The Roots of Health Inequality and The Value of Intra-Family Expertise*

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Abstract

Mounting evidence points to a stark correlation between income and health, yet the causal mechanisms behind this gradient are poorly understood. This paper examines the impact of information on health, and whether differential access to information contributes to the health-income gradient. Our empirical setting, Sweden, allows us to shut down inequality in formal access to health care, and to leverage administrative population-wide tax data linked to birth and medical records. We first document that a strong health-SES gradient persists in this environment; the gradient emerges early in life and steepens with age. We then study the effect of information on health over the life cycle, using the presence of a health professional in the family as a broad measure of exposure to information about health. Intuitively, such exposure may capture intra-family transfers of knowledge, as well as persistent "nagging" about health investments or behaviors. For identification, we exploit "admissions lotteries" into medical schools and variation in the timing of a medical degree. We find that having a health professional in the family prolongs older generations' life span, reduces their likelihood of suffering from common lifestyle-related conditions, and improves their preventive investments; we document similar improvements in health and health capital investments in adolescence, early childhood, and in-utero. Further, we show that information affects individuals throughout the income distribution and that asymmetric exposure to information about health can account for as much as 20% of the health-SES gradient. The interaction between poverty and exposure to information that determines individual investments into their own health can thus play a significant role in generating and perpetuating health inequality - even in environments that nearly eradicate systemic differences in access to healthcare, provide generous social insurance, and have extensive social safety net programs.

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1 Introduction

Poorer people have worse health at birth, are sicker in adulthood, and die younger than richer people. Indeed, mounting evidence across various disciplines reveals stark correlations between health capital throughout the course of life and a range of measures of socioeconomic status (SES), such as education, social class, and income (see, e.g., Marmot et al., 1991; Case et al., 2002; Deaton, 2002; Currie, 2009; Lleras-Muney, 2018).

Establishing why socioeconomic status and health are strongly correlated has proven to be hard, however. The proposed channels can be classified into four broad themes. First, early-life health disparities, which may arise due to differential conditions *in utero* or differential genetic capital, may directly perpetuate economic inequality throughout the life cycle, as individuals in poor health at birth are likely to accumulate lower earnings and wealth throughout life (Currie, 2011; Aizer and Currie, 2014; Persson and Rossin-Slater, 2018).[1] Second, individuals with lower incomes on average tend to invest less in their health, having a worse diet, a higher likelihood of smoking, higher rates of obesity, lower rates of physical activity, less utilization of preventive healthcare, and lower adherence to medication.[2] The third hypothesis is environmental (broadly understood) – individuals on the lower rungs of the income ladder tend to have jobs that involve more manual labor, experience more stress, and live in more polluted areas.[3] Finally, health disparities across the income distribution could be driven by differential treatment conditional on disease, due to differences in formal insurance coverage, the quality of available medical care, or individuals' ability to navigate the health care system.[4] While differential access to insurance across the income distribution is the focus of much of the current policy discussion, the relative contributions of these channels to the gradient between health and socio-economic status remain unknown.

In this paper, we investigate one factor that may be driving differential health investments and behaviors across the income distribution: the role of information. In particular, we examine the impact of information on health over the life cycle, and whether differential access to information contributes to the health-income gradient. As in the work that has measured the importance of information and norms transmitted within families about welfare or innovation cultures (Bertrand et al., 2000; Dahl et al., 2014; Bell et al., 2017), we use the presence of a health professional within the family as a broad measure of exposure to information about health. Intuitively, such exposure may capture intra-family transfers of knowledge (pure "information"), as well as persistent nudging or reminders about health investments (raising the "salience" of beneficial behaviors).

[1] For more evidence on the causal relationship between early-life health and future economic outcomes, see, e.g., Black et al. (2007); Oreopoulos et al. (2008); Bharadwaj et al. (2018). Almond and Mazumder (2011) document a causal link between low birthweight and disability in adulthood. In the context of Sweden, Bharadwaj et al. (2017) provide causal estimates of own birthweight on a range of own outcomes, including mortality.

[2] See, e.g., Rehm et al. (2016) on dietary intake, Hiscock et al. (2012) on smoking, and Ogden et al. (2010) on obesity. The formation of these health behaviors is poorly understood (Hut and Oster, 2018 provides the most recent example), and recent evidence emphasizes differences in education (e.g. Allcott et al., 2017), peer imitation (e.g. Fowler and Christakis, 2008, Rosenquist et al., 2010a, Rosenquist et al., 2010b, Salvy et al., 2012) or costs (e.g. Walker et al., 2010, Allcott et al., 2017 and the broader literature on food deserts; Meckel, 2017 on a food program for mothers).

[3] See, e.g., Clougherty et al. (2010) on types of employment, Kunz-Ebrecht et al. (2004) on stress, and Isen et al. (2017) on pollution exposure. Also see Finkelstein et al. (2018) and Bjorkegren (2018) for estimates of the causal effect of location on elderly mortality and youth health, respectively.

[4] Differential access to formal insurance has traditionally been one of the impediments to studying the health-inequality gradient in the United States, as insurance coverage varies significantly across income and within income across stages of life. Differences in health by income have thus traditionally been partially attributed to differential access to care resulting from differential coverage. While Americans at the upper end of the income distribution are likely to be covered by employer-sponsored health insurance from birth until they turn 65, coverage is more sporadic in the lower quartiles of the income distribution and may involve moving in and out of insurance coverage throughout the lifecycle.

Our point of departure is the observation that differential exposure to information about health across the income distribution can generate and perpetuate the health-SES gradient. Individuals are exposed to many sources of information about health and health behaviors: family members, friends, peers at school and at work, health care providers, and public health information campaigns. Each individual is exposed to a unique stream of such information, of varying quality and frequency, throughout life, which shapes her beliefs about the costs and benefits of personal investments into health. If individuals at the lower rungs of the income distribution receive lower quality or less frequent information *and* this leads to sub-optimal investments into their health, then such differences in information can sustain the health-SES gradient – even in environments that fully eradicate differences in formal access to healthcare. Our broad goal is to shed light on, first, whether the provision of information improves health outcomes; and second, to quantify the importance of this channel in sustaining health inequality.

Investigating the causal impact of information on health and the importance of this channel in perpetuating health inequality requires addressing three key challenges. First, as emphasized by Currie (2011), analyses of health inequality, while ubiquitous, suffer from a lack of comprehensive data on health outcomes, which often stem from self-reported health rather than medical records, coupled with a lack of detailed measures of socioeconomic status. While Chetty et al. (2016) overcome this by linking mortality data to tax records, an analysis of health outcomes other than mortality requires data linking individual medical records to detailed measures of income. Second, measuring the quality and quantity of information about health that is available to an individual is inherently challenging. The third challenge relates to selection. Individuals receive streams of information relevant to their health from many sources throughout their lifetime, and this exposure is not randomly assigned. Thus, it is difficult to separate the impacts of information from the possible influences of other unobservable differences between informed and uninformed individuals.

The contribution of this paper is to address these challenges by bringing novel data to the documentation of the health-income gradient, and by constructing a new measure of information about health for which we can leverage quasi-random variation in assignment - individuals' exposure to a health professional in their family.

We address the first challenge by leveraging Swedish administrative population-wide tax records linked to inpatient, outpatient, prescription drug, and birth records. Beyond the availability of data, Sweden is a particularly attractive empirical context because its universal health insurance system allows us to examine health inequality in the absence of differences in formal access to health care. The opposite side of the coin, of course, is that the very presence of universal health insurance, coupled with Sweden's generous social safety net, may eradicate socioeconomic differences in health, rendering it a bad candidate for analyses of health inequality. Despite equalized formal access to insurance, however, three robust stylized facts on health inequality emerge in our data.

First, there is a strong socioeconomic gradient in mortality. Among men at the lowest demi-decile of the income distribution at age 55 (i.e., individuals at the five lowest income percentiles), 71 percent are no longer alive by age 80; among men at the highest demi-decile, the corresponding figure is 29 percent. In fact, we find that despite Sweden's universal health insurance and developed social safety net, the gradient in log-mortality

at age 75 conditional on pre-retirement income rank is *identical* to that in the United States.[5] Second, there are similarly steep gradients in several of the most important health ailments in the adult population that are commonly linked to "lifestyle" causes – heart attacks, heart failure, stroke, lung cancer, and type 2 diabetes – and a *reverse* gradient in preventive health care measures such as Human Papilloma Virus (HPV) vaccination by age 20 (the only non-mandatory vaccine during our sample period). Third, health disparities emerge early in life and tend to grow throughout childhood and adolescence. Already at birth, children born into disadvantage have less health capital and are more likely to have experienced maternal smoking in utero. Before teenage years, they have had more inpatient admissions and display a higher prevalence of asthma and ADHD – the two largest diagnoses groups among children.[6]

To address the two remaining challenges – the difficulty of measuring information about health and the non-random allocation of health-related information – we zoom in into an environment where we can precisely measure individuals' exposure to a certain type of information, and where the institutional environment provides several sources of variation for causal identification. The measure of information we exploit is the presence of a health professional in a family. We hypothesize that close relatives of a health professional may be exposed to information as well as persistent "nagging" about health, healthy behaviors, and prevention.[7] This, in turn, may alter individuals' investments into their own health. If health investments are important for health outcomes, then we may observe better health, and possibly lower mortality, among individuals with access to such intra-family information.

Indeed, we show that conditional on individual income rank at age 55, those with a child who is a doctor or a nurse are more likely to be alive at age 80, and less likely to suffer from chronic lifestyle-related conditions. Further, children born into families with a health professional are substantially less likely to have been exposed to smoking *in utero* and more likely to have been vaccinated against HPV by their teenage years. All of these differences are larger or weakly larger at the lower end of the income distribution.[8] These differences remain economically and statistically significant when we control non-parametrically for a wide range of observable demographics, in the spirit of the identification strategy pursued by Bronnenberg et al. (2015) and Johnson and Rehavi (2016).

Comparing demographically equivalent individuals with and without a health professional in the extended family may still yield a biased estimate of the effect of intra-family exposure to information if *un*observables are correlated with this exposure, however. To assuage these concerns, we also pursue two quasi-experimental approaches to identify causal effects. First, we leverage a set of medical school "admission lotteries." In Sweden,

[5] Data from the United States used in this comparison is reported by the Health Inequality Project https://healthinequality.org/. Also see Sjogren and Hartman (2018) for an analysis of how mortality inequality has evolved over time in Sweden.

[6] A large body of research on early-life health has documented that poor children are born less healthy than their advantaged counterparts; also, see, e.g., Currie and Moretti (2007) and Royer (2009) for evidence of intergenerational correlations with early life health in the US.

[7] In addition to transmitting information, having a health professional in the family can affect relatives' health through what we call a "social capital channel." For example, physicians in the family could help their relatives get faster or better care. As the social capital channel is inherently non-scalable as a policy measure, we do not focus on this mechanism in our analysis. Instead, we emphasize health investments and health outcomes that are likely altered by information rather than through the social capital channel. Section 5.1 discusses the mechanism and presents evidence consistent with the information channel being an important driver of our results.

[8] We rank children by their parents' household income percentile at birth.

a centralized admission process usually generates sharp GPA thresholds for admission to any university program. Due to substantial grade inflation (Diamond and Persson, 2016), however, the cutoff for all medical schools hit the top GPA starting in 2002, and admission was randomized within the group of applicants with the highest possible GPA. Our identification strategy leverages this randomization, by comparing family members of applicants to medical school with a top GPA who were admitted and not admitted to medical school.

Our results show substantial effects of gaining admission (and hence matriculating to medical studies) on the medical school applicant's older and younger members of the extended family (including grandparents, parents, siblings, children, cousins, and in-laws). Within eight years of the applicant's matriculation, older relatives are 3 percentage points less likely to have a heart attack and 5 percentage points less likely to be diagnosed with heart failure. These effects appear to be driven by increased health investments, as the same relatives are about 30% more likely to be consuming medication preventing heart attacks. Younger relatives are also more likely to undertake health investments, being 20 percentage points more likely to be vaccinated against HPV by the age of 20. We also find that children have fewer inpatient stays, suggesting general health improvements.

While the medical school lottery resembles an "ideal experiment," this design only permits a relatively short follow-up period, as the lotteries were recent. This precludes studying outcomes such as mortality and the onset of some lifestyle-related chronic conditions, as the parents of medical school applicants are relatively young (while grandparents are frequently already deceased). The small sample size also limits our ability to study heterogeneity by income. We therefore complement this analysis with a second quasi-experimental approach to identify causal effects: event studies that compare individuals' health before and after their child receives either a medical degree *or a law degree*. The comparison of morbidity and mortality profiles at older ages between parents of doctors and lawyers is motivated by the fact that doctors and lawyers are both high-social status professions with similar income distributions; we verify that the parents of lawyers and doctors also have similar income distributions in the data. Individual and year fixed effects purge our estimates of any permanent differences in health across individuals and of national trends in treatment availability, and our event study graphs reveal little trends in health outcomes that predate the arrival of a health professional or lawyer in the family.

We find that "getting" a doctor in the family leads to a substantial long-run improvement in health and mortality of older relatives. The parents of a medical doctor are 2.5 percentage points less likely to have died by age 80 twenty years after the child matriculates in medical school, which corresponds to a 16% decline in mortality. The parents of doctors are also significantly less likely to be diagnosed with heart attacks, heart failure, and diabetes. These effects on chronic conditions emerge gradually, which points to improved health behaviors over a long time period. Consistent with our lottery analyses, the effects start being marginally statistically significant at around year 8 after matriculation and grow continuously afterwards. Overall, we conclude that exposure to a health professional in the family leads to long-run improvements in health and mortality at older ages.

While the results from our three identification strategies are not directly comparable due to the different samples and time horizons, they deliver largely overlapping insights, underscoring their credibility. We investigate the mechanism and find that the improvements in longevity and health capital of medical professionals' relatives

do not appear to stem from preferential access to fancy, restricted, or expensive treatments. Instead, they appear to be driven by intra-family transmission of health-related information that increases preventive investments and behavioral changes. What's more, these behavioral changes are – from society's perspective – simple and cheap, such as adherring to prescribed drugs, getting vaccinated, and not smoking while pregnant. These findings suggest that the benefits accruing to medical professionals' family members may be scalable through policies that mimic intra-family information transmission and promote these simple behavioral changes.

Next, we turn to an analysis of how the effect of exposure to a health professional on the family members' health varies across the income distribution. We re-estimate our non-parametric analyses and the event study specifications separately for individuals with income above and below the median, respectively. From the event studies, we then calculate the long-term "health bonus" from having a doctor child, for each income group. Across the two empirical approaches and across all outcomes, we find that the treatment effects are the same or even more pronounced at the lower end of the income distribution.

Having established substantial effects of information on health outcomes and health behaviors for individuals at both higher and lower rungs of the income distribution, we turn to the implications of these findings for health inequality. We start by examining whether the poor are likely to have lower baseline levels of information than the rich on average. We use two proxy measures of information: educational attainment and our particular measure of exposure to a health professional in the extended family. Both suggest that there is likely a 3 to 1 ratio of exposure to information, broadly defined, at the top versus the bottom halves of the income distribution.

