					
Composition Effect					
Age and Gender	-0.395	-0.349***	-0.284***	-0.420***	-0.223***
	(0.242)	(0.119)	(0.080)	(0.093)	(0.085)
Education	-0.123	-0.082	0.003	0.022	0.009
	(0.090)	(0.052)	(0.030)	(0.034)	(0.029)
Occupation	0.149	0.087	0.045	0.021	-0.040
	(0.140)	(0.071)	(0.039)	(0.041)	(0.040)
Family Composition	0.252	0.046	0.157*	0.221**	0.146**
	(0.219)	(0.123)	(0.082)	(0.087)	(0.072)
Wealth	0.082	0.129	0.124*	0.151*	0.063
	(0.206)	(0.110)	(0.069)	(0.083)	(0.056)
Risk Behavior	-0.052	-0.028	-0.011	-0.014	-0.004
	(0.060)	(0.031)	(0.014)	(0.016)	(0.007)
Geography	-0.116	-0.048	-0.034	-0.043	-0.007
	(0.134)	(0.076)	(0.041)	(0.048)	(0.040)
Nationality	-0.261**	-0.069	-0.057	-0.057	-0.038
	(0.121)	(0.067)	(0.047)	(0.054)	(0.043)
Elasticity Effect					
Age and Gender	4.826***	0.935	-0.135	0.070	-0.518
	(1.595)	(0.743)	(0.651)	(0.534)	(0.420)
Education	-0.359	-0.238	-0.103	-1.041***	-0.497*
	(0.937)	(0.548)	(0.386)	(0.325)	(0.272)
Occupation	2.260***	1.353***	0.341	0.158	0.101
	(0.810)	(0.467)	(0.689)	(0.649)	(0.321)
Family Composition	-1.591	0.146	-0.059	0.064	0.561
	(1.298)	(0.687)	(0.505)	(0.534)	(0.563)
Wealth	0.855	-0.051	-0.855	-1.102	-1.923***
	(1.479)	(0.881)	(0.892)	(0.804)	(0.500)
Risk Behavior	2.144*	2.687***	0.456	-0.839*	-0.604
	(1.227)	(0.697)	(0.925)	(0.440)	(0.379)
Geography	-1.271	0.091	0.245	0.375	0.126
	(0.869)	(0.452)	(0.331)	(0.357)	(0.319)
Nationality	-0.561	-0.423	-0.388*	-0.346	-0.258
	(0.516)	(0.286)	(0.226)	(0.221)	(0.188)
Constant	-8.101***	-5.483***	-0.017	2.579*	3.099***
	(3.107)	(1.722)	(1.780)	(1.500)	(1.133)

*Notes: Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

2.6. Conclusion

Knowledge about immigrant health is essential for policy makers because it affects health care costs, immigrants' labor market participation, and thus the generation of tax revenues. Using data from the Italian Health Condition Survey of 2012/13 and by combining unconditional quantile regressions with Oaxaca-Blinder decompositions at various quantiles of both the physical and mental health distributions, we examine differences in physical and mental health between natives and immigrants as well as between short- and long-stay immigrants. The main scope of our paper is to move beyond the consideration of mean impacts because effects at the bottom and top of the health distribution may be notably different and health care costs are much more affected by the lower part of the health distribution. In particular, it is crucial to identify which factors are associated with a worsening of the left tail of the health distribution because this part entails larger costs for both the individuals and the health care system, highlighting the necessity of going 'beyond the mean'.

Our findings reveal a HIE for both physical and mental health, which seems to shrink over time, especially at the lower tail of the health distributions. The lower health status exhibited by long-term immigrants compared to short-stay immigrants is mainly attributable to the elasticity effect. The predominance of the elasticity effect suggests applying either health or social policies to prevent any deterioration in immigrants' physical and mental health conditions (Doorslaer and Koolman, 2004). However, the results of our detailed decompositions reveal that observed characteristics (such as age, gender and occupation) are generally associated with better health for long-stay immigrants compared to short-stay immigrants. Instead, the negative elasticity effect of some unobserved characteristics is responsible for lower health levels among long-term immigrants compared to short-term immigrants.

This finding is not consistent with explanations of immigrants' health deterioration over time based on the type of occupation, a 'negative acculturation', or selection effects. The only explanation for the deterioration of immigrants' health over time that is compatible with our findings is related to difficulties in accessing the health care system (lack of knowledge, linguistic barriers, discrimination, etc.). If immigrants with more critical health conditions do not receive adequate health services, their health is likely to worsen faster over time and this could explain the large unobserved component at the bottom of the distributions. In general, our results underline the importance of improving the data collection on health determinants to identify the determinants of the unobserved component.

Assuming that immigrants indeed lack access to health services, policy makers could avoid any deterioration in immigrants' health conditions through health policies aimed to improve immigrants' access to health care services. Generally, these can involve either the legislative system (by improving the health rights of immigrants) or the specific responses of health care systems to immigrants' health rights (Vázquez et al., 2011). As immigrants in our analysis have a complete entitlement to national health care programs, Italian policy makers could avoid any deterioration in immigrants' health conditions by improving the response of the Italian health care system to immigrants.

This could be achieved either by targeting the providers (e.g. by improving the knowledge of health care practitioners on culturally adapted healthcare) or the users (e.g. by increasing health literacy) (Rechel, 2011). In addition, given that health differences are particularly pronounced at the bottom of the health distributions, policy interventions need to be tailored especially to immigrants with poor health conditions. More generally, the fact that long-term immigrants could actually exhibit lower levels of health compared to short-term immigrants because of a worse access to health care services should be a warning for all those countries that suffer from inequalities in immigrants' access to health services (for Europe, see e.g. Guidi et al., 2015).

As we provide a distributional analysis of the HIE over the health distribution for Italy, our findings cannot be interpreted as casual or be generalized. However, we provide a new approach to the study of the HIE, which can be useful to better analyze it in other countries and longitudinal settings. Beside controlling for factors that could prevent an equal access to health care services, future research could improve the analysis by using numeric measures of wealth (e.g. income). This would help to better discern the (usually important) role of income in explaining immigrant differences in health. Lastly, inspired by our results and in line with the general economic theory (Grossman, 1972; Cropper, 1977; Chang, 1996), future research could also investigate the role that a worse access to health services may have in discouraging investments in health or diminishing their effectiveness.

3. Under Pressure: A Gender Analysis of the Influence of the Great Recession on Mental Health*

Abstract. This paper estimates the contribution of different demographic and socioeconomic factors to changes in the distribution of mental health for men and women during the Great Recession in Italy. To this end, we combine unconditional quantile regressions with Oaxaca-Blinder decompositions on data from the 2004/05 and 2012/13 Italian Health Condition Surveys. Our results suggest a detrimental influence of the Great Recession on Italians' mental health, with larger effects at the bottom of the health distribution for men and at the median for women. For men, these negative shifts are mainly due to unfavorable changes in both the endowments and the 'health returns' of permanent full-time jobs and wealth as well as to the negative 'health returns' of household size. For women, negative shifts at the median are mainly attributable to worse wealth endowments and negative 'health returns' of unobservable characteristics. Yet, the economic crisis does not seem to have influenced the main determinants of the gender gap in mental health. The main driverrs of the gap, which is in favor of men and focuses at the lower tail of the distribution, is men's better endowments of permanent full-time jobs and certain types of inactivity as well as their better 'health returns' in relation to both permanent full-time jobs and unobservable characteristics.

JEL Codes: I14, J16, C21.

Keywords: Economic crisis; mental health; gender inequalities; unconditional quantile regression; decomposition analysis; Italy

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3.1. Introduction

In 2008, due to the subprime mortgage crisis that hit the US in 2007, economies all around the world entered the most severe economic downturn since the 1930s (UN, 2011). This global economic turmoil, which because of its intensity and duration is sometimes called the Great Recession, led to sharp increases in unemployment rates and considerable decreases in wages as well as living standards worldwide (UN, 2011). Previous research has shown that economic crises and the related negative consequences – including the Great Recession – negatively affect mental health (for a review, see Frasquilho et al., 2015). Such mental health deterioration comes at a high cost to both individuals and society, including direct economic costs related to health care services, support services, and disability payments and indirect economic costs due to negative spillovers on families and declining productivity (Bubonya et al., 2017).

While previous research has identified different channels through which economic crises affect mental health, it has not assessed how economic crises affect the gender gap in mental health. However, examining which factors contribute to gender disparities in mental health is essential to develop new prevention, diagnosis, and treatment approaches aimed at reducing such disparities (Gahagan et al., 2015). Moreover, Mazeikaite et al. (2019) is the only study that exploits decomposition methods to identify the relative contribution of different demographic and socioeconomic factors to changes in mental health during a period of economic recession. Yet, investigating to what extent each factor contributes to these changes is fundamental to prevent the detrimental influence of recession on mental health. Last, previous research has only focused on mean effects without assessing whether periods of economic recession have different effects across the distribution of mental health. Yet, moving beyond the consideration of mean impacts is key, as effects at the extremes of the mental health distribution may be different from those at the mean. Consequently, going 'beyond the mean' allows to identify the factors associated with a deterioration of the left tail of the health distribution, which leads to larger costs for both the individuals and the health care system.

In this paper, we complement the existing literature in several ways. First, we perform a gender analysis of the influence of the Great Recession on mental health in Italy, looking at its influence on the gender gap in mental health. Second, we estimate the relative contribution of different demographic and socioeconomic factors to changes in mental health during the economic crisis, not only distinguishing to what extent these changes are associated with a different endowment of observable characteristics (as in Mazeikaite et al., 2019) but also to what extent these changes are associated with different 'health returns' of these characteristics. Last, we quantify the importance of these factors across the entire distribution of mental health.

For this purpose, we couple unconditional quantile regressions with Oaxaca-Blinder (OB) decompositions at various quantiles of the mental health distribution. The decomposition analysis is useful for advising policy makers on an appropriate set of policies to prevent any detrimental influence of economic crises on mental health. Indeed, fiscal or labor market policies operate on differences in the endowment of observable characteristics, e.g. income and occupation, while health and social policies operate on the 'health return' of these characteristics, i.e. on the association between observable characteristics and health (Doorslaer and Koolman, 2004).

For our empirical analysis, we use the last two available waves (2012/13, 2004/05) of the Italian Health Condition Survey (INHS) conducted by the Italian National Institute of Statistics (ISTAT, 2016). Considering an EU country is appealing because, in the EU, crisis-related factors, such as job and income insecurity were exacerbated by the adoption of austerity policies, which led to public spending cuts in social welfare (OECD, 2013). Within the EU, Italy was one of the countries most affected by the recession,[1] suffering from a considerable rise in unemployment rates and a worsening of economic and living standard conditions (ISTAT, 2013), as well as of population mental health (ISTAT, 2014b).

Our results suggest a deterioration in mental health conditions for both men and women, which we interpret as an aftermath of the Great Recession. Effects differ across gender, with

[1] Between 2008 and 2012 the Italian Gross Domestic Product (GDP) decreased by 5.8% while, for instance, in France it remained almost stationary and in Germany it increased by 2.5% (ISTAT, 2013).

larger negative shifts at the bottom of the health distribution for men and at the median for women. For men, this negative shift is mainly due to unfavorable changes in both the endowments and the'health returns' of permanent full-time workers and wealth as well as to the negative 'health returns' of household size. For women, the negative shift is mainly attributable to worse wealth endowments and negative 'health returns' of unobservable characteristics. Yet, the economic crisis does not seem to have influenced the main determinants of the gender gap in mental health. What drives the gap, which is in favor of men and focuses at the lower tail of the distribution, is men's better endowments of certain types of employment and inactivity as well as their better 'health returns' in relation to both permanent full-time jobs and unobservable characteristics. To counter the influence of economic crises on population mental health, our results suggest to combining mental health policies with fiscal and labor market policies, tailoring them differently according to gender. Moreover, we advocate for a more comprehensive data collection on the mental health determinants to better identify the factors hidden behind the unobserved component.

The rest of the paper is structured as follows. Section 3.2 summarizes previous research on the relationship between economic crises and mental health. Section 3.3 illustrates the empirical strategy and Section 3.4 presents the data and variables used in the empirical analysis. Section 3.5 reports our estimation results and Section 3.6 concludes.

3.2. Literature Review

Previous research on the influence of economic recessions on population health shows mixed patterns of both negative and positive effects (for a review, see Karanikolos et al., 2013). In periods of economic turmoil, for instance, suicides may increase, but overall mortality may decline because of a decrease in infectious diseases and road traffic accidents (Fishback et al., 2007). Focusing only on mental health, however, the effect of economic downturns is overall negative (Frasquilho et al., 2015). This is because of both growing socioeconomic risk factors, such as financial strain, unemployment, and other job-related problems (Frasquilho et al., 2015) as well as cuts in public expenditure on health (Quaglio et al., 2013).

Concerning the Great Recession, mental health research at the international level has primarily investigated suicide rates (Chang et al., 2013; Lopez Bernal et al., 2013; Barr et al., 2012; Reeves et al., 2012; Stuckler et al., 2011) and established a positive relationship. However, these results can suffer from biases in the classification and interpretation of the circumstances of suicides (Baumert et al., 2008). Moreover, suicide rates may not be as effective as other mental health indicators in detecting the effect of economic downturns on mental health and, thus, advising preventive measures (Odone et al., 2017). On the other hand, evidence based on other mental health indicators is scant and, overall, suggests a positive impact of economic crises on the prevalence of depressions, anxiety disorders, and pathological addictions (see e.g. Bartoll et al., 2013 and Gili et al., 2012 for Spain, Simou and Koutsogeorgou, 2014 for Greece, and McInerney et al., 2013 for the US).

The mental health literature at the Italian level has also focused on suicide rates (De Vogli et al., 2013a; Mattei et al., 2019, 2014; Pompili et al., 2014) and death rates due to mental and behavioral disorders (De Vogli et al., 2013b), showing that they increased during the Great Recession. These increases were associated with both the rise in unemployment and the decrease in GDP per capita that characterized the crisis (Mattei et al., 2019, 2014; De Vogli et al., 2013b) and concerned mainly men (Mattei et al., 2019, 2014; Pompili et al., 2014).

Only few scholars have analyzed specific indicators of mental health. Using the 2005 and 2013 waves of the INHS, Odone et al. (2017) find that the risk of poor mental health (given by a dichotomized measure of the mental component summary score, MCS) increased between 2005 and 2013. This held especially for men compared to women and for young men (25-29 years) compared to their older counterparts. These authors also show that vulnerable individuals (i.e. less educated and unemployed individuals as well as those with lower socioeconomic status) have a higher risk of poor mental conditions, but not differently affected by the crisis, suggesting that the crisis increased the share of vulnerable people instead of worsening their conditions.

Using the same INHS waves and the MCS, Sarti and Vitalini (2016) show that the population groups that experienced a worsening in mental health conditions are those most affected by the crisis, i.e. those with economic and unemployment problems. According to these authors, these individuals are characterized by a low level of education, by living in the South of Italy or on its islands, and are more frequently male (Sarti and Vitalini, 2016). Yet, both Odone et al. (2017) and Sarti and Vitalini (2016) do not consider the working age population younger than 25 and 30 years, respectively, which was among the most affected by the rise in both unemployment (ISTAT, 2014a) and atypical employment (ISTAT, 2013) during the crisis.

Only Fiori et al. (2016) analyze the younger adult labour force (18-39 years). These authors use the 2005 and 2013 INHS waves and the Mental Health Inventory (MHI),[2] and find a significant and positive association between unemployment and employment insecurity and poor mental health (especially for men), which became stronger after years of recession. This relationship is partly explained by the experience of financial difficulties and mediated by individuals' educational level (Fiori et al., 2016).

In general, not all scholars acknowledge the fact that periods of economic downturn can affect mental health differently for men and women (Glonti et al., 2015). For instance, rises in unemployment and income insecurity are more likely to influence the mental health of men because they still hold the social role of the main household breadwinner[3] (Artazcoz et al., 2004) and because in single-income families, wages are more likely to be earned by men.

More generally, men and women experience different kinds of mental health problems. Women have a higher prevalence of mood, anxiety, and depression disorders compared to men (Riecher-Rössler, 2017), while men exceed women in substance-related disorders (Glonti et al., 2015). This is partly due to different genetic and biological factors and partly to different responses to environmental and social factors of men and women (WHO, 2002).

[2] The MHI is a disaggregated information that constitutes one of the four dimensions of the MCS. Yet, it is only available to ISTAT employees, such as one co-author of Fiori et al. (2016).

[3] Because of this social role, the social stigma of not having a job is greater for men that for women, who instead find in their family role a psychological compensation for not being employed (Artazcoz et al., 2004).

Understanding which factors contribute to the gender gap in mental health is key to develop new prevention, diagnosis, and treatment approaches (Gahagan et al., 2015). Genetic factors contribute only in part to this gap (Sullivan et al., 2000) and are difficult to address via health policies. From a policy perspective, it is therefore important to assess which other factors enhance or reduce gender disparities in mental health and if their contribution is affected by periods of economic recession. To the best of our knowledge, however, this has not be done by the literature so far.

Moreover, Mazeikaite et al. (2019) is the only study that exploits decomposition methods to answer a similar question. Specifically, these authors investigate how structural changes in demographic and socioeconomic factors contributed to changes in the prevalence of poor self-rated health between 2008 and 2013 in Ireland. Yet, as they apply a decomposition method for binary outcomes (Fairlie, 2005), they can only examine the effect of structural changes in observables, without assessing the effect of changes in the health return of these observables. However, to advise policy makers on the suitability of policies to avoid detrimental effects of periods of economic downturn on mental health, it is important to investigate changes in both observables and their 'health returns'. Indeed, fiscal polices act on differences in observables, while social and health policies operate on differential in their 'health returns' (Doorslaer and Koolman, 2004).

Last, the previous literature has only focused on mean impacts, without assessing whether periods of economic downturn have different effects across the mental health distribution. Yet, this information is crucial to prevent the impact of those factors that have a negative effect especially at the bottom of the distribution as it entails greater costs for both individuals and society. This paper identifies how composition and elasticity changes in demographic and socioeconomic factors contributed to changes in the distribution of mental health conditions of men and women during the Great Recession in Italy.

3.3. Empirical Strategy

Our application is based on Blinder-Oaxaca (Blinder, 1973; Oaxaca, 1973) (OB) decompositions, which allow the decomposition of differences in mental health conditions into a part that is due to differences in observable characteristics and a part that is explained by differentials in estimated coefficients. As a basis for our decomposition, we estimate the relationship between the covariates and our measure of mental health through the Recentered Influence Function (RIF) method developed by Firpo et al. (2009).

This method allows us to perform the OB decompositions at different quantiles of the mental health distribution. This is possible because the RIF method provides a linear approximation of the unconditional quantiles of the dependent variable, allowing the application of the law of iterated expectation to the quantile being approximated. Therefore, we can estimate the marginal effect of an explanatory variable using a simple regression of a function of the dependent variable, the RIF, on the independent variables X. In our analysis, the RIF of the dependent variable (in the formulas abbreviated by MH, i.e. mental health) is estimated directly from the data by first computing the sample quantile q_τ and then estimating the density of the distribution of the dependent variable at that quantile.

For a given observed quantile q_τ, the RIF is then generated. Depending on whether the value of the observation of the dependent variable is less than or equal to the observed quantile, the RIF takes one of two values:

$$RIF_i(MH; q_\tau) = q_\tau + \frac{\tau - 1\left[MH_i \leq q_\tau\right]}{f_{MH}\left(q_\tau\right)}, \tag{3.1}$$

where q_τ is the sample quantile that is observed, $1[MH_i \leq q_\tau]$ is an indicator variable equal to one if the value of the observation of the mental health status is less than or equal to the observed quantile and zero otherwise. $f_{MH}(q_\tau)$ is the kernel density of the mental health status estimated at the τ_{th} quantile. Then, the RIF from Equation (3.1) is used as a dependent variable in a OLS regression on the explanatory variables X. According to

Jones et al. (2015), it is equivalent to estimate a rescaled linear probability model, since the unconditional quantile of the mental health status, q_τ, can be obtained as:

$$q_\tau = E_x\left[E\left[\widehat{RIF}(MH; q_\tau)|X\right]\right], \tag{3.2}$$

where $\widehat{RIF}(MH; q_\tau)|X$ is the estimation of RIF conditional on explanatory variables X as defined in Equation (3.1). Given this linear approximation, we can apply the the law of iterated expectations and write:

$$q_\tau = E[X]\hat{\delta}_\tau \tag{3.3}$$

where $\hat{\delta}_\tau$ is the vector of unconditional quantile regression coefficients. It is then possible to estimate the marginal effect of a change in the distribution of the covariates X on the unconditional quantile of mental health status measured by the parameter.

A similar logic to the Oaxaca-Blinder decomposition at the mean applies also in the context of the RIF regression, as described in Equation (3.3) (Fortin et al., 2011). Formally, differences in estimated levels of mental health conditions between group 1 (males 2012/13, females 2012/13, males 2004/05, and males 2012/13) and group 2 (males 2004/05, females 2004/05, females 2004/05, and females 2012/13, respectively) at each quantile can be decomposed as follows:

$$\Delta^\tau_{MH} = \left[\widehat{RIF}(MH_1, q_{1\tau})\right] - \left[\widehat{RIF}(MH_2, q_{2\tau})\right] \tag{3.4}$$

$$\hat{\Delta}^\tau_{MH} = (\bar{X}_1 - \bar{X}_2)\hat{\delta}_2 + \bar{X}_1(\hat{\delta}_1 - \hat{\delta}_2), \tag{3.5}$$

where $\bar{X}_1$ and $\bar{X}_2$ are the sample means of the covariates X for the subsample of the two groups, and $\hat{\delta}_1$ and $\hat{\delta}_2$ represent the coefficients of the unconditional quantile regression for the subsample of the two groups.

The first term in Equation (3.5) (also called the 'composition' effect) is the part of differences in mental health that is explained by differences in observed explanatory variables between the two groups. Differentials in covariates across groups are weighted by the coefficients of the unconditional quantile regression from a model estimated on the subsample of group 2 ($\hat{\delta}_2$).

The second term in Equation (3.5) (also called the 'elasticity' effect) measures the part of differences in mental health that is explained by differentials in estimated coefficients. It also accounts for all potential effects of differentials in the constant term, i.e. in unobservable characteristics. Differentials in both the observed covariates and the estimated coefficients can then be decomposed into the contribution of each explanatory variable to each quantile. This is possible because the OB decomposition assumes additivity, thus letting the first and the second term in Equation (3.5) being equal to the sum of the contribution of the single explanatory variables.[4] The standard errors related to the estimation of the contribution of explanatory variables to the first and second part of Equation (3.5) are computed through the use of the delta method (Jann et al., 2008).

3.4. Data

We use data from the last two available waves (2012/13, 2004/05) of the Italian Health Condition Survey (INHS) conducted by the Italian National Institute of Statistics (ISTAT, 2016). The INHS, which encompasses information on our dependent variable only since 2004/05, ensures national representativeness. It comprises 49,811 households (119,073 individuals) in 2012/13 and 50,474 households (128,040 individuals) in 2004/05.[5] For our analysis, we only include the active population, i.e. individuals aged between 15 and 64 years. Considering only observations with information on all the variables considered in our study, we are left with a final sample of 157,144 individuals (36,803 males and 37,923 females in 2012/13, and 40,745 males and 41,673 females in 2004/05).

As dependent variable of our analysis, we use the mental component summary (MCS), which is a mental health index built on the basis of the answers given to the SF-12 (Short Form Health Survey) questionnaire.[6] The SF-12 investigates four multi-item dimensions

[4] Following Jann (2008), we transform the coefficients of all categorical variables in the model, such that that the detailed decomposition results are invariant to the selection of the reference category

[5] To produce representative descriptives and estimations, we apply weights provided by the ISTAT.

[6] For more details on the SF-12 questionnaire and its validation for Italy, see Apolone et al. (2005).

in relation to mental conditions: emotional state, social functioning, mental health, and vitality. The MCS ranges between 0 and 100, where higher scores denote better health.

The MCS has the merit of smoothing the reporting heterogeneity bias that fully self-assessed health indices suffer from (Bago d'Uva et al., 2008) as it is a 'quasi-objective' health index. Consequently, it regards diagnosed health issues or very particular aspects of an individual's health (Lindeboom and Kerkhofs, 2009), even if it relies on self-reported mental conditions (Ziebarth, 2010). Yet, the fact that it is based on self-assessed conditions is not bad per se because this provides otherwise unavailable information (Pfarr et al., 2012). Moreover, it bears noting that the MCS accounts for the multidimensionality of health assessment and allows a 'beyond the mean' analysis as it is a continuos variable.

Beside controlling for the presence of major physical health problems,[7] our empirical analysis controls for those factors that both the economic theory (Grossman, 1972; Cropper, 1977; Chang, 1996) and the empirical literature recognize as important health determinants, i.e. age interacted with gender, education, status in the labor market and job type,[8] wealth,[9] family composition, geographical characteristics, and nationality[10] (for a detailed discussion, see Subsection 2.4.2 in Chapter 2).[11]

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7 This variable is coded as a binary indicator that equals unity if a person suffers from any disability or major chronic disease as defined by the ISTAT – i.e. diabetes, myocardial infarction, angina pectoris, other heart diseases, stroke, cerebral hemorrhage, chronic bronchitis, emphysema, liver cirrhosis, malignant tumor, parkinsonism, Alzheimer's and senile dementia – and zero otherwise.

8 Since this chapter focuses on the job dynamics that were exacerbated by the economic crisis, we define the job type according to whether it is a permanent or temporary full- or part-time job instead of a white or blue collar job as in Chapter 2. Moreover, as our regression results did not show statistically significant differences between permanent and temporary part-time workers, we aggregate them into a single category. It is also worth mentioning that we cannot distinguish between voluntary and involuntary part-time jobs as this information is not available in the 2004/05 INHS wave. However, according to ISTAT (2013), between 2008 and 2012, the rise in part-time employment concerned merely the involuntary component.

9 Wealth is proxied by a self-evaluation of the economic resources of the family in the last year (i.e. absolutely inadequate wealth, poor wealth, appropriate wealth, and excellent wealth). Moreover, we also used an indicator of housing wealth, but it turned out to be insignificant and its inclusion did not alter the results. For the sake of brevity, we therefore omit it in the final analysis.

10 The INHS does not contain information on irregular migrants, thus, in this study, we only refer to regular migrants, who have full access to the national health care system.

11 Since this chapter focuses on mental health, we did not include smoking behavior to avoid possible endogeneity problems. Moreover, as in Chapter 2, we tested for possibly relevant interactions (i.e. between education and income as suggested by Grossman and Kaestner, 1997 as well as between labor market status and education or economic situation as suggested by Fiori et al., 2016). However, these interactions did not provide further insights and were thus omitted in our final analysis.

