THE ROOTS OF HEALTH INEQUALITY AND THE VALUE OF INTRA-FAMILY
EXPERTISE

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ABSTRACT

Mounting evidence documents a stark correlation between income and health, yet the causal mechanisms behind this gradient are poorly understood. This paper examines the impact of access to expertise on health, and whether unequal access to expertise contributes to the health-income gradient. Our empirical setting, Sweden, allows us to shut down inequality in formal access to health care; we first document that strong socioeconomic gradients nonetheless persist. Second, we study the effect of access to health-related expertise – captured by the presence of a health professional in the extended family – on health. Exploiting "admissions lotteries" into medical schools and variation in the timing of degrees, we show that access to intra-family medical expertise has far-reaching health consequences, at all ages: It raises longevity, improves drug adherence and reduces the occurrence of lifestyle-related disease in adulthood, raises vaccination rates in adolescence, and reduces tobacco exposure in utero. Third, we show that the effects of expertise are larger at the lower end of the income distribution – precisely where access to expertise is scarcer. Unequal access to health-related expertise can account for as much as 18% of the health-SES gradient, and may thus play a significant role in sustaining health inequality.

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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).

There is less evidence, however, on the exact pathways between SES and health. Multiple channels have been proposed. First, early-life health disparities driven by differential *in utero* conditions or genetic capital may perpetuate economic inequality (see, e.g., Currie, 2011; Aizer and Currie, 2014; Persson and Rossin-Slater, 2018).[1] Second, differences in health investments through diet, addictive behaviors, physical activity, and utilization of healthcare could lead to differential health outcomes.[2] Third, individuals on the lower rungs of the income ladder tend to have jobs that involve more manual labor, may 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] The relative contributions of these channels (or existence of others) to the health-SES gradient remain unknown.

In this paper, we investigate one possible underlying factor: the role of (unequal) access to health-related expertise. Intuitively, if health-related expertise improves health investment decisions, then an unequal distribution of expertise across the income ladder would induce a socioeconomic gradient in health. The goal of this paper is to shed light on, first, whether better access to expertise improves health; and second, to quantify the importance of this channel in sustaining health inequality. We use the presence of a health professional within the family as a broad measure of access to health-related expertise.

Investigating the causal impact of access to health-related expertise on health and the importance of this channel in perpetuating health inequality requires addressing two challenges. First, as emphasized by Currie (2011), analyses of health inequality, while ubiquitous, suffer from a lack of comprehensive data on health outcomes, often relying on 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 inequality in health outcomes other than mortality requires data linking individual medical

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[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. (2018a). Almond and Mazumder (2011) document a causal link between low birthweight and disability in adulthood. In the context of Sweden, Bharadwaj et al. (2018b) 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., 2010, Rosenquist et al., 2011, 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. (2018a) and Björkegren (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.

records to detailed measures of income. Second, 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 impact of better access to expertise from other unobservable differences between individuals with and without such access.

We address the first challenge by leveraging Swedish administrative population-wide tax records linked to inpatient, outpatient, prescription drug, and birth records, described in Section 2. Beyond the availability of data, Sweden is a particularly attractive empirical context because its universal health insurance system allows us to shut down another often-hypothesized driver of health inequality: inequality in formal access to health care. In Section 3, we begin by documenting three robust facts in this setting: Health inequality emerges early in life, persists throughout adulthood, and is, at the end of life, as pronounced in Sweden as it is in the United States.[5] These facts underscore the importance of studying other drivers of health inequality, and motivate our subsequent analysis of the role of (unequal) access to expertise.[6]

To address the second challenge – non-random allocation of access to health-related expertise – we zoom into an environment where we can precisely measure individuals' access to expertise, and where the institutional setting provides several sources of variation for causal identification. We hypothesize that members of a health professional's extended family have informal access to health-related expertise, and that this may improve their investments into their own health capital. If so, then we may observe better health, and possibly lower mortality, among individuals with access to intra-family medical expertise.

Indeed, this is what we show in Section 4. We begin by comparing the mortality and health outcomes of individuals in families with and without a health professional in the raw data. We show that, conditional on individual income rank at age 55, individuals with a doctor or nurse in the extended family are more likely to survive until age 80 and less likely to suffer from chronic lifestyle-related conditions. Further, children with a health professional in the extended family are substantially more likely to have undertaken a preventive investment that we observe – HPV vaccination by age 20 – and less likely to have been exposed to tobacco *in utero*.[7] These patterns in the raw data remain economically and statistically significant when we control non-parametrically for a wide range of observable demographics, in the spirit of the identification strategies 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 access to expertise 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 "admissions lotteries." In Sweden, a centralized admission process usually generates sharp GPA thresholds for admission to any university program. Due to substantial grade inflation (see, e.g., Diamond and Persson, 2016), the cutoff for all medical schools hit the

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[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. 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.

[6]The idea of considering factors other than formal access to healthcare is consistent with the largely mixed findings of a voluminous literature (mostly in US settings) that has investigated the causal effect of health insurance – which lowers the price and ease of access to formal healthcare – on long- and short-run health outcomes (Finkelstein et al., 2018b; Sommers et al., 2017).

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

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 from the lottery analysis are consistent with our non-parametric findings and show far-reaching health benefits for the admitted applicants' extended family (including grandparents, parents, siblings, children, cousins, and in-laws). Among older relatives, access to intra-family expertise reduces the occurrence of lifestyle-related diseases and improves drug adherence. For example, eight years after the applicant's matriculation, older relatives are 3 (5) percentage points less likely to have had a heart attack (heart failure), and 27% more likely to adhere to medication that can prevent heart attacks. Among younger relatives, access to intra-family expertise also raises preventive investments: adolescents are 20 percentage points more likely to be vaccinated against HPV by the age 25. Further, 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 gradual onset of some lifestyle-related chronic conditions, as the parents of medical school applicants are relatively young (while grandparents are frequently already deceased). We therefore complement this analysis with a second quasi-experimental approach: event studies that compare individuals' health before and after their (often younger) family member receives either a medical degree *or a law degree.*[8] We find striking differences in the health and mortality profiles of the two groups in the raw data, and our results are confirmed in a rich regression specification that reveal little trends in health outcomes predating the arrival of a health professional or lawyer in the family. "Getting" a doctor in the family yields a 10% reduction in mortality 25 years after the doctor's matriculation, along with substantially lower rates of heart attacks, heart failure, diabetes, and lung cancer. These effects emerge gradually, which points to improved health behaviors over a long time period.

Despite the fact that the results from our three identification strategies are not directly comparable due to the different samples and time horizons, they deliver largely overlapping insights, which underscores their credibility. In sum, access to intra-family medical expertise improves physical health and raises investment in health capital, at all ages. Moreover, across all empirical approaches and outcomes, we find that the treatment effects are equal or more pronounced at the lower end of the income distribution, suggesting that the value of intra-family health expertise is larger among the poor.

Section 5 discusses the mechanism and the implications of our findings for health inequality. We find no evidence of income effects. Similarly, our results do not appear to stem from preferential treatment, e.g., through higher-cost procedures or faster care, which would come at the expense of patients who lack intra-family medical connections. Instead, intra-family transmission of health-related expertise increases preventive investments and induces behavioral changes that, from society's perspective, are simple, cheap, and inherently *not* "zero-sum": for example, adherence to low-cost but highly effective preventive drugs, take-up of universally accessible vaccines, and cessation of tobacco use during pregnancy.

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[8]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.

This, in turn, suggests that the benefits accruing to health professionals' family members may, at least in part, be scalable through policies that mimic intra-family provision of expertise and promote these preventive investments and behavioral changes. What's more, as we document weakly larger impacts of expertise at the lower end of the income distribution, such policies may have the potential to close part of the health-income gap (see, e.g., Lleras-Muney, 2018).

To explore this point, we use our results to create a "universal access to expertise" counterfactual. That is, we ask how the health-SES gradient would change if we gave everyone in society access to expertise. An input into this calculation, in addition to our estimated treatment effects, is the baseline distribution of access to expertise in society (in the absence of any policy intervention). Data from the European Social Survey shows that this distribution is skewed, with less expertise among low-SES individuals. Consequently, a larger share of low-SES individuals (than high-SES individuals) would *gain* expertise under a universal expertise counterfactual.

Our back-of-the-envelope calculation suggests that providing universal access to expertise, and thereby equalizing access to expertise across the income distribution, could close as much as 18% of the health inequality gap. While this universal expertise benchmark is instructive in its own right – not the least by emphasizing that unequal access to expertise can generate substantial health inequality, even in a setting with equalized access to health insurance – we close by discussing whether and how a policy maker may be able to mimic intra-family provision of expertise. We speculate that such policies could be driven by both public and private entities, encompassing public health interventions as well as targeted design of private health insurance plans.[9]

Our work builds on and contributes to several strands of the literature. While a broad literature studies the importance of the family as a source of insurance (see, e.g., Lee and Persson, 2016; Autor et al., 2017; Persson, Forthcoming) or shocks (e.g., Persson and Rossin-Slater, 2018), a smaller body of work examines the importance of the family as a nexus for transmission of expertise, information, and norms. For example, Hvide and Oyer (2018) study parent-child communication of industry-specific knowledge, and Bell et al. (2017) analyze parent-child transmission of know-how and norms relevant to innovation. We instead focus on familial transfers of health-related expertise; further, we do not restrict attention to the the nuclear family, but analyze these processes in the broader extended family.

Our focus on health-related expertise relates the paper 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) 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

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[9]To the extent that the power of intra-family communication about health stems from trust or detailed knowledge about the health history and habits that come with a relationship that spans a long period of time, effective policies may need to strive to mimic the depth of these relationships. One example of such a policy may be a nurse outreach program with a strong emphasis on the continuity of care (yielding a *long-term* relationship); further, Alsan et al. (2018) suggests that providers which resemble the patient (in their case, same-race providers) may gain more trust. 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 Appendix Section C for a more detailed discussion of this literature.

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, and to Artmann et al. (2019) who study healthcare use among parents of medical doctors in the Netherlands.[10]

More generally, our findings contribute to the literature documenting a positive association between educational attainment and own health and health behaviors (see, e.g., Cutler and Lleras-Muney, 2008; Cutler and Lleras-Muney, 2010; Meghir et al., 2018). Further, Currie and Moretti (2003) document positive spillovers of maternal education on child health as measured by birth weight.[11] 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 the papers cited above, on expertise and 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.[12] 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.[13] 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.[14]

2 Institutional setting and data

2.1 Healthcare in Sweden

Swedish healthcare is a textbook case of a universal health insurance system. The government runs a large public insurer and finances its expenditures from tax revenue. Coverage includes inpatient care, primary and specialty outpatient care, and prescription pharmaceuticals. Patients incur little out of pocket cost, paying at most a

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[10]Similarly, Bronnenberg et al. (2015) provide evidence on how expert knowledge among pharmacists affects their willingness to pay for branded (versus genetic) pharmaceuticals.

[11]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.

[12]See, e.g., Adler et al. (1994) 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, Engineering, and Medicine (2015), The Future of Children (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).

[13]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).

[14]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 expertise elicits a weakly larger response at the lower end of the income distribution.

small co-pay.[15] Further, the public safety net reduces existing out of pocket obligations for some particularly vulnerable groups. Thus, in practice, individuals at any point in the income distribution have the same formal access to healthcare.

2.2 Data

For the universe of individuals living in Sweden over an extended time period, we use detailed mortality and medical records, matched to individual-level tax and educational records and a mapping of family trees spanning up to four generations.[16] 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 1936 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 (recorded starting with 1961 and up until 2017), 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 connect all individuals born in 1936 or later to both their own parents, as well as to their siblings and descendants – 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 for the adult population (age 16-74) over a 27-year time period, 1990 - 2016. These records contain detailed, third-party reported information about labor income, financial income, government transfers, as well as self-reported information about self-employment income. We use individual work and business income in our analysis.[17] The average individual pre-tax work and business income (among individuals with a positive income) in the last year of our data (2016) is 298,597 SEK ($34,878) with a standard deviation of 256,047 SEK. In the same database, we also observe educational attainment at an annual level, which allows us to know when individuals complete their degrees and which subject they studied.

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 years 1997 to 2016, specialist outpatient records years 2001 to 2016, and prescription drug records years 2005 to 2017. The inpatient records contain information on the universe of a patient's visits to the hospital, including cases where the individual is

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[15]Once a patient's out-of-pocket cost for medical care reaches SEK 1100 ($120) 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, once a *household*'s total out of pocket spending reaches SEK 2300 ($247) over a twelve month period, the co-pay is zero for all subsequent prescription fills during the remainder of the twelve-month period. 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.

[16]Statistics Sweden provides detailed description of the administrative registry data at www.scb.se.

[17]We examined several alternative measures of income, varying whether government transfers and investment income is included or excluded in the income measure. We did not find that our results were sensitive to these alternative specifications, as these variations tend to be rank-preserving.

admitted and discharged on the same day. The outpatient data records all visits *outside of* primary care.[18] 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-9 and ICD-10) 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 the drug name, the active substance, the average daily dose, and the drug's Anatomical Therapeutic Chemical (ATC) classification code. 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, matching them 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.

Educational records   Finally, we merge in educational records for year 2007 and onwards. There are two types of records. First, we use high school GPA information. This allows us to find medical school applicants with top GPAs, who would be competitive for randomized admission spots. Second, we use college application information. As college admissions in Sweden are centralized, we can observe the full set of programs to which each individual applies in each application cycle. We also observe admission outcomes, allowing us to track who gets admitted into (undergraduate) medical programs.

3   Inequality in health: the facts

We begin by documenting three robust stylized facts about health inequality in our setting: Health inequality emerges early in life, persists throughout adulthood, and is, at the end of life, as pronounced in Sweden as it is in the United States – despite Sweden's universal health insurance and a generous social safety net. These facts underscore the importance of studying the role of factors other than social insurance in sustaining health inequality, and motivate our subsequent analysis of the importance of access to expertise.

Inequality in mortality   To study inequality in mortality, we start with all individuals that are alive at age 55. These individuals are still several years away from retirement, allowing us to measure their work-related income, but are old enough to allow us to observe their deaths within our sample period. For each individual in this sample, we define an indicator for whether (s)he has died by age 80 – one of the key outcomes throughout

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[18]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.

our paper. Panel A of Figure 1 plots the share of individuals that died by age 80 against individual income rank at age 55.[19] Despite Sweden's generous social safety net and equalized formal access to health care, there is a strong gradient in cumulative mortality at older ages conditional on surviving to 55.[20] At the very bottom of the income distribution, more than 40% have died by age 80; at the very top, the corresponding number is below 25%.