Given that we find substantial effects of information on health, this uneven allocation of information can induce a socioeconomic gradient in health outcomes. What's more, if individuals at the lower rungs of the income distribution have noisi*er* beliefs than their more advantaged counterparts, they may be particularly responsive to the provision of information, as we find in some of our analyses. This suggests that those who face the greatest information scarcity also *need information the most*. Such an interaction between poverty and the value of health information can further escalate health inequality. Indeed, taking into account both the difference in the baseline level of information as well as the difference in the treatment response slope, our back of the envelope computation suggests that policies that mimic intra-family information transmission and eliminate the information asymmetry across the income distribution could close as much as 20% of the health inequality gap.[9]

Beyond the wider literature on health inequality, our work contributes to the literature on the economic role of families as a source of insurance (see, e.g., Persson, Forthcoming; Lee and Persson, 2016; Autor et al., 2017), shocks (e.g., Persson and Rossin-Slater, 2018), or information transmission (e.g., Hvide and Oyer, 2018). Further, we contribute to the large and growing literature in many fields that analyzes the impact of information, broadly defined, on health behaviors, including the following most recent examples of studies: Hut and Oster (2018) analyze one particular but important health behavior – diet – and show that dietary habits fail to respond to an individual's own disease diagnosis or to governmental diet recommendations. Fadlon and Nielsen (2017)

[9]Such policies may include, e.g., nurse outreach programs targeted at the poor. Having a health professional in the family can essentially be thought of as one extreme on the spectrum between "unconnected" to the health care system and "connected within the family" on the other (the case that we study). Existing literature documents positive health impacts of interventions that lie "in between" on this spectrum, such as nurse home visiting programs (see, e.g., Wüst (2012); Hjort et al. (2017)) and community health care centers (see, e.g., (Bailey and Goodman-Bacon, 2015)). See the Appendix for a more detailed discussion of this literature.

study how individuals respond to a family member experiencing a sudden health shock (non-fatal heart attacks or strokes), finding that spouses and adult children increase their consumption of preventive care (cholesterol-lowering medication) in response. Our results are consistent with theirs in that they underscore the importance of one's family for models of health behaviors. We explore a different mechanism, however: rather than salience of a health condition or the arrival of information about genetic disposition towards a disease, we analyze the role of spillovers from expert knowledge in the family. Our focus on expertise about health relates to Johnson and Rehavi (2016) who show that female physicians are less likely to receive a c-section when they themselves give birth, suggesting that their expertise on the health costs of this procedure affects their own health care consumption. Similarly, Bronnenberg et al. (2015) provide evidence on how expert information among pharmacists affects their willingness to pay for branded (versus genetic) pharmaceuticals. We study the impact of expertise with a wider lens, analyzing impacts on a broad set of diseases, on individuals other than the medical professional herself.

Focusing on information stemming from education in particular, there is a large literature documenting a strong positive association between educational attainment and own health (see, e.g., Cutler and Lleras-Muney, 2008). Currie and Moretti (2003) exploit college openings to document positive spillovers of maternal education on child health as measured by birth weight.[10] We build on this literature by considering a precise type of education – a medical degree – and by analyzing spillovers across large family trees.

Finally, contrary to all of the papers cited above, on information broadly defined or on educational attainment in particular, we quantitatively explore the implications of our findings for the broader question of the roots of health inequality, relating our work to a plethora of research on health inequality.[11] Here, we make two distinct contributions. First, we deliver estimates of the health-income gradient and show that it steepens over time using comprehensive, non-self-reported data on both health outcomes and precise measures of income.[12] Second, we provide quasi-experimental evidence on one particular causal mechanism underlying the health-income gradient, and show that it may play an important role in sustaining health inequality.[13]

The remainder of the paper proceeds as follows. Section 2 discusses our institutional setting and data, and Section 3 sets the stage by documenting health inequality in Sweden. In Section 4, we examine the impact of intra-family information on health. Section 5 discusses the implications of our findings for understanding the presence and persistence of health inequality. Section 6 concludes the paper.

[10] McCrary and Royer (2011) also establish a positive effect of maternal education on infant health. Further, Lundborg and Majlesi (2018) exploit a Swedish compulsory schooling reform to document spillovers in the opposite direction, from children's education to parental longevity. Also see Kuziemko (2014) on intra-family spillovers of education.

[11] See, e.g., Adler et al. (1994a) for a review of early evidence on a socioeconomic gradient in health and mortality and Currie (2011) for a review of health inequality early in life. See also, e.g., Fuchs (1992, 2004), Cullen et al. (2012), National Academies of Sciences and Medicine (2015), Princeton-Brookings (2015), Currie and Schwandt (2016), Seligman et al. (2016), Almond et al. (2017), Dwyer-Lindgren et al. (2017), Fuchs and Eggleston (2018), and Thakrar et al. (2018).

[12] The fact that the gradient weekly steepens throughout childhood and adolescence is consistent with evidence (using less granular measures of socioeconomic status) from the United States by Case et al. (2002), from Canada by Currie and Stabile (2006), and from the United Kingdom by Case et al. (2008).

[13] Our exercise relates to that of Aizer and Stroud (2010), who show that the arrival of novel information – in particular, the Surgeon General's recommendation, made in 1964, that women should refrain from smoking during pregnancy – induced women with higher education to respond but elicited little response among mothers with lower educational attainment, thus increasing inequality at birth. Our findings, in contrast, suggest that intra-family information elicits a weakly larger response at the lower end of the income distribution.

2 Institutional setting and data

2.1 Healthcare in Sweden

Swedish healthcare operates under the umbrella of a textbook universal health insurance system. The government runs a large public insurer and finances its expenditures from tax revenue. Coverage includes inpatient care, outpatient care, and prescription pharmaceuticals.[14] Visits to inpatient or outpatient providers entail at most a small copay and often are free. Once a patient's out-of-pocket cost reaches SEK 1100 (roughly $135) over a twelve month period, the co-pay is zero for all subsequent care during the remainder of the twelve-month period. Similarly, for prescription drugs, patients pay a share of the total cost of drugs covered by public insurance, but once a *household*'s total out of pocket spending reaches SEK 2200 (roughly $270) over a twelve month period, the co-pay is zero for all subsequent prescription fills during the remainder of the twelve-month period.[15] Thus, in practice, not only is formal access to health and prescription drug insurance universal, but copays are so low that all care is affordable even at the lowest end of the income distribution.

2.2 Data

For the universe of individuals living in Sweden over an extended time period, we use detailed mortality and health records, matched to individual-level tax records and a mapping of family trees spanning up to four generations. Here, we describe the overall structure of the data; in subsequent sections, we define the variables and sub-populations that we use in each part of the analysis.

Overall sample We have data on the universe of individuals born between 1932 and 2016 that were living in Sweden in 1961 or at some later point in time. For these individuals, we know the exact year and month of birth, as well as the year of death (from 1961 until 2016), and whether the individual was born in Sweden. From Statistics Sweden we obtain a file that connects each individual in this sample to the individual's mother and father. Equipped with these data, we can thus connect all individuals born in 1932 or later to both their own parents, as well as to their later-born relatives – children, nieces, nephews, and grandchildren. Similarly, for later-born cohorts, these data allow us to identify parents, aunts, uncles, and grandparents.

Socioeconomic information We merge these data to annual income tax records from the database LISA for the adult population (age 16-74) over a 23-year time period, 1990 - 2016. These records contain detailed, third-party reported information about labor income, financial income, as well as self-reported information about self-employment income. In the LISA database, we also observe educational attainment at an annual level, which allows us to distinguish individuals acquiring medical or nursing degrees.

[14] Not all procedures are covered by public insurance. For example, while public insurance covers breast reconstruction following a mastectomy (removal of breast tissue as part of treatment of breast cancer), it does not generally cover cosmetic breast enlargement.

[15] For the purposes of calculating a household's total out-of-pocket drug spending, a household is defined as one adult plus all children aged 18 or below that reside in the same abode.

Healthcare records To construct measures of health outcomes, health investments, and healtcare utilization throughout individuals' lives, we merge in information from inpatient records, specialist outpatient care records, prescription drug records, and cause of death records. Inpatient records cover the years 1995 to 2016, specialist outpatient records the years 2001 to 2016, and prescription drug records the years 2005 to 2017. The inpatient records contain information on the universe of a patient's visits to the hospital that result in a hospital admission, including cases where the individual is admitted and discharged on the same day. The outpatient data records all visits *outside of* primary care. Primary care is provided at municipal "Care centrals" (*Vårdcentraler*); data from these centers has historically not been collected, limiting our ability to analyze individuals' utilization of primary care, except for the case of care during pregnancy, which is recorded separately. For each inpatient admission and outpatient specialist visit, the data contain rich information on the date of the visit, the associated International Classification of Diseases (ICD) diagnosis codes, procedure codes, and the length of stay (for inpatient admissions). Drug records contain the universe of an individual's prescription drug purchases made in pharmacies, but do not include over the counter drugs or drugs administered in hospitals. For each prescription drug purchase, the data contain information about drug name, active substance, average daily dose, and the drug's Anatomical Therapeutic Chemical (ATC) code.[16] The ATC classification allows us to link drugs to diseases.

Birth records We further merge in complete medical birth records, for the time period between 1995 to 2016, matched to individual tax records. The birth records contain data on the month and year of birth, birth weight, birth length, head circumference, gestation (in days), and a variety of diagnosis codes at birth. We also have variables from the electronic medical records related to pregnancy and delivery: tobacco use during pregnancy, pregnancy risk factors (diabetes, kidney disease, epilepsy, asthma, hypertension, or urinary infection), the first date of prenatal care and the number of prenatal visits, caesarean section (c-section) delivery, induction of labor, and the occurrence of any complications at delivery.

3 Inequality in health: the facts

Beyond the availability of data, Sweden is a particularly attractive empirical context because its universal health insurance system allows us to examine health inequality in the absence of differences in formal access to health care. The opposite side of the coin, of course, is that the very presence of universal health insurance, coupled with Sweden's generous social safety net, may eradicate socioeconomic differences in health, rendering it a bad candidate for analyses of health inequality. Despite equalized formal access to insurance, however, three robust stylized facts on health inequality emerge in our data, illustrated in Figure 1.

Inequality in mortality To study the overall pattern of inequality in mortality in Sweden, we take all individuals that are alive at age 55 for whom we observe work-related earnings (either from employment or self-

[16] The ATC is an international therapeutic class classification system of pharmaceuticals developed by the World Health Organization.

employment) at ages 53 and 54. For each individual in this sample, we define an indicator for whether an individual has died by age 80. Panel A of Figure 1 plots the share of individuals that died by age 80 against an individual's own income rank at age 55.[17] To calculate the individual's income rank, we average two years of income data, measured when the individual is aged 53 and 54, respectively, and rank individuals within birth cohort and gender.[18]

As is clearly visible in Panel A of Figure 1, despite Sweden's generous social safety net and equalized formal access to healthcare, there is a strong gradient in cumulative mortality. We investigate, but do not separately report, mortality by gender. Among men at the lowest demi-decile of the income distribution at age 55 (i.e., individuals at the five lowest income percentiles), 71 percent are no longer alive by age 80; among men at the highest demi-decile, the corresponding share is 29 percent. Mortality by age 80 is significantly lower for women, which is a well-known fact in the public health literature. While female mortality is lower at all points in the income distribution, we observe a very similar gradient. Women at the lowest income levels have a 25 percentage point lower probability of being alive relative to their richest peers, 20 percent of whom are not alive by age 80. Overall across genders, as we see in Panel A, among individuals at the bottom of the income distribution who are alive at age 55, more than 50% will have died by age 80 as compared to fewer than 25% of those at the top of the income distribution.

These results mimic the income gradients that have been recently documented in the United States (Chetty et al., 2016). In Figure 2, we report the estimates of log-income mortality at age 75 relative to income rank at ages 60 for the US and 61 for Sweden.[19] For this combination of age at death and age of income measurement we were able to obtain comparable estimates from the Swedish and US tax records (the latter as reported in Chetty et al., 2016). As Figure 2 shows, the slopes of the mortality gradients are identical in the US and Sweden, despite Sweden's universal health insurancee and considerably more generous social safety net.[20]

Inequality in health outcomes in adulthood To measure inequality in health outcomes in adulthood, we start by defining indicator variables that capture any occurrence, at the individual level, of five important chronic conditions that are commonly linked to lifestyle causes and that we can measure precisely using diagnosis codes: heart attack, heart failure, stroke or other ischemic heart diseases, lung cancer, and type 2 diabetes.[21] Panel B of Figure 1 displays the share of individuals in the sample that are diagnosed with at least one of these conditions against individual income rank at age 55.[22]

The panel displays a steep gradient in the presence of these lifestyle-related conditions in the adult population. As with mortality, we also observe (but do not report for brevity) persistent differences between men and women throughout the income distribution. While there are strong gradients for both genders, women have lower levels of cardiovascular conditions. The income gradient is also strongly pronounced in each of the underlying conditions

[17] The shape of the gradient remains the same if we use the household income rank.
[18] We observe both income at ages 53 and 54 as well as survival till 80 for cohorts born in Sweden between 1930 to 1934.
[19] For these comparisons, we adjust our measure of income, so that it corresponds closer to the US adjusted gross income measure. In particular, we add capital-based income and do not include individuals with zero or negative income levels.
[20] See Adler et al. (1994a) for a review of early evidence of a socioeconomic gradient in mortality across different countries.
[21] See Appendix for exact diagnoses (ICD-9 and ICD-9) that we use to define these conditions.
[22] While heart attacks and strokes are per se acute medical events, they commonly result in a chronic need for follow up check-ups and treatment, making it useful to think about them as chronic conditions.

separately. For example, only about seven percent of men and fewer than five percent of women at the top of the income distribution have diabetes, while the rates are over 15 percent for men and 13 percent for women at the bottom of the income distribution. Similarly, relative to individuals at the top of the income distribution, those at the bottom are twice as likely to experience a heart attack. Further, men are more than twice as likely to suffer a heart attack than women, and this difference persists throughout the income distribution. Given the high mortality rate associated with a heart attack event, these patterns are consistent with our observed differences in mortality by income and gender.

For younger adults we define indicators that capture two particular measures of preventive health investments: HPV vaccination by age 20 and *not* using hormonal birth control at age 20.[23] We report the gradient in HPV vaccination in Panel C of Figure 1. We now use a different x-axis: individuals' *parental household income* rank in the year before the individual's birth, that is, we measure the x-axis 21 years before our measure of the y-axis. To calculate the parental household income rank at birth, we average two years of annual earnings of the child's mother and father, measured one and two years before the child's birth, respectively; sum them into household income; and rank households within each *child's* birth cohort.

Panel C of Figure 1 displays the share of females that has been vaccinated against HPV by age 20. The figures shows a sharp *reverse* gradient in this preventive health measure. Almost no women born into households at the bottom of the income distribution get vaccinated against HPV, while six percent of women with parents at the top of the income distribution get vaccinated - before the vaccine becomes part of the national vaccination program in 2007 (right y-axis). The gradient is slightly concave for the hormonal birth control measure. The highest rate of contraceptive purchases are observed at the 70th percentile of the income distribution, with circa 55 percent of young women purchasing the birth control pill. The rate is lowest at the bottom of the income distribution, at 35 percent. Only 50 percent of the women born into the richest households purchase contraceptives at age 20. As we report in the Appendix, physicians themselves substitute away from hormonal contraception, which is consistent with the reversal of the slope at the top of the income distribution.

Early emergence of the health-SES gradient Our discussion so far has focused on the presence of an income-health gradient in a cross-section of the older adult and younger adult populations. We next ask whether the gradient already emerges in early life. Knowing where the gradient starts in the life cycle can help formulate or reject hypotheses about the pathways that lead to the gradient, and also point to the most efficient timing of potential policy interventions.

Several of the health outcomes analyzed above – cancers, type 2 diabetes, and heart attacks – are extremely rare in children, however. To examine the presence of an SES-health gradient early in life, we must focus on outcomes that are already relevant in childhood.