3.5. Results

3.5.1. Descriptive Statistics

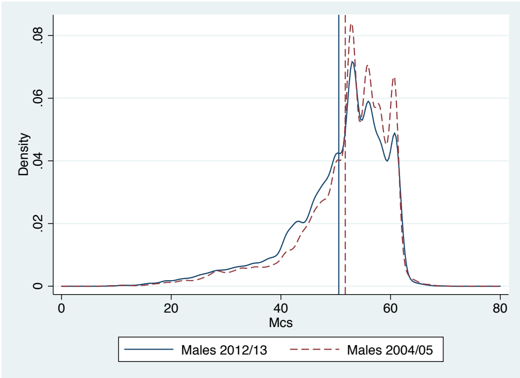
Table 3.1 and Figure 3.1 show the differentials in the MCS distributions of males (females) in 2012/13 compared to males (females) in 2004/05. They suggest a negative influence of the economic crisis on mental health for both genders, although it is larger for men: the average MCS of men is about 1.3 points (2.5%) lower in 2012/13 compared to 2004/05, while the one of women is only 0.8 points (1.6%) lower. Moving beyond the consideration of the mean impacts, we observe that men's differences in mental health are concentrated at the bottom of the MCS distribution, while the ones for women are larger at the median. In 2012/13, men's MCS values at the 10th and 25th percentiles of the distribution are 2 and 1.6 points (6.2% and 3.5%, respectively) lower than in 2004/05. Instead, the MCS value at the median for women is 1.4 points (2.8%) lower in 2012/13 than in 2004/05. Consequently, the gender gap in mental health, which is in favor of men, has shrunk at the extremes and has increased in the central part of the MCS distribution (the disadvantage for females moved from -14% in 2004/05 to -10% in 2012/13 at the first decile and from -3.5% in 2004/05 to -5.5% in 2012/13 at the median).

Table 3.1.: Mental Component Score by Gender (2012/13 – 2004/05)

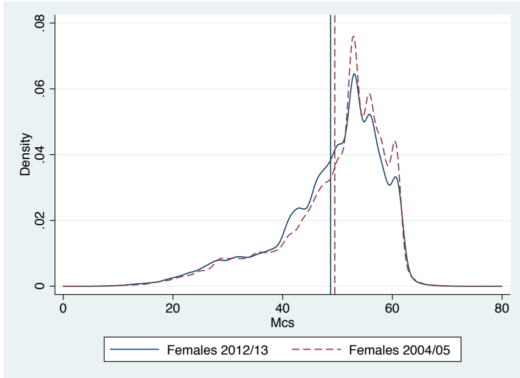
	Males 2012/13 (M_{12})	Males 2004/05 (M_{04})	Females 2012/13 (F_{12})	Females 2004/05 (F_{04})	M_{12}-M_{04}	F_{12}-F_{04}	M_{04}-F_{04}	M_{12}-F_{12}
Mean	50.47	51.72	48.69	49.51	-1.25***	-0.82***	2.21***	1.78***
Q10	30.31	32.32	27.32	27.90	-2.01***	-0.57***	4.43***	2.99***
Q25	43.80	45.40	40.47	40.89	-1.60***	-0.42***	4.51***	3.32***
Q50	51.13	51.54	48.33	49.75	-0.42***	-1.41***	1.80***	2.80***
Q75	55.55	55.72	54.07	54.43	-0.17***	-0.36***	1.29***	1.48***
Q90	58.74	59.32	57.97	57.87	-0.58***	0.10***	1.45***	0.77***

*Notes: The significance levels of the mean differences were calculated using a two-sided t-test. *** Significant at 1%; ** significant at 5%; *significant at 10%. Sample weights applied.*

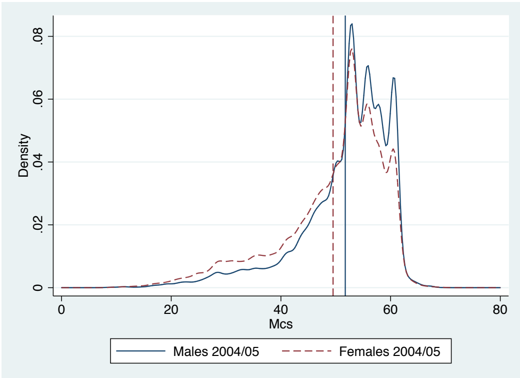
The lower values of MCS presented by both genders in 2012/13 may be simply due to some long-term population trends (ISTAT, 2018a), such as the aging of the population (in our sample, the mean age of men and women increase by 1.3 and 1.5 years, respectively), the increase in the shares of both single households (+2.8% for males and +2.3% for fe-



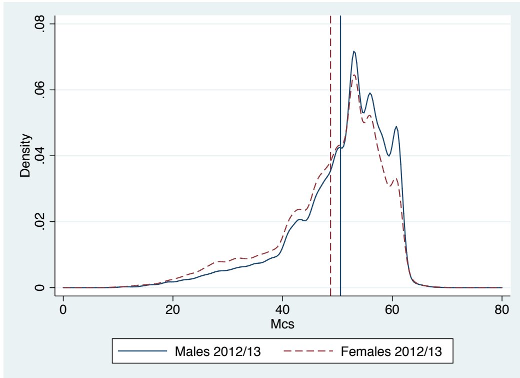
MCS, Males 2012/13 and 2004/05



MCS, Females 2012/13 and 2004/05



MCS, Males and Females 2004/05



MCS, Males and Females 2012/13

Figure 3.1.: MCS Distributions and Means of Males and Females in Italy (2012/13 – 2004/05)

males) and single parent households (+1.3% for men and +1.7% for women), as well as the decrease in household size (-7.7% for males and -6.8% for females; see Table B1 in Appendix B). Indeed, the health depreciation rate increases with age inducing older people to invest less in health (Grossman, 1972) and consequently have worse mental health conditions than younger individuals (Marmot et al., 2012). In addition, living alone is associated with poor mental health (Smith and Victor, 2019) and individuals in single parent families tend to exhibit worse mental health conditions than persons in families with both parents (Barrett and Turner, 2005).

On the other hand, these negative differences in MCS may be triggered by specific crisis-related trends (ISTAT, 2013), which appear to be larger than those just mentioned.[12]

[12] MCS differences between 2004/05 and 2012/13 are likely to be influenced by the crisis and not merely reflect previous trends. Indeed, also Odone et al. (2017) report that the risk of poor mental health was

For instance, household wealth decreases notably for both genders between 2004/05 and 2012/13 and lower levels of wealth are associated with worse health conditions (Chang, 1996; Hernandez et al., 2006). In the same period, there is also a general increase in the share of unemployed persons (about 6% for both men and women), which could result in a lower level of mental health (Krug and Eberl, 2018).[13]

Furthermore, we observe a decrease in the share of full-time workers (both permanent and temporary) and an increase in the share of part-time workers. The reduction in the share of permanent full-time workers was larger among men (-4.7% compared -1% among women), while both the decrease in the share of temporary full-time workers and the rise in part-time jobs was more pronounced among women (-0.8% compared to -0.6% for men and +1.5% compared to +0.9%, respectively). This is not surprising as, especially in Italy, men have permanent full-time contracts more frequently than women (Pirani and Salvini, 2015). Yet, precarious employment can have severe adverse consequences in terms of mental health (Moscone et al., 2016).

Between 2004/05 and 2012/13, we also observe an increase in educational levels, which can have a protective effect on health (Grossman, 1972, Cutler and Lleras-Muney, 2006). The expansion of tertiary education, which mainly concerns women (+4.2% compared to +2.3% for men), may be due to the 2001 introduction of the '3+2' (unitary two-tier) university system, which has led to a decline in university drop-out rates (Di Pietro and Cutillo, 2008). Yet, it may also be related to the fact that during the recession, in response to both the rise in unemployment and the decrease in the probability to become and remain employed (ISTAT, 2014a), young people invested more in tertiary education. The share of immigrants (similar for men and women in 2004/05) increased over time, especially for women.[14] We expect positive composition effects associated with immigrant status because, as shown in Chapter 2, in 2012/13 both short- and long-term Italian immigrants exhibited better men-

higher in 2013 compared to 2005, but not in 2005 compared to 2000, which suggests that the increase reported between 2005 and 2013 is associated with the Great Recession.

13 Our regression results do not show statistically significant differences between long- and short-term unemployed, and thus, we combine them into one category.

14 This may reflect the constant rise in the demand of domestic workers, which mainly concerns immigrant women, in response to factors such as demographic aging (CENSIS, 2013).

tal health conditions than native Italians. In the following subsections, we analyze how all these characteristics are associated with mental health at different quantiles of the health distribution and their relative contributions to changes in mental health during the Great Recession.

3.5.2. RIF Regression Results

The RIF regression results for the MCS are shown separately for males and females in Tables B2-B5 in Appendix B. In each table, the OLS regression results are reported in Columns 1-2, while the RIF regression results at the 10th, 25th, 50th, 75th, and 90th percentile of the MCS distribution are shown in Columns 3-12.

The estimated correlations between age, wealth, and mental health are in line with previous evidence for both genders. Mental health status decreases with both age and poor levels of wealth and these deteriorations are larger at the bottom of the distribution, especially in 2012/13. Having physical health problems is also negatively associated with mental health and this holds for both genders and years, especially at the bottom decile and quartile of the health distribution. Education does not show the expected protective correlation with mental health. Instead, it seems to have a (small) negative correlation with mental health for both men and women across the entire distribution, especially in 2012/13. For both genders, a positive education gradient emerges only in 2004/05 in relation to high education, compared to low education, at the bottom of the distribution. Yet, the coefficients are very small in magnitude, albeit slightly larger for women.

In 2004/05, among men, all occupation categories are associated with a worsening of the entire mental health distribution, compared to permanent full-time employees, with larger effects at the bottom, and for unemployed, part-time employees, and non-participants (excluding retirees for whom there is basically no effect). Among women, the correlation between occupation and mental health is more diverse. Higher shares of unemployed, part-time employees, and non-participants (excluding retirees) are also associated with worse mental health, but only at the bottom of the distribution and with smaller effects compared to men. Temporary part-time jobs are negatively associated with mental health across the entire distribution, but the coefficients are very small and rarely significant. In the upper part of the distribution, instead, non-participation is positively correlated with mental health, although the coefficients are again very small in magnitude.

In 2012/13, for men, there are almost no significant differences in mental health among employees. Negative effects remain significant only for self-employed and are somewhat larger than in 2004/05. Unemployment is again associated with a leftward shift of the entire health distribution, with larger effects at the bottom and with respect to 2004/05. Inactivity, instead, exerts a similar effect as in 2004/05. For women, negative correlations remain significant only for unemployed individuals and they are two to three times larger than in 2004/05. Among females, inactivity has also a similar effect as in 2004/05. There is a larger coefficient only for students at the bottom of the health distribution. This change in the magnitude of the coefficients is relatively large compared to men, causing that the coefficients of men and women are more similar.

In 2004/05, the association of the family composition is negligible and rarely significant for both genders. In 2012/13, a clearer negative association emerges for single parents compared to single for both men and women. Regardless of gender, people residing in the Centre-North of Italy have poorer mental health conditions than those living in the South (especially at the bottom of the distribution), although this negative association is weaker in 2012/13 than in 2004/05. As expected, there is a positive correlation between immigrant status and mental health for both men and women and in both years, especially at the bottom of the health distribution.

3.5.3. Oaxaca-Blinder Decomposition Results

Tables 3.2-3.5 illustrate the decomposition results of differentials between males (females) in 2012/13 and males (females) in 2004/05, as well as between males and females, at different MCS quantiles. If we observe a negative (positive) difference, a given MCS quantile is lower (higher) among males (females) in 2012/13 with respect to males (females) in

2004/05 or among females compared to males. In each table, Panel A shows the total differentials and how these are divided between the overall composition and elasticity effects. Panel B reports the detailed decompositions, i.e. the specific contribution of wide groups of explanatory variables (age, physical health problems, education, type of employment, unemployment, inactivity, family composition, wealth, geography, immigrant status, and the constant term) to the composition and elasticity effects. When interpreting the results, note that the estimated coefficients of the categorical variables represent deviations from the grand mean. Thus, differentials in the constant terms describe overall unexplained differentials and not differentials in the quantiles related to the reference category. This guarantees detailed decomposition results to be invariant to the selection of the reference category.

In 2004/05, males exhibit better mental health than females across the entire distribution of health (Table 3.2). Their advantage is higher at the bottom of the health distribution (+21% at the first decile and +7.9% at the 25th percentile) where composition effects, which are positive and therefore in favor of men, account for the majority of the health differentials. The detailed decomposition reveals that these composition effects (and those up to the 75th percentile) are mainly due to inactivity. This is almost completely driven by the 'other inactive' category, which consists mainly of homemakers in the case of women and of persons unfit for work or in other conditions (e.g. wealthy and detained persons) in the case of men.[15] This result reflects the fact that the number of men in the 'other inactive' category is very small compared to females. Indeed, in 2004/05, the number of male homemakers is close to zero.

[15] Detailed decomposition results for each covariate are available upon request. Here, we prefer not to include these categories for the sake of enhancing the readability of the tables.

Table 3.2.: Decomposition Results of Differentials between Males in 2004/05 and Females in 2004/05 in Mental Component Score

	Q10	Q25	Q50	Q75	Q90
$\Delta_{M_{04}-F_{04}}$	5.866***	3.212***	0.371***	1.576***	0.561***
	(0.220)	(0.123)	(0.048)	(0.054)	(0.050)
Panel A					
Composition Effect	5.531***	1.840***	0.331***	0.188**	0.031
	(0.469)	(0.199)	(0.071)	(0.078)	(0.046)
Elasticity Effect	0.335	1.372***	0.040	1.388***	0.530***
	(0.526)	(0.231)	(0.085)	(0.094)	(0.068)
due to covariates	-2.949	-0.681	-0.109	0.117	0.242
due to constant	3.285	2.053	0.149	1.271	0.288
Panel B: Detailed decomposition					
Composition Effect					
Age	0.054***	0.042***	0.022***	0.029***	0.016***
	(0.016)	(0.011)	(0.006)	(0.007)	(0.004)
Physical Health Problems	-0.142***	-0.066***	-0.017***	-0.012***	-0.003***
	(0.029)	(0.013)	(0.004)	(0.003)	(0.001)
Education	-0.011	-0.007	0.002	0.004*	0.001
	(0.008)	(0.004)	(0.002)	(0.002)	(0.001)
Type of Employment	1.348***	0.554***	0.091***	0.040	-0.002
	(0.142)	(0.074)	(0.029)	(0.033)	(0.020)
Unemployment	-0.005	-0.005	-0.001	-0.000	-0.000
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)
Inactivity	4.215***	1.280***	0.216***	0.110*	0.011
	(0.409)	(0.170)	(0.060)	(0.066)	(0.039)
Family Composition	0.033	0.018	0.006	0.013*	0.006
	(0.028)	(0.016)	(0.007)	(0.007)	(0.005)
Wealth	0.048***	0.032***	0.012***	0.008***	0.003***
	(0.015)	(0.009)	(0.003)	(0.002)	(0.001)
Geography	-0.014**	-0.010***	-0.002	-0.003*	-0.003***
	(0.006)	(0.004)	(0.002)	(0.002)	(0.001)
Immigrant Status	0.006	0.003	0.001	0.001	0.001
	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)
Elasticity Effect					
Age	-0.231***	-0.096***	-0.025	-0.028*	0.022*
	(0.045)	(0.025)	(0.010)	(0.012)	(0.011)
Physical Health Problems	0.041	0.136***	0.052***	-0.003	0.037***
	(0.090)	(0.043)	(0.014)	(0.014)	(0.012)
Education	0.126	0.062	0.028	0.027	0.007
	(0.152)	(0.089)	(0.037)	(0.040)	(0.035)
Type of Employment	1.559***	0.602***	0.130***	0.111***	0.081**
	(0.176)	(0.092)	(0.035)	(0.040)	(0.035)
Unemployment	-0.067	-0.069**	-0.030**	-0.014	-0.006
	(0.063)	(0.033)	(0.012)	(0.015)	(0.013)
Inactivity	-4.042***	-1.215***	-0.213***	-0.125*	-0.064
	(0.426)	(0.184)	(0.067)	(0.073)	(0.052)
Family Composition	-0.703	0.061	0.047	0.168	0.048
	(0.651)	(0.366)	(0.141)	(0.161)	(0.151)
Wealth	0.595*	0.014	-0.036	0.046	0.112
	(0.351)	(0.189)	(0.072)	(0.081)	(0.081)
Geography	-0.073	-0.068*	-0.030**	-0.026	0.024
	(0.063)	(0.035)	(0.014)	(0.016)	(0.015)
Immigrant Status	-0.155***	-0.106***	-0.031**	-0.039*	-0.021
	(0.049)	(0.032)	(0.013)	(0.017)	(0.014)
Constant	3.285***	2.053***	0.149	1.271***	0.288
	(0.843)	(0.457)	(0.175)	(0.198)	(0.181)

*Notes: *** Significant at 1%; ** significant at 5%; *significant at 10%. Sample weights applied. Standard errors, which are reported in parentheses, are clustered at family-level.*

Interestingly, up to the 75th percentile, the elasticity effects associated with inactivity are of similar magnitude and go in the opposite direction. Again, the elasticity effects of inactivity are mainly driven by the 'other inactive' category, meaning that men experience larger negative consequences of certain type of inactivity compared to females. Yet, given that the number of males in certain types of inactivity is much lower than the one of females, the mental health distribution of men is better than the one of women.

Since the composition and elasticity effects of inactivity basically cancel out, we look at the determinants of the gender gap in mental health net of the effects of inactivity. In this case, the composition effects generally decrease (e.g. from +5.531 to +1.317 points at the first decile and from +1.840 to +0.561 points at the 25th percentiles) and, up to the 75th percentile, are mainly due to the positive composition effects of the type of unemployment. These are mainly driven by permanent full-time workers. In other words, men work in typical jobs more than women, leading to better mental health conditions.

Regarding the elasticity effects net of the inactivity, they generally increase (e.g. from +0.335 to +4.378 points at the first decile and from +1.372 to +2.587 points at the 25th percentiles). These elasticity effects are mainly due to both the differentials in the constant term, i.e. unobserved characteristic, and, up to the median, the effects of the type of unemployment. The latter are again mainly driven by the permanent full-time workers' category: the 'health returns' of having a typical job are better for males than for females. At the top of the health distribution the positive 'health returns' of having a typical job carry on to be important in explaining the MCS differentials, although the positive 'health returns' of both family composition (mainly household size) and wealth become also relevant in explaining the MCS differences.

Before analyzing the gender gap in 2012/13, we assess how the crisis affected the mental health of men (Table 3.3) and women (Table 3.4) separately. While the previous literature concerning Italy has focused on mean impacts (see e.g. Sarti and Vitalini, 2016), our aim is to verify the influence of the Great Recession across the entire distribution of health. Indeed, changes at the top and at the bottom of the health distribution can have very different consequences in terms of health care costs. By showing an increase in the prevalence/risk of poor mental health between 2012/13 and 2004/05 (which occurred especially for men), Odone et al. (2017) detect that the crisis decreased the health conditions at the left tail of the health distribution. However, it is unknown what happened at the top of the distribution. In addition, our study aims to advance the understanding on the topic by disentangling to what extent the heterogeneous effects that the crisis had among men and among women are due to different endowments of observable characteristics (e.g. poor wealth or unemployment) or to different 'health returns' of these characteristics among each group.

Table 3.3.: Decomposition Results of Differentials between Males in 2012/13 and Males in 2004/05 in Mental Component Score

	Q10	Q25	Q50	Q75	Q90
$\Delta_{M_{12}-M_{04}}$	-1.961***	-1.515***	0.229***	-0.350***	-0.003
	(0.256)	(0.127)	(0.059)	(0.069)	(0.054)
Panel A					
Composition Effect	-1.196***	-0.731***	-0.262***	-0.197***	-0.073***
	(0.099)	(0.053)	(0.021)	(0.024)	(0.016)
Elasticity Effect	-0.765***	-0.785***	0.490***	-0.154**	0.070
	(0.270)	(0.135)	(0.061)	(0.072)	(0.055)
due to covariates	-1.129	-1.345	-0.435	-0.378	-0.321
due to constant	0.364	0.560	0.925	0.225	0.392
Panel B: Detailed decomposition					
Composition Effect					
Age	-0.132***	-0.109***	-0.059***	-0.078***	-0.040***
	(0.026)	(0.016)	(0.007)	(0.009)	(0.005)
Physical Health Problems	-0.087***	-0.040***	-0.010***	-0.007***	-0.002**
	(0.031)	(0.014)	(0.004)	(0.003)	(0.001)
Education	0.030	0.007	-0.021***	-0.018**	-0.004
	(0.028)	(0.016)	(0.007)	(0.008)	(0.005)
Type of Employment	-0.307***	-0.126***	-0.021***	-0.010	-0.000
	(0.031)	(0.015)	(0.006)	(0.006)	(0.004)
Unemployment	-0.096**	-0.094***	-0.023***	-0.004	-0.007
	(0.041)	(0.021)	(0.008)	(0.009)	(0.005)
Inactivity	-0.114***	-0.043***	-0.011***	-0.006**	0.001
	(0.023)	(0.009)	(0.003)	(0.003)	(0.002)
Family Composition	-0.054***	-0.034***	-0.014***	-0.002	0.004
	(0.019)	(0.011)	(0.004)	(0.005)	(0.003)
Wealth	-0.525***	-0.340***	-0.123***	-0.084***	-0.036***
	(0.052)	(0.029)	(0.011)	(0.012)	(0.007)
Geography	-0.004	0.001**	0.000	0.000	-0.000
	(0.011)	(0.006)	(0.002)	(0.003)	(0.002)
Immigrant Status	0.094***	0.046	0.022**	0.012	0.011*
	(0.032)	(0.020)	(0.009)	(0.010)	(0.007)
Elasticity Effect					
Age	-0.094**	0.007	-0.003	0.041***	-0.007
	(0.045)	(0.023)	(0.011)	(0.013)	(0.011)
Physical Health Problems	-0.140	0.104**	-0.047***	-0.011	-0.051***
	(0.113)	(0.045)	(0.018)	(0.019)	(0.014)
Education	0.106	0.082	0.036	0.051	0.046
	(0.153)	(0.078)	(0.037)	(0.043)	(0.033)
Type of Employment	-0.234	-0.192	0.074	0.060	0.045
	(0.291)	(0.129)	(0.056)	(0.065)	(0.052)
Unemployment	-0.215*	-0.051	-0.047**	-0.098***	-0.060***
	(0.124)	(0.056)	(0.023)	(0.027)	(0.020)
Inactivity	-0.232**	-0.026	-0.027	0.029	0.044*
	(0.105)	(0.051)	(0.024)	(0.029)	(0.025)
Family Composition	-0.670	-0.927***	-0.321*	-0.302	-0.120
	(0.746)	(0.359)	(0.168)	(0.203)	(0.157)
Wealth	0.198	-0.374*	-0.076	-0.144	-0.170
	(0.402)	(0.201)	(0.096)	(0.126)	(0.112)
Geography	-0.060	0.047	-0.002	-0.006	-0.043***
	(0.072)	(0.036)	(0.016)	(0.020)	(0.016)
Immigrant Status	0.211**	-0.014	-0.022	0.003	-0.007
	(0.094)	(0.057)	(0.026)	(0.031)	(0.024)
Constant	0.364	0.560	0.925***	0.225	0.392*
	(0.955)	(0.456)	(0.210)	(0.257)	(0.205)

Notes: See Table 3.2.

Table 3.4.: Decomposition Results of Differentials between Females in 2012/13 and Females in 2004/05 in Mental Component Score

	Q10	Q25	Q50	Q75	Q90
$\Delta_{F_{12}-F_{04}}$	-0.440	-0.929***	-1.313***	0.563***	-0.460***
	(0.268)	(0.154)	(0.081)	(0.069)	(0.079)
Panel A					
Composition Effect	-0.523***	-0.489***	-0.185***	-0.145***	-0.122***
	(0.102)	(0.064)	(0.024)	(0.027)	(0.031)
Elasticity Effect	0.083	-0.441***	-1.128***	0.708***	-0.338***
	(0.282)	(0.162)	(0.083)	(0.074)	(0.084)
due to covariates	-0.483	0.629	-0.076	0.049	-0.096
due to constant	0.566	-1.070	-1.052	0.658	-0.242
Panel B: Detailed decomposition					
Composition Effect					
Age	-0.119***	-0.110***	-0.056***	-0.045***	-0.053
	(0.024)	(0.016)	(0.007)	(0.007)	(0.008)
Physical Health Problems	-0.142***	-0.082***	-0.023***	-0.011***	-0.008
	(0.032)	(0.018)	(0.005)	(0.003)	(0.002)
Education	0.072**	0.044*	0.003	-0.017*	-0.014
	(0.038)	(0.023)	(0.009)	(0.010)	(0.011)
Type of Employment	-0.012	-0.004	0.000	0.001	0.003
	(0.011)	(0.006)	(0.003)	(0.003)	(0.003)
Unemployment	-0.038	-0.033	0.003	0.009	-0.002
	(0.037)	(0.021)	(0.008)	(0.009)	(0.010)
Inactivity	0.030	-0.001	-0.007	-0.005	0.001
	(0.026)	(0.015)	(0.006)	(0.007)	(0.007)
Family Composition	-0.094***	-0.048***	-0.013***	-0.013***	-0.007
	(0.023)	(0.012)	(0.004)	(0.005)	(0.005)
Wealth	-0.495***	-0.421***	-0.153***	-0.119***	-0.077
	(0.049)	(0.032)	(0.012)	(0.012)	(0.012)
Geography	-0.017	-0.008	-0.002	-0.001	-0.003
	(0.013)	(0.007)	(0.003)	(0.002)	(0.003)
Immigrant Status	0.291***	0.174***	0.063***	0.057***	0.038
	(0.038)	(0.027)	(0.011)	(0.014)	(0.016)
Elasticity Effect					
Age	-0.214***	-0.088**	-0.041**	-0.010	0.004
	(0.062)	(0.035)	(0.019)	(0.017)	(0.021)
Physical Health Problems	0.031	-0.056	-0.140***	-0.057***	-0.036
	(0.114)	(0.053)	(0.023)	(0.018)	(0.019)
Education	0.120	0.120	0.080**	0.069**	0.121
	(0.124)	(0.074)	(0.040)	(0.035)	(0.039)
Type of Employment	0.355**	0.217**	0.016	0.022	-0.017
	(0.167)	(0.093)	(0.049)	(0.042)	(0.049)
Unemployment	-0.197*	-0.115*	-0.078***	-0.019	-0.007
	(0.110)	(0.060)	(0.030)	(0.027)	(0.031)
Inactivity	-0.053	-0.148*	-0.018	-0.025	-0.060
	(0.158)	(0.089)	(0.048)	(0.042)	(0.048)
Family Composition	-1.278*	-0.086	-0.269	-0.090	-0.234
	(0.766)	(0.436)	(0.236)	(0.206)	(0.235)
Wealth	0.728*	0.749***	0.360**	0.224*	0.144
	(0.420)	(0.274)	(0.144)	(0.125)	(0.159)
Geography	-0.043	0.007	-0.042*	-0.035*	-0.033
	(0.075)	(0.042)	(0.022)	(0.020)	(0.024)
Immigrant Status	0.068	0.027	0.056*	-0.029	0.023
	(0.092)	(0.062)	(0.034)	(0.034)	(0.040)
Constant	0.566	-1.070*	-1.052***	0.658***	-0.242
	(0.948)	(0.549)	(0.291)	(0.253)	(0.298)

Notes: See Table 3.2.