It is instructive to briefly put these numbers in relation to the income gradient in mortality that has recently been documented in the U.S.. Figure 2 plots one-year log-mortality against own income rank in both countries, for three combinations of age at death and age of income measurement for which we were able to construct estimates that can can be directly compared to those reported for the U.S. in Chetty et al. (2016). In the first two panels of Figure 2, we plot log-mortality at age 75 against income rank at age 61 in the U.S. and age 60 for Sweden (a year before the earliest retirement ages in the respective countries), separately for men (Panel A) and women (Panel B).[21] We observe substantially lower mortality, at *any* point in the relative income distribution, in Sweden relative to the U.S., consistent with the notion that universal health insurance and a broad safety net may raise a society's overall level of well-being; however, the slopes of the mortality gradients are nearly identical in the two countries. The subsequent four panels of Figure 2 plot log-mortality at ages 60 and 40, by gender, against (gender-cohort-specific) income rank ventile measured two years earlier. While mortality inequality estimated at earlier ages is lower in Sweden than in the U.S. – especially age-40 inequality among women – the Swedish data reveals a pronounced mortality gradient at all three ages.[22]

Inequality in health outcomes in adulthood To measure inequality in health outcomes in adulthood, we start by defining indicators variables that capture any occurrence, at the individual level, of four common conditions that can be linked to lifestyle causes and that we can measure precisely in our data: heart attack, heart failure, lung cancer, and type 2 diabetes. Panel B of Figure 1 displays the share of individuals aged 55 or older that have a history of being diagnosed with at least one of these conditions, against individual income rank at age 55. The panel displays a steep gradient in the presence of these lifestyle-related conditions in the adult population. Individuals at the bottom ventile of the income distribution are more than twice as likely to have at least one of these conditions (20 percent) than individuals at the top ventile (10 percent). The income gradient is strongly pronounced in each of the four underlying conditions.

For younger adults – who do not have a high prevalence of the chronic conditions analyzed above – we

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[19]We use work-related income defined as the sum of income from employment-related activities as well as (positive) business income from self-employment. To calculate the individual's income rank, we measure individual's income at age 55, and rank individuals within birth cohort and gender. We use cohorts born in Sweden between 1936 and 1937, for whom we observe both income at age 55 and survival until age 80. The shape of the gradient remains the same if we use household income rank.

[20]We investigate, but do not separately report, mortality by gender. Among men at the at the 5th percentile of the income distribution at age 55, 48 percent are no longer alive by age 80; among men at the 95th percentile, the corresponding share is 25 percent. Female mortality is lower at all points in the income distribution, but we observe a very similar gradient. Women in the lowest 5 percent of the income distribution have a 11 percentage point lower probability of being alive than their most advantaged peers, 18 percent of whom are not alive by age 80.

[21]For these comparisons, we adjust our income measure so that it corresponds to the U.S. (positive) Adjusted Gross Income (AGI) measure, as used in Chetty et al. (2016). In particular, we add capital-based income and non-disability government transfers; we continue excluding individuals with zero or negative income levels.

[22]See Adler et al. (1994) for a review of early evidence of a socioeconomic gradient in mortality across different countries and a discussion of possible drivers.

examine a measure of preventive health investments: HPV vaccination by age 20.[23] We report the gradient in HPV vaccination among females 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 (i.e., 21 years earlier).[24] The solid triangles mark aggregate vaccination levels in our data, while the hollow circles are estimated separately for year 2007, which was the first year the vaccine was available in Sweden. The figure shows a sharp *reverse* gradient in this preventive health measure. Only about 10 percent of women born into households at the bottom of the income distribution get vaccinated against HPV, while 40 percent of women with parents at the top of the income distribution do. In 2007, the first year that the vaccine was available in Sweden (right y-axis), the levels of vaccination are an order of magnitude lower than in the aggregate data. The gradient is similar in shape, however, highlighting that young adults coming from more affluent households were much more likely to be early adopters of the new vaccine. This evidence of a gradient in the early adoption of a new medical technology is consistent with the argument in Link and Phelan (1995) and Cutler et al. (2006) that differential adoption of new medical technologies could be an important driver of health inequality. Our paper sheds light on a potential mechanism that could drive such differences in adoption.

Early emergence of the health-SES gradient   Having documented pronounced gradients in mortality, adult health, and youth preventive investments in Sweden, we now investigate whether the gradient emerges already in early life. This can help formulate or reject hypotheses about the mechanisms that lead to the gradient, and also point to the most efficient timing of potential countervailing forces such as exposure to expertise.

The lifestyle-related health outcomes analyzed above are rare early in life. Hence, to examine the extent of the health gradient in childhood, we zoom in into one of the most common chronic conditions in childhood - asthma.[25] Panel A of Appendix Figure A1 reports the gradient. We define an indicator that turns on when children have a record of an asthma diagnosis in their inpatient or outpatient records at ages zero to five. We observe a substantially higher prevalence of asthma among children growing up in lower-SES households than among their more advantaged counterparts.

Further, 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 or during pregnancy and an indicator for whether the child experiences a risky birth.[26] The gradient in tobacco use, depicted in Panel D of Figure 1, is remarkable, with more than 30 percent of mothers in the bottom income ventile using tobacco around the time of pregnancy, as compared to slightly above 5 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., Centers for Disease Control and Prevention, 2017); the steep gradient in tobacco exposure in-utero thus implies that babies born into

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[23]Human Papillomavirus (HPV) has been linked to several types of cancer, including cervical cancer.

[24]To calculate 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.

[25]Asthma is affecting nearly ten percent of all children in the United States (Chorniy et al., 2017); and in Sweden, already at age five roughly 11 percent are affected by asthma.

[26]A risky birth is defined as whether the mother has any of the following conditions during pregnancy: chronic kidney diseases, diabetes, epilepsy, lung diseases, systemic lupus erythematosus (SLE), ulcerative colitis, hypertension, or urinary tract infections.

disadvantaged households have received substantively lower health investments already before birth. Similarly, as shown in Panel B of Appendix Figure A1, adverse events at birth are more likely at the bottom of the income distribution than at the 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.[27]

Finally, to track the evolution of the health gradient over the life cycle, we use a health measure that is relevant at all ages: the number of inpatient visits. Panel C of Appendix Figure A1 displays the gradient in the number of inpatient visits in the first five years of life. While we observe a pronounced gradient already at age 5, it steepens substantially over the course of the life cycle, as illustrated in Panel D of the same figure, which displays the same outcome in the five years from 45 to 50.

In sum, this section documents that the health-SES gradient emerges early in life and persists and gradually steepens throughout the life cycle – despite Sweden's broad social safety net. This underscores the importance of studying the role of factors other than social insurance in sustaining health inequality. In the remainder of this paper, we examine one such potential piece of the puzzle: differential exposure to health-related expertise.

4 Access to expertise and health outcomes

4.1 Measuring access to health expertise

We are interested in measuring whether access to health-related expertise affects individuals' investments into their health and their subsequent health outcomes. Access to expertise may affect individuals through multiple mechanisms. Experts can transmit new knowledge about the costs and benefits of healthy behaviors and health investments, or they can remind, nudge or corroborate existing knowledge, making it more salient and trustworthy.

While it is intuitive that exposure to any or all of these underlying mechanisms may lead to more health investments and better health outcomes (indeed, the provision of knowledge has traditionally been one of the most common policy instruments), investigating the causal role of access to expertise is challenging. First, individuals receive streams of information and reminders relevant to their health from many differences sources throughout their lifetime, and these flows may be hard to measure; second, exposure to expertise is typically not randomly assigned. To overcome these challenges, we zoom in into an environment where we can precisely measure individuals' exposure to expertise, and where the institutional environment provides several sources of variation for causal identification: 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 expertise in the familial environment. This "access to expertise" channel encompasses transmission of (new) health-related knowledge to family members in a variety of informal settings; as well as reminding 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

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[27]The lowest rate of adverse events, however, occurs in the middle of the income distribution, where mothers are have access to more resources, but are still relatively young.

affect health through what we call the "access to care" channel: this, in turn, encompasses a variety of ways in which individuals may leverage the intra-family social capital and connections to the health care system to get better (for example, more expensive) or faster treatment.[28]

Throughout our analysis, we are interested in investigating the importance of the "access to expertise" channel, for two reasons. First, increasing access to health-related expertise in the population is fundamentally a scalable public policy. (In Appendix Section C, we review the extensive literature on several existing interventions that at their core all aim to increase health-related expertise in the population, such as nurse outreach programs, efforts to improve the continuity of primary care, and public health campaigns against smoking or for cancer screening.) The "access to care" channel in contrast, is fundamentally not scalable, as it implies individuals with family connections in the health care system getting ahead of those lacking such connections. This makes any policy that increases access to care, holding the total amount of healthcare resources fixed, a zero sum policy. Second, historically, the "extensive" margin of disease prevention through changes in social and individual investments into health - that we hypothesize can be affected by access to health expertise - has had a larger effect on population health than the "intensive" margin of moving from a lower to a higher quality of care provider, or getting care faster within a given system (Cutler and Lleras-Muney, 2008).

In this section, we analyze the impact of having a health professional 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 "access to expertise" channel being an important driver of our results.

4.2 Non-parametric evidence

We use the records of higher education to find individuals with health professional degrees - physicians and nurses - among the cohorts of working age adults in our analytic sample.

We define two groups of individuals who may benefit from (differential degrees of) access to expertise: the health professionals' *narrow* and *extended* families, respectively. The narrow family is defined as the health professional's spouse, parents, parents-in-law, children, and children-in-law. The extended family further includes the health professional's siblings, aunts and uncles, grandparents, and cousins.

We start by documenting differences in health between individuals in families with and without a health professional. Panel 3A of Figure 3 revisits the mortality gradient from Figure 1A, but now plots it separately for individuals with and without a health professional in the *extended* family.[29] We drop observations for individuals who are educated as health professionals themselves.

Panel 3A reveals two clear patterns in the raw data. First, there is a visually detectable difference in the probability of being alive at age 80, which persists throughout the income distribution: Conditional on income

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[28]Interestingly, in their ongoing work Artmann, Oosterbeek and van der Klaauw (2019) are finding - in the Dutch setting - that having a physician in the family in fact *does not* result in substantially increased access to care (on the contrary, it sometimes leads to less use), neither in terms of the quantity nor in terms of the price of care.

[29]Recall that the x-axis is the percentile of the individuals' age-55 work income rank, where work income includes wage income and self-employment income, but excludes government transfers and capital income. Our results are not sensitive to whether we include or exclude the other two sources of income. We use work income in our preferred specifications, as intuitively this is a broader measure of socio-economic status, pre redistribution programs. We restrict the sample to individuals with positive work income. As we condition on work income, we implicitly condition on being alive at age 55. Our results are also not sensitive to replacing individual income rank with household income rank.

rank, individuals with an extended relative who is educated as a physician or a nurse are more likely to survive to age 80. Second, this mortality difference is larger at the bottom of the income distribution.

We estimate the magnitude of the difference in cumulative mortality by age 80 at each income decile using the following OLS specification:

$$Y_i = \sum_{d=1}^{d=10} \delta_{d(i)} HP_i + \beta X_i + \epsilon_i \tag{1}$$

Here, Y_i is the mortality (or health) outcome of interest for individual i, HP_i is an indicator variable that takes the value of 1 if individual i has at least one medical professional in the family, and X_i is a set of demographic controls that are included in some specifications. The first term is a sum of indicators for having a medical professional in the family interacted with income rank deciles. The coefficients of interest are $\delta_{d(i)}$ that measure the average difference in the health outcome between individuals with and without a health professional in the extended family, for each age-55 income decile $d(i)$. We report the results of this regression in Panel 3B. The dashed line reports the estimates of $\delta_{d(i)}$ without any controls; thus, these estimates measure the raw vertical distance between the two plotted lines in Panel 1A. We estimate that, on average, individuals that have at least one extended family member who is a doctor or a nurse are 5.9 percentage points less likely to have died by the age of 80 conditional on being alive at age 55. This is a large difference relative to the average probability of having died by age 80 in the full sample, which is 31 percent, as it implies an 19 percent reduction in the probability of death. This is equivalent in magnitude to moving from the 70th to 100th percentile in the income rank distribution. Further, the difference varies by income rank, ranging from 7 percentage points on average in the lower half of the distribution to 4 percentage points in the upper half of the distribution.

Next, we examine whether these differences remain when controlling non-parametrically for a wide range of observable demographics, in the spirit of the identification strategies pursued by Bronnenberg et al. (2015) and Johnson and Rehavi (2016). The solid line in Panel 3B, as well as Panel A of Table 1, report results from regression equation (1) including the vector of observables X_i.[30] The pattern remains qualitatively the same across all income deciles: Individuals with a health professional in the family are less likely to have died by age 80, and the difference is on average larger at the lower end of the income distribution.

We now 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, heart failure, type II diabetes, and lung cancer, by whether or not an individual has a health professional in the extended family. The conditions are aggregated into a z-score index. The raw data again shows a visible separation in the prevalence of these chronic conditions between individuals with and without a health professional in their extended families. As the dashed line in Panel D suggests, the differences in the raw data are larger at the bottom of the income distribution. Moreover, less than 50% of the difference can be explained by our rich set of observables, leaving us with a clear pattern (solid line) of significantly lower prevalence of lifestyle-related conditions among older individuals with health professionals in their families. As Panel B in Table 1 documents, the difference remains on average larger at lower income levels.

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[30]The vector of controls includes fixed effects for: own income rank percentile, highest-earning relative's income percentile, year of birth, gender, individual's (discretized) educational attainment, and county of residence at age 55.

Figure 4 reports similar analyses for younger ages. In Panels A and B we examine the probability of young women receiving the HPV vaccine by age 20. 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. About two thirds of the differences persist when we control for observable characteristics, as can be seen in Panel C in Table 1 as well as in the solid line in Panel B of Figure 4.

Finally, panels 4C and 4D report the same analysis for the probability of being exposed to tobacco use *in utero*. We observe large differences in tobacco exposure rates for an unborn child in families with and without a health professional (including the mother of the child herself), especially at the lower deciles of the income distribution.[31] A child with parents in the first two deciles of the income distribution who has a health professional in the family is up to 8 percentage points less likely to have been prenatally exposed to tobacco than a child who has no medical professionals in the family. As Panel 4D and Panel D in Table 1 document, the gap in tobacco exposure rates monotonically declines with income rank and gets close to a precise zero at the top of the income distribution. While a substantial portion of the differences can be attributed to differences in observable demographics, observables do not account for the full gap, leaving a significant discrepancy of up to nearly 5 percentage points (or 14%) at the lower end of the income distribution (Panel D in Table 1). Further, observable differences cannot fully explain the pattern of a monotonically increasing gap with declining a income rank.

Figures 5 and 6 examine the heterogeneity in our non-parametric results along the intensive margin of exposure to a health professional in the family. We examine two dimensions of heterogeneity: geographic proximity, and proximity along the family tree. The left-hand side panels in Figures 5 and 6 report the estimated differences in health outcomes between: (i) individuals with a health professional in their broad (but not narrow) family and those individuals without any health professional relative (dashed lines); as well as (ii) between individuals with a health professional in their narrow family and those without any health professional (solid line). The differences in health outcome at each point in the income rank distribution are reported from the OLS regressions with the full set of controls as in Panels B, D of Figure 3, as well as the respective Panels in Figure 4). The right-hand side panels report the same analysis, but now splitting the sample by geographically close (solid line) and far (dashed line) health professional relatives. We define two family members as being geographically close if they have lived in the same county for more than 50% of the time during which they are observed in the sample.[32]

We consistently find - for both older and younger relatives - that the effects of a health professional in the family are substantially more pronounced if the health professional is a close relative. The differences are especially clear when zooming in onto the lower part of the income distribution. For example, at lower income rungs, having a health professional relative who is farther away along the family tree has very little effect on the prevalence of lifestyle-related conditions after age 55 (Panel C), while the effect is very pronounced for having a close relative who is a health professional. These results are intuitive, as we would expect the communication about health to be both more frequent and more open among closer family members. The results are more

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[31]Notably, we find even larger differences when we consider only (children of) expecting mothers that are healthcare professionals themselves. There is almost *no gradient* in the probability of tobacco exposure *in utero* among children of these mothers, with a level difference of up to minus 20 percentage points relative to the general population. Figure A2 in the Appendix illustrates this striking difference.

