The Causal Effects of Education on Family Health: Evidence from Expanding Access to Higher Education

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Abstract

Exploiting the geographical expansion of the Finnish university system, we study the causal effects of education on family health. We find that education has positive impacts not only on individuals' health but also on their parents' health later in life. An additional year of education decreases the probability of mental health-related hospitalization~~s~~ and drug use by 3–4 percentage points while having less significant impacts on early mortality. As for the spillover effects, it increases a mother's probability of old age survival by 2–3 percentage points, whereas the estimated effects on parents' mental health and a father's survival are less significant.

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1. Introduction

Health disparities by education level remain substantial in both developed and developing countries. The findings from the U.S. from a study by Case and Deaton (2021) show that the difference in adult life expectancy between college-educated and non-college-educated citizens increased from two to three years during the last thirty years. In this paper, we focus on Finland, where the education-health gradient has not been much less steep than in the U.S. despite a lower level of income inequality. According to the OECD (2021), the gap in life expectancy at age 30 between the highest and lowest education levels was 5.1 years for Finnish men and 3.6 years for Finnish women in 2019. These gaps were only slightly higher, 5.2 for men and 4.5 years for women, in Mexico, a developing country that has a 15-percentage-point higher Gini coefficient than Finland (OECD, 2023).

From the point of view of seeking policies that improve society's wellbeing, a crucial question is whether the relationship between education and health is causal. In other words, can better health be considered a non-monetary return to education that makes educational investments valuable beyond their private monetary returns? Thus far, experimental and quasi-experimental evidence regarding this question has been inconclusive, as studies have found that education affects individuals' own health outcomes, including mortality, obesity, and health behaviors, only in some contexts (see Galama et al., 2018; Xu et al., 2021). However, even in the absence of direct health effects, society could benefit from its members' educational attainment through the spillover effects on others' health. Recently, the literature has begun to accumulate credible evidence on a spillover effect emerging within families where individuals' education influences their parents' later-life health (Lundborg and Majlesi, 2018; De Neve and Fink, 2018; Ma, 2019; Cornelissen and Dang, 2022).[1]

Contributing to these lines of research, our study aims to 'kill two birds with one stone' by presenting quasi-experimental evidence on both the direct health effects of years of education and the upward intergenerational effects on parental health. Our analysis utilizes Finnish full-population register data containing information on individuals' mortality and mental health problems and those of their mothers and fathers. For causal inference, we adopt the approach of Suhonen and Karhunen (2019), which exploits the plausibly exogenous variation in individuals' attained years of education arising from changes in the geographical access to university education. These changes occurred due to the opening of new universities and the geographical expansion of the Finnish university system between the late 1960s and the late 1970s. Using data from this period, we construct two alternative instruments for a child's years of education. The first instrument is based on the changes in distance to the nearest university, while the second instrument captures the detailed variation in the supply and potential demand for student places in universities.

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1 Theoretical arguments mainly point towards a positive causal link from a child's education to her own and her parents' health: education can make individuals better producers of health, provide them with better resources for health investments, and incentivize them to remain capable of working and living longer (Grossman, 1972; Galama et al., 2018). However, opposing arguments have also been presented. Galama et al. (2018) argue that the greater wealth earned via education may also increase the consumption of unhealthy goods. Education may also cause stress and entail significant opportunity costs, especially for low achievers in compulsory education (Avendano et al., 2020). Furthermore, having an educated child can provide old-age parents with many advantages in terms of their physical and mental health, but possible undermining factors also exist: more successful children often have higher opportunity costs of taking care of their parents personally and may also be required to move further away from them than less successful ones (Lundborg and Majlesi, 2018).

Our results suggest that education is, in several ways, favorable to family health. We find that an additional year of education decreases one's probability of mental health-related hospitalizations and drug use by 3–4 percentage points and increases a mother's probability of survival until the ages of 70–80 by 2–3 percentage points. The evidence regarding the effects on one's own or a father's survival is, again, weaker. The results also suggest that the effect of child's education on parental survival varies by the child's gender and is, overall, stronger with a daughter's education than a son's education. Moreover, we find that, apart from affecting education and health outcomes, an individuals' greater access to university is positively linked to their later-life income and the probability of remaining geographically close to their parents as they approach old age, which could serve as mechanisms behind the observed positive health effects of the natural experiment.

These results contribute in several ways to the large, yet inconclusive literature reviewed by Galama et al. (2018) and Xue et al. (2021) on the health effects of education. While most previous observational studies have used compulsory schooling reforms as natural experiments to identify the causal effect of education on health,[2] we deviate from these studies by using the geographical expansion of higher education.[3] Establishing and expanding regional universities has been a common policy used

[2] A number of studies draw on policy changes from high-income countries such as the United States (Lleras-Muney, 2005), the United Kingdom (Clark and Royer, 2013; Davies et al., 2016), the Netherlands (van Kippersluis et al., 2011), Sweden (Meghir et al., 2018), and France (Albouy and Lequien, 2009). Recent papers provide evidence for middle- and low-income countries, for example, China (Jiang et al., 2020), Romania (Malamud et al., 2023), and Zimbabwe (Kondirolli and Sunder, 2022).

3 A few previous studies have used other types of natural experiments related to higher education to study the health effects of education. Buckles et al. (2016) and Lacroix et al. (2019) exploited military draft lotteries in the U.S. and Canada, respectively, to show the significant reducing effects of college attendance on mortality.

for improving access to higher education in many countries, and the unique Finnish context and data enable us to provide rare evidence on the health consequences of education induced through this policy. Thus, our results also contribute to the growing evidence on the effects of higher education institutions on regional development, which has primarily focused on local educational attainment (Howard & Weinstein, 2022; Russell et al., 2022), invention and technological change (Blundell et al., 2022; Andrews, 2023; Carneiro et al., 2023), and the intergenerational effects on children's outcomes (Currie and Moretti, 2003; Suhonen and Karhunen, 2019). The previous results of Suhonen and Karhunen (2019) indicate that the Finnish government's policy of expanding the higher education system into six new regions between the late 1950s and early 1970s had small positive effects on the local youth's educational attainment and, perhaps more importantly, positive spillover effects on children's educational attainment and school performance. As our new results indicate positive effects on family health, there is piling evidence of significant social benefits from the Finnish higher education expansion.

We also depart from most of the previous literature by examining the mental health effects of education, which have received little attention compared to the mortality effects. While developed countries have reached high levels of physical health and life expectancy, depressive disorders and other mental health problems comprise an increasing share of the total disease burden and entail significant indirect costs, for instance, in the form of lower labor supply (Avendano et al., 2020; Böckerman et al., 2021). Therefore, understanding the mechanisms of mental health problems, including the role of educational attainment and educational reforms, is of high policy relevance. The nascent literature on this topic has, thus far, indicated that compulsory schooling reforms have resulted in positive mental health effects in China (Jiang et al., 2020) and Zimbabwe (Kondirolli and Sunder, 2022), but not in

Gonzalez et al. (2022) again utilized the variation in access to college induced by a military coup in Chile to document a negative effect of higher education on mortality.

developed countries, such as Britain (Adendano et al., 2020) or Finland (Böckerman et al., 2021).[4] However, our results demonstrate that a different type of educational policy reform—that of higher education expansion—can have positive mental health effects within the context of a developed country.

Last, our paper also speaks to the intergenerational transmission of human capital, the causal evidence of which has mainly focused on the transmission of human capital from parents to children (see Holmlund et al., 2011). The existing quasi-experimental evidence on transmission occurring in the opposite direction, from children to parents, is scarcer and mainly arises from compulsory schooling reforms such as those implemented in Tanzania (De Neve and Fink, 2018), China (Ma, 2019), Sweden (Lundborg and Majlesi, 2018), and Vietnam (Cornelissen and Dang, 2022). Alongside the findings of Lundborg and Majlesi (2018) from Sweden, our evidence of the positive effects on parents' survival in Finland indicate that children's education can be important for the health of the aging population even in the context of a developed welfare state in which parents are, in material and financial terms, relatively independent of their children, unlike in developing countries. It is noteworthy that Lundborg and Majlesi (2018) only found positive effects from a daughters' education on a father's survival, while our findings indicate more systematic positive effects. Thus, past higher education expansion policies might have resulted in stronger intergenerational spillover effects in Nordic countries than compulsory schooling reforms; the previous results of Suhonen and Karhunen (2019) regarding the spillover effects from parents' education to children's education also point toward this conclusion.

This paper proceeds as follows. Section 2 discusses the institutional context of the study and the natural experiment arising from the Finnish university expansion. Section 3 describes the data used and

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[4] The results of Lager et al. (2017) suggest that the Swedish compulsory schooling reform even resulted in negative effects on individuals' emotional control.

the construction of the key variables. Section 4 discusses the empirical strategy. Section 5 reports the results of the empirical analysis, and Section 6 concludes.

2. Background

2.1. Institutional context

The implications of education for family health likely depend on the examined economic, cultural, and institutional context. The main sample of individuals used in this study comprises all of Finland's residents born between 1948 and 1961 and their mothers and fathers, who were born in the first half of the 20th century. These parents were born in an industrializing agricultural society that rapidly became a high-income welfare state during the post-war period, around the time when their offspring were young. The Finnish death statistics (Statistics Finland, 2023a) show that this development coincided with remarkable improvements in the life expectancy of the Finnish population, which was only 50 years for men and 55 years for women in the 1920s when the average parent of our sample was born. The life expectancy of men and women grew to 66 and 74 by 1971 and to 79 and 84 by 2021, respectively. Thus, the studied parent cohorts lived or continue to live significantly longer than the previous generations. Apart from life expectancy, there was a steady increase in educational attainment: between 1970 and 2021, the share of the tertiary-educated among adults aged 25 years and older increased from 10% to 37%, while the share of adults with only basic education decreased from 76% to 21% (Statistics Finland, 2023b). Thus, there is also a strong population-level association between the development of educational attainment and longevity.

A notable aspect of the Finnish institutional context is that, due to the relatively generous welfare system and low-income inequality, educational attainment should be, in material and financial terms, relatively unimportant for individuals' health. Finnish parents are also relatively economically independent of their children during their old-age years. To a large degree, this holds for all of the studied parent cohorts who were born after 1905, partly due to several policies implemented early on in Finland. By the time adult children's legal responsibility for supporting their parents was abolished in 1970, a relatively generous social insurance system was already in place, including a universal public health insurance (founded in 1964) and a public pension system with a guaranteed minimum pension and earnings-based work pension.[5] By the late 20th century, Finland's formal elderly care system was also already somewhat developed thanks to changes in social and health care legislation[6] and a growing supply of public and private services provided for elderly people in their private homes, nursing homes, and sheltered housing.[7] Given such a supportive welfare system for the elderly in Finland, direct economic transfers from children to their parents are likely to be relatively unimportant in terms of generating a causal link between children's education and parental health.

