HOUSEHOLD AND INDIVIDUAL ECONOMIC RESPONSES TO DIFFERENT HEALTH SHOCKS: THE ROLE OF MEDICAL INNOVATIONS

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ABSTRACT

This study provides new evidence regarding the extent to which medical care mitigates the economic consequences of various health shocks. To obtain causal effects, I focus on the role of medical scientific discoveries and leverage the longitudinal dimension of unique administrative data on adults in Sweden, their partners, and their working-age children. The results indicate that medical innovations strongly mitigate the negative economic consequences of a health shock, including subsequent losses for the individual and close relatives, and income inequalities within these groups. Such mitigating effects are highly heterogeneous across diseases that cause health shocks. These results support the view that the economic repercussions of health shocks have been overlooked, and there is a lack of focus on the efficiency of medical care for specific health conditions.

JEL codes: I12; I14; I24; J22; J24; O31

Key words: medical innovation; health shock; family income; difference-in-differences-in-differences approach; Sweden

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Data Availability Statement: The individual-level data (SIP) used in this article are drawn from Swedish administrative registers and are confidential. However, this access is not unique, and others can gain similar access by following a procedure described by Statistics Sweden. Researchers interested in obtaining this type of data can apply for permission from the Ethical Review Board. All processing of individual data by the researcher takes place on servers located at Statistics Sweden via secure remote terminal access. Statistics Sweden preserves the data and codes for the long term for each project, and I received access from the Centre for Economic Demography (Lund University). I can openly provide program files used in this study and will be happy to assist as best I can with any application aiming to replicate the results of the study.

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Introduction

The role of medical care in health recovery after health shocks is well understood. However, little is known about the extent to which medical care can mitigate the economic consequences of health shocks, due to which an individual's economic outcomes, including labor force participation and earnings, tend to drop substantially and often fail to recover in the long term (Dobkin et al., 2018; García-Gómez, 2011; Lenhart, 2019). Limited studies have demonstrated the ability of new drugs and medical procedures to compensate for a large proportion of such economic losses.[1] However, the beneficial economic effects of medical care for several diseases are becoming clearer due to the universal progress in medical care in recent decades. Furthermore, such economic effects are not experienced only by the affected individual. The onset of disease in one individual creates an economic burden—in terms of additional informal care and household duties or the necessity to work more to secure income—for other household members (Fadlon and Nielsen, 2021; García-Gómez et al., 2013; Jeon and Pohl, 2017), and may even affect close relatives residing outside the household (Frimmel et al., 2020; Schmitz and Westphal, 2017). Additionally, the magnitude of economic losses due to health shocks varies significantly across individuals and neither vanishes nor equalizes when welfare transfers are considered (Lundborg et al., 2015; Meyer and Mok, 2019).

This study assesses the proportion of economic losses caused by various health shocks that can be mitigated by medical care. This study focuses on adults in Sweden aged 40–70 years, suffering with diseases of varying severities and prognosis, and their close relatives, specifically their partners and working-age children. Data on these individuals are available in unique administrative registers on a longitudinal basis and cover numerous cohorts, allowing the implementation of a quasi-

[1] Several studies have established the economic impacts of medical innovation on experimental or quasi-experimental study designs, including drugs and therapies for prostate and breast cancer (Jeon and Pohl, 2019), drugs and therapies for coronary heart disease (Stephens and Toohey, 2021), antiretroviral therapy against AIDS (Thirumurthy et al., 2008), and Cox-2 inhibitors for arthropathies (Bütikofer and Skira, 2018; Garthwaite, 2012).

experimental research design and the application of machine learning. The data are rich in economic and welfare outcomes that provide important insights into various mechanisms through which medical care reduces the economic loss of a given health shock. The medical care measures used in this study refer to disease-specific treatment and comprise medical scientific discoveries, such as the cumulative number of approved new molecular entities (hereafter, drugs) and patents granted to medical procedures in diagnostics, therapy, and surgery. The study intends to establish the beneficial economic effects of medical care on average and across subgroups to assess whether any heterogeneity observed is economically meaningful, thus presenting a complete account of different welfare schemes. This study offers a novel investigation of the moderating economic effects of medical care, both generally and specifically, while capturing the entire range of diseases in the population.

This study dually focuses on medical innovations' total and heterogeneous effects, thus revealing the sources of rising income inequalities. As a result, it exhibits the following three important aspects. First, this study establishes the relative scope in which medical care mitigates the negative economic consequences of a health shock as well as the remaining loss. Even today, in a developed context such as Sweden, policy-makers view medical care as expenditure rather than an investment (Lundberg, 2018). The findings of this study elucidate the economic returns of medical care and demonstrate the need for more resources, for instance, to ensure that incomes are insulated from health shocks. Second, the study demonstrates that a health shock's negative consequences affect not only the affected individuals but also their close relatives; further, medical care partially compensates for the losses of a wider group, thus increasing the potential returns on medical investments. Concentrated progress in medical care for the most common diseases makes heterogeneity in the moderating effects of medical care inevitable (Cutler et al., 2012). Finally, this study provides a comprehensive account of the various sources of this heterogeneity, highlighting the groups most affected by health shocks in the setting of a developed country—namely, Sweden.

Identifying the causal effects of health shocks and medical care on economic outcomes poses two methodological challenges. In this regard, the present study benefits from recent studies in applied economics that have succeeded in addressing these challenges. The first challenge involves isolating health shocks' causal effects on economic outcomes. To document the differences of health shocks' effects on economic outcomes across treatment schemes, I adopt the methodological approach proposed by Fadlon and Nielsen (2021). This approach compares individuals who contracted a disease (a heart attack or a stroke) to those not-yet-diseased within a relatively short period of time; herein, the health shock's timing can be considered "random." The second challenge involves estimating the ability of medical care to reduce the disease's tragic impact. Jeon and Pohl's (2019) study applied a difference-in-differences (DDD) approach, wherein the economic effects of prostate and breast cancer varied by the year of diagnosis. In their study, individuals diagnosed later were expected to benefit more from medical care than those diagnosed earlier because more innovative drugs and medical procedures are available to treat the disease over time.

In this study, I combine and extend the aforementioned quasi-experimental approaches to different health shocks from the entire range of diseases observed in Swedish registers for adults aged 40–70 years. Applying a DDD approach, I estimate medical innovation's impact on the economic outcomes of both the individual and their close relatives in terms of an innovation-induced reduction in economic losses caused by a specific health shock. To construct counterfactuals for individuals who experienced a health shock, I leverage a longitudinal dimension of the individual-level data and matched each of these individuals to an individual who suffered from the same health shock (in terms of diagnosis) two years in the future and who is similar in several observed characteristics. Interestingly, this combination of shrinking the time window between the groups of diseased and not-yet-diseased individuals and matching cancels the influence of time-dependent unobservable factors across not only severe and unanticipated diseases (e.g., cancers or certain circulatory diseases), but also degenerative ones (e.g., mental or musculoskeletal), which are generally difficult to contrapose.