[32]County ("län") is the top level geographic division in Sweden, with 21 counties as of 2019. The largest county (Stockholm) has 2.3 million individuals, while the smallest (Gotland) has about 59 thousand people.

mixed for geographic proximity. We observe in Figure B that the mortality effect at the lower rungs of the income distribution is almost entirely driven by geographically close relatives, while the effects are similar at higher income rungs. For lifestyle-related diseases, there is almost no difference in the effects of having a health professional relative who lives far or nearby. For young children, the family tree and geographic proximity are often hard to separate, as children are likely to live in the same household as a close relative. In both cases, however, we find that HPV vaccination is more pronounced among young adults exposed to a health professional who is either a close family member or lives close by. For tobacco exposure, there is little difference on either of the intensive margins at the top of the income distribution, while the intensity of exposure appears more important at the bottom of the income distribution. These results suggest that intensity of access to expertise is crucial for health production. Frequent communication with close family members generates consistent two-way information flows that are typically not present and not emphasized in the interactions within a formal healthcare system.

While we control flexibly for a wide range of individual characteristics in this analysis, akin to the identification strategies pursued by Bronnenberg et al. (2015) and Johnson and Rehavi (2016), a remaining concern is that the presence of an HP in the family may be correlated with *un*observables. We therefore use two additional identification strategies to quantify the causal impact on health and longevity of having a health professional in the extended family.

4.3 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.[33] "Medical school" in the Swedish context refers to an undergraduate major in medicine - medical training starts directly in college and not in a post-graduate professional school. 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. 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 submits a rank ordered list of programs to the UHR. The applicant is not required to apply to programs only in the same discipline. For example, an applicant 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.[34] The applicant with the highest GPA gets her preferred choice, the second highest ranked applicant gets

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[33]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).

[34]There are also other quotas allocating applicants. 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 can add some extra points to the GPA.

the highest available choice for which she qualifies, and so on. For competitive programs, in which demand exceeds supply, this process generates GPA admission cutoffs for each program, around which admission is effectively randomized.

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 university 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 7 displays the maximum, minimum, and median GPA cutoffs for admissions to Sweden's six medical schools from 1998 to 2017.[35] 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 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.[36]

While the randomization of students with 20.0 into admission resembles a perfect RCT, one aspect of the institutional context complicate our analysis. Applicants who are not admitted on their first attempt, have the option of re-applying in subsequent application cycles.[37] The possibility of 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 choose to 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 this, we exploit admission on the student's *first* application attempt an instrument for whether an individual eventually becomes a medical student and ultimately graduates with a medical degree. We proceed by estimating the following two stage least squares (2SLS) relationship (and the associated intent to treat (ITT) relationship):

$$Y_{j(i)} = \delta MD_i + \beta_1 x_{j(i)} + \kappa_1 X_i + \epsilon_1 \tag{2}$$

[35]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.

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

[37]While waiting for the next application cycle, applicants may try to increase their admission chances, either by taking the scholastic aptitude test and attempting admission through the alternative quota, or by working.

$$MD_i = \gamma A_i + \beta_2 x_{j(i)} + \kappa_2 X_i + \epsilon_2 \tag{3}$$

In equation (2), $Y_{j(i)}$ is the health outcome of interest for applicant i's family member j (we consider all members of the extended family, as discussed above). MD_i is an indicator variable that takes the value of 1 if applicant i matriculated into a medical program. X_i and $x_{j(i)}$ are vectors of observable demographics of applicant i and his or her family member $j(i)$; these are not necessary for identification but improve precision.

The demographic covariates for the applicant and family member, respectively, include year of birth fixed effects, a gender dummy, and an indicator for whether the individual was born in Sweden. All regressions also include fixed effects for the type of relative that $j(i)$ is to applicant i (grandparent, parent, child, aunt or uncle, sibling, sibling's child, or cousin), and for family member $j(i)$'s own level of education. Further, we control for the number of medical schools the individual i applies to in the first application round, as this mechanically affects the probability of admission (to a program).

The coefficient of interest in equation (2) is δ, which measures the effect on health outcomes of having a family member get medical training. This coefficient may be biased if individuals whose relatives are in worse (or better) health systematically select into medical training. To address this concern, we instrument for MD_i with A_i as specified in equation (3). A_i takes the value of 1 if student i was admitted to medical school in the first application cycle. The resulting estimate of δ measures the effect of having a family member initiate medical school for the group of compliers (LATE). Here, the compliers are family members of applicants who went to medical school because they won admission in their first application cycle, but who would not have matriculated in a medical school had they lost this first lottery. The standard errors 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, parents-in-law, spouses, own children, aunts and uncles, siblings, siblings' children, and cousins.

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 matriculation into medical school. Among applicants admitted in the first application cycle, 96% matriculated into a medical program. Among those who were not admitted in their first cycle (but could re-apply), the corresponding figure is 59%, giving us a large and precise first stage of 37 percentage point difference in the matriculation probability.

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).[38] Accepted and rejected applicants were equally likely to be born in Sweden (97 percent in the accepted

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[38]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 chose this route for 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

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 the father was born in Sweden) for all observables except age. We conclude that the evidence in Table 2 is consistent with an essentially random breaking of ties in medical school admission decisions for this group of highest GPA students. We thus proceed to use the first application cycle admission decision as an instrument for whether an individual matriculates into medical school.

We report results (ITT and LATE estimates) separately for older and younger relatives of the health professional, as the sets of relevant health outcomes and health investments differ.

Health of older relatives Table 3 reports our estimates of the effect of an individual gaining a medical education on the health outcomes of relatives aged 50 and above. 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 observe in our sample. This time horizon captures the period of medical education, which typically lasts for 6 years, and the first two years after medical school completion.

For older relatives, we consider two sets of outcomes: (i) outcomes that capture preventive investments, and (ii) outcomes that capture physical health, in particular the life-style related conditions analyzed above. For preventive investments we focus on those that are likely to reduce the risk of life-style related conditions, and those that can be measured precisely in our data. In a final step, we aggregate all the specific outcomes into a single health index. All outcomes are scaled in per 1,000 individuals to aid in interpretation.

Preventive investments We consider eight measures of preventive investments that can be observed in our data: adherence to three types of drugs that reduce the risk of cardiovascular disease; adherence to diabetes drugs; take-up of Vitamin D (among women, for whom this vitamin is recommended in old age); adherence to asthma medication; the occurrence of preventable hospitalizations, and addiction to alcohol or drug substances.

Columns (1), (2), and (3) report the intent to treat (ITT) effects (with and without controls), and the local average treatment effect (LATE), respectively. In columns (4) and (5) we report two different benchmarks that are useful for interpreting the ITT and LATE coefficients. Column (4) reports a simple mean among family members of applicants who loose the lottery on their first application attempt. In column (5) we report the complier mean among control compliers. Within our control group, we observe individuals that decide not to attempt another medical school application when they loose the lottery. Conceptually, this group of individuals

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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 the year of birth non-parametrically in our regressions.

includes (untreated) compliers and never takers. From 2, we see that only 4% of individuals that win the lottery do not matriculate into a medical school, so the share of never-takers in our data is extremely low. In that case, family members of individuals who loose the lottery and do not re-apply, are predominantly compliers. Computing the mean of outcomes among the family members of these individuals allows us to directly estimate the mean of potential outcomes under no treatment for compliers. This is what we report in Column (5).

We first study effects on adherence to chronic medication. We measure adherence as the probability of purchasing medication conditional on having any condition that may warrant the need for this medication.[39] We consider three common cardiovascular drugs: statins (for lowering high cholesterol), blood thinners (for reducing the chance of blood clots), and beta blockers (used for prevention and treatment in multiple cardiovascular conditions). Individuals in the treatment group, i.e., relatives of individuals who win the medical school lottery in their first application attempt, are substantially more likely to adhere to these medications. The effects are economically large for all three outcomes, and statistically precise for statins and blood thinners. For example, on average 247 out of 1,000 individuals in the control group purchase blood thinners, while in the treatment group it is 31 more people per 1,000 - a 13% increase (ITT). The effect of having a relative matriculate into medical school (on the compliers) is in turn larger, with 69 more people taking the blood thinning medication, which represents a 25% increase off of the control complier mean (LATE). The relative increases are qualitatively similar for the other two cardiovascular drugs: 27% and 9% increases in adherence to statins and beta blockers, respectively (LATE). Further, older family members of lottery winners are 20% (ITT) more likely to adhere to diabetes medication conditional on having the disease. Female older relatives also take prescription strength (rather than over-the-counter) vitamin D (vitamin D deficiency is common with aging, especially among women) at higher rates: 32 out of 1,000 women in the conditional complier mean take the vitamin, while 41 per 1,000 more do among treatment compliers (LATE). We find positive but noisy differences in adherence to asthma medication. We find no systematic evidence of a decline in what we measure as preventable hospitalizations for older adults, but find some evidence of a decreased probability of addiction-related diagnoses in medical data, which captures addiction to alcohol or drug substances.

Physical health We next turn to the analysis of the effect on physical health, in particular conditions that commonly are considered to be linked to lifestyle decisions. We find that 42 out of 1,000 individuals in the control group have a heart attack during our observation period. Among individuals whose relative wins the medical school lottery, the rate declines by 18 out of 1,000 people - a remarkable decrease of 44% (ITT). Exposure to a health professional among compliers leaves this group with only 14 per 1,000 individuals with a heart attack. Importantly, as we are measuring the effects over a relatively short time frame, we cannot ascertain whether this decline is permanent or represents a short-run delay of this acute cardiovascular event.[40] We find similarly large effects on the probability of being diagnosed with heart failure: a decline of 27 per 1,000 individuals (ITT), or

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[39]In addition to the controls discussed above, the subset of regressions where the outcome captures individuals' drug purchases also includes controls for the presence of asthma, type II diabetes, heart failure, ischemic heart diseases, stroke, hyperlipidemia, or hypertension.

[40]In general, our estimates are not inconsistent with the results of related clinical trials; however, the direct comparison is hard to achieve for two key reasons: first, our timeline is actually long for the world of clinical trials, hence only few trials have been run over a comparable time period; second, nearly all large-scale clinical trials test the effect of one medication at a time, so that the composite effect of higher exposure to several cardiovascular medications at a time - which we are clearly observing in the data - is unknown.

51 per 1,000 among compliers (LATE), off of the mean of 74 per 1,000 cases in the control group and 101 among control compliers. We do not find any evidence of a reduction of type II diabetes or lung cancer.

To address the issue of inference with multiple outcomes and to improve statistical power, we aggregate all eleven measures into a "health index," following the approach in Kling et al. (2007). We first orient all outcomes in the same qualitative direction (for example, for statins more is "good," while for addiction less is "good"). We then construct a z-score for each outcome (subtracting the control group mean and dividing by the control group standard deviation) and take an unweighted average across all outcomes.[41] The result suggests that, among older adults, exposure to a family member who matriculates into medical school yields a large and statistically precise improvement in health.

In the analysis of medical school lotteries, 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 on 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 "access to care" channel is an important driver of these results. While in training, future physicians are exposed to a lot of information, but they cannot directly write drug prescriptions and are unlikely to have strong professional networks to enable them to help their family members "jump lines." We return to the long-run analysis of the prevalence of chronic conditions and mortality in Section 4.4, where we use a different empirical strategy to examine these important outcomes.

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 - cheap and simple - investments into their health, than similar individuals in families without a physician in training, and hence without informal access to health expertise.

Health of younger relatives   Table 4 reports estimated effects of exposure to health expertise on the health outcomes of younger relatives.[42] We measure health outcomes starting in year $t+1$ after matriculation and until year $t+6$.[43] We consider eight outcomes that are either preventive investments or health outcomes that are plausibly amenable to health expertise: HPV vaccination, not using hormonal contraceptives, having substance addiction, experiencing injury or poisoning that require a hospitalization, the number of inpatient stays, and occurrence of respiratory infections, intestinal infections, and chronic tonsil diseases.[44]

Columns (1), (2), and (3) again report intent to treat (ITT) effects without and with covariates, and the local average treatment effect (LATE), respectively. Among female relatives aged 10 to 25, we estimate a large and

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[41]The index is on average equal to zero in the control group, by construction, since we are normalizing the z-score to the control group mean.

[42]Recall that these include the health professional's siblings, cousins, own children, or siblings' children.

[43]We take a shorter time window for younger relatives. There are fewer younger than older relatives in the sample, while they experience adverse health events much less frequently. A shorter follow-up window allows us to increase the sample size, and unlike for the chronic conditions of the older relatives, for the conditions of the younger relatives, we would expect the effects to appear faster.

[44]We consider *not* using hormonal contraceptives as a positive health investment, since we find overwhelming evidence of physicians themselves substituting away from hormonal birth control. Concerns about the side effects of these medicines that have been documented in the clinical literature may drive this observation, although we cannot pin down the exact underlying mechanism with certainty.

positive effect on take-up of the HPV vaccine. While 119 out of 1,000 individuals are vaccinated in the control group (174 among compliers), our estimates imply increases of 62 per 1,000 (ITT) and 202 per 1,000 (LATE) – an increase of more than 200% among compliers.[45] We estimate similarly large effects for the avoidance of hormonal contraception. While 655 out of 1,000 young women aged between 10 to 20 do not use hormonal contraception in the control group, 132 women (20% more) refrain from this form of contraception among those with a lottery winner (in the first application attempt) in the extended family (ITT).

We further find large effects of being exposed to a health professional in the family on the probability of having an injury or poisoning that warrants a visit to a hospital (in inpatient or outpatient specialist care). The rate of substance addiction that warrants a visit to a hospital or specialist care among young individuals in the control group is 19 per 1,000; the corresponding number in the treatment group is significantly lower at 7 per 1,000 - a decline of 63% (ITT).

Our estimates for inpatient stays paint a similar picture. We find that younger relatives of those who win the lottery have a third of the number of inpatient stay days. We do not capture any differences in the rates of severe injuries or poisoning (which are experienced by about a quarter of individuals in the sample), and we also do not find that being exposed to a health professional lowers the rates of respiratory infections, intestinal infections, or chronic tonsillitis.

Overall, we conclude that for younger generations, having a new doctor-in-training in the family appears to have positive effects on health: We see lower prevalence of addiction, fewer inpatient days, and a larger probability of preventive investments. Finally, we summarize our eight measures into a health index, constructed in the same way as for the older family members. The estimate suggests that, among younger family members, informal exposure to a health professional yields economically and statistically significant improvements in health.

