# The Long-Term Health Consequences of Expanding Access to Higher Education

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**Abstract**

This study examines whether increasing young individuals' access to higher education by creating and expanding higher education institutions affects their survival or mental health, or those of their parents. Our quasi-experimental analysis leverages changes in access to university resulting from the geographical expansion of the Finnish university system in the 1960s and 1970s. The results suggest that greater access to university for 19-year-olds reduces their probability of mental health-related hospitalization and drug use while also generating positive spillovers on their mothers' longevity. However, we do not find strong effects on individuals' early mortality, fathers' old-age survival or parental mental health.

**Keywords:** Higher education; Access to education; Returns to education; Intergenerational spillovers; Mental health; Mortality; Quasi-experimental

**JEL Codes:** I15, I23, I26, J14, J24

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# 1 Introduction

Health disparities by education level remain substantial in both developed and developing countries. Recently, Case and Deaton (2021) showed that the difference in adult life expectancy between college-educated and non-college-educated U.S. citizens even increased from two to three years during the past thirty years. Steep education-health gradients also appear in many countries with a much lower level of income inequality compared to that in the U.S. For example, in Finland, the focus of this paper, the gap in life expectancy at age 30 between those with tertiary attainment and those with below upper secondary attainment was 5.1 years for men and 3.6 years for women in 2017 (OECD, 2021).

From a policy perspective, 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 educational investment, making such investment valuable beyond its private financial benefits? Thus far, experimental and quasi-experimental evidence on this question has been inconclusive, as studies have found education to affect individuals' own health outcomes, including mortality, obesity, and health behaviors, only in some contexts (Galama et al., 2018; Xue et al., 2021). However, even in the absence of direct health effects, society could still benefit from increased educational attainment through spillover effects on others' health. Recent research has begun to accumulate credible evidence of such spillover effects within families, showing that an individual's education can influence their parents' later-life health (Lundborg and Majlesi, 2018; De Neve and Fink, 2018; Ma, 2019; Cornelissen and Dang, 2022).

Building on these lines of research, our study examines the long-term health effects of increasing young individuals' access to higher education by creating and expanding higher education institutions. While such policies have been widely implemented in many countries to boost educational attainment, evidence on their health effects remains scarce and primarily concerns the expansion of local college availability in the U.S. (Currie and Moretti, 2003; Fletcher and Noghanibehambari, 2024; Cowan and Tefft, 2025) and Germany (Kamhöfer et al., 2019).[1] Using Finnish full-population register data on individuals' mortality and

[1] These studies exploit region-by-cohort variation in the number of colleges (Fletcher and Noghanibehambari, 2024), colleges per inhabitant (Currie and Moretti, 2003; Cowan and Tefft, 2025), or students per

mental health, and those of their mothers and fathers, our study presents quasi-experimental evidence on both the direct health effects of expanding access to higher education and its spillover effects on parental health.

Our causal inference builds on the work of Suhonen and Karhunen (2019), leveraging plausibly exogenous variation in local access to university for 19-year-olds caused by the expansion of the Finnish university system between the late 1960s and late 1970s.[2] During this period, the Finnish government, motivated by regional policy goals, enabled the expansion of the system of research universities outside the largest urban regions by means of opening new universities in five new cities, which previously did not have a university. As this expansion mainly took place in small and mid-sized cities located in economically disadvantaged regions, our study specifically sheds light on the health consequences of a higher education expansion policy aimed at equalizing opportunities. We construct two alternative measures of individuals' exposure to this educational expansion: the first is based on municipality-level changes in distance to the nearest university, while the second, a 'gravity-based' measure, captures detailed municipality-by-year variation in the supply and potential demand for universities' student places.[3]

Our regression analyses, which control for municipality and cohort fixed effects, show that higher education expansion benefits family health in multiple ways. We find that increased local access to university for 19-year-olds positively affects their later mental health, as evi-

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inhabitant (Kamhöfer et al., 2019) to identify the effects of college availability on young individuals' later-life outcomes. Currie and Moretti (2003) document positive effects on infant health among the children of mothers exposed to increased access as well as improvements in maternal health behavior. Fletcher and Noghanibehambari (2024) find positive effects on individuals' longevity. Cowan and Tefft (2025) and Kamhöfer et al. (2019) explore various survey-based health behaviors and outcomes; the first study finds positive health effects mainly for white males, whereas the latter study reports positive effects on physical (but not mental) health.

[2]While Suhonen and Karhunen (2019) used the Finnish university expansion as a natural experiment to examine the spillover effects of parents' education on their offspring's education, they did not examine effects on mental health outcomes or upward intergenerational effects on parental health. Moreover, their study focused on parents born between 1936 and 1956 and their children, whereas our main focus is on individuals born between 1948 and 1961 and their parents. The cohorts in the current study were, unlike those studied by Suhonen and Karhunen (2019), also highly exposed to the expansion of the Finnish university system into the region of Lapland in 1979. Despite these small differences in research design, the results of Suhonen and Karhunen (2019) are likely to be informative about the underlying mechanisms of the health effects examined in the current study.

[3]A note about terminology: in this paper, the effects of expanding access to higher education are studied using variation in the geographical accessibility of such education, and the terms *access* and *accessibility* are often used interchangeably to refer to *geographical accessibility*.

denced by lower cumulative probabilities of hospitalization and prescription drug purchases due to mental health disorders by age 55. Additionally, we observe a positive spillover effect on the longevity of affected individuals' mothers, measured by cumulative survival probabilities at ages 70, 75, and 80. However, we do not find strong evidence of effects on individuals' early mortality (at age 55), fathers' old-age survival, or parents' mental health-related hospitalizations. Examining potential mechanisms behind these positive health effects, we find that improved access to university significantly increases individuals' years of education, later-life income, and likelihood of remaining geographically close to their parents as they age.

The health effects implied by our main results appear somewhat modest in magnitude. For example, a 100-kilometer reduction in distance to university is associated with approximately half-a-percentage-point changes in the cumulative probabilities of mental health disorders and a mother's old-age survival. However, since the corresponding effects on average educational attainment are also modest, the *local average treatment effects (LATE)* for those whose educational attainment was directly influenced by the changes in access to university may be substantial. Therefore, similar to previous studies (e.g., Currie and Moretti, 2003; Suhonen and Karhunen, 2019; Fletcher and Noghanibehambari, 2024), we complement our intention-to-treat analysis with an instrumental variables analysis to estimate the LATEs of educational attainment. Assuming that increased access to university affects health outcomes solely through higher educational attainment, our results suggest that an additional year of education has large effects—typically in the range of 2 to 5 percentage points—on an individual's probability of mental health-related hospitalization, prescription drug use, and a mother's probability of old-age survival.

Our results contribute in several ways to the broad but inconclusive literature reviewed by Galama et al. (2018) and Xue et al. (2021) on the health effects of education. While previous observational studies have mostly investigated these effects through compulsory schooling reforms implemented in various countries,[4] our study is among the first studies—along with

[4] A number of studies analyze policy changes in high-income countries such as the United States (Lleras-Muney, 2005), the United Kingdom (Clark and Royer, 2013; Davies et al., 2018; Avendano et al., 2020), 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, including China (Jiang et al., 2020), Romania (Malamud et al., 2023), and Zimbabwe (Kondirolli and Sunder, 2022).

Currie and Moretti (2003), Kamhöfer et al. (2019), Fletcher and Noghanibehambari (2024), and Cowan and Tefft (2025)—to provide evidence on the long-term health consequences of higher education expansion.[5] By focusing on this policy, our study also contributes to the growing literature on the effects of higher education institutions on regional development, which has examined outcomes such as educational attainment (Frenette, 2009; Suhonen and Karhunen, 2019; Russell et al., 2024) as well as invention and technological change (Toivanen and Väänänen, 2016; Blundell et al., 2022; Andrews, 2023; Carneiro et al., 2023). The previous findings of Suhonen and Karhunen (2019) suggest that the Finnish government's policy of expanding the higher education system into new regions between the late 1950s and early 1970s had small but positive effects on local youth's educational attainment and, perhaps more importantly, positive spillover effects on the educational attainment and school performance of their children. As our new results indicate positive effects on family health, there is growing evidence of significant social benefits from Finland's higher education expansion.

We also differ from most of the previous literature by providing insights into the mental health effects of education, which have received less attention compared to its mortality effects. While developed countries have reached high levels of physical health and life expectancy, depressive disorders, and other mental health problems account for 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 factors contributing to mental health problems, including the role of educational attainment and educational reforms, is highly relevant for policy. The nascent literature on this topic has so far indicated that compulsory schooling reforms have had positive mental health effects in China (Jiang et al., 2020) and Zimbabwe (Kondirolli and Sunder, 2022), but not in developed countries, such as Britain (Avendano et al., 2020) or Finland (Böckerman et al., 2021).[6] The prior evidence regarding the mental health effects of access to higher

[5]Other studies have used different natural experiments related to higher education to assess its health effects. Buckles et al. (2016) and Lacroix et al. (2021) exploited military draft lotteries in the U.S. and Canada, respectively, to demonstrate that college attendance significantly reduces mortality. González et al. (2024) utilized variation in college access caused by a military coup in Chile, finding a negative effect of higher education on mortality.

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

education is limited. As a possible indication of positive mental health effects, Cowan and Tefft (2025) found self-reported health to be positively affected by college accessibility in the U.S., particularly among white males. However, Kamhöfer et al. (2019) found no significant relationship between college availability and a mental component score among the respondents of a German questionnaire. To our knowledge, our study is the first to examine the mental health effects of access to higher education using population-wide register-based mental health data–and one of the first to show evidence of positive mental health effects from a major educational policy reform 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 the reverse transmission, from children to parents, is more limited 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), Vietnam (Cornelissen and Dang, 2022), and Britain (Potente et al., 2023). Our evidence of the positive effects of children's educational access on parental survival suggests that children's educational access and attainment can be important for the health of the aging population even in developed welfare states, where parents are, in material and financial terms, relatively independent of their children, unlike in developing countries. This conclusion aligns with that of Lundborg and Majlesi (2018) based on the effects of the Swedish compulsory schooling reform. However, while Lundborg and Majlesi (2018) only identified positive effects of a daughter's education on a father's survival, our findings indicate a different pattern of heterogeneous effects: positive effects of children's geographical access to university on parental survival are only detected for mothers, and these positive effects arise through both sons' and daughters' higher educational access.

# 2 Background

## 2.1 Institutional context

The impact of educational access and attainment on family health likely depends on the economic, cultural, and institutional context under study. 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, most of whom were born in the first half of the 20th century. These parents were born in an industrializing agricultural society that rapidly transformed into a high-income welfare state during the post-war period, around the time their children 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 a strong population-level correlation between increasing educational attainment and longevity.

A key feature of the Finnish institutional context is that, due to a generous welfare system and low-income inequality, educational access and attainment are relatively unimportant for individuals' health in material and financial terms. Finnish parents are also relatively economically independent of their children during their old-age years. This largely applies to all of the studied parent cohorts, partly due to early policy implementations in Finland. By 1970, when adult children's legal obligation to support their parents was abolished, Finland already had a relatively generous social insurance system, including universal public health insurance (introduced in 1964) and a public pension system with both a guaranteed minimum pension and an earnings-based work pension.[7] By the late 20th century, Finland's formal

[7]The original public pension system, based on mandatory fees paid by wage earners and firms, was

elderly care system was also already somewhat developed thanks to changes in social and health care legislation[8] and a growing supply of public and private services provided for elderly people in their private homes, nursing homes, and sheltered housing.[9] 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 educational access 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' access to university education resulting from the significant geographical expansion of the Finnish university system during the post-war period. While the 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 to 1979 due to 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—yet most 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 additional cities: Vaasa, on the west coast, 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 established in Rovaniemi in 1979 following a decision made by the Finnish government in 1977.

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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.

[8]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.

[9]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.

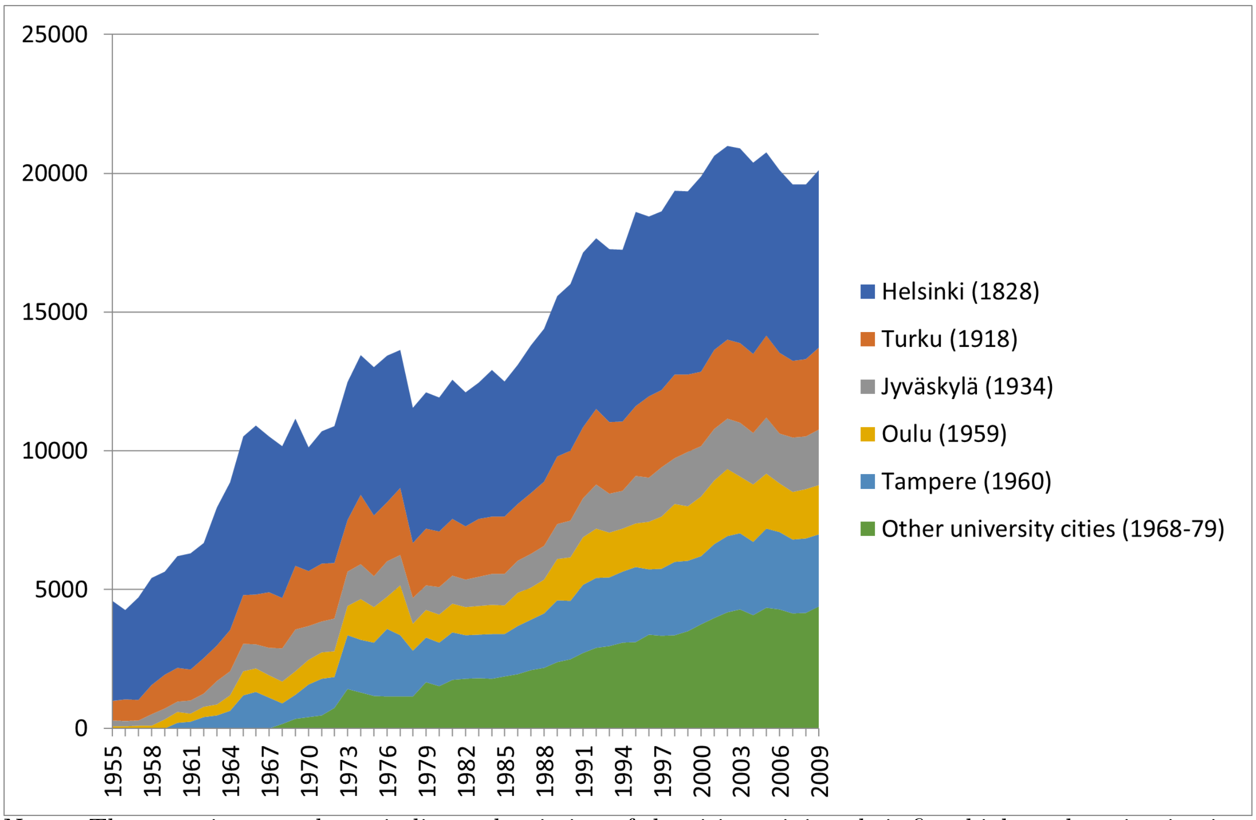
Notable features of the newly established university institutions were their initially small student intake rates and their specializations in a narrow selection of fields of study. The universities in Vaasa and Lappeenranta initiated as specialized institutions focusing on business and engineering, respectively, while the three other universities were multidisciplinary institutions: the one in Joensuu focused on educational sciences, humanities, and natural sciences, the one in Kuopio specialized in medicine and natural sciences, and one in Rovaniemi offered degrees in educational sciences, social sciences, and law. As shown in Figure 1, which depicts the number of new university students by city from 1955 to 2009, student intake at 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-based 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.

In Figure 2, the areas that were most highly exposed to the university openings between 1968 and 1979 are compared with the remaining Finnish areas in terms of the evolution of access to higher education and demographics. Here, all municipalities in which the distance to the nearest university was reduced by at least 50 kilometers during the expansion period are treated as high-exposure areas.[10] This definition is also used to construct the treatment and control groups for the event study analyses (see Section 5.1).

The first two sub-figures of Figure 2 show that, in the mid-1960s, the high-exposure areas were significantly disadvantaged in terms of access to higher education. The average distance to the nearest university was 182 kilometers for 19-year-olds in these areas, compared to only 61 kilometers in other areas. Furthermore, there were no universities in the high-exposure

[10]For a map showing the locations of the high-exposure municipalities, see Figure B1 in Appendix B.

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 in the Statistical yearbooks of Finland (years 1955–1980) and the KOTA database of the Ministry of Education and Culture (years 1981–2009).

areas, whereas outside these areas, the ratio between the number of new university students and the number of matriculation candidates—participants in the spring-term exit exams of upper secondary education—was 0.9, pointing toward a high supply of student places relative to potential demand. However, within the next 20 years, a rapid regional convergence in access to higher education took place. From 1979 onward, the average gap in distance to university stabilized at 5–7 kilometers, whereas the gap in the supply-demand ratio had been reduced to 0.16 by 1985. An important observation from sub-figure (b) of Figure 2 is that this convergence was, to a large extent, due to a gradual reduction in the supply-demand ratio, from over 0.9 to below 0.4, outside the high-exposure areas. Thus, overall, potential demand for university education grew faster than its supply in Finland, while the opposite development mainly took place in the areas that were highly exposed to the opening of new universities.

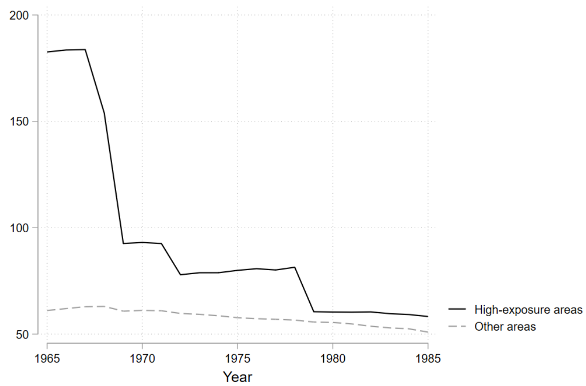
Sub-figures (c)–(f) of Figure 2 describe the evolution of certain key demographics concerning the 18–70-year-old residents of the high-exposure areas and other areas between 1970 and 2000.[11] The main takeaway from these graphs is that, throughout the examined period, the high-exposure areas were relatively sparsely populated and disadvantaged in terms of mean years of education and income, as well as mental health (as indicated by higher mental health-related hospitalization rates), compared to the rest of the country. This reflects the fact that the expansion took place outside Finland's largest urban areas——particularly Helsinki, Turku, Tampere, and Oulu——which remained the main growth centers during the decades following the expansion. Thus, while the higher education expansion policy largely offset regional differences in access to higher education, it was not associated with significant convergence in many other regional outcomes.

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

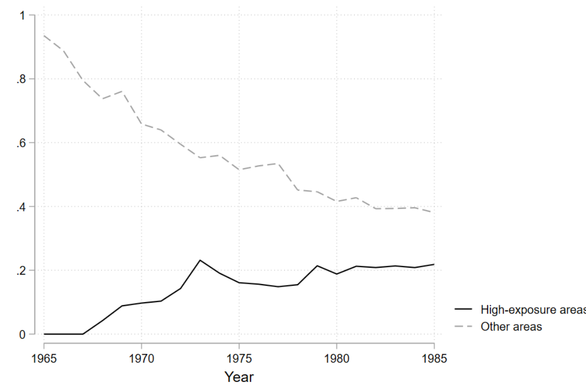
[11] The mental health-related hospitalization rates are shown only from 1972 onward, as the hospitalization rates obtained for 1970 and 1971 using the combined census and hospitalization data (see subsection 4) are very low: 0.4% and 0.6%, respectively. Therefore, the hospitalization information for these years is unlikely to be nationally representative.

Figure 2: Evolution of access to higher education and demographics in areas most highly exposed to the university openings between 1968 and 1979 (distance to university decreased by 50 km or more) and in other areas.