In line with Odone et al. (2017), we find that at the bottom of the MCS distribution (which indicates poor levels of mental health), MCS levels are lower in 2012/13 compared to 2004/05, especially for men (-6.1% at the first decile and -3.3% at the 25th percentile). Yet, while for males the main reduction in MCS levels occurs precisely at the left tail of the health distribution, for females the main reduction occurs at the median (-2.6%).

At the bottom of the MCS distribution for men, the composition effects and elasticity effects due to covariates explain much of the lower mental health levels exhibited by males in 2012/13 compared to males in 2004/05. In accordance with the previous literature (Sarti and Vitalini, 2016; Fiori et al., 2016), we find that these negative composition effects are largely due to changes in the composition of employment (mainly a decrease in the number of males with a permanent full-time job) and in lower wealth endowments. However, we find that the increase of the number of unemployed men plays a more marginal role. In addition, our results show that the 'health returns' of the type of employment (primarily permanent full-time employment) and wealth (only poor and inadequate wealth at the first decile) worsened over time and that these 'health returns' are the major contributors to the elasticity effects at the bottom of the MCS distribution together with the negative 'health returns' of the family composition (mainly household size).

For females, unlike for males, where differentials are larger (i.e. at the first decile and quartile), the composition effects related to labor market conditions explain hardly anything of these differentials. In contrast, lower wealth endowments keep explaining a great extent of the compositional part of the health differentials between females in 2012/13 and females in 2004/05. This could be due to the fact that Italy is still a male breadwinner society. Thus increases in unemployment and income insecurity are more likely to influence the mental health of men than of women (Artazcoz et al., 2004). Yet, the main contributing factors to the females' health differentials at the first decile and quartile are differentials in the constant term, i.e. in some unobserved factors. Interestingly, these are reduced by 'health returns' of wealth that, over time, improved.

As a consequence of the fact that in 2012/13, the MCS distribution of males reduced mainly at the bottom and the one of females at the median, in 2012/13 the gender gap in mental health – which is still in favor of men – shrank at the bottom of the distribution (from +21% to +15.9% at the first decile and from +7.9% to +6.5% at the 25th percentile) and increased at the median (from +0.7% to +4%; Table 3.5). As in 2004/05, the gender differentials in MCS are mainly due to both (positive) composition and (negative) elasticity effects related to inactivity. Again, they are of similar magnitude and almost entirely driven by the 'other inactive' category. Net of these inactivity effects, the drivers of the gap remain men's better endowment of certain types of employment (i.e. permanent full-time jobs) and better 'health returns' with respect to permanent full-time jobs and unobservable characteristics.

Table 3.5.: Decomposition Results of Differentials between Males in 2012/13 and Females in 2012/13 in Mental Component Score

	Q10	Q25	Q50	Q75	Q90
$\Delta_{M_{12}-F_{12}}$	4.345***	2.626***	1.913***	0.663***	1.018***
	(0.254)	(0.124)	(0.072)	(0.064)	(0.068)
Panel A					
Composition Effect	3.366***	1.164***	0.406***	0.340***	0.171***
	(0.383)	(0.135)	(0.060)	(0.067)	(0.061)
Elasticity Effect	0.979**	1.463***	1.507***	0.323***	0.847***
	(0.466)	(0.182)	(0.093)	(0.090)	(0.091)
due to covariates	-2.104	-2.220	-0.620	-0.514	-0.075
due to constant	3.083	3.683	2.126	0.837	0.922
Panel B: Detailed decomposition					
Composition Effect					
Age	0.107***	0.057***	0.030***	0.029***	0.024***
	(0.024)	(0.013)	(0.007)	(0.007)	(0.006)
Physical Health Problems	-0.102***	-0.035***	-0.014***	-0.009***	-0.006***
	(0.033)	(0.011)	(0.005)	(0.003)	(0.002)
Education	0.006	-0.003	0.007	0.017***	0.012**
	(0.019)	(0.009)	(0.005)	(0.005)	(0.005)
Type of Employment	0.616***	0.197***	0.042	0.035	0.018
	(0.129)	(0.058)	(0.030)	(0.035)	(0.030)
Unemployment	-0.012	-0.007	-0.003	-0.003	-0.002
	(0.009)	(0.005)	(0.002)	(0.002)	(0.002)
Inactivity	2.751***	0.928***	0.326***	0.253***	0.111**
	(0.323)	(0.109)	(0.047)	(0.053)	(0.049)
Family Composition	0.062*	0.035**	0.018**	0.016*	0.014*
	(0.035)	(0.015)	(0.007)	(0.009)	(0.008)
Wealth	0.013	0.010	0.006	0.006	0.005*
	(0.024)	(0.011)	(0.005)	(0.004)	(0.003)
Geography	-0.013*	-0.005*	-0.002	-0.001	-0.001
	(0.007)	(0.003)	(0.001)	(0.001)	(0.001)
Immigrant Status	-0.061***	-0.014***	-0.004*	-0.005	-0.003
	(0.013)	(0.005)	(0.002)	(0.003)	(0.002)
Elasticity Effect					
Age	-0.178***	-0.016	0.003	-0.010	0.016
	(0.060)	(0.032)	(0.019)	(0.018)	(0.020)
Physical Health Problems	-0.113	0.306***	0.155***	0.043**	0.032*
	(0.113)	(0.047)	(0.023)	(0.019)	(0.019)
Education	0.053	-0.016	-0.045	-0.005	-0.068*
	(0.127)	(0.065)	(0.038)	(0.036)	(0.036)
Type of Employment	1.408***	0.427***	0.216***	0.142***	0.121**
	(0.191)	(0.089)	(0.051)	(0.046)	(0.048)
Unemployment	-0.136	-0.064	-0.024	-0.103***	-0.062**
	(0.113)	(0.050)	(0.028)	(0.024)	(0.026)
Inactivity	-2.902***	-0.784***	-0.338***	-0.215***	-0.061
	(0.353)	(0.132)	(0.065)	(0.064)	(0.064)
Family Composition	-0.085	-0.784**	-0.018	-0.036	0.166
	(0.740)	(0.352)	(0.203)	(0.174)	(0.196)
Wealth	0.070	-1.005***	-0.437***	-0.286**	-0.161
	(0.425)	(0.235)	(0.137)	(0.130)	(0.142)
Geography	-0.079	-0.025	0.013	0.001	0.015
	(0.069)	(0.033)	(0.019)	(0.018)	(0.020)
Immigrant Status	-0.143*	-0.259***	-0.145***	-0.046*	-0.074***
	(0.082)	(0.047)	(0.027)	(0.026)	(0.028)
Constant	3.083***	3.683***	2.126***	0.837***	0.922***
	(0.942)	(0.461)	(0.263)	(0.241)	(0.267)

Notes: See Table 3.2.

The last step of the analysis involves testing whether the changes in MCS between 2004/05 and 2012/2013 are different for men and women. Table 3.6 corroborates our previous findings showing that, at the bottom of the distribution, the decline in mental health is larger among men compared to women (-1.521 points in the first decile), while at the median it is larger among women compared to men (+1.542). Moreover, we observe that the difference in the changes of elasticity effects is larger than the difference in the changes of composition effets over the entire distribution of the MCS.

Focusing first on the differences in changes in compositional effects, we find that the difference in the association of employment type, unemployment, inactivity, and immigrant status is larger for men compared to women, especially in the bottom-middle part of the distribution. For instance, while the composition effect of men regarding employment status declined by 0.307 (Table 3.3), it remained almost unchanged for women (-0.012; Table 3.4), such that the overall difference in the MCS is reduced by 0.295 points.

Turning to differences in changes in elasticity effects, we also note different changes in mental health due to unfavorable associations with the type of employment at the bottom of the distribution. While the elasticity effect of men regarding employment status decreased by -0.234 points between 2004/5 and 2012/13 (Table 3.3), it increased for women by 0.355 points (Table 3.4). As a consequence, the overall difference in the MCS is reduced by 0.589 points. Similarly, the elasticity effect of men regarding wealth in the first quartile has reduced over time, while that of women has increased, leading to a smaller gap in the MCS.

Table 3.6.: Test of the Difference in Changes in Mental Component Score for Men and Women

	Q10	Q25	Q50	Q75	Q90
$\Delta_{\Delta M - \Delta F}$	-1.521***	-0.586***	1.542***	-0.913***	0.457***
	(0.354)	(0.159)	(0.083)	(0.083)	(0.078)
Panel A					
Composition Effect	-0.674***	-0.242***	-0.077**	-0.052	0.049
	(0.133)	(0.077)	(0.032)	(0.038)	(0.037)
Elasticity Effect	-0.848**	-0.344**	1.618***	-0.861***	0.408***
	(0.352)	(0.174)	(0.084)	(0.089)	(0.086)
Panel B: Detailed decomposition					
Composition Effect					
Age	-0.014	0.001	-0.003	-0.033***	0.013
	(0.034)	(0.025)	(0.011)	(0.012)	(0.012)
Physical Health Problems	0.055	0.041*	0.013**	0.004	0.006***
	(0.044)	(0.023)	(0.006)	(0.004)	(0.002)
Education	-0.042	-0.036	-0.025**	-0.001	0.010
	(0.047)	(0.029)	(0.012)	(0.013)	(0.012)
Type of Employment	-0.295***	-0.122***	-0.021***	-0.011	-0.003
	(0.032)	(0.017)	(0.006)	(0.007)	(0.005)
Unemployment	-0.059	-0.061**	-0.026**	-0.012	-0.005
	(0.050)	(0.028)	(0.011)	(0.013)	(0.011)
Inactivity	-0.144***	-0.042**	-0.004	-0.000	-0.000
	(0.035)	(0.018)	(0.007)	(0.008)	(0.008)
Family Composition	0.039*	0.014	-0.002	0.010	0.011*
	(0.024)	(0.015)	(0.005)	(0.007)	(0.006)
Wealth	-0.030	0.081**	0.030**	0.035**	0.041***
	(0.068)	(0.039)	(0.015)	(0.015)	(0.014)
Geography	0.012	0.009	0.002	0.001	0.003
	(0.013)	(0.007)	(0.003)	(0.003)	(0.003)
Immigrant Status	-0.197***	-0.127***	-0.041***	-0.045**	-0.026
	(0.046)	(0.030)	(0.012)	(0.018)	(0.018)
Elasticity Effect					
Age	0.120	0.094**	0.039*	0.051**	-0.011
	(0.078)	(0.044)	(0.022)	(0.024)	(0.022)
Physical Health Problems	-0.171	0.160**	0.093***	0.046*	-0.015
	(0.173)	(0.067)	(0.026)	(0.026)	(0.022)
Education	-0.014	-0.037	-0.043	-0.018	-0.075
	(0.209)	(0.117)	(0.056)	(0.053)	(0.047)
Type of Employment	-0.588*	-0.409**	0.058	0.038	0.062
	(0.331)	(0.169)	(0.077)	(0.078)	(0.068)
Unemployment	-0.018	0.063	0.031	-0.079***	-0.052*
	(0.161)	(0.082)	(0.035)	(0.030)	(0.031)
Inactivity	-0.179	0.121	-0.009	0.054	0.104**
	(0.190)	(0.121)	(0.054)	(0.051)	(0.050)
Family Composition	0.607	-0.841	-0.052	-0.212	0.114
	(1.113)	(0.565)	(0.292)	(0.246)	(0.228)
Wealth	-0.530	-1.123***	-0.436***	-0.369**	-0.313*
	(0.644)	(0.355)	(0.148)	(0.163)	(0.189)
Geography	-0.017	0.040	0.040	0.028	-0.010
	(0.103)	(0.052)	(0.025)	(0.027)	(0.028)
Immigrant Status	0.143	-0.042	-0.079**	0.033	-0.030
	(0.122)	(0.078)	(0.037)	(0.045)	(0.042)
Constant	-0.202	1.630**	1.977***	-0.434	0.634*
	(1.357)	(0.698)	(0.349)	(0.312)	(0.328)

*Notes: Standard errors are bootstrapped with $R = 1,000$ replications. *** Significant at 1%; ** significant at 5%; *significant at 10%.*

3.6. Conclusion

In this paper, we analyze the contribution of different demographic and socioeconomic factors to changes in the distribution of mental health for men and women during the Great Recession in Italy. This kind of knowledge is essential in preventing the detrimental influence that future recessions can have on individuals' mental health. Specifically, we perform unconditional quantile regressions in combination with Oaxaca-Blinder decompositions on data from the 2004/05 and 2012/13 waves of the Italian Health Condition Survey. First, our results suggest that the Great Recession exerted a negative influence on the mental health conditions of both men and women, with larger effects at the bottom of the health distribution for men and at the median for women. This result highlights the need to go 'beyond the mean' in analyzing the influences of recessions on mental health and suggests tailoring policy interventions to groups of individuals with specific health conditions according to gender.

Second, our results reveal that, for men, these negative shifts are mainly due to unfavorable changes in both the endowments and the 'health returns' of permanent full-time jobs and wealth as well as to the negative 'health returns' of household size. Instead, for women, these negative shifts are mainly attributable to worse wealth endowments and negative 'health returns' of unobservable characteristics. As changes in mental health of both genders are due to changes in both elasticity and composition effects, policy makers may opt for a combination of mental health policies with fiscal and labor market policies (Doorslaer and Koolman, 2004). Moreover, they may tailor them differently according to gender. In the case of men, for instance, policy makers could think about implementing polices to support both income and the supply of permanent full-time jobs as well as about health policies designed to mitigate the mental burden related to having large families.

Concerning instead the gender gap in mental health, the economic crisis does not seem to have influenced its main determinants. The drivers of the gap, which is in favor of men and focuses at the lower tail of the distribution, remain men's better endowments of certain types of employment (i.e. permanent full-time jobs) as well as their better 'health returns' in relation to both permanent full-time jobs and unobservable characteristics. Therefore, to reduce the gender gap in mental health, it seems advisable to improve women's access to typical jobs through both employment and health policies. Our results also advocate for a better data collection on mental health determinants in order to uncover the hidden drivers behind the unobserved components.

It bears noting that we perform a distributional analysis. Thus our results cannot be generalized or interpreted as casual. Instead, they rather provide an indication on the set of policies that could be implemented to counter the negative influence that economic crises can have on mental health. For each policy that our results may suggest, further research is needed to identify specific causal mechanisms on which to operate. In addition, as other studies on the topic (see e.g. Odone et al., 2017), we employ a 'before and after approach'. To better investigate the effects that economic recessions have on mental health, one would require direct measurements of the recession as well as longitudinal data to derive trends and establish whether observed health differences are actually influenced by the crisis or merely reflect previous trends.

4. The Lasting Effect of Early Childhood Health on Education: Evidence from the Asian Financial Crisis*

Abstract. This paper estimates the lasting effect of early childhood health (proxied by height-for-age z-scores) on later educational performance. We account for the endogeneity of child health by employing an instrumental variable approach where height differentials among children are identified by using exposure in early years of life to the Asian financial crisis that hit Indonesia in late 1997. Using longitudinal data from the Indonesia Family Life Survey, we find that poor health conditions in childhood have a considerable impact on the likelihood to fail at least one grade in primary school. Our analysis suggests that the health conditions that are critical for child development are those of the second and the third year of life.

JEL Codes: I14, I20, C26, O53.

Keywords: Child health; education; instrumental variables; financial crisis; Indonesia

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4.1. Introduction

During the past decades, several scholars have shown that early childhood health is critical for the subsequent development of a child, particularly regarding his/her later educational achievements. On the one hand, less healthy or malnourished children are more likely to have lower cognitive abilities (Duc, 2011) and to perform worse at school (Glewwe et al., 2001), which in turn may imply lower future earnings (Vogl, 2014). On the other hand, these children are subject to higher morbidity risks and thus more likely to enroll later in school or have lower educational attainments (Lo Bue, 2019). More generally, research from both medical and social sciences identifies the gestation period and the first three years of life as the 'critical period' in which the occurrence of shocks significantly affect later health and socioeconomic outcomes of a child (see e.g. Majid, 2015; Cutler et al., 2010; Maluccio et al., 2009; Waber et al., 1981). This is because during this time growth and brain development occur more rapidly than in others periods (Victora et al., 2010; Huttenlocher, 2002). However, the question of which period affects child development the most within this 'critical period' is still open.

Using longitudinal data from the Indonesia Family Life Survey (IFLS), this paper aims to assess the lasting effect of early childhood health (proxied by height-for-age z-scores) on later educational performance (measured by grade failure), accounting for the endogeneity of child health. Aside from offering us the opportunity to exploit a previously unexplored exogenous shock to enrich our understanding on the topic, Indonesia represents an interesting case study because, although it has grown significantly in the last twenty years, it needs to ameliorate on many indicators of school performance reducing disparities among regions and provinces (WB, 2011). We perform an instrumental variable (IV) analysis where height differentials among children are identified by using exposure in early years of life to the Asian financial crisis that hit Indonesia in late 1997. Our identifying assumption is that the health conditions of very young children exposed to the crisis were deteriorated by a reduced use of health services, a worse nutritional intake, and health shocks or transitory reductions in child care resulting from absent or unhealthy parents.

This article adds to the previous literature in several ways. First, it extends previous human capital research, contributing to the still ongoing debate on the causal link between child health and subsequent education achievement. Previous cross-sectional studies show positive correlations between these two crucial components of individual human capital (see e.g. Behrman and Deolalikar, 1988) without, however, addressing endogeneity.[1] Randomized field experiments, which focus on precise nutrition and health interventions, overcome this weakness, generally documenting a positive causal link between these two aspects (Maluccio et al., 2009; Ozier, 2018). Few other studies take an approach similar to ours and investigate the impact of child health on later educational outcomes by combining instrumental variable techniques with longitudinal data (Lo Bue, 2019; Alderman et al., 2009; Yamauchi, 2008; Alderman et al., 2006, 2001b; Glewwe et al., 2001).[2] All of them, with the exception of the one of Duc (2011),[3] detect a large and generally statistically significant impact of child health on following educational achievements.

A second contribution of our paper lies in the attempt to shed light on the effect that an event, such as a financial crisis, can have on child development. Indeed, past studies relying on IV techniques identify differences in height among children by using different instrumental variables, such as mother's height and birth weight (Duc, 2011), weight-for-age z-scores and community health facilities (Yamauchi, 2008), older sibling's height (Glewwe et al., 2001), exposure in early childhood to wildfires (Lo Bue, 2019), crop loss, drought, and flood (Alderman et al., 2009), civil war and drought (Alderman et al., 2006), as well as food price shocks (Alderman et al., 2001b).

By exploiting variations in the exposure to the Asian financial crisis in Indonesia, we add to the literature that investigates the effect of the Asian financial on the education of Indonesian children (Levine and Ames, 2003; Cameron, 2009, 2001; Hartono and Ehrmann,

1 In addition, cross-sectional studies suffer from recall biases due to the use of retrospective measures of child health, which result in biased estimates. Recall biases go toward zero in the case of classical measurement errors and in an unknown direction otherwise (Glewwe and Miguel, 2008).

2 For a detailed description of this literature, see Lo Bue (2019).

3 Duc (2011) finds a significant impact of child health (at one year) on cognition (at five years) only for preterm born children. However, he clarifies that this finding does not mean that early childhood health is not an important determinant of following cognitive abilities, rather that it is important to account for in utero conditions when addressing this kind of empirical question.

2001; Jones and Hagul, 2001; Frankenberg et al., 1999). Contrary to the literature, which measures the impact of the crisis directly on educational outcomes, we focus on the effect of crisis on education via its impact on childhood health' outcomes, thus focusing on its indirect impact. Moreover, while the previous studies on the topic concentrated on the short-term impact of the crisis by looking at educational outcomes during the crisis, we focus on its long-term impact by analyzing how the crisis affected grade failure throughout the elementary school period after the crisis.

Last, this paper contributes to previous research that aims to disentangle when and until when a shock occurring in the 'critical period' is likely to affect later child development. Some studies (Majid, 2015; Almond et al., 2009; Almond, 2006) test the 'fetal-origin' hypothesis alone (Barker, 1998), providing evidence that the gestation period is important in shaping later health and wellbeing of an individual. In contrast, other studies (Maccini and Yang, 2009; Glewwe and King, 2001) show that the period that matters most for the development of an individual is the first year (Maccini and Yang, 2009) or the second and third years of life (Alderman et al., 2006; Glewwe and King, 2001). Other scholars identify the first two years (including pregnancy) as the window of opportunity for preventing growth failure (Black et al., 2013, 2008; Ruel et al., 2008). All these evidences may differ for various reasons, such as the use of different methodologies, measures of child health, and/or sample size. We attempt to shed further light on this issue by exploiting an exogenous variation and a large longitudinal dataset.

Our findings confirm the negative effect that poor health conditions in childhood exert on later educational performance, also providing evidence of a lasting indirect effect of the Asian financial crisis on education of Indonesian children. We find that the health conditions that are most critical for child development are those of the second and third year of life. In line with the results of Alderman et al. (2006); Glewwe and King (2001); Lo Bue (2019), we therefore do not find any strong support for the 'fetal-origin' hypothesis, nor for the fact that health conditions in the first year of life have a lasting impact on educational outcomes.

The structure of the paper is as follows. Section 4.2 provides background information on the Asian financial crisis in Indonesia and the effect it exerted on children. Section 4.3 illustrates the theoretical framework and the empirical strategy, Section 4.4 presents the data, Section 4.5 discusses the regression results and the robustness checks, and Section 4.6 concludes.

4.2. Background

4.2.1. The Asian Financial Crisis in Indonesia

The Asian financial crisis began in Thailand when the Thai bath, which was allowed to float, devalued abruptly in July 1997. This collapse quickly involved neighboring economies, with the Indonesian rupiah coming under pressure in the last half of 1997. Capital flights exacerbated the crisis, transferring it to the banking sector. Although the contagion was fast, the financial and banking crisis only started to severely affect Indonesia in November 1997 (Hartono and Ehrmann, 2001). The situation promptly worsened after the crash of the Indonesian rupiah in January 1998, when it lost more than two thirds of its value within a few days. For the majority of the Indonesian population, the timing and the gravity of the crisis was unexpected: just before the crisis hit the country, President Suharto announced measures to expand the economy, being way too optimistic in forecasting the economic performance of the country (Thomas et al., 2004).

In 1998, production contracted, real gross domestic product per capita decreased by about 13%, and inflation hovered around 77%. The increase in food prices did not translate in a general advantage for agricultural producers. As the crisis afflicted the labor market (real wages more than employment), landless and small farmers suffered the burden of the crisis (Bresciani et al., 2002). Only large farmers benefitted from the crisis, as their export crop cultivations increased in profitability (Bresciani et al., 2002).

The economic uncertainty was followed by a political crisis that culminated with the resignation of President Suharto in May 1998 after more than three decades of rule. This situation further exacerbated the negative currency and inflation dynamics, which affected individuals throughout the income distribution (Thomas et al., 2004). The crisis reached its pick between August 1998 and December 1998 (Cameron, 2009): food prices skyrocketed and real wages dropped. Yet, since then the situation improved: in 1999 food prices fell substantially (Cameron, 2009), nominal wage caught up (Bresciani et al., 2002), and new elections were held. Hence, it was between November 1997 and December 1998 that households were under the greatest pressure and during which the threat of a deterioration in child health was highest.

4.2.2. Effects on Children

Despite the tremendous financial meltdown that hit the country, the social impact of the crisis was less severe than expected. Although the poverty rate increased from 11% to about 20% and real wages collapsed, some indices were surprisingly robust to such economic turmoil (Cameron, 2009). Regarding education indicators, for instance, schools did not close, enrollments were maintained, the anticipated increase in dropouts did not occur (Hartono and Ehrmann, 2001), and both genders were well protected (Cameron, 2001; Levine and Ames, 2003). Evidence from the annual National Socio-Economic Survey (Susenas) from the Central Bureau of Statistics (BPS) shows that school enrollment rates did not significantly chang during the crisis; only for junior secondary schools (children aged 13-15 years) they slightly declined from 77.5% to 77.2% between 1997 and 1998, but rebounded beyond the pre-crisis level in 1999 (Jones and Hagul, 2001).

Ministry of Education's data mirrors these findings for both enrollment and dropout rates, which increased from 3.2% to 6% only at junior secondary school level in 1998 (Hartono and Ehrmann, 2001).[4] Also in the 1999/2000 school year, primary and secondary school enrollment rates did not diminish significantly (Jones and Hagul, 2001). Moreover,

[4] Two alternative data sources exhibit a larger influence of the crisis on education between 1997 and 1998, even if in both cases the figures are much smaller than initially forecasted. Specifically: i) the IFLS data shows larger variations in enrollments and dropouts rates, with some differences across socio-economic status and geographic areas (Frankenberg et al., 1999); ii) the 100 Villages Survey data exhibits a larger decrease in enrollments at junior secondary level, which however rebounded in 1999 (Cameron, 2001). Yet, it is noteworthy to note that evidence from the IFLS relies on the IFLS2+ wave, which only re-interviewed a 25% subsample of the IFLS households, while evidence from the 100 Villages Survey focuses on rural areas and is thus not nationally representative.

child labor declined during the crisis, probably because of a decrease in demand due to an excess of adult supply in the labor market (Cameron, 2009; Levine and Ames, 2003). Within the explanations given for the limited influence of the crisis on education there are the government attempts to maintain the spending on education (also through grants and scholarship programs), the non-dramatic increase of school fees, the relaxed uniforms requirements, and the fact that children who did not pay school fees did not have to leave school (Cameron, 2009).

Concerning instead children's health indicators during the crisis, some significantly deteriorated while others surprisingly did not, with no significant differences across gender (Levine and Ames, 2003). For example, according to Susenas data, mortality rates decreased from 4.8% in 1996 to 3.4% in 1999 for children under one year and from 0.7% to 0.4% for children aged 1-5 years (Levine and Ames, 2003). However, among ill children aged 0-15 years, the percentage of treated halved between 1997 and 1999 (Levine and Ames, 2003). Between 1997 and 1998, a substantial decline in overall use of health services emerged also for children under 5 and under 9 from the 100 Villages Survey data (Cameron, 2001) and the IFLS data (Frankenberg et al., 1999), respectively.