2.2. Finnish university expansion

As in the previous Finnish study by Suhonen and Karhunen (2019), our empirical analysis exploits changes in young individuals' geographical access to university education arising from the considerable geographical expansion of the Finnish university system during the post-war period. While the

[5] The original public pension system, based on mandatory fees paid by wage earners and firms, was established in 1937. The roots of the current system were laid in 1957, when a minimum retirement pension and additional earnings-based pensions were introduced. Since then, the system has been reformed several times to improve its financial sustainability and incentives to work.

[6] The Primary Health Care Act (1972) and Social Welfare Act (1982) were particularly important, as these laws strengthened and clarified the role of the public sector in the provision of services for senior citizens.

[7] Apart from formal care, Finland's health and elderly care policy has, since 2006, subsidized the informal care provided at home by a family member, which may, to some extent, strengthen the dependence of parents on their children.

expansion began in 1959 with the opening of the University of Oulu in northern Finland, our analysis focuses on the later wave of university openings from 1968−79, due to the data availability issues discussed in Section 3.

By 1960, the university network already covered the Helsinki metropolitan area and four other major cities, Turku, Tampere, Jyväskylä, and Oulu; however, most of the Finnish regions still lacked institutions providing university education and research. In 1966, after a half-decade of planning and political debate, the Finnish parliament approved the expansion of the university network into four more cities: Vaasa, on the west coast of Finland, and Lappeenranta, Joensuu, and Kuopio in eastern Finland. The first students enrolled at the University of Vaasa in 1968, at the Lappeenranta University of Technology and the University of Joensuu in 1969, and at the University of Kuopio in 1972. The last new university main campus, that of the University of Lapland, was founded in Rovaniemi in 1979 following a decision made by the Finnish government in 1977.

Notable features of the newly established university institutions were their initially small student intake rates and their specializations in a narrow selection of fields of study (see Suhonen and Karhunen, 2019). However, as indicated in Figure 1, which describes the number of new university students by city from 1955–2009, the student intake of these institutions increased over time, which was partly due to the establishment of new faculties and departments within the institutions. However, while the previously established universities located in Helsinki, Turku, Tampere, Oulu, and Jyväskylä continued to grow considerably after the mid-1960s, their relative share of the total university enrollment decreased continuously until the 2000s. Thus, the examined period marks the beginning of a long period of geographical decentralization in the history of the Finnish university system. The gradual expansion of the new institutions, combined with the changes in cohort sizes and the potential demand for university education, gives rise to the use of the gravity-model measure of the access to university discussed in Section 3, which accounts for much finer differences in the exposure of different areas and cohorts to the university expansion compared to the distance-to-university measure.

[INSERT FIGURE 1 HERE]

In terms of justifying the exogeneity of our natural experiment, it is important to emphasize that the final decisions regarding the creation of universities in new regions were likely unforeseeable by the common citizens because of the involvement of opposing forces in the decision-making process. As described by Eskola (2002), the expansion decisions made in 1966 and 1977 were highly influenced by the decentralization and regional development goals of the Centre Party, which led the coalition government at the time. Furthermore, politicians, civil servants, and citizens from several cities openly campaigned for establishing a university in their cities. However, on the opposite side, many of the old universities' academics were strongly against decentralization, expressing concerns about the likely adverse effects of a scattered allocation of scarce resources on the quality of education and research. These conflicting forces and interests resulted in a complex political process, the final outcomes of which were arguably difficult to anticipate.[8]

In a previous study examining the impacts of the Finnish university expansion, Suhonen and Karhunen (2019) found that a decrease in distance to university at age 19 resulting from the opening of a university within 100 kilometers from one's place of birth increased educational attainment by 0.1 years and had significant spillover effects on children's educational attainment. However, the study only found significant impacts on women's probability of enrolling in or graduating from university education, whereas men's educational attainment was found to increase only through a higher participation in vocational education, likely because of local spillovers across the educational sectors

8 For a more comprehensive discussion of the Finnish university expansion and its use as a natural experiment, see Toivanen and Väänänen (2016) and Suhonen and Karhunen (2019).

due to the overall expansion of supply. Furthermore, the study found that greater access to university decreased regional mobility in early adulthood; in particular, individuals became more likely to remain in their region of birth at age 34.

3. Data and descriptive statistics

As our primary data source, we use Statistics Finland's longitudinal full-population data, which are based on registers collected on Finland's residents between 1970 and 2019. These data contain most of the information required for our analysis, including individuals' and their parents' dates of birth and death, municipalities of birth and residence, completed educational qualifications, and annual income. As the earliest Statistics Finland data were collected in the beginning of the 1970s, the individuals who died or permanently emigrated from Finland earlier are not included in the data. Furthermore, we impose two additional restrictions on the sample of individuals used for the analysis. First, as we are interested in the effects of individuals' final educational attainment, we exclude the individuals who died before the year of their 23rd birthday and, thus, likely missed the chance of ever graduating from higher education. Second, we exclude the individuals' parents who reached the age of 65 by 1970 and, thus, were positively selected into the data based on survival at this age.

Since we focus on the changes in 19-year-olds' access to university between 1968 and 1979, our main analyses employ cohorts born between 1948 and 1961 who reached the age of 19 during, shortly before, or shortly after this period.[9] Compared to the earlier study of Suhonen and Karhunen (2019) that examined university openings from 1959−72 and the cohorts from 1936−56, we focus on the later part of the university expansion period and the younger cohorts. This restriction is important because we

9 In the reduced-form event study analyses, we use a slightly larger number of cohorts (1946–63) to obtain more pre- and post-treatment cohorts for the first and last university openings.

require representative information on the individuals' parents that is only available for those who reached their adulthood after or near the first observation years of the Statistics Finland data, that is, the early 1970s.[10] Moreover, focusing on the later period of the university expansion allows us to exploit a natural experiment with stronger first-stage effects, as the findings of Suhonen and Karhunen (2019) suggest that the university openings from 1968−72 had more significant local effects on educational attainment than those from 1959−60.

We merge the Statistics Finland data with the mental health outcome data provided by the Finnish Institute for Health and Welfare (THL) and the Social Insurance Institution of Finland (KELA). To examine mental health-related hospitalizations for our sample of individuals and their parents, we use the Discharge Register from the THL, which includes inpatient discharges in specialized public health care for the Finnish population over the period 1970–2018. The reliability of the Discharge Register is of high quality (Sund, 2012). Our main mental health outcome describes whether an individual had at least one inpatient hospitalization spell annually due to at least one of the following diagnosed mental health disorders (included in categories ICD-10: F, ICD-8 and ICD-9: 290–319): (1) dementia, deterioration in memory, thinking, behavior, and the ability to perform everyday activities; (2) schizophrenia, a mental disorder characterized by hallucinations, delusions, and cognitive deficits; (3) other psychoses that are not related to emotions or moods (nonaffective psychosis); (4) bipolar disorder, an affective psychosis involving emotional and mood abnormalities (and manic episodes); (5) depressive disorder, which can include repeated episodes of severe depression or chronic mild-grade depression (dysthymia); (6) severe anxiety, stress, and neurotic disorders, which can interfere with daily activities, such as job performance, school work, and social relationships; (7) substance-use disorder,

10 The original parent-child link constructed in the early 1970s was based on parents and children belonging to the same household. Therefore, the link is unavailable for many individuals who had already moved away from their family of origin in the early 1970s.

which includes all psychiatric hospitalizations related to alcohol or substance abuse or addiction; and (8) alcohol-use disorder, which is a subset of (7). Given that the probability of one's hospitalization depends on, among other things, her longevity, we only account for hospitalizations up to age 55 in the sample of individuals (children) and up to age 70 in the parent-child sample.

Our secondary mental health outcome data, provided by the KELA, covers all publicly reimbursed medicine purchases due to diagnosed mental health disorders between 1995 and 2018. All residents of Finland are covered by national health insurance and are entitled to benefits, such as reimbursement for medication, which can cover up to 100% of the medication price depending on the specific medication. The KELA data enable us to identify the reimbursed purchases of the following types of mental health-related drugs: psycholeptics, antipsychotics, antipanic agents, sleeping pills, psychoanaleptics, and antidepressants. These data complement the hospitalization data by allowing for the detection of mild mental health disorders not requiring in-patient hospital treatment. However, as the KELA data are only available from 1995 onwards, the representativeness of the information varies by the individuals' year of birth and is especially low for the parents of individuals in the data. Therefore, we do not use the KELA data in the analysis of the parent-child sample. As for the sample of individuals (children), we account for all of the mental health-related drug purchases occurring between 1995 and the year of the individuals' 55th birthday.

Our main explanatory variable, years of education, is based on the individual's highest completed educational qualifications, determined at age 49, in the following manner: 9 years for no post-compulsory education; 12 years for a secondary-level degree (ISCED levels 3–4), 14 years for a short-cycle tertiary degree (ISCED level 5), 16 years for a bachelor's degree (ISCED level 6), 18 years for a master's degree (ISCED level 7), and 22 years for a PhD or licentiate degree (ISCED level 8). Our instrumental variables analysis exploits variation in years of education, which is related to the municipality-by-cohort-level variation in 19-year-olds' access to university. Following Suhonen and

Karhunen (2019), we use two alternative access-to-university measures: 1) the distance to the nearest university; and 2) the gravity-model measure of access to university defined as follows:

$$Access_{m,t} = \sum_{k=1}^{K_t} \frac{S_{k,t}}{C_{k,t} d_{km}^{½}}, \tag{1}$$

where $S_{k,t}$ is the number of new university students, approximating the supply of university education, in municipality *k*, and year *t*; d_{km} is the distance between municipalities *k* and *m*. Similar to Suhonen and Karhunen (2019), we set the value of the distance-decay parameter as ½, which corresponds to a relatively high degree of mobility across distant municipalities, and we adjust the supply by the amount of potential demand for university education in municipality *k* and year *t* given by:

$$C_{k,t} = \sum_{l=1}^{L} \frac{N_{l,t}}{d_{kl}^{\alpha}}, \tag{2}$$

where $N_{l,t}$ is the number of graduates from general upper secondary education (i.e., potential university applicants) in municipality *l* and year *t*, and d_{kl} is the distance between municipalities *k* and *l*. To facilitate an easier interpretation of the results, we scale the gravity-model measure by its standard deviation for the oldest cohort in our sample, that is, those born in 1948.