To obtain a DDD indicator, I further exploit a yearly dimension within a disease group to link scientific discoveries in medical care, such as newly approved drugs and recently granted patents.

Such a design-based DDD approach enables further analysis of inequalities to mitigate the economic effects of medical care. Recent methodological studies have argued that in the presence of heterogeneous treatment effects, fixed-effects models, such as those used in this study, may create a weighting problem and thereby distort the effects under analysis (Goodman-Bacon, 2021). The year-to-year construction of the cohorts—implemented as a part of this study's empirical strategy—solves this problem (Novgorodsky and Setzler, 2019) and addresses whether the economic consequences between family members and the individual are equal or distinguished by the severity of the disease responsible for the health shock, gender, education, marital (cohabitation) status, and age. It also allows me to explore how medical care affects these inequalities. In particular, knowledge of the exact drug or medical procedure that most significantly moderates the negative economic effects of the disease helps reveal the underlying mechanisms. Therefore, I further apply a machine learning (ML) approach to define the most effective (in terms of mitigating economic effects) medical innovations for certain diseases.

This study has three main findings. First, an individual's health shock leads to negative economic consequences, including income loss for the individual (5%), the partner (46%), and the nuclear family (32%). It also leads to income inequalities, which are most pronounced in the disease and marital (cohabitation) status of the individual. This finding supports the inability of welfare transfers to provide equity and insurance after a negative health event. Second, medical innovations reduce the negative economic consequences of health shocks. A one standard deviation increase in medical innovations reduces the individual's income loss in full (6%), the partner's income loss by half (22%), and wage loss of working-age children by a fourth (2%), and substantially mitigates income inequalities. Medical innovations return 58 773 SEK per year: equivalent to a fifth of the average annual family income in 2021. Medical innovations increase an individual's labor force participation (through restored health and decreased recovery time) and lessen relatives' burden to

provide informal care. Third, the mitigating economic effects of medical innovations are heterogeneous, especially for diseases causing health shocks and marital (cohabitation) status. Such differential patterns stem from the income responses of the partner who, for certain diseases, provides additional informal care in concordance with the increased consumption of medical care.

This study offers several contributions to the economics literature. First, it contributes to the applied microeconomic literature on the impact of single medical innovations on economic outcomes (Garthwaite, 2012; Stephens and Toohey, 2021; Jeon and Pohl, 2019) by broadening the evidence to include all diseases observable in the population and highlighting the most effective medical innovations across all population groups. Further, it adds to the growing literature on the economic consequences of health shocks and their heterogeneity (García-Gómez, 2011; Lundborg et al., 2015; Dobkin et al., 2018) by assessing the value of the innovation-induced reduction of economic losses due to health shocks. The focus on single diseases to measure the heterogeneities in health shocks' economic consequences is also new to the literature. Finally, my findings contribute to empirical studies on the economic responses of close relatives to an individual's health and labor force participation shocks (Fadlon and Nielsen, 2021; García-Gómez et al., 2013) by establishing that the benefits of medical innovations are not limited to the individual.

Second, this study complements more general and diverse literature on the aggregate productivity of medical care (Cutler and McClellan, 2001; Murphy and Topel, 2006; Bloom et al., 2020; Scannell et al., 2012; Fonseca et al., 2021; Cutler et al., 2021) by demonstrating plausible causal gains of medical innovations based on a quasi-experimental design. The estimates of the impacts of medical innovations on family income from this study can be used to calibrate the value of health gains in terms of consumption. This aspect of the study partially overlaps with previous literature on the allocation of the productivity effects of medical innovations that cover the most common diseases, such as cancer and heart disease (Berndt et al., 2002; Cutler et al., 2007; Cutler et al., 2012; Glied and Lleras-Muney, 2008). This study presents findings on the heterogeneous economic responses to

medical care in a context with a mature welfare and public health system, taking Sweden as an example country.

The remainder of this study is organized as follows. Section I outlines the conceptual model of the analyses performed in this study, such as the family health production model. Section II describes the data used in the analysis, including longitudinal individual-level data and a series of medical scientific discoveries. Section III presents the empirical strategy: the DDD and ML approaches. Section IV presents estimates of the effects of an individual's health shock on personal economic outcomes and a wider group of family members. Based on the magnitude of the economic loss, I estimate the portion of the economic loss mitigated by medical scientific discoveries and analyze the heterogeneity of these mitigating effects across individuals' characteristics. Finally, I present the results from an ML analysis that includes the most effective medical discovery for each disease in terms of the magnitude of the mitigating effect on family income. Section IV concludes the study with robustness analyses. Finally, Section V presents my conclusions.

I. Conceptual framework

To theorize how medical innovations influence health and household income, I draw on the Grossman (1972, 2000) model of health production—specifically, its more recent extensions for family health production (Jacobson, 2000; Bolin et al., 2002). In this extended model, the resources available for health production are not only individuals' personal income but also their total family income. The development of the extended model can be described as follows:

$$(1)\ \partial W/\partial t = r \cdot W + \omega_i(H_i, M_i, E_{p,i}) \cdot h_{p,i} + \omega_p(H_f, M_i, E_{p,f}) \cdot h_{p,f} + B - p \cdot (M_i + M_p) - q \cdot X$$

where r is the market interest rate and ω and h is the wage rates (i.e., labor market earnings rate of return on human capital) and time spent at work, respectively, which are functions of health *(H)* and the level of education and on-the-job training (*E)*. *B* represents transfers; p and q are the prices of

medical care (M) and other goods (X), respectively.[2] The subscripts i and p denote the individual and the partner, respectively. Hence, an individual's health affects market income in two ways: 1) through its effect on the wage rate and 2) through its impact on the amount of time a healthy individual is available for work. In this model, decreased health may also decrease savings rates (through $r \cdot W$) because individuals are allowed to borrow and lend capital.

The development of the stock of health for an individual (partner) can be described as follows:

$$(2)\ \partial H_{i(p)} / \partial t = I_{i(p)} - \delta_{i(p)} \cdot H_{i(p)}$$

where $I_{i(p)}$ is the gross investment in health and $\delta_{i(p)}$ is the rate of depreciation. That is, adverse health events are negative investments (depreciation) in health that can be offset by positive investments. Health investments for a family member are a function of medical care ($M_{i(p)}$), personal and other family members' time used in health production ($h_{H,i}$ and $h_{H,p}$), and productivity in health production ($E_{H,i}$ and $E_{H,p}$).

The time restrictions for each family member are expressed as follows:

$$(3)\ \Omega_{i(p)} = h_{\omega,i(p)} + h_{X,i(p)} + h_{H,i,p} + h_{H,p,i} + h_{S,i(p)}$$

where $h_{S,i}$ is the duration of the sickness $(h_{S,i} = h_{S,i}[H_I])$.