We therefore turn to two of the most common chronic childhood conditions, obstructive airway diseases (which include asthma) and ADHD. Asthma and ADHD are affecting nearly ten and eleven percent of all children in

[23]The HPV vaccine protects individuals from acquiring Human Papillomavirus (HPV) which have been linked to several types of cancer, including cervical cancer. We treat *not* using birth control as a preventive investment because we observe that physicians themselves substitute away from hormonal contraception towards other means of contraception (conditional on a range of characteristics including age).

the United States, respectively (Chorniy et al., 2017); and in Sweden, already at age five roughly 35 percent are affected by obstructive airway diseases[24] and two and a half percent are diagnosed with ADHD. To capture airway diseases early in life (reported in Appendix), we define an indicator that turns on when children have a record of an obstructive respiratory diagnosis in their inpatient or outpatient records at ages zero to five. To track the evolution of this gradient over the course of the life time, we construct similar indicators capturing the use of the same broad group of respiratory medication at ages 35 to 40 and 45 to 50 (when individuals are more likely to suffer from other respiratory obstructive diseases than asthma). For ADHD, reported in the Appendix as well, we construct an indicator that takes the value of one if a child has an ADHD diagnosis recorded in outpatient or inpatient records (as either primary or secondary, teciary, etc.). There are steep SES-gradients in both asthma and ADHD.

We illustrate the development of the gradient over time in these two conditions in the Appendix. We observe a substantially higher prevalence of respiratory diseases among children than among adults; however, the gradient is flatter (although still pronounced) earlier in life and gradually steepens at the bottom of the income distribution. We see a similar fanning out of the gradient for mental health conditions: While a gradient emerges in early childhood, it steepens over the life cycle. Children aged zero to five at the bottom of the income distribution are approximately 3 times more likely to have an ADHD diagnosis in their records than their peers at the top of the income ladder. For adults aged 45 to 50, individuals at the bottom of the income distribution are nearly *twice* as substantially more likely to be diagnosed with depression (as ADHD is rare) as those at the top. The number of inpatient stays displays a similarly steep gradient, which further steepens over time.

Finally, to assess whether there is a gradient even earlier in life, we create two measures of the prenatal environment: an indicator for whether the mother is using tobacco right before and during pregnancy and an indicator for whether the child experiences a complicated birth along a number of dimensions such as birth weight, Apgar score, and others. The gradient in tobacco use, depicted in Panel D, is remarkable, with nearly 30 percent of mothers in the bottom income percentiles using tobacco around the time of pregnancy, as compared to aout 6 percent of mothers at the top of the income distribution. Tobacco use and especially smoking is known to be associated with substantial risks to the fetus, including an increased risk of miscarriage, pre-term birth, and low birth weight (see, e.g., CDC, 2017); the steep gradient in tobacco exposure in -utero thus implies that babies born into poverty are likely to obtain substantively lower health investments already before birth. Similarly, adverse events at birth (reported in the Appendix) are more likely at the bottom of the income distribution than at the very top, *despite* the fact that mothers are almost eight years older at the top of the income distribution and the latent probability of a high risk pregnancy increases with maternal age. The lowest rate of adverse events, however, occurs in the middle of the income distribution, where mothers are relatively younger, but still have more resources.

Overall, the data suggest that already at birth, children of parents at the lower end of the income distribution are less healthy than their more advantaged counterparts, and by a young age they have had more inpatient stays and have acquired more chronic conditions. This underscores the importance of parental influences and

[24] While this includes asthma, it is a broader category and thus cannot be directly compared to the U.S. figure

investments early in life and, potentially, before birth. Further, examining the gradient for related conditions over the life cycle reveals that the gradient weekly steepens as individuals age.

4 Exposure to health information and health outcomes

We are interested in measuring whether exposure to health-related information affects individuals' investments into their health and their subsequent health outcomes. In the context of this study, we define "health-related information" broadly as knowledge about the costs and benefits of healthy behaviors, as well as exposure to reminders or other nudges that make this information more salient. While it is intuitive that better knowledge and more frequent exposure to reminders of what may sustain and improve one's health likely leads to more health investments and better health outcomes (indeed, information provision has traditionally been one of the most common policy instruments), investigating the causal role of access to such information is challenging. First, individuals receive streams of information and reminders relevant to their health from many differences sources throughout their lifetime; second, this exposure is not as good as randomly assigned. In this paper, we zoom in into an environment where we can precisely measure individuals' exposure to a particular source of health-related information: the presence of a health professional (HP) in the family.

Having an HP in the family can affect individuals' health in a variety of ways, which we can broadly classify into two distinct channels. First – and this is our channel of interest – having an HP in the family is likely to increase access to health-related information in the familial environment. This "information channel" encompasses a multitude of ways in which intra-family medical expertise can be transmitted: an HP can relay (new) health-related knowledge to family members in a variety of informal settings; an HP may also frequently remind family members to invest into their health by undertaking beneficial health behaviors, avoiding harms, adhering to medications, and doing regular check-ups. Second, having an HP in the family may affect health through what we call the "social capital" channel: this, in turn, encompasses a variety of ways in which individuals may leverage the intra-family connection to the health care system to get better or faster treatment.

Throughout our analysis, we are interested in investigating the importance of the "information channel," for two reasons. First, increasing access to health-related information in the population is a scalable public policy. (We discuss the exact ways in which this can be done more in Section 5, and also includes a discussion of the literature on various health outreach programs in the Appendix.) The "social capital channel," in contrast, is not scalable, as it involves individuals who have family connections in the health care system "getting ahead of" those lacking such connections.[25] In the current section, we analyze the impact of an HP on the extended family's health; we then return to a discussion about the mechanism in Section 5.1 – there, we present evidence consistent with the information channel being an important driver of our results.

We use the records of higher education to find individuals with health professional degrees among the cohorts of work age adults in our analytic sample. We consider extended families of these individuals as being exposed to

[25] Moreover, historically, disease prevention through social and individual investments into health has always had a larger effect on population health than what can be accounted for by variation in the quality of care conditional on the average level of medical advancement Cutler and Lleras-Muney (2008).

health-related information: parents, children, siblings, grandparents, aunts and uncles, cousins, and the same in-law relatives. In addition to improving our statistical power, considering the extended family has the advantage of allowing us to observe "treated" individuals at many points in the income distribution, which will be important for our discussion in Section 5.

4.1 Non-parametric evidence

We start by documenting differences in health across otherwise demographically equivalent families with and without a health professional in the family. Panels 3A and 3B of Figure 3 revisit the mortality gradient from Figure 1A. We now plot the probability of being alive at age 80, separately for individuals with and without a health professional in the family. We observe a visually detectable separation in this mortality measure, which is persistent throughout the income distribution. Conditional on the income rank, individuals with a child who is a doctor or a nurse are more likely to be survive to age 80 conditional on being alive at age 55. We estimate the magnitude of the difference in cumulative mortality at each income decile using the following OLS specification:

$$Y_{it} = \sum_{d=1}^{d=10} \delta_{d(i)} I_{it} + \beta X_{it} + \epsilon_{it} \tag{1}$$

Here, Y_{it} is the health (or mortality) outcome of interest for individual i at time t, X_{it} is a set of time-varying demographic controls, and I_{it} is an indicator variable that takes the value of 1 if individual i has a medical professional in the family at time t. The first term is a sum of indicators for having a medical professional in the family interacted with income deciles. The coefficients of interest are $\delta_{d(i)}$, which measure the average difference in the health outcome across individuals with and without a health professional in the family for each income decile $d(i)$ at age 55. The dashed line in Panel 3B of Figure 3 reports the estimates of $\delta_{d(i)}$ without demographic controls - these estimates measure the raw vertical distance between the two curves of Panel 1A. We estimate that, on average, individuals that have at least one child who is a doctor or a nurse (and are not a doctor or a nurse themselves) are 4 percentage points less likely to have died by the age of 80. This is a large difference relative to the average probability of having died by age 80 in the full sample, which is 45 percent for men and 31 percent for women, as it implies a 10 (13) percent reduction in the probability of death for men (women). This is equivalent in magnitude to moving from the 100th to 85-90th percentile in the income distribution. As panel 3A illustrates, the (level) effects are heterogeneous across income levels.

Individuals at the lowest income deciles with a health professional child in the family are 8 percentage points less likely to have died by age 80 relative to individuals in the same income decile that do not have a health professional in the family. This difference shrinks as we go up in income rank. As Table 1 documents, larger differences in mortality across families with and without a health professional at lower income deciles is not driven by observable differences in the demographics of the elderly individuals or their families. Panel A of Table 1 reports the estimates of $\delta_{d(i)}$ with a full set of demographic controls, and we observe only a slight attenuation of the differences in mortality levels. The pattern remains the same across income deciles - individuals with a health professional child at the bottom income decile are 5 percentage points less likely (9.4% reduction) to have

died by age 80, while the difference is 2 percentage points (8.3% reduction) at the highest income decile.

We next revisit the prevalence of chronic conditions that are commonly considered to be linked to lifestyle decisions throughout the life-cycle. In panel C of Figure 3 we report differences in the probability of having the following conditions: heart attack, stroke, heart failure, other ischemic heart diseases, type II diabetes, and lung cancer, by whether or not an individual has an HP child. The conditions are aggregated into a z-score index. The raw data do not suggest that parents of health professionals are less likely to have these chronic conditions. However, once we account for differences in observable demographics, a clear pattern emerges, suggesting that parents of health professionals are less likely to have these common conditions. Panel 3D plots the estimated differences with an without controls for observables. Panel B of Table 1 reports the coefficients. As with mortality, we observe that the effect is small at the top of the income distribution and more pronounced at lower income levels.

Figure 4 reports similar analyses for younger ages. In Panels A and B we examine the probability of young adults getting the HPV vaccine and not using hormonal birth control (as discussed above, we find that physicians themselves substitute away from hormonal contraception, and hence consider similar behavior by younger adults to be a positive health investment). We observe large differences in the probability of these health investments across young adults with and without a health professional in the family across all points in the income distribution. The differences are not sensitive to controlling for observable characteristics and are persistent across all levels of income as can be seen in Panel C in Tale 1.

Finally, panels 4C and 4D report the same analysis for the probability of smoking around pregnancy. We observe large differences in smoking rates across families with an without a health professional, especially at the lower deciles of the income distribution (albeit not at the very first decile). An unborn child with a health professional in the family in the second decile of the income distribution is almost 8 percentage points less likely to be exposed to tobacco in utero than an unborn child who has no medical professionals in the family. As Panel 4D documents, expect for the first decile, where differences are small, the gap in smoking rates monotonically declines with income ranks and gets closer to zero (although still remains at 2 percentage points) at the top of the income distribution. As Panel D in Table 1 suggests, a substantial share of differences in smoking rates are attributable to observable differences across families. However, observables cannot account for the full gap - we still observe one to two percentage point lower smoking rates in families where the mother or her relatives are a health professional. The observable differences do not account for the patterns of higher gaps at the lower ranks of the income distribution, while they can explain the gap at the highest income decile.

Recognizing that having a doctor or a nurse in the family is not random, we pursue two additional identification strategies that allow us to get closer to estimating the causal impact of having a health professional - and hence access to better quality and more frequent information - in the extended family, on the health and longevity of family members.

4.2 Leveraging randomization in medical school admissions

Our second research design exploits the fact that admission to medical school in Sweden, for a subset of years, contained an element of randomization.[26] "Medical school" in the Swedish context refers to an undergraduate major in medicine, as medical training starts in college rather than in a professional school after a general college degree. Students choose their undergraduate majors before starting higher education, apply to specific departments, and follow a curriculum recommended by the department.

University applications in Sweden are centralized and handled by a governmental agency, *Universitets- och högskolerådet* (henceforth UHR). All prospective students interested in studying for all degrees and at all universities apply through the same system.[27] There are two university application cycles per year, for programs starting in the fall and spring semesters, respectively. In each application cycle, a prospective student who wants to apply to a university in Sweden submits a rank ordered list of programs, which the student is interested in, to the UHR. For example, a student may rank the medical school program at the Karolinska Institute in Stockholm as her first alternative, the medical school program at Gothenburg University as her second alternative, a program in business at Lund University as her third alternative, and so on.

The centralized agency allocates the bulk of the applicants to programs by ranking them by their high-school GPA.[28] The applicant with the highest GPA gets her preferred choice, the second highest ranked applicant gets the highest available choice for which she qualifies, and so on. This process generates GPA admission cutoffs for each program, around which admission is effectively randomized.[29]

The high-school GPA ranges from 0.0 to 20.0. Since the inception of this grading system in 1997, grade inflation has been substantial (see, e.g., Diamond and Persson, 2016). The share of students graduating from high-school with a GPA of 20.0 increased from less than 0.1 percent in 1997 to 0.8 percent in 2008 (Vlachos, 2010) – an increase of more than 800 percent. As a consequence, many programs saw their GPA admission cutoffs steadily increase over time. For medical school programs, which generally have the highest cutoffs of any programs in Sweden, this process eventually led to the cutoff hitting the 20.0 mark at all of Sweden's medical schools.

Figure 5 displays the maximum, minimum, and median GPA cutoffs for admissions to Sweden's medical schools from 1998 to 2017.[30] Prior to the fall 2002 application cycle, the admission cutoffs were gradually increasing over time, with slightly higher cutoffs in the fall than in the spring (reflecting the fact that more students apply right after graduating high school in the preceding summer). Starting in the fall of 2002 and during the subsequent fifteen application cycles (until the spring of 2010), both the highest and the lowest cutoffs

[26] There are no tuition fees for post-secondary education in Sweden. To cover living expenses, most students are eligible for financial support (part loan/part grant) from The Swedish Board of Student Finance (CSN).

[27] The name of the agency handling admissions has been changing over time; UHR is the current name.

[28] There are also other quotas allocating a smaller number of slots. The most important of these alternative quotas is the one allocating applicants to slots based on their scores on the Swedish Scholastic Aptitude Test (SSAT, in Swedish *högskoleprovet*). In addition, five years of work experience yield some extra points to the GPA.

[29] This holds so long as demand exceeds supply for a program; when this is not the case, the GPA admission cutoff reflects the lowest GPA of the applicants that qualifies for the program in question. For medical programs, demand always exceed supply. The large nursing programs are also highly competitive.

[30] Sweden has six medical schools during the time period for which we observe admissions data, with a seventh added in 2010 (in Örebro). In the years when not all schools' cutoffs are 20.0, the highest admission cutoff is typically to the Karolinska Institute in Stockholm or to Lund University.

were 20.0. Thus, admission to any medical school in the country necessitated the highest possible GPA of 20.0, and the admission was *randomized* by the UHR within this group. Our primary identification strategy leverages this randomization, by comparing applicants to medial school with a GPA of 20.0 who were admitted and not admitted to medical school.[31]

While the randomization of students with 20.0 into admission resembles a perfect RCT, in reality there are a few aspects of the institutional context that complicate our analysis. We discuss each in turn.

Other admission quotas. While the bulk of the university slots are allocated based on the GPA, in the years that we study a smaller quota is allocated based on applicants' scores on the Swedish Scholastic Aptitude Test (SSAT, in Swedish *högskoleprovet*).[32] An applicant to medical school who both has a high-school GPA and a SSAT score automatically applies in both categories. While we do not observe these additional test scores, the presence of this second quota implies that the probability of admission to medical school is greater than zero among students with a GPA below the GPA cutoff, as they can be admitted in the second quota. Thus, the GPA cutoffs are "fuzzy"; not "sharp."