4.4 The event of a family member becoming a health professional

While the Swedish medical school lotteries resemble an RCT and thus represent a near-ideal setting to examine causal effects, the short follow-up period precludes us from studying the long-run impact of exposure to expertise on older adults. We therefore complement this research design with event studies that exploit the timing of the arrival of a health professional in the family. Consistent with the analysis in Section 4.3, we define the event of a family member matriculating into medical school as the start of exposure to expertise.[46] Which families experience this event is not random. However, we can still assess whether having a doctor in the family impacts the health of family members by observing how the trends in health evolve over time for families that experience this event relative to the trends in health in (similar) families that do not.

In particular, we compare the families of individuals trained as medical doctors to the families of individuals trained as lawyers. Both types of families have similar socio-economic status, with income distributions that are skewed towards the top ventiles (although family members are present at all points in the income distribution). Moreover, admittance into law school – a similarly prestigeous education – also requires a high GPA.

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[45]Interestingly, even in the families of compliers, we still only estimate an about 40% take up of this routinely recommended vaccine.

[46]We do not require that the medical profession is pursued after college, though in practice the vast majority pursue medicine.

We need two key identifying assumptions that appear plausible in our context. First, we require that access to health expertise arrives to families after an 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 appear plausible given the long timeline that typically accompanies the decision to pursue a medical degree and the slow process of chronic disease development.

Before turning to a formal regression specification, we investigate whether the assumptions we require for identification, as well as the hypothesized effects, are supported by the raw data. Figure 8 documents raw differences in the probability of adverse health outcomes between individuals with a child who received a medical degree versus a law degree. In Panel 8A, we plot mortality. In particular, we take the five cohorts of individuals born in Sweden between 1936 to 1940, and select individuals who have at least one child with a medical or law degree. We exclude individuals who are health professionals themselves (either a doctor or a nurse) or who have a health professional spouse.[47] In this sample, we compute the share of individuals that died by each calendar year starting with year 1980 (i.e. starting when the individuals are aged 40 to 45). We keep individuals in the sample even if they die, so the figure records cumulative mortality. Panel 8B confirms that individuals in our two samples have identical average age. (This is what we would expect absent any dramatic–and unlikely–differences in the probability of having a lawyer or a doctor child across the 1936 to 1940 cohorts.) In earlier years, mortality rates are visually identical between the two groups. Around 1995 (ages 55 to 60), however, a diversion emerges between the mortality trends of lawyer-parents (hollow circles) and doctor-parents (filled triangles). Throughout years 1997 to 2017, parents of doctors are dying at a slower rate than parents of lawyers. The difference becomes economically and statistically significant over time, converging to a difference of 243 per 1,000 individuals having died among lawyers' parents by 2017, as compared to 208 per 1,000 individuals among doctors' parents. The difference of 35 per 1,000 lives (or 14%) is statistically significant at less than 1% level.[48]

In Panels 8C to 8F, we repeat a similar exercise for our set of four chronic, lifestyle-related conditions: heart attacks, heart failure, type II diabetes, and lung cancer. As our medical claims data starts much later than our mortality data, we track individuals starting in year 1997 (up until 2016). To be able to observe individuals prior to older age when the onset of conditions is already likely to have had started (and to increase precision), we increase the sample size by pooling the cohorts from 1936 to 1961. This cohort choice implies that we track individuals' chronic diagnoses from the age of 36 to 81. We observe remarkably similar patterns across all of these conditions. As with mortality, in the early years of our data, the prevalence of chronic conditions is indistinguishable among individuals with a lawyer and a doctor child. Eventually, significant differences emerge, however, with parents of doctors having a persistently lower prevalence of all four chronic conditions. By the end of our sample period, in 2016, parents of doctors will have had 3 per 1,000 fewer heart attacks (7% fewer compared to the base of 42 heart attacks per 1,000 individuals in the lawyer-child sample); 4 per 1,000 fewer cases

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[47]For lawyer-parents we further exclude those who had a child that became a nurse, while for the physician-parents, we exclude those who had a child that became a nurse before another child became a doctor.

[48]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.

of heart failure (10% fewer relative to the base of 40 per 1,000 among lawyer-parents); 8 per 1,000 fewer cases of type II diabetes (11% fewer relative to 76 per 1,000 among lawyer-parents), and finally 2 per 1,000 fewer cases of lung cancer (18% fewer relative to the lawyer-parents baseline of 11 per 1,000 cases). All of these differences are again economically large and highly statistically precise.

These sharp patterns in the raw data support our event study approach, as they suggest both that the deviation in the trend of chronic condition incidence and mortality happens long after individuals' children are likely to decide to start their (undergraduate) degrees in law or medicine. Further, we observe non-trivial differences in the incidence of chronic conditions and mortality between these two groups of parents at older ages, despite their largely similar socio-economic standing (as illustrated in Appendix Figure A4).

We now turn to a more formal analysis of these patterns and 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. While for simplicity we considered only parent-child link above, we now expand our analysis to the full set of relatives and consider health outcomes of parents, parents-in-law, as well as aunts and uncles of a medical doctor or a lawyer. 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, in which we include the entire vector of age fixed effects to account for the fact that age is one of the most important determinants of health.

The set of κ_τ:s are event time fixed effects and separately capture the evolution of health in event time. The coefficients of interest are σ_τ that measure the impact of a health 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 starts training as a physician (or a lawyer). We normalize σ_{-1} to zero, so that all other σ_τ's are interpreted as changes in health relative to one year before the young family member matriculates into a medical or a law program. For a subset of families with a health professional (or lawyer) in the family, we do not observe the time at which they acquire their medical (or legal) degrees. Rather than excluding these individuals from the sample, we impute the timing of their degrees using high school completion year.[49]

Figure 9 illustrates our results. We consider two main long-run outcomes: mortality and chronic conditions at older ages. For each health outcome, we plot the estimated σ_τ:s against τ. Coefficient estimates for negative

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[49]For all individuals for whom we observe the year in which they acquire a medical (or law) degree, we count back 6 (or 5) years to define the matriculation year, as these are the common lengths of the undergraduate medical and legal programs. In event studies that examine mortality, we consider cohorts born in 1936 to 1940. In 17% of cases for doctor-relatives and 21% of cases for lawyer-relatives, we do not observe the exact year in which the relative acquired a medical or a legal degree. For these observations, we impute the age of matriculation as the year of high school graduation. In the analysis of chronic conditions, we observe the exact graduation date in 97% and 96% of cases, and impute the rest using high school graduation year.

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 familial health. Our estimates strongly support this assumption, which is consistent with our observations in the raw data on parental mortality and morbidity.

Panel (A) illustrates the impact of having a family member trained as a physician on the probability of death.[50] We observe a clear slow-down in the relative mortality rate among relatives of doctors (as compared to the relatives of lawyers) that starts emerging around year 8 after the young relative matriculates into college. The mortality gap then steadily widens for two decades. As Column (1) in Table 5 reports, the point estimates suggest a 1.7 percentage point decrease in the probability of death by event time 25, which corresponds to a 10 percent decline off the mean among relatives of lawyers, which is 17%.

Panel (B) of Figure 9 captures the impact on the aggregated incidence of lifestyle-related chronic conditions. We plot the same "lifestyle" index that we examined in the non-parametric analysis, which is a z-score incorporating the following conditions: heart attack, heart failure, type II diabetes, and lung cancer. Consistent with the observations in the raw data and our lottery-based results, we observe a significant divergence in health between relatives of doctors and lawyers that emerges around year 5 post college matriculation. The divergence widens for two decades post college matriculation, as can also be seen in Column 1, Panel B of Table 5.

We report separate event study results for the four chronic conditions underlying the lifestyle index in Appendix Table A1, and graphically in Appendix Figure A5). We observe that differences emerge at around year 9 post matriculation in the probability of having a heart attack and at around year 5 for congestive heart failure. The differences persist and expand over time. We observe a similar pronounced divergence in the incidence of type II diabetes and lung cancer. Fifteen years after matriculation, relatives of doctors are 1 percentage point (23 percent) less likely to have a diabetes diagnosis and 20 percent less likely to have lung cancer. These long-run patterns are consistent with the idea that responses to exposure to expertise include the formation of healthier behaviors and the adoption of new preventive measures, and that these long-run processes yield cumulative health benefits that grow important over time.

As in the non-parametric analysis, we further examine the heterogeneity of our event study effects by income and proximity - both geographically and along the family tree. Columns (2) to (7) in Table A1 report the results. As in the non-parametric analysis, we find that individuals with income in the lower half of the distribution are more affected (we find 35% higher impact in the fist half of the income distribution) by exposure to expertise.[51] Further, family members that live closer to each other geographically benefit more, which is consistent with the importance of rich and persistent information transmission between the family member and the health professional, playing a key role in our results. We do not find substantial differences in the impact on mortality along the family tie dimension, while the impact on chronic conditions is stronger among closer family members.

Overall, we conclude that having a relative with a medical education has positive and quantitatively significant health benefits. These effects are present both at the top and at the bottom of the income distribution. In families

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[50]The outcome is an indicator taking the value of 1 if the individual has died by time t, and the value zero otherwise (i.e., if the individual is still alive in time t. The outcome thus captures the timing of death.

[51]To facilitate the heterogeneity analysis by income and geography, we switch our sample to younger cohorts - 1946 to 1955. While our mortality records go far back, the information on income and geography is available for a more recent time period only. The difference in samples accounts for the differences in relative and point estimates across the specifications.

with a physician, older relatives live longer and are less likely to experience common chronic conditions such as diabetes or a heart failure. Our event study results on long-run outcomes are qualitatively and quantitatively in line with our non-parametric and (short-run) lottery-based analyses, despite the fact that the three analysis samples are different and cover different time frames.

5   Exposure to expertise and health inequality

5.1   Mechanisms

So far we have used three strategies to estimate the same empirical object - how the presence of a health professional in the family affects the health of family members. Having a health professional in the family is likely to affect individuals though multiple channels. We have focused our analysis on a set of outcomes that we argue are amenable to expertise, but that are unlikely to respond to other mechanisms. We lay this argument out in more detail in this section.

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 in the family could stem from access to care rather than access to expertise. This "social capital" channel would imply that health professionals get their family members more or better *healthcare* rather than to more or better *expertise* - for example, by getting them quicker appointments or advocating for costlier treatments.

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 flexibly control for individual income as well as for the income of the highest-earning relative. In the event studies, to address the potential concern of income effects, we contrast family members of physicians to family members of lawyers, who have similar overall income profiles.

There are 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 for two reasons. The time horizon we consider encompasses primarily the years of training rather than the years of working as a physician. Further, 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).[52] 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

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

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 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 in the Swedish setting.[53]

Social capital   Another mechanism through which the presence of health professionals in the family can affect health outcomes is what we refer to as the access to care (or "social capital") mechanism, where the impact runs through preferential informal access to healthcare within the formally equal system.

It is instructive to distinguish between the access to expertise and access to care channels, which in principle may exist in tandem, as they have distinct policy implications. Conceptually, responses that stem from improved access to expertise may be scalable through policy interventions; we discuss this in more detail later in this section. Benefits that stem from improved access to formal care, in contrast, cannot be scaled with fixed healthcare resources, almost by definition: If the family members of health professionals bypass other patients who lack connections, then this implies a zero-sum game where connected patients benefit at the expense of unconnected ones. Hence, it is important to understand whether there is any evidence suggesting the presence of the (potentially scalable) access to expertise channel. To do this, we focused our analysis in section 4 on outcomes that are more likely to be amenable to expertise and less likely to depend on access to care.

Specifically, for older adults, we considered a set of chronic 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. Further, improvements in these outcomes are not zero-sum: one patient avoiding a heart attack does not come at the expense of another patient avoiding a heart attack, and so on. Second, we considered preventive investments by older adults related to these lifestyle conditions: adherence to chronic cardiovascular medication, consumption of drugs for diabetes and asthma, and taking prescription strength Vitamin D. A response in adherence to such drugs would very likely be driven by the expertise channel (which, broadly defined, includes the provision of information about the benefits of these drugs; as well as reminders, nudges, and "nagging" about drug adherence) rather than the access to care channel, as these medications are cheap and easily obtainable – they are off patent, and included on the national prescription drug insurance formulary.[54] We further investigated addiction and *avoidance* of (potentially costly) hospitalizations, neither of which we would expect to respond to access to care.

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 or a non-hormonal method of contraception, for example, does not come at the expense of another patient obtaining the same treatment. We also documented a reduction in the number of inpatient stay days among family members of health care professionals; under the access to care channel, we would have expected the reverse. Further, the rates of addiction and infections is likely

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[53]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.

[54]In the lottery analysis, our results "show up" while physicians are still in training, and hence cannot prescribe these medications themselves. This rules out "ease-of-prescribing"-effects.

to be diagnosed at higher rates conditional on the true prevalence of the disease among families with links to the healthcare system; despite this, we consistently find either negative results or noisy zeros. In a nutshell, effects on all these outcomes likely do not reflect the impact of access to care.

In sum, we establish impacts on outcomes that are inherently *not* zero-sum; that are driven by decisions that individuals make in their everyday lives as opposed to actions by physicians within the healthcare system (lifestyle decisions such as diet and exercise, tobacco use during pregnancy, and so on); and that involve adherence to cheap and readily available drugs. These are outcomes for which "connections" to the healthcare system likely matter very little. This is consistent with the fact that, in our lottery analysis, the "treated" group is exposed to a young physician – either in medical school, or in the first two years after finishing medical training – who likely has few connections.

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

First, we investigate whether family members of health professionals obtain more expensive heart attack treatments. The underlying idea is as follows. There are two common invasive therapies, one of which is substantially more expensive than the other, and one non-invasive (drug) therapy, which is the cheapest; under the "social capital" hypothesis, connected patients may be more likely to get a relatively expensive treatment option (holding severity of the condition constant).[55] We find no evidence of differences in the probability of getting an invasive (versus non-invasive) heart attack treatment 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 the duration of postpartum care is generally rationed in the Swedish healthcare system – mothers are discharged as early as six hours after childbirth, while mothers in the U.S. are legally entitled to stay for up to 48 hours, depending on the state – 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 access to care channel for cancer treatment, as existing literature has documented that connections appear relevant for the choice and speed of cancer treatments (Fiva et al., 2014). Here, we do find a smaller time window between the first diagnosis of breast cancer and breast cancer surgery among family members of health professionals. However, there is no pronounced income gradient in the prevalence of cancers, nor in mortality attributable to cancer.[56] This suggests that, at the population level, the access to care channel does not generate substantial differences in cancer-related outcomes across the income

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[55]The two invasive therapies are coronary artery bypass grafting (CABG) and percutaneous coronary intervention (PCI), with the former being a more expensive open heart surgery.

[56]In fact, if anything, we observe an *inverse* SES-gradient in cancers, which likely is driven by competing risks with cardiovascular diseases as well as more screening at the upper end of the income distribution. The exception is lung cancer; however, it accounts for a very small share of all cancers.

distribution.