Equations 1 through 3 indicate that medical innovations (i.e., new drugs or medical procedures) are positive investments in health that reduce the decline in health capital through the following three channels: First, they directly reduce health shocks' negative consequences (i.e., restore health). Second, they decrease the time spent on health production, thus increasing the time spent on market production and income. Third, medical innovation affects the partner's income. The effect of a health shock on the partner's earnings is ambiguous: The partner may compensate for the income loss by either increasing their labor force participation or—due to increased time spent on the individual's

[2] In the case of universal public health insurance and the absence of out-of-pocket expenses, as seen in Sweden, increased medical care (i.e., costs) is absorbed by taxes with no direct effect on family income.

health recovery or household work—decreasing their labor force participation. Consequently, the impact of medical innovations on a partner's income is ambiguous because they either reduce or increase their partner's out-of-work time. The model also allows for the influence of parental health on children. In the context of the extended family, which is relevant for this study, adult children can also be affected because they often provide informal care. In sum, the model suggests considering both ultimate and provisional outcomes, such as total family income, combined personal and partner's income, labor income, sickness and welfare payments, and capital income. Further, adult children's incomes are also analyzed.

The Grossman model explicitly formulates how an individual's characteristics moderate a health shock's effects. An important aspect is the health shock's severity. In this model, the depreciation rate of health capital is an increasing function of age. However, the onset of either chronic or functional impairments at a similar age may have different consequences for the individual's and partner's labor force participation and welfare uptake (McClellan, 1998). This implies that, in principle, the effect of *B* (transfers) may depend on health, medical care, and the efficiency of their utilization. Additionally, productivity in the health production of the individual experiencing a health shock and his/her partner affects the strength of the response to health investments. As an illustration, individuals with a higher education level may be more efficient health producers, and hence, reap greater benefits from medical innovation. In principle, a similar argument can justify gender differences in responses to health investments (Fuchs, 2004), which have also been analyzed in this study. A final important aspect that was explicitly introduced by the extended model—as compared to the classical model where each individual is a sole producer of his/her own heath—is the marital (cohabitation) status of the individual. In the case of disease onset in an individual, the scope of informal care provided by the partner is substantial for either severe diseases or for older adults (Pandey et al., 2019; Bjørnelv et al., 2020).

II. Data

This study begins with a description of the data to lay the foundation for the empirical strategy, which is further described in Section IV. The data were then classified into the following two datasets: (1) data derived from individual income and health registers, which provide longitudinal individual records. (2) time series of medical scientific discoveries for each disease, drawn from the databases of national approval authorities.

a. INDIVIDUAL-LEVEL DATA

Information on individuals studied in this article was obtained from the administrative longitudinal registers of the total Swedish population—combined with the use of unique personal identifiers in the Swedish Interdisciplinary Panel (SIP).[3] SIP includes data on demographic characteristics, income, labor market participation, education, and health. The main study population comprised individuals aged 40–70 years, including adults of working age (below 60 years) and older adults. Individuals in the latter age group were included because, in the context of the study, they had the possibility of early and postponed retirement that could be affected by the health shock and because numerous medical innovations were introduced for diseases more pronounced in older age. Information on the outcomes of individuals' close relatives, including partners and adult children, was also obtained. Children aged 25–40 years were considered to avoid the overrepresentation of children in older cohorts and the influence of own children's health shocks on the outcomes. I extracted information on individuals and their close relatives for the period 1978–2008, which is as wide as the overlap allowed between different registers.

[3] I have used the database "Swedish Interdisciplinary Panel," which was hosted at the Centre for Economic Demography at Lund University (Statistics Sweden, 2011-2021). This is an extract and a compilation of multiple registers (through unique personal identifiers) of individuals born between 1930 and 1995 and of their siblings, parents, and children. Lazuka (2020) provides details about the sources and reliability of the data.

To identify individuals who had experienced health shocks due to certain diseases, I utilized information on inpatient hospital admissions.[4] Inpatient hospital admissions involve considerable economic consequences, are identifiable, and guarantee access to the newest medical technologies, including diagnostics, therapies and drugs (Dobkin et al., 2018; Lundborg et al., 2015). I applied three exclusion criteria to the hospitalization data. First, I focused on the first hospital admissions of individuals who had not been admitted in the three preceding years to minimize the possibility of obtaining anticipated health shocks. Second, I limited admissions to those individuals for whom specific medical technology could be identified, and hence excluded stays related to pregnancy, external causes, and symptoms. Finally, the causes of hospitalizations should align with the data on medical innovation, as described in Section II.b. The obtained hospitalization records, combined with residence records, allowed me to define 1 409 751 individuals who had experienced a health shock at some point from 40–70 years of age ("ever-treated").

The SIP provides a rich set of variables to determine an individual's income and its sources. The main outcome variable is disposable family income in real terms, which has been empirically regarded as the ultimate outcome of all economic consequences of a health shock (O'Donnell et al., 2015). This variable was calculated in terms of net taxes, which can be considered equivalent to efficiency in the context of public health insurance and the absence of out-of-pocket expenses, as seen in Sweden. Further, I utilized personal disposable income and various economic variables that quantify its sources, such as disposable income, wages, capital income, and payments for sick leave, unemployment, and disability. The group of welfare variables should compensate for the absence of health variables, which should ideally be studied as outcomes. The construction of counterfactuals for the individuals who experienced health shocks required that potential control individuals appear

[4] The inpatient hospital register has covered all 24 counties in Sweden since 1987. Between 1977 and 1987, this coverage was gradually increased by including seven previously missing counties. The populations of these counties for older cohorts were excluded from the analysis (4.51% of all observations). For the period under study, I employed 3-digit ICD codes from ICD revisions 8, 9, and 10.

in the future; such a sample relying on future survival means that neither hospitalizations nor mortality could be considered. To avoid the influence of compositional changes across the disease groups due to differential mortality, income information was included only for the full calendar years when the individual was alive. I used economic outcomes in the relative form (the inverse hyperbolic sine, [IHS]) to ease the interpretation of the results.

Finally, I added information on the economic outcomes of close relatives, calculating and then including the income of the partner and other household members.[5] Adult children could provide informal care instead of the partner and receive the related allowance; hence, I also extracted their income, wages, and welfare payments.

b. MEDICAL INNOVATIONS

Undoubtedly, the provision of medical care depends on the economic performance of the working population; therefore, I approximated medical care with medical scientific discoveries that are exogenous to the individual's income or propensity to contract a disease. The main sources of these data are the registries of the Swedish authorities responsible for the approval of medical innovations. I created disease groups within which medical innovations are measured in a trade-off between clinically meaningful categories—as defined by Elixhauser et al. (2015)—and the availability and consistency of the ICD codes for hospitalization causes over the study period. The

[5] Family income is identified based on the income of at most two generations who have a relationship with each other and reside on the same property. Such relationships include marriage, cohabitation with a common child (children), or an adoption. To obtain the spouse's income, I subtracted personal income from family income. However, for working-age unmarried (non-cohabitating) individuals who live with their parents, this residual represents the income of their parents. Therefore, I refer to this outcome as to the "income of the partner or other household members." The components for family and personal disposable income are the same throughout the period under analysis. There were several changes in the registration of welfare payments and its conditions in the study period. This should not be problematic because, as further described in Section III.b, treated and control individuals were matched exactly on the calendar year.

final list of 91 disease groups (see Appendix A Table) was verified by health experts (Lindström and Rosvall, 2019). Innovations in each disease group were made annually during the study period.