The option to re-apply. An applicant who is not admitted in the first application cycle has the option of re-applying in subsequent application cycles. While waiting for the next application cycle, applicants may try to increase their admission chances, either by taking the aptitude test or by working. The possibility of the re-application implies that individuals that are not admitted in a particular cycle may still eventually gain admission and become physicians; thus, even conditional on a GPA of 20.0, being lotteried in or out is not a "sharp" allocation of students to medical schools. At the same time, not all students who are declined admission in their first application round, reapply. Instead, they may choose to pursue other professions. Thus, being admitted on the applicant's first application cycle (which is effectively random) affects the probability of the applicants eventually matriculating into a medical program.

Given these two considerations, we exploit admission in the student's *first* application cycle as an instrument for whether an individual eventually becomes a medical student and ultimately a physician. We proceed by estimating the following 2SLS relationship:

$$Y_{j(i)} = \delta MD_i + \beta_1 x_{j(i)} + \kappa_1 X_i + \epsilon_{j(i)} \tag{2}$$

$$MD_i = \gamma A_i + \beta_2 x_{j(i)} + \kappa_2 X_i + \epsilon_i \tag{3}$$

In equation 2, $Y_{j(i)}$ is the health outcome of interest for individual i's family member $j(i)$, measured for a period of time after matriculation - we consider 6 and 8 years after matriculation. MD_i is an indicator variable that takes the value of 1 if individual i matriculated into a medical program. $x_{j(i)}$ and X_i are vectors of observable demographics for individual i's family member $j(i)$ and individual i, respectively. The demographic controls for both the medical school applicant and the applicant's family members include year of birth, gender, and whether

[31] Randomization is not common, but is present in multiple higher education settings across different countries. See Ketel et al. (2016) on the return to medical school admission lotteries in the Netherlands, as well as Cathleen Stasz (2007) on the overview of lottery use in multiple countries.

[32] The test is administered by the Swedish Council for Higher Education. The admission process is similar to the process based on GPA (i.e., the student with the highest test score gets her preferred slot, and so on). The test is not mandatory.

or not the individual is born in Sweden. We also include controls for the type of relative that $j(i)$ is to applicant i (grandparent, parent, child, aunt or uncle, sibling, sibling's child, and cousin), and for family member $j(i)$'s level of education. Since individuals can choose how many medical schools to rank in their applications and that would mechanically affect their probability of getting admitted to a medical program, we further control for the number of applications.

The coefficient of interest in equation 2 is δ, which measures the effect of having a relative undertake training in medicine on health outcomes. This coefficient may be biased if individuals whose relatives are in worse (or better) health select into medical training. To address this concern, we instrument for MD_i with A_i in equation 3. A_i takes the value of 1 if student i was admitted to medical school in the first application cycle. The standard errors in the regressions are clustered at the family level.

We observe ten years of complete application and admissions records, starting in the fall of 2007 and ending in the Spring of 2016. Our baseline sample of applicants includes all applicants to medical school in Sweden up until the spring of 2010, when the cutoff score was 20.0, who had a GPA of exactly 20.0. Our sample of family members include all their grandparents, parents, own children, aunts and uncles, siblings, siblings' children, cousins, and in-laws.

Table 2 displays the mean of observable baseline demographics as well the probability of matriculating into medical studies for two groups of applicants: those who were admitted (188 applicants) and those who were not admitted (555 applicants) in their first application cycle. First, we see a large difference in the outcome of acquiring a medical degree - among students who were admitted in the first application cycle, 92% completed medical training. Among those who were not admitted on their first cycle (but could re-apply later), 60% completed medical training. We see no statistically significant differences in 15 out of 16 observable characteristics of the applicants, as we would expect if the admission decisions were randomized conditional on the perfect GPA.

The accepted and rejected students were equally likely to be women (57 percent in the accepted group) and had an equal number of siblings (1.82 in the accepted group). They had similar ages, although the accepted group is statistically (but not economically) significantly older (19.67 in the accepted group vs. 19.48 in the rejected group). The difference in age stems from the institutional nuances of the admission system – applicants can strengthen their applications by gaining five years of work experience; so, if there is a big time gap between the first and subsequent applications for some applicants who strengthen their applications, we may in a small number of cases mis-classify the first application cycle and capture individuals who gained work experience before re-applying. The differences in age shrinks substantially when we zoom in into small subsamples, where we can more conservatively define the first application cycle and focus on high school graduates from the same year – the sample of these individuals, however, is too small to perform our analysis. Hence, we keep the sample in Table 2, and control for age in our regressions.

Accepted and rejected applicants were equally likely to be born in Sweden (97 percent in the accepted group), and to have parents that were born in Sweden (87 percent of fathers and 86 percent of mothers born in Sweden for the accepted group). Both groups had similar parental household income and father's income, both measured before the applicant's high school graduation and before the first medical school application cycle. A similar share

of applicants had lost their father, or mother, or one of the grandparents by the year before the first application to medical school in the admitted and non-admitted groups (in the admitted group, 1 percent of fathers, 1 percent of mothers, 57 (48) percent of paternal (maternal) grandfathers, and 32 (30) percent of paternal (maternal) grandmothers were deceased prior to the student's application.)

In sum, 15 out of 16 observables are balanced across the admitted and non-admitted groups, and the t-test comparisons are far from any conventional significance levels with the lowest p-value of 0.33 (for whether father born in Sweden) for all observables except age. We conclude that the evidence in Table 2 is consistent with an essentially random component in medical school admissions for this group of high-achieving students. This, in turn, supports our use of the first application cycle admission decision as an instrument for whether an individual ultimately matriculates into medical training.

Tables 3 and 4 report the results of 2SLS and first stage regressions from Equations 2 and 3. We consider the average effects on the health of all older relatives (Table 3) separately from the effects on younger generations (Table 4), as very different measures of health outcomes and health investments are relevant for each group. In what follows we describe the 2SLS results in more detail.

Health of older relatives Table 3 reports our 2SLS estimates of the effect of an individual gaining a medical education on the health outcomes of relatives age 50 and older. For each relative, we track health outcomes starting in year $t+1$ after matriculation and until $t+8$, which is the maximum time horizon that we can observe individuals in our sample. This time horizon captures the period of medical education (typically 6 years) as well as the start of work as a physician.

Column (2) of Table 3 reports the results on the probability of having a heart attack. The point estimate is negative and statistically significant at 10% level. It suggests a large reduction in the incidence of a heart attack of 3 percentage points relative to the sample mean of 4 percent. We observe a similarly large effect on the incidence of heart failure - the compliers to the lottery instrument experience a reduction in heart failure of 5 percentage points, which is a 70% decline relative to the sample mean of 7 per 100 individuals being diagnosed with heart failure. We do not observe economically or statistically pronounced effects on other ischemic heart disease (column 3), diabetes (column 5), or lung cancer (column 6). Column (1) reports the results on the composite index that is the average of z-scores for each condition in columns (2) to (6). Given the noisy estimates for three out of two conditions, the index has a large standard error, but the point estimate is consistent with a decline in the incidence of these lifestyle-related chronic conditions.

Columns (7) to (9) report differences in the probability of adhering to chronic medication for older relatives. We measure adherence as the probability of purchasing the medication conditional on having any condition that may warrant the need for this medication. We consider three common cardiovascular drugs - statins (for lowering high cholesterol), anticoagulants (for reducing the chance of blood clots by thinning the blood), and hypertensives (for decreasing high blood pressure). Columns (8) and (9) report the results separately for statins and anticoagulants, while column (7) reports the result of a composite index that includes all three medication classes. We find economically and statistically pronounced increases in these measures of preventive investments

(many of these medication are recommended as preventive treatments that can reduce cardiovascular risks). Older family members of lottery winners are 8 percentage points more likely to purchase statins and 7 percentage points more likely to purchase blood-thinning medication. These are increases of 28% and 18% respectively, relative to the sample mean.

It is important to interpret the magnitude of these local average treatment effects in the context of who the lottery compliers are likely to be. The compliers in these case are individuals who are high achieving students, who pursue medicine if they get admitted on the first application try, but would have otherwise pursued other subjects. These students are thus less likely to be selecting into medicine because of their family background, health of family members, or a strong affinity to health per se. Hence, we would expect the treatment effect on these individuals to be larger, as enrolling into medical studies generates a larger change in the salience of health for their families.

In the current analysis we are restricted to examining a shorter time horizon and have a limited sample, which likely accounts for the imprecise estimates for some conditions. At the same time, focusing on the shorter time horizon has the advantage of shedding light into the potential mechanisms at play in our findings. Since we mostly observe family members exposed to physicians in the family during their training and early on in their career, we can with high certainty exclude the possibility that the "social" capital channel is an important driver of these results. While in training, the future physicians are exposed to a lot of information, but they are unlikely to have strong professional networks to enable them to help their family members "jump lines." Nevertheless, as we are interested in examining the emergence of the treatment effects on such long-run outcomes as chronic conditions and mortality, we return to longer-horizon estimates in our third empirical strategy that examines the event of a family member matriculating into medical studies.

Overall, the point estimates in our analysis are consistent with the idea that older relatives of a physician are in better health and that they undertake more investments into their health, than similar individuals in families without a physician in training.

Health of younger relatives Table 4 reports our 2SLS estimates of the effect of an individual gaining a medical education on the health outcomes of his or her younger relatives, who can be, for example, siblings, cousins, own children, and siblings' children. We again measure health outcomes starting in year $t+1$ after matriculation and until year $t+8$.

In Columns (1) and (2), we present results for our "preventive" health measures. Column (1) documents that young relatives of the medical doctor are 45 percentage points less likely to be on hormonal birth control. The estimate is precise and very large, corresponding to a 66 percent increase in the probability of not taking hormonal contraceptives relative to the mean of 68 percent. The estimate for the probability of getting an HPV vaccine is similarly large, and suggests that the younger relatives of a medical doctor are 20 percentage points more likely to get the HPV vaccine, which is almost twice the mean of 12 percent.

In Column (3), we examine the effects of a health professional on ADHD diagnosis. Given the possibility of differential compliance with medication regimens, we do not include the records for ADHD medication in our

analysis. We find large effects on ADHD, suggesting a decline of 2 percentage points among compliers, relative to the mean of 1 percent in the overall sample. Our estimates for inpatient stays in column (4) paint a similar picture. We find that younger relatives among compliers have 0.3 fewer inpatient admissions, which is both statistically and economically significant relative to the mean of 0.28 admissions in the full sample. Finally in column (5) we obtain a negative, but noisy estimate on the index of adverse birth events that combines the measures of per-term births, low birth weight, small gestational age, low Apgar scores, heart massage use, mask ventilation, and incubation.

Overall, we conclude that for younger generations, having a new doctor in the family appears to have positive effects on health - we see lower prevalence of mental health, fewer inpatient admissions and a larger probability of preventive investments. The results on hormonal birth therapy raise the question of whether medical training leads to less affinity for hormonal contraceptives.

4.3 The event of a family member becoming a medical professional

Our final research design exploits the timing of the arrival of a health professional in the family. We define the arrival of a health professional as the individual completing a medical degree, independently of whether this profession is pursued after schooling. Which families experience this arrival is not random. However, we can still assess whether having a medical professional in the family impacts the health of family members by observing how the trends in health change for families that experience this event relative to the trends in health in (similar) families that do not. Specifically, we will compare families of health professionals to families of lawyers. We need two key identifying assumptions that appear plausible in our context. First, we require that the "information" of interest arrives to families after the individual starts medical training. Second, for our results to be consistent with a causal interpretation, we need to assume that individuals do not decide to undertake medical training based on the *trend* in the health of their extended family members. These assumptions appears plausible given the long timeline that typically accompanies the decision to pursue a medical degree, and the time it takes to learn to navigate the healthcare system. We will verify empirically whether these assumption are supported in the data.

We estimate the following event study-style specification:

$$Y_{it} = \alpha_i + \sum_{\tau} \sigma_\tau D_{\tau,it} * Doc_i + \sum_{\tau} \kappa_\tau D_{\tau,it} + \gamma_t + \beta * X_{it} + \epsilon_{it} \tag{4}$$

In this specification, Y_{it} is the health outcome of interest for individual i at time t. The individual fixed effects α_i measure time-invariant unobserved determinants of individual i's health. Year fixed effects γ_t non-parametrically control for general time trends in population health and allow us to account for secular trends in healthcare delivery and medical innovation. X_{it} is a set of time-varying demographic controls - most importantly these include age fixed effects to account for the fact that age is one of the most important determinants of health.

The coefficients of interest are σ_τ that measure the impact of a medical professional arriving into the family

on the family members' health relative to the arrival of a lawyer into the family. τ measures the number of years since the arrival of the health professional relative to time t. The range of τ's varies by outcome, depending on the availability of data. We do not impose a time break and allow the data to flexibly reveal any changes in the health patterns around the time when a family member becomes a medical professional. We normalize σ_{-1} to zero, so that all other σ_τ's are interpreted as changes in health relative to one year before there is a doctor or a nurse in the family. For a subset of families with a health professional (or lawyer) in the family, we do not observe the time at which they acquired their medical (or legal) degrees. Rather than excluding these individuals from the sample, we impute the timing of their degrees from their birth year and high school completion year.

In the specifications that focus on the arrival of a physician in the family, we use families of lawyers as a control because these families likely have broadly comparable demographic and socio-economic status. Both types of families are more concentrated in the top ventiles of the income distribution (although they are present at all points in the income distribution), and moreover law degrees also require individuals to have graduated from high school with high grades. We focus the subsequent discussion on long-run outcomes for older relatives, as these are the primary types of outcomes that we cannot capture in the lottery analysis. We estimate, but do not report until the next Section, the event study results for all of our outcomes.

Figure 6 illustrates the results of the event study analyses for the health of adults in response to the arrival of a physician in the family. We consider two main health outcomes: mortality and chronic conditions at older ages. For each health outcome, we plot the estimated σ_τ:s against τ. The coefficient estimates for negative τ:s allow us to assess whether the data support the assumption that individuals are not sorting into the medical profession based on trends in their parents' health. The data unequivocally support this assumption for both health outcomes.

Panel (A) illustrates the impacts on the probability of parents dying. We observe a clear slow down in the relative mortality rate among parents of health professionals that starts emerging around year 10 after the child of the adult patient matriculates into medical (versus legal) studies. The mortality gap steadily widens for about a decade afterwards. The point estimates suggest a 2 percentage point decrease in the probability of dying at event time 20, which corresponds to about a 13 percent decline off the mean among lawyer parents, which is 15%.

Panel (B) captures impacts on the incidence of chronic conditions, including heart attacks, heart failure, diabetes, other ischemic heart diseases, and lung caner. We observe strong negative patterns that are even more pronounced than the mortality effect. After around a decade from the time a child obtains a medical degree, parents in the families with the doctor are substantially less likely to have diagnoses of these chronic conditions in their inpatient and outpatient records. We have examined each underlying condition separately. Similarly to the results in the lottery analysis, we observe large differences that emerge relatively early in the probability of having a heart attack or being diagnosed with congestive heart failure. Unlike the lottery results that only followed individuals for up to 8 years, in this analysis we observe that the profiles for the prevalence of diabetes start diverging significantly between the parents of physicians versus parents of lawyers starting at about a decade after their children matriculate into the respective fields of study. This is consistent with the idea that information

about health and health behaviors, as well as the emergence of disease is a long-run, cumulative process that has traditionally been hard to capture empirically, given the general scarcity of long-run longitudinal data that we are able bring to bear in this analysis.

Overall, we conclude that having a child with a completed medical degree has positive, and quantitatively significant, benefits for the health of the medical professional's relatives.[33] In families with a physician, the parents are less likely to die, and less likely to have common chronic conditions such as diabetes or heart failure; they are also less likely to experience acute health shocks, such as a heart attack.