To be clear, our investigation into access to care mechanisms is not exhaustive – this, however, is beyond the scope of our paper. Overall, our focus on expertise-amenable outcomes allows us to argue that there exists an effect of health professionals on their family members' health *that does not run through social capital*, and hence that may be scalable. Moreover, our results point to simple interventions such as encouragement of vaccination, promotion of adherence to basic chronic medication, and aid in cessation of tobacco use among pregnant women. It is noteworthy that any interventions that increase these beneficial behaviors will have only a small effect on health care expenditure. Moreover, they are cheap when compared to other potential interventions aimed at improving population health, such as expansions of access to expensive treatments conditional on having a disease.

5.2   Implications for the health-income gradient

So far we have showed that there is an average treatment effect of being exposed to a health professional in the family on health. We have also documented that the effects on health do not accrue only at the top of the income distribution, but instead are similar, or even more pronounced, in the first half of the income distribution. We now use these findings to create a "fully-informed" counterfactual. That is, we ask how the health-income gradient would change if we made everyone in society exposed to expertise. We then discuss potential policy interventions that could "mimic" intra-family expertise (without raising the number of health professionals in families) for moving towards this counterfactual.

To create our counterfactual, we need two inputs: (i) the impact of expertise on health at different points in the income distribution; and (ii) the baseline distribution of access to expertise in society today, i.e., in the absence of any policy intervention.

It is straightforward to see why we need (i), and our finding that the beneficial effects of exposure to health-related information are weakly larger at the lower end of the income distribution already suggests that a policy that makes everyone exposed to expertise could close part of the health-SES gradient. If, in addition, individuals at the lower end of the income distribution have access to less expertise, then this would further reinforce the impact of policies that provide access to expertise on overall health inequality (as a larger share of individuals at the lower end of the income distribution would move from "unexposed" to "exposed" under such a counterfactual). Thus, we turn to a discussion of (ii).

The baseline distribution of expertise It seems a priori reasonable to hypothesize that individuals at the higher rungs of the income ladder have access to more expertise. Intuitively, they likely have had a longer formal education, have access to more informed friends and relatives, a higher ability to search for information on their own, and possibly more "mental bandwidth" to remember to take prescribed medications, among other channels (Mullainathan and Shafir, 2013). Table 6 provides empirical evidence in support of this idea. Here, we use data for Sweden from two waves of the European Social Survey, run in 2004 and 2014, when the health-related questionnaires were included. We use six measures that may reflect the degree of access to health-related expertise: (i) whether individuals agree to the statement that "a doctor always tells the truth;" (ii) whether

they prefer to see the same doctor over time; (iii) whether they regularly eat fruits; (iv) whether they regularly eat vegetables; (v) whether they exercise regularly; and (vi) whether they smoke. The first two measures are in principle indicative of the "demand" for expertise and trust-based relationships, which we would expect to be higher if access to expertise outside of the formal healthcare environment is scarcer. The latter four measures are indicative of individuals' health behaviors.

We relate these survey responses to whether the individual has a college degree. This is a measure of socioeconomic status that is both available in the survey and allows us to connect the survey evidence to our administrative data, since in the administrative data we observe the share of individuals with a college degree at any point in the income distribution. As columns (1)-(6) of Table 6 illustrate, we find a strong correlation between formal education and our proxy measures for exposure to health expertise. This is consistent with the idea that individuals with lower socioeconomic status have access to less health-related expertise at baseline.[57]

Given this evidence, in our counterfactual calculation we use the share of individuals with a college degree as a proxy measure for the prevalence of access to expertise. Figure A3 in the Appendix plots the share of individuals with a college degree across the income distribution in Sweden. For the cohorts for which we consider mortality outcomes by age 80 - 1936 to 1937 - 7% of individuals had a college degree in the lower half of the income distribution, while 31% had a college degree in the top half of the income distribution.[58] The large difference in formal education – and in the health-related survey responses associated with it in the ESS data – across the income distribution suggests that access to the type of expertise that is relevant for making decisions about health behaviors and health investments likely is substantially scarcer at the lower end of the SES spectrum than at the top.

A counterfactual: universal access to expertise In Figure 10, we combine our findings into a back-of-the-envelope calculation of the potential effect of providing universal access to expertise on the mortality-income gradient. We make the following two assumptions: First, we assume a uniform treatment effect of access to expertise on mortality of 10% across the income distribution. This is our aggregate estimate from the event study (which is consistent with the estimate from our non-parametric analysis); thus, it is a conservative estimate of the impact on mortality at the lower end of the income distribution. Second, we assume that the baseline level of expertise follows the same distribution as the college share, so that we start from a situation in which 7% of individuals in the first half of the income distribution have access to expertise, while 31% do at the top. Under these two assumptions, we compute the counterfactual mortality levels that would result, in the top and the bottom halves of the income distribution, respectively, under a policy that gives universal access to expertise.

To compute counterfactual morality as the bottom (top) half of the income distribution, we start with observed mortality by age 80 (at the level reported in Figure 1A). We then assume that a hypothetical policy moves the percentage of individuals that have access to expertise by 93 (69) percentage points (moving everyone to 100%), and that these "treated" individuals experience a 10% reduction in mortality.[59] The calculation

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[57]As a sanity check on the ESS survey data, we also verify that individuals without a college degree report being in worse health in Column (7) of the Table.

[58]The gap in formal education is comparable for younger cohorts. In a pooled sample across all cohorts for whom we can observe formal education levels, 16% of individuals have a college degree in the bottom half of the income distribution, and 44% in the top half.

[59]The resulting formula for counterfactual mortality is: observed mortality within the income group times the treatment effect

suggests that a policy that creates universal access to health-related expertise by successfully mimicking intra-family communication would shrink the mortality-income gap substantially: from the observed mortality gap of 0.076 between the top and the bottom halves of the income distribution, to 0.063. This corresponds to a 18% reduction in the mortality-SES gradient.

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

Towards closing the health inequality gap While the benchmark of universal expertise is instructive in its own right – not the least by emphasizing that unequal access to expertise can, on its own, sustain substantial health inequality – we now speculate as to whether our findings point to particular policy interventions that may be able to scale up the beneficial impact of access to expertise.

One view of our results is that they emphasize the limits of government intervention. Sweden provides cheap and universal access to inpatient and specialized care, prenatal care, primary care, prescription drugs, and vaccines; and yet substantial inequality remains. Our results indicate that this remaining inequality could in part stem from decisions that individuals make outside of the healthcare system, such as whether to undertake beneficial lifestyle investments, whether to adhere to prescribed (and cheap) drugs, whether to take up vaccines, and whether to cease tobacco use during pregnancy.

On the other hand, our results suggest that a policy that were able to "mimic" what health professionals do for their family members – and thus induce better drug adherence, a higher immunization rate, and cessation of tobacco use in pregnancy, for example – would have the potential to make a substantial dent in population health and reduce health inequality. It is thus worthwhile to consider the specific features of intra-family communication, and whether a policy maker may be able to replicate (some of) those. If intra-family health professionals simply transfer knowledge to their family members, then any information provision campaign may be effective. To the extent that the power of intra-family communication about health stems from trust or detailed knowledge about the health history and habits that come with a relationship that spans a long period of time, effective policies may need to strive to mimic the depth of these relationships. We speculate that elements of such a policy could include nurse outreach programs with a strong emphasis on the continuity of care (yielding *long-term* relationships), coupled with a strengthening of the role of a trusted and easily accessible - both in terms of geographic location and the administrative hurdles - general practitioner who knows patients, and potentially their whole family, over a long period of time. Further, Alsan et al. (2018) suggests that providers which resemble the patient (in their case, same-race providers) may gain more trust. Finally, given the heterogeneous effects across the income distribution, such programs specifically targeted at the poor may have the largest potential to reduce health inequality.

(1-0.1), divided by (1-0.1*0.07) for the first half of the income distribution, and divided by (1-0.1*0.31) for the second half. The denominator term re-scales the numerator to account for the differences in the baseline levels of access to expertise and hence the share of individuals that gets treated.

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.

A common explanation (and a policy focus) for the existence and persistence of health-SES gradients is the difference in formal access to healthcare across the SES-spectrum. Our evidence suggests that this explanation can only be one piece of the puzzle when it comes to understanding the origins of SES-gradients (as crucially distinct from levels) in health. Using rich administrative data from Sweden, we document that strong socioeconomic gradients in mortality and morbidity persist in Sweden, across a range of ages and conditions, *despite* equalized formal access to healthcare and a well-developed social safety net. This fact motivates us to examine a mechanism other than access to formal health insurance and healthcare that may perpetuate socio-economic gradients in health.

Specifically, we investigate whether access to health-related expertise - throughout an individual's lifetime - can improve (the level) of health outcomes, while differences in access to such expertise at different points on the socio-economic ladder can sustain inequality in health outcomes.

To create a quantifiable metric of access to expertise, we zoom into an environment where we can precisely measure individuals' exposure to health-related expertise: the presence of a health professional in the family. Using non-parametric evidence, event studies, and exploiting "admissions lotteries" into medical school, we find that access to expertise has an important impact on health (level): children and adults that are "exposed" to a health professional in the family live longer, are significantly healthier, are more likely to engage in preventive health behaviors, and are more likely to adhere to medication. What's more, the benefits of access to expertise appear to be weakly larger for individuals at the bottom of the income distribution.

These estimates imply that the scarcity of access to expertise in households at the lower rungs of the socio-economic ladder could create and sustain inequality in health outcomes — even in an environment with fully equalized access to formal healthcare, generous social insurance programs, and a wide social safety net. It is encouraging, however, that the benefits accruing to medical professionals' family members appear to be scalable. Our analysis suggests that access to expertise improves health not through preferential treatment, but rather through intra-family transmission of "low-tech" (and hence, cheap) determinants of health, likely ranging from the sharing of nuanced knowledge about healthy behaviors, to reminders about adherence to chronic medication, to frequent and trustful communication about existing health. This implies that public health policies, as well as carefully designed public and private health insurance contracts that successfully mimic intra-famiy transmission of health-related expertise, would have the potential to close a significant share - our estimates suggest as much as 18% - of the SES-mortality gap.

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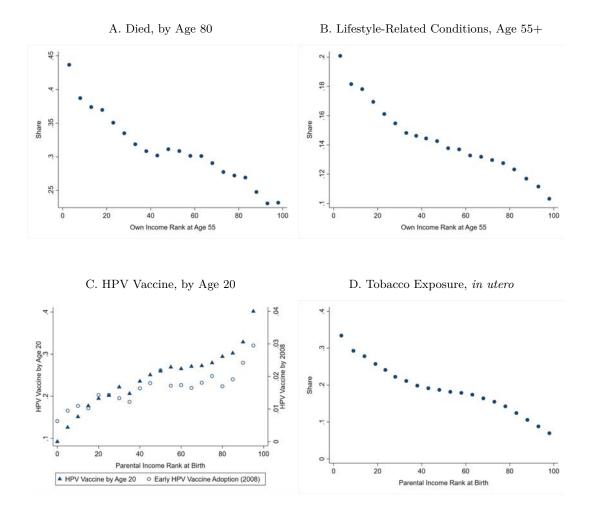
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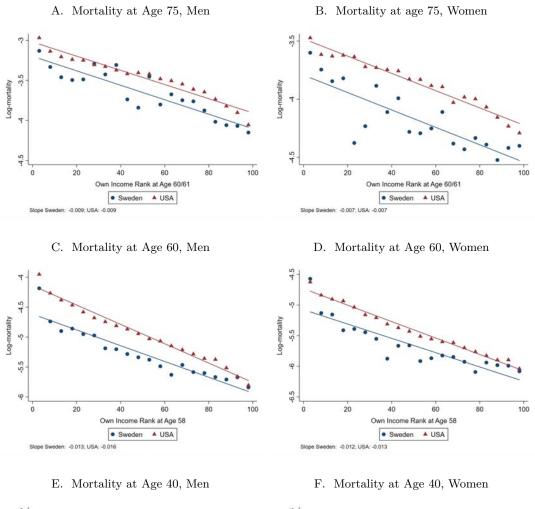
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Figure 1: Income Gradients in Mortality and Morbidity over the Lifecycle

A. Died, by Age 80

B. Lifestyle-Related Conditions, Age 55+

C. HPV Vaccine, by Age 20

D. Tobacco Exposure, *in utero*

Figures show the share of individuals with the specified health condition (vertical axis) by ventile of own income rank at age 55 or parental income rank at birth (horizontal axis). Individuals with zero or negative (parental) work-related income are excluded. Own income rank is assigned based on each individual's own income at age 55 relative to other people in the same gender-birth cohort. 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 attack, heart failure, lung cancer, or diabetes. Panel A restricts the sample to birth cohorts 1936-1937; panel B restricts the sample to individuals born between 1936-1961 and alive at age 55 and year 1997 (first year of inpatient claims). Panel C restricts the sample to females born between 1995-1997 and alive at age 20. Tobacco exposure *in utero* in panel D measures whether the mother used any type of tobacco within 3 months before or during pregnancy; the sample is restricted to children born in 1995-2016.

Figure 2: Income Gradients in Mortality in the US and Sweden

A. Mortality at Age 75, Men

Slope Sweden: -0.009; USA: -0.009

B. Mortality at age 75, Women

Slope Sweden: -0.007; USA: -0.007

C. Mortality at Age 60, Men

Slope Sweden: -0.013; USA: -0.016

D. Mortality at Age 60, Women

Slope Sweden: -0.012; USA: -0.013

E. Mortality at Age 40, Men

Slope Sweden: -0.018; USA: -0.020

F. Mortality at Age 40, Women

Slope Sweden: -0.007; USA: -0.016

Figures compare mortality rates by income rank ventile between Sweden and the US. We report mortality at age 40, 60 and 75 conditional on ventiles of income rank at age 38, 58, and 60 (Sweden) or 61 (US), respectively. US mortality data is derived from the data reported by the Health Inequality Project https://healthinequality.org/. The sample for Sweden is restricted to the same birth cohorts as in the US data. Income is measured as the equivalent of the US AGI adjustable gross income (includes 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 of log-mortality rate on income rank percentile, separately by country and gender. We cannot reject the statistical equivalency of the slopes measuring the mortality gradient for men at age 40 and at age 75 (*p*-values 0.46 and 0.87, respectively), as well as for women at age 75 (*p*-value 0.96). We reject the equivalency for the mortality gradient for men at age 60 and for women at age 40 (*p*-values 0.00), and for women at age 60 at the 10% significance level (*p*-value 0.05).
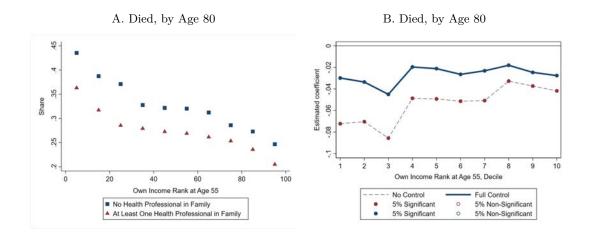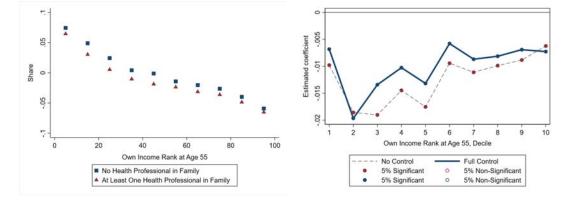
Figure 3: Health Professional in the Family and Health at Older Ages: Non-Parametric Evidence