When merging the access-to-university measures with the individual-level data, our main approach is to define access to university at age 19 based on the individual's parent's municipality of residence either in 1970 (for cohorts 1948–52) or in the year of the individual's 18th birthday (for cohorts 1953–61).[11] Given the mobility of families, this approach more accurately approximates access to

[11] If a person has two parents who live in different municipalities, we define access to university based on the mother's municipality in the individual-level analyses. With the parent-child-level data, we measure the access to university based on the municipality of the parent in question.

university at the given age compared to that employed by Suhonen and Karhunen (2019), which relies on the individuals' municipality of birth.[12]

Table 1 summarizes the employed sample of around one million individuals and reports these individuals' average survival rate, mental health outcomes, and income at age 55 by education level. The statistics indicate significant disparities in physical and mental health by education level, particularly among men. Of the worst-off group, men with only primary education, as many as 10.9 percent passed away and 18.0 percent were hospitalized due to mental health disorders by the year of their 55th birthday. In contrast, among the most highly educated group of men holding a master's degree or higher, the corresponding mortality and hospitalization rates were only 2.3 and 5.0 percent, respectively. For women, early mortality and mental health-related hospitalizations are generally rarer, but the corresponding gaps between high- and low-educated women are still notable: primary-educated women have nearly a 4-percentage-point-higher probability of dying, and nearly an 8-percentage-point-higher probability of being hospitalized due to mental health disorders by age 55 than those with a master's degree or higher.

[INSERT TABLE 1 HERE]

The statistics in Table 1 further show that, while early mortality and mental health-related hospitalizations are relatively uncommon, the use of mental health-related drugs is widespread: according to the KELA register data, as many as 42 percent of women and 31 percent of men have made at least one purchase of mental health-related drugs by age 55. However, the differences in this

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[12] Given the concerns about the possible endogeneity of the individuals' parents' later residential location with respect to the university expansion, we also constructed alternative instruments based on the individuals' birth location. Overall, the estimates obtained using these instruments were less precise but provided the same conclusions as our main results.

outcome across the education groups are modest, and, only among men, those with tertiary education distinctly demonstrate a lower tendency to purchase mental health-related drugs compared to those with lower levels of education. Finally, Table 1 illustrates that, in addition to being healthier and more likely to be alive, the highly educated earn significantly more in middle age compared to the low educated: the ratio of average annual income between the highest and lowest education levels is 3.0 and 2.7 for men and women, respectively.

Table 2 summarizes the linked parent-child sample, which contains over 1.8 million parent-child pairs, and reports the average parental outcomes by the child's education level. In the data, there is a strong positive association between individuals' education and their parents' longevity: only 58 percent of the mothers and 32 percent of the fathers of primary-educated individuals survive until age 80, but the parental survival rates increase notably with the education level. A clear majority of the parents of individuals with a master's degree or higher (73 percent of mothers and 50 percent of fathers) reach age 80. There is also a positive relationship between education and the parents' mental health. In particular, the fathers of primary-educated individuals have a 2.9-percentage-point (56-percent) higher probability of being hospitalized due to mental health disorders by age 70 compared to the fathers of individuals with a higher tertiary degree. The corresponding difference for mothers by the child's education is 1.9 percentage points (40 percent).

[INSERT TABLE 2 HERE]

Table 2 further demonstrates that various other outcomes, including the parents' years of education and income and the geographical proximity of the individuals and their aged parents, are correlated with the child's education level. In line with common observations, more highly educated individuals have more highly educated and high-earning parents but are also more likely to reside in a different area than their 55–65-year-old parents. Thus, a host of possible factors can explain the observed differences in the parents' longevity and mental health by the child's education.

4. Empirical strategy

Our strategy for identifying the effect of years of education on the health of one's family builds on the uneven changes across municipalities in the above-described access-to-university measures. Closely following the earlier study of Suhonen and Karhunen (2019), we conduct the analysis in two parts. First, we conduct an event study analysis by examining the changes in an individual's educational attainment and the health outcomes of her family around the event of a decrease in her distance to university at age 19. Our baseline event study results are based on the following two-way fixed effects (TWFE) specification:

$$y_{ijmc} = \alpha + \sum_{r=\underline{r}}^{\overline{r}} \beta_r d_{m,c+19-r} + \gamma_m + \delta_c + \varepsilon_{ijmc}, \tag{3}$$

where subscripts i, j, m, and c identify the individual, the parent, the individual's municipality of birth, and the individual's cohort of birth, respectively; y_{ijmc} and ε_{ijmc} are the dependent variable and the error term for the parent-child pair ij, respectively (subscript j is suppressed when the individual-level data are used); and γ_m and δ_c control for the municipality and cohort fixed effects, respectively. In the estimation of all the regression equations, we acknowledge a possible broader-level regional heterogeneity in education and health outcomes by clustering the error terms at the level of 70 sub-regions that roughly correspond to the local labor market areas.[13]

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[13] In the estimation of the effects of education on parental health, we considered, similar to Lundborg and Majlesi (2018), weighting the parent-child observations by the inverse of the number of children per parent to place an equal weight on each parent's outcomes in the estimation. However, as the weighted and unweighted estimates are highly similar, we report only the unweighted ones.

In equation (3), the treatment indicator $d_{m,c+19-r}$ describes the change in the individual's distance to university due to a university opening occurring at least $\underline{r}$ years before or at most $\overline{r}$ years after the year of her 19th birthday. We examine the impacts of two different types of changes in the distance to university: a change in the binary indicator for the presence of a university within 100 km and changes of varying magnitude in the continuous distance-to-university measure. The latter approach amounts to estimating the average effect of all the changes in the distance to the nearest university by assuming a linear relationship between distance and the outcome of interest (see Schmidheiny and Siegloch, 2019). The results of the event study analysis are helpful in validating our instrumental variables approach, as we can assess whether there are sharp changes in individuals' or their parents' outcomes occurring simultaneously with changes in the instrument and/or whether there is evidence of pre-trends in the outcomes.

The recent difference-in-differences literature has underlined a potential bias in the estimates obtained by a TWFE regression in the context of a staggered research design similar to ours (see Borusyak et al., 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). To assess whether our baseline estimates using the TWFE approach are robust, we provide additional estimates using the approach recently proposed by Callaway and Sant'Anna (2021) in Appendix A. As the non-parametric event study estimates are highly similar to the baseline TWFE estimates, we have confidence that our baseline estimates are not highly contaminated by the problems raised in the recent literature that can arise from the use of TWFE in the context of a staggered design.

To estimate the causal relationship between education and family health, we instrument the individual's years of education with her access to university at age 19, while controlling for the municipality and cohort fixed effects, as follows:

$$Health_{ijmc} = \beta_0 + \beta_1 Educ_{ijmc} + \theta_m + \mu_c + \varepsilon_{ijmc} \tag{4}$$

$$Educ_{ijmc} = \alpha_0 + \alpha_1 Access_{m,c+19} + \gamma_m + \delta_c + \vartheta_{ijmc}, \tag{5}$$

where $Access_{m,c+19}$ is one of the two access measures defined in Section 3, that is, *distance to university* or the *gravity-model measure* of access to university. When included in the TWFE regression, the first instrument only accounts for changes in the geographical location of universities relative to the individual's location due to the university openings, whereas the latter instrument relates finer-level changes in universities' student intake to the potential demand determined by the number of general upper secondary school graduates. While the latter instrument is much stronger, it also depends on a larger number of potential factors, such as local cohort sizes, demographics, and the supply of general secondary education, making it more susceptible to endogeneity problems.

While the baseline specification (4)–(5) only controls for the municipality and cohort fixed effects, we conduct robustness checks using a specification that also controls for the individual's first language (Finnish, Swedish, or other), the parents' highest education level (six categories ranging from primary education to licentiate and doctorate degrees), and the average of the parents' income. The parental characteristics are measured using census data from the year of the individual's 15$^{\text{th}}$ birthday or from the closest available year (1970, 1975, or 1980).

Both the event study and instrumental variables results rely on the parallel trends assumption, which could be violated by a non-random selection of individuals into the treatment, that is, the groups affected by the changes in access to university at different times or with different intensity. However, several facts suggest that non-random selection is not of major concern in the current setting. First, the access measures are based on the residential location chosen by the individuals' parents and are, therefore, theoretically exogenous from an individual perspective. Second, as explained in Section 2.2, the university expansion itself contained random elements given the complex political process leading to it, which alleviates concerns about the non-random sorting or assignment of families into the treatment. Third, our validity and robustness checks, as well as those of Suhonen and Karhunen (2019), provide very little indication that particular types of families or areas, in terms of the observable socio-economic variables, were exposed to the changes in access to university more than others.[14]

Unlike the reduced-form event study analysis, the instrumental variables analysis also explicitly assumes that a change in one's access to university only affects her own and her parents' health via a change in one's years of education. This exclusion restriction could be violated by the direct or other indirect effects of the university expansion on family health. A hypothetical direct channel arises from the possibility that the university openings and expansion, in some ways, affected the healthcare treatment received by the individuals and their parents due, for example, to their effect on the number or quality of the healthcare providers in their municipality of residence. Of the hypotheses related to indirect channels, perhaps the most obvious is that the university expansion did not only affect the education and labor market prospects of the children's generation but also that of the parents' generation, which could be reflected in the parents' health. One may argue that many of the possible long-term effects of the university openings on the local labor markets and services eventually accrue to the parents of children of all ages and, therefore, are reasonably well captured by the municipality fixed effects. Furthermore, at the time of the expansion, the parents in our data were arguably too old (on average 43 in 1968) to have been significantly affected via educational attainment. These arguments are supported by the results reported in Section 5.3, which suggest that, in most cases, the instruments are not significantly related to parent's educational attainment or income.

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[14] Suhonen and Karhunen (2019) compared the average pre-expansion characteristics of the municipalities that were most strongly affected by the university openings from 1959–72 in terms of distance to university and the remaining municipalities included in the control group, finding only minor differences. Furthermore, adjusting the estimates for these municipal differences did not have a significant impact on the first- or second-stage results of their instrumental variables analysis.

5. Results

5.1. Event study results

We first show simple parametric event study estimates obtained using two-way fixed effects (TWFE) regressions for our outcomes of interest. Figure 2 presents the event study graphs regarding the effects of a decrease in the 19-year-old cohort's distance to university on their later educational attainment and health. The results obtained by the binary and continuous treatment indicators are highly similar and suggest that a decrease in distance to university to <100 km, or by 100 km, relates to roughly 0.1 to 0.2 years of additional educational attainment among the five first treated cohorts compared to the youngest non-treated cohort.

The event study results regarding an individual's survival probability and incidence of mental health problems are less clear, and, for the first treated cohort turning 19 in the university opening year, none of the changes in these variables is highly significant. However, as many of the estimates for the younger cohorts are statistically significant, we obtain evidence of lagged effects from the treatment. In particular, the changes in the binary and continuous treatment indicators are related to a significantly (up to a 0.7-percentage-point) higher probability of survival until age 55 for the cohorts turning 19 one or more years after the beginning of the treatment compared to the reference group, who turned 19 one year before the treatment. The results for both treatment indicators further demonstrate lagged negative effects in the range of one half to one percentage point on the probability of mental health-related hospitalization and mental health-related drug purchases for the 19-year-old cohorts 3–4 years after the beginning of the treatment. The estimated lead effects in Figure 2 are mainly statistically insignificant and do not provide systematic evidence of pre-trends in the outcomes. The clearest lead effect appears in the probability of mental health-related drug purchases, which is negatively associated with the binary and continuous treatment intensities four years before the beginning of the treatment.