5 Information and health inequality

5.1 Information interpretation

One concern with interpreting the estimates of all three of our empirical strategies is that getting a medical doctor in the family is likely to affect individuals though multiple channels, and not only through the (albeit broad) information channel that we are interested in capturing. There are two key other potential interpretations. First, our results could be driven driven by an income effect. Second, the effect of a health professional could stem from the "social capital channel" briefly discussed in Section 4 above, whereby health professionals get their family members quicker appointments for doctor visits, or any other preferential treatment. We discuss each in turn.

Income effects If there are economic returns to becoming a medical doctor (Ketel et al., 2016), so that becoming a physician also affects the economic well-being of the household, then we might be concerned that our estimates simply reflect the fact that families with a physician are richer.

There are several pieces of evidence that suggest that our results are unlikely to be driven by income effects. In our OLS analysis we extensively control for income levels non-parametrically. In the event studies, to address the potential concern of income effects, we contrast parents of physicians and lawyers, who have similar overall income profiles. There are further several points to consider in the lottery analysis. First, we directly test whether there are income gains to "winning" the medical school lottery over the time horizon we consider, and we find no such effect at any conventional level of statistical significance. This is intuitive when we consider who becomes a health professional: For the highest achieving students who apply to medical schools, the most common second-preferred option after medical school is another high-income occupation, such as business or engineering (we can directly observe this in the university applications data, which contains each applicant's rank ordered list of university programs).[34] Second, in the 2SLS specifications for the health outcomes of younger generations, we are effectively measuring effects on the siblings and cousins of physicians, since only very few young doctors have children of their own over the time horizon that we consider. The income of the physician is unlikely to have a direct effect on the physician's sibling's or cousin's household incomes. Finally, when we focus on the

[33] Note that in Sweden, it is extremely rare for individuals to reside with their children, even at a very old age; the social norm is that parents live alone and, if this is no longer possible, move into a long-term care facility (which is part of the municipal social insurance system). Thus, our results do not reflect an in-house caregiver effect.

[34] This finding differs from Ketel et al. (2016) who do find financial returns to medical school in the Dutch setting. This likely reflects the differential distributions of salaries and details of the educational systems in the two countries.

older generations (in the 2SLS specifications as well as in the event studies), then any economic returns to the profession of the child are indirect, since parents, aunts/uncles, and grandparents are not likely to live in the physician's household.[35]

Social capital Another mechanism that can link the presence of health professionals in the family and health outcomes is what we refer to as the "social capital" mechanism, where the impact of a health professional in the family runs through preferential informal access to healthcare within a formally equal system. It is instructive to distinguish between the information and social capital channels (which in principle are always likely to exist in tandem), as they have drastically different policy implications. Conceptually, the information channel is scalable and can plausibly be imitated by policy makers, for example through investments into information campaigns, emphasis on the continuity of care, strengthening of the role of a general practitioner who knows patients over a long period of time, and through nurse outreach programs. "Social capital," in contrast, cannot be scaled with fixed healthcare resources—it almost by definition implies a zero-sum game where the benefits that accrue to the family members of health professionals come at the expense of other patients who lack such connections. Hence, it is important to understand whether the (potentially scalable) information channel exists. To do this, we focus our analysis in section 4 on outcomes that are more likely to be amenable to the information channel and less likely to benefit from social capital.

Specifically, for older adults, we consider, first, a set of cardiovascular and metabolic conditions. The prevalence and onset of these conditions is commonly attributed to lifestyle behaviors and adherence to medication rather than to any expensive (and hence potentially in shortage in the Swedish health care system) clinical interventions. Second, we consider preventive behaviors in older adults related to these lifestyle conditions: adherence to chronic cardiovascular medication, which could be delaying or preventing acute cardiovascular events. A response in adherence to such drugs would very likely be driven by the information channel (which includes nagging about drug adherence) rather than a social capital channel, as these medications are easily obtainable, cheap, and recommended to patients of older age groups.[36]

Similarly, responses in the outcomes that we consider for the younger relatives are unlikely to stem from social capital-type mechanisms. One patient obtaining the HPV vaccine, for example, does not come at the expense of another patient obtaining the same vaccine. We have also examined quitting prenatal smoking (which clearly is not rationed) and the number of prenatal visits (which are free in Sweden). In a nutshell, effects on these outcomes very likely do not reflect impacts of social capital.

In addition to focusing our analysis on outcomes that are likely *not* driven by a social capital channel, we also seek to examine the importance of the social capital channel directly. To do this, we investigate several outcomes that we can capture in the data that reflect expensive or potentially rationed health care services, for which responses likely would reflect the impact of connections rather than information:

First, we investigate whether family members of HPs obtain more expensive heart attack treatments. The

[35] The Swedish social insurance system stipulates widespread municipal care for the elderly that need long-term care, so even in those cases any possible economic gains of the physician child are likely to be of secondary importance for health outcomes.

[36] Here, we verify that our results "show up" in the lottery analysis before HPs themselves can prescribe these medications to rule out ease of prescribing effects.

underlying idea here is that there are two common invasive therapies, one which is substantially more expensive than the other, and one non-invasive (drug) therapy, which is the cheapest; thus, connected patients may be more likely to get a relatively expensive treatment option (holding severity of the condition constant). We find no evidence of differences in the probability of invasive heart attack treatments across patients with and without an HP in the extended family. Further, we find no difference in the intensity of invasive treatment conditional on getting an invasive (i.e. surgery rather than drugs) treatment.

Second, we investigate whether family members of health professionals have systematically longer stays in the hospital after childbirth (conditioning on a wide range of characteristics capturing postpartum maternal health and the child's health at birth). Despite the fact that hospital stay after childbirth is generally considered rationed and scarce in the Swedish system, we do not find any differences in the length of stay across patients with and without an HP in the family.

Third, we examine the importance of the social capital channel for cancer treatment, as existing literature has documented that the social capital channel appears to be particularly important for cancer treatment. Here, we do find a smaller time window between the first diagnosis of breast cancer and breast cancer surgery among family members of HPs. However, there are no pronounced SES gradients in the prevalence of cancers nor in mortality attributable to cancer. (In fact, if anything, we observe an *inverse* SES gradient in cancers due to competing risks and more likely screening at the upper end of the income distribution.) This suggests that, at the population level, the social capital channel does not generate substantial differences in cancer-related outcomes across the income distribution.

To be clear, our investigation into social capital mechanisms is not exhaustive – this, however, is beyond the scope of our paper. Overall, our focus on information-amenable outcomes allows us to argue that there exists an effect of health professionals on their family members' health *that does not solely run through social capital*, and hence that may be scalable. Moreover, the positive effects on health that we estimate not only appear to be scalable, but to stem from simple interventions, such as encouragement of vaccination and adherence to basic chronic medication, and discouragement of smoking during pregnancy. It is noteworthy that any interventions that increase these beneficial behaviors will have only a small effect on health care expenditure – all of these are cheap from society's perspective relative to the value of life. Moreover, they are cheap when compared to other potential interventions to raise population health, such as expansions of access to expensive treatments conditional on disease.

5.2 Implications for the health-income gradient

Having argued that there is an average treatment effect of being exposed to an HP in the family on health, and that this treatment effect at least partly runs through a broad information channel (for the outcomes we consider), we next examine whether the effect of an HP on family members' health varies across the income distribution. Specifically, we re-estimate our non-parametric analyses and event study specifications by income ranks above and below the median. Table 5 reports the results for all aggregated outcomes (index measures) that we have considered in our three empirical strategies. Columns (1), (4), and (7) repeat the results on the

full samples for reference. Columns (2) and (3) report OLS estimates on the subsamples above and below the median income rank, while columns (5) and (6) report the corresponding event studies estimates.

OLS estimates in columns (2) and (3) suggest that the impact of having an HP in the family on health are similar or even sometimes *larger* at the lower end of the income distribution. For example, the preventive behaviors of older adults appear to be primarily affected among adults with below-median income. The mortality effects are also larger in absolute value in the first half of the income distribution (a 5 percentage points decline in mortality versus a 3 percentage points decline). The conclusion from the event study results in columns (5) and (6) is analogous. The estimates are similar in magnitude in the first and the second halves of the income distribution. For adverse birth events, while we do not observe economically or statistically significant changes in outcomes in the aggregate, we do find a pronounced decline in adverse birth events in the first half of the income distribution. Thus, we again conclude that the effect on health outcomes does not accrue only to the top earners. Instead, we observe that treatment effects are similar, or even more pronounced, in the first half of the income distribution.

These findings suggest that policy interventions that successfully "mimic" intra-family communication (provision of information, consistent reminders, etc.) likely would have effects on health at any point in the income distribution – and potentially larger effects at the lower end of the income distribution. Thus, such interventions would have the potential to close part of the health-SES gradient. If, in addition, the *baseline* level of information – in the absence of any intervention – is lower at the bottom of the income distribution, then this would further reinforce the impact of information provision policies on overall inequality.

It is reasonable to hypothesize that individuals at the lower rungs of the income ladder hold less information to start with and hence on average will be more affected by policies that mimic intra-family communication. Intuitively, individuals who are higher up in the income distribution may have more own information, more informed friends, be more able to search for information on their own, and so on. These individuals will update less than those at lower rungs of the income distribution on any given piece of additional information. Figure 7 provides suggestive evidence in support of this idea: Individuals at the lower half of the income distribution are less likely to have high education (16% versus 44%, Panel A), and are less likely to be exposed to HPs in the family (1% versus 3% for physicians and 5% versus 8% for physicians and nurses, Panel B).

This evidence suggests that exposure to information that is relevant for making decisions about health behaviors and health investments is substantially scarcer in the lower portions of the income distribution. In Figure 8, we provide a back-of-the-envelope calculation, using our estimates, of the potential effect of information provision on the mortality-income gradient. We make the following two assumptions: First, we assume that the treatment effect of policies that imitate intra-family informational spillovers on mortality is 16% at the top and bottom half of the income distribution. This is our aggregate estimate, and hence is a conservative estimate of the impact on the lower end of the income distribution. Second, we assume that the baseline level of information follows the same distribution as higher education, so that 16% of individuals in the first half of the income distribution are exposed to information, while 44% at the top are informed. Under these two assumptions we compute counterfactual mortality levels that would result in the top and the bottom half of the income distribution under an

information-provision policy.[37] The calculation suggests that an information-provision policy that successfully mimics intra-family communication would shrink the mortality-income gap substantially: from the observed mortality gap of 0.119 between the top and the bottom half of the income distribution, to 0.095. This corresponds to a 20% reduction in survival gap.

This illustrative computation has important implications for health inequality, as it suggests that the asymmetry in the quality and frequency of information across the socio-economic gradient can generate and sustain a significant share of the health-SES gradient, *even* in the presence of the equalized formal access to healthcare, extensive social insurance programs and a generous safety net.

6 Conclusion

Growing evidence across various disciplines reveals stark correlations between health capital throughout the course of life and a range of measures of socioeconomic status, such as education, social class, and income. Yet, the mechanisms underlying these associations are poorly understood.

This paper investigates whether the quality and quantity of information about health improves health outcomes; and seeks to evaluate the importance of this channel in sustaining health inequality. Knowing the extent to which information improves health outcomes is a key input into any optimal policy aimed at reducing inequality in health and human capital, as information provision and design of interactions between patients and the primary care system are some of the most readily available policy instruments.

Investigating the causal impact of information on health behaviors and the importance of this channel in perpetuating health inequality requires addressing three key challenges, however. First, analyses of health inequality, while ubiquitous, suffer from a lack of comprehensive data on health outcomes, coupled with a lack of detailed measures of socioeconomic status. Second, measuring individuals' quality and quantity of health-related information is notoriously difficult. Third, individuals receive streams of information relevant to their health from many sources throughout their lifetime; and this exposure is not randomly assigned.

The contribution of this paper is to address these challenges by bringing novel data to document the health-income gradient, and by constructing a new measure of the quality and quantity of information for which we can leverage quasi-random variation in assignment. We leverage an empirical setting that allows us to shut down differences in formal access to health care – Sweden – and use population-wide tax data linked to birth records, inpatient and outpatient records, and prescription drug records. Despite equalized formal access to insurance and a well-developed social safety net, we document strong socioeconomic gradients in mortality and morbidity. Moreover, health disparities and differences in health investments emerge early in life and tend to grow throughout childhood and adolescence.

To address the second challenge – the measurement and the non-random allocation of health-related informa-

[37] To compute counterfactual morality as the bottom (top) half of the income distribution, we start with observed mortality by age 80. We then assume that the information treatment moves the percentage of informed individuals by 84 (56) percentage points, and these individuals experience a 16% reduction in mortality. The resulting formula for counterfactual mortality is: observed mortality with the income group divided by (1+0.16)-0.16*0.16) for the first half of the income distribution, and divided by (1+0.16)-0.16*0.44) for the second half.

tion – we zoom in into an environment where we can precisely measure individuals' exposure to a certain type of information about health and the health care system: the presence of a health professional in a family. Using non-parametric evidence, event studies, and exploiting "admissions lotteries" into medical school, we show that children and adults that are "exposed" to a health professional in the family have significantly better health, are more likely to engage in preventive health behaviors, and are more likely to adhere to medication.

These effects do not appear to stem from preferential treatment, but from intra-family transmission of health-related information. This suggests that the benefits accruing to medical professionalsâ family members may be scalable through information provision policies that mimic intra-family communication (information transmission, frequent reminders, etc.).

Given these far-reaching effects of access to information, an uneven allocation of information across the income distribution would induce a socioeconomic gradient in health outcomes. We document evidence consistent with a sharp socioeconomic gradient in access to information, both in general educational attainment and in our particular measure of information. What's more, we document a second order interaction effect – individuals at the lower rungs of the income distribution appear to be particularly responsive to the provision of information. In conjunction with information scarcity at the low end of the income distribution, this can amplify the role of information in sustaining the health-income gradient. Indeed, our estimates suggest that policies that successfully can mimic intra-famiy communication about health would close as much as 20 percent of the SES-mortality gap.