A. Died, by Age 80

B. Died, by Age 80

C. Lifestyle-Related Conditions, Age 55+

D. Lifestyle-Related Conditions, Age 55+

Panels A and C plot the share of individuals with the specified health condition by decile of own income rank at age 55. The outcome in Panel C is a z-score index of four underlying conditions: heart attack, heart failure, type II diabetes, and lung cancer; the index is constructed as specified in the text. We start with the same data samples as defined in Figure 1. The samples are 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 member of their broad family (spouse, sibling, cousin, child, child-in-law, niece/nephew, grandchild) has a university degree in medicine or nursing. We exclude individuals who hold a degree in medicine or nursing 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 (solid line) and without (dashed line) covariates. Coefficients are reported as filled circles if they are estimated at more than 5% statistical significance, and as hollow circles otherwise. The covariates include fixed effects for individual's own income rank percentile and income rank percentile of the highest-earning relative, year of birth fixed effects, gender dummy, fixed effects for discretized education levels, fixed effects for the county of residence at age 55). Standard errors are clustered at the family level.
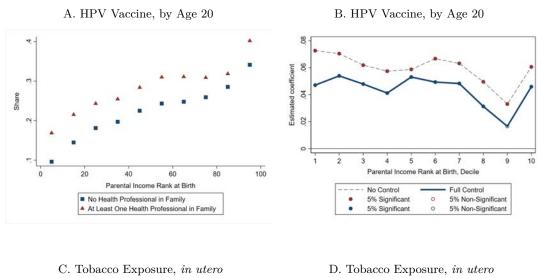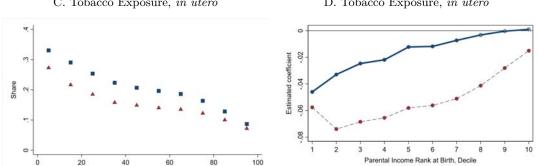
Figure 4: Health Professional in the Family and Health at Younger Ages: Non-Parametric Evidence

A. HPV Vaccine, by Age 20

B. HPV Vaccine, by Age 20

C. Tobacco Exposure, *in utero*

D. Tobacco Exposure, *in utero*

Panels A and C plot the share of individuals with the specified health condition by decile of parental income rank at birth. We start with the same data samples as defined in Figure 1. The samples are 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 member of their broad family (sibling, cousin, parent, aunt/uncle, grandparent, spouse, parent-in-law) 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 (solid line) and without (dashed line) covariates. Coefficients are reported as filled circles if they are estimated at more than 5% statistical significance, and as hollow circles otherwise. The covariates include fixed effects for parental income rank percentile and income rank percentile of the highest-earning relative, year of birth fixed effects, gender dummy, fixed effects for mother's county of residence before birth; covariates in Panel D further add fixed effect for birth order, mother's education, and maternal age. Standard errors are clustered at the family level.

Figure 5: Health Professional in the Family and Health at Older Ages: Heterogeneity

A. Died by Age 80

B. Died by Age 80

C. Lifestyle-Related Conditions, Age 55+

D. Lifestyle-Related Conditions, Age 55+

Figures replicate the analyses in Panels 3B and 3D (specifications with the full set of covariates) of Figure 3 for sub-samples of the data. Panels A and C re-estimate conditional differences in mortality and the prevalence of lifestyle-related conditions separately for individuals that have a broad, but no narrow, health professional in the family (dashed line), and for individuals that have a narrow health professional (solid line), relative to individuals that have no health professionals. A broad family tie is defined as having a health professional, who is a sibling, cousin, niece/nephew, or a grandchild. A narrow family tie is defined as having a health professional, who is a child, child-in-law, or a spouse. Panels B and D split the same based on geographic proximity. An individual is defined to have a nearby health professional relative (solid line) if both reside in the same county in the same year for more than 50% of the years that are observed between 1991 and 2016. The individual is defined to have a far health professional relative otherwise (dashed line). In all regressions, the comparison group is the set of individuals without any health professional relative.

Figure 6: Health Professional in the Family and Health at Younger Ages: Heterogeneity

A. HPV Vaccine, by Age 20

B. HPV Vaccine, by Age 20

C. Tobacco Exposure, *in utero*

D. Tobacco Exposure, *in utero*

Figures replicate the analyses in Panels 4B and 4D (specifications with the full set of covariates) of Figure 4 for sub-samples of the data. Panels A and C re-estimate conditional differences in mortality and the prevalence of lifestyle-related conditions separately for individuals that have a broad, but no narrow, health professional in the family (dashed line), and for individuals that have a narrow health professional (solid line), relative to individuals that have no health professionals. A broad family tie is defined as having a health professional, who is a sibling, cousin, aunt/uncle, or a grandparent. A narrow family tie is defined as having a health professional, who is a parent, parent-in-law, or a spouse. Panels B and D split the same based on geographic proximity. An individual in Panel B is defined to have a nearby health professional relative (solid line) if the individual's parents reside in the same county in the same year for more than 50% of the years that are observed between 1991 and 2016. An unborn child in Panel D is defined to have a nearby health professional relative (solid line) if in the year of birth, a health professional relative lived in the same county as the mother. The individuals are defined to have a far health professional relative otherwise (dashed line). In all regressions, the comparison group is the set of individuals without any health professional relative.
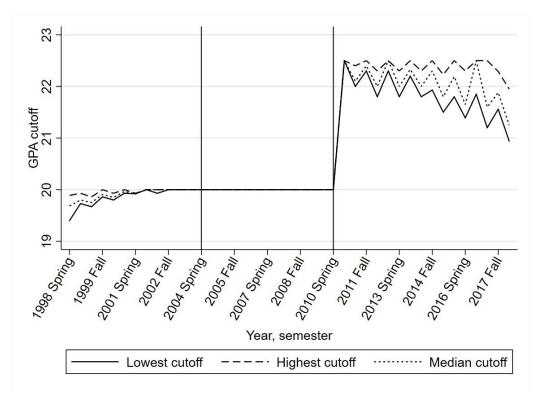
Figure 7: GPA Cutoffs for Admission into Medical Programs

Figure plots the time series of the GPA cutoffs for undergraduate medical programs with the lowest, median, and highest cutoff. Each observation is a school and (semi-annual) application cycle, starting from 1998 to 2017.
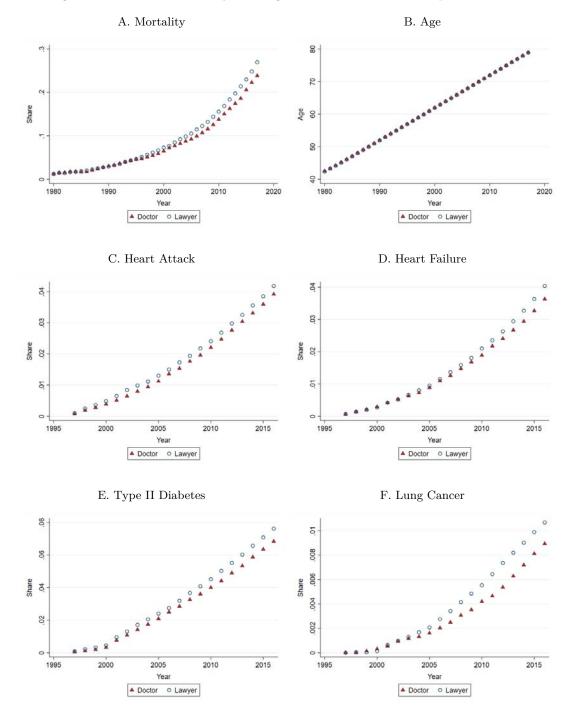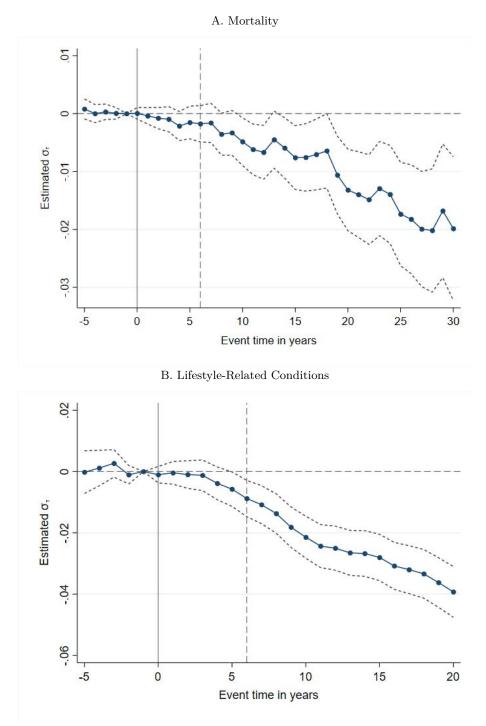
Figure 8: Doctor in the Family and Log-Run Health Bonus: Descriptive Evidence

A. Mortality   B. Age

C. Heart Attack   D. Heart Failure

E. Type II Diabetes   F. Lung Cancer

Panel A records the cumulative share (y-axis) of individuals born in Sweden in 1936-1940, who have died by a given calendar year (x-axis). Panel B records the average age of the same individuals by calendar year, keeping deceased individuals in the sample. Panels C to F record the share of individuals born in Sweden between 1936 and 1961, who have acquired the specified chronic condition by a given calendar year (x-axis). Deceased individuals are kept in the balanced sample. In all panels the sample is restricted to individuals who at some point in their lifetime had a child that matriculated in the study of either law or medicine. The outcomes are shown separately for the group of individuals whose child matriculated into medical (filled triangles) or legal (hollow circles) studies. We exclude observations if at least one parent is a health professional (a physician or a nurse) herself or himself. Parents with a child who became a nurse before another child became a doctor are not included in the "doctor" sample; parents that have a child trained as a lawyer and another child trained as a doctor (or nurse) are excluded from the "lawyer" sample.

Figure 9: Doctor in the Family and Long-Run Health Bonus: Event Studies

A. Mortality

B. Lifestyle-Related Conditions

Figures plot coefficients σ_τ and 95% confidence intervals against relative time τs from the event study specification in Equation 4. Panel A restricts the sample to family members born in Sweden between 1936 and 1940. Panel B restricts the sample to family members born in Sweden between 1936 and 1961. In both Panels, we exclude family members who are themsevles a health professional, or have a health professional spouse. Family members with a relative became a nurse before another relative became a doctor are dropped from the "doctor" sample; family members with both a lawyer and a health professional relative are dropped from the "lawyer" sample. Panel B excludes individuals that have died before the first year of clinical records—1997. The regressions are centered at event year -1, i.e., one year before the year of matriculation in a medical or legal degree. The dashed vertical line marks the average graduation time for physicians. Standard errors are clustered at the family level.
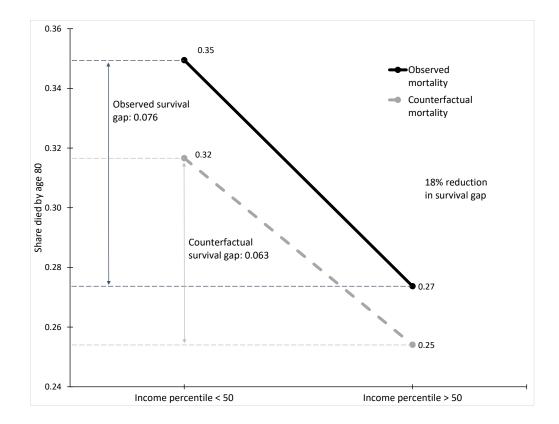
Figure 10: Access to Expertise and Income-Mortality Gradient

Figure plots the observed and counterfactual gradient in mortality. The sample is defined as in Figure 1, Panel A. The top solid line ("observed mortality") plots observed average probability of individuals surviving until age 80 conditional on being alive at age 55, across the first half and the second half of the income rank distribution at age 55 (among 1936-1937 cohorts). The points on the bottom line ("counterfactual mortality") are computed as follows. We multiply observed mortality within each income group by the treatment effect (1-T) and then re-scale the result by (1-T*s) to account for the differences in the underlying prevalence of access to expertise. T is the treatment effect of access to expertise (estimated at 10% for mortality, following the non-parametric results in Table 1 and the event study estimates in Figure 9A); s is the share of individuals with access to expertise in the baseline, proxied by the college completion rate (among 1936-1937 cohorts) of 7% and 31% percent at the bottom half and top half of the income distribution, respectively.

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Table 1: Health Professional in the Family and Health Outcomes

Panel A: Died, by age 80

	(1)	(2)	(3)	(4)	Income rank decile: (5)	(6)	(7)	(8)	(9)	(10)
Health Professional in Family	-0.030	-0.034	-0.044	-0.019	-0.021	-0.027	-0.023	-0.018	-0.025	-0.028
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Mean of Dep. Var.	0.41	0.36	0.34	0.31	0.30	0.30	0.29	0.27	0.26	0.23
Std. Dev. of Dep. Var.	0.49	0.48	0.47	0.46	0.46	0.46	0.46	0.44	0.44	0.42
R-Squared	0.051	0.042	0.053	0.043	0.039	0.029	0.034	0.022	0.030	0.026
No. of Obs.	11,454	12,850	12,777	12,928	12,882	12,823	12,786	12,681	12,252	13,396

Panel B: Index of lifestyle-related conditions, age 55+

	(1)	(2)	(3)	(4)	Income rank decile: (5)	(6)	(7)	(8)	(9)	(10)
Health Professional in Family	-0.007	-0.020	-0.013	-0.010	-0.013	-0.006	-0.009	-0.008	-0.007	-0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Mean of Dep. Var.	0.07	0.04	0.02	-0.00	-0.01	-0.02	-0.02	-0.03	-0.04	-0.06
Std. Dev. of Dep. Var.	0.66	0.63	0.60	0.57	0.57	0.55	0.54	0.53	0.51	0.48
R-Squared	0.081	0.080	0.083	0.079	0.081	0.078	0.078	0.076	0.076	0.069
No. of Obs.	191,979	215,131	215,099	215,522	214,393	213,476	211,081	205,246	203,877	213,377

Panel C: HPV vaccine, by age 20

	(1)	(2)	(3)	(4)	Income rank decile: (5)	(6)	(7)	(8)	(9)	(10)
Health Professional in Family	0.047	0.054	0.048	0.041	0.053	0.049	0.048	0.031	0.017	0.046
	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
Mean of Dep. Var.	0.11	0.16	0.20	0.21	0.24	0.26	0.27	0.28	0.30	0.37
Std. Dev. of Dep. Var.	0.31	0.37	0.40	0.41	0.43	0.44	0.44	0.45	0.46	0.48
R-Squared	0.054	0.052	0.059	0.059	0.062	0.074	0.073	0.086	0.088	0.113
No. of Obs.	11,327	12,568	12,516	12,469	12,539	12,427	12,511	12,500	12,471	13,683

Panel D: Tobacco exposure, *in utero*

	(1)	(2)	(3)	(4)	Income rank decile: (5)	(6)	(7)	(8)	(9)	(10)
Health Professional in Family	-0.046	-0.033	-0.025	-0.022	-0.012	-0.012	-0.007	-0.003	-0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Mean of Dep. Var.	0.33	0.28	0.24	0.21	0.19	0.18	0.17	0.15	0.12	0.08
Std. Dev. of Dep. Var.	0.47	0.45	0.43	0.40	0.39	0.38	0.38	0.36	0.32	0.27
R-Squared	0.126	0.090	0.074	0.070	0.071	0.067	0.061	0.054	0.045	0.031
No. of Obs.	162,206	188,607	191,521	192,979	193,267	193,549	193,523	192,929	191,630	205,000

Notes: Tables report the results of OLS regressions of the outcome of interest on an indicator for having a health professional in the family, estimated separately for each decile (reported in columns (1) to (10)) of the individual's (or parental) income rank. Each regression includes the full set of covariates. Health professional in the family is a indicator variable that equals one if the individual has at least one relative with a completed medical or nursing degree. In panels A and B, the set of relatives includes spouse, sibling, cousin, child, child-in-law, niece/nephew, grandchild. In panels C and D, the set of relatives includes sibling, cousin, parent, aunt/uncle, grandparent, spouse, and parent-in-law. Panel A restricts the sample to individuals born in Sweden between 1936-1937. Panel B restricts the sample to individuals born in Sweden between 1936-1961 and alive at age 55. Panel C restricts the sample to females born in Sweden between 1995-1997 and alive at age 20. Panel D restricts the sample to children born in Sweden between 1995 and 2016. Covariates in Panels A and B include fixed effects for individual's own income rank percentile and income rank percentile of the highest-earning relative, year of birth fixed effects, gender dummy, fixed effects for discretized education levels, fixed effects for the county of residence at age 55). Covariates in panel C include fixed effects for parental income percentile at birth, highest-earning relative's income percentile, year of birth, gender, mother's county of residence in the year before child birth. Covariates in panel D include fixed effects for parental income percentile at birth, highest-earning relative's income percentile, year of birth, gender, mother's county of residence in the year before child birth, maternal birth order, mother's education, maternal age. Standard errors are clustered at the family level.