A medical innovation measure used in this study is the cumulative number of new molecular entities, which refer to novel chemical compounds that create the basis for new drugs. I selected it as my preferred measure because it captures the role of one component of innovation in medical care (Kesselheim et al., 2013). I linked the drugs to specific diseases in the following three steps. First, the Swedish Medical Products Agency (*Läkemedelsverket*) was utilized to obtain a detailed registry of all drugs, their underlying molecular entities, and the dates of approval of both national and international origin to treat a particular disease in Sweden.[6] Second, as each drug also supplied information on the Anatomical Therapeutic Chemical code of the underlying molecular entity and therapeutic indications, I was able to successfully match their combinations with the three-digit ICD codes—available from the Theriaque database (Husson, 2008). Finally, to validate the series, I cross-checked the appearance of the most important drugs with those in both the World Health Organization Model List of Essential Medicines (WHO, 2019) and relevant systematic assessments (Kesselheim and Avorn, 2013).

Another complementary measure of medical innovation that was used in this study was patents granted for diagnostics, therapeutics, and surgical treatment. This information was obtained from the Swedish Patent Database run by the Swedish Patents and Registration Agency (*Patent- och Registreringsverket*) using a search procedure practiced by advisory experts.[7] A database with detailed information, such as the International Patent Classification (IPC) code, taken together with the patent in a searchable format, is a useful tool for finding technology and innovation patents within

[6] Available at https://www.lakemedelsverket.se. Based on this registry's extract listing of all drugs approved for each year in 1950–2006, I constructed a cumulative series of active ingredients. Drugs disapproved during this period were excluded from the series.

[7] Available at https://tc.prv.se/spd. This registry covers all patents granted—both in force and no longer in force. I constructed cumulative panels based on the extract listing for each year from 1950–2006.

a certain field, their origins, and the dates they were in force. First, I limited the IPC codes to those covering surgery, electrotherapy, magnetotherapy, radiation therapy, ultrasound therapy, medical devices, and diagnostics.[8] Second, based on the names of diseases in the corresponding ICD versions within each disease group, I formulated combinations of keywords to conduct inclusive yet independent searches (available upon request). Based on the IPC codes and keywords, I conducted a search for the number of patents granted per disease group and year in the heading and text of patents. Patents defined the final year of treatment in this study: They ended in 2006 because the law prohibited the granting of patents for surgical/therapeutic treatment and diagnostics.

Figure 1 presents the cumulative number of drugs and patents that were obtained and eventually used in the estimations, together with their means within aggregated disease groups. I use a cumulative number of drugs for two reasons: 1) It measures the stock of medical knowledge. 2) Commonly, a combination of new and old medical innovations is most efficient. The content and ranking of innovations based on the obtained series generally correspond to the categorizations provided by relevant benchmark studies for pharmaceutical (Lichtenberg, 2003; Kesselheim and Avorn, 2013) and non-pharmaceutical innovations (Fuchs and Sox, 2001; Fermont et al., 2016). Since I employed measures of medical innovations that were ready for use in healthcare, I preferred a lag of one year for each to capture the correct timing when the technology was implemented, as well as to take into account its exogenous nature. Most previous studies select the preferred lag length after examining the empirical exercise itself, thus making any hypothesis testing irrelevant (Hirschauer et

[8] They correspond to the subchapter in A61 "Medical or Veterinary Science; Hygiene," which includes the following categories linked to diagnostics/therapy/surgery: A61B "Diagnosis, Surgery, Identification"; A61F "Filters implantable into blood vessels, Prostheses, etc."; A61M "Devices for introducing media into or on to the body, etc."; and A61N "Electrotherapy, Magnetotherapy, Radiation therapy, Ultrasound therapy." I excluded patents granted for A61K "Preparations for medical, dental, or toilet purposes," which makes the variable measuring patents complementary to that for drug approvals.

al., 2018).[9] To compare the findings of this study with those of previous studies, I present the results with a longer lag length in Section IV.e.

[Insert Figure 1 here]

III. Empirical strategy

a. DDD APPROACH

This study aims to define the extent to which medical innovations mitigate a health shock's negative consequences. This formulation implies a causal inference; therefore, I applied a DDD approach and estimated medical innovations' impact on economic outcomes as an innovation-induced "reduction" in economic loss due to a health shock. This can be considered as the difference between the two DD estimators (Goodman-Bacon, 2021). To form the first DD estimator (DD_{idst}), I compared the evolution of the economic outcomes of individuals who had experienced the health shock ("ever-treated") to the "control" individuals. For adult children's outcomes, a comparison was made between their parents. To form the second DD estimator, one needs to use the variation in DD_{idst} by at least one more dimension; in this case, these differentially affected groups appeared because the number of medical innovations varies over time and across diseases.[10] To obtain a triple-difference

[9] Gross et al. (1999) regressed current funding on research in the medical sciences on current health measures. Cutler et al. (2012) related the current number of grants and publications to the decline in infant mortality from the end of the 15-year period to the current period. Lichtenberg (2015) found that lags of ten or more years yielded a statistically significant effect of cumulative drug approvals on the years of life saved. To account for the delay in the appearance of the innovation in question and its widespread use in healthcare, Jeon and Pohl (2019) used a five-year lag of cumulative drug approvals and patent applications to measure their heterogeneous effects on employment reduction after cancer diagnosis.

[10] While conducting this mental exercise, one can also flip the order of the DD estimators. That is, the first DD can indicate the evolution of outcomes between individuals with access to different levels of innovations, regardless of whether they experienced the health shock. The difference between these DD estimators (i.e., DDD) can be constructed because some individuals already experienced the health shock, while some did not.

coefficient, where one of the differences varies across the values of a continuous variable (i.e., medical innovations), I estimated the following DDD specification:

$$(4)\ Y_{itds} = \alpha_i + \beta_1 post_{idst} + \beta_2 DD_{idst} + \beta_3 DD_{idst} M_{ds} + \beta_4 post_{idst} M_{ds} + \xi_{Dt} + u_{itds}$$

In this equation, Y_{itds} is an outcome for an individual i in year t, who either experienced a health shock due to disease d in year s ("ever-treated") or an outcome for another individual who serves as a counterpart to the treated individual ("control"). The outcomes are determined by the conceptual model, and include family income and its sources in absolute and relative forms, as well as the economic outcomes of adult children. DD_{idst} is an indicator for years during and after a negative health shock experienced by an individual due to disease d in year s (i.e., three years before and two years after the health shock, including the hospitalization year); $post_{ts}$ is an indicator for years during and after the health shock; M_{ds} denotes the lagged cumulative number of approved drugs or granted patents (in separate models) available to treat disease d in year s; and α_i represents individual fixed effects.[11] ξ_{Dt} represents event-year fixed effects specific to each aggregated group of diseases.