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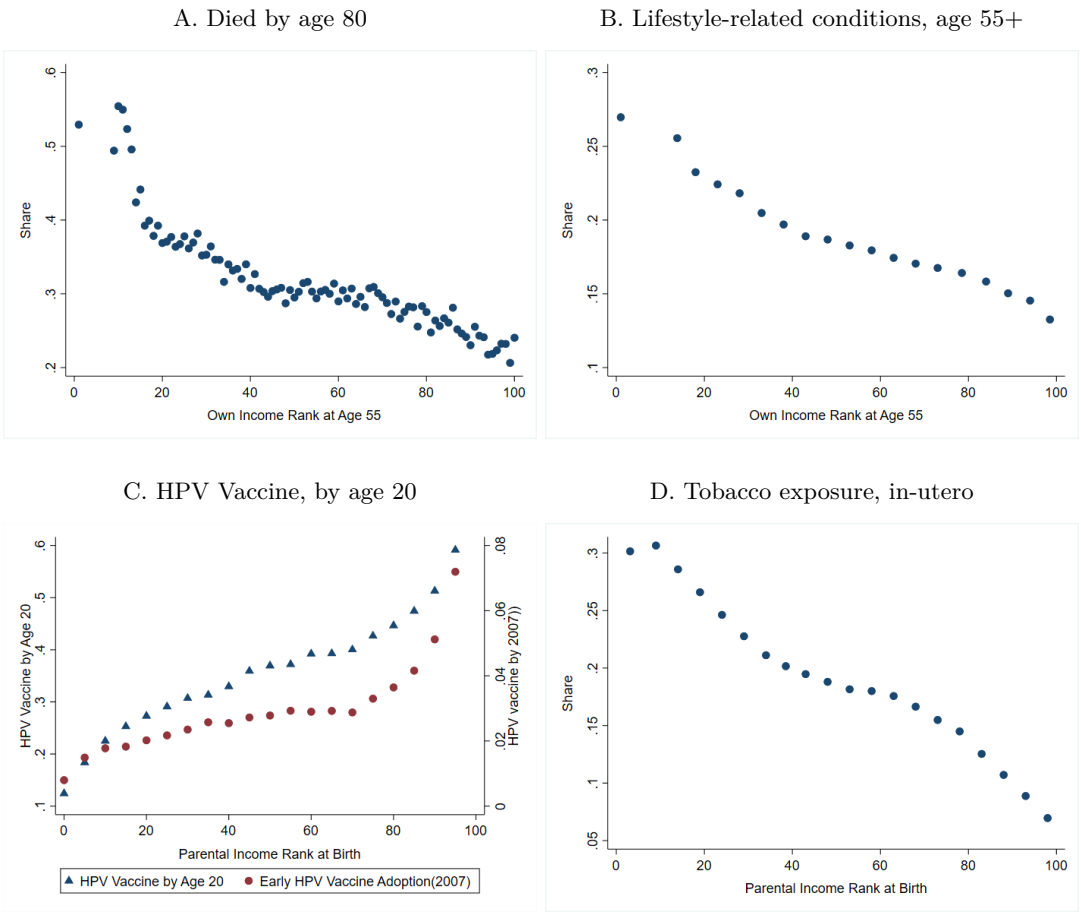
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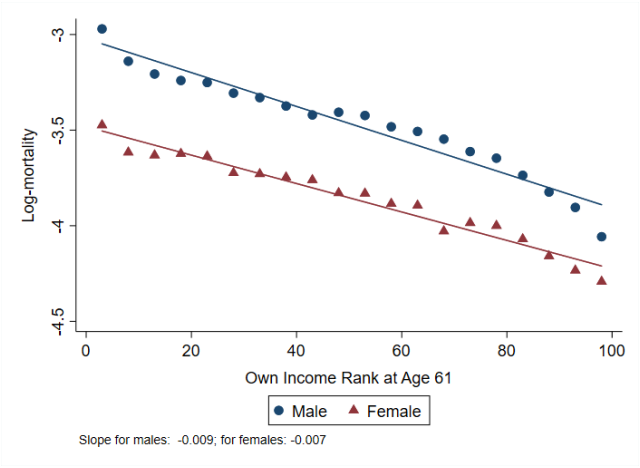
Figure 1: Income Gradients in Mortality and Morbidity over the Lifecycle



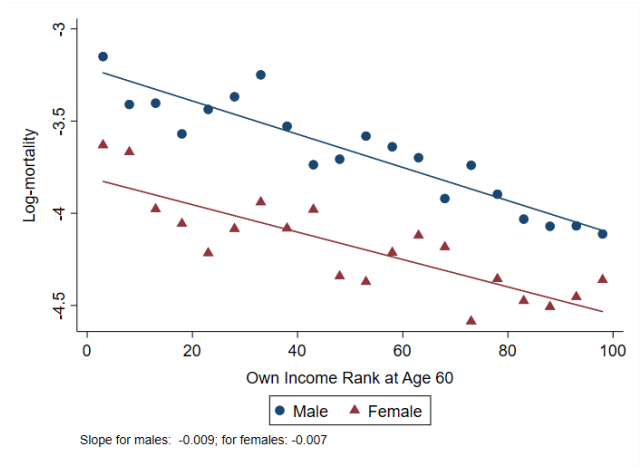
Notes: These figures are binned scatter plots of the share of individuals with relevant outcomes versus own income percentile at age 55 or parental income percentile at birth. Own income percentile ranks at age 55 are assigned based on each individual's own income at age 55 relative to other people in the same gender-birth cohort bin. Parental income ranks at birth are assigned based on the average of parents' incomes in the two years before the child was born relative to other parents with children in the same birth cohort. Panel B is defined as having diagnoses codes for any of the following conditions after age 55: heart attacks, heart failure, other ischemic heart disease, stroke, lung cancer, diabetes. Panel A restricts sample to birth cohorts 1936-1937; panel B restricts sample to individuals born between 1936-1961 and alive at age 55 and year 1995 (first year of inpatient claims). Tobacco use around pregnancy in panel D: any type of tobacco within 3 months and during pregnancy, sample restricted to children born in 1995-2016.

Figure 2: Income-mortality gradient in the US and Sweden

A. US: Log-mortality at age 75



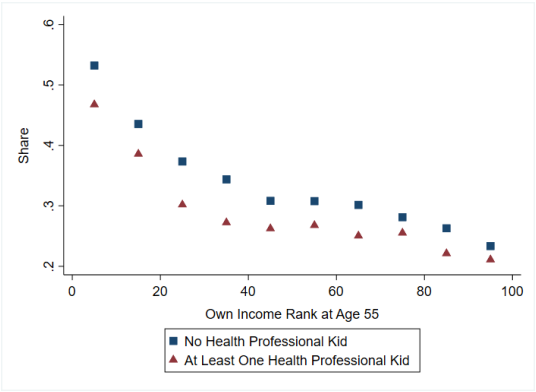
B. Sweden: Log-mortality at age 75



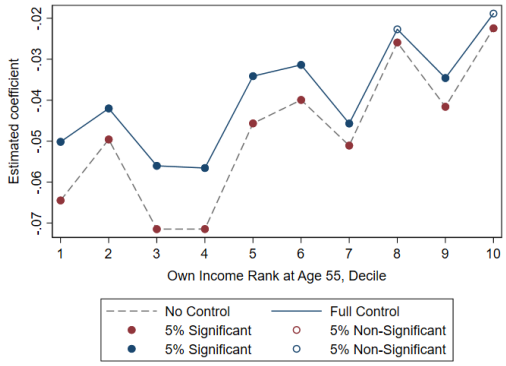
Notes: The panels compare mortality rates by income rank between the United States and Sweden, using age groups for which comparable data was available. We report mortality at age 75 conditional on ventiles of income rank at age 60 (for the US) and age 61 (for Sweden), sample restricted to individuals born in 1938-1939. US mortality data is computed using data reported by the Health Inequality Project https://healthinequality.org/. Income in all panels is measured as the equivalent of the US adjustable gross income (AGI; work-related income, self-employment income, and capital income), not including individuals with zero or negative income levels. The note in each panel reports the estimated slope of a linear regression between log-mortality rate and the income rank, separately by gender. We cannot reject the statistical equivalency of the slopes measuring the mortality gradient at age 75 for either gender (p-value: 0.84 and 1 for males and females, respectively).

Figure 3: Health Professionals in Families and Health of Older Adults: Non-Parametric Evidence

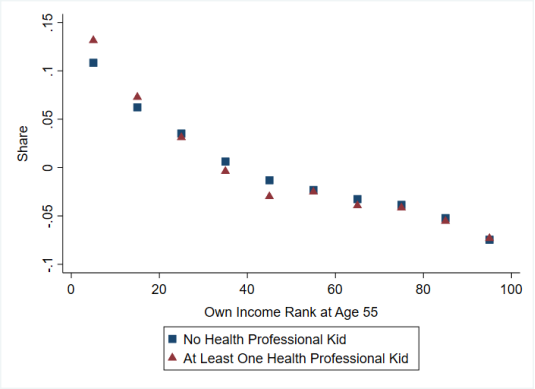
A. Died by Age 80



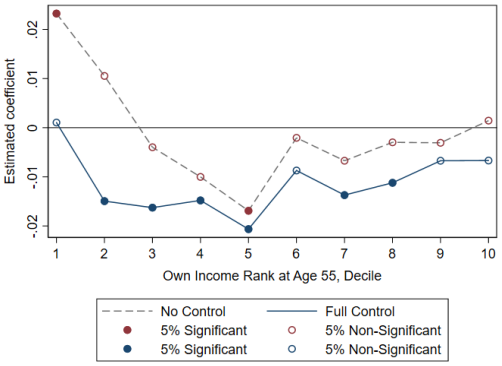
B. Died by Age 80



C. Lifestyle-related conditions



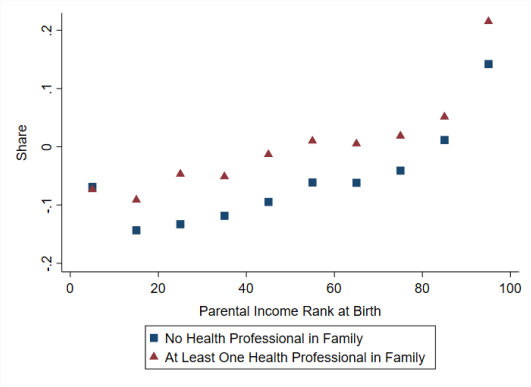
D. Lifestyle-related conditions



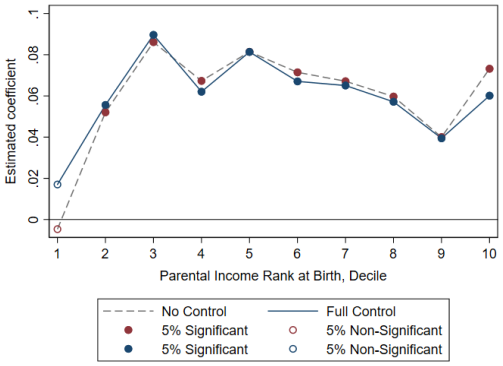
Notes: Panels A, C plot the share of individuals with relevant outcomes by the decile of own income rank at age 55. The sample is split by whether an individual has a health professional in the family. Individuals are assigned to the sample "with a health professional" if at least one of their relatives (across family ties as described in the manuscript) has a university degree in medicine or nursing. We exclude individuals who are doctors or nurses themselves. Panels B and D report coefficients from OLS regressions of each outcome on the dummy indicating whether the person has a health professional in the family, with an without a large set of observable demographics used as control variables. The samples are the same as in Figure 1.

Figure 4: Health Professionals in Families and Health at Younger Ages: Non-Parametric Evidence

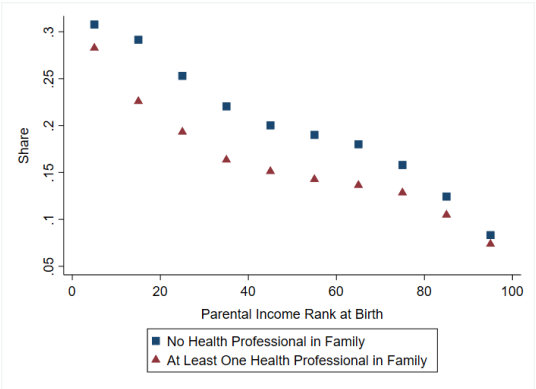
A. Preventives, young adults



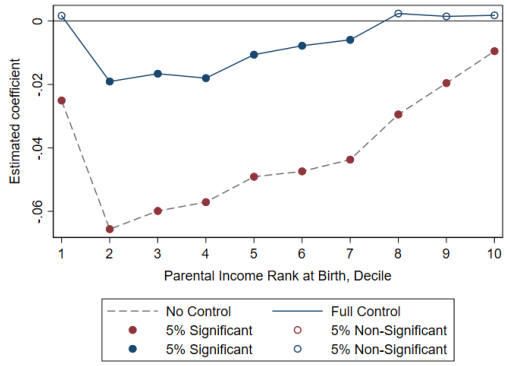
B. Preventives, young adults



C. Tobacco exposure, in-utero

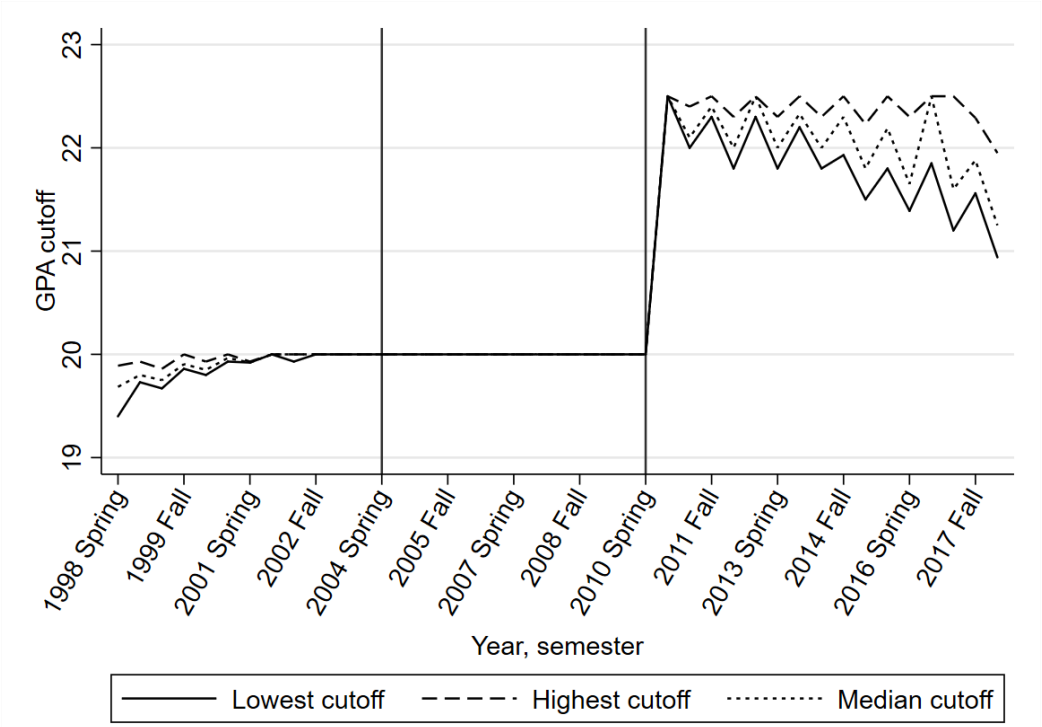


D. Tobacco exposure, in-utero



Notes: Panels A and C plot of the share of individuals with relevant outcomes by the decile parental income rank before birth. The sample is split by the presence of a health professional in the family. Individuals are assigned to the sample "with a health professional" if at least one of their relatives (across family ties as described in the manuscript) has a university degree in medicine or nursing. Panels B and D report coefficients from OLS regressions of each outcome on the dummy indicating whether the person has a health professional in the family, with an without a large set of observable demographics used as control variables. The samples are the same as in Figure 1. Panels A and B combine the indicator for HPV vaccination and not using hormonal birth control into an index computed as an unweighted average of z-scores for each outcome.