In particular, the use of public health services diminished, especially for poor and middle-income households (Frankenberg et al., 1999; Cameron, 2001), although this trend reversed in 1999 thanks to the dissemination of the Social Safety Net health card program (Cameron, 2001; Pradhan et al., 2007). The change in the usage of health services was likely driven by an unfavorable change in both prices and quality of public health services as well as a decrease in mothers' available time for child care as they tended to work more during the crisis and not by a decrease in private purchasing power (Levine and Ames, 2003; Frankenberg et al., 1999; Cameron, 2001).

With specific reference to nutritional status, the evidence is mixed. Between 1997 and 1998, the 100 Villages Survey data (Cameron, 2001) and the IFLS data (Frankenberg et al., 1999) do not show a deterioration in the nutritional status of children under 5 and under 9 years, respectively.[5] However, age-disaggregated data (Utomo, 2002) exhibit an increment in the proportion of underweight children between 6 and 24 months between 1996 and 1998.

To sum up, previous evidence suggests that investments in children decreased during 1998. However, while investments in education have been largely maintained, those in health seem to have been more affected by the crisis. Particularly, youngest children have suffered from a reduced use of health services and from a deterioration in nutritional status. Our paper examines whether these health-related deficiencies persisted and translated into a worse subsequent educational performance.

4.3. Theoretical Framework and Empirical Strategy

We consider investments in child health as a component of a life cycle dynamic programming problem solved by the family of a child, subject to the constraints imposed by both family and community resources to the child as he/she ages (for a formal statement, see Cunha et al., 2006). Once the family's optimization problem is solved, we obtain the following reduced-form equation, which relates a child's health H (proxied by height-for-age z-scores) to his/her later educational achievement E (measured by a binary indicator for primary school's grade failure):

$$E_{itj} = \beta_0 + \beta_1 H_{it-1} + \boldsymbol{\beta}_2 \boldsymbol{I}_{it} + \boldsymbol{\beta}_3 \boldsymbol{F}_{it} + \boldsymbol{\beta}_4 \boldsymbol{C}_{it} + \delta_j + \varepsilon_{itj} \quad (4.1)$$

where $\boldsymbol{I}_{it}$, $\boldsymbol{F}_{it}$, and $\boldsymbol{C}_{it}$ are vectors of individual, family, and community characteristics that influence the educational performance of an individual i at time t and δ_j are sub-district fixed effects, which control for unobserved characteristics that are constant across individuals within the same sub-district j (e.g. access to local government programs and unob-

5 In those years, there is however evidence of a deterioration in the body mass index of adults, indicating that parents might have protected the nutritional status of their children to their own detriment (Cameron, 2001).

served aspect of local environment).[6] Lastly, ε_{itj} is a disturbance term that encompasses an unobserved child-specific component (i.e. child's motivation for learning and innate ability), an unobserved home-invariant component (i.e. parental attitudes and tastes toward child health and education), and an idiosyncratic error term component.[7]

In estimating Equation (4.1), we face an endogeneity problem because in general the error term is correlated with our parameter of interest H_{it-1}. First, H_{it-1} and E_{itj} are both affected by parental preferences toward child health and education, which are reflected in the way in which parents allocate resources among their children once they realize their children's motivation for learning and innate ability (Glewwe et al., 2001). For instance, if parents have a preference toward children equality, they might decide to invest more in their less endowed children in order to equalize future earnings among their children (Yamauchi, 2008). Second, there may be other unobserved factors that correlate with both H_{it-1} and E_{itj}, thus leading to an omitted variable bias. Finally, H_{it-1} may be measured with errors. Therefore, the estimation of the Equation (4.1) via ordinary least squares (OLS) is likely to be biased downwards or upwards. For instance, the estimated impact of H_{it-1} would be downward biased if parents tried to equalize learning performances among their children, while it would be upward biased if they invested unfairly in their most endowed children (Glewwe et al., 2001).

According to Glewwe et al. (2001), the best way to address the endogeneity problem implied by our empirical model would be to combine maternal fixed effects, which wipe out the bias given by the correlation between H_{it-1} and the home-invariant part of the error term, with an instrumental variable strategy, which removes the correlation between

6 We use sub-districts of birth to minimize any potential selective migration bias, which would rise endogeneity problems in the sub-district variables. Yet, as shown in Table C1 in Appendix C, the results are essentially identical using sub-district of birth, sub-district in 2000, or sub-district in 2007 fixed effects. This is due to the fact that, in the considered period, there were no significant episodes of migration between sub-districts in our sample. One could be more precise by using, e.g., community fixed effect. However, we refrain from doing so, to avoid relying on too few degrees of freedom and producing unreliable estimates.

7 One could argue that E_{itj} might also be affected by the current child's health H_{it}, thus leading to a bias in the estimation of the effect of H_{it-1} on E_{itj} to the extent that H_{it-1} and H_{it} are correlated. However, based on the findings of previous research investigating the relation between health and education (see e.g. Glewwe et al., 2001), we assume that it is child health in early childhood that affects later educational performance of a child. Mani (2012), who also uses the IFLS data, supports this assumption by finding limited evidence of catch-up growth in Indonesia.

H_{it-1} and the remaining part of the error term. Since we cannot rely on maternal fixed effects because we do not observe enough pairs of siblings in the age range of our interest, we try to capture the home-invariant part of the error term by using maternal education as a proxy for family socioeconomic status and parents' attitudes toward children.[8] We then employ an instrumental variable approach identifying differences in height among children by using exposure in early years of life to the financial crisis that hit Indonesia in late 1997. In addition, we take advantage of the longitudinal nature of our data, which allows us to directly measure our main variable of interest, H_{it-1}, at one point in time during preschool age and thus avoid recall errors typical of retrospective variables in cross-sectional data (Wooldridge, 2002).

Given the binary nature of our dependent variable and our continuous endogenous measure of child health, we apply an instrumental variable Probit model (IV-Probit). We can therefore respecify our model as:

$$E^*_{itj} = \alpha H_{it-1} + \boldsymbol{\beta} \boldsymbol{x}_{itj} + u_{itj} \tag{4.2}$$

$$H_{it-1} = \boldsymbol{\Pi}_1 \boldsymbol{x}_{1itj} + \Pi_2 x_{2i} + \boldsymbol{v}_{itj} = \boldsymbol{\Pi} \boldsymbol{x} + \boldsymbol{v}_{itj} \tag{4.3}$$

$$E_{itj} = \begin{cases} 0 & if \quad E^*_{itj} < 0 \\ 1 & if \quad E^*_{itj} \geq 0. \end{cases} \tag{4.4}$$

Equation (4.2), along with Equation (4.4), is the structural equation and Equation (4.3) is a reduced form for H_{it-1}, which is endogenous if u_{itj} and $\boldsymbol{v}_{itj}$ are correlated. $\boldsymbol{x}_{1itj}$ is the vector of our exogenous variables (i.e. $\boldsymbol{I}_{it}$, $\boldsymbol{F}_{it}$, $\boldsymbol{C}_{it}$, δ_j), x_{2i} is our instrumental variable, α and $\boldsymbol{\beta}$ are structural parameters, and $\boldsymbol{\Pi}_1$ and Π_2 are a matrix and a vector of reduced-form parameters, respectively. By assumption, (u_{itj}, v_{itj}) has a zero mean, bivariate normal distribution, and is independent of the vector of observed exogenous factors $\boldsymbol{x}$.[9] Var(u_{itj}) is normalized to one to identify the model and thus give the parameters in Equation (4.2) an average partial effect interpretation (for further details, see Wooldridge, 2010). We esti-

8 We refrain from including also paternal education as it is highly correlated with maternal education.

9 If this assumption is violated, one could cluster standard errors to control for the lack of independence (Maddala, 1983).

mate Equations (4.2)-(4.4) by maximum likelihood estimation (MLE), using the `ivprobit` command in `Stata`.

4.4. Data

We use data from the Indonesian Family Life Survey (IFLS), which is an ongoing longitudinal survey that encompasses five waves conducted in 1993, 1997, 2000, 2007, and 2014 (also known as IFLS1, IFLS2, IFLS3, IFLS4, and IFLS5, respectively). The longitudinal nature and the timing of the IFLS data make them particularly suited to answer our empirical question, although they have also other attractive features. First, they provide a large bulk of information at the individual, household, and community level on several economic, social, and health aspects. Second, the IFLS data have a good geographic coverage, with the baseline including 13 of the 27 provinces of Indonesia that represent 83% of the population. Last, the IFLS data present exceptionally high re-contact rates compared to other longitudinal surveys in developing countries, thus diminishing the probability of incurring in a non-random attrition bias.[10]

We focus on preschool children up to 6 years[11] who lived in the IFLS communities during the 2000 survey wave (i.e. after the financial crisis) and for whom there were anthropometric, demographic, and socioeconomic information available (2,979 children).[12] We then tracked these children after seven years (i.e. in IFLS4) or after 14 years (i.e. in IFLS5) to retrieve information on their educational performance, thus remaining with a final sample of 2,855 children (for the assessment of a potential attrition bias, see Subsection 4.5.3).

[10] Of the initial 7,224 IFLS1 households (corresponding to 22,000 individuals), in the IFLS2 94.4% of the households were re-contacted, in the IFLS3 95.3%, in the IFLS4 93.5%, and in the IFLS5 92% (see Frankenberg et al., 1995; Frankenberg and Thomas, 2000; Strauss et al., 2004, 2009, 2016 for detailed information about IFLS1, IFLS2, IFLS3, IFLS4, and IFLS5, respectively.)

[11] In Indonesia, children start primary school at 6 or 7 years. Primary school lasts six years and it is followed by three years of junior secondary school and by three years of general or vocational senior secondary school (for more information on the Indonesian school system, see Suryadarma et al., 2006).

[12] We also take advantage of the IFLS waves prior to the 2000 wave, in order to recover missing information or information on household characteristics before the financial crisis.

4.4.1. Identifying Exposure to the Asian Financial Crisis

We define a child as being exposed to the financial crisis if he/she was in his/her second or third year of life between November, 1997 and December, 1998, thus during the most severe period of the crisis (1,442 children). Therefore, the control group are those children who are younger than one year or older than three years during the treatment period (1,413 children).

The choice of the treatment period is determined by previous research, which identifies the first three years of life (including pregnancy) as the 'critical period' in which a shock can significantly affect the subsequent development of a child. Yet, while previous studies (Hoddinott and Kinsey, 2001; Shrimpton et al., 2001) and our regression results (see Table C2 in Appendix C) show that child development is not sensitive to shocks occurred after the third year of life, there is no agreement on which period shocks affect child development the most within the first three years of life. Thus, we tested for different age ranges and detected that the financial crisis negatively affected child health in the second and third year of life (see Table C3 in Appendix C).

4.4.2. Variables and Descriptive Statistics

Our indicator of educational performance is a dummy variable that is equal to unity if a child ever failed a grade in primary school and zero otherwise. We choose to focus on grade failure instead of other outcomes used by the past literature (Lo Bue, 2019; Alderman et al., 2009; Yamauchi, 2008; Alderman et al., 2006, 2001b; Glewwe et al., 2001), either because they vary very little within our sample (as, e.g., in the case of age on starting school) or because we cannot control for the fact that they are age-dependent (as, e.g., in the case of grades attained or completed and test scores) given that our treatment status is based on age. In addition, we concentrate on educational achievements during elementary school to avoid the selection bias resulting from children not enrolled in school (in our sample, only 13 children never enrolled in primary school).[13]

[13] In Indonesia primary school marks the beginning of compulsory education, is free, and does not suffer from gender differences in attainment. Every village was provided with a primary school by the 1970's

Child health is proxied by height-for-age z-scores (HAZ) calculated according to the World Health Organization (WHO) 2006 growth standards (WHO, 2006). These standards are based on data from the WHO Multicentre Growth Reference Study (MGRS) undertaken between 1997 and 2003 in six different countries (Brazil, Ghana, India, Norway, Oman, and North America). The WHO (2006) growth standards provide the first single international standard that depicts how children should grow, provided they were properly fed (including via breastfeeding) and raised in optimal conditions.[14] Following the majority of the literature in this field, we focus on HAZ instead of weight-for-age z-scores (WAZ) or other available indicators of child health, because it reflects early childhood long-term investments in health and nutrition (WHO, 1997) that have been discovered to affect later educational achievements (see e.g. Alderman et al., 2006).

Beside the variable of interest, the main specification includes a number of exogenous characteristics that may influence the educational achievement of a child: his/her sex, birth order (as older children, who may have benefited from a better allocation of parental time and resources, may perform better in school than younger children, see De Haan, 2010; Sulloway, 2007) and ethnicity (as the ethnic groups' structural position may affect the child's learning environment and the ethnic groups' cultural orientation may or may not encourage his/her educational achievement, see Kao and Thompson, 2003), his/her mother's education (as it proxies the level of child care within the family), the student-teacher ratio at community level (as it measures quality of schooling), an indicator of whether the child lives in an urban area, and two morbidity indicators at the community level, i.e. whether the community has sewerage and piped water systems.

and the government's stated goal of universal primary school education was reached in the mid-1980's (Cameron, 2001). In contrast, secondary school enrollment remains low because of, for instance, inadequate economic resources, gender, and lack of availability of secondary school (Suryadarma et al., 2006).

14 Growth standards differ from growth references because they are prescriptive, i.e. they define how children in optimal health and nutrition conditions should grow, instead of being descriptive, i.e. of simply illustrating how children grew in a specific time and place. Although growth references offer a basis for comparison, they are not norms, thus departures from the pattern they describe do not necessarily indicate a non-normal growth (De Onis et al., 2007). In addition, according to the WHO, growth references need to be updated every decade. Before developing the WHO (2006) growth standards, the WHO recommended the use the 2000 Clinical Growth Charts (CDC) growth references. However, the latter are only based on one country (the United States) and lead to higher expected standard deviation in HAZ compared to the WHO 2006 charts (De Onis et al., 2007).

Table 4.1 shows that almost 13% of our sample failed at least a grade during primary school. On average, our sample has also lower height compared to the MGRS sample of properly grown children: given sex and age, child height is -1.67 standard deviations below the reference median value. Concerning the children exposed to the crisis, we note that on average they are shorter and more prone to grade failure than non-exposed children. Moreover, stunted children (i.e. children with an HAZ less than -2) perform on average worse in primary school than non-stunted children: the 15.9% of stunted children fail at least one grade during primary school, while only 10.3% of non-stunted children do so (the difference of 5.5 percentage point is significant at the 1% level). Child health and later educational achievement appear therefore to be correlated.

Table 4.1.: Summary Statistics for the Overall Sample and by Treatment Status

	All		Non-Treated (NT)		Treated (T)		NT-T
	Mean	St. Dev.	Mean	St. Dev.	Treated	St. Dev.	
A. Outcome							
Grade failure	0.127	–	0.086	–	0.167	–	-0.081***
B. Control variables							
HAZ (in 2000)	-1.666	1.529	-1.484	1.756	-1.843	1.244	0.359***
% of stunted (HAZ < -2)	0.431	–	0.401	–	0.460	–	-0.059***
Male	0.527	–	0.556	–	0.498	–	0.058***
Birth order	2.230	1.442	2.190	1.428	2.268	1.456	-0.078
Javanese	0.381	–	0.377	–	0.386	–	-0.009
Sundanese	0.138	–	0.135	–	0.141	–	-0.006
Other ethnicity	0.481	–	0.488	–	0.474	–	0.015
Mother's education	7.330	4.334	7.512	4.298	7.152	4.363	0.360**
Age on starting school	6.250	0.732	6.255	0.723	6.246	0.741	0.009
Private school	0.143	–	0.125	–	0.160	–	-0.035***
Distance (min) to school	14.058	55.014	11.503	10.886	16.543	76.441	-5.040**
Household size	5.224	1.732	5.163	1.703	5.284	1.758	-0.120*
Log of real PCE	12.600	0.632	12.584	0.617	12.615	0.646	-0.032
Log of real PCE (in 1997)	12.173	0.720	12.242	0.755	12.119	0.688	0.123***
Student-teacher ratio	16.254	4.713	16.206	4.686	16.301	4.740	-0.095
Urban community	0.501	–	0.504	–	0.497	–	0.007
Village has sewerage	0.632	–	0.631	–	0.632	–	-0.002
Village has piped water	0.585	–	0.587	–	0.583	–	0.003

*Notes: The significance levels of the mean differences were calculated using a two-sided t-test. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Instead, we only observe small differences in the other covariates used in the main analysis or in the robustness checks: compared to non-exposed children, exposed children are more often females, their mothers are slightly less educated, they go more often to private schools, travel few minutes longer to go to school, have a somewhat larger household size, and a slightly lower per capita expenditures in 1997. The following section investigates the nature of the relationship between child health and subsequent educational performance, assessing wether causality can be claimed.

4.5. Results

4.5.1. Instrument validity

Before we start with the analysis of child health on later educational performance, we check the validity of our instrument, which basically consists in the fulfillment of two conditions. First, our instrument has to be relevant, i.e. sufficiently correlated with our endogenous indicator of child health. Second, it has to be exogenous, i.e. correlated with a child's subsequent educational performance only through its correlation with child health.

Our instrument consists of the shock derived from the exposure in early years of life to the Asian financial crisis that hit Indonesia in late 1997. As seen in Section 4.2, during the most severe period of the crisis, children have suffered from a reduced use of health services and a deterioration in nutritional status. This could have in turn negatively affected children's health. The crisis had also a negative effect on adults' nutritional status and mothers' available time for child care as the latter worked more during the crisis. Consequently, this could have been translated into a decrease in child health, due to transitory reductions in child care or health shocks resulting from absent or unhealthy parents.

Table 4.2 illustrates the first stage estimate of the effect of the exposure to the Asian financial crisis on child health as measured by HAZ. It corroborates the result of Table 4.1, showing that exposed children are significantly shorter than non-exposed ones: on average, they experience a reduction of 35.7% of a standard deviation in HAZ. It bears noting that this result is lower compared to the one of Lo Bue (2019), who finds a 90% reduction of a standard deviation in HAZ in children aged 1-3 years exposed to wildfires, and the one of Alderman et al. (2006), who detect a 73% reduction of a standard deviation in HAZ in children who experienced the drought between the first and the third year of life. The relevance of our instrument is further confirmed by a F statistic of 41.03, which is far above the recommended threshold for a strong instrument (Staiger and Stock, 1997).

Table 4.2.: Exposure to the Asian Financial Crisis and Child Health: First Stage Estimate

	Coeff.	Std. Err.
Exposure to the crisis	-0.357***	(0.108)
Male	-0.107*	(0.058)
Birth order	-0.026	(0.021)
Sundanese	-0.136	(0.097)
Other ethnicity	-0.251***	(0.061)
Mother's education	0.049***	(0.008)
Student-teacher ratio	0.021***	(0.007)
Urban community	0.310***	(0.069)
Village has sewerage	-0.131*	(0.078)
Village has piped water	0.017	(0.077)
Constant	-2.064***	(0.182)
SD-FE	Yes	
No. of observations	2,855	
No. of SD-FE	21	
Kleinbergen-Paap F statistic	41.03***	

*Notes: SD-FE = Sub-District Fixed Effects. Standard errors are clustered at the year-month of birth level and are reported in parentheses. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Turning to the second requirement for instrument validity, there are mainly two situations in which the exclusion restriction could be questioned in our case. On the one hand, the crisis could have reduced school quality and availability. On the other hand, it could have decreased household economic resources and thus education expenditures.

Regarding the first aspect, although during the most severe period of the crisis schools did not close, their income was affected by inflation (Hartono and Ehrmann, 2001). Yet, ad-hoc government spending on education helped in filling this funding gap, thus maintaining school quality and avoiding an increase in school fees (Hartono and Ehrmann, 2001).

With respect to the second point, instead, between 1997 and 1998 Thomas et al. (2004) document a reduction in both households' real education expenditures and share of education expenditures. This was the case especially among poor households that tried to protect the investments in the education of older children (15-19 years) compared to the one of younger siblings (10-14 years). However, the biggest cut was made on expenditures for school uniforms and, as described in Section 4.2, these reductions do not seem to have significantly affected education indicators.

More generally, we identify children that were exposed to the crisis in their earliest years of life and who attended school many years later. Thus, they are likely to not have experienced the effect of the aforementioned mechanisms (especially at the primary school level). Given all these considerations, we proceed in presenting the empirical findings of our IV analysis.

4.5.2. Empirical Results

Table 4.3 reports the OLS and the two-stage least squares (2SLS) estimates of Equation (4.1) along with the results of our preferred IV-Probit model. The OLS and the 2SLS estimates provide interesting comparisons as they give insights into both the direction and the extent of the endogeneity bias and the strength of our relation of interest, respectively.

Table 4.3.: Child Height and Later Educational Performance: OLS, 2SLS, and IV-Probit Estimates

	OLS		2SLS		IV-Probit	
	Coeff.	Std. Err.	Coeff.	Std. Err.	AME	Std. Err.
HAZ (in 2000)	-0.008*	(0.004)	-0.233***	(0.065)	-0.169***	(0.015)
Male	0.063***	(0.012)	0.043**	(0.017)	0.031**	(0.015)
Birth order	0.000	(0.004)	-0.006	(0.006)	-0.005	(0.004)
Sundanese	-0.066***	(0.016)	-0.095***	(0.028)	-0.073***	(0.017)
Other ethnicity	0.003	(0.013)	-0.051*	(0.028)	-0.035**	(0.015)
Mother's education	-0.012***	(0.002)	-0.000	(0.004)	-0.000	(0.003)
Student-teacher ratio	0.004***	(0.001)	0.009***	(0.002)	0.006***	(0.001)
Urban community	-0.020	(0.016)	0.049*	(0.028)	0.036**	(0.016)
Village has sewerage	0.018	(0.017)	-0.011	(0.024)	-0.009	(0.017)
Village has piped water	-0.000	(0.017)	0.003	(0.025)	0.004	(0.017)
Constant	0.179***	(0.035)	-0.327**	(0.156)	–	–
SD-FE	Yes		Yes		Yes	
No. of observations	2,855		2,855		2,855	
No. of SD-FE	21		21		21	
Hausman test	–		27.784***		–	
Wald test	–		–		33.41***	

*Notes: SD-FE = Sub-District Fixed Effects and AME = Average Marginal Effects. Standard errors are clustered at the year-month of birth level and are reported in parentheses. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Focusing on the role of child health on later educational achievement, we observe that the OLS coefficient is significant only at the 10% level and almost nil. In contrast, the 2SLS estimate is highly significant and substantially larger in magnitude: a one standard deviation increase in HAZ leads to a 23.3 percentage points reduction in the likelihood to fail at least one grade in primary school. Consistently with other studies on this topic (see e.g. Glewwe et al., 2001; Alderman et al., 2006), controlling for the endogeneity bias implied by our model leads to a substantially larger effect of child health on schooling performance, indicating a downward bias in the OLS estimate. As discussed in Section 4.3, the latter can be in part ascribed to the correlation between child health and the child-specific component of the error term and in part to measurement error bias.

Yet, although the 2SLS model might provide a good approximation of the average effect of child health on education (Wooldridge, 2010), it fails to consider the binary nature of our dependent variable. This leads to three main issues: i) predicted probabilities can be negative or larger than one; ii) a unit change in a regressor can lead to a change in probability larger than one; and iii) a unit change in a regressor has a constant effect.

The average marginal effect (AME) of child health on education resulting from the IV-Probit model is somewhat smaller in magnitude compared to the AME appoximated by the 2SLS model: a one standard deviation increase in HAZ leads to a 16.9 percentage points reduction in the likelihood to fail at least a grade in primary school.

Regarding the other covariates, we observe that the likelihood of failing at least one grade during primary school is higher among males, in schools with higher student-teacher ratios, and in urban communities, while it is lower among Sundanese and children of other ethnicity compared to Javanese.[15] The fact that males are more likely to have worse educational achievements than females is consistent with previous evidences (Lo Bue, 2019; Bank, 2006) and it may partially be related to higher returns to schooling of females compared to males (Deolalikar, 1993).

[15] IV-Probit coefficients are reported in Table C4 in Appendix C.

4.5.3. Robustness Checks

Our preferred IV-Probit estimate indicates a negative causal relation between poor child health and subsequent educational performance. In this sub-section, we consider potential concerns about this result that might put its robustness into question.

As many scholars have warned against attrition bias in using longitudinal data, we first verify that our study does not suffer from any sample attrition bias that can rise because of deaths, incomplete information on key variables, or the process of cross-checking information across waves. Following the method proposed by Fitzgerald et al. (1998) and Alderman et al. (2001a), we estimate a linear probability model where the outcome variable is equal to one if our measure of educational performance is not observed in IFLS4 or IFLS5 and zero otherwise (Table C5 in Appendix C). In the specification, we include the same control variables used in the main analysis. We find that a child is less likely to be observed if he/she has a higher birth order, is of an ethnicity other than Sundanese with respect to be Javanese, and his/her mother has a higher education. Yet, the coefficients of the latter are almost nil, thus we are relieved from any concern about attrition bias based on observables.

Another concern might be that our estimates do not just capture the impact of the Indonesian financial crisis, but also the effect of the wildfires that affected part of the country before the start of the crisis. Specifically, the Indonesian wildfires heavily spread in Sumatra and Kalimantan in early September 1997, when fires were commonly used by small farmers to clean land before planting new crops went out of control due to the drought created by El Niño Southern Oscillation (Lo Bue, 2019). The wildfires only extinguished in November 1997.[16] Lo Bue (2019) analyzes the effect of the drought, wildfires, and associated smoke/haze on height-for-age of very young children and, through this effect, their lasting consequences on cognitive and educational outcomes. By defining a child as exposed to the shock if he/she was living in Sumatra or Kalimantan and was aged 12 to

[16] According to Gellert (1998), in early 1998, the wildfires restarted in East Kalimantan, where they lasted until April 1998. However, these fires were not a source of concern like those of 1997 because they concerned a small and low populated region mainly composed of forests rather than crops.

36 months when the forest fires began (i.e. on 5 September 1997), this author finds that child health has a positive impact on both the readiness to enter school and the number of completed grades of schooling.

We therefore assess whether our results are driven by the occurrence of the wildfires by using the shock deriving from the exposure in early years of life to the Indonesian wildfires as instrument instead of the Indonesian financial crisis. Table C6 in Appendix C shows the first stage estimates of alternative exposures to the Indonesian wildfires on child health: Column (1) illustrates the estimates when we define exposure as in Lo Bue (2019), while Column (2) presents the results when we define as exposed all the children living in Sumatra or Kalimantan in 1997 (thus all the children under the age of 3).