Eq.4 enables the exclusion of four main sources of bias from the main effect of interest β_3, which should represent the causal effect of a medical innovation on income and its sources, i.e., the innovation-induced difference in the Average Treatment Effect on the Treated (ATET). First, the bias related to the permanent differences between individuals that affect both the outcome and treatment differs based on the presence of individual fixed effects.[12] Second, changes in the outcomes over time—similar to all individuals—are also mechanically ruled out due to the inclusion of the post-

A similar model was used by Jeon and Pohl (2019), who studied the impact of medical innovations for breast and prostate cancer; hence, in their study, medical innovations varied only between years.

[11] In Eq.4, the effects of three terms—an indicator for the individuals who experienced a health shock, M_{ds}, and their interaction—are absorbed by the individual fixed effects.

[12] As soon as an individual was matched, they received a new unique individual (experimental) number that was different from their original individual number. That is, observations for individuals who participated both as controls ($t \in [-8; -4]$) and then as treated ($t = 0$) are considered and constructed as being independent of each other.

treatment dummy $post_{idst}$ and matching within the same observation years (see below). Finally, two sets of time-varying biases are also excluded: 1) the biases specific to each level of medical innovation, controlled by the interaction $post_{idst}M_{ds}$ and necessary for a complete DDD specification, such as structural breaks in different years; 2) the effects of time-varying factors common to an aggregated disease group (ξ_{Dt}), such as time trends in medical innovations and outcomes.

Conditional on the absence of the anticipation of treatment, the DDD approach relies on the "parallel trends" assumption, which states that there are no time-varying shocks specific to comparison groups (between "ever-treated" and "control" groups and between those at each level of medical innovation); I constructed the "control" group to ensure that this assumption holds. Fadlon and Nielsen (2021) demonstrated that individuals who suffered a heart attack or stroke in the near future were valid counterfactuals for individuals who had the same health shock in the year of analysis. I adopted and developed this approach for a broader set of diseases (see Section III.b for more details). I matched each "ever-treated" individual with others within the pool of individuals based on the following criteria: 1) hospitalized due to the same cause in two years; 2) had the same gender; and 3) well-aligned with the propensity score predicted from several observable characteristics. This mechanically ruled out the calendar, gender, and age effects. Due to the no-anticipation condition (recall that "ever-treated" individuals were previously restricted to those not hospitalized three years before the observed hospitalization), it was also possible to rely on a formal *t*-test for the absence of pre-trends (Novgorodsky and Setzler, 2019).

b. CONSTRUCTION OF THE COUNTERFACTUALS

As described previously, recognizing valid counterfactuals (in terms of the pre-trends) to the "ever-treated" individuals was crucial for the identification strategy. Here, I describe in detail the matching procedure and the results of the diagnostic tests.

In this study, I matched "ever-treated" individuals to similar individuals who experienced a health shock in the future, inspired by Fadlon and Nielsen's (2021) methodology. Their study focused

on heart attacks and strokes, which are both sudden and severe, and obtained valid counterfactuals when matched individuals who were hospitalized/died from these causes in year *t* to those who were hospitalized/died from these causes in year *t*+5. The present study focuses on more diseases, thereby narrowing the time window to *t*+2 within the disease group (91 in total); observable characteristics are matched to obtain valid counterfactuals.[13] The propensity score was predicted based on three characteristics. First, the year of birth was chosen because the range of the cohorts under study was quite dispersed. The second and third characteristics, years of schooling and IHS earnings for the pre-treatment age period 38–39, potentially affect the development of economic outcomes. To choose the most efficient matching procedure, I followed Austin (2014), who suggested using propensity score matching with a calliper of 0.2 standard deviations and no replacements.

From the original sample of "ever-treated" individuals, I matched 1 340 485 (or 95%), without being particularly restrictive; two diagnostic tests were conducted on the obtained sample. The first test compared standard deviations for the observable characteristics with a threshold value of 0.1, which has been proposed to indicate a small imbalance between the "ever-treated" and matched individuals (Austin, 2009). Figure 2 presents the results of this test for the study sample in total and for an aggregated disease group, each of which indicated no imbalance. In a DDD framework, the balancing test does not ensure the parallelism of pre-trends in the outcomes between the comparison groups. Therefore, as a second test, I calculated the mean of the economic outcome by a comparison group across event years—before and after a health shock.

[Insert Figure 2 here]

Figure 3 presents the mean of family income by a comparison group across event years, while Appendix B contains other economic outcomes for the individual, partner, and working-age children.

[13] This is the smallest window possible: For the pre-treatment period, three years is the minimum time to detect non-linearity in outcomes based on *t* and *F*-tests; for the treatment period, the year after hospitalization, *t+1*, is the first year when the negative effect of hospitalization is fully realized.

The pattern of family income and other economic outcomes reveals remarkable similarity in the development of the outcome for the comparison groups before the event year of $t = 0$, that is, the year of the health shock (i.e., hospitalization) for the treated individuals. The observation of no pre-trends could be made for both severe and unanticipated diseases—cancers or circulatory diseases—and those usually understood as chronic and anticipated—mental/nervous or metabolic diseases. The absence of visible pre-trends is probably caused due to the following reason: When there were a number of events preceding hospitalization (e.g., an earlier diagnosis or job loss), both groups of individuals experienced a deterioration in economic outcomes, resulting in similar pre-trends during a time window of two years (Novgorodsky and Setzler, 2019). In the year of the health shock and afterwards, the relative family income declined rapidly among the affected individuals, providing primary evidence for the appearance of economic loss in the family; in contrast, control individuals showed no change.

[Insert Figure 3 here]

An investigation of the pre-trends of "ever-treated" and matched individuals was insufficient because a DDD would, in addition, use variations of these groups across the levels of medical innovation; therefore, I further performed two formal tests to assess the absence of non-linear pre-trends for relative family income separately by disease group. For the first test, I followed Borusyak et al.'s (2021) suggestion to estimate a fully dynamic specification (i.e., event study) of the underlying DD models, where several distant pre-treatment event years are treated as reference categories, and non-linear pre-trends are detected with an *F*-test. Across each of the 91 disease groups for men and women, this test was performed by omitting $t = -3$ and $t = -1$. However, the outcome of such a test, relying on the sample size, tends to confirm the existence of pre-trends—even though these pre-trends are economically insignificant, thus potentially biasing the ATET to zero. To avoid such a problem, Rosenbaum and Rubin (1985) suggested using a standardized difference, which is an indicator neutral to the sample size. Therefore, as a second test, I calculated the standardized differences in the outcomes between treated individuals and their counterfactuals for each disease group.