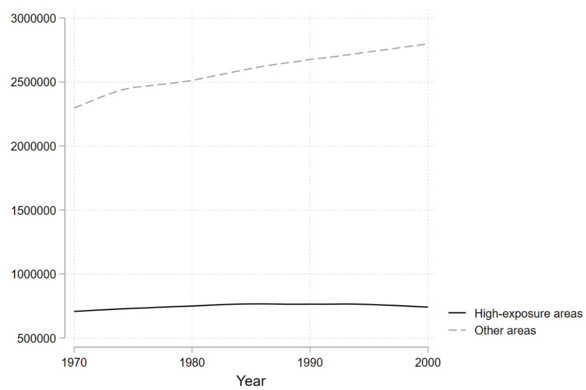
(a) Mean distance to the nearest university (from municipality of birth), 19-year-olds



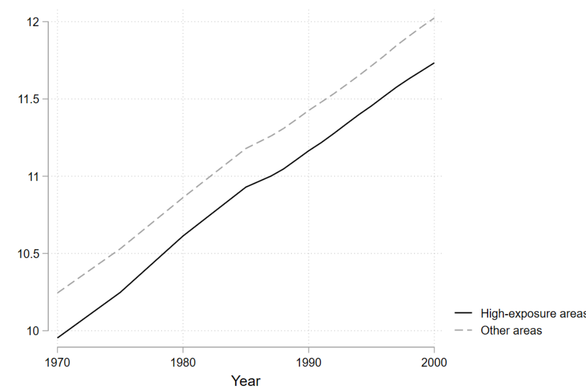

(b) New university students/matriculation candidates



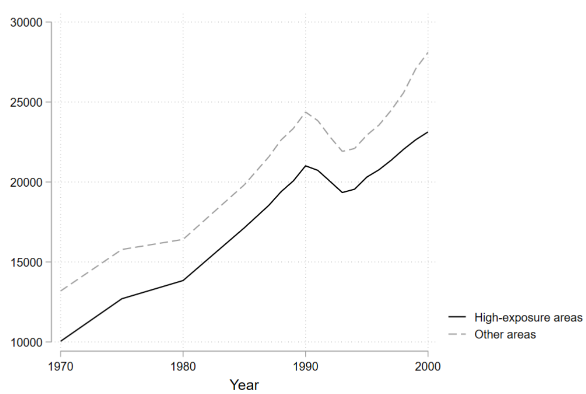

(c) Population, 18-70-year-olds



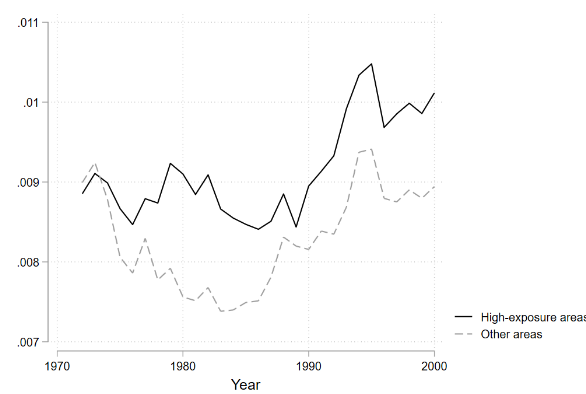

(d) Mean years of education, 18-70-year-olds




(e) Mean income (2019 euros), 18-70-year-olds




(f) Mental health-related hospitalization rate, 18-70-year-olds




Source: (a), (c)–(f): The authors' own calculations based on Statistics Finland's census data from 1970, 1975, 1980, 1985, and 1987–2000 and the Discharge Register of the Finnish Institute for Health and Welfare (1972–2000); (b): The Statistical yearbooks of Finland and the KOTA database of the Ministry of Education and Culture (new university students), and the authors' own calculations based on the registries of the Finnish Matriculation Examination Board (matriculation candidates).

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.[12] Furthermore, politicians, civil servants, and citizens from several cities openly campaigned for establishing a university in their cities. Conversely, many academics from older universities opposed decentralization, fearing that dispersing scarce resources would negatively impact 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.[13]

## 2.3 Expected health effects of expanding access to higher education

Opening new universities and increasing the supply of higher education can influence individuals' and their parents' mental health and longevity in various ways. In particular, improved access to higher education in a specific area can increase higher education attendance among local youth, which may translate into long-lasting health benefits for these individuals and their parents.

The health benefits of education may arise via multiple channels. Education can enhance individuals' ability to maintain their health, provide them with better resources for health investments, and incentivize them to remain productive and live longer (Grossman, 1972; Galama et al., 2018). Higher education can also lead to healthier career paths characterized by safer working conditions, more skilled and healthier colleagues, and higher health insurance coverage (Avendano et al., 2020; Fletcher and Noghanibehambari, 2024). While Finland offers universal health insurance and public healthcare services to its residents, individuals entering higher education can benefit from having access to free-of-charge student healthcare

[12] According to Moisio and Vasanen (2008), the building of the regional university network was one of the main forms of the Finnish government's regional policy from the late 1950s to the late 1980s, along with the relocation of garrisons and the extension of air surveillance into remote areas, the creation of government-owned industries in eastern and northern Finland, and investments in the road network and telecommunications connections. While these other government ventures could, in principle, correlate with changes in access to university—thereby distorting the estimated effects of these changes—we are not aware of any policy interventions that would have targeted exactly the same birth cohorts in the same municipalities as the university openings.

[13] For a more information on the Finnish university expansion and its use as a natural experiment, see Toivanen and Väänänen (2016) and Suhonen and Karhunen (2019).

services during their studies.[14] Furthermore, in Finland, highly educated residents are more likely to have access to free-of-charge, low-congestion occupational healthcare services during their careers (Amnesty International, 2023).

Lundborg and Majlesi (2018) and others have also argued that the health benefits of education can further extend to one's parents because education potentially increases overall family resources to be used for health inputs and might turn individuals into better-informed and more efficient care providers for their parents. Parents could also experience positive mental health effects from having highly educated offspring. However, potential drawbacks also exist: more successful children often have higher opportunity costs of providing personal care and may need to move farther away from their parents. Lundborg and Majlesi (2018) argue that distant intergenerational relations can be harmful to elderly parents' health, for instance, by increasing the pathogenic stress they experience.

Despite the various favorable mechanisms discussed above, many previous studies, especially those focusing on compulsory schooling reforms, have failed to find significant health effects from educational reforms (Galama et al., 2018). However, the health effects induced by a higher education expansion are likely to differ from those associated with a compulsory schooling reform, because these reforms concern fundamentally different educational treatments. Compulsory schooling reforms typically extend the length of time spent in general education among 14–16-year-old adolescents, whereas higher education expansions target older youth and concern more advanced and specialized educational programs. Therefore, possible health effects arising, for example, from human capital accumulation, peer effects, and marital sorting during studies can be very different for the two types of policies. Furthermore, increasing the mandatory schooling age can have adverse health effects due to causing stress and entailing significant opportunity costs for low achievers (Avendano et al., 2020), whereas such adverse effects are less likely to exist in the context of increasing the supply of non-mandatory education and training.

In a previous study examining the effects of the Finnish university expansion, Suhonen and Karhunen (2019) found that reducing 19-year-olds' distance to a university—by

[14] The Finnish Student Health Service, offering primary care and dentistry services for higher education students nationally, was founded in 1954. Thus, these services were already available in the period investigated in our study.

opening a university within 100 kilometers of their birthplace—increased these individuals' educational attainment by 0.1 years, increased their probability of finding a highly educated partner, and had significant spillover effects on their children's school performance and educational attainment. Based on this evidence and the theoretical mechanisms discussed above, one might expect to find that the university expansion had positive effects on these 19-year-olds' later-life health outcomes through their higher educational attainment and possibly also through that of their children and spouse. Moreover, there could be upward intergenerational effects on the health outcomes of the individuals' parents—possibly even through the education of these parents' grandchildren.

As pointed out by Fletcher and Noghanibehambari (2024), higher education expansions may have various regional impacts, for example, by changing local occupational compositions and job prospects, which complicates the identification of the mechanisms through which the estimated health effects of access to higher education operate. The opening of new medical schools, such as the one in the city of Kuopio (1972), may, in particular, affect local health outcomes in various ways, such as by increasing the local supply of the medical workforce and by improving access to healthcare (Hashem et al., 2022).

From the point of view of studying the health effects of education, another complication is that the effects of expanding access to specific types of educational institutions can spill over to other parts of the education system. For example, Mountjoy (2022) discusses the U.S. context, where greater access to two-year colleges can divert students from beginning studies at four-year colleges. Frenette (2009), in turn, showed evidence that expansions of the Canadian university system into new cities diverted some individuals from local lower-level post-secondary institutions. Similarly, Suhonen and Karhunen (2019) argued that, in Finland, expanded university opportunities attracted some students away from vocational colleges and schools—Finland's closest equivalents to American and Canadian lower-level institutions—freeing slots in vocational institutions and allowing some individuals to complete at least some form of post-compulsory education instead of remaining at the lowest education level.[15] These findings suggest that, in the Finnish context, possible health effects

[15] One might suspect that local changes in access to university during the 1960s and 1970s coincided with other shifts in access to education, potentially creating spurious correlations between university accessibility measures and post-compulsory education completion. However, controlling for a rich set of municipality-

of higher education expansion may arise not only from higher education attainment but also at the margin of attending post-compulsory education.

It is also worth pointing out that educational reforms can have long-term health consequences by affecting young individuals' regional mobility patterns. The opening of a university in a young person's home region could increase their educational attainment and probability of out-migration from the home region, for example, because education can increase the earnings gains from moving (Haapanen and Böckerman, 2017). However, for some individuals, the mobility implications of a new university could be the opposite, for instance, by increasing their probability of studying near home and early-adulthood attachment to their home region (Suhonen and Karhunen, 2019). The existing evidence on the effects of higher education expansion on regional mobility appears to be somewhat limited and inconclusive. Frenette (2009) found that the opening of universities in new Canadian cities was associated with substantial out-migration of local youth from these cities. The evidence from the Finnish university expansion points in the opposite direction: Suhonen and Karhunen (2019) found that a reduced distance to university was associated with a higher probability of remaining in one's region of birth at age 34. However, Suhonen and Karhunen (2019) did not find significant evidence suggesting that the university openings reduced local youths' likelihood of enrolling in more distant universities. Nevertheless, following the argument of Lundborg and Majlesi (2018) regarding possible health benefits from close proximity between parents and their adult children, there could be positive mobility-related health effects from the Finnish university expansion.

Finally, previous studies have suggested that the health effects of education and educational reforms can be heterogeneous by gender, which motivates examining gender differences in the current study. Galama et al. (2018) conclude that the evidence for positive individual-level health effects of education is, overall, weaker for women than for men. The reasons for these differences are unclear, and Galama et al. (2018) suggest multiple possible underlying mechanisms. For example, women's pregnancy can attenuate differences in health behaviors and lifetime earnings across more and less educated women, while the effects of education

by-cohort-level factors related to educational access, including individuals' distance to the nearest technical school, technical college, commercial institute, and upper secondary school, as well as the local birth cohort size, Suhonen and Karhunen (2019) showed that such factors do not confound their results.

operating through the formation of social ties, such as marriage, can also differ for men and women. The previous evidence of gender-specific health effects of access to higher education mainly comes from the studies of Fletcher and Noghanibehambari (2024) and Cowan and Tefft (2025) regarding the U.S. college expansion. Both studies found the health effects of college accessibility to be more pronounced for men than for women, which can be partly explained by the expansion having larger effects on men's college attainment.

We can also expect to find differences in the upward intergenerational effects of education by parental gender. For example, as a financially vulnerable group, mothers could benefit more from a highly educated child's resources (Lundborg and Majlesi, 2018). In this regard, however, the empirical evidence is mixed: the results by Lundborg and Majlesi (2018) from the Swedish compulsory schooling reform point toward more significant effects on fathers' than mothers' mortality, whereas De Neve and Fink (2018) found stronger effects for mothers in the Tanzanian context.

# 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 for 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. Since the earliest Statistics Finland data were collected at the beginning of the 1970s, individuals who died or permanently emigrated from Finland before this period are not included in the data. Furthermore, we exclude individuals who died before reaching the year of their 19th birthday from the sample for our analysis, as these individuals were unlikely to have been affected by changes in access to post-secondary education.

Since we focus on changes in 19-year-olds' access to university between 1968 and 1979, our main analyses use cohorts born between 1948 and 1961 who reached the age of 19 during, shortly before, or shortly after this period.[16] Compared to the earlier study by Suhonen and

[16] In the event study analyses reported in subsection 5.1, we use a slightly larger number of cohorts

Karhunen (2019), which examined university openings from 1959 to 1972 and the cohorts from 1936 to 1956, we focus on the later phase of the university expansion and the younger cohorts. This restriction is important because we require representative information on the individuals' parents, which is only available for those who reached adulthood after or near the first observation years of the Statistics Finland data—that is, the early 1970s.[17] Moreover, focusing on the later period of the university expansion allows us to exploit a natural experiment with stronger effects on educational attainment: the findings of Suhonen and Karhunen (2019) suggest that the university openings from 1968 to 1972 had more significant local effects on individuals' years of education than those in 1959 and 1960.

We merge the Statistics Finland data with 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 THL, which includes inpatient discharges in specialized public health care for the Finnish population between 1970 and 2018. The reliability of the Discharge Register is high (Sund, 2012). Our main mental health outcome variable indicates whether an individual had at least one inpatient hospitalization spell annually due to at least one of the following diagnosed mental health disorders (ICD-10: F, ICD-8 and ICD-9: 290–319): (1) dementia, involving deterioration in memory, thinking, behavior, and the ability to perform everyday activities; (2) schizophrenia, characterized by hallucinations, delusions, and cognitive deficits; (3) other psychoses unrelated to emotions or moods (nonaffective psychosis); (4) bipolar disorder, an affective psychosis involving emotional and mood abnormalities (including 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, schoolwork, and social relationships; (7) substance use disorder, including psychiatric hospitalizations related to alcohol or substance abuse or addiction; and (8) alcohol use disorder, a subset of (7). Given that the probability of hospitalization depends

(1943–63) to include more pre- and post-treatment cohorts for the first and last university openings.

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

on, among other factors, an individual's 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 KELA, cover all publicly reimbursed medicine purchases for diagnosed mental health disorders between 1995 and 2016. All residents of Finland are covered by national health insurance and are entitled to benefits, such as reimbursement for medications, which can cover up to 100% of the medication price depending on the specific medication. The KELA data enable us to identify 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 that do not require inpatient hospital treatment. However, since the KELA data are only available from 1995 onwards, the representativeness of the information varies by individuals' year of birth and is especially low for the parents 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 mental health-related drug purchases occurring between 1995 and the year of the individuals' 55th birthday.[18]

The main explanatory variables in our analysis include two alternative municipality-by-cohort-level measures for a 19-year-old individual's access to university, similar to those used by Suhonen and Karhunen (2019): 1) distance to the nearest university,[19] and 2) gravity-based university access defined as follows:

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

where $S_{k,t}$ represents the number of new university students, approximating the supply of

[18]The individuals in our main estimation sample were 34–47 years old in 1995. Therefore, the length of the period over which mental health-related drug purchases are observed varies from 8 to 21 years. In Appendix B (Table B4), we also report results obtained for an outcome variable measured at ages 47–55 for each individual. These results are partly less precise than our main results, but provide similar conclusions of the mental health effects of access to higher education.

[19]Our analysis of geographical distances is based on the 2007 municipal classification which includes 416 municipalities. Distances between the municipalities are determined by computing geodesic distances between the municipalities' center coordinates using a user-written Stata command *vincenty*. For each municipality, we determine a within-municipality distance—municipal residents' expected distance to the center—as one half of the distance to the nearest neighboring municipality.

university education, in municipality $k$, and year $t$; $d_{km}$ is the distance between municipalities $k$ and $m$; and $\alpha$ is a distance-decay parameter indicating the sensitivity of individuals' choices to travel distances.[20] As the level of demand and competition for universities' student places is an important factor affecting accessibility, the gravity-based measure (1)—which is based on the formulation of Joseph and Bantock (1982)—adjusts the supply by the 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 $N_{l,t}$ represents the number of spring-term matriculation examination candidates in upper secondary schools (i.e., potential university applicants) in municipality $l$ and year $t$, and $d_{kl}$ is the distance between municipalities $k$ and $l$. When computing the gravity-based measure, we assume—following Suhonen and Karhunen (2019)—that for both equation (1) and (2) $\alpha = 0.50$, which corresponds to a relatively high degree of mobility between distant municipalities.[21]

To facilitate a clearer interpretation of the estimated effects of access to university, we adjust the accessibility measures as follows. First, since distance to university, unlike the gravity-based measure, is a *negative* indicator of accessibility, we multiply this measure by -1 to make the results for the two accessibility measures easier to compare. We also scale distances by 1/100. That it, the estimated effects of distance to university are always expressed in terms of a 100-kilometer decrease in distance. Second, as the changes in the gravity-based measure do not have a straightforward interpretation, we scale this measure by its 'pre-expansion' standard deviation—specifically, the standard deviation for the oldest cohort in our main sample (the cohort born in 1948).

When merging the university accessibility measures with the individual-level data, our main approach is to define—as in Suhonen and Karhunen (2019)—geographical access to university for a 19-year-old based on their municipality of birth. In a robustness check, we

[20]Gravity-based measures have been used in urban and geographical studies, for example, to measure the accessibility of jobs and healthcare services (Geurs and Van Wee, 2004).

[21]Table B3 in Appendix B show that the results for our main outcomes remain highly robust when increasing or decreasing the distance-decay value by 0.25. When assuming a very low level of mobility ($\alpha = 1.00$), the estimates are closer to zero and less precise.

use the parental municipality of residence in the year of the individual's 18th birthday (or the closest year available) as the primary location measure,[22] while using municipality of birth as the location measure for those with missing parental municipality data. Given the geographical mobility of families, the alternative approach more accurately approximates access to university for 19-year-olds and thus involves a lower risk of measurement error bias in the estimated effects than the approach based solely on municipality of birth. As the residential location choices of parents after their children's birth might be, to some extent, endogenous with respect to the university expansion, the alternative approach is associated with a higher risk of selection bias. However, our findings are highly robust to the choice between these two approaches (see the alternative results reported in Appendix B, Tables B1 and B2).

Table 1 summarizes the sample of approximately 1.2 million individuals and reports their cumulative health outcomes at age 55, as well as average income at ages 50 and 55, by education level (based on the highest educational degree completed by age 50). The statistics indicate significant disparities in physical and mental health by education level, particularly among men. Among the worst-off group, men with only primary education, 14.7 percent passed away and 16.9 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 are only 3.4 and 5.3 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 a 4.5-percentage-point higher probability of dying, and a 6.1-percentage-point higher probability of being hospitalized due to mental health disorders by age 55, compared to those with a master's degree or higher.[23]

[22]Given that residential location data are only available from 1970 onward, we approximate parental municipality in the year of the 18th birthday for cohorts born before 1952 based on the parent's municipality in 1970. If a person has two parents living in different municipalities, we define access to university based on the mother's municipality in the individual-level analyses. For the parent-child-level data, we measure access to university based on the municipality of the parent in question.

[23]The scatter plots included in Appendix B (Figure B3) further show that the two measures of access to higher education—distance to university and gravity-based university access—are likewise correlated with both individuals' years of education and their probability of mental health-related hospitalization. According

Table 1 further shows 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 40 percent of women and 30 percent of men made at least one purchase of mental health-related drugs by age 55. However, the differences in this outcome across the education groups are modest, and among women those with only primary education even demonstrate a lower tendency to purchase mental health-related drugs compared to those with higher levels of education.[24] 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. For example, the ratio of average annual income at age 55 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 1.9 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 35 percent of the fathers of primary-educated individuals survive until age 80, but parental survival rates increase notably with education level. A clear majority of the parents of individuals with a master's degree or higher (72 percent of mothers and 51 percent of fathers) reach age 80. There is also a positive relationship between education and parental mental health. In particular, the fathers of primary-educated individuals have a 2.8-percentage-point (48-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 2.3 percentage points (41 percent). Table 2 further demonstrates that more highly educated individuals have more highly educated and high-earning parents but

to the lines fitted in these graphs, an increase in distance to university by 100 kilometers relates to a 0.33-year increase in educational attainment and a 0.4-percentage-point reduction in the probability of mental health-related hospitalization. A one-standard-deviation-unit increase in gravity-based university access is again associated with a 0.12-year higher educational attainment and a 0.4-percentage-point lower hospitalization probability.

[24]It is likely that the differences in mental health-related hospitalizations and drug purchases across educational groups do not only reflect differences in mental health but also differences in access to healthcare. As pointed out in subsection 2.3, educational attainment is likely to be positively correlated with access to healthcare in Finland. Therefore, the true association between education and mental health might be more positive than that implied in Table 1.

are also more likely to reside in a different area than their 55–65-year-old parents. Thus, many factors can explain the observed differences in the parents' longevity and mental health by the child's education.