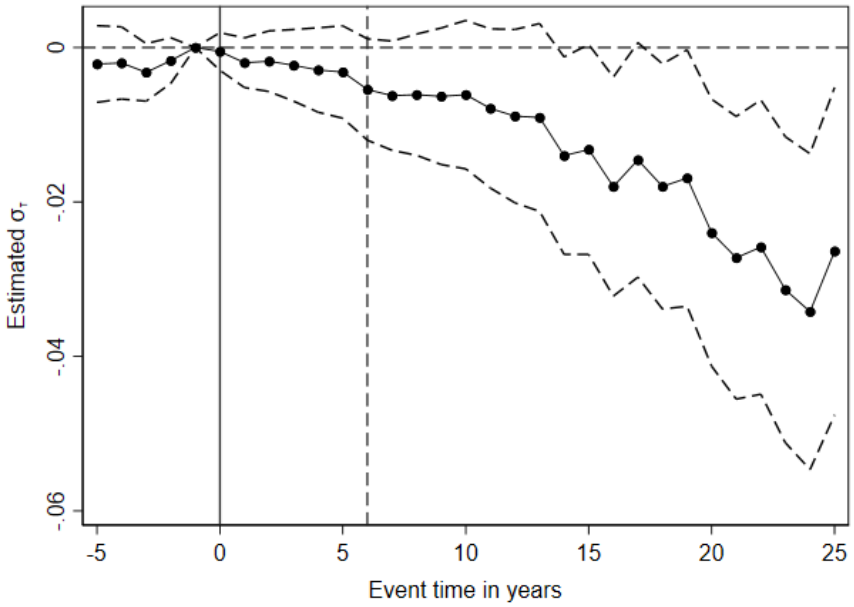
Figure 5: Medical Programs: Grade Cutoffs for Admission



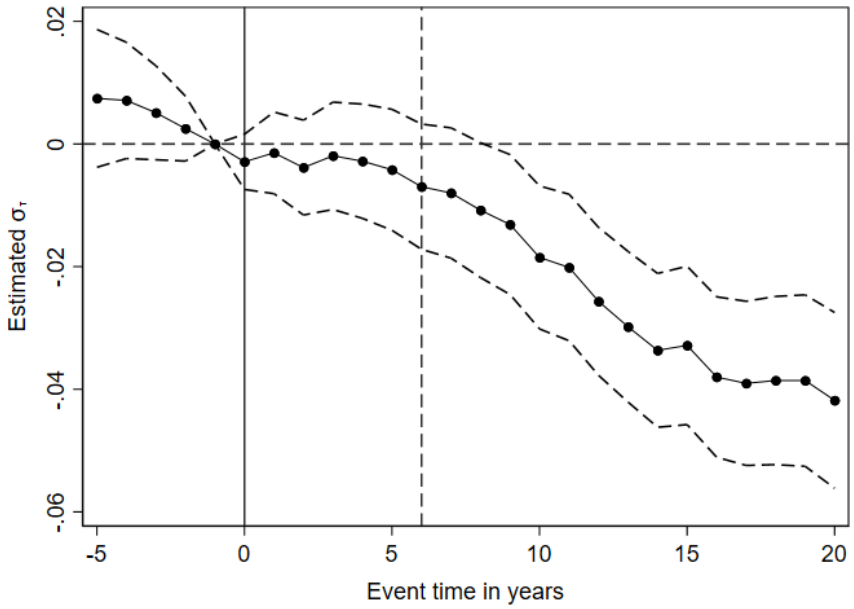
Notes: This figure plots the lowest, median, and highest GPA cutoff for medical programs in Sweden in each application cycle from 1998 to 2017.

Figure 6: Long-run Health Bonus of Having a Doctor in the Family

A. Die by Age 80



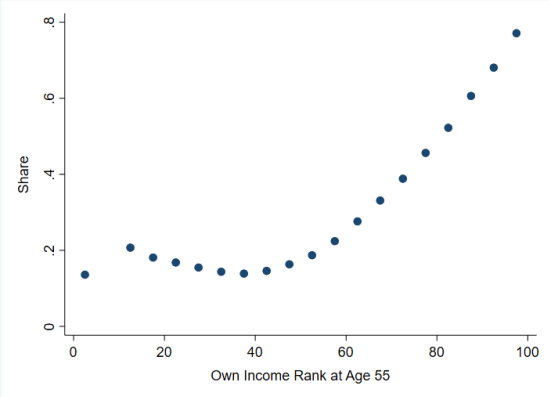
B. Lifestyle-related Conditions



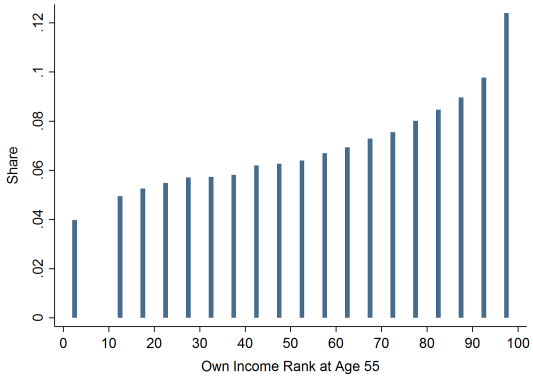
Notes: The figures plot coefficients σ_τ and 95% confidence intervals against relative time τs in event study specifications. The event studies compare the health profiles of individuals whose child matriculates into university studies of medicine to those whose child matriculates into the study of law. The sample is restricted to individuals born between 1936 and 1961. We exclude parents who are themsevles health professionals. The regressions are centered at 6 years before (solid vertical line) graduation year (dashed vertical line). Standard errors clustered at the individual level.

Figure 7: Distribution of Salience: Suggestive Evidence

A. Distribution of higher education by income



B. Distribution of health professional exposure

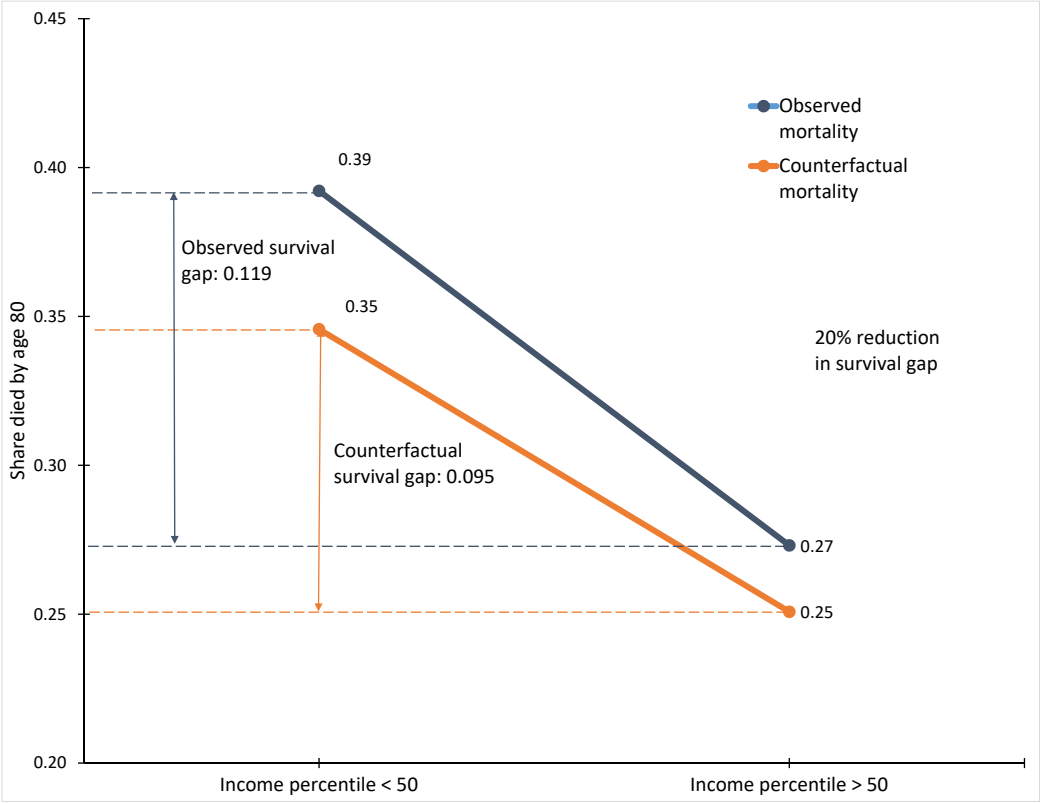


Notes: Panel A is a binned scatterplot that reports the share of individuals age 55 and older with a completed college degree (or higher) by income rank ventiles. Own income rank ventile at age 55 is assigned based on each individual's own income at age 55 relative to other people in the same gender-birth cohort bin. Panel B reports the share of individuals age 55 and older with a health professional - a physician or a nurse - child, by income rank ventile of the parent. Income includes only work-related and self-employment income and does not include capital income. Individuals with zero income are included in the sample in the first ventile. Taking education as a salience proxy, Panel A suggests that 16% of individuals in the first half of the income distribution were exposed to salience, as compared to 44% in the top half, which is a factor 2.8 difference.

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Figure 8: Salience and SES Gradient

Counterfactual SES gradient under asymmetric baseline salience



Notes: The top line ("observed mortality") plots observed average probability of individuals surviving until age 80 conditional on being alive at age 55, across the first five and the last five deciles of income rank at age 55. The sample is defined as in Figure 1, Panel A. The points on the bottom line ("counterfactual mortality") are computed as follows: observed mortality within the income group divided by ((1+T)-T*s). T is the treatment effect of salience (estimated at up to 16% for mortality) and s is the share of salience in the baseline, proxied by the share of college completion at 16% and 44% percent at the bottom half and top half of the income distribution, respectively.

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Table 1: Health Outcomes of Individuals with and without a Health Professional in the Family

Panel A: Died by age 80

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Health Professional Kid	-0.050***	-0.042**	-0.056***	-0.057***	-0.034**	-0.031**	-0.046***	-0.023*	-0.035***	-0.019*
	[0.018]	[0.019]	[0.016]	[0.015]	[0.014]	[0.014]	[0.013]	[0.013]	[0.012]	[0.010]
Mean, Dep. Var	0.53	0.43	0.37	0.34	0.30	0.30	0.30	0.28	0.26	0.23
S.D. Dep. Var	0.50	0.50	0.48	0.47	0.46	0.46	0.46	0.45	0.44	0.42
R-Squared	0.038	0.032	0.027	0.032	0.029	0.026	0.017	0.013	0.015	0.013
Obs	16,979	11,681	15,262	15,253	15,238	15,276	15,222	15,247	15,217	16,746

Panel B: Index of Lifestyle-related Conditions, Age 55+

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Health Professional Kid	0.001	-0.015**	-0.016***	-0.015***	-0.021***	-0.009*	-0.014***	-0.011***	-0.007*	-0.007*
	[0.007]	[0.007]	[0.006]	[0.005]	[0.005]	[0.005]	[0.004]	[0.004]	[0.004]	[0.004]
Mean, Dep. Var	0.11	0.06	0.03	0.01	-0.01	-0.02	-0.03	-0.04	-0.05	-0.07
S.D. Dep. Var	0.70	0.66	0.63	0.59	0.57	0.56	0.54	0.54	0.52	0.48
R-Squared	0.070	0.093	0.085	0.088	0.084	0.087	0.086	0.083	0.084	0.078
Obs	285,627	156,833	234,263	234,657	233,698	231,484	228,615	222,078	215,979	225,175

Panel C: Index of Preventive Investments, Young Adults

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Health Professional in Family	0.017	0.056***	0.090***	0.062***	0.081***	0.067***	0.065***	0.057***	0.039***	0.060***
	[0.018]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.014]	[0.014]	[0.014]	[0.014]
Mean, Dep. Var	-0.07	-0.13	-0.12	-0.10	-0.08	-0.04	-0.05	-0.03	0.02	0.16
S.D. Dep. Var	0.59	0.63	0.66	0.67	0.69	0.70	0.70	0.70	0.72	0.76
R-Squared	0.042	0.033	0.040	0.035	0.039	0.047	0.046	0.053	0.053	0.072
Obs	11,725	13,096	13,037	13,042	12,988	12,927	13,043	12,999	13,066	14,370

Panel D: Tobacco Exposure, In-utero

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Health Professional in Family	0.002	-0.019***	-0.017***	-0.018***	-0.011***	-0.008***	-0.006***	0.002	0.001	0.002
	[0.005]	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]
Mean, Dep. Var	0.32	0.29	0.24	0.21	0.19	0.18	0.17	0.15	0.12	0.08
S.D. Dep. Var	0.46	0.45	0.43	0.41	0.39	0.39	0.38	0.36	0.33	0.27
R-Squared	0.102	0.083	0.071	0.069	0.070	0.066	0.061	0.053	0.044	0.031
Obs	159,827	193,047	196,580	198,304	198,622	198,894	198,963	198,338	197,040	210,629

Notes: Panel A restricts sample to individuals born in Sweden between 1936-1937. Panel B restricts sample to individuals born in Sweden between 1936-1961 and alive at age 55. Panel C restricts sample to females born between 1995-1997 and alive at age 20. Panel D restricts sample to children born in Sweden between 1995 and 2016. Health professional kid is a dummy that equals one if the individual has at least one child with a completed medical or nursing degree. Health professional in the family is a dummy that equals one if the child or an adolescent has a health professional parent, grandparent, aunt, uncle, sibling, or cousin. Covariates in panels A and B include fixed effects of own income percentile rank at age 55, birth year fixed effects, educational attainment fixed effects, gender, and county of residence at age 55 fixed effects. Covariates in Panel C include parental income percentile rank at birth fixed effects, birth cohort fixed effects, and mother's county of residence in the year before the child was born fixed effects. Covariates in panel D include parental income percentile rank at birth fixed effects, birth order fixed effects, children's birth cohort and gender fixed effects, mother's education fix effects, maternal age, and mother's county of residence in the year before the child was born fixed effects.

Table 2: Medical School Lotteries: Balance on Baseline Observables

	Admitted	Not Admitted	p-value
Medical degree in 2015	0.92	0.60	0.00
	[0.27]	[0.49]	
Demographics			
Female	0.57	0.60	0.41
	[0.50]	[0.49]	
Age	19.67	19.48	0.03
	[1.23]	[1.03]	
Number of siblings	1.82	1.80	0.84
	[1.06]	[1.06]	
Born in Sweden	0.97	0.95	0.45
	[0.18]	[0.21]	
Father born in Sweden	0.87	0.85	0.33
	[0.33]	[0.36]	
Mother born in Sweden	0.86	0.85	0.64
	[0.34]	[0.36]	
Parental income (10k krona, inflation-adjusted)			
Year before high school graduation	94.00	90.42	0.52
	[62.26]	[64.27]	
Year before first application	93.65	90.91	0.63
	[63.63]	[64.89]	
Father's income (10k krona, inflation-adjusted)			
Year before high school graduation	55.25	54.04	0.80
	[53.93]	[56.86]	
Year before first application	54.41	54.11	0.95
	[54.19]	[57.33]	
Relative deceased by year of first application			
Father	0.01	0.01	0.63
	[0.07]	[0.10]	
Mother	0.01	0.01	0.63
	[0.07]	[0.10]	
Paternal Grandfather	0.57	0.55	0.69
	[0.50]	[0.50]	
Paternal Grandmother	0.32	0.35	0.46
	[0.47]	[0.48]	
Maternal Grandfather	0.48	0.51	0.52
	[0.50]	[0.50]	
Maternal Grandmother	0.30	0.28	0.64
	[0.46]	[0.45]	
Obs	188	555	

Notes: Sample restricted to students who (i) have a high school GPA of 20.0 and (ii) applied to medical schools for the first time during application cycles fall 2007-spring 2010. Column 1 reports mean values of selected observable demographics for applicants who were admitted to a medical school after their first application attempt. Column 2 reports the same outcomes for applicants that were not admitted after the first application attempt. Column 3 reports the p-value of a two-sided t-test.