In both cases, we do not find any significant relationship between the wildfires' exposure and the child health of the sampled children. In addition, the F statistics are almost nil, thus revealing the weakness of both instruments. These results can be due to the fact that the wildfires' damage consisted mainly in burning of wild forests and in the associated smoke/haze (Dauvergne, 1998). Therefore, the wildfires did not severely affected primary sources of nutrition, for example. We also notice that Lo Bue (2019) applies an instrumental variable-mother-fixed-effects estimator on an average sample of 374 observations and 177 fixed effects. In any case, we detect that our estimates only capture the effect of the Indonesian financial crisis.

Last, in Table C7 in Appendix C, we address the robustness of our results to the inclusion of additional covariates, which we choose not to include in the main analysis because they are likely to be endogenous (they may depend on parental preferences toward child health and education). In Columns (1)-(4), we add the age on starting school as children who start school later tend to perform better in school (McEwan and Shapiro, 2008; Bedard and Dhuey, 2006), the type of school as children are more prone to repeat school years in public schools than private schools (Jones and Hagul, 2001), the household size as children from larger families may have lower educational levels (Li et al., 2008), and the per capita expenditures (PCE), which approximate household income as children from poorer families tend to have worse educational outcomes (Akee et al., 2010; Blanden and Gregg, 2004).

Concerning income, some scholars suggest that child educational outcomes are explained by permanent family characteristics, such as permanent income levels rather than by current parental income (Chevalier et al., 2013; Carneiro and Heckman, 2004; Cameron and Heckman, 1998). This is because both cognitive and non-cognitive skills are formed early in the life cycle and these skills beget future skills (Carneiro and Heckman, 2004). We support this claim by finding no relationship between current PCE and children's educational performance. Of all the covariates added the only characteristics that exert a significant and negative influence on child's likelihood of repeating a grade are age on starting school and attending a private school. The estimated effect of child health on later educational performance, however, remains nearly the same as the effect estimated in the main analysis. In an alternative specification (Column (5)), we replace current PCE with its pre-crisis level (i.e. in 1997) to test whether the effect of child health on education attributed to the Indonesian financial crisis is driven by household poverty, but we cannot support this hypothesis.

4.6. Conclusion

Previous research has shown that child health is key for later educational outcomes, identifying the fetal period and the first three years of life as the 'critical period' in which the occurrence of a shock significantly affects child development. However, whether there is a causal link between child health and later educational achievement and what is the period that affects child development the most within the so called 'critical period' remain open questions.

Using longitudinal data from Indonesia, this paper contributes to the literature by testing the effect of early childhood health (proxied by height-for-age z-scores) on subsequent educational performance (measured by grade failure) and by shedding light on the period that matters most for child development. We account for the endogeneity of child health by performing an instrumental variable analysis where height differentials among children are identified by using exposure in early years of life to the Asian financial crisis that hit

Indonesia in late 1997. Moreover, we show the effect that an event, such as a financial crisis, can have on child development. Lastly, we add to the literature on the Indonesian crisis by investigating its long-term and indirect effect (rather than its short-term and direct impact) on education.

Our results show that poor health conditions in childhood exert a significant positive effect on the likelihood to fail at least a grade in primary school. From a policy perspective, it is therefore important to consider child health and education as cooperative aims rather than competing goals. This would enhance cost-effectiveness of interventions designed to improve these two important aspects of human capital, especially in those countries that struggle to meet the Sustainable Development Goal and that often operate in contexts of economic hardships. Yet, this policy implication is not only important in countries that still need to work toward stable development paths (as in the case of Indonesia, although it has grown significantly in recent years). It is also relevant for all those countries that, in periods of economic downturn, struggle in allocating economic resources to health and education. This means, for instance, that during periods of economic recession, also developed countries could devote economic resources to protect children's health or nutritional status (especially of the poor) without competing with resources devoted for education. Instead, our results imply that this would help these countries to protect their socio-economic development in a more cost-effective way.

By using a previously unexplored exogenous shock, our results also corroborate previous evidence showing that exposure to shocks during early childhood exert a lasting effects on individuals, regardless of any remedy taken to alleviate the impact of the shock (see e.g. Currie and Almond, 2011). Specifically, they provide evidence of a lasting effect of the Indonesian financial crisis on education.

Last, we find that the health conditions that are most critical for child development are those of the second and third year of life. This finding is in line with the results of (Alderman et al., 2006; Glewwe and King, 2001; Lo Bue, 2019), who do not find any strong support for the 'fetal-origin' hypothesis, nor for the fact that health conditions in the first year of life have a lasting impact on educational outcomes. Nonetheless, our study cannot rule out with certainty the hypothesis that health conditions during pregnancy and the first year of life are important in shaping the educational achievements of a child. Indeed, this lack of evidence may also be due to sample size or measurement issues. To corroborate our results, future research could therefore deepen further the topic, e.g. by exploiting different contexts and shocks.

In addition, given that our findings are only based on between-age variation, some caution has to be paid. Indeed, the financial crisis could have heterogeneously affected different regions of Indonesia. We only estimate an average impact across various intensities of the crisis, thus assuming that the crisis was already great enough to alter the health of a child. To better investigate the effect that a financial crisis can have on child development, future research could try to exploit contexts with regional variations in exposure to a crisis. Finally, although our data set is exceptionally large and longitudinal, it would be important to use a data set that allows to account for parental attitudes and tastes toward child health and education (Alderman et al., 2001b).

5. Conclusions

This thesis is a compendium of three empirical studies that contribute to the understanding of drivers and consequences of health inequalities among different groups of individuals in Italy (i.e. natives and immigrants / men and women) and Indonesia (i.e. healthy and unhealthy children). Such information can be used by policy makers to address health differences and their consequences in these countries and consequently reduce costs associated with them. Moreover, this thesis also adds to the previous literature from a methodological point of view. Chapters 2 and 3 propose a new approach that goes 'beyond the mean' to analyze the 'healthy immigrant effect' (HIE) and the influence of economic downturns on health, while Chapter 4 uses a previously unexplored exogenous shock to enrich our understanding of the effect of different health conditions on educational outcomes. In the following, we summarize the main findings of these studies, discuss their policy implications, and make suggestions for future research.

In Chapter 2, we analyze the HIE and its evolution over time, by looking at physical and mental health differences between Italians and immigrants as well as between short- and long-term immigrants. By coupling quantile regression and decomposition techniques, we move beyond the consideration of mean impacts, thus taking a novel empirical approach compared to the previous literature. From a policy perspective, understanding the drivers of health inequalities across the entire distribution is crucial as gaps in health conditions at the tails of the health distribution imply very different consequences in terms of health care costs compared to gaps at the mean.

Our findings support the need to go 'beyond the mean' in analyzing the HIE. We detect a HIE for both physical and mental health, which seems to shrink over time, especially at the lower tail of the health distributions. The lower health conditions exhibited by long-term immigrants compared to short-stay immigrants are mainly due to the elasticity effect. Its predominance suggests using either health or social policies to prevent any deterioration in health conditions of immigrants. However, our detailed decomposition results reveal that observed characteristics (such as age, gender and occupation) are generally associated with better health conditions for long-stay immigrants compared to short-stay immigrants. Instead, what leads long-term immigrants to have lower health levels is the negative elasticity effect of some unobserved characteristics. This finding is not consistent with explanations of immigrants' health deterioration over time based on the type of occupation, 'negative acculturation', or selection effects. The only explanation for the deterioration of immigrants' health over time that is compatible with our findings is related to difficulties in accessing the health care system (lack of knowledge, linguistic barriers, discrimination, etc.). Consequently, we advocate for policies that improve immigrants' access to health care services, such as increasing health literacy. In addition, given that health differences are particularly pronounced at the bottom of the health distributions, policy interventions should be tailored to immigrants with poor health conditions. Our results also underline the importance of improving the data collection on health determinants to identify the determinants of the unobserved component.

Chapter 3 analyzes the contribution of demographic and socioeconomic characteristics to changes in the distribution of mental health across genders during the Great Recession in Italy, by using unconditional quantile regressions in combination with Oaxaca-Blinder decompositions. Our results suggest that the Great Recession had a negative bearing on the mental health conditions of both men and women. Health differences are notably larger at the lower tail of the health distributions for men and at the median for women, highlighting the added value of using quantile regression techniques for the analysis of the influence of economic crises on mental health.

As we find that changes in mental health of both genders are due to changes in both the elasticity and composition effects, policy makers are encouraged to opt for a mix of mental health policies and labor market policies. Yet, given that our results are heterogeneous across both gender and the health distributions, these policies should be designed differently for men and women and tailored to groups of individuals with specific health conditions. Regarding men, it would be important to implement policies that increase both income and the supply of permanent full-time jobs. Instead, concerning women, we call for policies that enhance their employment situation. Concerning instead the gender gap in mental health, the economic crisis does not seem to have influenced its main determinants. To reduce this gap, it seems advisable to improve women's access to typical jobs through both employment and health policies. Last, as in Chapter 3, our results advocate for a better data collection on mental health determinants in order to uncover what are the hidden drivers behind the unobserved components.

Chapter 4 investigates the effect of early childhood health on later educational performance by using longitudinal data from Indonesia and accounting for the endogeneity of child health by instrumenting it with early life exposure to the Asian financial crisis that hit Indonesia in late 1997. Our analysis shows that poor health conditions during childhood have a positive bearing on the likelihood to fail at least one grade in primary school. From a policy perspective, it is therefore important to consider child health and education as cooperative aims rather than competing goals. This would enhance the cost-effectiveness of interventions designed to improve these two important aspects of human capital, especially in those countries that struggle to meet the Sustainable Development Goals and that often operate in contexts of economic hardships. Our results also reveal that the health conditions that are most critical for later educational performance are those of the second and third year of life.

As Sen (2002) emphasizes, health inequalities are among the most worrying types of contemporaneous inequalities. Tackling them is thus one of the most important endeavors of humanity. This thesis addresses health inequalities by investigating its determinants and consequences in relation to groups of individuals of particular interest. Yet, some challenges remain for future research.

Chapters 2 and 3 provide distributional analyses that impede to interpret the findings in a causal way or generalize them. Instead, they rather indicate the set of policies that could be implemented to alleviate health inequalities between natives and immigrants as well as men and women, respectively. For each of the suggested policies, further research is needed to identify specific causal mechanisms on which to operate.

Although Chapter 4 exploits exogenous variation induced by the financial crisis that hit Indonesia, it does not inform on possible heterogeneous effects that an economic crisis can have on different regions of a country. To better understand the link between health and educational performance, future research could try to exploit contexts that entail significant regional variations in exposure to a crisis. In addition, our study cannot indisputably conclude that health conditions during pregnancy and the first year of life are not important in shaping later educational achievements. Indeed, this lack of evidence may also be due to sample size or measurement issues. To corroborate our results, future research could deepen further the topic, e.g. by exploiting different contexts and shocks.

All our results point to the direction that even though health inequalities are a big challenge for mankind, we still lack the data to analyze them appropriately. We observe that notable shares of the health inequalities between immigrants and natives are due to unobservables, which emphasizes the need to collect data on further factors that might explain health inequalities between these groups, such as linguistic barriers and discrimination. Moreover, to causally identify the impact of economic downturns on health, longitudinal data are required that allow to control for unobserved heterogeneity. Last, to gather a more complete understanding of the relationship between children's health and their educational performance, it is important to gather data on parental attitudes toward health and education.

On a more general level, this thesis shows the importance of analyzing relationships by going beyond the mean effects. This enables us to find heterogeneous effects for different groups of the study population. Therefore, we would like to encourage researchers to resort quantile regression techniques and analyze heterogeneous effects.

A. Appendix to Chapter 2

Table A1.: Summary Statistics – Explanatory Variables

	Natives (N)	Short-stay Immigrants (I_s)	Long-stay Immigrants (I_l)	N-I_s	N-I_l	I_l-I_s
F (14-17)	0.022	0.050	0.022	-0.028**	0.000	-0.028**
F (18-34)	0.098	0.293	0.190	-0.195***	-0.092***	-0.103***
F (35-44)	0.085	0.120	0.158	-0.035**	-0.074***	0.038**
F (45-54)	0.089	0.065	0.098	0.024**	-0.009**	0.033***
F (55-64)	0.077	0.034	0.046	0.044***	0.031***	0.012
F (65-74)	0.069	0.014	0.013	0.055***	0.056***	-0.001
F (75+)	0.079	0.000	0.009	0.079***	0.071***	0.009***
M (14-17)	0.022	0.031	0.023	-0.009	-0.001	-0.008
M (18-34)	0.103	0.256	0.164	-0.152***	-0.061***	-0.092***
M (35-44)	0.084	0.083	0.156	0.002	-0.072***	0.073***
M (45-54)	0.085	0.042	0.077	0.043***	0.008*	0.035***
M (55-64)	0.076	0.008	0.033	0.068***	0.043***	0.025***
M (65-74)	0.061	0.002	0.008	0.059***	0.053***	0.006**
M (75+)	0.050	0.003	0.004	0.047***	0.046***	0.001
High Education	0.123	0.078	0.107	0.045***	0.016***	0.029**
Middle Education	0.353	0.336	0.404	0.018	-0.051***	0.069***
Low Education	0.523	0.586	0.488	-0.063**	0.035***	-0.098***
White Collar Job	0.175	0.013	0.038	0.162***	0.137***	0.025***
Blue Collar Job	0.126	0.387	0.442	-0.260***	-0.315***	0.055**
Self Employed	0.111	0.089	0.095	0.021	0.016***	0.006
Unemployed	0.095	0.193	0.168	-0.098***	-0.073***	-0.025
Not Participating	0.493	0.318	0.257	0.175***	0.236***	-0.061**
Single	0.181	0.367	0.235	-0.186***	-0.054***	-0.132***
Childless Couple	0.211	0.162	0.126	0.050**	0.085***	-0.036*
Couple with Child(ren)	0.509	0.378	0.560	0.130***	-0.052***	0.182***
Single Father	0.019	0.040	0.015	-0.021	0.003	-0.024*
Single Mother	0.080	0.054	0.064	0.027**	0.017***	0.010
Excellent Wealth	0.019	0.016	0.013	0.004	0.007***	-0.003
Appropriate Wealth	0.606	0.293	0.366	0.313***	0.240***	0.073***
Poor Wealth	0.316	0.570	0.485	-0.254***	-0.169***	-0.085***
Abs. Inadequate Wealth	0.059	0.122	0.137	-0.063***	-0.078***	0.015
Housing Wealth Index	0.186	-1.039	-0.930	1.225***	1.116***	0.109
Habitual Smoker	0.190	0.183	0.197	0.007	-0.007	0.014
Occasional Smoker	0.019	0.017	0.023	0.002	-0.003	0.005
Non Smoker	0.791	0.800	0.780	-0.009	0.010	-0.020
North West	0.260	0.322	0.340	-0.062**	-0.080***	0.019
North East	0.186	0.238	0.264	-0.052**	-0.077***	0.026
Centre	0.194	0.255	0.254	-0.060**	-0.060***	-0.000
South	0.242	0.148	0.102	0.095***	0.141***	-0.046**
Islands	0.117	0.038	0.040	0.079***	0.077***	0.002
Very Small City	0.293	0.261	0.259	0.032	0.035***	-0.002
Small City	0.271	0.292	0.252	-0.021	0.019*	-0.039
Medium City	0.170	0.227	0.189	-0.057**	-0.019**	-0.037
Large City	0.266	0.221	0.300	0.045*	-0.034***	0.079***
EU	–	0.288	0.306	–	–	0.019
Europe Non-EU	–	0.229	0.256	–	–	0.026
Africa	–	0.198	0.196	–	–	-0.001
West Asia	–	0.116	0.081	–	–	-0.035*
East Asia	–	0.095	0.065	–	–	-0.030
America	–	0.075	0.096	–	–	0.021

*Notes: Numbers are weighted. The significance levels of the mean differences were calculated using a two-sided t-test. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table A2.: Determinants of the Physical Component Summary for Natives, OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
F (14-17)	2.106***	(0.143)	5.329***	(0.345)	5.520***	(0.424)	0.850***	(0.117)	0.412***	(0.099)	0.270	(0.182)
F (18-34)	-0.214**	(0.090)	0.581***	(0.209)	-0.598**	(0.283)	-0.456***	(0.067)	-0.334***	(0.057)	0.102	(0.105)
F (35-44)	-1.791***	(0.106)	-1.246***	(0.269)	-4.005***	(0.337)	-1.544***	(0.077)	-1.174***	(0.058)	-0.521***	(0.103)
F (45-54)	-3.281***	(0.114)	-2.908***	(0.327)	-7.644***	(0.366)	-2.682***	(0.076)	-1.770***	(0.054)	-1.075***	(0.094)
F (55-64)	-5.534***	(0.140)	-7.061***	(0.457)	-14.372***	(0.461)	-3.827***	(0.083)	-2.289***	(0.055)	-1.597***	(0.096)
F (65-74)	-8.748***	(0.175)	-15.241***	(0.670)	-22.752***	(0.544)	-5.051***	(0.089)	-2.687***	(0.058)	-1.899***	(0.100)
F (75+)	-16.652***	(0.187)	-44.645***	(0.831)	-42.267***	(0.523)	-6.611***	(0.081)	-3.075***	(0.057)	-2.353***	(0.098)
M (14-17)	2.138***	(0.145)	5.173***	(0.407)	5.419***	(0.429)	0.985***	(0.106)	0.652***	(0.095)	0.042	(0.172)
M (35-44)	-1.380***	(0.104)	-1.990***	(0.269)	-2.850***	(0.333)	-0.998***	(0.077)	-0.871***	(0.060)	-0.449***	(0.104)
M (45-54)	-2.433***	(0.107)	-2.621***	(0.290)	-5.517***	(0.349)	-1.894***	(0.077)	-1.454***	(0.057)	-0.832***	(0.099)
M (55-64)	-4.148***	(0.127)	-4.763***	(0.390)	-9.373***	(0.412)	-3.052***	(0.082)	-2.087***	(0.055)	-1.401***	(0.095)
M (65-74)	-6.397***	(0.164)	-9.315***	(0.587)	-15.603***	(0.526)	-4.325***	(0.092)	-2.627***	(0.058)	-2.037***	(0.096)
M (75+)	-12.403***	(0.212)	-28.238***	(0.882)	-31.614***	(0.623)	-5.874***	(0.092)	-2.930***	(0.058)	-2.178***	(0.099)
High Education	1.059***	(0.100)	2.221***	(0.315)	2.857***	(0.324)	0.540***	(0.065)	0.169***	(0.043)	0.155**	(0.073)
Middle Education	0.984***	(0.074)	2.083***	(0.253)	2.568***	(0.238)	0.490***	(0.044)	0.156***	(0.028)	0.166***	(0.048)
White Collar Job	-0.002	(0.096)	-1.872***	(0.259)	-0.719**	(0.327)	0.469***	(0.069)	0.261***	(0.046)	0.359***	(0.077)
Self Employed	0.473***	(0.099)	-0.327	(0.256)	0.622*	(0.335)	0.443***	(0.072)	0.377***	(0.048)	0.686***	(0.082)
Unemployed	0.654***	(0.112)	0.756**	(0.309)	0.557	(0.366)	0.450***	(0.075)	0.550***	(0.053)	1.053***	(0.093)
Not Participating	-0.848***	(0.101)	-4.312***	(0.308)	-2.661***	(0.332)	0.039	(0.065)	0.252***	(0.043)	0.420***	(0.071)
Single	-1.224***	(0.116)	-4.158***	(0.445)	-3.171***	(0.352)	-0.353***	(0.061)	-0.049	(0.039)	-0.056	(0.065)
Childless Couple	-0.417***	(0.102)	-0.356	(0.368)	-1.260***	(0.322)	-0.280***	(0.056)	-0.159***	(0.032)	-0.056	(0.054)
Single Father	-0.609***	(0.205)	-1.915***	(0.690)	-2.164***	(0.651)	-0.124	(0.129)	0.048	(0.098)	-0.147	(0.153)
Single Mother	-0.535***	(0.115)	-2.554***	(0.405)	-1.473***	(0.344)	-0.075	(0.066)	0.071	(0.046)	0.400***	(0.087)
Excellent Wealth	0.941***	(0.209)	2.389***	(0.651)	2.108***	(0.669)	0.535***	(0.129)	0.389***	(0.095)	0.136	(0.151)
Poor Wealth	-1.462***	(0.074)	-3.917***	(0.276)	-4.505***	(0.227)	-0.531***	(0.040)	-0.006	(0.026)	0.255***	(0.044)
Abs. Inadequate Wealth	-2.213***	(0.167)	-7.141***	(0.602)	-6.890***	(0.482)	-0.716***	(0.082)	0.077	(0.054)	0.752***	(0.098)
Housing Wealth Index	0.328***	(0.032)	1.147***	(0.125)	0.759***	(0.096)	0.081***	(0.016)	0.015	(0.010)	0.036**	(0.017)
Habitual Smoker	0.425***	(0.074)	1.310***	(0.241)	0.847***	(0.234)	0.001	(0.045)	0.071**	(0.030)	0.412***	(0.055)
Occasional Smoker	0.371**	(0.169)	1.097**	(0.501)	0.811	(0.558)	0.055	(0.118)	-0.008	(0.085)	0.386**	(0.151)
North West	0.858***	(0.092)	3.114***	(0.332)	2.092***	(0.282)	0.195***	(0.052)	-0.147***	(0.034)	0.144**	(0.057)
North East	0.493***	(0.093)	1.984***	(0.333)	1.045***	(0.284)	0.137***	(0.052)	-0.101***	(0.034)	0.281***	(0.056)
Centre	0.361***	(0.095)	1.468***	(0.346)	1.038***	(0.294)	0.072	(0.054)	-0.097***	(0.035)	0.068	(0.060)
Islands	-0.008	(0.104)	-0.363	(0.378)	0.027	(0.312)	0.163***	(0.057)	0.052	(0.040)	0.047	(0.066)
Small City	0.402***	(0.081)	0.729**	(0.290)	0.857***	(0.248)	0.250***	(0.045)	0.149***	(0.029)	0.183***	(0.049)
Medium City	0.741***	(0.091)	1.926***	(0.327)	1.794***	(0.278)	0.346***	(0.051)	0.191***	(0.033)	0.086	(0.055)
Large City	0.675***	(0.088)	1.835***	(0.316)	1.782***	(0.271)	0.224***	(0.050)	0.159***	(0.032)	0.134**	(0.055)
Constant	54.669***	(0.128)	43.750***	(0.409)	59.651***	(0.405)	57.550***	(0.083)	58.326***	(0.060)	58.136***	(0.099)
No. of observations	96,778											

*Notes: Sample weights applied. Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively. Reference group is a male individual aged 18-34, having low education and a blue-collar job, living in a household in which lives a couple with child(ren), having appropriate wealth, not smoking, and living in a very small city in the South.*

Table A3.: Determinants of the Physical Component Summary for Short-stay Immigrants, OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
F (14-17)	0.138	(0.853)	0.886	(1.816)	0.193	(0.701)	-0.161	(0.496)	-0.027	(0.415)	-0.563	(1.034)
F (18-34)	-0.502	(0.643)	-2.733*	(1.597)	-0.046	(0.436)	-0.226	(0.256)	-0.109	(0.230)	-0.287	(0.641)
F (35-44)	-1.183	(0.910)	-2.705	(1.873)	-0.657	(0.571)	-0.438	(0.323)	-0.299	(0.252)	-0.039	(0.725)
F (45-54)	-0.804	(0.908)	-2.384	(2.315)	-0.375	(0.635)	-0.539	(0.413)	-0.126	(0.337)	0.217	(0.911)
F (55-64)	-6.101***	(1.612)	-13.574***	(4.419)	-3.406***	(0.907)	-2.694***	(0.366)	-1.661***	(0.252)	-1.327*	(0.725)
F (65-74)	-14.365***	(3.780)	-30.029***	(5.915)	-5.257***	(0.752)	-2.880***	(0.432)	-1.630***	(0.361)	-1.415	(1.002)
F (75+)	0.000	(.)	0.000	(.)	0.000	(.)	0.000	(.)	0.000	(.)	0.000	(.)
M (14-17)	0.213	(0.971)	-0.622	(2.127)	0.144	(1.024)	-0.013	(0.701)	0.482	(0.515)	-0.220	(1.358)
M (35-44)	0.442	(0.856)	0.849	(1.572)	0.692	(0.474)	0.414	(0.295)	0.174	(0.283)	0.619	(0.830)
M (45-54)	0.351	(0.705)	1.449	(1.624)	0.395	(0.651)	-0.447	(0.495)	-0.233	(0.357)	-0.376	(1.050)
M (55-64)	-9.424**	(3.863)	-18.997**	(9.064)	-3.516**	(1.618)	-2.042**	(1.015)	-1.485***	(0.287)	-1.822**	(0.706)
M (65-74)	-8.412	(8.738)	-13.537	(14.055)	-1.011	(2.678)	-2.933***	(0.579)	-1.376***	(0.439)	-0.281	(0.983)
M (75+)	-9.872***	(3.631)	-27.148*	(14.835)	-5.933***	(0.717)	-2.929***	(0.440)	-1.409***	(0.397)	-0.846	(1.053)
High Education	-0.140	(0.802)	1.684	(1.591)	-0.240	(0.650)	-0.380	(0.356)	-0.172	(0.299)	-0.977	(0.647)
Middle Education	0.377	(0.641)	-0.389	(1.416)	-0.383	(0.363)	0.019	(0.224)	0.083	(0.173)	0.679	(0.514)
White Collar Job	1.599	(1.067)	5.803***	(2.105)	-0.465	(1.408)	-0.216	(0.888)	-0.590	(0.487)	-1.811***	(0.577)
Self Employed	1.027	(0.678)	2.429	(1.474)	0.005	(0.616)	0.110	(0.356)	0.126	(0.312)	0.261	(0.720)
Unemployed	0.661	(0.619)	0.417	(1.604)	0.150	(0.421)	0.030	(0.272)	-0.189	(0.224)	0.289	(0.665)
Not Participating	0.078	(0.774)	0.332	(1.883)	-0.255	(0.467)	0.117	(0.273)	0.070	(0.235)	-0.243	(0.676)
Single	0.109	(0.707)	1.021	(1.614)	-0.054	(0.457)	0.084	(0.269)	-0.075	(0.238)	-0.840	(0.621)
Childless Couple	-0.398	(0.744)	0.221	(1.851)	0.114	(0.475)	-0.147	(0.310)	-0.263	(0.242)	-1.062*	(0.633)
Single Father	2.223*	(1.298)	3.037*	(1.598)	1.250**	(0.609)	-0.192	(0.563)	0.023	(0.527)	0.860	(1.413)
Single Mother	1.144	(0.930)	2.734	(2.217)	0.523	(0.725)	-0.280	(0.454)	0.108	(0.327)	-0.180	(0.919)
Excellent Wealth	0.008	(0.747)	-0.761	(2.154)	-0.112	(0.833)	0.550	(0.511)	-0.314	(0.862)	0.465	(1.025)
Poor Wealth	-1.405**	(0.566)	-2.102	(1.292)	-0.556	(0.363)	-0.392*	(0.227)	-0.231	(0.186)	-0.475	(0.500)
Abs. Inadequate Wealth	-0.385	(0.838)	-0.720	(1.833)	-0.792	(0.520)	-0.400	(0.318)	-0.104	(0.263)	1.081	(0.814)
Housing Wealth Index	-0.320	(0.320)	-0.686	(0.504)	-0.175	(0.140)	-0.097	(0.082)	-0.023	(0.065)	0.068	(0.143)
Habitual Smoker	-0.435	(0.666)	-0.617	(1.286)	-0.738*	(0.447)	-0.455*	(0.257)	-0.452**	(0.202)	0.007	(0.527)
Occasional Smoker	1.136	(0.990)	4.267***	(1.511)	-0.059	(1.024)	0.546	(0.575)	-0.241	(0.638)	0.115	(2.116)
North West	0.321	(0.695)	4.047**	(1.776)	0.281	(0.523)	-0.104	(0.317)	-0.240	(0.263)	-0.342	(0.707)
North East	-0.183	(0.762)	2.114	(1.752)	0.394	(0.504)	0.247	(0.307)	0.130	(0.271)	0.350	(0.778)
Centre	0.044	(0.691)	1.541	(1.944)	0.104	(0.537)	0.073	(0.329)	-0.251	(0.265)	-0.572	(0.688)
Islands	0.567	(1.012)	-0.651	(3.103)	0.504	(0.794)	0.560	(0.449)	0.613	(0.389)	2.629**	(1.284)
Small City	-0.291	(0.616)	-0.064	(1.373)	-0.306	(0.404)	-0.044	(0.253)	-0.116	(0.221)	-0.102	(0.562)
Medium City	-0.054	(0.625)	0.600	(1.640)	-0.129	(0.443)	0.124	(0.286)	-0.152	(0.245)	0.133	(0.676)
Large City	-1.596*	(0.878)	-3.119*	(1.763)	-0.644	(0.460)	-0.027	(0.299)	0.082	(0.240)	0.343	(0.669)
Europe Non-EU	-0.747	(0.699)	-2.218	(1.508)	-0.615	(0.430)	-0.001	(0.270)	-0.020	(0.234)	0.389	(0.608)
Africa	-1.763*	(0.982)	-3.926**	(1.916)	-0.679	(0.459)	-0.336	(0.292)	-0.063	(0.250)	0.495	(0.786)
West and South-Central Asia	-0.562	(0.769)	-1.292	(1.586)	-0.685	(0.657)	-0.288	(0.390)	-0.228	(0.314)	-0.219	(0.667)
East Asia	0.757	(0.802)	-1.124	(2.464)	-0.105	(0.578)	0.185	(0.335)	0.037	(0.332)	0.639	(0.856)
America	-0.681	(0.871)	-3.841*	(2.273)	-0.427	(0.597)	-0.159	(0.366)	-0.237	(0.306)	-0.043	(0.875)
Constant	56.495***	(1.226)	52.232***	(2.801)	56.272***	(0.769)	57.175***	(0.465)	58.230***	(0.406)	59.154***	(1.058)
No. of observations							598					