[INSERT FIGURE 2 HERE]

After the effects of an individual's distance to university on her own long-term outcomes, we move on to investigating the spillover effects within the family by using the parent's survival and probability of mental health-related hospitalization as dependent variables. The event study results in Figure 3 provide evidence of such spillover effects. When using the continuous treatment indicator, many of the estimates indicate that a 100 km decrease in an individual's distance to university relates to up to a one half percentage point increase in her parent's cumulative survival probabilities at ages 70, 75, and 80. Furthermore, the decrease in the continuous distance variable relates to a decrease of approximately 0.2 to 0.4 percentage points in the parent's probability of mental health-related hospitalization. The event study results using the binary treatment indicator (individual's distance to university <100 km) mainly point in the same direction, but they are less precise and, therefore, inconclusive. The estimated lead effects in Figure 2 do not provide systematic evidence of pre-trends in the parental outcomes.

[INSERT FIGURE 3 HERE]

5.2. Instrumental variables (IV) results

First-stage results

The estimated first-stage effects of the two alternative instruments described in Section 3 on an individual's education are presented in Table 3. The first row of the table shows that both of these instruments have significant explanatory power over the years of education of the directly affected generation and that the first-stage effects are stronger for men than for women. The estimates using the distance-to-university instrument in columns (1) and (2) show that having a 100-km-higher distance to university decreases the educational attainment by 0.11 years for women and 0.15 years for men. However, the somewhat low cluster-robust F-statistics indicate a possible weak instrument problem, especially in the women's sample (F=6.8 for women and F=15.3 for men). Therefore, we complement the analysis with a stronger instrument, the gravity-model measure of access to university, the first-stage results for which are in columns (3) and (4) of Table 3. These results indicate a strong positive relationship between access to university and educational attainment: a one standard deviation higher access is associated with a 0.44-year increase in years of education among women and a 0.55-year increase in years of education among men. Importantly, the gravity-model-based instrument produces more precise and stronger estimates with considerably larger F-statistics (F=152.7 and F=206.9 for the women's and men's samples, respectively) than the instrument based on mere distances.

[INSERT TABLE 3 HERE]

The remaining rows of Table 3 break down the effects of access to university on the years of education by the level of education. Similar to the previous results by Suhonen and Karhunen (2019), these results indicate that, apart from lifting some individuals from secondary to lower tertiary education, a higher local access to university also enables some individuals to complete any post-compulsory education. As pointed out in Section 2.2., this pattern arises from an increased sorting of some individuals (particularly men) to vocational secondary education, which likely results from local spillovers across educational sectors due to the overall expansion of the supply side (see Suhonen and Karhunen, 2019). These findings make a difference in the interpretation of the IV results presented in the following sub-sections, as part of the effects on an individual's years of education may arise from a higher completion of secondary education, rather than tertiary education.

Individual outcomes

Table 4 reports the OLS and IV estimates for the relationships between an individual's years of education and four long-term outcomes examined at the age of 55: the cumulative survival probability, the cumulative probabilities of mental health-related hospitalization and drug purchase, and annual income. Given that IV estimates with and without the additional controls (first language and parental education and income) are highly similar, it appears unlikely that selection into the treatment based on the background characteristics confounds our estimates.

[INSERT TABLE 4 HERE]

According to the baseline OLS estimates reported in column (1) of Table 4, an additional year of education is associated with a 0.4-percentage-point higher survival probability among women and a one-percentage-point higher survival probability among men. However, based on the IV estimates obtained using distance to university as the instrument in columns (2) and (3), the causal effect of education on survival is unclear, as none of the estimates is significantly different from zero. The IV estimates in columns (4) and (5) obtained using the gravity-model measure as the instrument are more precise. These results indicate that an additional year of education increases men's survival probability by 1.5 percentage points, whereas the estimated effects on women's survival are approximately zero.

Most of the results in the middle of Table 4 suggest that higher educational attainment decreases the probability of mental health disorders. According to the baseline OLS results for women, an additional year of education is associated with a one-percentage-point lower probability of mental health-related hospitalization and a half-percentage-point lower probability of purchasing mental health-related drugs. The respective associations for men are higher: 1.6 and 0.7 percentage points. In most cases, the IV estimates concerning mental health effects exceed the baseline OLS estimates. When using the distance-to-university instrument (columns (2) and (3)), the IV results indicate that an additional year of education decreases the probability of mental health-related hospitalization by around 3 percentage points for women and by around 4 percentage points for men as well as men's probability of mental health-related drug purchases by around 4 percentage points (the estimate for women is of similar size but statistically insignificant). The IV estimates obtained using the alternative instrument (columns (4) and (5)) are once again more precise and mainly point towards similar effect sizes;

however, the estimate regarding the effect on women's probability of mental health-related hospitalization is, in this case, close to zero and insignificant.

The estimates at the bottom of Table 4 indicate that, apart from having positive mental health effects, a higher educational attainment results in significant monetary returns at age 55. Both the OLS and IV estimates indicate that these returns are, in absolute terms, larger for men than for women. The implied causal effects on men's income are around 10,600–11,200 euros (per additional year of education) with the distance-to-university instrument and around 8,400–9,400 euros with the gravity-model instrument, whereas the estimated effects on women's income are around 2,200–2,300 euros and statistically significant only when using the gravity-model instrument. Therefore, it is conceivable that better economic outcomes partly explain the observed health benefits of education, at least in the case of men.

Parental outcomes

The results in Table 5 suggest that, apart from the individuals' mental health, the health benefits of education likely extend to the parents' longevity. When examined at the parental age of 70, the positive OLS association between an additional year of a child's education and a parent's cumulative survival probability is stronger for fathers (1.1 percentage points) than for mothers (0.6 percentage points). However, this difference diminishes when examining parental survival at older ages: a year of a child's education is associated with a 1.1-percentage-point higher mother's cumulative survival probability and a 1.3-percentage-point higher father's cumulative survival probability at age 80. In most cases, the IV estimates regarding parental survival are larger than the OLS estimates. The estimated causal effect of one year of education on a mother's cumulative survival probability is systematically around 2–3 percentage points regardless of the instrument and model specification used. The evidence of the effects on a father's survival is less robust, and statistically significant effects are only found when using the gravity-model instrument. With this instrument, an additional year of education is implied to have around a 2–3-percentage-point positive effect on a father's probability of remaining alive at ages 70 and 75, whereas the estimates concerning a father's survival at age 80 are lower and statistically insignificant.

While education appears to affect parental survival, we do not find strong evidence of effects on a parent's mental health measured by the cumulative probability of mental health-related hospitalization at age 70. While the OLS estimates of this association are negative, the IV estimates are not statistically different from zero.

[INSERT TABLE 5 HERE]

The results in Table 6 break down the effect of education on parental health by the offspring's gender. In these sub-sample analyses, the distance-to-university instrument provides imprecise IV estimates that are mainly indistinguishable from each other and from zero, whereas the results based on the gravity-model instrument are easier to interpret. Overall, the results show a stronger positive link between a daughter's education and parental survival than between a son's education and parental survival. We systematically find, using both instruments, that a daughter's education increases a mother's probability of remaining alive at age 70, with the estimated effect of one year of a daughter's education being 5.1 percentage points (using the distance-to-university instrument) or 4.0 percentage points (using the gravity-model instrument).

[INSERT TABLE 6 HERE]

As for the remaining parental survival outcomes, statistically significant results are only obtained using the gravity-model instrument. With this instrument, the results indicate that one year of a daughter's education also increases a mother's cumulative probability of survival at ages 75 and 80 by 4.7 percentage points and a father's cumulative probability of survival at ages 70 and 75 by around 3 percentage points. An additional year of a son's education is also indicated to have significant positive effects, 3.2 and 2.2 percentage points, on a father's cumulative survival probabilities at ages 70 and 75, respectively, and a smaller positive effect (1.5 percentage points) on a mother's cumulative survival probability at age 75. All the estimated effects of a child's education on the parents' mental health by the child's gender are again statistically insignificant.

5.3. Additional results

Table 7 sheds further light on the validity of our IV approach and mechanisms driving the results by showing additional reduced-form estimates obtained using TWFE regressions similar to that in equation (5). The results reported in the first four rows have been obtained by using parental education and income as placebo outcomes: since these parental outcomes were, to a large extent, already shaped before the Finnish university expansion, they should not be significantly affected by our instruments. The results demonstrate that an individual's distance to university has no significant impact on her parents' years of education or parental income measured at ages 55, 60, and 65. However, the alternative gravity-model instrument is negatively and significantly related to a mother's years of education and income at ages 55, 60, and 65, as well as with a father's income at age 65. However, the magnitudes of these relationships are small compared to those between one's access to university and her own education and income. Furthermore, as these relationships are negative, there is no indication that the IV estimates on the effects of one's education on parental health would be biased upwards due to the parents directly benefitting from the greater local access to university in terms of a higher level of education and income. In contrast, these estimates could be biased downwards due to the implied negative effects.

[INSERT TABLE 7 HERE]

In the last three rows of Table 7, we examine another potential factor affecting family health outcomes: the parent's and child's geographical proximity measured using dummies for the child and parent living in the same sub-region when the parent approaches old age. As pointed out in Section 2.2, the previous results of Suhonen and Karhunen (2019) suggest that individuals exposed to a decreased distance to university were more likely to remain in their region of origin as an adult, which would imply a positive connection regarding access to university and the parent's proximity. The results on the bottom of Table 6 suggest that such a positive connection exists, although it appears to grow significantly weaker as the parent becomes older. For instance, the results indicate that a 100-kilometer decrease in one's distance to university decreases the probability of living in the same sub-region with the mother by 2 percentage points by the time the mother is 55 years old but has no significant impact 10 years later. Nevertheless, these results indicate that the closer proximity of the parent and individual may serve as a mechanism underlying the positive effects from the individual's access to university to family health outcomes.

6. Concluding remarks

Exploiting a natural experiment arising from the Finnish university expansion during the 1960s and 1970s, we have provided two types of evidence on the health effects of education. First, our results suggest that the individuals' years of education have positive cumulative effects on their mental health outcomes by middle age, while mainly insignificant effects on their early mortality. These findings contribute to a large but still controversial body of literature on the causality of the education-health nexus (Galama et al., 2018; Xue et al., 2021). Second, we found evidence that individuals' education positively affects their parents' longevity, while having no significant impact on their parents' mental health. These findings extend the thus-far scant evidence on the spillover effects of the individuals' own education on their family members' health (Lundborg and Majlesi, 2018; De Neve and Fink, 2018; Ma, 2019; Potente et al., 2020; Cornelissen and Dang, 2022).