Table 3: Effect of Physicians on Health of Their Families (2SLS): Older Relatives

	Chronic Conditions						Preventive Behavior		
	(1) Index	(2) Heart Attack	(3) Other Ischemic	(4) Heart Failure	(5) Type II Diabetes	(6) Lung Cancer	(7) Index	(8) Statins	(9) Anti-coagulants
Matriculated	-0.084	-0.034*	-0.015	-0.051*	0.016	0.005	0.185**	0.082**	0.066*
	[0.095]	[0.020]	[0.035]	[0.027]	[0.027]	[0.010]	[0.079]	[0.041]	[0.038]
First Stage									
Coefficient	0.527***						0.435***		
	[0.059]						[0.037]		
F statistic	80.5						135.7		
Mean dep. var	0.20	0.04	0.09	0.07	0.07	0.01	0.56	0.29	0.37
S.D. dep. var	0.86	0.19	0.29	0.25	0.26	0.08	1.01	0.45	0.48
Obs	1,532	1,532	1,532	1,532	1,532	1,532	3,134	3,134	3,134

Notes: This table reports estimation results from the two stage least squares regression described in equations (2) and (3). Standard errors are clustered by family. The sample is restricted to medical school lottery applicants' family members that are age 50 or older. All regressions control for the family member's birth year fixed effects, gender, educational attainment, relationship with the applicant (e.g., grandparents), and a dummy indicating whether the family member was born is Sweden, and the applicant's birth year fixed effects, gender and a dummy that equals one if the applicant was born in Sweden. Health outcomes are tracked for 8 years after matriculation into medical school or the last medical school application. Index in column 1 is constructed as the mean of the z-score of heart attack, other ischemic diseases, heart failure, type II diabetes, and lung cancer. Index in column 7 is constructed as the mean of the z-score of statins, anticoagulants, and hypertension drugs uses. The sample sizes in columns (1)-(6) differ from columns (7)-(9) due to differences in the years of data available for inpatient and outpatient admission versus prescription drug records.

Table 4: Effect of Physicians on Health of Their Families (2SLS): Younger Relatives

	(1) HPV Vaccine	(2) No Hormonal Contraceptives	(3) ADHD	(4) Number of Inpatient Stays	(5) Adverse Birth Events
Matriculated	0.202*	0.450**	-0.021*	-0.327***	-0.045
	[0.119]	[0.177]	[0.011]	[0.125]	[0.190]
First Stage					
Coefficient	0.293***		0.315***		0.341***
	[0.057]		[0.033]		[0.050]
F statistic	26.7		91.0		45.7
Mean dep. var	0.12	0.68	0.01	0.28	0.03
S.D. dep. var	0.33	0.47	0.11	1.22	0.67
Obs	514	514	4,113	4,113	563

Notes: This table reports estimation results from the two stage least squares regression described in equations (2) and (3). Standard errors are clustered by family. The sample is restricted to medical school lottery applicants' family members that are female and aged 10-20 (columns 1 and 2), female and male relatives younger than 30 (column 3 and 4), and all births after the applicant's last application attempt (column 5). All regressions control for the family member's birth year fixed effects, gender, educational attainment, relationship with the applicant (e.g., grandparents), and a dummy indicating whether the family member was born is Sweden, and the applicant's birth year fixed effects, gender and a dummy that equals one if the applicant was born in Sweden. Inpatient stays and outpatient visits due to pregnancy, childbirth and 6 weeks after delivery are excluded from analyses. Health outcomes are tracked for 8 years after matriculation into medical school or the last medical school application. Adverse birth events is an index that includes the following outcomes: preterm, low birth weight, small gestational age, low Apgar, and using heart massage, mask ventilation, or incubation; the index is constructed as the mean of the z-score of all these outcomes.

Table 5: Effect of Physicians on the Health of their Families, Heterogeneity by Income

	OLS			Event Study			2SLS
	All	Below Median Income	Above Median Income	All	Below Median Income	Above Median Income	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Died by age 80	-0.04	-0.05	-0.03	-0.02	-0.02	-0.01	-0.002
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
Lifestyle-related diseases	-0.01	-0.01	-0.01	-0.03	-0.03	-0.03	-0.08
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.10)
Preventive index, older	0.001	0.01	-0.003	0.02	0.03	0.02	0.19
	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.01)	(0.08)
Preventive index, younger	0.06	0.07	0.06	0.27	0.23	0.28	0.96
	(0.00)	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)	(0.42)
Adverse birth events	-0.004	-0.01	0.00	-0.01	-0.07	-0.01	-0.05
	(0.00)	(0.00)	(0.00)	(0.03)	(0.04)	(0.03)	(0.19)

Notes: This table reports the results of OLS and event study analyses when we split the sample by above and below median income. Event study coefficients for mortality are reported for event time 20 (i.e. 20 years after matriculation into a medical course of study). For all other outcomes, the coefficients are reported at event time 15. All regressions control for demographic observables. Index in row 2 "lifestyle-related diseases" is constructed as the mean of the z-score of heart attack, other ischemic diseases, heart failure, type II diabetes, and lung cancer. Index in row 3 "preventive index, older" is constructed as the mean of the z-score of purchasing statins, anticoagulants, and hypertension drugs conditional on having chronic diseases that require the use of these medications. Index in row 4 "peventive index, younger" includes z-scores for having immunization against HPV and not using hormonal birth control among female relatives aged 10-20. Index in row 5 "adverse birth events" is an index that includes the following outcomes: preterm, low birth weight, small gestational age, low Apgar, and using heart massage, mask ventilation, or incubation; the index is constructed as the mean of the z-score of all these outcomes.

APPENDIX

Further related literature

Interventions of patient education

The goal of patient education is to assist patients in improving their health and to mobilize patients to play an active role in their own care. Thereby, patient education programs have shown to be an effective tool to promote health and to reduce costs. In a recent review, Stenberg et al. (2018) discuss 56 health economic evaluations of face-to-face interventions for people living with chronic illness[38]. The authors find that, regardless of study design and time horizon, interventions that promote patient education are beneficial in terms of decreased hospital admissions, fewer visits to emergency departments or general practitioners, and in terms of increased quality-adjusted life-years.

These findings comply with the results of the literature reviews that focus on education interventions tailored at patients with specific chronic diseases. For example, Wang et al. (2017) present a review of randomized control trial studies that investigated the effectiveness of self-management education for patients with COPD. The authors highlight that such interventions are a useful strategy to improve the disease-specific knowledge and the quality of life for patients with COPD. Furthermore, these programs have shown to reduce respiratory-related hospital admissions and emergency department visits. However, the literature finds no significant reduction in the smoking rate or in the mortality rate. The literature review by Anderson et al. (2017) focuses on the educational component of cardiac rehabilitation for patients with coronary heart disease. Their study comprises 22 randomized control trials that assigned patients to different educational interventions which ranged from face-to-face counseling to residential stays with follow-up sessions. Patients in the control groups received usual medical care in cardiac rehab that comprises exercise counseling and training and psychological support. In conclusion, there is no evidence that education-based interventions can reduce total mortality, the risk of heart attack or the number of hospitalization when compared to regular cardiac rehab. Still, there is some indication for a reduced risk of fatal and/or non-fatal cardiovascular events and for improvements in the health-related quality of life. Similarly, Menichetti et al. (2017) focus on randomized control trials that promote patient engagement among older adults mainly suffering from osteoporosis, diabetes or cardiovascular-related health problems. The authors note that such interventions often demonstrate better effects on patient compliance and medical adherence if they combine educational, behavioral, and affirmative strategies. Most interventions focused on the educational dimension by providing knowledge to patients or incorporated behavior-based strategies such as goal setting, action planning and self-monitoring. Only a small number of studies focused affective strategies such as positive thinking, motivational interviewing or relaxation.

In the context of obesity and weight management, behavior-based interventions include the promotion of dietary changes and physical activity. LeBlanc et al. (2018) investigate the impact of primary-care relevant weight loss and weight loss maintenance interventions among overweight or obese adults. Their review comprises

[38]The main diagnosis considered in these studies are COPD, asthma, chronic pain, heart disease, and diabetes.

89 clinical trials that examine the effectiveness of behavior-based interventions and 35 trials that focus on the effectiveness or harms of weight loss medication interventions. While medication-based interventions were associated with higher rates of harms, both types of interventions contributed to weight loss and the reduction of the risk of developing diabetes. However, most studies did not report on the effect on health outcomes such as mortality, cardiovascular events, or quality of life. For children and adolescents, O'connor et al. (2017) find that behavior-based interventions with a longer period of exposure, exceeding 26 estimated hours of contact, were more likely to yield significant reductions in excess weight. Moreover, behavioral weight management interventions for children and youth were associated with a small but robust mean reduction in the body mass index, with small improvements in blood pressure and quality of life (Peirson et al., 2015).

Several studies have shown that brief opportunistic interventions delivered in a primary care setting can be an effective tool to promote a healthy lifestyle. Aveyard et al. (2016) investigate whether a 30 second intervention delivered by a trained general practitioner is acceptable and effective at reducing body weight in patients with obesity. In this randomized control trial, patients who were assigned to receive the brief intervention also received referral to behavioral weight loss programs. The authors conclude that the greater uptake of behavioral support was the main cause for the weight difference between the treatment and control group. Kaner et al. (2018) review the literature on brief alcohol interventions and find some evidence for the reduction of excessive alcohol consumption compared to minimal or no intervention. In the context of smoking cessation, Aveyard et al. (2012) and Stead et al. (2013) find that brief medical advice and the offer of behavioral or pharmaceutical assistance can increase the frequency and the success of quit attempts. Hence, Aveyard et al. (2012) conclude that primary care physicians may be more effective in promoting smoking cessation by offering support to all smokers rather than only to those who are interested in support. In addition, Vidrine et al. (2013) find that smokers are significantly more likely to enroll in cessation treatments when they are directly contacted by telephone-based tobacco cessation services rather than being encouraged to call such quitlines on their own.

An extensive body of literature examines the role and effectiveness of social media interventions in public health and medicine. A comprehensive synthesis of this literature can be found in Giustini et al. (2018).[39] The authors note that social media has been used more frequently in public health in order to educate the general population. Numerous studies have considered the use of social media in interventions for diet and physical activity (Chang et al., 2013; Williams et al., 2014), for diabetes (Gabarron et al., 2018), for cancer prevention and management (Han et al., 2018), and for the promotion of sexual health (Gold et al., 2011; Swanton et al., 2015). Strecher et al. (2008) and Chakraborty et al. (2018) examine the impact the "Project Quit," a web-based smoking cessation randomized trial which used individually tailored intervention components such as hypothetical success stories and behavioral counseling messages. Both studies find a negative effect on the number of cigarettes smoked per day and a positive effect on the number of quit attempts.

[39]The authors also provide a living systematic review of review studies which can be found here http://hlwiki.slais.ubc.ca/

Community health programs and primary care nurses

In a recent literature review, Najafizada et al. (2015) summarize the contribution of community health worker (CHW) interventions in high-income countries in three aspects. First, the literature has documented that CHWs have contributed to health-related issues in communities. This includes improvements in diabetes and asthma management, healthy heart lifestyle, maternal and child health services, healthy eating habits, blood pressure reduction, patient enrolment in research, child development, early intervention services, health care utilization, and disease prevention. Second, evaluations of interventions have indicated their potential to reduce health disparities in marginalized populations as they address health issues related to culture, ethnicity, race, gender and language. Finally, because of the focus on primary health care, health promotion and disease prevention, CHW interventions have demonstrated both actual and potential control of high costs of medical services and inappropriate use of emergency services. Bailey and Goodman-Bacon (2015) is the first rigorous evaluation of the long-term health benefits of community health centers (CHC) that increased access to primary health care for the poor. Their event study exploits the gradual expansion of the CHC in the US from 1965 to 1974 to estimate the impact on the county-level mortality rate. The authors find that, within one decade after CHCs were established in a county, the age-adjusted all-cause mortality rate had declined by 2 percent on average. This effect is primarily driven by the reduction in cardiovascular-related deaths among adults age 50 and above. Further, the authors conclude that long-term benefits of primary care and lower medication costs enabled by CHCs are the main mechanisms for the mortality effect.

Furthermore, professional nurses play an increasingly important roll in the provision of primary health care. Coster et al. (2017) and Laurant et al. (2018) consider the impact of nurses working as substitutes for primary care physicians and conclude that, for chronic conditions in particular, trained nurses might provide equal or even better quality of care and produce equal or better health outcomes for patients. Further, nurse-led care may allow longer consultations and may be more efficient in promoting patient adherence to treatment and patient satisfaction. Fergenbaum et al. (2015) present a systematic review on the effectiveness of care in the home compared to usual medical care for patients with chronic health failure. Their review comprises 6 randomized control trials that provided home visits primarily by a single health professional and consisted of nurse-led education in relevant aspects of disease self-care managements, lifestyle habits and preventive activities, and medication review. In summary, there is the trend that home-visiting programs reduce the number of hospital and emergency department visits, reduce all-cause mortality and improve quality of life. The cost-effectiveness analysis revealed that care in the home is both more effective and less cost intensive than usual medial care for patients with chronic heart failure.

In the Swedish setting, Agvall et al. (2013) and Liljeroos and Strömberg (2018) investigate the impact of introducing nurse-led heart failure clinics in primary health care. The authors note that, most frequently, elderly patients with heart failure receive treatment by general practitioners. However, previous studies found that primary health care suffers from suboptiomal medication prescription, limited provision of disease-specific education, and patient non-compliance with medication and non-adherence to lifestyle recommendations (see, e.g.: Giezeman et al. (2017)). Contrary, nurse-led heart failure clinics offer optimized medical treatment and

provide education and support for self-care. Previous research showed that these clinics could significantly decrease hospital readmission and all-cause mortality[40] While such outpatient clinics had been established at most Swedish hospitals, nurse-led heart failure clinics in primary care were scarce. Liljeroos and Strömberg (2018) investigate the impact of the region-wide introduction of nurse-led heart failure clinics in primary care in the Sörmland County Concil. In a pre-post analysis, the authors compare official health registry data for in-hospital care utilization and for medical treatment of patients with follow-up in primary care. In summary, the nurse-led clinics for follow-up primary care were associated with lower hospital care utilization including reduced hospital admissions, hospital days and emergency room visits. Moreover, the results suggest an improvement in health care providersâ adherence to prescribing and optimizing heart failure treatment. Agvall et al. (2013) investigate the impact of a randomized, open-label trial that included 160 patients and offered a heart failure management program to the intervention group. This nurse-led primary care program included disease-specific education and regular follow-up visits to optimize the medical treatment. The control group continued to receive the usual treatment as recommended by the general practitioner. In conclusion, the heart failure management program significantly reduced the number of hospital admissions and instances of health care contact. Although the period of participation was limited to 1 year, the authors conclude that a more optimized treatment program would probably improve the long-term prognosis of heart failure patients.

Early childhood interventions

A growing literature has documented that early life interventions have a positive effect on infant mortality and can promote health in the long-run, suggesting that conditions in infancy are a relevant source of health and socioeconomic disparities in later life (see, e.g., Almond et al. (2017)). For a universal home visiting program implemented in Denmark, Wüst (2012) shows that the intervention had a positive and significant effect on the infant first-year survival rate in Danish towns and was most effective in the majority of small and medium-sized municipalities. The authors suggests that the main driver of the program's impact was the promotion of breastfeeding and appropriate infant nutrition. In a related study, Hjort et al. (2017) examine the long-term impact of the Danish home visiting program as treated children are 45 to 64 years old. They find that participation is associated with higher survival rates and with improved health measured by the number of overnight hospital stays and the likelihood of a cardiovascular disease diagnosis. Butikofer et al. (2015) investigate the long-term impact of mother and child health care centers in Norway and find that the increasing access to well-child visits had a positive effect on health, education and earning of treated infants when they reach age 30 to 40. Moreover, the authors find a stronger impact for children from lower socioeconomic background and the results suggest that the program could reduce the intergenerational persistence in educational attainment. Similarly, Sweden saw the introduction of a nurse home visiting program in the early 1930's and Bhalotra et al. (2017) find that, in the long-run, the infant care provided by the nurses reduced the probability of dying by age 75.

[40] Gandhi et al. (2017) present a systematic review of 16 randomized control trials that aimed to find out the impact of multidisciplinary in-hospital heart failure clinics. The results showed that patients had a lower incidence of heart failure hospitalization and all-cause mortality when followed up at such a clinic for at least 3 months.