Table 1: Summary statistics. Mean outcomes by education.

| Outcome | Women, by education | | | | | Men, by education | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Any | Primary | Secondary | Lower tertiary | Higher tertiary | Any | Primary | Secondary | Lower tertiary | Higher tertiary |
| Survival, age 55 | 0.959 | 0.935 | 0.961 | 0.974 | 0.980 | 0.897 | 0.853 | 0.894 | 0.948 | 0.966 |
| MH-related hospitalization, by age 55 | 0.078 | 0.105 | 0.085 | 0.051 | 0.044 | 0.131 | 0.169 | 0.143 | 0.071 | 0.053 |
| MH-related drug purchase, by age 55 | 0.396 | 0.348 | 0.417 | 0.406 | 0.423 | 0.295 | 0.276 | 0.311 | 0.289 | 0.295 |
| Income | | | | | | | | | | |
| Age 50 | 30 836 | 22 636 | 26 084 | 36 122 | 59 249 | 42 204 | 29 225 | 34 263 | 54 396 | 93 668 |
| Age 55 | 32 670 | 23 694 | 27 417 | 38 394 | 63 703 | 42 860 | 30 155 | 34 742 | 55 788 | 90 758 |
| Number of individuals | 604 780 | 163 383 | 238 998 | 155 341 | 47 058 | 627 074 | 197 610 | 263 173 | 116 845 | 49 446 |

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

| Outcome | Mothers, by child's education | | | | | Fathers, by child's education | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Any | Primary | Secondary | Lower tertiary | Higher tertiary | Any | Primary | Secondary | Lower tertiary | Higher tertiary |
| Parent's survival | | | | | | | | | | |
| Age 70 | 0.856 | 0.828 | 0.852 | 0.878 | 0.890 | 0.684 | 0.640 | 0.672 | 0.719 | 0.756 |
| Age 75 | 0.770 | 0.723 | 0.765 | 0.804 | 0.826 | 0.554 | 0.497 | 0.541 | 0.597 | 0.643 |
| Age 80 | 0.645 | 0.580 | 0.640 | 0.692 | 0.723 | 0.410 | 0.349 | 0.397 | 0.455 | 0.505 |
| Parent's MH-related hospitalization, by age 70 | 0.068 | 0.077 | 0.071 | 0.059 | 0.055 | 0.076 | 0.087 | 0.080 | 0.065 | 0.059 |
| Parent's years of education | 9.76 | 9.32 | 9.56 | 10.02 | 11.15 | 10.05 | 9.44 | 9.71 | 10.47 | 12.08 |
| Parent's income | | | | | | | | | | |
| Age 55 | 12 005 | 9 683 | 11 237 | 13 629 | 17 223 | 23 440 | 18 373 | 20 550 | 27 018 | 37 806 |
| Age 60 | 11 874 | 9 625 | 11 134 | 13 413 | 17 030 | 21 098 | 16 193 | 18 285 | 24 479 | 35 315 |
| Age 65 | 11 911 | 10 045 | 11 243 | 13 116 | 16 506 | 19 294 | 14 838 | 16 857 | 22 096 | 31 816 |
| Parent and child living in same sub-region | | | | | | | | | | |
| Parental age 55 | 0.741 | 0.822 | 0.762 | 0.683 | 0.612 | 0.758 | 0.826 | 0.777 | 0.710 | 0.667 |
| Parental age 60 | 0.693 | 0.795 | 0.722 | 0.621 | 0.505 | 0.705 | 0.799 | 0.735 | 0.642 | 0.542 |
| Parental age 65 | 0.662 | 0.775 | 0.695 | 0.584 | 0.440 | 0.666 | 0.775 | 0.702 | 0.596 | 0.467 |
| Number of parent-child pairs | 988 115 | 239 670 | 419 068 | 241 175 | 88 202 | 922 984 | 214 270 | 393 449 | 230 236 | 85 029 |
| Number of parents | 512 872 | 175 709 | 288 124 | 192 461 | 74 319 | 469 348 | 156 836 | 266 973 | 182 201 | 71 114 |

# 4 Empirical strategy

Our strategy for identifying the direct and indirect health effects of the Finnish higher education expansion relies on differences in the above-described university accessibility measures across municipalities and cohorts, which we use to measure individuals' differential exposure to the expansion. Closely following Suhonen and Karhunen (2019), we begin by conducting an event study analysis to examine changes in an individual's educational attainment and the health outcomes of their family around the time of a decrease in the distance to university in their municipality of residence. Our baseline event study results are based on the following two-way fixed effects (TWFE) specification:

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

where subscripts $i$, $j$, $m$, and $c$ denote the individual, the parent, the individual's municipality of residence, and the individual's birth cohort, respectively. $y_{ijmc}$ and $\epsilon_{ijmc}$ represent the dependent variable and the error term for the parent-child pair $ij$, respectively (subscript $j$ is omitted when using individual-level data). The terms $\gamma_m$ and $\delta_c$ control for municipality and cohort fixed effects, respectively.

In all regression estimations, we account for potential regional heterogeneity in outcomes by clustering standard errors at the level of 70 sub-regions, which roughly correspond to local labor market areas. When estimating effects on parental outcomes, we weight parent-child observations by the inverse of the number of children per parent, following Lundborg and Majlesi (2018), to ensure that each parent's outcomes receive equal weight in the estimation.[25]

In equation (3), the treatment indicator $d_{m,c+19-r}$ captures the change in an individual's distance to university due to a university opening occurring $r$ years before or after their 19th birthday. In a standard manner, we normalize the lead effect at $r = -1$ to zero. In

[25] Table A2 in Appendix A demonstrates that the two-way fixed effects estimates for the effects of a 50-kilometer shorter distance to university on parental survival are smaller when weights are not applied, i.e., when parents are weighted according to their number of children. The table further shows that, in most cases, the weighted two-way fixed estimates are closer to the non-parametric estimates obtained by the method of Callaway and Sant'Anna (2021). Thus, overall, the unweighted two-way fixed effects estimates appear to be negatively biased.

the estimation of equation (3), we use birth cohorts 1943–1966 that turned 19 years old between 1962 and 1985. Therefore, as 6 lead and lagged terms of the treatment indicator are available for each treatment year (1968, 1969, 1972, and 1979), we allow the lead and lagged effects of the treatment to vary within an effect window delimited by endpoints $\underline{r} = -7$ and $\bar{r} = 7$, while assuming constant effects beyond these endpoints (see Schmidheiny and Siegloch, 2023). We use two alternative treatment indicators: a binary indicator for whether the distance to the nearest university decreases by 50 kilometers or more[26] and a continuous indicator capturing the magnitude of all changes in distance during the period 1968–1979. The latter approach estimates the average effect of all changes in distance, assuming a linear relationship between distance and the outcome of interest (see Schmidheiny and Siegloch, 2023).

The results of the event study analysis help validate our quasi-experimental design by assessing whether sharp changes in individuals' or their parents' outcomes coincide with changes in distance to university and whether any pre-trends exist. However, it is worth noticing that the changes in distance to university are likely, to some extent, also affect the outcomes of individuals who turned 19 before a new university was opened near their place of residence. As shown in Figure B2 in Appendix B, the age of 19 was the mode of the age distribution among the first-year university students in Finland between 1975 and 1980, but still 65 percent of these students were older than 19. This age dispersion could show up as anticipatory effects in the event study graphs. However, as only 30 percent of the new students were over 21 years of age, these anticipatory effects are likely to be modest further than a few years away from the treatment year.

Recent difference-in-differences literature has highlighted potential bias in estimates obtained from TWFE regressions in staggered research designs like ours (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak et al., 2024). To assess the robustness of our baseline TWFE estimates, we provide additional estimates using the method recently proposed by Callaway and Sant'Anna (2021) in Appendix A. Since the non-parametric event study estimates

[26]To ensure a staggered design, we account only for the first year in which distance to university decreased by 50 km or more in a given municipality when constructing the binary treatment indicator. However, our data include only three municipalities where more than one such event occurred between 1968 and 1979.

closely align with the baseline TWFE estimates, we are confident that our main findings are not significantly biased by the issues raised in the recent literature on TWFE in staggered settings.

To obtain more precise estimates of the health effects of the changes in access to university, we estimate the following 'static' TWFE regressions for the health outcomes of individuals born between 1948 and 1961 and those of their parents:

$$Health_{ijmc} = \beta_0 + \beta_1 Access_{m,c+19} + \theta_m + \mu_c + \epsilon_{ijmc} \tag{4}$$

where $Health_{ijmc}$ is individual $i$'s or parent $j$'s health outcome, and $Access_{m,c+19}$ represents one of the two university accessibility measures defined in Section 3: *distance to university* or *gravity-based university access*. Controlling for municipality fixed effects, the first measure only captures changes in individuals' distance to university due to the university openings, whereas the latter measure additionally accounts for changes in universities' student intake and potential demand from matriculation examination candidates, providing a more precise approximation of the changes in accessibility. However, as the changes in the gravity-based measure are driven by many factors such as local cohort sizes, demographics, and secondary education supply, it is more susceptible to endogeneity concerns.

The baseline specification (4) only controls for municipality and cohort fixed effects. As a robustness check, we estimate an alternative specification that includes controls for an individual's first language (Finnish, Swedish, or other), parents' highest education level (six categories ranging from primary education to licentiate and doctorate degrees) and average parental income as well as indicators for a missing mother and father. Parental characteristics are measured using census data from the year of the individual's 15th birthday or the closest available year (1970, 1975, or 1980). We also explore potential mechanisms underlying the estimated health effects of access to university by replacing $Health_{ijmc}$ with variables describing individuals' and their parents' education, income, and residential location in equation (4).

The identification of the effects of higher education expansion hinges on the parallel trends assumption, which could be violated if individuals or their families were non-randomly selected into groups affected by the expansion at different times or to different degrees. However, as discussed in subsection 2.2, the university expansion involved random elements due to the complex political decision-making process, reducing concerns about non-random sorting of families into treatment groups. Additionally, our validity and robustness checks discussed in Section 5 provide little evidence that the estimated health effects of expanding access to higher education would be driven by selection.

Our main analysis examines the health effects of access to university separately for men and women and includes multiple health outcomes and model specifications. Therefore, testing the statistical significance of each estimate separately might lead to overstating the number of significant estimates. To assess the severity of this problem, we adopt two alternative approaches that adjust the naive p-values for multiple testing: the two-stage method by Benjamini et al. (2006), which controls the false discovery rate (FDR), and the more conservative Šidák-Holm step-down correction, which controls the family-wise error rate (FWER).[27] In Appendix B, Tables B5 and B6 compare the naive p-values for our main estimates with the FDR- and FWER-based measures. These comparisons suggest that our conclusions are, overall, highly robust to accounting for the multiple hypothesis problem: the sharpened q-values of Benjamini et al. (2006) are well in line with the naive p-values, whereas the Šidák-Holm adjusted p-values indicate that the significance of some of the effects of the distance-to-university measure (e.g., that on mothers' survival at age 75) could be substantially overstated.

In the final step of our analysis, we assess the health effects of education induced by higher education expansion, using variations in the university accessibility measures across municipalities and cohorts as a source of plausibly exogenous variation in an individual's years of education $Educ_{ijmc}$.[28] Our two-stage least squares (2SLS) specification is given by:

[27]To implement the method of Benjamini et al. (2006), we use the Stata code provided by Anderson (2008). The Šidák-Holm correction amounts to sorting $K$ unadjusted p-values into ascending order ($p_1 \leq p_2 \leq ... \leq p_K$) and computing $1-(1-p_1)^K, \max[p_1, 1-(1-p_2)^{K-1}], ..., \max[p_{K-1}, p_K]$ (see Appendix C of Jones et al. (2019)).

[28]Years of education are based on individuals' highest completed educational qualifications, determined at age 50, in the following manner: 9 years for no post-compulsory education; 12 years for a secondary-level degree (ISCED levels 3), 13 years for a post-secondary non-tertiary degree (ISCED level 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).

$$Health_{ijmc} = \beta_0 + \beta_1 Educ_{ijmc} + \theta_m + \mu_c + \epsilon_{ijmc} \tag{5}$$

$$Educ_{ijmc} = \alpha_0 + \alpha_1 Access_{m,c+19} + \gamma_m + \delta_c + \nu_{ijmc}. \tag{6}$$

We interpret the 2SLS estimate for parameter $\beta$ as the local average treatment effect (LATE) of an additional year of education, identified for individuals whose educational attainment increased due to improved access to university. Unlike the reduced-form estimates in equation (4), the 2SLS estimates rely on the assumption that changes in access to university affect an individual's and their parent's health solely through changes in the individual's years of education. The estimates could be biased if the university expansion had other types of effects on family health. A potential confounding channel arises if university openings and expansion influenced the healthcare services individuals and their parents received, for example, by altering the number or quality of healthcare providers in their municipality of residence. Another possibility is that the university expansion affected not only the education and labor market prospects of the children's generation but also those of the parents' generation, which could, in turn, influence parental health. One could argue that, if the university expansion impacted local labor markets and services, the health effects of these changes are likely dispersed across many cohorts of individuals and parents. Therefore, such effects could be 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 in terms of their own educational attainment. These arguments are supported by the results reported in subsection 5.3, which indicate that the instruments are not positively associated with parental educational attainment or income.

# 5 Results

## 5.1 Event study results

We begin by presenting event study results from the estimation of equation (3). Figure 3 shows the estimated changes in the later educational attainment and health outcomes of 19-year-olds before and after a decrease in their distance to university due to a university opening. The figure demonstrates that the two alternative treatment indicators—the continuous indicator measuring the change in distance to university in kilometers (scaled by 1/100) and the binary indicator for whether distance to university decreased by 50 kilometers or more—produce approximately identical results.

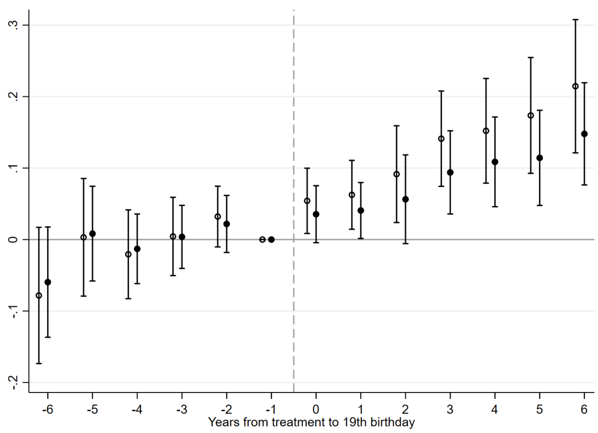
The event study graph in sub-figure (a) of Figure 3 suggests that individuals' educational attainment is, to some extent, responsive to the treatment. A decrease in distance to university by at least 50 kilometers is associated with an increase of 0.05 to 0.21 years in educational attainment among the treated cohorts, compared to the youngest untreated cohort. Using the continuous treatment indicator, a 100-kilometer decrease in distance to university is associated with a 0.04-year increase in educational attainment among the first treated cohort, with lagged treatment effects varying between 0.04 and 0.15 years. With both treatment indicators, we observe an increasing pattern in the magnitude of the lagged treatment effects. There are no clear signs of pre-trends in educational attainment among the cohorts turning 19 before the treatment. While the point estimates for the lead term at $r = -6$ are sizable, -0.08 years and -0.06 years for the binary and continuous treatment indicators, respectively, none of the lead effects are statistically significant at the 5 percent level.[29]

The event study results in sub-figure (b) of Figure 3 do not indicate any significant relationship between a shorter distance to university and the cumulative survival probability at age 55: the point estimates for this relationship are negligible, varying from -0.2 to 0.3 percentage points, and are not statistically different from zero. However, sub-figures (c) and (d) provide some evidence of positive mental health effects following the treatment. While the estimated effects on the cumulative probability of mental health-related hospitalization by age 55 are small and statistically insignificant for the first three post-treatment periods, the following lagged effects for the cohorts turning 19 three to six years after the treatment are larger and partly significant at the 5 percent level. For these periods, the results using the binary treatment indicator point to lagged negative effects varying from -1.1 to -0.5

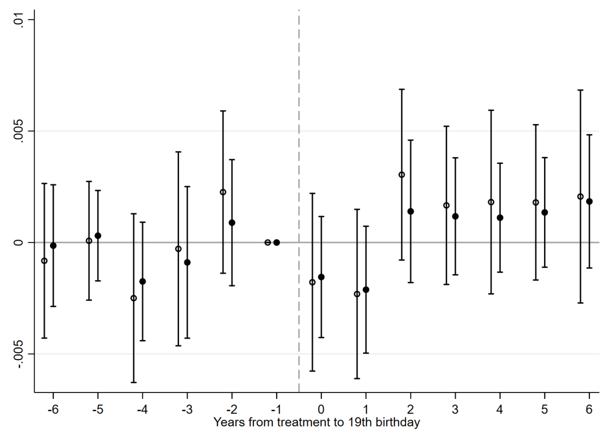
[29]When conducting non-parametric event study analyses using the method of Callaway and Sant'Anna (2021) (see Appendix A), we also examined the longer-term lead and lagged effects beyond $r = -6$ and $r = 6$. While these results, reported in Appendix B (Figure B9), show certain pre-treatment differences in the changes in years of education across the treatment and control groups, these changes do not form a systematic pattern; that is, they resemble random deviations from the mean.

Figure 3: Event study results: Education, survival, and mental health (MH) for cohorts turning 19 before and after a decrease in distance to university.

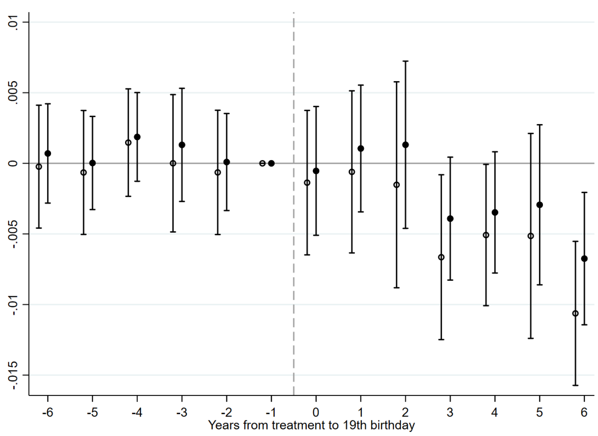
(a) Years of education, age 50



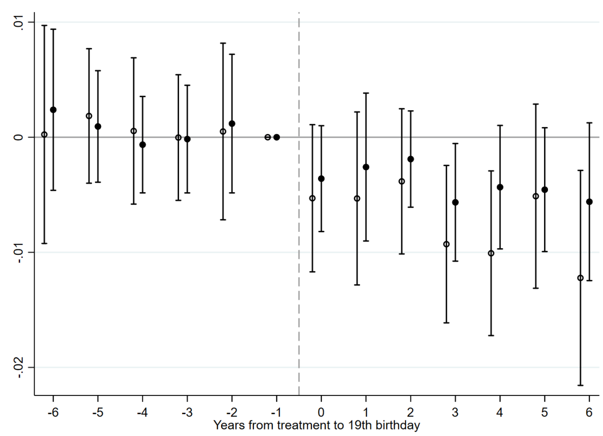

(b) Survival, age 55




(c) MH-related hospitalization, by age 55




(d) MH-related drug purchase, by age 55




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 decreases by 50 km or more), 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 95% confidence intervals are adjusted for sub-region-level clustering (70 clusters).

percentage points, while the effects using the continuous indicator vary from -0.7 to -0.3 percentage points. Furthermore, we obtain non-negligible, albeit only weakly statistically significant, point estimates for the immediate effect of the treatment on the cumulative probability of mental health-related drug purchases by age 55, pointing to 0.5-percentage-point and 0.4-percentage-point reductions in this probability using the binary and continuous treatment indicators, respectively. The estimates for the lagged effects are likewise large, varying from -1.2 to -0.4 percentage points with the binary indicator and from -0.6 to -0.2 percentage points with the continuous indicator, and are partially significant at the 5 percent level.

Sub-figures (c) and (d) of Figure 3 do not provide any indication of anticipatory mental health effects for individuals whose 19th birthday occurs at most six years before the treatment. This finding gives us confidence that the indicated improvements in the mental health outcomes of the post-treatment cohorts are caused by the reductions in distance to university. A possible explanation for the observed strengthening of the mental health effects over time may arise from the similar pattern observed in the educational attainment effects.