We also detected heterogeneity in the family spillover effects of education, as a daughter's education was found to have stronger effects on parental survival than a son's education. This pattern resembles that found by Lundborg and Majlesi (2018) in Sweden. However, while they found the causal link to be strongest between a daughter's education and her father's survival, our results suggest that the effect on the same-sex parent dominates that on the opposite-sex parent.

Naturally, caution is required when generalizing these results to other contexts. Besides appearing in a particular historical and institutional context, the effects were only identified for individuals affected by our access-to-university instruments (compliers), a group that may not be representative of the studied cohorts. Our results suggest that, while increasing the educational attainment of this group, the improved local access to university also made these individuals more likely to remain geographically close to their parents. It is unclear whether this type of negative effect on mobility holds more generally. We also found that a greater access to university increases one's later-life earnings, which, together with the geographical proximity of the parent and child, serves as a plausible mediator of the indicated positive effects on family health.

Our study provides some important insights regarding the health benefits of education. Comparing our results to prior evidence that primarily arises from compulsory schooling reforms implemented in advanced countries, it is conceivable that educational expansion at the higher education level has larger overall health benefits than expansion at the lower levels of the educational system. Furthermore, our results suggest that accounting for the spillover effects of an individual's education on others' health is an important factor to be accounted for in the overall assessment of educational policies. Last, our results indicate that the offspring's education plays an important role in improving parental health in old age, even in developed countries like Finland with supportive social security and services available for the aging population.

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Appendix A: Robustness of event study results

Following the recent difference-in-differences literature (Borusyak et al., 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021), we assess the robustness of our two-way fixed effects (TWFE) event study results by comparing these results to those obtained by the non-parametric approach of Callaway and Sant'Anna (2021). This approach is based on estimating the group-time average treatment effects for each group determined by the timing of the treatment, which, in our case, is the year when the distance to university decreased in a particular municipality. Unlike the TWFE approach, the Callaway and Sant'Anna (CS) approach does not use the already-treated units as control units, and, therefore, the results are robust to the potential dynamic patterns of the treatment effects. The CS method also avoids the arbitrary weighting of groups treated in different years implicit in the TWFE approach.

In our robustness check, we focus on the binary treatment indicator (individual's distance to university <100 km), as the CS approach is not applicable to the case of continuous and not-strictly-staggered treatment. In addition to the estimates based on the unconditional parallel trends assumption, we use the doubly robust estimator to produce estimates conditioning on the individual's first language and parental education and income.

The CS estimates reported in Figures A1 and A2 have been obtained by aggregating the group-time average treatment effects weighted according to the event study weights of Callaway and Sant'Anna (2021). In the figures, the lead effects estimated by the CS approach are always expressed relative to the previous period, whereas the effects at $r \in [0,4]$ are, similar to TWFE results, expressed relative to period $r = -1$. According to the figures, with very few exceptions, both the unconditional and conditional CS estimates are highly similar to the baseline TWFE estimates. Thus, while the TWFE estimates use the already-treated municipality-cohort groups as control units, the relatively many never-treated municipalities in the sample likely make the event study estimates highly robust for this problem. Notably, as shown in Tables A1 and A2, the CS estimates aggregated using the difference-in-differences weights are systematically larger than the corresponding TWFE estimates, which is in line with the negative weighting problem discussed in the literature (e.g., Borusyak et al., 2021). However, comparing the ratios of the first-stage and second-stage reduced-form estimates obtained by the CS and TWFE methods, the negative weighting problem affects, to a lesser extent, our conclusions about the causal effect of years of education.

[INSERT FIGURE A1 HERE]

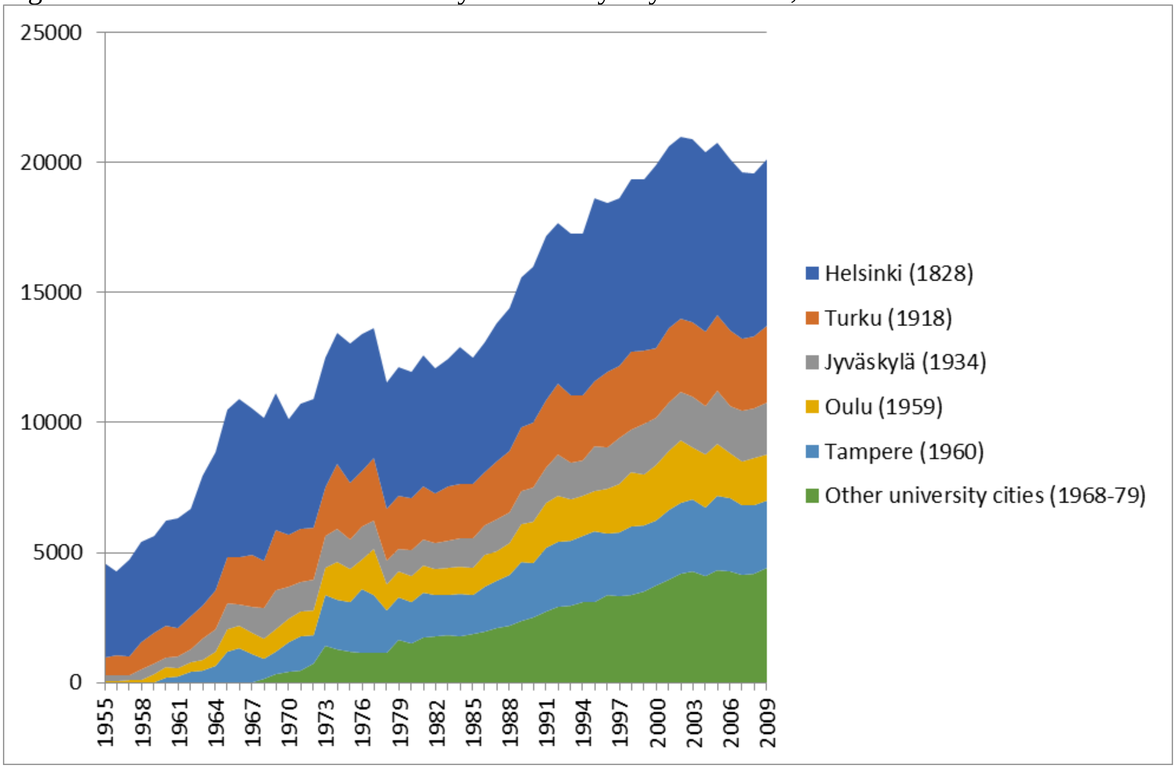
[INSERT FIGURE A2 HERE]

[INSERT TABLE A1 HERE]

[INSERT TABLE A2 HERE]

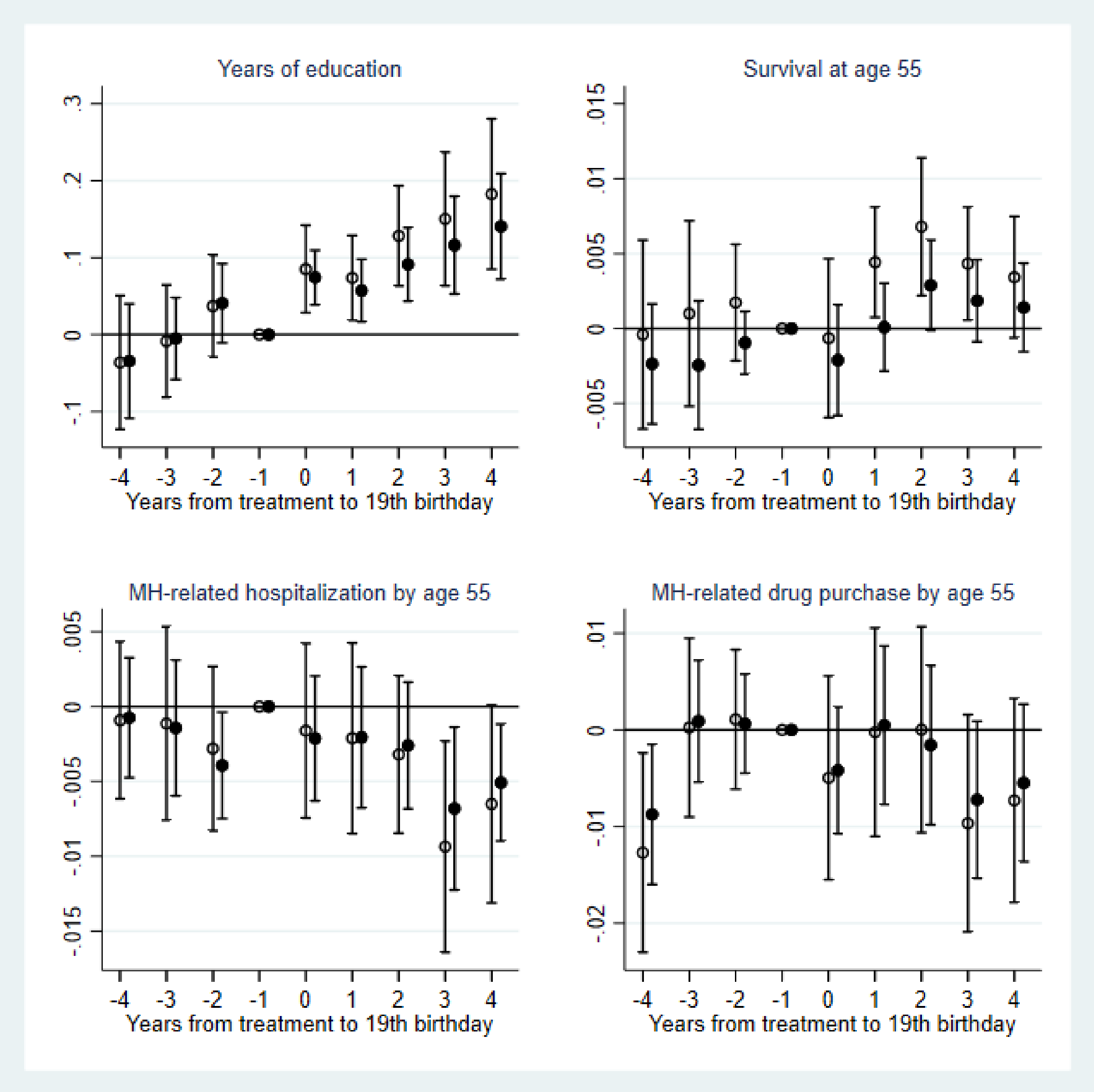
FIGURES AND TABLES

Figure 1. The number of new university students by city in Finland, 1955-2009.