Table 2: Medical School Lotteries: Balance of Baseline Observables

	Admitted (1)	Not Admitted (2)	p-value (3)
Medical School Matriculation	0.96 (0.01)	0.59 (0.02)	0.00
Demographics			
Female	0.57 (0.50)	0.60 (0.49)	0.41
Age	19.67 (1.23)	19.48 (1.03)	0.03
Number of siblings	1.82 (1.06)	1.80 (1.06)	0.84
Born in Sweden	0.97 (0.18)	0.95 (0.21)	0.45
Father born in Sweden	0.87 (0.33)	0.85 (0.36)	0.33
Mother born in Sweden	0.86 (0.34)	0.85 (0.36)	0.64
Parental income (10k krona, inflation-adjusted)			
Year before high school graduation	94.00 (62.26)	90.42 (64.27)	0.52
Year before first application	93.65 (63.63)	90.91 (64.89)	0.63
Father's income (10k krona, inflation-adjusted)			
Year before high school graduation	55.25 (53.93)	54.04 (56.86)	0.80
Year before first application	54.41 (54.19)	54.11 (57.33)	0.95
Relative deceased by year of first application			
Father	0.01 (0.07)	0.01 (0.10)	0.63
Mother	0.01 (0.07)	0.01 (0.10)	0.63
Paternal Grandfather	0.57 (0.50)	0.55 (0.50)	0.69
Paternal Grandmother	0.32 (0.47)	0.35 (0.48)	0.46
Maternal Grandfather	0.48 (0.50)	0.51 (0.50)	0.52
Maternal Grandmother	0.30 (0.46)	0.28 (0.45)	0.64
Number of Observations	188	555	

Notes: Table reports the probability of medical school matriculation and the sample mean (standard deviation in parentheses) of observable demographics for 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. The sample in Column 1 includes applicants who were admitted to a medical school on their first application attempt. Column 2 reports the same outcomes for applicants who lost their first application lottery. Column 3 reports the *p*-value of a two-sided *t*-test for the equivalence in means between Columns (1) and (2).

Table 3: Doctor in the Family and Health at Older Ages: Medical School Lottery Evidence

Outcomes per 1,000 Individuals	ITT		LATE (3)	Control Mean (4)	Control Complier Mean (5)	Obs (6)
	No Covariates (1)	With Covariates (2)				
A. Health Index	40 (16)	46 (17)	106 (41)	0	4	3134
B. Preventive Health						
Statins	23 (17)	34 (18)	79 (41)	281	293	3134
Blood Thinners	31 (15)	30 (15)	69 (34)	247	273	3134
Diabetes Drugs	8 (8)	15 (9)	34 (20)	74	76	3134
Beta Blockers	10 (16)	13 (16)	29 (37)	302	309	3134
Asthma Drugs	9 (15)	4 (16)	8 (36)	179	187	3134
Vitamin D	11 (10)	18 (11)	41 (25)	32	27	1642
Preventable Hospitalizations	-14 (38)	-2 (42)	-4 (78)	197	235	1532
Addiction	-8 (8)	-13 (9)	-25 (17)	26	30	1532
C. Physical Health						
Heart Attack	-12 (10)	-18 (11)	-34 (20)	42	48	1532
Heart Failure	-21 (13)	-27 (14)	-51 (27)	74	83	1532
Lung Cancer	3 (5)	3 (5)	5 (10)	6	6	1532
Type II Diabetes	-11 (14)	8 (15)	16 (27)	77	72	1532

Notes: Table reports the results of estimating Equation 2 for older (age 50 and above) family members of medical school "lottery" participants. Outcomes are tracked for 8 years after the applicant's matriculation into a medical school or the last medical school application. Sample size varies across outcomes due to differences in pharmaceutical and clinical data availability. Aggregate health index is an unweighted mean of z-scores of all individual outcomes. Column 2 and 3 report ITT and LATE estimates with a full set of covariates, including family member's birth year fixed effects, gender, educational attainment, family tie fixed effects (e.g., sibling, parent, etc.), whether the family member was born in Sweden, the applicant's birth year fixed effects and gender, whether the applicant was born in Sweden, and the number of medical schools that the applicant applied to in the first application cycle. In regressions using statins, blood thinners, diabetes drugs, beta blockers, and asthma drugs as the outcome, we also control for whether the family member has asthma, type II diabetes, heart failure, ischemic heart diseases, stroke, hyperlipidemia, or hypertension. Standard errors clustered by the applicant are reported in parentheses. Column 4 reports mean outcomes in the control group, i.e., among family members of applicants who lost the lottery on the first medical school application attempt. Column 5 reports mean outcomes among the "control compliers," i.e., family members of applicants who lost the lottery on the first medical school application attempt and *did not* subsequently re-apply to medical schools.

Table 4: Doctor in the Family and Health at Younger Ages: Medical School Lottery Evidence

Outcomes per 1,000 individuals	ITT No Covariates (1)	ITT With Covariates (2)	LATE (3)	Control Mean (4)	Control Complier Mean (5)	Obs (6)
A. Health Index	33 (16)	39 (17)	125 (55)	0	38	4113
B. Preventive Health						
HPV Vaccination	42 (26)	62 (26)	202 (89)	119	174	1192
No Hormonal Contraceptives	72 (49)	132 (49)	450 (177)	655	604	514
Addiction	-12 (4)	-12 (4)	-38 (13)	19	15	4113
Injury/Poisoning	2 (16)	1 (16)	3 (52)	265	251	4113
C. Physical Health						
Number Inpatient stays	-80 (33)	-103 (38)	-327 (125)	302	278	4113
Respiratory Infection	-5 (7)	-5 (7)	-16 (23)	38	30	4113
Intestinal Infection	-3 (4)	-4 (4)	-13 (13)	18	14	4113
Chronic Tonsil Diseases	4 (6)	4 (6)	13 (19)	21	13	4113

Notes: Table reports the results of estimating Equation 2 for younger family members (younger than 30) of medical school "lottery" participants. Outcomes are tracked for 6 years after the applicant's matriculation into a medical school or the last medical school application. Row 2 (HPV vaccination) and Row 3 (no hormonal contraceptives) restrict the sample to females aged between 10 and 25 and females aged between 10 and 20, respectively. Aggregate health index is an unweighted mean of z-scores of all individual outcomes. Column 2 and 3 report ITT and LATE estimates with a full set of covariates, including family member's birth year fixed effects, gender, educational attainment, family tie fixed effects (e.g., sibling, parent, etc.), whether the family member was born in Sweden, the applicant's birth year fixed effects and gender, whether the applicant was born in Sweden, and the number of medical schools that the applicant applied to in the first application cycle. Standard errors clustered by the applicant are reported in parentheses. Column 4 reports mean outcomes in the control group, i.e., among family members of applicants who lost the lottery on the first medical school application attempt. Column 5 reports mean outcomes among the "control compliers," i.e., family members of applicants who lost the lottery on the first medical school application attempt and *did not* subsequently re-apply to medical schools.

Table 5: Doctor in the Family and Health: Event Study Evidence

		Heterogeneity by					
		Income		Family Tie		Geographic Proximity	
	Pooled	Below Median	Above Median	Close	Far	Close	Far
Outcomes	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Mortality							
τ=-5	0.001	0.001	0.000	0.000	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)
τ=+15	-0.008	-0.008	-0.004	-0.006	-0.007	-0.010	-0.004
	(0.003)	(0.002)	(0.001)	(0.005)	(0.005)	(0.002)	(0.002)
τ=+25	-0.017			-0.020	-0.019		
	(0.005)			(0.007)	(0.008)		
Mean of Dep. Var. (at τ=+15/25)[a]	0.166	0.043	0.029	0.177	0.167	0.032	0.032
% Effect (at τ=+15/25)	10.2	18.6	13.8	11.3	11.4	31.3	12.5
No. of Obs.	1,222,675	1,132,787	1,652,427	461,996	474,659	1,338,214	1,603,283
B. Lifestyle Conditions Index[b]							
τ=-5	-0.000	0.006	-0.007	0.007	0.002	-0.001	0.002
	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
τ=+10	-0.021	-0.023	-0.019	-0.020	-0.015	-0.028	-0.022
	(0.003)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
τ=+15	-0.028	-0.026	-0.025	-0.028	-0.022	-0.035	-0.026
	(0.004)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
Mean of Dep. Var. (at τ=+15)[a]	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No. of Obs.	5,077,267	1,843,234	2,670,101	2,034,144	2,319,347	2,282,660	2,699,245

[a] Among family members of lawyers
[b] z-score index includes four conditions: heart attack, heart failure, type II diabetes, and lung cancer

Notes: Table reports coefficients σ_τ from the event study specification in Equation 4. The event time, sample restriction, and the set of family members included in the analysis are described in Section 4.4. Column (1) reports pooled results for 1936-1940 cohorts (mortality) and 1936-1961 cohorts (chronic conditions). Columns 2 and 3 split the sample by whether the individual's income rank within his/her gender-birth cohort is below or above the 50th percentile, with income measured at age 55 in Panel B and at age 45 in Panel A. Earlier age of income measurement reduces selection on survival when analyzing the mortality of "high" and "low" income groups separately. To be able to observe income at a younger age, we adjust the set of cohorts to individuals born between 1946-1955 in Columns 2 and 3. Individuals with a zero or negative income are dropped from analyses in Columns 2-3. Columns 4 and 5 split the full sample by the type of family tie: parents-children in "close" family tie and aunts/uncles vs. nieces/nephews in "far." Individuals with both ties are excluded from analyses in Column 5. Columns 6 and 7 split the sample by geographic distance. Family members are classified as living "close" if their place of residence is recorded to be in the same county for more than 50% of the years between matriculation (into law or medicine) and the last year of data (2016). Given data restrictions, the geographic split is performed on the same sample of 1946-1955 cohorts as the income split in Columns 2 and 3 (income and geography are recorded in the same data; the records do not go far enough for older generations). We observe these cohorts for a shorter period of time, estimating the regression up to event time 15. When available, coefficients are reported for event years -5, 10, 15 and 25 (i.e. 5 years before, and 10, 15 and 25 years after matriculation into the study of medicine or law). The lifestyle conditions index in Panel B is constructed as the mean of the z-scores of indicators for a heart attack, heart failure, type II diabetes, and lung cancer; by construction the index is normalized to zero for the "control" group of lawyer family members. All regressions include the main effects and the interactions between event year dummies and the dummy for having a doctor in the (broad) family. The regressions further include the following covariates: age fixed effects, calendar year fixed effects, and individual fixed effects. Standard errors clustered by family are in parentheses.

Table 6: Survey Evidence on the Prevalence of Health Expertise

	Prefer Seeing Same Doctor (1)	Believe Doctor Always Tells Truth (2)	Regular Vegetables (3)	Regular Fruit (4)	Regular Sport (5)	Not Smoking (6)	Good Health (7)
No College Degree	0.06	-0.07	-0.19	-0.16	-0.06	-0.14	-0.06
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
No. of Obs.	927	927	738	738	738	738	927
Mean of Dep. Var.	0.70	0.28	0.77	0.55	0.56	0.84	0.76
Std. Dev. of Dep. Var.	0.46	0.45	0.42	0.50	0.50	0.36	0.43
Age Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Weights Used	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey Year	2004	2004	2014	2014	2014	2014	2004

Notes: Table reports OLS relationship between the level of education and health-related behaviors. The analysis is based on 2004 and 2014 waves of European Social Survey for Sweden. The sample is restricted to working age individuals between age 30 and 60. We regress the outcome of interest on an indicator for having no college education (defined as not having a "completed tertiary education"). The OLS regression uses post-stratification survey weights and controls for age fixed effects. Binary outcome variables were constructed from underlying categorical survey responses to the following 7 questions or statements: 1) "Prefer same doctor for all everyday health problems"; 2) "Doctors keep whole truth from patients"; 3) "How often eat vegetables or salad, excluding potatoes"; 4) "How often eat fruit, excluding drinking juice"; 5) "Do sports or other physical activity, how many of last 7 days"; 6) "Cigarettes smoking behavior"; 7) "Subjective general health". For example, "Prefer seeing the same doctor" takes the value of 1 if individuals answered "Same for all health problems" in response to the question of whether they "Prefer same doctor for all everyday health problems."
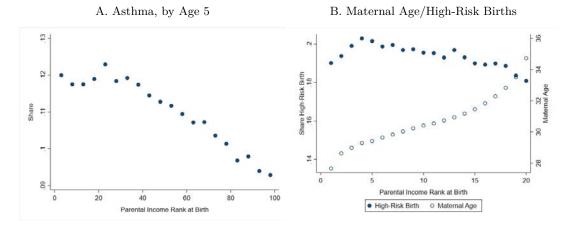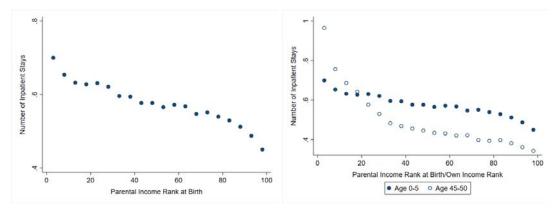
APPENDIX

A Figures and tables

Figure A1: Early Emergence of the Health-SES Gradient

A. Asthma, by Age 5

B. Maternal Age/High-Risk Births

C. Number of Inpatient Stays, by Age 5

D. Number of Inpatient Stays over Life Cycle

Figures plot the share of individuals with relevant outcomes for each ventile of income rank. Parental income rank at birth is assigned based on the average of parental incomes in the two years before the child was born relative to other parents with children in the same birth cohort. Income rank for adults aged 45-50 in Panel D are assigned based on each individual's own income at age 40 relative to other individuals in the same gender-birth cohort. Births in Panel B are defined as high risk if the mother has any of the following conditions during pregnancy: chronic kidney diseases, diabetes, epilepsy, lung diseases, systemic lupus erythematosus, ulcerative colitis, hypertension, or urinary tract infections. Inpatient stays due to pregnancy, childbirth and the puerperium are excluded from the count of inpatient stays in Panels C and D.
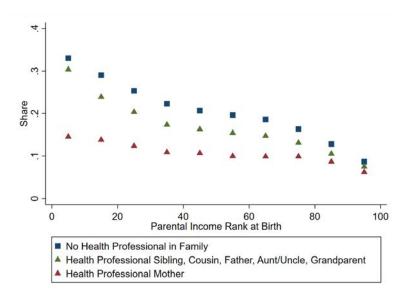
Figure A2: Tobacco Exposure, *in utero*

Figure plots the share of children exposed to tobacco *in utero* by decile of parental income rank at birth. Parental income rank at birth is assigned based on the average of parental incomes in the two years before the child was born relative to other parents with children in the same birth cohort. We start with the same data sample as defined in Figure 4C. The sample is split by whether an individual has a health professional relative or a health professional mother. Individuals are assigned to the sample "with a health professional" if at least one member of their broad family (sibling, cousin, father, aunt/uncle, grandparent) has a university degree in medicine or nursing. Individuals are assigned to the sample "with a health professional mother" if the mother has a university degree in medicine or nursing.