After discussing the effects of individuals' distance to university on their long-term outcomes, we now turn to the estimated spillover effects on parental health outcomes, as reported in Figure 4. These results provide some support for positive spillover effects, as decreases in a child's distance to university are, in some cases, positively and significantly associated with post-treatment changes in parents' cumulative survival probability, particularly that observed at age 70. However, the lagged effects of the treatment on parental survival appear to weaken over time. For example, sub-figure (a) shows that a decrease in a child's distance to university by 50 kilometers or more is associated with approximately a one-percentage-point increase in the probability of parental survival at age 70 among the parents of the first three treated child cohorts, whereas the following lagged effects are smaller, between 0.3 and 0.6 percentage points, and statistically less significant. The results regarding parental survival at ages 75 and 80 in sub-figures (b) and (c) are more ambiguous, and only a single post-treatment effect—the first one on parental survival at age 80—is statistically significant at the 5 percent level. Furthermore, none of the estimated effects on parents' mental health-related hospitalizations, reported in sub-figure (d), are significantly different from zero.

Figure 4 does not show systematic evidence of pre-trends in any of the parental outcomes. However, there are signs of an anticipatory effect on parental survival at $r = -6$, coinciding with that observed for individuals' years of education in Figure 3.

The additional event study results included in Appendix B provide further insights into the heterogeneity of the treatment effects and the validity of the research design. The separate event study results for women and men, shown in Figure B4, suggest that the changes in distance to university have highly similar effects on women's and men's education and mental health outcomes. The most discernible difference is that the post-treatment effects on years of education appear to manifest more slowly for women than for men. The separate event study results for fathers and mothers in Figure B5 again show certain differences in both the magnitude and precision of the estimated effects. Regarding parental survival at age 70, we see evidence of a statistically significant positive effect for fathers coinciding with the treatment, whereas the lagged effects are closer to zero and somewhat imprecisely estimated. The estimates regarding mothers' survival at age 70 are more systematically positive and more precisely estimated. Therefore, the fading out of the effect on parental survival observed in Figure 4 is largely driven by fathers. Moreover, we see evidence of an anticipatory increase in mothers' cumulative survival probability at ages 75 and 80 occurring two years prior to the treatment. These anticipatory effects offer an explanation for the weak post-treatment effects indicated in sub-figures (b) and (c) of Figure 4.[30]

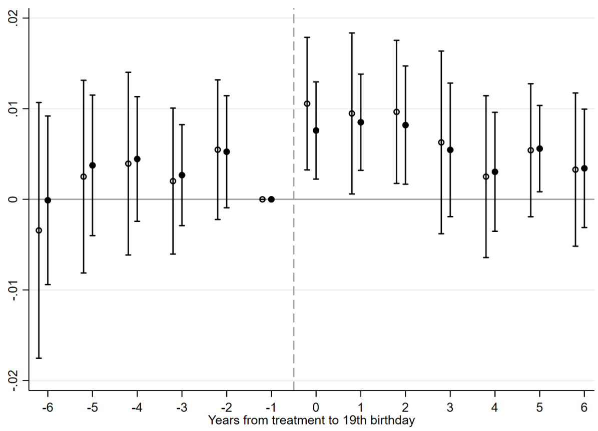
The event study results in Figure B6 in Appendix B provide further support for the validity of the research design. These results demonstrate that the treatment is not associated with any significant pre- or post-treatment changes in individuals' family background, measured in terms of parental education and income in the year of their 15th birthday (or the closest year available). Nevertheless, the minor fluctuations in the point estimates warrant examining the sensitivity of the regression estimates in the following sections.

Finally, Figures B7 and B8 report event study results obtained after excluding individuals who were highly exposed to the 1972 university opening, which took place in the city of

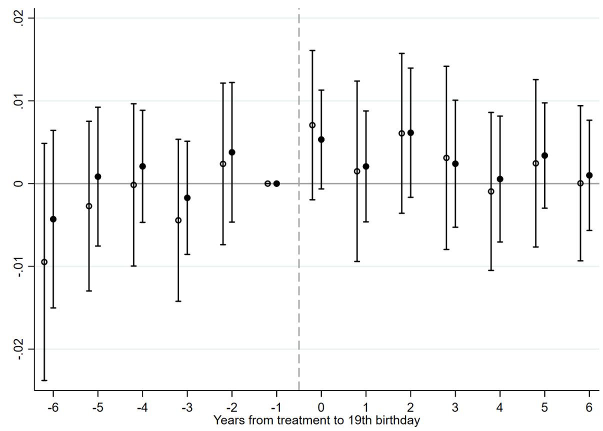
[30]These anticipatory effects are possibly explained by treatment effects on the educational outcomes of children who were around 20–21 years old in the university opening year. A weak indication of such spillover effects can be found in the event study results for women's education in Appendix B (Figure B4).

Figure 4: 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.

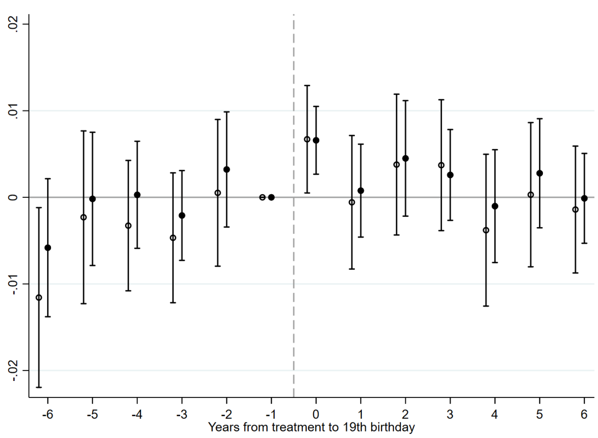
(a) Parent's survival, age 70



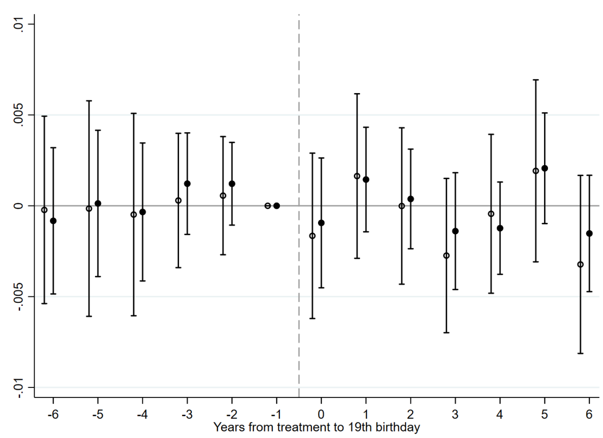

(b) Parent's survival, age 75




(c) Parent's survival, age 80




(d) Parent's MH-related hospitalization, by age 70




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 decreases by 50 km or more), and the solid circles are for the estimated effects of a continuous treatment (any decrease in distance to university at age 19). The 95% confidence intervals were adjusted for sub-region-level clustering (70 clusters).

Kuopio, from the estimation sample. As pointed out in subsection 2.3, this event could have had significant implications for the development of regional health outcomes, as the new university founded in that year included a medical school. However, the results in the additional event study graphs are approximately similar to those in Figures 3 and 4, suggesting that higher access to medical education is not significantly driving the results.

### 5.2 Main results: Health effects of access to university

Having confirmed that university openings between 1968 and 1979 are associated with significant changes in individuals' and their parents' health outcomes, we now turn to examining the average effects of access to university, as estimated using equation (4) and the two alternative accessibility measures. Table 3 shows the estimated effects on individuals' survival and mental health, separately for men and women, both with and without controlling for the additional covariates (first language, parental education and income, and indicators for a missing mother/father). Since the estimates are highly robust to the inclusion of these additional controls, it seems unlikely that the results are significantly confounded by non-random sorting of families across municipality-by-cohort cells.

In line with the event study results, the small and statistically insignificant estimates in the first two columns of Table 3 suggest that a shorter distance to university has no significant implications for either women's or men's cumulative survival probability at age 55.[31] The corresponding results obtained using the gravity-based measure are more ambiguous, being more sensitive to the choice of model specification: with including the additional covariates in the model, the estimate for women changes from zero to negative (-0.006), while the positive estimate for men (0.011) approximately halves. Therefore, while these results indicate some heterogeneous effects on early mortality by gender, they should be interpreted cautiously.

The remaining results in Table 3 primarily support the conclusion that greater access to university has positive implications for individuals' mental health, as reflected in lower cumulative probabilities of being hospitalized or purchasing drugs due to mental health

[31]The previous study of Suhonen and Karhunen (2019) showed that parents' shorter distance to university did not significantly affect their cumulative survival probabilities at ages 50 or 60 among parent cohorts born between 1936 and 1956. Our analysis complements these findings by showing that a similar result holds for individuals born between 1948 and 1961 (including those without children).

Table 3: Effects of an increase in access to university on survival and mental health.

| | Decrease in distance to university (/100 km) | | Increase in gravity-based university access | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| A. Survival, age 55 | | | | |
| Women | 0.0006 | -0.0017 | 0.0003 | -0.0059** |
| | (0.0010) | (0.0019) | (0.0013) | (0.0024) |
| Men | 0.0010 | -0.0015 | 0.0110*** | 0.0051 |
| | (0.0019) | (0.0026) | (0.0029) | (0.0034) |
| B. MH-related hospitalization, by age 55 | | | | |
| Women | -0.0036*** | -0.0032** | -0.0022 | -0.0026* |
| | (0.0012) | (0.0012) | (0.0015) | (0.0014) |
| Men | -0.0036 | -0.0031 | -0.0107*** | -0.0113*** |
| | (0.0026) | (0.0028) | (0.0026) | (0.0032) |
| C. MH-related drug purchase, by age 55 | | | | |
| Women | -0.0048* | -0.0053* | -0.0131*** | -0.0198*** |
| | (0.0027) | (0.0029) | (0.0038) | (0.0033) |
| Men | -0.0066*** | -0.0063*** | -0.0135*** | -0.0154*** |
| | (0.0018) | (0.0020) | (0.0045) | (0.0044) |
| Additional covariates | 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, parental education and income (at the individual's age of 15), and indicators for a missing mother/father. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

disorders by age 55. According to the point estimates, a 100-kilometer decrease in distance to university is associated with a 0.3–0.4-percentage-point reduction in women's hospitalization probability. The corresponding estimates for men are of the same magnitude but much more imprecise, and therefore not statistically significant. Using the gravity-based measure, the effect on women's hospitalization is small ($\geq -0.003$) and statistically not highly significant, whereas the effect for men is significant at the one percent level, indicating that an increase in access to university by one standard deviation unit (corresponding to its pre-expansion standard deviation measured for the 1948 cohort) reduces men's hospitalization probability by 1.1 percentage points.

The results at the bottom of Table 3 further suggest that access to university significantly affects the cumulative probability of mental health-related drug purchases by age 55 among both genders. A 100-kilometer decrease in distance to university is associated with a 0.6–0.7-percentage-point lower probability of drug purchases among men, whereas the effect for women is smaller (0.5 percentage points) and statistically less significant. The results using the gravity-based measure again indicate large and statistically significant effects for both genders: an increase in access to university by one standard deviation unit is estimated to decrease the probability of mental health-related drug purchases by 1.3 or 2.0 percentage points among women, and by 1.4 or 1.5 percentage points among men, depending on the model specification.

The results regarding parental health outcomes, reported in Table 4, indicate that increased access to university for individuals also has significant effects on parental survival. However, in line with the event study results discussed in subsection 5.1, the effects appear to differ between mothers and fathers. The results using both accessibility measures systematically show that positive effects only accrue to mothers, while the point estimates for fathers are negative but highly imprecise, and therefore not distinguishable from zero. A 100-kilometer decrease in distance to university is estimated to increase mothers' cumulative survival probability at ages 70, 75, and 80 by approximately half a percentage point. A one-standard-deviation-unit increase in gravity-based university access is estimated to increase mothers' cumulative survival probability at age 70 by 0.9 percentage points, while the estimated effects at ages 75 and 80 are higher, varying from 1.6 to 2.1 percentage points. The estimated effects on mothers' and fathers' probabilities of mental health-related hospitalization by age 70, reported at the bottom of Table 4, are consistently small and statistically insignificant.

The results in Table 5 break down the effects of access to university on parental health by the offspring's gender. The results indicate that positive effects on mothers' survival may arise via both genders' higher access to university, whereas no significant effects on fathers' survival are detected for either the father-daughter or father-son subsample. The evidence for a positive relationship between daughters' access to university and mothers' survival is particularly strong when examining mothers' cumulative survival probability at age 70, as both daughters' distance to university and gravity-based university access are significantly associated with this probability. At the higher age thresholds, only the effect

Table 4: Effects of an increase in children's access to university on parental survival and mental health.

| | Decrease in distance to university (/100 km) | | Increase in gravity-based university access | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| A. Parent's survival, age 70 | | | | |
| Mother | 0.0052*** | 0.0051*** | 0.0095*** | 0.0089*** |
| | (0.0017) | (0.0017) | (0.0027) | (0.0028) |
| Father | -0.0027 | -0.0027 | -0.0074 | -0.0086 |
| | (0.0034) | (0.0033) | (0.0085) | (0.0073) |
| B. Parent's survival, age 75 | | | | |
| Mother | 0.0054*** | 0.0052** | 0.0177*** | 0.0164*** |
| | (0.0020) | (0.0020) | (0.0020) | (0.0024) |
| Father | -0.0042 | -0.0042 | -0.0047 | -0.0061 |
| | (0.0045) | (0.0044) | (0.0091) | (0.0079) |
| C. Parent's survival, age 80 | | | | |
| Mother | 0.0055* | 0.0053** | 0.0206*** | 0.0199*** |
| | (0.0028) | (0.0027) | (0.0027) | (0.0030) |
| Father | -0.0034 | -0.0033 | -0.0067 | -0.0071 |
| | (0.0041) | (0.0039) | (0.0096) | (0.0085) |
| D. Parent's MH-related hospitalization, by age 70 | | | | |
| Mother | 0.0018 | 0.0020 | -0.0024 | -0.0015 |
| | (0.0015) | (0.0014) | (0.0043) | (0.0042) |
| Father | 0.0018 | 0.0020 | 0.0017 | 0.0028 |
| | (0.0022) | (0.0022) | (0.0050) | (0.0044) |
| Additional covariates | 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, parental education and income (at the child's age of 15), and indicators for a missing mother/father. The parent-child observations are weighted by the inverse of the number of children per parent. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

of daughters' gravity-based university access on mothers' survival is statistically significant. Then again, the two measures of sons' access to university are not significantly related to mothers' survival at age 70, but the effects of these measures are significant at the higher age thresholds. Furthermore, the results do not provide significant evidence of an effect on parents' mental health-related hospitalizations in any of the subsamples.

Table 5: Effects of an increase in children's access to university on parental survival and mental health by parent's and child's gender.

| | Mother-daughter (1) | Mother-son (2) | Father-daughter (3) | Father-son (4) |
|---|---|---|---|---|
| A. Survival, age 70 | | | | |
| Decrease in distance to university (/100 km) | 0.0069** | 0.0025 | -0.0022 | -0.0036 |
| | (0.0029) | (0.0024) | (0.0029) | (0.0042) |
| Increase in gravity-based university access | 0.0141*** | 0.0035 | -0.0127 | -0.0061 |
| | (0.0025) | (0.0036) | (0.0078) | (0.0091) |
| B. Survival, age 75 | | | | |
| Decrease in distance to university (/100 km) | 0.0047 | 0.0054** | -0.0025 | -0.0063 |
| | (0.0033) | (0.0027) | (0.0047) | (0.0052) |
| Increase in gravity-based university access | 0.0177*** | 0.0127*** | -0.0094 | -0.0072 |
| | (0.0028) | (0.0029) | (0.0077) | (0.0109) |
| C. Survival, age 80 | | | | |
| Decrease in distance to university (/100 km) | 0.0046 | 0.0060** | -0.0048 | -0.0018 |
| | (0.0038) | (0.0030) | (0.0049) | (0.0053) |
| Increase in gravity-based university access | 0.0162*** | 0.0149*** | -0.0100 | -0.0098 |
| | (0.0039) | (0.0036) | (0.0098) | (0.0101) |
| D. MH-related hospitalization, by age 70 | | | | |
| Decrease in distance to university (/100 km) | 0.0010 | 0.0022 | 0.0000 | 0.0023 |
| | (0.0015) | (0.0018) | (0.0024) | (0.0030) |
| Increase in gravity-based university access | -0.0033 | -0.0028 | -0.0003 | 0.0006 |
| | (0.0053) | (0.0039) | (0.0045) | (0.0056) |

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

## 5.3 Mechanisms

The evidence presented above has suggested that individuals' high exposure to the Finnish university expansion is positively linked to their mental health and their mothers' longevity. As pointed out in subsection 2.3, there can be multiple mechanisms behind these positive effects. While our data do not permit us to disentangle among many of the detailed mechanisms, we can explore some of the broad channels by examining results for alternative dependent variables.

In line with the event study results presented in subsection 5.1, the first row of Table 6 shows that both university accessibility measures have significant explanatory power over individuals' years of education. Therefore, the positive health effects can, to a significant extent, arise through individuals' higher educational attainment and the various health benefits of education discussed in subsection 2.3. Table 6 demonstrates that the estimated effects of access to university—particularly the effects of the gravity-based measure—on women's and men's years of education are larger when controlling for additional covariates. Moreover, the effects are systematically stronger for men than for women. A 100-kilometer decrease in distance to university is estimated to increase women's educational attainment by 0.07 years (0.09 years with covariate adjustment) and men's educational attainment by 0.11 years (0.14 years with covariate adjustment). Similarly, an increase in gravity-based university access by one standard deviation unit is associated with increases of 0.38 years and 0.39 years (0.46 years and 0.51 years with covariate adjustment) in women's and men's education, respectively.

As an introduction to the two-stage least squares results reported in the next subsection, Table 6 also presents the cluster-robust F-statistics for the accessibility measures, which provide insight into their strength as instruments. Indicating a potential weak instrument problem, the F-statistics for the distance-to-university measure are relatively low: at the highest, 5.2 for the women's sample and 16.6 for the men's sample. In contrast, the gravity-based measure serves as a sufficiently strong instrument, with F-statistics of well above 200 for both genders.

Table 6: Effects of an increase in access to university on educational outcomes and income.

| | Decrease in distance to university (/100 km) | | | | Increase in gravity-based university access | | | |
|---|---|---|---|---|---|---|---|---|
| | Women | | Men | | Women | | Men | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Years of education, age 50 | 0.0680** | 0.0853** | 0.1143*** | 0.1383*** | 0.3768*** | 0.4580*** | 0.3915*** | 0.5108*** |
| | (0.0308) | (0.0373) | (0.0281) | (0.0367) | (0.0234) | (0.0312) | (0.0252) | (0.0287) |
| | F=4.9 | F=5.2 | F=16.6 | F=14.2 | F=241.3 | F=216.0 | F=259.8 | F=317.1 |
| Primary education | -0.0103 | -0.0104 | -0.0228*** | -0.0241*** | -0.0771*** | -0.0703*** | -0.0933*** | -0.0947*** |
| | (0.0071) | (0.0068) | (0.0070) | (0.0071) | (0.0057) | (0.0081) | (0.0056) | (0.0063) |
| Secondary education | -0.0021 | -0.0047 | 0.0100* | 0.0080* | 0.0155** | -0.0054 | 0.0577*** | 0.0417*** |
| | (0.0047) | (0.0042) | (0.0052) | (0.0042) | (0.0076) | (0.0090) | (0.0042) | (0.0039) |
| Lower tertiary education | 0.0128** | 0.0132** | 0.0115*** | 0.0121*** | 0.0695*** | 0.0685*** | 0.0393*** | 0.0409*** |
| | (0.0051) | (0.0053) | (0.0035) | (0.0038) | (0.0045) | (0.0053) | (0.0034) | (0.0034) |
| Higher tertiary education | -0.0004 | 0.0020 | 0.0013 | 0.0040*** | -0.0078* | 0.0071** | -0.0037* | 0.0121*** |
| | (0.0020) | (0.0020) | (0.0014) | (0.0014) | (0.0046) | (0.0033) | (0.0020) | (0.0014) |
| Tertiary education X distance to first tertiary institution | | | | | | | | |
| < 100 km | 0.0010 | 0.0019 | 0.0060*** | 0.0077*** | 0.0114 | 0.0173** | 0.0103*** | 0.0196*** |
| | (0.0030) | (0.0034) | (0.0021) | (0.0026) | (0.0069) | (0.0081) | (0.0031) | (0.0027) |
| > 100 km | 0.0022 | 0.0038 | 0.0031* | 0.0046** | 0.0303*** | 0.0382*** | 0.0087*** | 0.0164*** |
| | (0.0033) | (0.0038) | (0.0018) | (0.0021) | (0.0046) | (0.0055) | (0.0026) | (0.0030) |
| Income, age 50 | -198.62 | -43.23 | 740.39 | 1081.50** | -787.09*** | 280.21 | 503.71 | 2296.87** |
| | (164.47) | (167.39) | (464.27) | (503.76) | (236.05) | (173.81) | (952.65) | (900.08) |
| Income, age 55 | -54.64 | 118.17 | 964.48** | 1299.71** | 382.89 | 1516.15*** | 3006.17*** | 4750.75*** |
| | (239.44) | (309.79) | (435.96) | (552.86) | (442.40) | (520.70) | (531.72) | (472.27) |
| Additional covariates | No | Yes | No | 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, parental education and income (at the individual's age of 15), and indicators for a missing mother/father. 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 also breaks down the effects of access to university on years of education by education level. Consistent with the previous findings of Suhonen and Karhunen (2019) discussed in subsection 2.3, these results suggest that, in addition to enabling some individuals to progress from secondary to lower tertiary education, greater local access to university also facilitates the completion of any post-compulsory education due to the overall increase in the local supply of such education. This finding is important for interpreting the indicated positive health effects of access to higher education, as part of these effects may stem from a higher completion rate of secondary education rather than tertiary education. Moreover, the results suggest that the negative spillover effects on the probability of remaining at the primary level of education are markedly larger for men than for women. Therefore, the health effects arising from these spillovers are also likely to be higher for men.