Most disease groups successfully passed both tests (see table in Appendix B). Of the 91 disease groups, 89 had no pre-trends at a 5% significance level according to the results of the *F*-test. On one occasion, for the group of individuals diagnosed with in-situ neoplasms at admission, pre-trends were both statistically and economically meaningful. On another occasion, for ischemic heart disease, the results of the test indicated an income difference of 0.6% between the comparison groups prior to the health shock, which further reduced income by 60%, suggesting that the pre-trends were unable to nullify the health shock's impact. In another test, the standardized difference was below a threshold of 0.1 for a comprehensive set of 88 disease groups and indicated a marginal imbalance for the rest. The results of both tests generally supported the a priori expectation of similarity in pre-treatment behavior of individuals who had experienced a health shock in the current year and those who experienced the same event in a subsequent two-year window across various diseases. In an earlier version of this study conducted by Lazuka (2021), in which several disease groups with significant pre-trends were excluded from the estimation sample, the results were almost identical to those presented here. Thus, due to the similarity of the results and the focus of the study on a broad set of diseases, I based my further estimations on the sample of all 91 disease groups.

Table 1 presents the descriptive statistics of the estimation sample, which comprises 2 243 040 experimental individuals (i.e., those with separate identifiers if the individual participated as both a treated and control individual) and 11 032 884 observations. The most common causes of hospitalization were circulatory system diseases (23%); neoplasms (17%); digestive organ diseases (17%); musculoskeletal, urinary, mental, and respiratory diseases (5%–10%), and others (3% combined). There were also 9 763 843 observations of working-age children whose mothers or fathers had experienced health shocks.

[Insert Table 1 about here]

c. HETEROGENEOUS DDD EFFECTS AND AN ML APPROACH

This study also estimated the heterogeneous mitigating effects of medical innovations. In this section, I first describe how these effects are accurately estimated with the three-way fixed effects estimator in a design-based sample, and then present the approaches used in this study.

Recent methodological literature has revealed that OLS regressions with fixed effects may produce estimates far from ATET in the presence of heterogeneous effects—due to a weighting problem (Callaway and Sant'Anna, 2020; Sun and Abraham, 2020).). The solution proposed to solve this problem—estimating the cohort-average treatment effects and appropriately aggregating them—is similar to the empirical approach applied in the present study. As mentioned earlier, I matched each treated individual to the not-yet-treated individual, extracted the same pre- and post-treatment years for each pair, and stacked all pairs with duplicates in regressions. This solved two problems related to weighting. First, there were no negative weights in my estimation, meaning that the DD and DDD estimates could not be of different signs compared to the ATET. Second, the availability of treatment pairs ensured that differential treatment groups received equal weights and contributed equally to the estimates in the two-way fixed-effects regression. To verify this, I estimated the aggregated ATETs following the approach of Callaway and Sant'Anna (2020), and obtained results nearly identical to those reported in the main body of the study (available upon request).

The year-to-year construction of the cohorts—implemented as a part of this study's empirical strategy—solves the weighing problem and addresses whether the economic consequences between the family members and individuals are equal or distinguished by the severity of the disease responsible for the health shock, gender, education, marital (cohabitation) status, and age. Further, it evaluates the effects of medical care on these inequalities. I answer these questions by estimating Eq.4 for subsamples of individuals distinguished by related characteristics. In relation to the disease causing the health shock, I estimated the heterogeneous effects by single disease instead of an aggregated disease group because aggregated disease-by-event-year fixed effects (ξ_{Dt}) can no longer

be introduced due to collinearity with a DDD indicator. More preferably, samples distinguished by a single disease do not suffer from the problem of correlated trends in medical innovation due to the inclusion of only one series of medical innovations at a time (cf. Jeon and Pohl, 2019).

While the estimation of the heterogeneous DDD effects provide a general picture of the distribution of the benefits of medical innovation, its ability to reveal the mechanisms of such effects is limited. Therefore, as a second step, I applied an ML approach that allowed me to identify the most effective medical innovations (i.e., in terms of the economic response) within certain disease groups. The most effective innovations should be identified based on their mitigating economic effects; thus, I leveraged the model-based recursive partitioning proposed by Zeileis et al. (2008), which relies on Eq.4 (without ξ_{Dt}), and selected the year of the health shock (i.e., time of hospital admission) in a categorical form as a partitioning variable. This method enables the assessment of parameter instability with respect to the values of the year of the health shock. If there is some overall instability, it selects the year associated with the highest parameter instability. To avoid overfitting with such a large dataset, I applied both a p-value of 0.001 for the detection of parameter instability and post-pruning with Bayes information criteria. After determining the year when medical innovation produced the largest economic impact for each disease group, I returned to the primary sources of data on medical innovation to identify the exact drugs and patents responsible for the effects.

IV. Results

a. ECONOMIC LOSSES DUE TO THE HEALTH SHOCKS

Firstly, I present the estimates for the economic responses due to the health shock (i.e., β_2) for the individual and the individual's close relatives, including their partner and adult children.[14] It is

[14] The estimates were obtained based on Eq.4, where the interaction effects involving medical innovation, M_{ds}, were excluded.

important to measure the magnitude and dynamics of these responses for these groups as well as define how these responses align with the conceptual model of family health production.

Table 2 presents the estimates of the impact of the individual's health shock on the total family disposable income for two years and for each event year. The overall impact of an individual's health shock on family income is usually ambiguous because it is the ultimate outcome of multidirectional responses. These include, but are not limited to, a reduction in the individual's labor force participation due to short- and long-term health incapacity, an increase in social benefits received to compensate for the related income loss, and ambiguous labor force participation responses of household members and close relatives (Riphahn, 1999; Fadlon and Nielsen, 2021). Consistent with previous studies, I find that a family suffers a net income loss when an individual experiences a health shock. On average, the results show that following the health shock, family income declines by 32%, which is equal to 103 331 SEK per individual year in terms of the real income of the counterfactuals. There was no sign of shrinkage in family income loss in the second year after the health shock. According to studies that considered health shocks due to various diseases, the magnitude of the loss is similar to that in other European Union countries (García-Gómez et al., 2013).

[Insert Table 2 here]

Regarding the individual, Table 2 shows that the income loss is only 5% or 9644 SEK and emerges due to several counterbalancing responses. However, there is a substantial reduction in wages (38%, or 83 008 SEK). Unsurprisingly, the results also show that a reduction in wages is compensated by a large increase in the uptake of different welfare payments (3.4 times).[15] The responses by type of welfare payment are provided in Table C1 in Appendix C. These results show a large increase in absenteeism due to illness (2.4 times), which is a job-based income insurance

[15] Only the income outcomes are provided as net taxes; all other variables are gross and were partially subject to taxation. Therefore, the responses in welfare payments and self-insurance—and those in wages—do not equal the responses in income.

covering periods of short-term sickness. Furthermore, the individual responses in terms of social benefits suggest that, along with hours worked, productivity also declined after the health shock. Health shocks force individuals to exit the labor force (a 33% increase in unemployment payments), obtain disability insurance (an 18% increase in disability pension payments), and self-insure (a 4% increase in capital income). Finally, the results indicate the permanent nature of the deterioration in health capital because income loss does not shrink over time, while the wage and disability effects almost double.