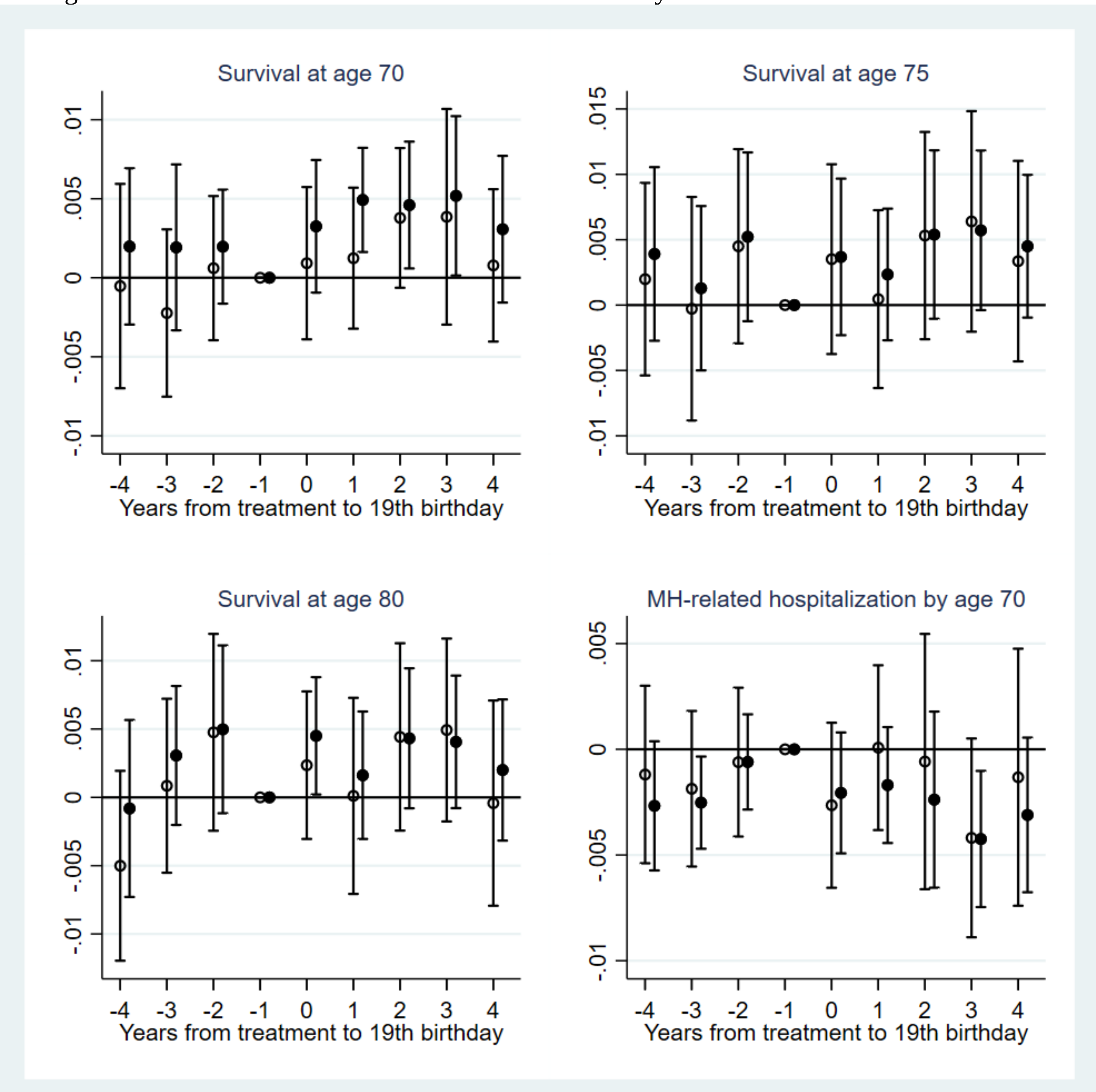
Notes: The years in parentheses indicate the timing of the cities gaining their first higher education institution. The city-specific figures are based on institution-level statistics published by Statistics Finland (1969, 1973, 1983) and Ministry of Education and Culture (2012).

Figure 2. Event study results: Education, survival, and mental health (MH) for cohorts turning 19 before and after a decrease in distance to university.



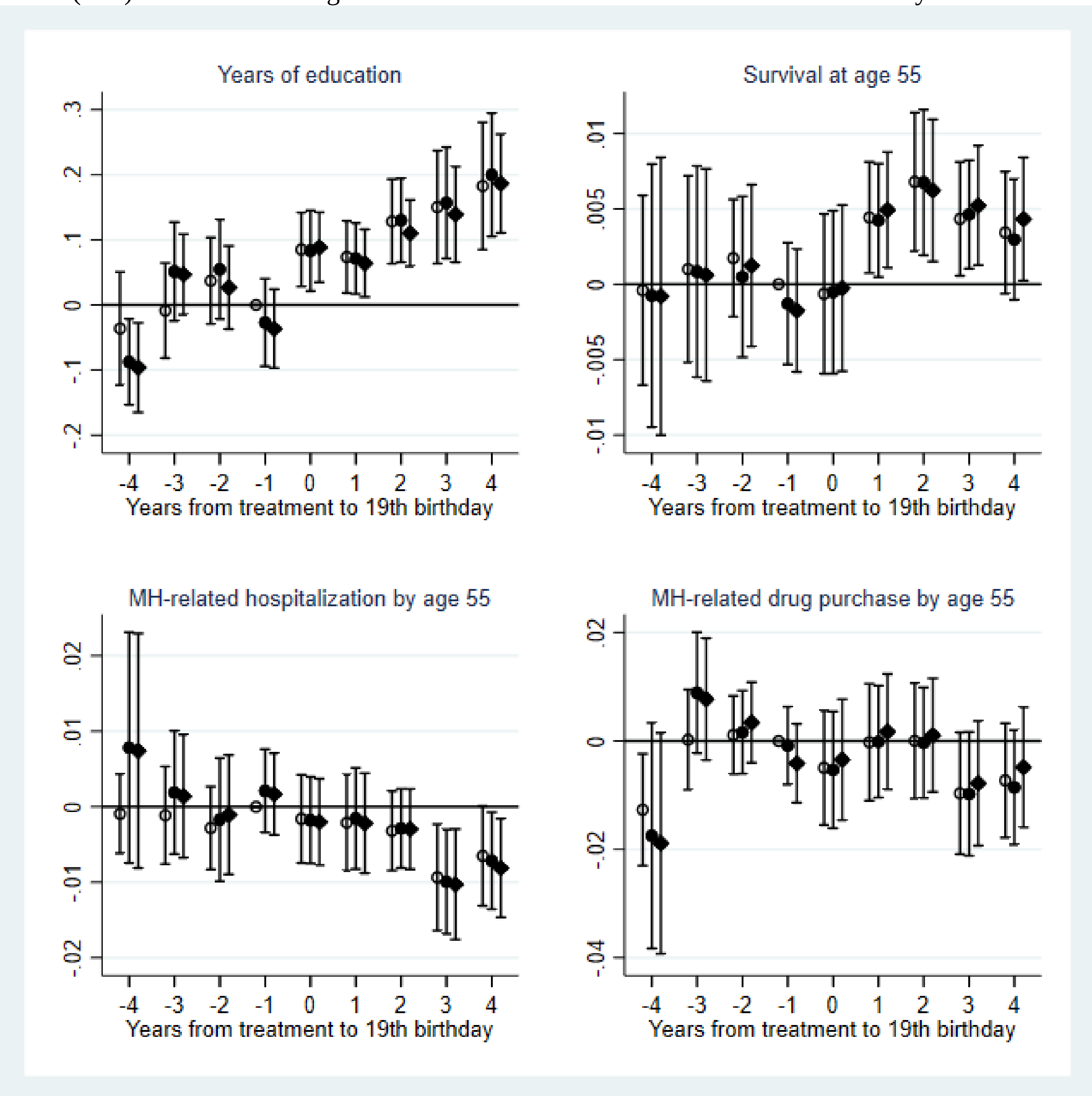
Notes: The estimates are from regression models controlling for cohort and municipality. The hollow circles are for the estimated effects of a binary treatment (distance to university at age 19 < 100 km), and the solid circles are for the estimated effects of a continuous treatment (any decrease in distance to university at age 19 per 100 km). The confidence intervals are adjusted for sub-region-level clustering (70 clusters).

Figure 3. Event study results: Parent's survival and mental health (MH) for the parents of child cohorts turning 19 before and after a decrease in distance to university.



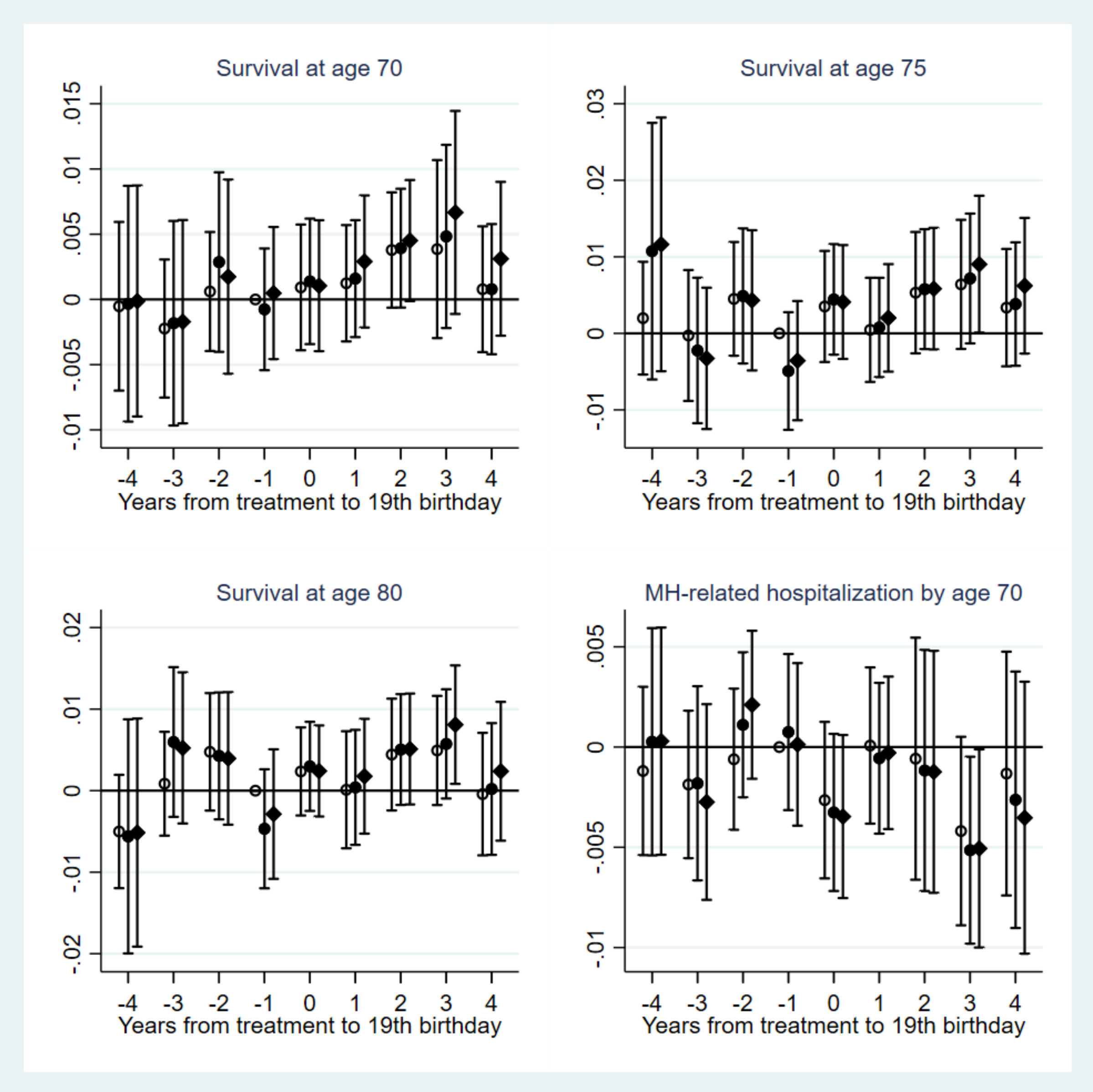
Notes: The estimates are from regression models controlling for child's cohort and municipality. The hollow circles are for the estimated effects of a binary treatment (distance to university at age 19 < 100 km), and the solid circles are for the estimated effects of a continuous treatment (any decrease in distance to university at age 19). The confidence intervals were adjusted for sub-region-level clustering (70 clusters).