Table 6 further sheds some new light on the regional mobility implications of the changes in access to university, showing results for two outcome variables, which interact an indicator for the completion of tertiary education (associate's degree or higher) with an indicator for whether the first tertiary-level degree was completed less than or more than 100 kilometers from one's home municipality.[32] The results indicate that greater access to university is positively associated with both graduations taking place near home and distant graduations. Among men, the probability of graduating within 100 kilometers from home increases more than the probability of a distant graduation, whereas for women, the effects on distant graduations are more significant. As we find no evidence of negative effects on the likelihood of graduating more than 100 kilometers from home, changes in study location are unlikely to be a key mechanism driving the estimated health effects of access to university in this context. These findings align with those of Suhonen and Karhunen (2019) discussed in subsection 2.3.

The estimated effects of increased access to university on individuals' later-life income, measured at ages 50 and 55, are reported at the bottom of Table 3. These results suggest that, in the long run, there are positive monetary returns to greater access to university, but

[32]A person's home municipality is determined based on their parental municipality in the year of their 18th birthday (or the closest year available), or based on their municipality of birth if the parental municipality is unobserved. In our main sample (cohorts 1948–1961), 60 percent of higher education degree holders completed their first degree less than 100 kilometers from home, while 38 percent completed it farther away. The location of the first higher education institution was missing for 1.9 percent of the sample.

mainly for men. The estimated returns are notably larger after controlling for the additional covariates, particularly when using the gravity-based access measure. According to the covariate-adjusted specification, a 100-kilometer decrease in distance to university increases men's annual income by 1,082 euros at age 50 and by 1,300 euros at age 55, whereas the corresponding estimates for women are small and statistically insignificant. Furthermore, the covariate-adjusted specification suggests that a one-standard-deviation-unit increase in gravity-based university access is associated with 2,297-euro and 4,751-euro increases in men's income at age 50 and 55, respectively. For women, significant positive returns are only found at age 55. One-standard-deviation-unit higher gravity-based university access relates to 1,516-euro higher women's income at this age.

While the education and income effects reported in Table 6 provide a potential explanation for the positive effects of increased access to university on family health, the results in Table 7 offer little evidence that these health effects can be attributed to positive changes in parental education or income. Specifically, the estimated effects of a decrease in distance to university on parents' years of education and parental income at ages 55, 60, and 65 are consistently close to zero and mainly statistically insignificant. The gravity-based access measure is again negatively and significantly related to mothers' and fathers' years of education, mothers' income at ages 55, 60, and 65, as well as with fathers' income at age 65. While the negative association between gravity-based university access and parents' education is closer to zero ($\geq -0.05$ years) after adjusting for the additional covariates, including parental education and income measured at the children's age of 15, the negative association with parental income remains significant. However, as these relationships are negative, there is no indication that the estimated effects of gravity-based university access, e.g., on mothers' survival are explained by mothers directly benefiting from the greater local access to university in terms of a higher level of education and income. This conclusion is in line the broad regional trends discussed in subsection 2.2, which suggest that the Finnish university expansion was not followed by a significant regional convergence in educational attainment or income.[33]

[33]Table B2 in Appendix B reports the corresponding results obtained using the alternative gravity-based access measure which is primarily based on parental municipality at the children's age of 18 and, therefore, contains less measurement error compared to that based on children's municipality of birth. These results do

not show significant evidence of negative relationships between gravity-based university access and parental education or income. Therefore, the negative estimates reported in Table 7 could reflect measurement error biases. However, despite these differences, our main results regarding the effects of gravity-based university access on individuals' and their parents' health outcomes are highly similar to those reported in Tables B1 and B2.

Table 7: Effects of an increase in children's access to university on additional parental outcomes.

| | Decrease in distance to university (/100 km) | | | | Increase in gravity-based university access | | | |
|---|---|---|---|---|---|---|---|---|
| | Mothers | | Fathers | | Mothers | | Fathers | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Parent's years of education | -0.0059 | 0.0133* | -0.0325 | -0.0058 | -0.1426*** | -0.0447** | -0.1801*** | -0.0464*** |
| (latest observed) | (0.0152) | (0.0077) | (0.0228) | (0.0085) | (0.0239) | (0.0189) | (0.0307) | (0.0126) |
| Parent's income, age 55 | -144.79* | -97.6493 | -20.75 | 66.96 | -337.44*** | -411.30** | -196.09 | -182.79 |
| | (80.36) | (63.4377) | (121.80) | (94.56) | (112.19) | (196.44) | (268.59) | (458.53) |
| Parent's income, age 60 | -112.44 | -95.4682 | 19.43 | 3.10 | -622.31*** | -686.85** | -401.11 | -685.70 |
| | (101.20) | (101.0371) | (143.18) | (126.74) | (184.11) | (271.93) | (289.12) | (516.31) |
| Parent's income, age 65 | -71.73 | -47.67 | -289.61* | -378.23* | -703.29*** | -690.28** | -1782.14*** | -2054.48*** |
| | (99.56) | (96.35) | (168.99) | (210.90) | (264.25) | (337.36) | (241.19) | (526.12) |
| Parent and child living in same | 0.0147** | 0.0139* | 0.0185** | 0.0179** | 0.0490*** | 0.0465*** | 0.0657*** | 0.0640*** |
| sub-region, parental age 55 | (0.0073) | (0.0071) | (0.0083) | (0.0080) | (0.0070) | (0.0065) | (0.0088) | (0.0084) |
| Parent and child living in same | 0.0093* | 0.0084* | 0.0117** | 0.0109** | 0.0277*** | 0.0241*** | 0.0421*** | 0.0393*** |
| sub-region, parental age 60 | (0.0049) | (0.0046) | (0.0057) | (0.0054) | (0.0056) | (0.0052) | (0.0057) | (0.0055) |
| Parent and child living in same | 0.0071* | 0.0061 | 0.0086 | 0.0081 | 0.0209*** | 0.0167*** | 0.0342*** | 0.0315*** |
| sub-region, parental age 65 | (0.0041) | (0.0038) | (0.0054) | (0.0051) | (0.0047) | (0.0046) | (0.0051) | (0.0050) |
| Additional covariates | No | Yes | No | 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, parental education and income (at the child's age of 15), and indicators for a missing mother/father. The parent-child observations are weighted by the inverse of the number of children per parent. Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

In the last three rows of Table 7, we examine another potential factor influencing family health outcomes: the geographical proximity between parent and child, measured using indicators for whether they live in the same sub-region when the parent approaches old age. As noted in subsection 2.3, the previous findings 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 adults, implying a positive relationship between access to university and parental proximity. The results at the bottom of Table 7 support this connection, though the effect appears to weaken significantly as the parent ages. For instance, the results in column (1) indicate that a 100-kilometer decrease in distance to university increases the probability of living in the same sub-region as one's mother by 1.5 percentage points when she is 55 years old, but this effect is less than 1 percentage point and when examined 5 or 10 years later. The corresponding effects on a child's proximity are slightly higher for fathers but diminish similarly over time. Nevertheless, in line with the hypotheses discussed in subsection 2.3, these findings suggest that closer proximity between parent and child may serve as a mechanism linking individuals' access to university with positive family health outcomes, including their mothers' higher longevity.

### 5.4 Local average treatment effects of an additional year of education

In our final analysis, we aim to assess the health benefits of an additional year of education resulting from changes in access to university by examining two-stage least squares (2SLS) estimates from the estimation of models (5)–(6). As a benchmark, we also report the corresponding ordinary least squares (OLS) estimates of equation (5). While the exclusion restriction of the instruments is untestable, we have ruled out some of the most apparent confounding factors, for example, by demonstrating that changes in access to university are not positively related to parental education or income. Therefore, a plausible explanation for the observed positive effects on individuals' mental health and their mothers' longevity is that they largely reflect the impact of attaining a higher educational level or the subsequent effects of this educational choice on later-life income and residential location.

Table 8 presents the OLS and 2SLS estimates for the relationship between an individual's years of education and long-term health outcomes. According to the baseline OLS estimates in column (1) of Table 8, an additional year of education is associated with a 0.4-percentage-point increase in survival probability among women and a 0.9-percentage-point increase among men. However, based on the 2SLS estimates obtained using distance to university as an instrument in columns (2) and (3), the causal effect of education on survival remains unclear, as none of the estimates are significantly different from zero. The 2SLS estimates in columns (4) and (5), which use the gravity-based accessibility measure as an instrument, are more precise and partly significant at the 5 percent level, indicating a positive effect on men's survival and a null or negative effect on women's survival. However, these results are difficult to interpret because of the sensitivity of the estimates to the covariate adjustment, arising from the sensitivity of the reduced-form results shown in Table 3. Thus, overall, the evidence of the early-mortality effects of education is weak.

Most of the results in Table 8 suggest that higher educational attainment significantly reduces the probability of mental health disorders. According to the baseline OLS results, an additional year of education is associated with 1-percentage-point and 1.5-percentage-point decreases in women's and men's probabilities of mental health-related hospitalization by age 55, respectively. The corresponding negative relationship between education and the probability of purchasing mental health-related drugs by age 55 is approximately half a percentage point among both genders. In most cases, the 2SLS estimates indicate a moderately lower but a statistically more precise relationship between education and mental health after controlling for the additional covariates–which is consistent with the first-stage effects of the instruments being larger in the covariate-adjusted models (see subsection 5.3). The 2SLS estimates for mental health effects mainly exceed the baseline OLS estimates. When using the distance-to-university instrument, the covariate-adjusted 2SLS results (column 3) indicate that an additional year of education decreases the probability of mental health-related hospitalization by approximately 4 percentage points for women, as well as reducing men's probability of mental health-related drug purchases by about 5 percentage points. In column (3), the estimates regarding men's hospitalization probability and women's drug purchases are likewise sizable, -2 percentage points and -6 percentage points, respectively, but lack of

Table 8: Effects of years of education on survival and mental health. OLS estimates and 2SLS estimates using two alternative instruments.

| | OLS | 2SLS (IV: Distance to university) | | 2SLS (IV: Gravity-based university access) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| A. Survival, age 55 | | | | | |
| Women | 0.0039*** | 0.0088 | -0.0197 | 0.0007 | -0.0130** |
| | (0.0002) | (0.0155) | (0.0232) | (0.0034) | (0.0052) |
| | | [0.8314] | [0.3083] | [0.1570] | [0.0020] |
| Men | 0.0090*** | 0.0086 | -0.0111 | 0.0280*** | 0.0100 |
| | (0.0003) | (0.0155) | (0.0201) | (0.0070) | (0.0066) |
| | | [0.7535] | [0.2746] | [0.0393] | [0.8845] |
| B. MH-related hospitalization, by age 55 | | | | | |
| Women | -0.0097*** | -0.0529* | -0.0380** | -0.0059 | -0.0057* |
| | (0.0002) | (0.0273) | (0.0194) | (0.0039) | (0.0030) |
| | | [0.0114] | [0.0523] | [0.5789] | [0.2057] |
| Men | -0.0146*** | -0.0314 | -0.0223 | -0.0274*** | -0.0221*** |
| | (0.0003) | (0.0223) | (0.0191) | (0.0068) | (0.0062) |
| | | [0.4378] | [0.6954] | [0.0553] | [0.2446] |
| C. MH-related drug purchase, by age 55 | | | | | |
| Women | -0.0046*** | -0.0699 | -0.0620* | -0.0348*** | -0.0432*** |
| | (0.0004) | (0.0449) | (0.0362) | (0.0099) | (0.0073) |
| | | [0.0657] | [0.0898] | [0.0002] | [0.0000] |
| Men | -0.0051*** | -0.0573*** | -0.0455*** | -0.0346*** | -0.0301*** |
| | (0.0005) | (0.0195) | (0.0162) | (0.0116) | (0.0087) |
| | | [0.0005] | [0.0047] | [0.0048] | [0.0065] |
| 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, parental education and income (at the individual's age of 15), and indicators for a missing mother/father. p-values for tests of endogeneity are reported in brackets ($H_0$: education is exogenous). Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

statistical power. The 2SLS estimates obtained using the alternative instrument (columns (4) and (5)) are again more precise and generally suggest similar effect sizes. However, in this case, the estimated effect on women's hospitalization probability is only -0.6 percentage points and not statistically significant at the 5 percent level.

Although the 2SLS estimates in Table 8 often exceed the OLS estimates, the differences between the 2SLS and OLS estimates are often not statistically significant, as indicated by the p-values for regression-based tests of endogeneity (Cameron and Trivedi, 2005, pp. 275–276). This is the case for most of the estimates concerning survival and mental health-related hospitalization. However, the 2SLS estimates for the effects of education on mental health-related drug purchases are mainly significantly more negative than the baseline OLS estimates.

The results in Table 9 further indicate substantial spillover effects from children's education on parental longevity. When examined at parental age 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 (0.9 percentage points) than for mothers (half a percentage point). However, this difference diminishes when examining parental survival at older ages: a year of a child's education is associated with a one-percentage-point increase in a mother's cumulative survival probability and a 1.1-percentage-point increase in a father's cumulative survival probability at age 80. The 2SLS estimates regarding mothers' survival are systematically larger than the baseline OLS estimates, and the reported p-values for tests of endogeneity suggest that these differences are mainly statistically significant. When using the distance-to-university instrument, the estimated local average treatment effect (LATE) of an additional year of education on mothers' cumulative survival probability is consistently around 4 percentage points. The results using the alternative instrument suggest that the effect on mothers' survival increases over time, from approximately 2 percentage points (survival at age 70) to over 4 percentage points (survival at age 80). In line with the reduced-form results discussed in subsection 5.2, the 2SLS estimates regarding the effect of children's education on a fathers' survival have negative signs but are not statistically significant. Table 9 also indicates no significant effect of children's education on parents' cumulative probability of mental health-related hospitalization. While the OLS estimates suggest a negative association, the 2SLS estimates are not statistically different from zero.

In the results above, the 2SLS estimates of the effects of education on individuals' mental health-related drug purchases and their mothers' survival are larger in magnitude than the corresponding OLS estimates. In these cases, the direction of the differences between the 2SLS and OLS estimates is not consistent with typical selection bias, which overstates the

Table 9: Effects of children's years of education on parental survival and mental health. OLS estimates and 2SLS estimates using two alternative instruments.

| | OLS | 2SLS (IV: Distance to university) | | 2SLS (IV: Gravity-based university access) | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| A. Parent's survival, age 70 | | | | | |
| Mothers | 0.0051*** | 0.0415*** | 0.0383*** | 0.0215*** | 0.0187*** |
| | (0.0003) | (0.0148) | (0.0132) | (0.0068) | (0.0063) |
| | | [0.0073] | [0.0070] | [0.0182] | [0.0207] |
| Fathers | 0.0092*** | -0.0216 | -0.0213 | -0.0160 | -0.0183 |
| | (0.0002) | (0.0284) | (0.0260) | (0.0178) | (0.0145) |
| | | [0.2154] | [0.2409] | [0.1257] | [0.0919] |
| B. Parent's survival, age 75 | | | | | |
| Mothers | 0.0078*** | 0.0430*** | 0.0389*** | 0.0398*** | 0.0346*** |
| | (0.0003) | (0.0140) | (0.0128) | (0.0050) | (0.0047) |
| | | [0.0256] | [0.0270] | [0.0000] | [0.0000] |
| Fathers | 0.0109*** | -0.0337 | -0.0330 | -0.0101 | -0.0128 |
| | (0.0002) | (0.0391) | (0.0364) | (0.0193) | (0.0161) |
| | | [0.1860] | [0.2101] | [0.2081] | [0.1742] |
| C. Parent's survival, age 80 | | | | | |
| Mothers | 0.0099*** | 0.0464** | 0.0412** | 0.0522*** | 0.0432*** |
| | (0.0004) | (0.0186) | (0.0161) | (0.0075) | (0.0064) |
| | | [0.1287] | [0.1007] | [0.0000] | [0.0000] |
| Fathers | 0.0111*** | -0.0287 | -0.0260 | -0.0155 | -0.0154 |
| | (0.0002) | (0.0352) | (0.0319) | (0.0214) | (0.0176) |
| | | [0.2067] | [0.2467] | [0.1666] | [0.1660] |
| D. Parent's MH-related hospitalization, by age 70 | | | | | |
| Mothers | -0.0021*** | 0.0145 | 0.0149 | -0.0053 | -0.0032 |
| | (0.0001) | (0.0134) | (0.0120) | (0.0098) | (0.0088) |
| | | [0.1208] | [0.1049] | [0.8206] | [0.9049] |
| Fathers | -0.0032*** | 0.0146 | 0.0153 | 0.0036 | 0.0059 |
| | (0.0001) | (0.0190) | (0.0181) | (0.0106) | (0.0091) |
| | | [0.2971] | [0.2829] | [0.4798] | [0.3411] |
| 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, parental education and income (at the individual's age of 15), and indicators for a missing mother/father. The parent-child observations are weighted by the inverse of the number of children per parent. p-values for tests of endogeneity are reported in brackets ($H_0$: education is exogenous). Standard errors in parentheses are clustered at the sub-region level (70 clusters). Statistical significance: * p<0.1, ** p<0.05, *** p<0.01.

health effects of education. A possible interpretation of these differences is that the average health benefits of education are higher for the families of the 'marginal' individuals—whose educational attainment would have been lower in the absence of the higher education expansion—than for the wider population. Alternatively, the large 2SLS estimates could reflect certain 'side effects' of the higher education expansion. In particular, the indicated positive effects of the expansion on the probability of living close to one's elderly parents are in contrast with the average negative association between education and this probability reported in Section 3. Therefore, the possible health benefits associated with lower intergenerational distances, discussed in subsection 2.3, could partly explain the stronger health effects implied by the 2SLS estimates.

# 6 Concluding remarks

Exploiting a natural experiment arising from the Finnish university expansion during the 1960s and 1970s, we have provided credible evidence on the health effects of access to higher education—an area not extensively studied in previous literature. We have obtained two sets of main findings. First, our results suggest that increased local access to higher education has positive cumulative effects on individuals' mental health outcomes by middle age while having largely insignificant effects on early mortality. These findings contribute to the ongoing debate on the causal relationship between education and health (Galama et al., 2018; Xue et al., 2021). Second, we find evidence that greater access to higher education positively affects mothers' longevity, while having no significant impact on fathers' longevity or parental mental health. These findings expand the currently limited evidence on the spillover effects of educational investments on family members' health (Lundborg and Majlesi, 2018; De Neve and Fink, 2018; Ma, 2019; Potente et al., 2023; Cornelissen and Dang, 2022).