*Notes: Sample weights applied. Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively. Reference group is a male individual aged 18-34, having low education and a blue-collar job, being in a couple with child(ren), having appropriate wealth, not smoking, living in a very small city in the South, and with EU nationality.*

Table A4.: Determinants of the Physical Component Summary for Long-stay Immigrants, OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
F (14-17)	2.804***	(0.697)	10.865***	(3.278)	2.688***	(0.660)	0.776***	(0.291)	0.476	(0.356)	0.642	(0.635)
F (18-34)	-0.695**	(0.350)	-1.934	(1.736)	-1.224***	(0.420)	-0.645***	(0.144)	-0.639***	(0.140)	-0.692***	(0.243)
F (35-44)	-1.169***	(0.381)	-2.204	(1.900)	-2.035***	(0.477)	-0.924***	(0.160)	-0.920***	(0.158)	-0.617**	(0.266)
F (45-54)	-4.133***	(0.495)	-14.879***	(2.496)	-4.754***	(0.558)	-1.638***	(0.168)	-1.363***	(0.161)	-1.219***	(0.252)
F (55-64)	-3.728***	(0.642)	-13.414***	(3.430)	-4.344***	(0.744)	-1.826***	(0.219)	-1.536***	(0.203)	-1.388***	(0.293)
F (65-74)	-10.471***	(1.795)	-35.147***	(7.962)	-9.590***	(1.347)	-2.759***	(0.292)	-2.040***	(0.273)	-1.736***	(0.378)
F (75+)	-17.836***	(1.935)	-76.135***	(9.356)	-16.873***	(1.216)	-3.468***	(0.251)	-2.555***	(0.200)	-2.020***	(0.339)
M (14-17)	2.464***	(0.657)	11.675***	(2.778)	1.620**	(0.825)	0.291	(0.311)	0.608*	(0.348)	-0.097	(0.522)
M (35-44)	-0.583*	(0.348)	-0.612	(1.564)	-1.020**	(0.448)	-0.516***	(0.155)	-0.542***	(0.156)	-0.885***	(0.256)
M (45-54)	-2.194***	(0.421)	-5.099**	(2.231)	-3.131***	(0.617)	-1.402***	(0.185)	-1.280***	(0.172)	-1.124***	(0.275)
M (55-64)	-2.750***	(0.741)	-5.740*	(3.267)	-3.620***	(0.846)	-1.052***	(0.262)	-1.196***	(0.246)	-0.821*	(0.441)
M (65-74)	-8.475***	(1.858)	-34.639***	(10.386)	-9.124***	(1.858)	-2.577***	(0.374)	-2.206***	(0.286)	-2.054***	(0.360)
M (75+)	-13.025***	(3.080)	-48.210***	(16.668)	-12.797***	(2.516)	-3.705***	(0.199)	-2.577***	(0.191)	-2.139***	(0.300)
High Education	0.325	(0.374)	0.086	(2.112)	0.268	(0.505)	0.195	(0.165)	0.069	(0.151)	0.053	(0.218)
Middle Education	-0.139	(0.263)	-0.728	(1.325)	-0.298	(0.328)	-0.014	(0.104)	0.042	(0.098)	0.258*	(0.152)
White Collar Job	-0.647	(0.623)	-3.774	(3.269)	-0.319	(0.753)	0.053	(0.249)	0.129	(0.233)	-0.044	(0.330)
Self Employed	-0.456	(0.359)	-1.510	(1.966)	-1.179**	(0.530)	-0.197	(0.159)	-0.033	(0.145)	0.207	(0.242)
Unemployed	-0.184	(0.309)	-3.463**	(1.585)	-0.344	(0.395)	0.049	(0.125)	0.307**	(0.123)	0.546***	(0.210)
Not Participating	-1.678***	(0.396)	-8.119***	(2.071)	-1.116**	(0.436)	-0.174	(0.133)	0.009	(0.122)	-0.152	(0.183)
Single	-0.305	(0.338)	-2.436	(1.622)	0.121	(0.431)	-0.032	(0.137)	0.127	(0.132)	0.396*	(0.210)
Childless Couple	-0.331	(0.379)	-1.027	(1.846)	-0.332	(0.479)	-0.036	(0.150)	0.039	(0.145)	0.359	(0.220)
Single Father	-2.300	(1.701)	-5.108	(5.105)	-1.873	(1.452)	-0.861*	(0.446)	-0.433	(0.344)	-0.227	(0.504)
Single Mother	-0.180	(0.559)	-4.390	(2.984)	-0.245	(0.645)	0.178	(0.192)	0.474**	(0.196)	0.782**	(0.347)
Excellent Wealth	0.103	(0.872)	-1.441	(4.779)	0.718	(1.029)	0.194	(0.371)	0.080	(0.357)	-0.725**	(0.349)
Poor Wealth	-0.513**	(0.253)	-1.741	(1.224)	-0.736**	(0.335)	-0.116	(0.110)	-0.034	(0.107)	0.237	(0.155)
Abs. Inadequate Wealth	-1.771***	(0.447)	-9.832***	(2.226)	-2.621***	(0.521)	-0.281*	(0.158)	-0.054	(0.150)	0.952***	(0.257)
Housing Wealth Index	0.480***	(0.108)	1.854***	(0.527)	0.436***	(0.129)	0.090**	(0.040)	0.041	(0.037)	-0.003	(0.053)
Habitual Smoker	0.204	(0.275)	2.283	(1.457)	-0.033	(0.359)	-0.025	(0.113)	0.036	(0.109)	-0.038	(0.174)
Occasional Smoker	0.648	(0.528)	5.838***	(1.916)	-0.255	(0.885)	-0.709**	(0.285)	-0.188	(0.272)	0.830	(0.531)
North West	-0.813**	(0.369)	-3.244*	(1.847)	-0.880*	(0.482)	-0.346**	(0.159)	-0.023	(0.152)	0.167	(0.240)
North East	-1.756***	(0.398)	-6.843***	(1.901)	-1.784***	(0.505)	-0.489***	(0.160)	-0.268*	(0.151)	-0.020	(0.238)
Centre	-0.887**	(0.391)	-3.013	(2.037)	-1.271**	(0.504)	-0.236	(0.163)	-0.132	(0.153)	0.005	(0.243)
Islands	-0.369	(0.581)	-2.926	(3.023)	0.386	(0.692)	-0.130	(0.242)	0.213	(0.242)	-0.079	(0.359)
Small City	0.190	(0.319)	0.293	(1.560)	0.439	(0.386)	-0.049	(0.131)	0.026	(0.128)	-0.054	(0.194)
Medium City	0.557*	(0.313)	1.632	(1.616)	0.563	(0.412)	0.097	(0.136)	0.039	(0.130)	-0.130	(0.209)
Large City	-0.328	(0.436)	-1.543	(1.789)	-0.260	(0.520)	-0.224	(0.148)	-0.206	(0.143)	-0.346*	(0.202)
Europe Non-EU	-0.126	(0.329)	1.893	(1.655)	-0.477	(0.421)	-0.142	(0.134)	-0.023	(0.133)	-0.221	(0.200)
Africa	-0.066	(0.485)	0.855	(2.103)	-0.008	(0.558)	-0.051	(0.155)	0.037	(0.150)	-0.218	(0.238)
West and South-Central Asia	0.067	(0.500)	3.358	(2.475)	-0.419	(0.663)	-0.295	(0.212)	-0.024	(0.192)	-0.573**	(0.260)
East Asia	-0.034	(0.571)	1.794	(2.527)	0.399	(0.684)	-0.047	(0.237)	-0.096	(0.210)	-0.709***	(0.263)
America	-0.507	(0.469)	-0.554	(2.361)	-0.132	(0.580)	-0.241	(0.176)	-0.352**	(0.166)	-0.468*	(0.260)
Constant	57.315***	(0.540)	59.583***	(2.768)	57.691***	(0.650)	57.719***	(0.220)	58.357***	(0.218)	58.741***	(0.355)
No. of observations							4,926					

Notes: See Table A3.

Table A5.: Determinants of the Mental Component Summary for Natives, OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
F (14-17)	0.193	(0.261)	0.454	(0.707)	0.302	(0.521)	0.101	(0.347)	0.143	(0.268)	0.237	(0.316)
F (18-34)	-2.130***	(0.151)	-3.885***	(0.454)	-3.282***	(0.301)	-2.432***	(0.199)	-1.422***	(0.144)	-1.216***	(0.159)
F (35-44)	-3.058***	(0.158)	-4.904***	(0.473)	-4.539***	(0.314)	-3.510***	(0.211)	-2.244***	(0.151)	-2.054***	(0.161)
F (45-54)	-4.277***	(0.153)	-7.048***	(0.486)	-6.738***	(0.313)	-4.814***	(0.199)	-2.938***	(0.139)	-2.437***	(0.150)
F (55-64)	-4.225***	(0.171)	-7.125***	(0.535)	-6.501***	(0.341)	-4.843***	(0.217)	-2.857***	(0.154)	-2.426***	(0.167)
F (65-74)	-5.052***	(0.196)	-8.465***	(0.619)	-7.758***	(0.392)	-5.585***	(0.245)	-3.416***	(0.171)	-2.764***	(0.188)
F (75+)	-7.357***	(0.210)	-14.800***	(0.701)	-12.579***	(0.415)	-7.643***	(0.250)	-4.256***	(0.172)	-3.022***	(0.190)
M (14-17)	2.178***	(0.242)	3.095***	(0.617)	2.896***	(0.445)	2.193***	(0.325)	2.244***	(0.262)	2.035***	(0.339)
M (35-44)	-1.329***	(0.156)	-2.050***	(0.430)	-2.156***	(0.309)	-1.547***	(0.214)	-0.788***	(0.159)	-0.895***	(0.176)
M (45-54)	-2.518***	(0.154)	-4.037***	(0.452)	-4.043***	(0.310)	-2.718***	(0.206)	-1.698***	(0.150)	-1.634***	(0.163)
M (55-64)	-2.768***	(0.160)	-4.118***	(0.482)	-4.217***	(0.318)	-3.280***	(0.213)	-1.995***	(0.154)	-1.799***	(0.166)
M (65-74)	-2.301***	(0.187)	-3.270***	(0.554)	-3.465***	(0.371)	-2.692***	(0.245)	-1.888***	(0.178)	-1.631***	(0.198)
M (75+)	-4.576***	(0.221)	-8.086***	(0.691)	-7.537***	(0.435)	-5.151***	(0.271)	-2.988***	(0.190)	-2.087***	(0.212)
High Education	0.165	(0.134)	0.355	(0.396)	0.521*	(0.267)	0.305*	(0.177)	-0.177	(0.122)	-0.332***	(0.127)
Middle Education	0.217**	(0.095)	0.092	(0.286)	0.428**	(0.185)	0.340***	(0.118)	0.072	(0.082)	0.002	(0.085)
White Collar Job	-0.902***	(0.132)	-2.099***	(0.386)	-1.132***	(0.268)	-0.983***	(0.179)	-0.520***	(0.128)	-0.460***	(0.136)
Self Employed	-1.336***	(0.143)	-2.823***	(0.410)	-1.957***	(0.289)	-1.233***	(0.188)	-0.778***	(0.132)	-0.601***	(0.136)
Unemployed	-1.649***	(0.158)	-3.645***	(0.491)	-3.177***	(0.320)	-1.600***	(0.197)	-0.523***	(0.137)	-0.506***	(0.142)
Not Participating	-1.260***	(0.131)	-4.046***	(0.390)	-2.499***	(0.263)	-0.874***	(0.168)	-0.237**	(0.119)	-0.066	(0.126)
Single	-0.582***	(0.144)	-1.944***	(0.449)	-1.258***	(0.280)	-0.509***	(0.172)	-0.135	(0.117)	0.338***	(0.125)
Childless Couple	0.235*	(0.126)	-0.040	(0.368)	0.291	(0.240)	0.414***	(0.154)	0.276***	(0.107)	0.387***	(0.110)
Single Father	-1.041***	(0.322)	-2.451***	(0.909)	-2.000***	(0.640)	-0.994**	(0.398)	-0.562**	(0.260)	-0.225	(0.271)
Single Mother	-0.909***	(0.167)	-2.003***	(0.503)	-1.876***	(0.319)	-0.924***	(0.196)	-0.391***	(0.130)	-0.015	(0.138)
Excellent Wealth	0.964***	(0.285)	2.034***	(0.619)	0.426	(0.561)	1.038***	(0.363)	0.987***	(0.290)	1.163***	(0.367)
Poor Wealth	-2.457***	(0.099)	-4.632***	(0.291)	-4.188***	(0.192)	-2.628***	(0.118)	-1.416***	(0.080)	-0.965***	(0.082)
Abs. Inadequate Wealth	-5.404***	(0.222)	-13.005***	(0.732)	-9.555***	(0.418)	-4.800***	(0.223)	-2.348***	(0.140)	-1.327***	(0.156)
Housing Wealth Index	0.202***	(0.039)	0.451***	(0.121)	0.358***	(0.075)	0.224***	(0.046)	0.137***	(0.031)	-0.027	(0.033)
Habitual Smoker	-1.086***	(0.102)	-2.584***	(0.315)	-1.903***	(0.201)	-0.873***	(0.122)	-0.522***	(0.084)	-0.491***	(0.085)
Occasional Smoker	-0.843***	(0.250)	-1.029	(0.739)	-1.489***	(0.518)	-1.052***	(0.324)	-0.657***	(0.223)	-0.757***	(0.224)
North West	0.089	(0.124)	-0.663*	(0.355)	-0.112	(0.238)	0.295*	(0.152)	0.412***	(0.105)	0.128	(0.108)
North East	0.074	(0.123)	-0.914**	(0.358)	-0.374	(0.236)	0.318**	(0.150)	0.491***	(0.103)	0.145	(0.107)
Centre	-0.111	(0.130)	-1.050***	(0.376)	-0.479*	(0.248)	-0.044	(0.158)	0.335***	(0.110)	0.157	(0.114)
Islands	0.528***	(0.143)	0.296	(0.409)	0.408	(0.270)	0.794***	(0.171)	0.817***	(0.120)	0.590***	(0.129)
Small City	-0.253**	(0.109)	-0.571*	(0.310)	-0.119	(0.205)	-0.227*	(0.132)	-0.326***	(0.093)	-0.354***	(0.096)
Medium City	-0.064	(0.122)	-0.038	(0.348)	0.266	(0.231)	-0.069	(0.150)	-0.230**	(0.105)	-0.104	(0.112)
Large City	-0.332***	(0.119)	0.351	(0.341)	-0.098	(0.229)	-0.676***	(0.147)	-0.552***	(0.102)	-0.535***	(0.105)
Constant	54.279***	(0.178)	45.987***	(0.497)	53.445***	(0.344)	57.268***	(0.232)	59.517***	(0.170)	62.380***	(0.188)
No. of observations							96,778					

Notes: See Table A2.

Table A6.: Determinants of the Mental Component Summary for Short-stay Immigrants, OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
F (14-17)	1.114	(1.845)	1.760	(3.813)	0.317	(2.774)	-0.791	(2.211)	1.818	(2.603)	2.092	(2.787)
F (18-34)	-1.409	(0.953)	-2.230	(2.537)	-1.448	(1.388)	-1.741	(1.086)	-1.602	(1.032)	-0.783	(0.988)
F (35-44)	-2.298*	(1.265)	-4.690	(3.195)	-2.466	(1.789)	-2.099	(1.379)	-1.764	(1.289)	-1.111	(1.055)
F (45-54)	-3.318**	(1.653)	-6.210	(4.625)	-2.816	(2.098)	-1.752	(1.589)	-2.829**	(1.358)	-1.510	(1.224)
F (55-64)	-4.268**	(2.017)	-4.668	(5.839)	-6.909**	(3.164)	-4.523**	(2.189)	-3.413*	(1.994)	-3.225**	(1.428)
F (65-74)	-2.736	(3.554)	-8.168	(10.317)	0.790	(4.573)	-1.493	(3.453)	-5.058**	(2.369)	-2.721	(2.488)
F (75+)	0.000	(.)	0.000	(.)	0.000	(.)	0.000	(.)	0.000	(.)	0.000	(.)
M (14-17)	1.882	(1.955)	1.950	(4.066)	2.462	(2.289)	1.147	(2.969)	1.652	(2.822)	-1.622	(2.297)
M (35-44)	-0.715	(1.128)	1.366	(2.255)	-2.531	(2.003)	-0.261	(1.443)	-2.572**	(1.273)	-0.823	(1.300)
M (45-54)	-1.810	(1.607)	-1.432	(4.347)	-0.934	(2.251)	-2.016	(2.148)	-0.087	(2.048)	-2.263*	(1.165)
M (55-64)	-0.612	(3.415)	-10.835	(9.887)	-0.614	(3.764)	-0.782	(3.989)	5.403	(3.795)	-3.305**	(1.377)
M (65-74)	-2.925	(2.390)	3.263	(4.212)	2.650	(2.474)	-6.669	(5.535)	-7.888***	(1.878)	-4.197**	(1.660)
M (75+)	-5.712***	(1.853)	7.436	(4.769)	-19.492***	(2.649)	-10.406***	(2.004)	-7.427***	(2.096)	-2.522	(1.923)
High Education	-1.654	(1.238)	-2.310	(3.518)	-2.015	(2.035)	-0.611	(1.472)	-3.474***	(1.156)	-1.656*	(0.964)
Middle Education	-0.873	(0.933)	-0.729	(2.388)	-0.794	(1.339)	-1.313	(0.947)	-1.507*	(0.912)	-0.242	(0.701)
White Collar Job	2.400	(2.053)	7.068**	(3.081)	6.059***	(1.748)	1.996	(3.494)	0.897	(3.295)	-0.812	(0.939)
Self Employed	0.692	(1.183)	2.622	(2.940)	2.803*	(1.690)	0.460	(1.452)	-0.770	(1.227)	2.266*	(1.241)
Unemployed	0.937	(0.918)	0.288	(2.215)	1.458	(1.339)	2.026*	(1.121)	0.169	(1.063)	0.769	(0.826)
Not Participating	1.367	(1.101)	-0.422	(2.635)	2.018	(1.739)	2.024	(1.284)	1.294	(1.259)	2.768***	(1.009)
Single	-0.259	(1.134)	-3.023	(2.901)	-0.223	(1.532)	0.181	(1.200)	-0.390	(1.067)	-0.383	(0.813)
Childless Couple	1.769*	(1.033)	0.092	(2.282)	2.708*	(1.565)	2.281*	(1.309)	1.178	(1.214)	-0.145	(0.930)
Single Father	-0.719	(2.103)	-5.743	(6.793)	1.215	(2.696)	-1.814	(2.417)	-1.390	(2.615)	0.761	(2.909)
Single Mother	-0.837	(1.845)	-0.889	(4.007)	-0.912	(2.533)	-1.390	(1.765)	-0.214	(1.805)	1.891	(1.938)
Excellent Wealth	-1.108	(1.839)	0.753	(3.233)	0.156	(2.361)	-1.542	(3.180)	1.056	(2.621)	-3.548***	(0.941)
Poor Wealth	-0.682	(0.780)	-1.831	(1.913)	-1.208	(1.108)	-1.079	(0.983)	0.521	(0.940)	0.002	(0.766)
Abs. Inadequate Wealth	-4.034***	(1.313)	-4.416	(3.305)	-6.168***	(1.958)	-5.217***	(1.460)	-2.273*	(1.342)	-1.452	(1.090)
Housing Wealth Index	0.445	(0.310)	0.627	(0.749)	0.772*	(0.432)	0.406	(0.348)	0.177	(0.333)	0.024	(0.246)
Habitual Smoker	-1.994*	(1.034)	-5.130*	(2.754)	-2.448*	(1.456)	-1.548	(1.098)	0.129	(1.002)	-1.143	(0.854)
Occasional Smoker	0.276	(1.060)	3.233	(2.030)	6.094***	(1.463)	0.328	(2.790)	-4.871***	(0.974)	-2.034**	(0.837)
North West	-1.010	(1.282)	-1.029	(3.122)	-1.239	(1.773)	-1.118	(1.429)	-0.791	(1.345)	-1.963*	(1.019)
North East	-0.848	(1.255)	-0.227	(3.110)	-1.881	(1.813)	-0.543	(1.445)	-0.877	(1.327)	-0.206	(1.111)
Centre	-0.012	(1.193)	3.546	(2.579)	-0.059	(1.646)	-1.113	(1.480)	-1.178	(1.339)	-0.961	(1.076)
Islands	-0.632	(2.459)	-2.596	(5.219)	-0.235	(2.644)	0.271	(2.036)	1.270	(2.225)	-0.245	(1.849)
Small City	-0.151	(1.096)	-0.699	(2.420)	0.152	(1.540)	-0.059	(1.240)	-0.199	(1.166)	-0.317	(0.947)
Medium City	-0.687	(1.104)	-1.896	(2.829)	0.001	(1.624)	-0.131	(1.276)	-0.742	(1.128)	-1.753**	(0.817)
Large City	1.109	(1.189)	-1.695	(2.611)	1.689	(1.640)	2.428*	(1.325)	0.634	(1.281)	0.476	(0.996)
Europe Non-EU	-0.446	(1.086)	0.022	(2.730)	-1.057	(1.571)	-1.289	(1.188)	0.141	(1.266)	0.100	(1.076)
Africa	-0.993	(1.185)	0.049	(2.792)	-2.371	(1.708)	-1.685	(1.361)	0.073	(1.425)	-1.236	(1.052)
West and South-Central Asia	-1.282	(1.260)	0.831	(3.232)	-0.593	(1.806)	-2.862*	(1.566)	-1.367	(1.513)	-1.432	(1.264)
East Asia	-0.542	(1.738)	-0.250	(3.535)	-0.302	(2.436)	-0.671	(1.781)	-0.038	(1.816)	0.380	(1.538)
America	-1.622	(1.729)	-3.226	(4.195)	-2.265	(2.122)	-1.206	(1.672)	-0.216	(1.540)	-0.869	(1.174)
Constant	55.031***	(1.780)	49.354***	(4.673)	52.290***	(2.489)	57.253***	(1.970)	59.994***	(1.871)	62.355***	(1.712)
No. of observations							598					

Notes: See Table A3.