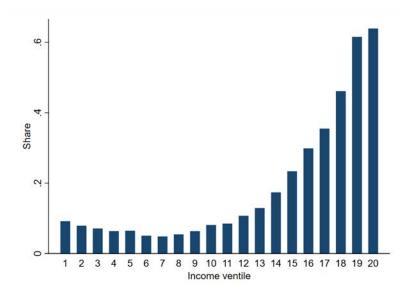Figure A3: Share with College Degree, by Income Ventile

Figure plots the share of individuals with a college degree by ventile of own income rank at age 55. The sample is defined as in Figure 3A.
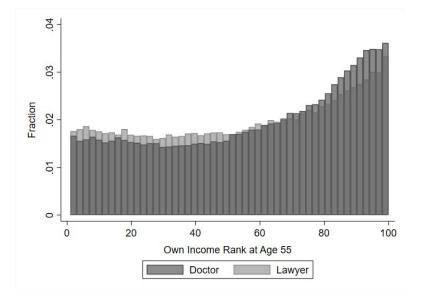
Figure A4: Income Distribution of the Event Study Sample

Figure plots own income rank at age 55 for the analysis sample used in the lifestyle-related conditions index event study (i.e., Figure 9B).

Figure A5: Doctor in the Family and Long-Run Health Bonus: Event Studies

A. Heart Attack

B. Heart Failure

C. Diabetes

D. Lung Cancer

Figures plot coefficients σ_τ and 95% confidence intervals against relative time τs from the event study specification in Equation 4. Sample restricted to family members born in Sweden between 1936 and 1961. In both Panels, we exclude family members who are themsevles a health professional, or have a health professional spouse. Family members with a relative became a nurse before another relative became a doctor are dropped from the "doctor" sample; family members with both a lawyer and a health professional relative are dropped from the "lawyer" sample. All panels exclude individuals that have died before the first year of clinical records—1997. The regressions are centered at event year -1, i.e., one year before the year of matriculation in a medical or legal degree. The dashed vertical line marks the average graduation time for physicians. Standard errors are clustered at the family level.

Outcomes	Pooled (1)	Income Below Median (2)	Income Above Median (3)	Family Tie Close (4)	Family Tie Far (5)	Geographic Proximity Close (6)	Geographic Proximity Far (7)

Heterogeneity by — Income: (2) Below Median, (3) Above Median; Family Tie: (4) Close, (5) Far; Geographic Proximity: (6) Close, (7) Far.

A. Heart Attack

Outcomes	Pooled	Below Median	Above Median	Close (FT)	Far (FT)	Close (GP)	Far (GP)
$\tau=-5$	0.000	0.002	-0.001	0.001	0.001	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\tau=+10$	-0.002	-0.003	-0.001	-0.002	-0.001	-0.002	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\tau=+15$	-0.003	-0.005	-0.002	-0.003	-0.003	-0.003	-0.005
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Mean of Dep. Var. (at $\tau=+15$)[a]	0.025	0.028	0.020	0.024	0.027	0.024	0.025
% Effect (at $\tau=+15$)	12.0	17.9	10.0	12.5	11.1	12.5	20.0
No. of Obs.	5,077,361	1,843,430	2,670,133	2,034,144	2,319,387	2,282,723	2,699,291

B. Heart Failure

Outcomes	Pooled	Below Median	Above Median	Close (FT)	Far (FT)	Close (GP)	Far (GP)
$\tau=-5$	0.000	-0.000	0.000	-0.000	-0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\tau=+10$	-0.003	-0.004	-0.002	-0.004	-0.003	-0.005	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\tau=+15$	-0.005	-0.005	-0.003	-0.005	-0.005	-0.006	-0.005
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean of Dep. Var. (at $\tau=+15$)[a]	0.022	0.025	0.015	0.020	0.025	0.022	0.021
% Effect (at $\tau=+15$)	22.7	20.0	20.0	25.0	20.0	27.3	23.8
No. of Obs.	5,077,361	1,843,430	2,670,133	2,034,144	2,319,387	2,282,723	2,699,291

C. Type II Diabetes

Outcomes	Pooled	Below Median	Above Median	Close (FT)	Far (FT)	Close (GP)	Far (GP)
$\tau=-5$	0.002	0.002	0.001	0.001	0.003	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\tau=+10$	-0.007	-0.005	-0.006	-0.006	-0.005	-0.008	-0.006
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
$\tau=+15$	-0.010	-0.006	-0.010	-0.008	-0.008	-0.013	-0.008
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Mean of Dep. Var. (at $\tau=+15$)[a]	0.044	0.048	0.034	0.043	0.048	0.045	0.042
% Effect (at $\tau=+15$)	22.7	12.5	29.4	18.6	16.7	28.9	19.0
No. of Obs.	5,077,361	1,843,430	2,670,133	2,034,144	2,319,387	2,282,723	2,699,291

Table A1: Doctor in the Family and Health: Event Study Evidence (Continued)

| | | Heterogeneity by | | | | | |
| | | Income | | Family Tie | | Geographic Proximity | |
Outcomes	Pooled (1)	Below Median (2)	Above Median (3)	Close (4)	Far (5)	Close (6)	Far (7)
D. Lung Cancer							
$\tau=-5$	-0.000	0.000	-0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\tau=+10$	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$\tau=+15$	-0.001	-0.002	-0.001	-0.002	-0.000	-0.002	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean of Dep. Var. (at $\tau=+15$)^a	0.005	0.006	0.004	0.005	0.006	0.005	0.004
% Effect (at $\tau=+15$)	20.0	33.3	25.0	40.0	0.0	40.0	0.0
No. of Obs.	5,077,361	1,843,430	2,670,133	2,034,144	2,319,387	2,282,723	2,699,291

^{a}Among family members of lawyers

Notes: Table reports coefficients σ_τ from the event study specification in Equation 4. The event time, sample restriction, and the set of family members included in the analysis are described in Section 4.4. Column (1) reports pooled results for 1936-1961 cohorts. Columns 2 and 3 split the sample by whether the individual's income rank within his/her gender-birth cohort is below or above the 50th percentile, with income measured at age 55. Individuals with a zero or negative income at age 55 are dropped from analyses. Columns 4 and 5 split the full sample by the type of family tie: parents-children in "close" family tie and aunts/uncles vs. nieces/nephews in "far." Individuals with both ties are excluded from analyses in Column 5. Columns 6 and 7 split the sample by geographic distance. Family members are classified as living "close" if their place of residence is recorded to be in the same county for more than 50% of the years between matriculation (into law or medicine) and the last year of data (2016). Coefficients are reported for event years -5, 10, and 15 (i.e. 5 years before, and 10, and 15 years after matriculation into the study of medicine or law). All regressions include the main effects and the interactions between event year dummies and the dummy for having a doctor in the (broad) family. The regressions further include the following covariates: age fixed effects, calendar year fixed effects, and individual fixed effects. Standard errors clustered by family are in parentheses.

B Identification codes for diseases and drug use

Diseases   We identify diseases using the following ICD-10 diagnosis codes:

Table B1: ICD-10 Codes

Conditions	ICD10 Codes
Heart Attack	I21, I22, I23
Heart Failure	I11, I13, I50
Type II Diabetes	E11, E13, E14
Lung Cancer	C34
Addiction	F10-F19
Injury/Poisoning	S0-S9, T0-T9
Respiratory Infection	J00-J06, J20-J22
Intestinal Infection	A00-A09
Chronic Tonsil Diseases	J35
Asthma	J45
Hypertension	I10
Hyperlipidemia	E78, I70
Ischemic Heart Diseases	I20-I25
Stroke	I60, I61, I63, I66, G45, G46
Pregnancy, Childbirth and the Puerperium	O00-O99

Drug use   Drug use is identified based on the following Anatomical Therapeutic Chemical (ATC) codes:

Table B2: ATC Codes

Drugs	ATC Codes
Statins	C10AA
Blood Thinners	B01AC
Diabetes Drugs	A10B
Beta Blockers	C07
Asthma Drugs	R03
Vitamin D	A11CB, A11CC
Hormonal Contraceptives	G03A excluding G03AD
HPV Vaccine	J07BM

C Further related literature

C.1 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. A Nurse–Family Partnership program in the US that provides regular home visits by certified nurses to low-income mothers from early pregnancy until the child reaches the age of two, has been found to have positive effects on birth outcomes and health in childhood (Agency for Healthcare Research and Quality, 2014). For a universal home visiting program implemented in Denmark, Wüst (2012) show 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 programâs impact was the promotion of breastfeeding and appropriate infant nutrition by visiting nurses. In a related study, Hjort et al. (2017) examine the long-term impact of the Danish home visiting program. They find that treated individuals that were visited by nurses in infancy experience better health mid-life: they have lower mortality rates, spend fewer nights at hospital, and are less likely to be diagnosed with cardiovascular diseases. Similarly, 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. Similarly, Sweden saw the introduction of a nurse home visiting program in the early 1930âs and Bhalotra et al. (2017) find that, in the long-run, the infant care provided by nurse home visits reduced the probability of dying by age 75 by seven percent.

C.2 Community health workers and access to primary care

Community health workers (CHWs) have been employed in many countries to provide health-related services to their fellow community members. Although there has not been many rigorous evaluations, most existing evidence suggests that CHWs increase takeup rates of a wide variety of healthy behaviors and improve disease management in the community, notably for health behaviors such as cancer screening and immunization, and management of diseases such as asthma, hypertension, and diabetes (see e.g., Norris et al., 2006; Haines et al., 2007; Najafizada et al., 2015). In addition, by assisting individuals in navigating the health care system, CHWs have been shown to improve access to medical services, especially for marginalized populations (Felix et al., 2011; Najafizada et al., 2015).

Access to primary care in the community setting has also been found to be an effective way to improve patients' health. Bailey and Goodman-Bacon (2015) use the rollout of community health centers (CHCs) in the U.S. from 1965 to 1974 to study the long-term health benefits of increased access to primary health care for the poor. The paper finds that, in one decade after CHCs were established, CHCs reduced age-adjusted all-cause mortality rates by 7 to 13 percent among the poor aged 50 and older, with the reduction primarily driven by the decline in cardiovascular-related deaths. The authors argue that having access to a regular source of care, lower

medication cost, and improved compliance with prescription drugs were the main mechanisms for the effects of CHCs on mortality.

Moreover, a growing body of evidence suggests that the ease of access to nurses improves the health of patients with chronic conditions. Fergenbaum et al. (2015) present a systematic review of six randomized control trials that study the effects of home visits with nurse-led guidance in disease self-care management. Home visiting programs result in fewer hospitalizations, fewer emergency department visits, and better patient quality of life. Studies on nurse-led clinics that provide disease knowledge and support for disease self-care management report similar health effects: these clinics significantly reduce patient emergency department visits, hospital readmissions, and mortality rates, and improve patient medication adherence (Agvall et al., 2013; Gandhi et al., 2017; Liljeroos and Strömberg, 2019).

C.3   Patient education

An extensive body of work has evaluated the effectiveness of patient education interventions, finding such programs to be generally effective in promoting population health. For chronic diseases, Stenberg et al. (2018) review existing studies - 56 face-to-face intervention among patients living with chronic illess - on the impact of education programs that target chronic obstructive pulmonary disease (COPD), asthma, chronic pain, heart disease, and diabetes patients. 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

Similarly, Wang et al. (2017) review randomized control trials that investigate effects of self-management education among patients with COPD. The paper highlights that such education programs improve patient disease-specific knowledge and quality of life, and reduce respiratory-related hospital admissions and emergency department visits. Anderson et al. (2017) focus on the educational component of cardiac rehabilitation for patients with coronary heart diseases. The study reviews 22 randomized control trials that assigned patients to different educational interventions that ranged from face-to-face counseling to residential stays with follow-up sessions. Patients in control groups received usual medical care in cardiac rehab that comprises exercise counseling and training and psychological support. The paper finds that, although there is limited evidence that education-based interventions reduce total mortality, the risk of a heart attack, or the number of hospitalizations, these interventions result in lower risks of cardiovascular events and better quality of life. Similarly, Menichetti et al. (2018) review randomized control trials that promote patient engagement among older adults with osteoporosis, diabetes or cardiovascular-related health problems. The authors find that such interventions often demonstrate positive effects on patient compliance with treatment regimens.

In the context of health behaviors, Aveyard et al. (2012) and Stead et al. (2013) show that medical advice and provision of behavioral or pharmaceutical assistance on smoking cessation increase the frequency and success of smoking cessation attempts. Kaner et al. (2018) review the literature on alcohol interventions provided by health professionals and conclude positive effects of these interventions on reducing excessive alcohol consumption. For weight control, Aveyard et al. (2016) show that a randomized trial that provides interventions delivered by trained

general practitioners improves body weight control among obese patients.

Another strand of literature examines the effects of public health education campaigns promoted by social media. A comprehensive summary of this literature can be found in Giustini et al. (2018). Many topics have been included in these social-media education campaigns, including health behaviors such as smoking cessation, healthy diet and physical activity (Chang et al., 2013; Williams et al., 2014; Swanton et al., 2015; Chakraborty et al., 2018), and prevention and management of diseases such as diabetes and cancer (Gabarron et al., 2018; Han et al., 2018). Existing studies generally suggest positive effects of these campaigns on population health.

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