Our analysis of alternative outcome variables reveals three key insights into the mechanisms underlying the observed positive health effects of access to higher education. First, consistent with earlier findings (Suhonen and Karhunen, 2019), improved local access to higher education is positively associated with years of education, suggesting that at least part of the observed health benefits may stem from education itself. However, since increased access is linked both to a higher probability of completing post-secondary education and to a lower probability of failing to complete any post-compulsory education, the health effects may arise from either or both of these educational margins. Second, our results suggest that improved local access to higher education increases the likelihood of individuals remaining geographically close to their aging parents, which may yield health benefits for both generations. Third, we find that access to higher education enhances later-life earnings, particularly among men, providing another plausible channel through which it positively affects family health.

We can further extend our conjecture regarding the potential underlying mechanisms based on the previous results of Suhonen and Karhunen (2019) concerning the intergenerational effects of the Finnish university expansion. Namely, their results suggested that greater access to university substantially increased both women's and men's chances of finding a highly educated partner. Therefore, while the direct monetary gains from greater access to university appear to be rather insignificant for women, indirect gains from a better-educated spouse could explain part of the positive mental health effects found for women. Moreover, Suhonen and Karhunen (2019) showed that both women's and men's improved access to higher education had positive spillover effects on the school performance and educational attainment of their offspring. This suggests that the positive mental health effects for women and men—and possibly even the positive survival effects for their mothers—could also be partly explained by positive spillover effects from the next generation.

Although our results suggest that a child's greater access to higher education involves many potential health benefits for both parents, we fail to find significant effects on fathers' survival. While it is unclear why the survival effects are positive for mothers but not for fathers, this pattern is consistent with the hypothesis that mothers represent a financially more vulnerable group and, therefore, are more likely to benefit from their children's higher education and income (Lundborg and Majlesi, 2018).

Reconciling our findings on the direct and indirect health effects of educational expansion with previous research offers important policy insights. First, based on comparing evidence from higher education-related natural experiments in advanced countries—including our study as well as Currie and Moretti (2003), Buckles et al. (2016), Kamhöfer et al.

(2019) Lacroix et al. (2021) González et al. (2024), Fletcher and Noghanibehambari (2024), and Cowan and Tefft (2025)—and evidence from compulsory schooling reforms (see Galama et al., 2018; Xue et al., 2021; Malamud et al., 2023), it appears that that expanding higher education is more likely to yield health benefits than extending compulsory schooling. Second, our findings, alongside prior research (Lundborg and Majlesi, 2018; De Neve and Fink, 2018; Ma, 2019; Cornelissen and Dang, 2022), indicate that the health benefits of educational policies extend beyond those directly affected, emphasizing the importance of considering spillover effects when evaluating such policies. Finally, our results, together with those of Lundborg and Majlesi (2018), suggest that offspring's educational access and attainment contribute to improved parental health in old age even in developed countries like Finland and Sweden, where extensive social security and elderly care services are available.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## Data availability

The data that support the findings of this study are available from Statistics Finland, the Finnish Institute for Health and Welfare, and the Social Insurance Institution of Finland. Restrictions apply to the availability of these data, which were used under license for this study. For information on accessing the data, see www.thl.fi, www.kela.fi, and www.stat.fi.

## Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to proofread the text. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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# Online Appendix

# The Long-Term Health Consequences of Expanding Access to Higher Education

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March 1, 2026

## Contents



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# Appendix A. Robustness of two-way fixed effects estimates

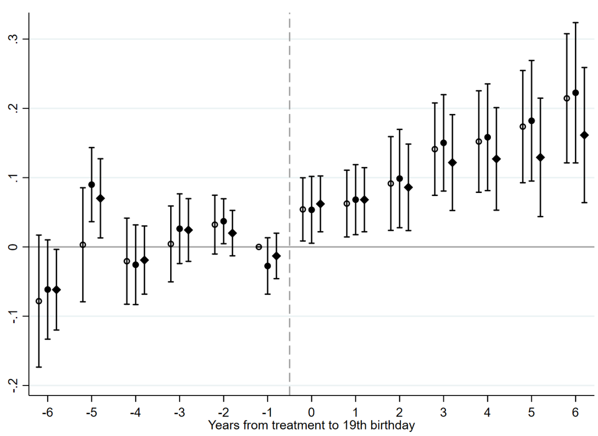
Following recent difference-in-differences literature (e.g., de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak et al., 2024), we assess the robustness of our two-way fixed effects (TWFE) event study results by comparing them to those obtained using the non-parametric approach of Callaway and Sant'Anna (2021). This approach estimates group-time average treatment effects based on the timing of treatment, which, in our case, corresponds to the year when the distance to university decreased in a particular municipality. Unlike the TWFE approach, the Callaway and Sant'Anna (CS) method does not use already-treated units as controls and is therefore robust to potential dynamic patterns in treatment effects. Additionally, the CS method avoids the arbitrary weighting of groups treated in different years, which is implicit in the TWFE approach. Here, we focus on the binary treatment indicator (a decrease in distance to university by 50 km or more), as the CS approach is not applicable to a continuous and non-strictly staggered treatment. In addition to estimates based on the unconditional parallel trends assumption, we use the doubly robust estimator to obtain estimates that condition on the individual's gender and first language, parental education and income, and indicators for a missing mother/father.

The CS estimates reported in Figures A1 and A2 are obtained by aggregating group-time average treatment effects, weighted according to the event study weights of Callaway and Sant'Anna (2021). The CS and TWFE event study results in Figure A2 are estimated without weighting the parent-child observations by the inverse number of children per parent, as implementing the user-written Stata command *csdid* with these weights proved problematic. According to the results, with very few exceptions, both the unconditional and conditional CS estimates closely align with the baseline TWFE estimates. This suggests that, although the TWFE estimates rely on already-treated municipality-cohort groups as controls, the relatively large number of never-treated municipalities in our sample likely enhances the robustness of the event study estimates.

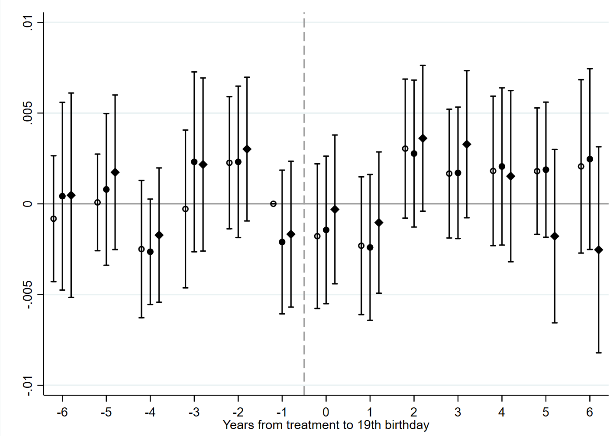
Notably, as shown in Tables A1 and A2, the CS estimates aggregated using difference-in-differences weights tend to be larger than the corresponding TWFE estimates. This pattern aligns with the negative weighting issue discussed in the literature (e.g., Borusyak et al., 2024). However, given the overlapping confidence intervals of the CS and TWFE estimates, the differences between the two sets of estimates are unlikely to be statistically significant in most cases.

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.

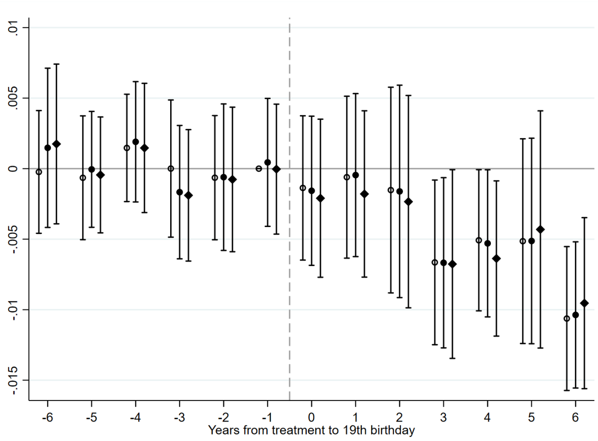
(a) Years of education, age 50



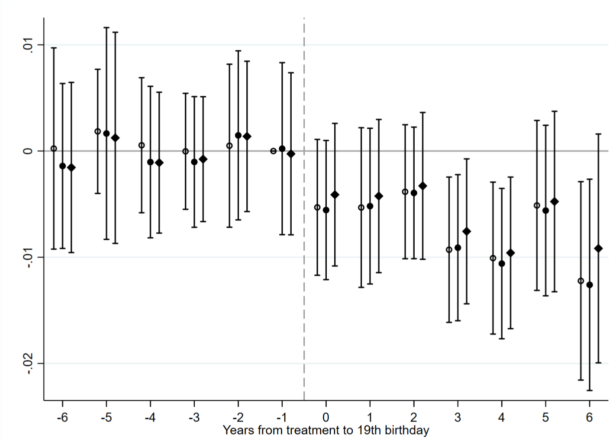

(b) Survival, age 55




(c) MH-related hospitalization, by age 55



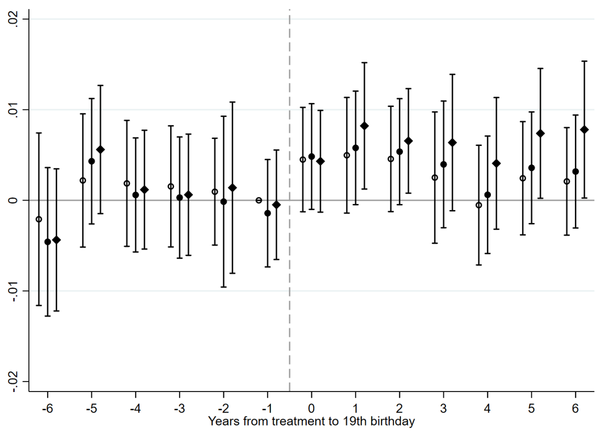

(d) MH-related drug purchase, by age 55



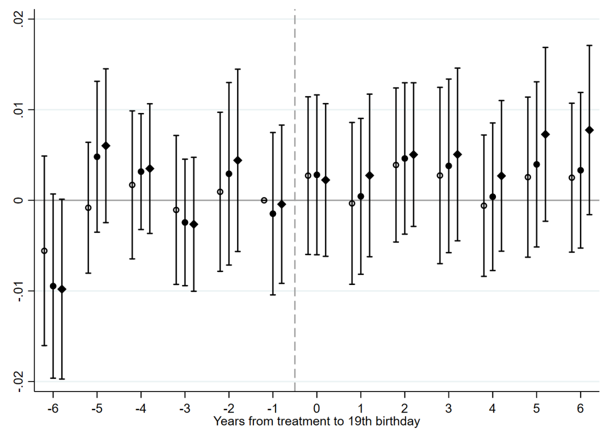

Notes: The estimates are for the effects of a binary treatment (distance to university at age 19 decreases by 50 km or more). The hollow circles mark the TWFE estimates obtained by regression models controlling for cohort and municipality. The solid circles and diamonds mark the unconditional and conditional 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 gender and first language, parental education and income (in the year of the individual's 15th birthday or closest year available), and indicators for a missing mother/father. The lead effects estimated by the CS approach are expressed relative to the previous period, whereas the effects at $r \in [0, 4]$ are expressed relative to period $r = -1$. The 95% 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.

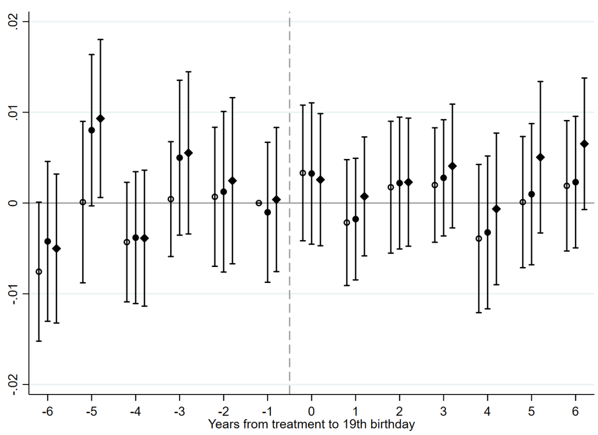
(a) Parent's survival, age 70



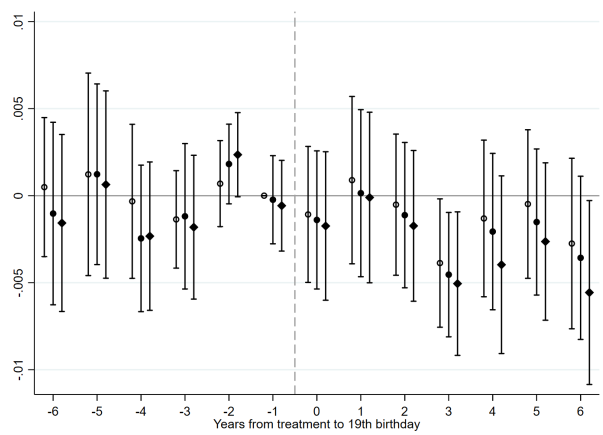

(b) Parent's survival, age 75




(c) Parent's survival, age 80




(d) Parent's MH-related hospitalization, by age 70




Notes: The estimates are for the effects of a binary treatment (distance to university at age 19 decreases by 50 km or more). 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 gender and first language, parental education and income (in the year of the individual's 15th birthday or closest year available), and indicators for a missing mother/father. The lead effects estimated by the CS approach are expressed relative to the previous period, whereas the effects at $r \in [0, 4]$ are expressed relative to period $r = -1$. The 95% confidence intervals were adjusted for sub-region-level clustering (70 clusters).

Table A1: Effects of a decrease in distance to university by 50 km or more on education, survival, and mental health (MH) using alternative estimation methods.

| | Two-way fixed effects | Callaway and Sant'Anna (2021) |
|---|---|---|
| | (1) | (2) |
| A. Years of education, age 50 | | |
| Women | 0.0970** | 0.1729*** |
| | (0.0417) | (0.0486) |
| Men | 0.1408*** | 0.2002*** |
| | (0.0367) | (0.0413) |
| B. Survival, age 55 | | |
| Women | 0.0011 | 0.0020 |
| | (0.0012) | (0.0018) |
| Men | 0.0011 | 0.0009 |
| | (0.0021) | (0.0025) |
| C. MH-related hospitalization, by age 55 | | |
| Women | -0.0041** | -0.0058** |
| | (0.0019) | (0.0023) |
| Men | -0.0065* | -0.0054 |
| | (0.0033) | (0.0036) |
| D. MH-related drug purchase, by age 55 | | |
| Women | -0.0067* | -0.0102*** |
| | (0.0036) | (0.0039) |
| Men | -0.0083*** | -0.0095** |
| | (0.0028) | (0.0042) |

Notes: The two-way fixed effects 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.

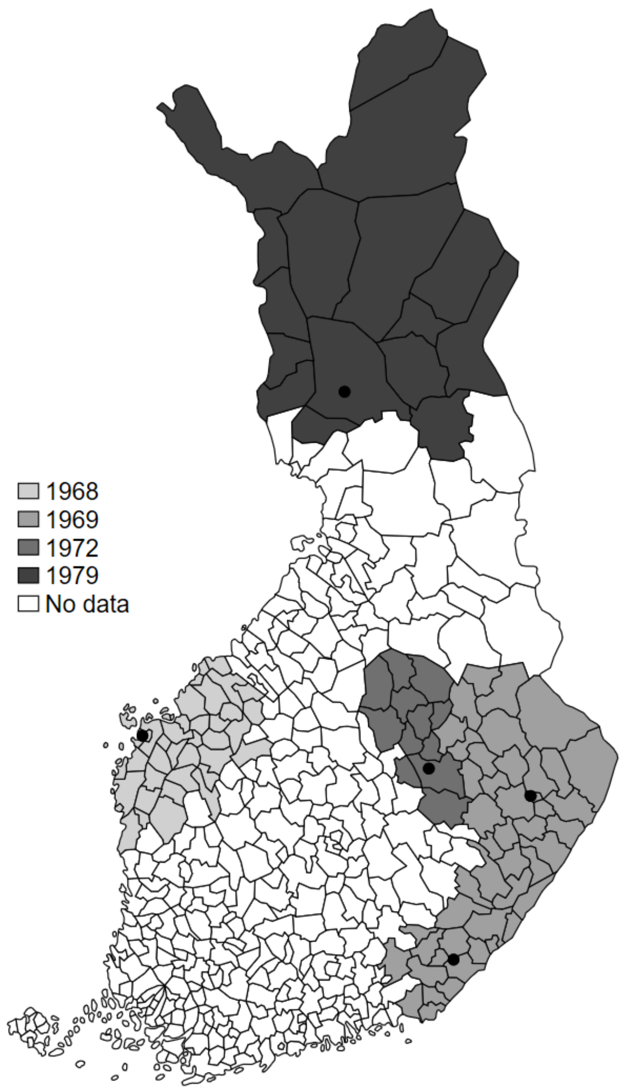
Table A2: Effects of a decrease in a child's distance to university by 50 km or more on parental survival and mental health (MH) using alternative estimation methods.

| | Two-way fixed effects | | Callaway and Sant'Anna (2021) |
|---|---|---|---|
| | (1) | (2) | (3) |
| A. Parent's survival, age 70 | | | |
| Mothers | 0.0073*** | 0.0047** | 0.0078** |
| | (0.0025) | (0.0019) | (0.0034) |
| Fathers | -0.0047 | -0.0055 | 0.0004 |
| | (0.0046) | (0.0037) | (0.0062) |
| B. Parent's survival, age 75 | | | |
| Mothers | 0.0083*** | 0.0052** | 0.0081* |
| | (0.0028) | (0.0026) | (0.0042) |
| Fathers | -0.0077 | -0.0075 | -0.0011 |
| | (0.0054) | (0.0049) | (0.0073) |
| C. Parent's survival, age 80 | | | |
| Mothers | 0.0078** | 0.0043 | 0.0050 |
| | (0.0034) | (0.0028) | (0.0039) |
| Fathers | -0.0069 | -0.0083* | -0.0009 |
| | (0.0046) | (0.0046) | (0.0064) |
| D. Parent's MH-related hospitalization, by age 70 | | | |
| Mothers | 0.0015 | 0.0000 | -0.0011 |
| | (0.0019) | (0.0020) | (0.0023) |
| Fathers | 0.0031 | 0.0017 | -0.0026 |
| | (0.0028) | (0.0024) | (0.0028) |
| Weighted by the inverse number of children per parent | Yes | No | No |

Notes: The two-way fixed effects 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.

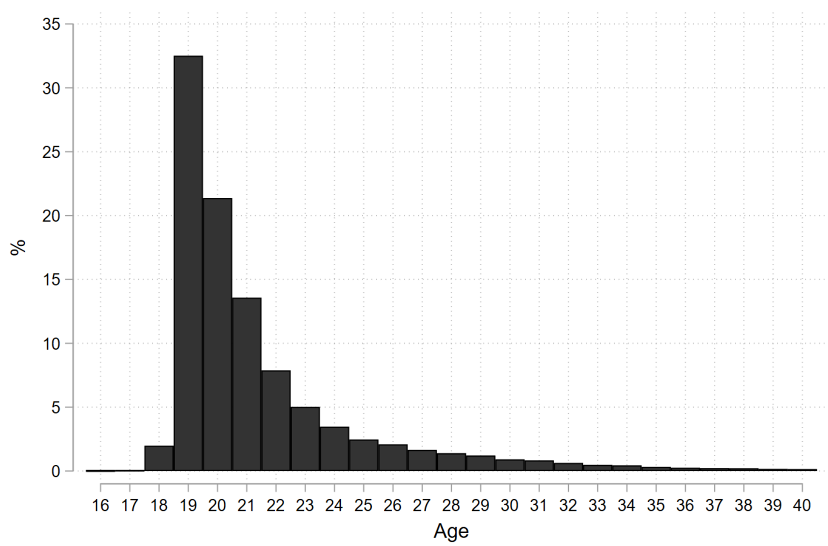
# Appendix B. Additional figures and tables

Figure B1: The locations of the universities opened between 1968 and 1979 (dots) and the municipalities most highly exposed to the university openings (distance to university decreased by 50 km or more).




Notes: The map uses the 2007 municipality classification, which includes 416 municipalities.