Table A7.: Determinants of the Mental Component Summary for Long-stay Immigrants, OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
F (14-17)	-0.307	(1.129)	-4.447	(3.492)	0.379	(1.616)	0.912	(0.999)	0.840	(1.190)	0.709	(1.066)
F (18-34)	-0.885*	(0.478)	-1.917	(1.436)	-0.175	(0.764)	-0.593	(0.420)	-0.806	(0.512)	-0.774*	(0.465)
F (35-44)	-1.264***	(0.466)	-1.545	(1.329)	-0.530	(0.791)	-1.160***	(0.444)	-1.844***	(0.529)	-1.410***	(0.456)
F (45-54)	-3.108***	(0.547)	-6.961***	(1.711)	-2.826***	(0.852)	-1.949***	(0.491)	-2.924***	(0.566)	-2.084***	(0.491)
F (55-64)	-2.429***	(0.690)	-3.458*	(2.011)	-1.264	(1.080)	-2.309***	(0.646)	-2.867***	(0.737)	-1.608**	(0.666)
F (65-74)	-2.277**	(1.050)	-6.311*	(3.540)	-2.630	(1.755)	-2.870***	(1.080)	-1.527	(1.270)	-2.292***	(0.825)
F (75+)	-7.994***	(2.007)	-24.364***	(6.942)	-9.951***	(2.805)	-5.015***	(1.296)	-4.156***	(1.361)	-1.893	(1.158)
M (14-17)	1.347	(1.147)	-3.107	(3.270)	1.272	(1.439)	2.031**	(0.978)	2.100*	(1.232)	3.644***	(1.317)
M (35-44)	-0.496	(0.462)	0.277	(1.271)	0.073	(0.792)	-0.495	(0.463)	-1.317**	(0.533)	-0.198	(0.497)
M (45-54)	-0.607	(0.513)	0.166	(1.461)	-0.108	(0.889)	-0.708	(0.524)	-1.519**	(0.597)	-0.560	(0.563)
M (55-64)	-2.863***	(0.757)	-5.922**	(2.649)	-3.903***	(1.364)	-1.930***	(0.726)	-2.606***	(0.828)	-2.379***	(0.555)
M (65-74)	-4.374**	(1.949)	-12.662*	(6.612)	-6.318**	(2.742)	-2.930**	(1.193)	-2.914**	(1.332)	-1.038	(1.288)
M (75+)	-4.306*	(2.615)	-20.966*	(11.119)	-4.619	(4.053)	-3.180	(2.325)	-1.598	(2.701)	-1.672	(2.326)
High Education	-0.226	(0.485)	-0.914	(1.351)	-1.087	(0.829)	-0.201	(0.486)	0.593	(0.565)	0.284	(0.502)
Middle Education	-0.457	(0.308)	-1.392	(0.865)	-0.712	(0.485)	0.132	(0.303)	0.061	(0.347)	0.003	(0.289)
White Collar Job	-1.026	(0.734)	-2.740	(1.941)	-0.409	(1.134)	-0.480	(0.743)	-0.666	(0.916)	-0.885	(0.944)
Self Employed	-0.940**	(0.454)	-1.731	(1.245)	-0.817	(0.780)	-0.811*	(0.480)	-1.322**	(0.530)	-1.079***	(0.418)
Unemployed	-2.167***	(0.433)	-6.029***	(1.313)	-2.855***	(0.663)	-1.358***	(0.373)	-0.735	(0.454)	-0.257	(0.343)
Not Participating	-0.580	(0.392)	-1.474	(1.163)	-0.561	(0.635)	-0.493	(0.373)	-0.456	(0.427)	0.296	(0.384)
Single	-1.009**	(0.458)	-2.119	(1.331)	-0.784	(0.678)	-0.902**	(0.413)	-1.263***	(0.479)	-0.853**	(0.421)
Childless Couple	-0.362	(0.469)	-0.881	(1.335)	0.276	(0.723)	0.246	(0.445)	-0.606	(0.508)	-0.567	(0.411)
Single Father	-0.927	(1.020)	2.814	(2.502)	1.126	(1.990)	-2.432*	(1.287)	-1.760	(1.225)	-0.842	(1.132)
Single Mother	-0.821	(0.647)	1.897	(1.699)	-1.822	(1.119)	-1.001	(0.645)	-0.771	(0.665)	-0.615	(0.477)
Excellent Wealth	1.159	(1.156)	0.325	(2.541)	0.791	(1.317)	0.567	(1.317)	1.835	(1.582)	2.045	(1.288)
Poor Wealth	-1.700***	(0.344)	-2.171**	(0.868)	-2.155***	(0.512)	-1.617***	(0.355)	-1.831***	(0.420)	-0.478	(0.341)
Abs. Inadequate Wealth	-4.504***	(0.579)	-10.604***	(1.668)	-5.438***	(0.808)	-2.825***	(0.485)	-3.027***	(0.565)	-1.456***	(0.437)
Housing Wealth Index	0.319**	(0.136)	0.572	(0.381)	0.294	(0.196)	0.286**	(0.129)	0.428***	(0.149)	0.466***	(0.132)
Habitual Smoker	-0.778**	(0.369)	-2.319**	(1.064)	-1.042*	(0.573)	-0.206	(0.337)	-0.317	(0.386)	-0.080	(0.323)
Occasional Smoker	-2.762**	(1.145)	-4.885	(3.138)	-3.079**	(1.472)	-1.751**	(0.836)	-2.004**	(0.855)	-0.623	(0.769)
North West	-0.572	(0.509)	-2.579*	(1.395)	-1.278*	(0.768)	-0.672	(0.493)	0.101	(0.570)	0.034	(0.444)
North East	-0.472	(0.517)	-3.927***	(1.461)	-1.877**	(0.779)	-0.406	(0.493)	0.562	(0.578)	0.560	(0.459)
Centre	-0.206	(0.518)	-1.889	(1.334)	-0.102	(0.764)	-0.154	(0.519)	0.199	(0.593)	0.199	(0.465)
Islands	0.573	(0.742)	0.795	(2.028)	-0.679	(1.271)	-0.027	(0.763)	0.652	(0.888)	1.073	(0.747)
Small City	-0.075	(0.436)	0.360	(1.193)	0.233	(0.662)	-0.262	(0.414)	0.241	(0.499)	-0.197	(0.390)
Medium City	0.015	(0.457)	0.799	(1.227)	0.348	(0.684)	-0.429	(0.440)	0.048	(0.517)	-0.301	(0.432)
Large City	-0.123	(0.464)	1.070	(1.283)	0.638	(0.663)	-0.479	(0.443)	-0.627	(0.506)	-0.552	(0.425)
Europe Non-EU	0.145	(0.436)	0.198	(1.171)	0.926	(0.646)	0.170	(0.411)	0.061	(0.467)	-0.460	(0.359)
Africa	0.373	(0.475)	0.947	(1.365)	0.134	(0.756)	0.322	(0.463)	0.852	(0.526)	0.512	(0.434)
West and South-Central Asia	1.234**	(0.610)	3.134**	(1.512)	1.436	(1.026)	0.712	(0.643)	0.802	(0.753)	0.607	(0.661)
East Asia	2.005***	(0.623)	4.146***	(1.241)	2.282**	(0.981)	1.725**	(0.698)	1.754*	(0.896)	0.669	(0.743)
America	0.601	(0.667)	-1.349	(1.804)	1.429	(0.882)	0.877	(0.597)	1.197*	(0.692)	0.803	(0.583)
Constant	54.677***	(0.704)	49.700***	(1.933)	51.249***	(1.113)	56.355***	(0.674)	60.330***	(0.783)	62.214***	(0.668)
No. of observations							4,926					

Notes: See Table A3.

Table A8.: Decomposition Results of Differentials between Natives and Long-stay Immigrants in Physical Component Summary

	Q10	Q25	Q50	Q75	Q90
Δ_{N-I_l}	-9.881***	-4.566***	-0.799***	-0.332***	-0.225**
	(0.819)	(0.243)	(0.068)	(0.063)	(0.093)
Panel A					
Composition Effect	-5.414***	-5.879***	-1.031***	-0.537***	-0.546***
	(0.229)	(0.216)	(0.039)	(0.024)	(0.034)
Elasticity Effect	-4.467***	1.313***	0.232***	0.206***	0.321***
	(0.812)	(0.292)	(0.074)	(0.066)	(0.098)
due to covariates	-4.481	2.783	0.006	-0.071	-0.115
due to constant	0.015	-1.470	0.226	0.277	0.436
Panel B: Detailed Decomposition					
Composition Effect					
Age and Gender	-6.046***	-6.824***	-1.266***	-0.621***	-0.527***
	(0.153)	(0.151)	(0.030)	(0.018)	(0.021)
Education	-0.069***	-0.084***	-0.016***	-0.005**	-0.006**
	(0.024)	(0.028)	(0.005)	(0.002)	(0.003)
Occupation	-1.328***	-0.754***	0.048**	0.061***	0.082***
	(0.094)	(0.101)	(0.020)	(0.014)	(0.023)
Family Composition	0.142***	0.029	-0.007	-0.010***	0.005
	(0.049)	(0.038)	(0.006)	(0.003)	(0.005)
Wealth	2.503***	2.148***	0.238***	0.014	-0.060***
	(0.161)	(0.131)	(0.020)	(0.012)	(0.021)
Risk Behavior	-0.011	-0.007	-0.000	-0.000	-0.004
	(0.010)	(0.007)	(0.000)	(0.001)	(0.003)
Geography	-0.605***	-0.388***	-0.027***	0.023***	-0.036***
	(0.062)	(0.051)	(0.009)	(0.006)	(0.009)
Elasticity Effect					
Age and Gender	-5.116**	3.866***	0.579***	0.151**	0.216**
	(2.275)	(0.402)	(0.078)	(0.071)	(0.108)
Education	-0.285	-0.384**	-0.042	-0.015	-0.030
	(0.590)	(0.157)	(0.048)	(0.043)	(0.063)
Occupation	-0.349	-0.244	-0.135**	-0.058	-0.099
	(0.756)	(0.200)	(0.061)	(0.056)	(0.082)
Family Composition	-0.951	0.176	-0.094	-0.025	0.053
	(1.393)	(0.402)	(0.118)	(0.094)	(0.142)
Wealth	-1.072	-1.029**	-0.121	-0.058	-0.214
	(1.626)	(0.405)	(0.127)	(0.120)	(0.131)
Risk Behavior	1.607*	-0.452	-0.241*	-0.061	0.076
	(0.892)	(0.411)	(0.125)	(0.117)	(0.223)
Geography	1.446**	0.811***	0.094*	0.030	0.010
	(0.668)	(0.164)	(0.053)	(0.053)	(0.076)
Nationality	0.238	0.038	-0.033	-0.036	-0.129**
	(0.510)	(0.137)	(0.045)	(0.041)	(0.055)
Constant	0.015	-1.470*	0.226	0.277	0.436
	(3.510)	(0.860)	(0.246)	(0.226)	(0.339)

*Notes: Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table A9.: Decomposition Results of Differentials between Natives and Long-stay Immigrants in Mental Component Summary

	Q10	Q25	Q50	Q75	Q90
Δ_{N-I_l}	-5.749***	-2.531***	-1.146***	-0.483**	-0.278
	(0.574)	(0.321)	(0.209)	(0.237)	(0.190)
Panel A					
Composition Effect	-0.029	0.029	-0.012	-0.055	-0.137
	(0.228)	(0.159)	(0.096)	(0.062)	(0.060)
Elasticity Effect	-5.721***	-2.559***	-1.134***	-0.428*	-0.141**
	(0.596)	(0.343)	(0.222)	(0.240)	(0.198)
due to covariates	-2.757	-0.009	-0.160	0.328	0.750
due to constant	-2.964	-2.550	-0.974	-0.757	-0.891
Panel B: Detailed decomposition					
Composition Effect					
Age and Gender	-1.571***	-1.422***	-0.913***	-0.542***	-0.370***
	(0.122)	(0.082)	(0.052)	(0.035)	(0.035)
Education	0.001	-0.013	-0.012**	-0.006*	-0.005
	(0.012)	(0.009)	(0.006)	(0.004)	(0.004)
Occupation	-1.018***	-0.542***	-0.243***	-0.101***	-0.051
	(0.121)	(0.083)	(0.052)	(0.037)	(0.039)
Family Composition	0.058	0.053**	0.044***	0.022**	0.014
	(0.037)	(0.025)	(0.015)	(0.009)	(0.010)
Wealth	2.295***	1.843***	1.068***	0.578***	0.241***
	(0.177)	(0.120)	(0.069)	(0.042)	(0.039)
Risk Behavior	0.018	0.015	0.008	0.005	0.005
	(0.019)	(0.014)	(0.007)	(0.004)	(0.004)
Geography	0.189***	0.095*	0.036	-0.011	0.029
	(0.058)	(0.038)	(0.026)	(0.018)	(0.018)
Elasticity Effect					
Age and Gender	-3.202**	-0.475	-0.006	0.086	0.081
	(1.447)	(0.613)	(0.331)	(0.378)	(0.305)
Education	-0.182	-0.283	-0.100	0.175	0.139
	(0.384)	(0.242)	(0.141)	(0.161)	(0.143)
Occupation	-0.215	0.135	0.111	-0.075	-0.132
	(0.465)	(0.279)	(0.180)	(0.215)	(0.215)
Family Composition	1.449*	0.566	-0.275	-0.300	-0.226
	(0.745)	(0.557)	(0.347)	(0.336)	(0.300)
Wealth	-0.598	0.019	-0.065	0.492	0.538
	(0.961)	(0.503)	(0.451)	(0.520)	(0.430)
Risk Behavior	-1.161	-0.375	-0.125	-0.390	0.098
	(1.325)	(0.635)	(0.366)	(0.368)	(0.330)
Geography	0.603	0.032	0.025	0.039	0.050
	(0.446)	(0.274)	(0.167)	(0.188)	(0.158)
Nationality	0.550*	0.371*	0.274**	0.301*	0.202
	(0.320)	(0.204)	(0.136)	(0.165)	(0.138)
Constant	-2.964	-2.550**	-0.974	-0.757	-0.891
	(2.457)	(1.280)	(0.804)	(0.896)	(0.784)

*Notes: Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table A10.: Decomposition Results of Differentials between Natives and Short-stay Immigrants in Physical Component Summary – Age 18-54

	Q10	Q25	Q50	Q75	Q90
Δ_{N-I_s}	-4.638***	-1.809***	-0.402***	-0.248**	-0.237
	(0.837)	(0.222)	(0.125)	(0.108)	(0.278)
Panel A					
Composition Effect	0.852**	0.170	0.010	-0.090***	-0.190***
	(0.342)	(0.123)	(0.024)	(0.022)	(0.053)
Elasticity Effect	-5.490***	-1.979***	-0.413***	-0.157	-0.047
	(0.895)	(0.252)	(0.127)	(0.110)	(0.281)
due to covariates	1.268	-1.390	-0.119	-0.345	0.464
due to constant	-6.758	-0.589	-0.294	0.188	-0.512
Panel B: Detailed Decomposition					
Composition Effect					
Age and Gender	-1.704***	-0.815***	-0.165***	-0.148***	-0.161***
	(0.161)	(0.074)	(0.015)	(0.013)	(0.019)
Education	0.345***	0.159***	0.028***	0.018***	0.035***
	(0.081)	(0.033)	(0.006)	(0.005)	(0.012)
Occupation	0.307**	0.249***	0.040***	0.019**	0.036
	(0.128)	(0.042)	(0.009)	(0.009)	(0.024)
Family Composition	0.563***	0.179***	0.044***	0.014	0.037
	(0.164)	(0.057)	(0.011)	(0.009)	(0.024)
Wealth	1.180***	0.324***	0.047***	-0.012	-0.128***
	(0.186)	(0.057)	(0.010)	(0.009)	(0.028)
Risk Behavior	-0.006	-0.005	-0.001	0.000	0.013*
	(0.013)	(0.005)	(0.001)	(0.001)	(0.008)
Geography	0.168**	0.080***	0.018***	0.019***	-0.022*
	(0.077)	(0.030)	(0.006)	(0.006)	(0.012)
Elasticity Effect					
Age and Gender	0.395	-0.296	-0.032	-0.048	0.038
	(0.708)	(0.204)	(0.102)	(0.093)	(0.245)
Education	0.078	-0.223	-0.116	-0.051	-0.266
	(0.521)	(0.226)	(0.111)	(0.096)	(0.200)
Occupation	0.907*	-0.315	-0.061	-0.115	-0.384**
	(0.546)	(0.396)	(0.213)	(0.124)	(0.171)
Family Composition	0.987	0.129	-0.102	0.093	0.242
	(0.684)	(0.261)	(0.186)	(0.144)	(0.431)
Wealth	-0.051	-0.456	0.014	-0.161	0.484
	(1.086)	(0.353)	(0.188)	(0.252)	(0.426)
Risk Behavior	0.026	-0.058	0.134	-0.124	-0.095
	(1.443)	(0.444)	(0.225)	(0.263)	(0.801)
Geography	-0.809	-0.087	0.062	0.100	0.454**
	(0.697)	(0.171)	(0.087)	(0.078)	(0.228)
Nationality	-0.265	-0.083	-0.018	-0.039	-0.009
	(0.496)	(0.130)	(0.072)	(0.062)	(0.153)
Constant	-6.758***	-0.589	-0.294	0.188	-0.512
	(1.996)	(0.768)	(0.431)	(0.438)	(1.138)

*Notes: Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table A11.: Decomposition Results of Differentials between Natives and Short-stay Immigrants in Mental Component Summary – Age 18-54

	Q10	Q25	Q50	Q75	Q90
Δ_{N-I_s}	-5.607***	-2.047***	-1.051*	-0.203	0.002
	(1.165)	(0.768)	(0.563)	(0.553)	(0.437)
Panel A					
Composition Effect	1.886***	0.740***	0.248*	0.041	-0.298***
	(0.534)	(0.234)	(0.142)	(0.104)	(0.107)
Elasticity Effect	-7.493***	-2.786***	-1.299**	-0.244	0.300
	(1.253)	(0.781)	(0.574)	(0.560)	(0.451)
due to covariates	-0.683	2.477	-1.261	-2.062	-1.855
due to constant	-6.810	-5.264	-0.038	1.818	2.155
Panel B: Detailed Decomposition					
Composition Effect					
Age and Gender	-0.884***	-0.631***	-0.403***	-0.280***	-0.270***
	(0.175)	(0.091)	(0.063)	(0.046)	(0.045)
Education	-0.049	0.002	-0.052**	-0.062***	-0.056**
	(0.087)	(0.037)	(0.025)	(0.021)	(0.023)
Occupation	-0.080	0.013	-0.074	-0.070*	-0.085**
	(0.212)	(0.095)	(0.051)	(0.037)	(0.040)
Family Composition	0.262	0.016	-0.048	-0.070	-0.165***
	(0.212)	(0.085)	(0.055)	(0.046)	(0.052)
Wealth	2.086***	1.105***	0.702***	0.460***	0.234***
	(0.338)	(0.146)	(0.089)	(0.062)	(0.057)
Risk Behavior	-0.138*	-0.062*	-0.034*	-0.024*	-0.028*
	(0.082)	(0.037)	(0.019)	(0.014)	(0.016)
Geography	0.690***	0.296***	0.156***	0.087***	0.071**
	(0.127)	(0.053)	(0.034)	(0.025)	(0.029)
Elasticity Effect					
Age and Gender	-0.779	-0.235	-0.112	0.176	-0.169
	(0.969)	(0.581)	(0.424)	(0.431)	(0.424)
Education	-0.562	-0.519	-0.075	-0.640*	-0.318
	(1.076)	(0.661)	(0.435)	(0.370)	(0.318)
Occupation	1.882*	1.538***	0.480	0.263	0.210
	(0.827)	(0.511)	(0.810)	(0.801)	(0.326)
Family Composition	-1.223	-0.057	-0.805	-0.177	0.018
	(2.134)	(0.959)	(0.679)	(0.674)	(0.607)
Wealth	0.344	0.059	-0.898	-0.852	-1.363**
	(1.737)	(1.199)	(1.021)	(0.989)	(0.562)
Risk Behavior	1.557	2.075***	0.193	-1.130**	-0.294
	(1.017)	(0.747)	(1.071)	(0.446)	(0.426)
Geography	-1.478	-0.312	0.068	0.298	0.058
	(1.034)	(0.556)	(0.394)	(0.432)	(0.382)
Nationality	-0.424	-0.073	-0.112	0.002	0.005
	(0.733)	(0.442)	(0.302)	(0.294)	(0.230)
Constant	-6.810*	-5.264***	-0.038	1.818	2.155*
	(3.242)	(1.877)	(1.912)	(1.555)	(1.182)

*Notes: Standard errors reported in parentheses and clustered at family-level. ***, **, * indicate significance at 1 %, 5 %, and 10 %, respectively.*

B. Appendix to Chapter 3

Table B1.: Summary Statistics – Explanatory Variables by Gender (2012/13 – 2004/05)

	Males 2012/13 (M_{12})	Males 2004/05 (M_{04})	Females 2012/13 (F_{12})	Females 2004/05 (F_{04})	M_{12}-M_{04}	F_{12}-F_{04}	M_{04}-F_{04}	M_{12}-F_{12}
15-24	0.157	0.161	0.147	0.153	-0.003	-0.006**	0.008***	0.010***
25-34	0.181	0.221	0.178	0.218	-0.041***	-0.041***	0.003	0.003
35-44	0.239	0.245	0.239	0.241	-0.006	-0.003	0.004	0.001
45-54	0.227	0.194	0.237	0.200	0.032***	0.037***	-0.005**	-0.010***
55-64	0.196	0.178	0.200	0.188	0.018***	0.012***	-0.010***	-0.004
Physical Health Problems	0.094	0.088	0.087	0.077	0.007***	0.010***	0.011***	0.007***
High Education	0.129	0.106	0.161	0.119	0.023***	0.042***	-0.013***	-0.032***
Middle Education	0.430	0.365	0.428	0.369	0.065***	0.059***	-0.004	0.003
Low Education	0.441	0.529	0.411	0.512	-0.088***	-0.101***	0.017***	0.029***
Perm. Full-Time	0.380	0.426	0.227	0.237	-0.047***	-0.010***	0.189***	0.152***
Temp. Full-Time	0.061	0.067	0.043	0.051	-0.006***	-0.008***	0.016***	0.018***
Part-Time	0.035	0.026	0.116	0.101	0.009***	0.015***	-0.075***	-0.081***
Self-Employed	0.182	0.199	0.074	0.076	-0.017***	-0.002	0.123***	0.108***
Unemployed	0.134	0.073	0.131	0.070	0.061***	0.061***	0.003	0.004
Student	0.105	0.098	0.110	0.104	0.007***	0.006**	-0.006**	-0.006**
Retired	0.077	0.088	0.049	0.047	-0.011***	0.003	0.041***	0.027***
Other Inactive	0.027	0.022	0.249	0.314	0.005***	-0.065***	-0.292***	-0.222***
Single	0.147	0.120	0.111	0.088	0.028***	0.023***	0.032***	0.036***
Couple	0.763	0.804	0.761	0.802	-0.041***	-0.040***	0.002	0.001
Single Parent	0.090	0.077	0.128	0.111	0.013***	0.017***	-0.034***	-0.038***
HH Size	3.234	3.311	3.227	3.294	-0.077***	-0.068***	0.016**	0.007
Excellent Wealth	0.020	0.038	0.018	0.036	-0.018***	-0.018***	0.002*	0.001*
Appropriate Wealth	0.585	0.666	0.583	0.658	-0.080***	-0.075***	0.008***	0.003
Poor Wealth	0.323	0.250	0.328	0.258	0.072***	0.070***	-0.008***	-0.006**
Abs. Inadequate Wealth	0.072	0.046	0.071	0.048	0.026***	0.023***	-0.002	0.001
North West	0.262	0.266	0.259	0.261	-0.004	-0.003	0.005*	0.004
North East	0.190	0.191	0.188	0.186	-0.000	0.002	0.005**	0.003
Centre	0.194	0.189	0.198	0.192	0.005	0.005	-0.003	-0.004
South	0.239	0.241	0.241	0.244	-0.001	-0.003	-0.004*	-0.002
Islands	0.114	0.114	0.115	0.116	-0.000	-0.002	-0.003	-0.001
Immigrant	0.085	0.050	0.097	0.048	0.035***	0.049***	0.002	-0.012***

*Notes: The significance levels of the mean differences were calculated using a two-sided t-test. *** Significant at 1%; ** significant at 5%; *significant at 10%. Sample weights applied.*

Table B2.: Determinants of the Mental Component Score for Males (2012/13), OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
15-24	2.797***	(0.216)	7.277***	(0.739)	3.386***	(0.351)	1.887***	(0.178)	1.640***	(0.224)	1.361***	(0.214)
25-34	0.931***	(0.162)	1.667***	(0.580)	1.187***	(0.262)	0.750***	(0.133)	0.634***	(0.163)	0.447***	(0.149)
45-54	-0.936***	(0.149)	-2.076***	(0.552)	-1.213***	(0.241)	-0.492***	(0.118)	-0.594***	(0.140)	-0.544***	(0.124)
55-64	-1.051***	(0.183)	-1.488**	(0.700)	-1.604***	(0.293)	-0.737***	(0.139)	-0.977***	(0.159)	-0.785***	(0.136)
Physical Health Problems	-3.987***	(0.220)	-14.553***	(0.915)	-4.977***	(0.325)	-2.056***	(0.139)	-1.230***	(0.154)	-0.833***	(0.126)
High Education	-0.228	(0.169)	-0.268	(0.601)	0.076	(0.276)	-0.246*	(0.140)	-0.563***	(0.168)	-0.394***	(0.151)
Middle Education	-0.377***	(0.114)	-1.071***	(0.410)	-0.234	(0.182)	-0.250***	(0.090)	-0.325***	(0.109)	-0.209**	(0.098)
Temp. Full-Time	-0.512**	(0.209)	-0.704	(0.677)	-1.082***	(0.363)	-0.275	(0.182)	-0.051	(0.225)	-0.185	(0.202)
Part-Time	-0.413	(0.278)	-0.680	(0.963)	-0.424	(0.451)	-0.107	(0.242)	-0.365	(0.286)	-0.441*	(0.245)
Self-Employed	-1.340***	(0.145)	-3.622***	(0.526)	-1.855***	(0.237)	-0.758***	(0.116)	-0.596***	(0.137)	-0.604***	(0.119)
Unemployed	-2.714***	(0.197)	-8.083***	(0.761)	-3.857***	(0.306)	-1.340***	(0.141)	-1.148***	(0.163)	-0.819***	(0.145)
Student	-1.714***	(0.237)	-7.399***	(0.824)	-2.307***	(0.380)	-0.843***	(0.199)	-0.077	(0.256)	0.123	(0.250)
Retired	0.129	(0.245)	-1.893**	(0.942)	-0.143	(0.381)	0.383**	(0.180)	0.729***	(0.213)	0.549***	(0.186)
Other Inactive	-4.702***	(0.405)	-16.858***	(1.624)	-5.891***	(0.559)	-1.953***	(0.243)	-1.373***	(0.273)	-0.667***	(0.252)
Couple	0.276	(0.189)	0.839	(0.698)	0.327	(0.297)	0.307**	(0.150)	0.100	(0.183)	-0.326**	(0.164)
Single Parent	-0.721***	(0.247)	-1.606*	(0.913)	-0.952**	(0.387)	-0.493***	(0.189)	-0.431*	(0.224)	-0.369*	(0.201)
HH Size	-0.076	(0.054)	0.023	(0.202)	-0.144*	(0.086)	-0.116***	(0.044)	-0.096*	(0.053)	0.004	(0.047)
Excellent Wealth	1.399***	(0.342)	2.579***	(0.968)	1.849***	(0.501)	1.184***	(0.291)	1.768***	(0.429)	1.517***	(0.427)
Poor Wealth	-2.066***	(0.126)	-5.045***	(0.444)	-2.805***	(0.198)	-1.385***	(0.099)	-1.147***	(0.118)	-0.723***	(0.104)
Abs. Inadequate Wealth	-4.722***	(0.266)	-14.443***	(1.076)	-6.244***	(0.382)	-2.517***	(0.173)	-1.993***	(0.194)	-1.117***	(0.176)
North West	-0.667***	(0.155)	-2.609***	(0.554)	-0.915***	(0.246)	-0.342***	(0.125)	0.031	(0.149)	-0.198	(0.132)
North East	-0.582***	(0.156)	-2.582***	(0.564)	-1.101***	(0.244)	-0.187	(0.123)	0.179	(0.150)	-0.022	(0.133)
Centre	-0.302*	(0.167)	-1.268**	(0.572)	-0.501*	(0.256)	-0.052	(0.133)	0.132	(0.161)	0.001	(0.143)
Islands	0.595***	(0.180)	0.563	(0.648)	0.446	(0.280)	0.484***	(0.139)	0.752***	(0.173)	0.512***	(0.162)
Immigrant	1.240***	(0.208)	5.156***	(0.662)	1.150***	(0.359)	0.360**	(0.183)	0.386*	(0.230)	0.243	(0.203)
Constant	53.051***	(0.231)	46.087***	(0.832)	50.714***	(0.368)	54.873***	(0.190)	58.144***	(0.229)	61.468***	(0.203)
No. of observations							37,420					