Figure A1. Comparison of event study estimates obtained by two-way fixed effects (TWFE) regressions and the method of Callaway and Sant'Anna (2021): Education, survival, and mental health (MH) for cohorts turning 19 before and after a decrease in distance to university.



Notes: The estimates are for the effects of a binary treatment (distance to university at age 19 < 100 km). The hollow circles mark the TWFE estimates obtained by regression models controlling for cohort and municipality. The solid circles and diamonds mark the unconditional and conditional estimates obtained by the approach of Callaway and Sant'Anna (2021). The conditional estimates have been obtained by the doubly robust estimator conditioning on the individual's first language and parental education and income. The confidence intervals were adjusted for sub-region-level clustering (70 clusters).

Figure A2. Comparison of event study estimates obtained by two-way fixed effects (TWFE) regressions and the method of Callaway and Sant'Anna (2021): Parent's survival and mental health (MH) for the parents of child cohorts turning 19 before and after a decrease in distance to university.



Notes: The estimates are for the effects of a binary treatment (distance to university at age 19 < 100 km). The hollow circles mark the TWFE estimates obtained by regression models controlling for child's cohort and municipality. The solid circles and diamonds mark the unconditional and conditional estimates obtained by the approach of Callaway and Sant'Anna (2021). The conditional estimates have been obtained by the doubly robust estimator conditioning on the individual's first language and parental education and income. The confidence intervals were adjusted for sub-region-level clustering (70 clusters).

Table 1. Summary statistics. Mean outcomes by education level.

Outcome	Women, by education				Men, by education			
	Primary	Secondary	Lower tertiary	Higher tertiary	Primary	Secondary	Lower tertiary	Higher tertiary
Survival, age 55	0.949	0.973	0.982	0.986	0.891	0.928	0.965	0.977
MH-related hospitalization, by age 55	0.121	0.083	0.050	0.043	0.180	0.135	0.067	0.050
MH-related drug purchase, by age 55	0.424	0.430	0.415	0.431	0.322	0.316	0.290	0.297
Income, age 55	24 065	27 797	38 701	64 026	30 391	35 081	56 197	91 304
N	104 834	201 504	139 450	43 834	143 908	229 403	106 718	46 278
% share	21 %	41 %	28 %	9 %	27 %	44 %	20 %	9 %

Table 2. Summary statistics. Mean parental outcomes by the child's education level.

Outcome	Mothers, by child's education				Fathers, by child's education			
	Primary	Secondary	Lower tertiary	Higher tertiary	Primary	Secondary	Lower tertiary	Higher tertiary
Survival, age 70	0.831	0.857	0.882	0.894	0.629	0.674	0.723	0.762
Survival, age 75	0.724	0.768	0.807	0.829	0.478	0.537	0.596	0.646
Survival, age 80	0.580	0.642	0.694	0.725	0.324	0.386	0.449	0.503
MH-related hospitalization, by age 70	0.066	0.061	0.050	0.047	0.081	0.073	0.059	0.052
Years of education	9.33	9.57	10.03	11.16	9.47	9.76	10.54	12.20
Income, age 55	9 759	11 332	13 734	17 353	18 449	20 652	27 123	37 975
Income, age 60	9 729	11 255	13 566	17 257	16 259	18 377	24 590	35 509
Income, age 65	10 119	11 295	13 168	16 577	15 131	17 069	22 285	32 070
Child living in same sub-region, age 55	0.819	0.758	0.678	0.606	0.822	0.771	0.703	0.659
Child living in same sub-region, age 60	0.793	0.721	0.619	0.503	0.795	0.731	0.637	0.536
Child living in same sub-region, age 65	0.775	0.695	0.584	0.441	0.773	0.700	0.594	0.465
N	233 623	412 252	238 543	87 576	192 327	360 013	215 556	80 429

Table 3. First-stage results. The effect of access to university at age 19 on educational attainment.

	Effect of distance to university (/100 km)		Effect of gravity-model measure	
	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
Years of education	-0.1083**	-0.1476***	0.4385***	0.5492***
	(0.0416)	(0.0377)	(0.0355)	(0.0382)
	F=6.8	F=15.3	F=152.7	F=206.9
Level of education				
Primary	0.0145*	0.0287***	-0.0774***	-0.1089***
	(0.0083)	(0.0079)	(0.0083)	(0.0069)
Secondary	0.0058	-0.0118**	0.0029	0.0548***
	(0.0054)	(0.0052)	(0.0105)	(0.0060)
Lower tertiary	-0.0195***	-0.0143***	0.0725***	0.0423***
	(0.0057)	(0.0038)	(0.0049)	(0.0047)
Higher tertiary	-0.0008	-0.0026	0.0020	0.0118***
	(0.0026)	(0.0020)	(0.0053)	(0.0023)
N	489 622	526 307	489 622	526 307

Notes: Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table 4. Effects of years of education on an individual's long-term outcomes. OLS estimates and IV estimates using two alternative instruments.

	OLS	IV: distance to university		IV: gravity-model measure	
	(1)	(2)	(3)	(4)	(5)
A. Survival, age 55					
Women	0.0044***	0.0121	0.0119	-0.0008	-0.0009
	(0.0001)	(0.0128)	(0.0122)	(0.0030)	(0.0036)
Men	0.0096***	-0.0002	-0.0004	0.0154***	0.0155***
	(0.0003)	(0.0118)	(0.0111)	(0.0047)	(0.0046)
B. MH-related hospitalization, by age 55					
Women	-0.0101***	-0.0275**	-0.0257**	-0.0043	-0.0037
	(0.0003)	(0.0134)	(0.0126)	(0.0046)	(0.0055)
Men	-0.0156***	-0.0373*	-0.0351*	-0.0270***	-0.0264**
	(0.0004)	(0.0204)	(0.0197)	(0.0099)	(0.0104)
C. MH-related drug purchase, by age 55					
Women	-0.0051***	-0.0400	-0.0379	-0.0305***	-0.0399***
	(0.0006)	(0.0385)	(0.0323)	(0.0117)	(0.0129)
Men	-0.0068***	-0.0417**	-0.0386**	-0.0339***	-0.0352***
	(0.0006)	(0.0191)	(0.0176)	(0.0087)	(0.0084)
D. Income, age 55					
Women	3687.22***	2173.46	2284.12	2357.02*	2248.53**
	(73.37)	(2071.85)	(1903.55)	(1212.17)	(874.75)
Men	5315.39***	11189.36***	10637.15***	9373.04***	8398.93***
	(124.95)	(2571.27)	(2263.36)	(2722.40)	(1929.42)
Additional covariates	Yes	No	Yes	No	Yes

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. The additional covariates include the individual's first language and parental education and income. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table 5. Effects of a child's years of education on parental survival and mental health. OLS estimates and IV estimates using two alternative instruments.

	OLS	IV: distance to university		IV: gravity-model measure	
	(1)	(2)	(3)	(4)	(5)
A. Survival, age 70					
Mothers	0.0056***	0.0281***	0.0270***	0.0188***	0.0172***
	(0.0003)	(0.0098)	(0.0093)	(0.0043)	(0.0045)
Fathers	0.0109***	0.0157	0.0148	0.0321***	0.0286***
	(0.0002)	(0.0165)	(0.0166)	(0.0072)	(0.0073)
B. Survival, age 75					
Mothers	0.0086***	0.0266**	0.0258**	0.0279***	0.0242***
	(0.0002)	(0.0110)	(0.0107)	(0.0044)	(0.0051)
Fathers	0.0130***	0.0027	0.0015	0.0248**	0.0184**
	(0.0002)	(0.0204)	(0.0205)	(0.0098)	(0.0092)
C. Survival, age 80					
Mothers	0.0111***	0.0194*	0.0200*	0.0252***	0.0196***
	(0.0003)	(0.0105)	(0.0103)	(0.0048)	(0.0056)
Fathers	0.0133***	-0.0016	-0.0024	0.0188	0.0112
	(0.0002)	(0.0189)	(0.0178)	(0.0127)	(0.0104)
D. MH-related hospitalization, by age 70					
Mothers	-0.0022***	0.0007	0.0008	-0.0072	-0.0054
	(0.0001)	(0.0107)	(0.0096)	(0.0088)	(0.0084)
Fathers	-0.0037***	0.0037	0.0050	-0.0078	-0.0044
	(0.0001)	(0.0152)	(0.0151)	(0.0099)	(0.0095)
Additional covariates	Yes	No	Yes	No	Yes

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. The additional covariates include the child's first language and parental education and income. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table 6. Effects of a child's years of education on parental survival and mental health by parent's and child's gender. IV estimates using two alternative instruments.