Further, Table 2 presents the results for the effect of an individual's health shock on the economic outcomes of both the partner (or other household members) and working-age children. Theoretically, the partner or adult children's response is ambiguous because an individual's health shock can stimulate different motivations for labor market activity. The evidence from a US study suggests that partners increase labor force participation to compensate for the lost income (Van Houtven and Coe, 2010). However, in the European setting, partners and children decrease labor force participation to provide informal care and compensate for the reduced household productivity of the individual (Riphahn, 1999; Frimmel et al., 2020; García-Gómez et al., 2013). The results of the current study support the latter scenario: The income response of the partner or other household members is negative and equal to 64 468 SEK (or 46%). Such changes seem permanent because the gap in this economic outcome between the treated and counterfactuals remains in force in the second year after the individual's health shock. As for working-age children, the results indicate a small decrease in their labor force participation (1793 SEK or 1%), which is fully compensated by welfare transfers and results in a zero net income loss.

If welfare payments cushion wage losses due to the onset of the health shock, irrespective of the severity and persistence of the health problems in the longer run, no differences in the family income responses across diseases are expected; however, this study's results indicate the opposite. Previous studies have shown that different health shocks affect an individual's earnings to different extents; for instance, the effects are particularly significant and permanent in the case of acute dramatic health

events—and milder but still permanent in cases of chronic diseases with slow degeneration (McClellan, 1998). Even in the Scandinavian context, spouses' labor force participation responses depend on whether the individual's health shock results in fatality (Fadlon and Nielsen, 2021). Table 3 presents the estimates for the economic responses to an individual's health shock according to the aggregated disease group. While the net family economic loss appears universally across the disease groups, its relative size differs, being the largest for cancers (93%); followed by, diseases of circulatory and blood-forming organs (40% each); moderate for the group of mental, respiratory, and infectious diseases (approximately 20% each); and smaller for the remaining groups (approximately 5%–10% each). Figure C1 in Appendix C presents the estimates for family income losses by disease, which indicate a large variation within aggregated groups.

[Insert Table 3 about here]

Importantly, reductions in the individual's wages and partner's incomes are universal yet extremely variable across diseases. Based on the estimates of the health shock on the sources of income of both the family and working-age children, I further distinguish several groups of health shocks (see also Table C2 and Figures C2–C4 in Appendix C). The first two groups are consistent with the previous literature. These include health shocks caused by severe and deadly diseases that lead to substantial income losses (neoplasms and circulatory diseases) and those caused by severe non-deadly yet long-lasting diseases for which losses due to work incapacity become fully insured (mental and musculoskeletal diseases). An additional group—not considered in the previous studies but apparent from the results in the present study—stems from less severe diseases requiring long-term treatment (e.g., diseases related to respiratory or blood-forming organs) that cause significant income losses for the partner, perhaps due to their decision to provide informal care or take charge of household work. In either case, whether a specific group of diseases or the most severe diseases, the partner's negative income responses are the most drastic. Meanwhile, working-age children tend to reduce their labor force participation in favor of caring for their parents who have experienced a health shock due to cancer or a nervous disease.

b. THE MITIGATING ECONOMIC IMPACT OF MEDICAL INNOVATIONS

In this section, I present the results of the mitigating impacts of medical care on the economic outcomes of the individual and his/her close relatives. Such mitigating impacts remain understudied in the literature focusing on the economic impacts of health shocks and their heterogeneity. Although there are studies that investigate the impact of health insurance on individuals' wages, health insurance is commonly approached from the employer's perspective (Currie and Madrian, 1999). Few studies have conclusively verified the substantial mitigating impacts of specific medical innovations on particular diseases (Bütikofer and Skira, 2018; Jeon and Pohl, 2019; Stephens and Toohey, 2021; Garthwaite, 2012). However, medical care consumption is an important and universal determinant of family health production; if medical care mitigates the negative consequences of the health shock, the full extent of the economic consequences of various health shocks remain underestimated in the context of different levels of medical care.

Table 4 presents the estimates for the mitigating impact of medical innovations—measured with one-year lags of newly-approved drugs and recently-granted patents, obtained from Eq.4—on the economic outcomes of the individual and his/her close relatives. As shown in the previous section, both family income and close relatives' income decline after an individual's health shock; therefore, the positive estimates with respect to medical innovations should be interpreted as the innovation-induced "reduction" in economic losses caused by the health shock. The estimates in Table 4 indicate three important findings. First, medical innovations significantly reduce individuals' and families' income losses. Grasping the size of the total mitigating effect—if interpreted in terms of one standard deviation of medical innovations—is easier. The mitigating impact of medical innovations on family income amounts to 10% ($0.755 \times 0.133 \times 100\%$) using drugs and 8% ($0.012 \times 6.563 \times 100\%$) using patents, and the combined impact amounts to 18%.[16] Referring to the latter magnitude of the overall

[16] It is possible to calculate the sum of both effects to obtain the combined impact of medical innovation because both these measurements are independent and complementary. For independent measurements, as provided in this study, the standard error (SE) of the coefficient estimate in terms of one standard deviation

decline in family income due to the health shock (32%, from Table 2), I find that medical discoveries moderated more than half of the family income loss. In absolute terms, medical innovations returned 58 773 SEK per individual year (328 030 SEK × 18%).

[Insert Table 4 about here]

Second, medical innovations have beneficial economic effects for both individuals and their partners. As for individual income, the combined effect of medical innovations amounts to 6% (0.238 × 0.133 × 100% + 0.004 × 6.563 × 100%). This result suggests that medical innovations reduce an individual's net economic loss to zero. Additionally, the partner's income loss is reduced by half owing to medical innovations. In principle, the response of the partner should be proportional to the reduction in informal care due to the quicker recovery of the individual; the finding concerning the relatively smaller responses for the partner than those for the individual may thus indicate a more complex picture, which is developed in the next section with an analysis of their heterogeneities. Beneficial mitigating effects are found for wages and unemployment payments that link these effects to the restored health capital and sickness absence payments related to reduced "unhealthy" time (see also Table C3 Appendix C). In line with the absence of income responses to the parental health shock, there are no clear mitigating effects for working-age children.