*Notes: *** Significant at 1%; ** significant at 5%; *significant at 10%. Sample weights applied. Standard errors, which are reported in parentheses, are clustered at family-level. Reference group is an individual aged 35-44, having low education, a permanent full-time job, single, having appropriate wealth, and living in the South.*

Table B3.: Determinants of the Mental Component Score for Males (2004/05), OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
15-24	2.588***	(0.189)	5.375***	(0.597)	3.574***	(0.342)	1.824***	(0.149)	2.350***	(0.185)	1.273***	(0.121)
25-34	1.112***	(0.140)	1.941***	(0.456)	1.646***	(0.258)	0.892***	(0.111)	1.132***	(0.131)	0.486***	(0.083)
45-54	-0.574***	(0.142)	-1.134**	(0.481)	-0.664**	(0.263)	-0.330***	(0.109)	-0.542***	(0.118)	-0.335***	(0.069)
55-64	-0.325*	(0.182)	0.046	(0.638)	-0.517	(0.337)	-0.356***	(0.134)	-0.384***	(0.141)	-0.296***	(0.075)
Physical Health Problems	-4.205***	(0.216)	-13.075***	(0.776)	-6.079***	(0.354)	-1.563***	(0.126)	-1.108***	(0.123)	-0.296***	(0.067)
High Education	0.167	(0.163)	0.839	(0.526)	0.548*	(0.298)	-0.091	(0.130)	-0.249*	(0.144)	-0.085	(0.085)
Middle Education	-0.111	(0.104)	0.168	(0.335)	-0.087	(0.193)	-0.295***	(0.081)	-0.189*	(0.096)	-0.028	(0.061)
Temp. Full-Time	-0.904***	(0.190)	-2.304***	(0.651)	-1.293***	(0.362)	-0.708***	(0.153)	-0.662***	(0.172)	-0.255**	(0.101)
Part-Time	-1.343***	(0.316)	-4.315***	(1.054)	-2.378***	(0.555)	-0.508**	(0.225)	-0.449*	(0.256)	-0.155	(0.155)
Self-Employed	-0.823***	(0.126)	-1.950***	(0.420)	-1.354***	(0.238)	-0.454***	(0.098)	-0.473***	(0.110)	-0.223***	(0.063)
Unemployed	-2.088***	(0.215)	-6.714***	(0.747)	-3.750***	(0.382)	-0.853***	(0.147)	-0.356**	(0.176)	-0.191*	(0.108)
Student	-1.388***	(0.221)	-5.616***	(0.702)	-2.408***	(0.385)	-0.455***	(0.168)	-0.063	(0.214)	0.281*	(0.144)
Retired	0.058	(0.222)	-1.181	(0.788)	-0.257	(0.411)	0.281*	(0.162)	0.235	(0.172)	0.064	(0.087)
Other Inactive	-5.271***	(0.476)	-19.016***	(1.556)	-6.326***	(0.656)	-1.110***	(0.235)	-0.602**	(0.259)	-0.098	(0.154)
Couple	0.198	(0.195)	0.420	(0.628)	0.346	(0.355)	0.282*	(0.148)	-0.126	(0.170)	-0.231**	(0.107)
Single Parent	-0.414	(0.254)	-0.781	(0.811)	-0.433	(0.445)	-0.144	(0.187)	-0.364*	(0.214)	-0.181	(0.143)
HH Size	0.094*	(0.054)	0.348**	(0.169)	0.179*	(0.094)	0.013	(0.041)	0.033	(0.049)	0.043	(0.031)
Excellent Wealth	0.150	(0.291)	-0.162	(0.889)	-0.519	(0.514)	0.188	(0.213)	0.370	(0.244)	0.379**	(0.158)
Poor Wealth	-1.708***	(0.126)	-3.952***	(0.407)	-2.915***	(0.230)	-1.100***	(0.094)	-0.769***	(0.107)	-0.251***	(0.065)
Abs. Inadequate Wealth	-3.447***	(0.309)	-9.330***	(1.029)	-5.322***	(0.494)	-1.538***	(0.185)	-0.838***	(0.220)	-0.403***	(0.120)
North West	-0.336**	(0.150)	-1.437***	(0.477)	-0.532**	(0.266)	0.180	(0.112)	0.045	(0.129)	-0.188**	(0.079)
North East	-0.678***	(0.139)	-2.438***	(0.457)	-1.040***	(0.256)	-0.041	(0.106)	-0.289**	(0.118)	-0.430***	(0.070)
Centre	-0.290*	(0.154)	-1.871***	(0.490)	-0.167	(0.271)	0.190	(0.117)	0.046	(0.134)	-0.178**	(0.084)
Islands	0.746***	(0.167)	0.739	(0.526)	1.235***	(0.301)	0.804***	(0.129)	0.745***	(0.154)	0.077	(0.093)
Immigrant	0.958***	(0.303)	2.678***	(0.885)	1.318**	(0.561)	0.623***	(0.239)	0.346	(0.286)	0.322*	(0.193)
Constant	52.563***	(0.226)	43.824***	(0.740)	49.663***	(0.415)	53.230***	(0.172)	57.463***	(0.200)	60.695***	(0.126)
No. of observations							41,857					

Notes: See Table B2.

Table B4.: Determinants of the Mental Component Score for Females (2012/13), OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
15-24	1.973***	(0.240)	4.430***	(0.787)	2.895***	(0.457)	1.515***	(0.304)	1.398***	(0.239)	1.592***	(0.293)
25-34	0.540***	(0.179)	0.403	(0.608)	0.559*	(0.334)	0.727***	(0.219)	0.588***	(0.166)	0.802***	(0.196)
45-54	-1.126***	(0.159)	-2.104***	(0.561)	-1.847***	(0.304)	-1.122***	(0.191)	-0.695***	(0.139)	-0.431***	(0.158)
55-64	-0.932***	(0.192)	-2.104***	(0.688)	-1.326***	(0.361)	-1.002***	(0.224)	-0.519***	(0.163)	-0.228	(0.189)
Physical Health Problems	-4.740***	(0.231)	-13.258***	(0.927)	-8.478***	(0.424)	-3.831***	(0.227)	-1.725***	(0.155)	-1.194***	(0.177)
High Education	-0.307*	(0.173)	-0.039	(0.585)	-0.065	(0.332)	-0.476**	(0.218)	-0.582***	(0.163)	-0.953***	(0.190)
Middle Education	-0.347***	(0.129)	-1.213***	(0.447)	-0.321	(0.240)	-0.195	(0.151)	-0.308***	(0.114)	-0.510***	(0.138)
Temp. Full-Time	-0.395	(0.289)	-1.430	(1.014)	-0.754	(0.549)	-0.444	(0.354)	-0.173	(0.265)	-0.056	(0.302)
Part-Time	0.083	(0.196)	-0.063	(0.676)	-0.166	(0.372)	0.080	(0.242)	0.244	(0.182)	0.235	(0.212)
Self-Employed	-0.247	(0.234)	-0.838	(0.789)	-0.282	(0.439)	0.296	(0.280)	-0.065	(0.205)	0.235	(0.233)
Unemployed	-0.930***	(0.214)	-3.444***	(0.762)	-2.088***	(0.400)	-0.485**	(0.247)	0.174	(0.182)	0.232	(0.210)
Student	-1.062***	(0.285)	-5.323***	(0.930)	-2.682***	(0.533)	0.055	(0.348)	0.307	(0.273)	0.829**	(0.334)
Retired	1.010***	(0.296)	1.535	(1.080)	1.412**	(0.560)	0.991***	(0.350)	0.722***	(0.260)	0.991***	(0.315)
Other Inactive	-0.200	(0.174)	-0.911	(0.601)	-0.795**	(0.327)	-0.013	(0.211)	0.201	(0.158)	0.127	(0.183)
Couple	0.458**	(0.217)	0.856	(0.743)	0.514	(0.398)	0.246	(0.251)	0.232	(0.188)	0.469**	(0.216)
Single Parent	-0.484*	(0.253)	-0.958	(0.881)	-1.309***	(0.467)	-0.751***	(0.286)	-0.352*	(0.209)	0.012	(0.239)
HH Size	-0.027	(0.059)	0.088	(0.201)	0.051	(0.108)	-0.119*	(0.072)	-0.097*	(0.054)	-0.128**	(0.063)
Excellent Wealth	0.442	(0.435)	2.224*	(1.177)	-0.804	(0.887)	0.579	(0.523)	0.964**	(0.421)	1.255**	(0.554)
Poor Wealth	-2.187***	(0.137)	-4.214***	(0.460)	-3.424***	(0.253)	-2.367***	(0.159)	-1.362***	(0.117)	-0.993***	(0.139)
Abs. Inadequate Wealth	-5.366***	(0.283)	-13.229***	(1.056)	-8.693***	(0.500)	-4.603***	(0.277)	-2.643***	(0.191)	-1.794***	(0.230)
North West	-0.664***	(0.175)	-2.090***	(0.588)	-1.193***	(0.325)	-0.579***	(0.206)	-0.092	(0.153)	-0.455**	(0.179)
North East	-0.844***	(0.176)	-2.699***	(0.598)	-1.887***	(0.325)	-0.646***	(0.204)	-0.029	(0.153)	-0.361**	(0.180)
Centre	-0.591***	(0.182)	-2.012***	(0.602)	-1.040***	(0.333)	-0.595***	(0.215)	-0.039	(0.160)	-0.176	(0.190)
Islands	0.345*	(0.195)	0.025	(0.640)	0.093	(0.352)	0.548**	(0.226)	0.713***	(0.172)	0.568***	(0.213)
Immigrant	2.266***	(0.201)	6.630***	(0.630)	3.821***	(0.376)	1.858***	(0.269)	0.861***	(0.202)	1.007***	(0.249)
Constant	50.713***	(0.286)	39.863***	(0.985)	48.005***	(0.531)	53.651***	(0.345)	57.211***	(0.258)	60.056***	(0.301)
No. of observations	38,530											

Notes: See Table B2.

Table B5.: Determinants of the Mental Component Score for Females (2004/05), OLS and RIF Estimates

	OLS		Q10		Q25		Q50		Q75		Q90	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
15-24	1.355***	(0.236)	0.486	(0.747)	1.427***	(0.416)	1.180***	(0.161)	1.475***	(0.193)	1.810***	(0.223)
25-34	0.527***	(0.154)	0.434	(0.470)	0.422	(0.290)	0.450***	(0.114)	0.470***	(0.129)	0.618***	(0.141)
45-54	-0.960***	(0.161)	-1.918***	(0.517)	-1.663***	(0.300)	-0.649***	(0.113)	-0.385***	(0.124)	-0.345***	(0.132)
55-64	-1.012***	(0.195)	-2.229***	(0.633)	-1.893***	(0.357)	-0.597***	(0.132)	-0.292**	(0.144)	-0.361**	(0.147)
Physical Health Problems	-4.688***	(0.244)	-13.614***	(0.917)	-7.840***	(0.434)	-2.233***	(0.135)	-1.072***	(0.140)	-0.780***	(0.136)
High Education	0.404**	(0.178)	1.432***	(0.540)	0.869***	(0.331)	0.088	(0.133)	-0.123	(0.149)	-0.077	(0.159)
Middle Education	-0.019	(0.125)	0.201	(0.385)	0.117	(0.228)	-0.008	(0.087)	-0.196*	(0.102)	-0.187*	(0.111)
Temp. Full-Time	-0.374	(0.250)	-0.864	(0.811)	-0.403	(0.475)	-0.412**	(0.186)	-0.218	(0.205)	-0.390*	(0.221)
Part-Time	-0.278	(0.198)	-1.118*	(0.624)	-0.451	(0.368)	-0.217	(0.144)	-0.094	(0.160)	-0.065	(0.178)
Self-Employed	-0.117	(0.222)	-0.425	(0.674)	-0.069	(0.410)	-0.036	(0.158)	0.099	(0.173)	-0.179	(0.180)
Unemployed	-0.331	(0.245)	-1.311*	(0.763)	-0.741*	(0.442)	0.019	(0.165)	0.303	(0.190)	0.079	(0.212)
Student	-0.274	(0.276)	-1.774**	(0.861)	-0.806*	(0.484)	-0.072	(0.186)	0.379*	(0.226)	0.653**	(0.268)
Retired	0.687**	(0.314)	1.180	(1.030)	1.046*	(0.588)	0.380*	(0.215)	0.536**	(0.234)	0.650***	(0.248)
Other Inactive	-0.089	(0.162)	-1.178**	(0.515)	-0.193	(0.299)	0.086	(0.113)	0.282**	(0.127)	0.172	(0.138)
Couple	0.600***	(0.231)	1.215	(0.740)	0.840**	(0.421)	0.277*	(0.161)	0.393**	(0.173)	0.260	(0.192)
Single Parent	-0.327	(0.276)	-0.898	(0.890)	-0.492	(0.491)	-0.090	(0.183)	-0.121	(0.197)	0.127	(0.216)
HH Size	0.064	(0.061)	0.441**	(0.177)	0.086	(0.109)	0.002	(0.042)	-0.076	(0.049)	-0.021	(0.056)
Excellent Wealth	0.905***	(0.272)	1.138	(0.782)	0.911*	(0.513)	0.627***	(0.201)	1.003***	(0.253)	1.161***	(0.315)
Poor Wealth	-2.071***	(0.144)	-4.245***	(0.457)	-3.567***	(0.258)	-1.308***	(0.094)	-1.021***	(0.106)	-0.577***	(0.117)
Abs. Inadequate Wealth	-3.733***	(0.307)	-7.772***	(0.979)	-6.795***	(0.548)	-2.192***	(0.184)	-1.292***	(0.205)	-0.689***	(0.222)
North West	-0.704***	(0.165)	-2.426***	(0.512)	-1.396***	(0.298)	-0.390***	(0.114)	0.147	(0.130)	-0.042	(0.143)
North East	-1.029***	(0.157)	-2.846***	(0.491)	-1.706***	(0.295)	-0.693***	(0.111)	-0.256**	(0.122)	-0.586***	(0.129)
Centre	-0.903***	(0.180)	-3.376***	(0.547)	-1.425***	(0.321)	-0.275**	(0.120)	0.130	(0.136)	-0.168	(0.150)
Islands	0.038	(0.198)	-0.656	(0.579)	0.020	(0.346)	0.183	(0.134)	0.498***	(0.156)	0.491***	(0.177)
Immigrant	2.307***	(0.279)	5.925***	(0.705)	3.538***	(0.518)	1.275***	(0.221)	1.164***	(0.286)	0.766**	(0.329)
Constant	50.456***	(0.291)	37.763***	(0.915)	47.395***	(0.533)	53.361***	(0.203)	55.723***	(0.229)	59.760***	(0.250)
No. of observations	42,789											

Notes: See Table B2.

C. Appendix to Chapter 4

Table C1.: IV-Probit Estimates of Child Height on Later Educational Performance. Alternative Sub-District Fixed Effects

	Birth SD-FE		2000 SD-FE		2007 SD-FE	
	AME	Std. Err.	AME	Std. Err.	AME	Std. Err.
HAZ (in 2000)	-0.169***	(0.015)	-0.169***	(0.015)	-0.171***	(0.016)
Male	0.031**	(0.015)	0.031**	(0.015)	0.033**	(0.016)
Birth order	-0.005	(0.004)	-0.005	(0.004)	-0.006	(0.004)
Sundanese	-0.068***	(0.017)	-0.068***	(0.017)	-0.073***	(0.017)
Other ethnicity	-0.035**	(0.015)	-0.035**	(0.015)	-0.035**	(0.015)
Mother's education	-0.000	(0.003)	-0.000	(0.003)	-0.000	(0.003)
Student-teacher ratio	0.006***	(0.001)	0.006***	(0.001)	0.006***	(0.001)
Urban community	0.037**	(0.017)	0.037**	(0.017)	0.040**	(0.017)
Village has sewerage	-0.007	(0.017)	-0.007	(0.017)	-0.012	(0.017)
Village has piped water	-0.002	(0.017)	-0.002	(0.017)	0.006	(0.017)
Constant	–	–	–	–	–	–
SD-FE	Yes		Yes		Yes	
No. of observations	2,842		2,842		2,821	
No. of SD-FE	21		23		22	

*Notes: AME = Average Marginal Effects. Standard errors are clustered at the year-month of birth level and are reported in parentheses. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table C2.: First Stage Estimate of Alternative Exposures to the Asian Financial Crisis on Child Health

	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Exposure to the crisis (pregnancy)	-0.348***	(0.097)	–	–	–	–	–	–	–	–	–	–
Exposure to the crisis (0-12 months)	–	–	-0.396***	(0.090)	–	–	–	–	–	–	–	–
Exposure to the crisis (12-24 months)	–	–	–	–	-0.303***	(0.091)	–	–	–	–	–	–
Exposure to the crisis (24-36 months)	–	–	–	–	–	–	-0.226**	(0.091)	–	–	–	–
Exposure to the crisis (36-48 months)	–	–	–	–	–	–	–	–	-0.086	(0.085)	–	–
Exposure to the crisis (48-60 months)	–	–	–	–	–	–	–	–	–	–	0.072	(0.098)
Male	-0.076	(0.059)	-0.084	(0.058)	-0.105*	(0.058)	-0.096	(0.059)	-0.088	(0.059)	-0.088	(0.059)
Birth order	-0.028	(0.022)	-0.024	(0.021)	-0.028	(0.022)	-0.030	(0.022)	-0.028	(0.022)	-0.028	(0.022)
Sundanese	-0.127	(0.098)	-0.133	(0.097)	-0.138	(0.098)	-0.133	(0.098)	-0.126	(0.099)	-0.132	(0.099)
Other ethnicity	-0.237***	(0.061)	-0.248***	(0.062)	-0.248***	(0.062)	-0.242***	(0.061)	-0.240***	(0.062)	-0.240***	(0.062)
Mother's education	0.052***	(0.008)	0.053***	(0.008)	0.051***	(0.007)	0.049***	(0.008)	0.050***	(0.008)	0.051***	(0.008)
Student-teacher ratio	0.021***	(0.006)	0.023***	(0.007)	0.022***	(0.007)	0.021***	(0.007)	0.021***	(0.007)	0.021***	(0.007)
Urban community	0.307***	(0.068)	0.304***	(0.069)	0.312***	(0.069)	0.312***	(0.069)	0.310***	(0.069)	0.310***	(0.069)
Village has sewerage	-0.142*	(0.075)	-0.140*	(0.076)	-0.132*	(0.077)	-0.129	(0.078)	-0.130*	(0.077)	-0.132*	(0.077)
Village has piped water	0.021	(0.077)	0.011	(0.077)	0.009	(0.077)	0.020	(0.077)	0.017	(0.077)	0.016	(0.077)
Constant	-2.150***	(0.160)	-2.159***	(0.167)	-2.157***	(0.164)	-2.150***	(0.174)	-2.226***	(0.169)	-2.257***	(0.162)
SD-FE	Yes		Yes									
No. of observations	2,855		2,855		2,855		2,855		2,855		2,855	
No. of SD-FE	21		21		21		21		21		21	
Kleinbergen-Paap F statistic	12.77		19.40		10.99		6.17		1.02		0.54	

*Notes: SD-FE = Sub-District Fixed Effects. Standard errors are clustered at the year-month of birth level and are reported in parentheses. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table C3.: Second Stage Estimate of Alternative Exposures to the Asian Financial Crisis on Child Health

	Pregnancy		0-12 months		12-24 months		24-36 months	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
HAZ (in 2000)	0.084	(0.051)	-0.041	(0.038)	-0.143***	(0.025)	-0.182***	(0.014)
Male	0.069***	(0.013)	0.060***	(0.012)	0.043***	(0.015)	0.022	(0.017)
Birth order	0.002	(0.005)	-0.002	(0.004)	-0.005	(0.004)	-0.006	(0.004)
Sundanese	-0.058***	(0.022)	-0.071***	(0.016)	-0.080***	(0.017)	-0.066***	(0.019)
Other ethnicity	0.027	(0.019)	-0.003	(0.015)	-0.028*	(0.016)	-0.040***	(0.015)
Mother's education	-0.017***	(0.002)	-0.011***	(0.002)	-0.004	(0.003)	0.002	(0.003)
Student-teacher ratio	0.001	(0.002)	0.004***	(0.001)	0.006***	(0.001)	0.006***	(0.001)
Urban community	-0.047**	(0.022)	-0.009	(0.020)	0.025	(0.018)	0.044***	(0.016)
Village has sewerage	0.029*	(0.018)	0.014	(0.017)	-0.002	(0.018)	-0.013	(0.017)
Village has piped water	-0.002	(0.017)	-0.000	(0.017)	0.003	(0.018)	0.003	(0.017)
Constant	–	–	–	–	–	–	–	–
SD-FE	Yes		Yes		Yes		Yes	
No. of observations	2,855		2,855		2,855		2,855	
No. of SD-FE	21		21		21		21	

*Notes: SD-FE = Sub-District Fixed Effects. Standard errors are clustered at the year-month of birth level and are reported in parentheses. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table C4.: Child Height and Later Educational Performance: IV-Probit Coefficients

	Coeff.	Std. Err.
HAZ (in 2000)	-0.611***	(0.045)
Male	0.111**	(0.056)
Birth order	-0.020	(0.015)
Sundanese	-0.274***	(0.069)
Other ethnicity	-0.128**	(0.055)
Mother's education	-0.001	(0.010)
Student-teacher ratio	0.022***	(0.005)
Urban community	0.131**	(0.059)
Village has sewerage	-0.033	(0.061)
Village has piped water	0.013	(0.063)
Constant	-1.788***	(0.118)
SD-FE	Yes	
No. of observations	2,855	
No. of SD-FE	21	

*Notes: SD-FE = Sub-District Fixed Effects. Standard errors are clustered at the year-month of birth level and are reported in parentheses. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table C5.: Robustness Check: Determinants of Attrition

	Coeff.	Std. Err.
HAZ (in 2000)	-0.001	(0.001)
Male	0.003	(0.003)
Birth order	0.003**	(0.001)
Sundanese	0.003	(0.006)
Other ethnicity	0.010**	(0.004)
Mother's education	0.001**	(0.001)
Student-teacher ratio	0.000	(0.000)
Urban community	0.004	(0.005)
Village has sewerage	0.001	(0.003)
Village has piped water	-0.001	(0.004)
Constant	-0.029***	(0.008)
SD-FE	Yes	
No. of observations	2,979	
No. of SD-FE	28	

*Notes: Notes: Dependent variable is equal to one if educational performance was not observed and 0 otherwise. SD-FE = Sub-District Fixed Effects. Standard errors are clustered at the year-month of birth level and are reported in parentheses. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table C6.: Robustness Check: First Stage Estimate of Alternative Exposures to the Indonesian Wildfires on Child Health

	(1)		(2)	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Exposure to the wildfires (12-36 months)	-0.011	(0.072)	–	–
Exposure to the wildfires (All)	–	–	-0.006	(0.072)
Male	-0.087	(0.059)	-0.088	(0.059)
Birth order	-0.028	(0.022)	-0.028	(0.022)
Sundanese	-0.130	(0.099)	-0.129	(0.099)
Other ethnicity	-0.238***	(0.060)	-0.239***	(0.060)
Mother's education	0.051***	(0.008)	0.051***	(0.008)
Student-teacher ratio	0.021***	(0.007)	0.021***	(0.007)
Urban community	0.310***	(0.069)	0.310***	(0.069)
Village has sewerage	-0.131*	(0.077)	-0.131*	(0.077)
Village has piped water	0.014	(0.078)	0.015	(0.078)
Constant	-2.245***	(0.169)	-2.248***	(0.169)
SD-FE	Yes		Yes	
No. of observations	2,855		2,855	
No. of SD-FE	21		21	
Kleinbergen-Paap F statistic	0.02		0.01	

*Notes: SD-FE = Sub-District Fixed Effects. Standard errors are clustered at the year-month of birth level and are reported in parentheses. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

Table C7.: Robustness Check: IV-Probit Estimates of Child Height on Later Educational Performance. Additional Covariates Added

	(1) AME	(2) AME	(3) AME	(4) AME	(5) AME
HAZ (in 2000)	-0.169***	-0.170***	-0.171***	-0.173***	-0.189***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Male	0.034**	0.032**	0.031**	0.033**	0.014
	(0.015)	(0.015)	(0.015)	(0.015)	(0.019)
Birth order	-0.004	-0.005	-0.001	-0.002	-0.005
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Sundanese	-0.073***	-0.076***	-0.074***	-0.080***	-0.052**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.022)
Other ethnicity	-0.035**	-0.040***	-0.036**	-0.038**	-0.022
	(0.016)	(0.015)	(0.014)	(0.015)	(0.017)
Mother's education	-0.001	-0.001	-0.000	-0.001	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Student-teacher ratio	0.006***	0.006***	0.006***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Urban community	0.035**	0.037**	0.039**	0.037**	0.042**
	(0.016)	(0.016)	(0.016)	(0.015)	(0.021)
Village has sewerage	-0.012	-0.013	-0.012	-0.017	-0.006
	(0.017)	(0.017)	(0.017)	(0.017)	(0.021)
Village has piped water	0.002	0.003	0.002	-0.000	-0.023
	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)
Age on starting school	-0.025***	-0.026***	-0.027***	-0.028***	-0.037***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)
Private school	–	-0.048*	-0.046*	-0.055**	-0.037
	–	(0.024)	(0.025)	(0.025)	(0.029)
Household size	–	–	-0.008*	-0.006	-0.009*
	–	–	(0.004)	(0.004)	(0.005)
Log of real PCE	–	–	–	0.010	–
	–	–	–	(0.019)	–
Log of real PCE (in 1997)	–	–	–	–	0.018
	–	–	–	–	(0.015)
Constant	–	–	–	–	–
	–	–	–	–	–
No. of observations	2,852	2,834	2,834	2,777	1,864
No. of SD-FE	21	21	21	21	18

*Notes: SD-FE = Sub-District Fixed Effects and AME = Average Marginal Effects. Standard errors are clustered at the year-month of birth level and are reported in parentheses. ***, **, and * indicate significance at 1 %, 5 %, and 10 %, respectively.*

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