	Mother-daughter	Mother-son	Father-daughter	Father-son
A. Survival, age 70				
IV: distance to university	0.0508**	0.0141	0.0447	-0.0027
	(0.0200)	(0.0172)	(0.0297)	(0.0238)
IV: gravity-model measure	0.0400***	0.0042	0.0320***	0.0328***
	(0.0087)	(0.0043)	(0.0103)	(0.0090)
B. Survival, age 75				
IV: distance to university	0.0203	0.0318	0.0347	-0.0184
	(0.0263)	(0.0213)	(0.0306)	(0.0267)
IV: gravity-model measure	0.0470***	0.0149**	0.0289***	0.0224*
	(0.0088)	(0.0069)	(0.0109)	(0.0125)
C. Survival, age 80				
IV: distance to university	0.0170	0.0208	-0.0020	-0.0028
	(0.0257)	(0.0188)	(0.0324)	(0.0265)
IV: gravity-model measure	0.0468***	0.0102	0.0176	0.0191
	(0.0095)	(0.0077)	(0.0127)	(0.0148)
D. MH-related hospitalization, by age 70				
IV: distance to university	-0.0053	0.0045	-0.0092	0.0124
	(0.0167)	(0.0127)	(0.0181)	(0.0171)
IV: gravity-model measure	-0.0073	-0.0072	-0.006	-0.0091
	(0.0122)	(0.0073)	(0.0090)	(0.0114)

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table 7. Effects of a child's access to university at age 19 on additional parental outcomes.

	Effect of distance to university (/100 km)		Effect of gravity-model measure	
	Mothers (1)	Fathers (2)	Mothers (3)	Fathers (4)
Years of education	-0.0070	0.0052	-0.0692**	0.0080
	(0.0120)	(0.0168)	(0.0264)	(0.0819)
Income, age 55	48.76	41.17	-619.54***	159.31
	(68.55)	(138.30)	(106.69)	(507.03)
Income, age 60	107.22	-30.99	-805.77***	69.98
	(91.02)	(160.75)	(128.60)	(356.25)
Income, age 65	51.37	216.88	-845.01***	-1117.17***
	(80.22)	(133.65)	(193.30)	(224.63)
Child living in same sub-region, age 55	-0.0196**	-0.0281**	0.0958***	0.1220***
	(0.0084)	(0.0108)	(0.0092)	(0.0114)
Child living in same sub-region, age 60	-0.0131**	-0.0177**	0.0602***	0.0869***
	(0.0060)	(0.0074)	(0.0075)	(0.0092)
Child living in same sub-region, age 65	-0.0069	-0.0137**	0.0367***	0.0623***
	(0.0054)	(0.0068)	(0.0064)	(0.0079)

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. Standard errors in parentheses are clustered by child's sub-region of birth (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table A1. Effects of a decrease in distance to university to <100 km on an individual's long-term outcomes. Comparison of difference-in-differences estimates obtained by two-way fixed effects (TWFE) and the method of Callaway & Sant'Anna (2021).

	TWFE estimates	CS estimates
	(1)	(2)
A. Years of education		
Women	0.1317**	0.2164***
	(0.0501)	(0.0624)
Men	0.1709***	0.1857***
	(0.0484)	(0.0512)
B. Survival, age 55		
Women	0.0026	0.0067***
	(0.0016)	(0.0017)
Men	0.0027	0.0005
	(0.0025)	(0.0032)
C. MH-related hospitalization, by age 55		
Women	-0.0040*	-0.0073***
	(0.0021)	(0.0025)
Men	-0.0078**	-0.0074**
	(0.0037)	(0.0037)
D. MH-related drug purchase, by age 55		
Women	-0.0051	-0.0093*
	(0.0048)	(0.0053)
Men	-0.0047	-0.0103
	(0.0042)	(0.0069)

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table A2. Effects of a decrease ina child's distance to university to <100 km on parental survival and mental health. Comparison of difference-in-differences estimates obtained by two-way fixed effects (TWFE) and the method of Callaway & Sant'Anna (2021).

	TWFE estimates	CS estimates
	(1)	(2)
A. Survival, age 70		
Mothers	0.0037**	0.0062**
	(0.0018)	(0.0030)
Fathers	0.0005	0.0022
	(0.0039)	(0.0054)
B. Survival, age 75		
Mothers	0.0038	0.0082*
	(0.0026)	(0.0043)
Fathers	0.0007	0.0055
	(0.0040)	(0.0057)
C. Survival, age 80		
Mothers	0.0033	0.0081**
	(0.0025)	(0.0035)
Fathers	-0.0032	0.0011
	(0.0034)	(0.0048)
D. MH-related hospitalization, by age 70		
Mothers	0.0003	-0.0020
	(0.0020)	(0.0024)
Fathers	0.0012	-0.0037
	(0.0029)	(0.0034)

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

SUPPLEMENTARY ONLINE APPENDIX (not for print)

Table B1. Effects of years of education on an individual’s long-term outcomes. IV estimates using access-to-university instruments based on the municipality of birth.

	IV: distance to university	IV: gravity-model measure
	(1)	(2)
A. Survival, age 55		
Women	0.0046	-0.0022
	(0.0160)	(0.0035)
Men	0.0060	0.0136***
	(0.0120)	(0.0042)
B. MH-related hospitalization, by age 55		
Women	-0.0365*	-0.0092**
	(0.0189)	(0.0045)
Men	-0.0403*	-0.0294***
	(0.0222)	(0.0093)
C. MH-related drug purchase, by age 55		
Women	-0.0676	-0.0426***
	(0.0523)	(0.0101)
Men	-0.0586***	-0.0393***
	(0.0191)	(0.0120)
D. Income, age 55		
Women	617.057	1572.731
	(2988.312)	(1447.127)
Men	11312.970***	10451.262***
	(3144.936)	(1818.782)

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table B2. Effects of a child's years of education on parental survival and mental health. IV estimates using access-to-university instruments based on the municipality of birth.

	IV: distance to university	IV: gravity-model measure
	(1)	(2)
A. Survival, age 70		
Mother	0.0323***	0.0139*
	(0.0111)	(0.0074)
Father	-0.0147	-0.0084
	(0.0235)	(0.0152)
B. Survival, age 75		
Mother	0.0352***	0.0270***
	(0.0118)	(0.0061)
Father	-0.0300	-0.0144
	(0.0339)	(0.0166)
C. Survival, age 80		
Mother	0.0340**	0.0251***
	(0.0144)	(0.0071)
Father	-0.0324	-0.0235
	(0.0305)	(0.0201)
D. MH-related hospitalization, by age 70		
Mother	0.0022	-0.0081
	(0.0128)	(0.0092)
Father	0.0026	-0.0051
	(0.0178)	(0.0097)

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table B3. Additional IV results. Effects of years of education on an individual's and her parent's probability of mental health-related hospitalization by diagnosis type (IV: distance to university).

	Women (1)	Men (2)	Mothers (3)	Fathers (4)
MH-related hospitalization, by diagnosis type				
Dementia	-0.0009	0.0000	-0.0055**	-0.0017
	(0.0009)	(0.0009)	(0.0022)	(0.0025)
Schizophrenia	-0.0142	-0.0027	0.0046	0.0039
	(0.0092)	(0.0062)	(0.0032)	(0.0026)
Other non-effective psychosis	0.0030	0.0000	0.001	0.0028
	(0.0066)	(0.0043)	(0.0038)	(0.0042)
Bipolar disorder	0.0028	0.0002	-0.0002	0.0000
	(0.0038)	(0.0042)	(0.0012)	(0.0014)
Depressive disorder	0.0059	-0.0078	-0.0019	0.0031
	(0.0103)	(0.0076)	(0.0055)	(0.0058)
Anxiety/stress-related/neurotic disorder	0.0019	-0.0112**	-0.0023	-0.0008
	(0.0049)	(0.0057)	(0.0019)	(0.0023)
Alcohol-use-related MH problem	0.0031	-0.0124	-0.0045	0.0085
	(0.0097)	(0.0130)	(0.0029)	(0.0103)
Substance-use-related MH problem	0.0028	-0.0126	-0.0068**	0.0064
	(0.0070)	(0.0125)	(0.0032)	(0.0100)

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. Standard errors in parentheses are clustered by child's sub-region of birth (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table B4. Additional IV results. Effects of years of education on an individual's and her parent's probability of mental health-related hospitalization by diagnosis type (IV: gravity-model measure).

	Women	Men	Mothers	Fathers
	(1)	(2)	(3)	(4)
MH-related hospitalization, by diagnosis type				
Dementia	0.0001	-0.0003	-0.0031***	0.0002
	(0.0002)	(0.0002)	(0.0008)	(0.0014)
Schizophrenia	-0.0068**	-0.0100***	0.0032**	0.0025*
	(0.0028)	(0.0024)	(0.0013)	(0.0014)
Other non-effective psychosis	-0.0067***	-0.0058***	-0.0018	-0.0011
	(0.0015)	(0.0020)	(0.0014)	(0.0025)
Bipolar disorder	-0.0013	-0.0003	-0.0010**	-0.0011
	(0.0011)	(0.0014)	(0.0005)	(0.0009)
Depressive disorder	-0.0018	-0.0022	-0.0021	-0.0035*
	(0.0023)	(0.0031)	(0.0041)	(0.0018)
Anxiety/stress-related/neurotic disorder	0.0001	-0.0081***	-0.0015*	0.0000
	(0.0018)	(0.0023)	(0.0008)	(0.0008)
Alcohol-use-related MH problem	0.0114***	-0.0006	-0.0057***	-0.0035
	(0.0038)	(0.0076)	(0.0015)	(0.0073)
Substance-use-related MH problem	0.0081**	-0.0056	-0.0069***	-0.0053
	(0.0032)	(0.0066)	(0.0020)	(0.0077)

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. Standard errors in parentheses are clustered by the child's sub-region of birth (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

Table B5. Additional IV results. Effects of years of education on the probability of mental health-related drug purchase by drug type.

	IV: distance to university		IV: gravity-model measure	
	Women (1)	Men (2)	Women (3)	Men (4)
MH-related drug purchase, by drug type				
Psycholeptics	-0.0291	-0.0307*	-0.0283**	-0.0360***
	(0.0346)	(0.0179)	(0.0141)	(0.0057)
Antipsychotics	-0.0199	-0.0204*	-0.0162***	-0.0197***
	(0.0148)	(0.0113)	(0.0041)	(0.0029)
Antipanic agents	-0.0309	-0.0191*	-0.0251***	-0.0203***
	(0.0250)	(0.0104)	(0.0053)	(0.0079)
Sleeping pills	-0.0184	-0.0276	-0.0295	-0.0281***
	(0.0279)	(0.0195)	(0.0183)	(0.0051)
Psychoanaleptics	-0.0209	-0.0388***	-0.0284***	-0.0292***
	(0.0276)	(0.0149)	(0.0091)	(0.0088)
Antidepressants	-0.0117	-0.0401**	-0.0204**	-0.0277***
	(0.0237)	(0.0156)	(0.0090)	(0.0084)

Notes: The estimates are from regression models controlling for cohort and municipality fixed effects. Standard errors in parentheses are clustered by the child's sub-region of birth (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.