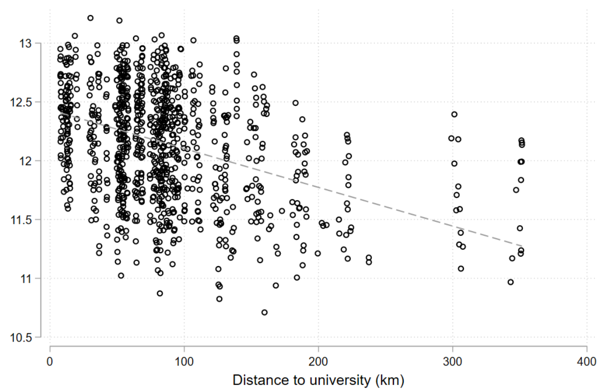
Figure B2: Age distribution of first-year university students in Finland between 1975 and 1980.



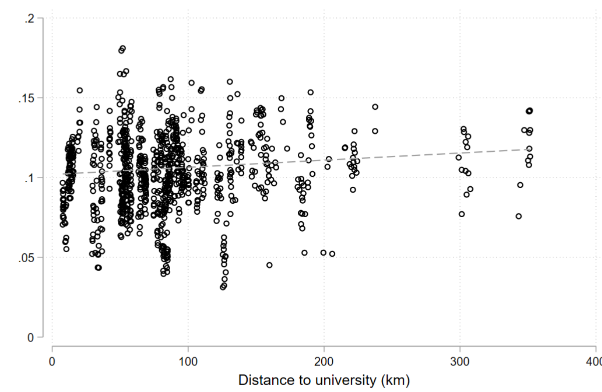

Source: Authors' own calculations based on Statistics Finland's register data on higher education students.

Figure B3: Association of access to university with education and mental health (MH).

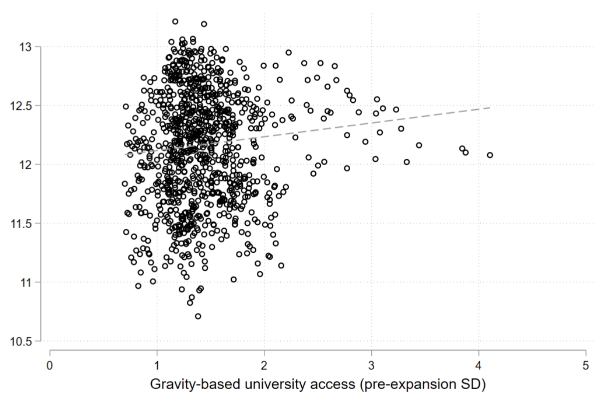
(a) Distance to university (age 19) and years of education (age 50)



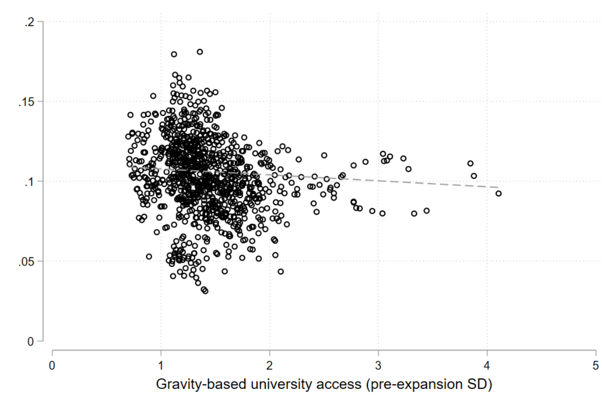

(b) Distance to university (age 19) and the cumulative probability of MH-related hospitalization (by age 55)




(c) Gravity-based university access (age 19) and years of education (age 50)



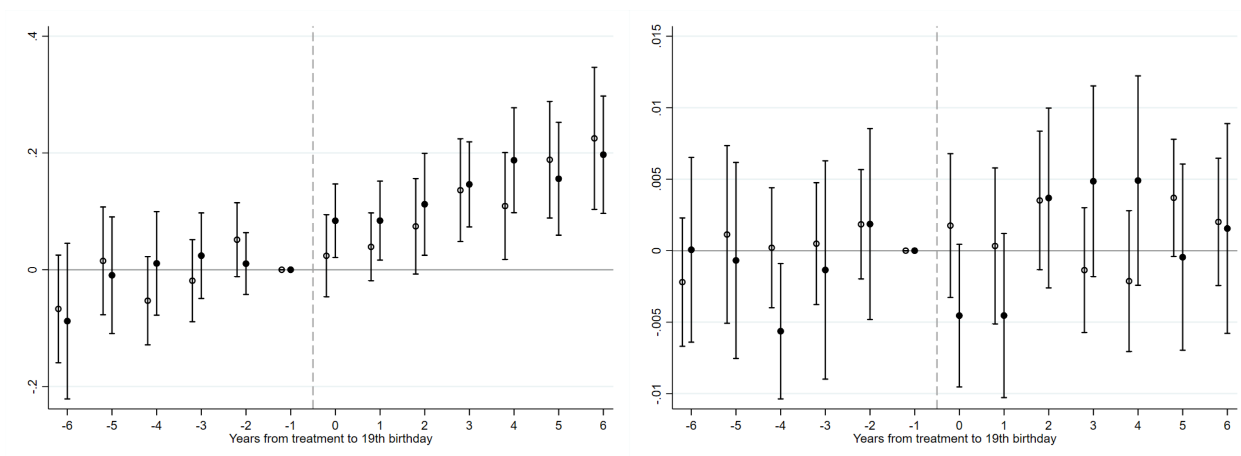

(d) Gravity-based university access (age 19) and the cumulative probability of MH-related hospitalization (by age 55)



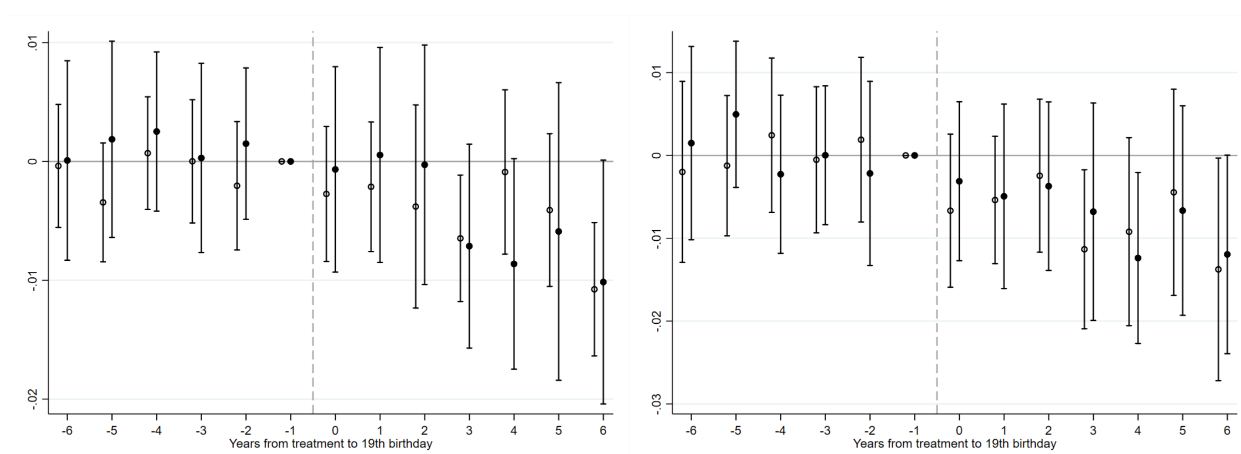

Notes: The hollow circles represent averages by cohort and sub-region of birth. The dashed lines represent fitted values from linear regressions weighted by the number of individuals in each group. SD = Standard deviation.

Figure B4: Event study results for women (hollow circles) and men (solid circles): Education, survival, and mental health (MH) for cohorts turning 19 before and after a decrease in distance to university by 50 km or more.

(a) Years of education, age 50 (b) Survival, age 55



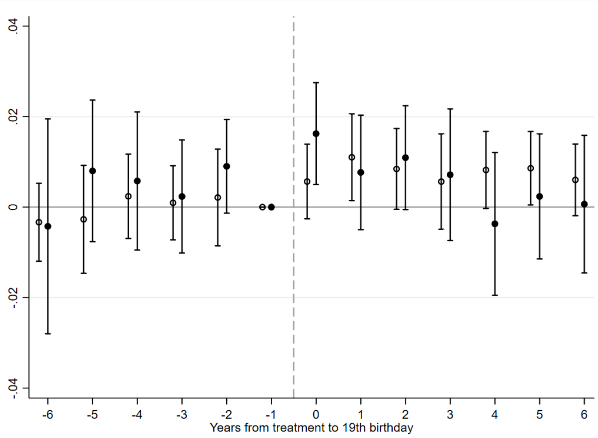

(c) MH-related hospitalization, by age 55 (d) MH-related drug purchase, by age 55



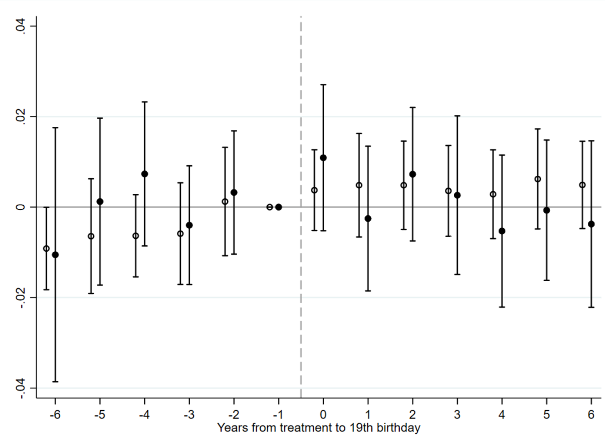

Notes: The estimates are from regression models controlling for cohort and municipality. The 95% confidence intervals are adjusted for sub-region-level clustering (70 clusters).

Figure B5: Event study results for mothers (hollow circles) and fathers (solid circles): Parent's survival and mental health (MH) for the parents of child cohorts turning 19 before and after a decrease in distance to university by 50 km or more.

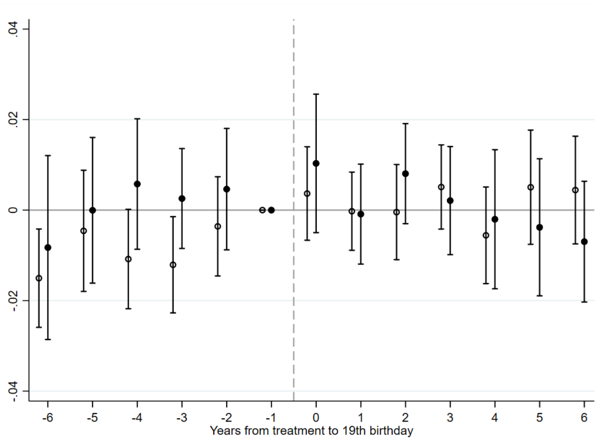
(a) Parent's survival, age 70



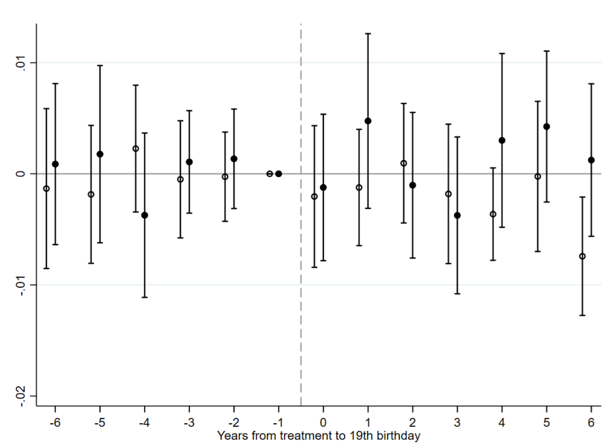

(b) Parent's survival, age 75




(c) Parent's survival, age 80



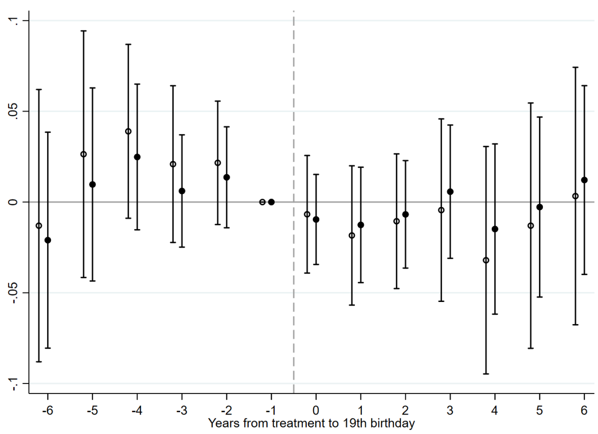

(d) Parent's MH-related hospitalization, by age 70



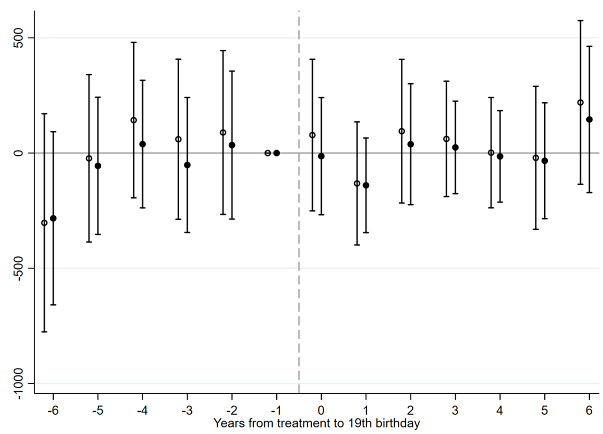

Notes: The estimates are from regression models controlling for child's cohort and municipality. The hollow circles are for the estimated effects of a binary treatment (distance to university at age 19 decreases by 50 km or more), and the solid circles are for the estimated effects of a continuous treatment (any decrease in distance to university at age 19). The 95% confidence intervals were adjusted for sub-region-level clustering (70 clusters).

Figure B6: Event study results: Parental education and income for cohorts turning 19 before and after a decrease in distance to university.

(a) Parental education



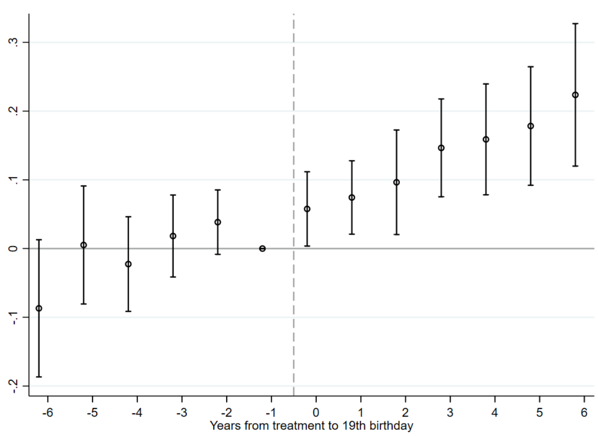

(b) Parental income



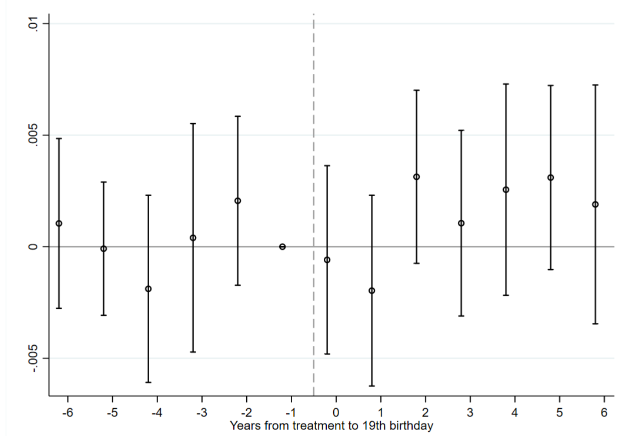

Notes: The parental outcomes are measured in the year of the individual's 15th birthday (or closest year available). Parental education is determined by taking the maximum of mother's and father's years of education, and parental income is the average of mother's and father's annual income. The estimates 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 decreases by 50 km or more), 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 95% confidence intervals are adjusted for sub-region-level clustering (70 clusters).

Figure B7: Robustness of the event study results: Individuals exposed to the 1972 university opening excluded from the estimation sample.

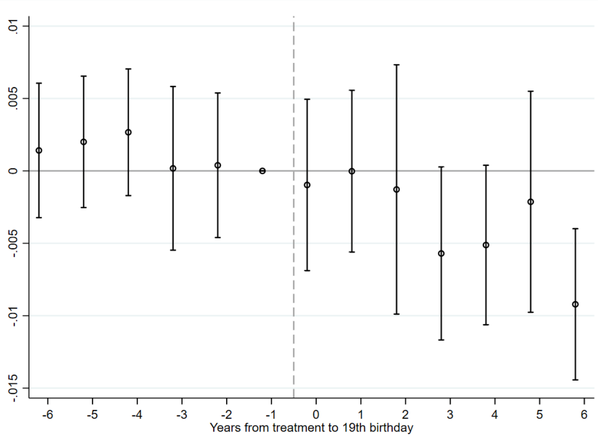
(a) Years of education, age 50



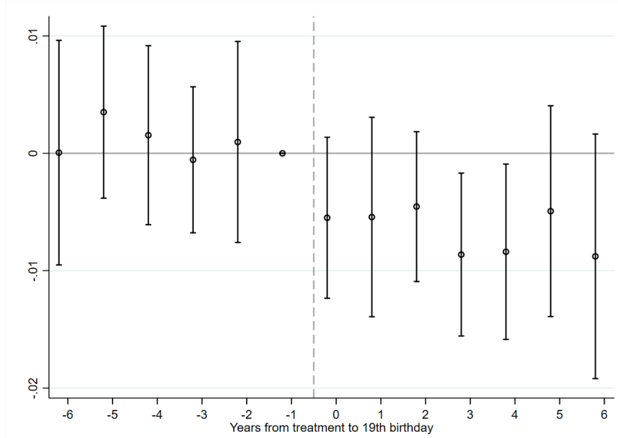

(b) Survival, age 55




(c) MH-related hospitalization, by age 55



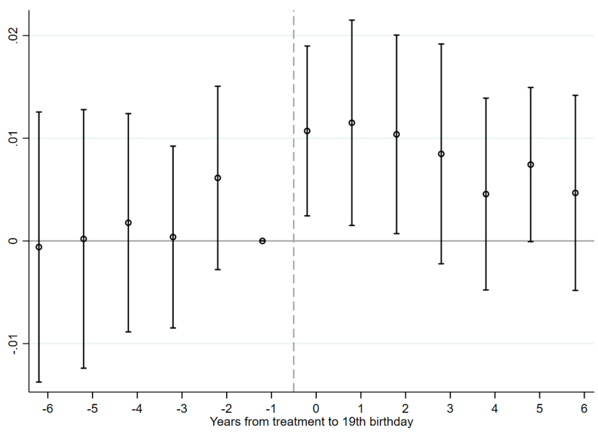

(d) MH-related drug purchase, by age 55



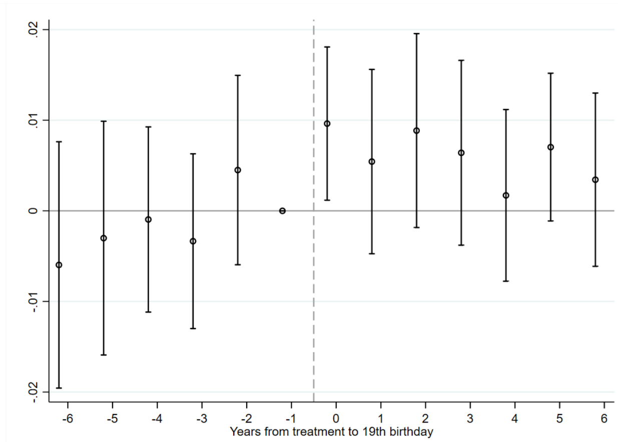

Notes: The estimates are from regression models controlling for cohort and municipality. The hollow circles are for the estimated effects of a binary treatment (distance to university at age 19 decreases by 50 km or more). The 95% confidence intervals are adjusted for sub-region-level clustering (70 clusters).

Figure B8: Robustness of the event study results: Individuals exposed to the 1972 university opening excluded from the estimation sample.

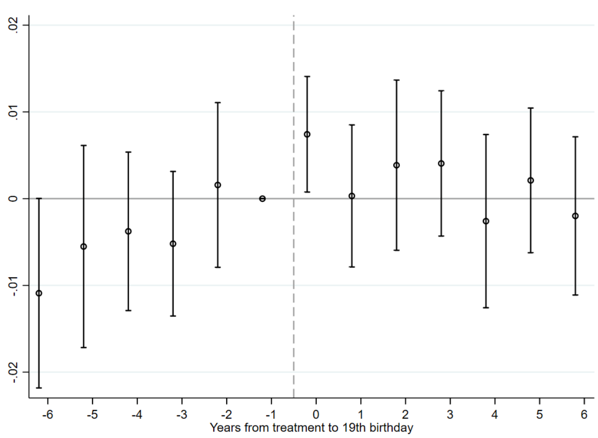
(a) Parent's survival, age 70



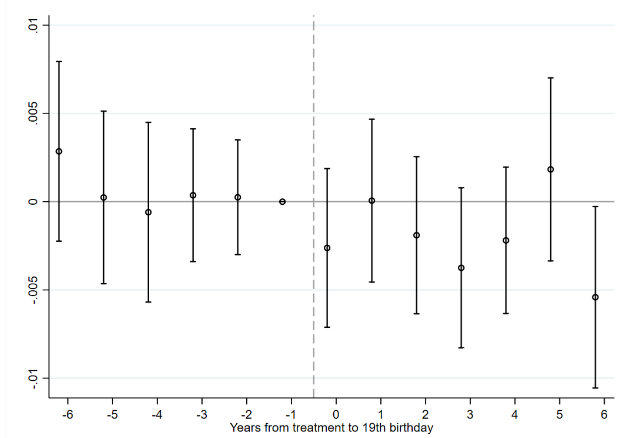

(b) Parent's survival, age 75




(c) Parent's survival, age 80



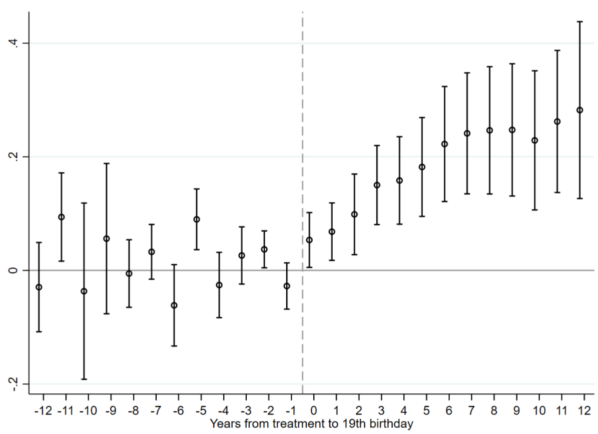

(d) Parent's MH-related hospitalization, by age 70



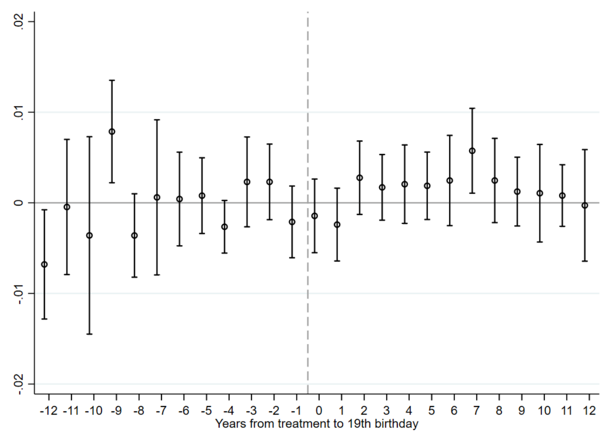

Notes: The estimates are from regression models controlling for child's cohort and municipality. The hollow circles are for the estimated effects of a binary treatment (distance to university at age 19 decreases by 50 km or more). The 95% confidence intervals were adjusted for sub-region-level clustering (70 clusters).

Figure B9: Event study results with long effect windows obtained by 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 by 50 kilometers or more.

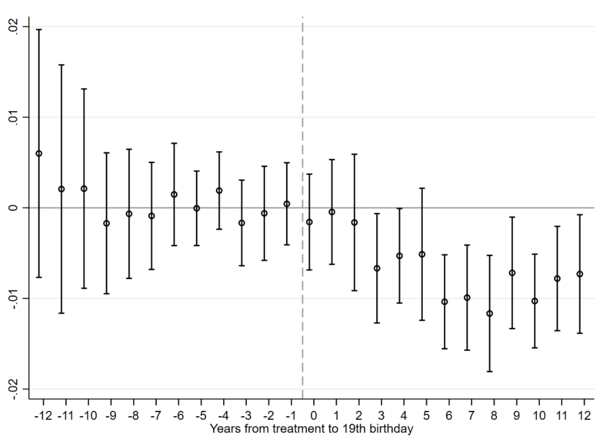
(a) Years of education, age 50



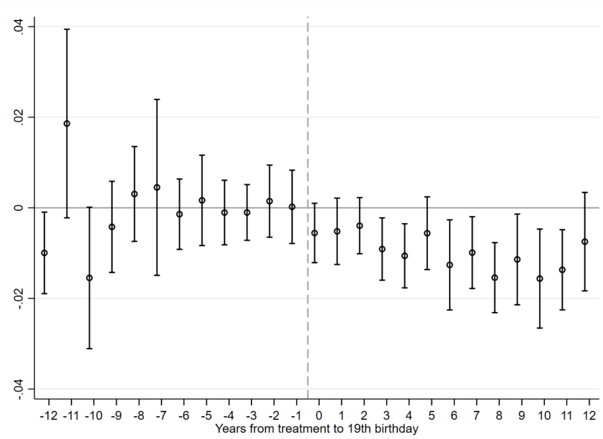

(b) Survival, age 55




(c) MH-related hospitalization, by age 55




(d) MH-related drug purchase, by age 55




Notes: The figure shows the unconditional estimates obtained by the approach of Callaway and Sant'Anna (2021). The lead effects are expressed relative to the previous period, whereas the effects at $r \in [0, 12]$ are expressed relative to period $r = -1$. The 95% confidence intervals were adjusted for sub-region-level clustering (70 clusters).

Table B1: Effects of an increase in access to university on individuals' outcomes using access measures based on parental municipality of residence (primarily) or municipality of birth (secondarily).

| | Decrease in distance to university (/100 km) | | Increase in gravity-based university access | |
|---|---|---|---|---|
| | Women | Men | Women | Men |
| | (1) | (2) | (3) | (4) |
| Survival, age 55 | 0.0011 | 0.0005 | 0.0013 | 0.0136*** |
| | (0.0012) | (0.0022) | (0.0009) | (0.0045) |
| MH-related hospitalization, by age 55 | -0.0037*** | -0.0040 | -0.0018 | -0.0127*** |
| | (0.0011) | (0.0027) | (0.0016) | (0.0029) |
| MH-related drug purchase, by age 55 | -0.0044 | -0.0058*** | -0.0116*** | -0.0157*** |
| | (0.0029) | (0.0020) | (0.0041) | (0.0043) |
| Years of education, age 50 | 0.0968** | 0.1304*** | 0.4659*** | 0.4937*** |
| | (0.0401) | (0.0357) | (0.0266) | (0.0331) |
| Primary education | -0.0145* | -0.0262*** | -0.0877*** | -0.1028*** |
| | (0.0082) | (0.0078) | (0.0063) | (0.0060) |
| Secondary education | -0.0022 | 0.0123** | 0.0128 | 0.0550*** |
| | (0.0051) | (0.0054) | (0.0091) | (0.0045) |
| Lower tertiary education | 0.0160*** | 0.0116*** | 0.0741*** | 0.0405*** |
| | (0.0055) | (0.0035) | (0.0040) | (0.0043) |
| Higher tertiary education | 0.0008 | 0.0023 | 0.0008 | 0.0073*** |
| | (0.0020) | (0.0017) | (0.0044) | (0.0019) |
| Income, age 50 | -198.30 | 1655.82*** | -468.75 | 139.06 |
| | (178.10) | (565.11) | (325.44) | (1820.37) |
| Income, age 55 | 108.14 | 1095.32** | 761.14** | 3479.26*** |
| | (265.61) | (476.91) | (371.27) | (1157.51) |
| Number of individuals | 491 601 | 529 144 | 491 601 | 529 144 |

Notes: Parental municipality is determined at the individual's age of 18. 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 an increase in a child's access to university on parental outcomes using access measures based on parental municipality of residence (primarily) or municipality of birth (secondarily).

| | Decrease in distance to university (/100 km) | | Increase in gravity-based university access | |
|---|---|---|---|---|
| | Mothers (1) | Fathers (2) | Mothers (3) | Fathers (4) |
| Parent's survival, age 70 | 0.0047*** | -0.0043 | 0.0116*** | -0.0064 |
| | (0.0017) | (0.0037) | (0.0027) | (0.0097) |
| Parent's survival, age 75 | 0.0043* | -0.0050 | 0.0189*** | -0.0039 |
| | (0.0023) | (0.0043) | (0.0032) | (0.0104) |
| Parent's survival, age 80 | 0.0044** | -0.0049 | 0.0218*** | -0.0033 |
| | (0.0021) | (0.0041) | (0.0030) | (0.0118) |
| Parent's MH-related hospitalization, | 0.0017 | 0.0013 | 0.0019 | 0.0016 |
| by age 70 | (0.0017) | (0.0022) | (0.0017) | (0.0022) |
| Parent's years of education | 0.0083 | -0.0110 | -0.0201 | 0.0444 |
| (latest observed) | (0.0120) | (0.0147) | (0.0271) | (0.0744) |
| Parent's income, age 55 | -17.10 | -61.25 | 285.75*** | 804.16 |
| | (69.04) | (139.19) | (83.55) | (579.38) |
| Parent's income, age 60 | -81.67 | 29.42 | -25.05 | 891.95* |
| | (84.28) | (162.37) | (124.67) | (470.48) |
| Parent's income, age 65 | -39.54 | -160.66 | -238.30 | -317.00 |
| | (75.85) | (122.50) | (205.85) | (286.75) |
| Number of parent-child pairs | 991 342 | 925 358 | 991 342 | 925 358 |

Notes: Parental municipality is determined at the individual's age of 18. 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: Effects of an increase in gravity-based university access using alternative distance-decay parameter ($\alpha$) values.

| | Women/mothers | | | Men/fathers | | |
|---|---|---|---|---|---|---|
| | $\alpha = 0.25$ | $\alpha = 0.75$ | $\alpha = 1.00$ | $\alpha = 0.25$ | $\alpha = 0.75$ | $\alpha = 1.00$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| A. Individuals' outcomes | | | | | | |
| Survival, age 55 | 0.0002 | 0.0004 | 0.0005 | 0.0105*** | 0.0101** | 0.0085* |
| | (0.0014) | (0.0012) | (0.0011) | (0.0026) | (0.0041) | (0.0050) |
| MH-related hospitalization, by age 55 | -0.0015 | -0.0025 | -0.0022 | -0.0112*** | -0.0093*** | -0.0074** |
| | (0.0014) | (0.0016) | (0.0017) | (0.0028) | (0.0027) | (0.0033) |
| MH-related drug purchase, by age 55 | -0.0124*** | -0.0127** | -0.0110* | -0.0145*** | -0.0118*** | -0.0093*** |
| | (0.0035) | (0.0048) | (0.0056) | (0.0049) | (0.0036) | (0.0034) |
| Years of education, age 50 | 0.3491*** | 0.3732*** | 0.3304*** | 0.3652*** | 0.3827*** | 0.3351*** |
| | (0.0276) | (0.0231) | (0.0468) | (0.0254) | (0.0513) | (0.0821) |
| B. Parental outcomes | | | | | | |
| Parent's survival, age 70 | 0.0090*** | 0.0090*** | 0.0077** | -0.0063 | -0.0087 | -0.009 |
| | (0.0029) | (0.0031) | (0.0034) | (0.0075) | (0.0088) | (0.0083) |
| Parent's survival, age 75 | 0.0167*** | 0.0170*** | 0.0147*** | -0.0037 | -0.0061 | -0.0068 |
| | (0.0021) | (0.0030) | (0.0042) | (0.0082) | (0.0096) | (0.0091) |
| Parent's survival, age 80 | 0.0192*** | 0.0203*** | 0.0182*** | -0.0062 | -0.0075 | -0.0074 |
| | (0.0026) | (0.0041) | (0.0055) | (0.0090) | (0.0095) | (0.0086) |
| Parent's MH-related hospitalization, by age 70 | -0.0014 | -0.0026 | -0.0023 | 0.0019 | 0.0019 | 0.0023 |
| | (0.0046) | (0.0042) | (0.0040) | (0.0051) | (0.0046) | (0.0040) |

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 B4: Effect of increase in access to university on the cumulative probability of mental health-related drug purchase at ages 47–55.

| | MH-related drug purchase, ages 47–55 | | | |
|---|---|---|---|---|
| | Women | | Men | |
| | (1) | (2) | (3) | (4) |
| Decrease in distance to university (/100 km) | -0.0050 | -0.0056* | -0.0078*** | -0.0078*** |
| | (0.0033) | (0.0033) | (0.0017) | (0.0017) |
| Increase in gravity-based university access | -0.0036 | -0.0099*** | -0.0090 | -0.0110 |
| | (0.0044) | (0.0037) | (0.0074) | (0.0073) |
| Additional covariates | 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, parental education and income (at the individual's age of 15), and indicators for a missing mother/father. 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 B5: Effects of an increase in access to university on survival and mental health. Statistical significance of estimates while accounting for multiple hypothesis testing.

| Outcome | University access measure | Group | Add. covariates | Estimate | Naive p-value | BKY q-value[a] | Šidák-Holm p-value[b] |
|---|---|---|---|---|---|---|---|
| Survival, age 55 | Distance-based | Women | No | 0.0006 | 0.558 | 0.261 | 0.962 |
| | Distance-based | Women | Yes | -0.0017 | 0.388 | 0.212 | 0.914 |
| | Distance-based | Men | No | 0.0010 | 0.601 | 0.265 | 0.962 |
| | Distance-based | Men | Yes | -0.0015 | 0.560 | 0.261 | 0.962 |
| | Gravity-based | Women | No | 0.0003 | 0.838 | 0.297 | 0.962 |
| | Gravity-based | Women | Yes | -0.0059** | 0.014 | 0.017 | 0.168 |
| | Gravity-based | Men | No | 0.0110*** | 0.000 | 0.003 | 0.007 |
| | Gravity-based | Men | Yes | 0.0051 | 0.138 | 0.116 | 0.736 |
| MH-related hospitalization, by age 55 | Distance-based | Women | No | -0.0036*** | 0.003 | 0.007 | 0.050 |
| | Distance-based | Women | Yes | -0.0032** | 0.011 | 0.015 | 0.149 |
| | Distance-based | Men | No | -0.0036 | 0.172 | 0.130 | 0.736 |
| | Distance-based | Men | Yes | -0.0031 | 0.281 | 0.154 | 0.862 |
| | Gravity-based | Women | No | -0.0022 | 0.151 | 0.120 | 0.736 |
| | Gravity-based | Women | Yes | -0.0026* | 0.071 | 0.067 | 0.586 |
| | Gravity-based | Men | No | -0.0107*** | 0.000 | 0.002 | 0.003 |
| | Gravity-based | Men | Yes | -0.0113*** | 0.001 | 0.003 | 0.014 |
| MH-related drug purchase, by age 55 | Distance-based | Women | No | -0.0048* | 0.082 | 0.070 | 0.586 |
| | Distance-based | Women | Yes | -0.0053* | 0.073 | 0.067 | 0.586 |
| | Distance-based | Men | No | -0.0066*** | 0.001 | 0.003 | 0.011 |
| | Distance-based | Men | Yes | -0.0063*** | 0.002 | 0.005 | 0.035 |
| | Gravity-based | Women | No | -0.0131*** | 0.001 | 0.003 | 0.017 |
| | Gravity-based | Women | Yes | -0.0198*** | 0.000 | 0.001 | 0.000 |
| | Gravity-based | Men | No | -0.0135*** | 0.004 | 0.007 | 0.052 |
| | Gravity-based | Men | Yes | -0.0154*** | 0.001 | 0.003 | 0.014 |

Notes: The estimates are from Table 3. Statistical significance: * p<0.1, ** p<0.05, *** p<0.01. [a] Sharpened q-values obtained by a two-stage method which controls the false discovery rate (Benjamini et al., 2006). [b] Adjusted p-values obtained by a step-down correction controlling the family-wise error rate.

Table B6: Effects of an increase in a child's access to university on parental survival and mental health. Statistical significance of estimates while accounting for multiple hypothesis testing.

| Parent's outcome | University access measure | Group | Add. covariates | Estimate | Naive p-value | BKY q-value[a] | Šidák-Holm p-value[b] |
|---|---|---|---|---|---|---|---|
| Survival, age 70 | Distance-based | Mothers | No | 0.0052*** | 0.002 | 0.010 | 0.060 |
| | Distance-based | Mothers | Yes | 0.0051*** | 0.003 | 0.011 | 0.075 |
| | Distance-based | Fathers | No | -0.0027 | 0.434 | 0.524 | 0.999 |
| | Distance-based | Fathers | Yes | -0.0027 | 0.408 | 0.524 | 0.999 |
| | Gravity-based | Mothers | No | 0.0095*** | 0.001 | 0.005 | 0.021 |
| | Gravity-based | Mothers | Yes | 0.0089*** | 0.002 | 0.010 | 0.053 |
| | Gravity-based | Fathers | No | -0.0074 | 0.387 | 0.524 | 0.999 |
| | Gravity-based | Fathers | Yes | -0.0086 | 0.244 | 0.484 | 0.994 |
| Survival, age 75 | Distance-based | Mothers | No | 0.0054*** | 0.008 | 0.022 | 0.173 |
| | Distance-based | Mothers | Yes | 0.0052** | 0.012 | 0.029 | 0.235 |
| | Distance-based | Fathers | No | -0.0042 | 0.364 | 0.524 | 0.999 |
| | Distance-based | Fathers | Yes | -0.0042 | 0.346 | 0.524 | 0.999 |
| | Gravity-based | Mothers | No | 0.0177*** | 0.000 | 0.001 | 0.000 |
| | Gravity-based | Mothers | Yes | 0.0164*** | 0.000 | 0.001 | 0.000 |
| | Gravity-based | Fathers | No | -0.0047 | 0.608 | 0.645 | 0.999 |
| | Gravity-based | Fathers | Yes | -0.0061 | 0.447 | 0.524 | 0.999 |
| Survival, age 80 | Distance-based | Mothers | No | 0.0055* | 0.052 | 0.105 | 0.673 |
| | Distance-based | Mothers | Yes | 0.0053** | 0.049 | 0.105 | 0.670 |
| | Distance-based | Fathers | No | -0.0034 | 0.408 | 0.524 | 0.999 |
| | Distance-based | Fathers | Yes | -0.0033 | 0.413 | 0.524 | 0.999 |
| | Gravity-based | Mothers | No | 0.0206*** | 0.000 | 0.001 | 0.000 |
| | Gravity-based | Mothers | Yes | 0.0199*** | 0.000 | 0.001 | 0.000 |
| | Gravity-based | Fathers | No | -0.0067 | 0.483 | 0.558 | 0.999 |
| | Gravity-based | Fathers | Yes | -0.0071 | 0.407 | 0.524 | 0.999 |
| MH-related hospitalization, by age 70 | Distance-based | Mothers | No | 0.0018 | 0.212 | 0.435 | 0.989 |
| | Distance-based | Mothers | Yes | 0.0020 | 0.159 | 0.325 | 0.969 |
| | Distance-based | Fathers | No | 0.0018 | 0.417 | 0.524 | 0.999 |
| | Distance-based | Fathers | Yes | 0.0020 | 0.377 | 0.524 | 0.999 |
| | Gravity-based | Mothers | No | -0.0024 | 0.587 | 0.645 | 0.999 |
| | Gravity-based | Mothers | Yes | -0.0015 | 0.718 | 0.784 | 0.999 |
| | Gravity-based | Fathers | No | 0.0017 | 0.740 | 0.784 | 0.999 |
| | Gravity-based | Fathers | Yes | 0.0028 | 0.532 | 0.614 | 0.999 |

Notes: The estimates are from Table 4. Statistical significance: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. [a] Sharpened q-values obtained by a two-stage method which controls the false discovery rate (Benjamini et al., 2006). [b] Adjusted p-values obtained by a step-down correction controlling the family-wise error rate.

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