The above findings on the mitigating economic effects of medical innovations pertain to a broad range of diseases and are novel to the applied economic literature; however, it is possible to juxtapose them with estimates for the aggregate productivity of medical care. Previous literature has provided significantly different estimates for the latter (Sheiner and Malinovskaya, 2016). The most recent studies have considered the realized utilization of medical care and labor productivity growth and provided an estimate of 0.7% for the annual productivity of medical care for the working-age population (Fonseca et al., 2021) and 1.5% for older adults (Cutler et al., 2021). For compatibility, I

(SD) of the medical innovations can be obtained using the following formula:

$SE_{combined}=\sqrt{(SE_{drugs}\cdot SD_{drugs})^2+(SE_{patents}\cdot SD_{patents})^2}$.

multiply the annual increase in the number of medical innovations by the estimates of β_3 for family disposable income as an outcome, which reflects the net taxes, and hence, medical care expenses. The corresponding estimate, with almost equal contributions of drugs and medical procedures, is 0.7%, which is in line with previous studies. However, this is an estimate of the lower bound for two reasons. First, as the event-year estimates from Table 4 demonstrate, the beneficial economic effects of medical care last for more than one year. Second, as presented above, medical care produces substantial positive spillover effects on labor force participation of both partners and working-age children.

c. HETEROGENOUS MITIGATING EFFECTS OF MEDICAL CARE

In this section, I present the results for the heterogeneous mitigating effects of medical innovations on the economic outcomes of both individuals and their close relatives. First, I analyze the heterogeneities in the mitigating effects of medical innovation on family income between individuals grouped by gender, age, marital (cohabitation) status, and education. Thereafter, I present the economic effects of each disease—covering all diseases examined in the study. To obtain a measure of the remaining loss (i.e., income inequality), the mitigating effects of medical care refer to the baseline economic losses in each subgroup. It is noteworthy that the sample used in this analysis was designed to balance the individual characteristics of the study; therefore, the effects presented below are not driven by compositional differences.

Heterogeneity in the economic effects of health shocks is predicted by the theoretical model of family health production, although any such heterogeneity can be diminished by both welfare systems, thus ensuring equity and/or medical progress in providing treatment against diseases with the largest detrimental effects. Several studies have established the beneficial economic effects of a limited set of medical innovations against specific diseases, such as new drugs and therapies to treat prostate and breast cancer (Jeon and Pohl, 2019), multiple interventions aimed at reducing coronary heart disease (Stephens and Toohey, 2021), antiretroviral therapy used to treat AIDS (Thirumurthy et

al., 2008), and Cox-2 inhibitors for the treatment of painful arthropathies (Bütikofer and Skira, 2018; Garthwaite, 2012). However, the mitigating economic effects of medical care on several other diseases—and whether these effects differ across individuals—remain unknown.

Table 5 presents the estimates of the mitigating income effects of medical innovation for the family and close relatives—obtained from Eq.4 based on subsamples of individuals distinguished by socio-economic characteristics. The results first show that the baseline income losses are unequal between families, implying that the existing welfare schemes do not ensure equity, which aligns with findings from previous studies in similar settings (García-Gómez et al., 2013; Lundborg et al., 2015). Along with these baseline heterogeneities, I find that the mitigating impacts of medical innovations on family income vary significantly. These effects, considered jointly as a family income response to a one standard deviation increase in medical innovations, are more significant for older adults (32%) versus younger individuals (13%), married (19%) versus unmarried individuals (no effect), and low (29%) versus highly educated individuals (9%). The impact on older adults could be explained by the fact that numerous medical innovations have been developed for diseases that are common in older age (cf. Cutler et al., 2021). The concentration of mitigating effects among married individuals indicates that partners (not parents who contribute to the family income of single individuals with whom they sharing housing) provide informal care and benefit from efficient medical care (cf. Pandey et al., 2019; Bjørnelv et al., 2020). Previous studies have found there is a gradient toward greater mitigating effects for the less educated, consistent with "efficiency" in the utilization of healthcare (Jeon and Pohl, 2017; Stephens and Toohey, 2021). This contradictory finding can be explained by the specificity of health shocks, which are not diagnoses (as in previous studies) but sudden inpatient hospitalizations guaranteeing immediate access to innovative drugs and procedures that are not otherwise accessible.

[Insert Table 5 about here]

The results also indicate that medical innovations substantially reduce not only the negative economic consequences of various health shocks but also the income inequalities caused by these

shocks. This role of medical innovations becomes apparent when one relates their mitigating effect to baseline economic loss. As an illustration, the baseline family income loss is estimated to be 36 percentage points greater for older adults than for younger individuals (59% versus 23%), and this difference is reduced by half with the usual provision of medical innovations (27% versus 10%). In line with the findings in the previous section, the magnitudes of the heterogeneities in the absolute impact of medical care are accentuated more significantly for the partner rather than for the affected individual or his/her working-age children. Medical innovations completely eliminate any relative income differences concerning the individual and his/her working-age children; however, for the partner and other family members, income differences remain significant yet diminished.

In the next step, I present the mitigating economic effects of medical innovations by disease (see Figure 4) for family income as an outcome. Most strikingly, heterogeneities in diseases are far greater than those in the other individual characteristics. Medical innovations were efficient for families whose members had experienced a health shock due to a neoplasm, circulatory disease, nervous disease, mental retardation, or any infectious disease, but had negligible mitigating effects for the rest. Innumerable diseases, common among adults and older adults, are efficiently mitigated by medical innovations. My results support previous findings that reported such effects when taking Sweden as an example country for diseases including prostate cancer (58%), breast cancer (22%), ischemic heart disease (39%), human immunodeficiency virus (HIV) (41%), and infectious arthropathies (4%). Additionally, the present study's results establish that medical innovations substantially reduce variability in the baseline income losses caused by shocks accompanied by different diseases, although such variability remains substantial for families of cancer patients.

[Insert Figure 4 here]

In Figures C5–C7 in Appendix C, I present the disease-specific mitigating effects on the incomes of the individual, their partner, and their working-age children. In fact, medical innovations reduced the income losses for the individuals experiencing health shocks due to most diseases, likely as a result of restoring their physical and mental working capacity. As demonstrated, partners or other

family members reduced their labor force participation due to increased consumption of medical care in the family, a pattern clearly emerging for many neoplasms, mental, respiratory, and blood-forming diseases. For example, medical innovations reduced the income loss on the part of the individual suffering from an affective disorder by 8% (i.e., restored their health capital) and increased the income loss for the partner of this individual by 22% (i.e., increased their time spent on this individual's healthcare or substituted for the individual's loss of household productivity). In situ neoplasms are another exemplary disease for which a 26% reduction in income loss for the individual is accompanied by a 64% increase in income loss for the partner. Such differential patterns within the family for certain diseases suggest that medical innovations, which have now become available for disease treatment, may differ depending on whether they require extra informal care or the partner assuming responsibility for household chores.

d. THE ANALYSIS OF SINGLE INNOVATIONS

In this section, I present the results from model-based recursive partitioning to reveal the most transformative medical innovations for selected diseases. Here, the aim is not only to identify these innovations but also to understand the within-family differences in responses to medical innovations available to treat certain diseases. I provide results for cancer, mental disorders, circulatory system diseases, and HIV that are significant in terms of incidence rates and the mitigating economic effects of medical innovation and exemplary for the partner's economic effects.

The results show that the most efficient medical innovations to treat cancer, the disease for which both the negative economic and mitigating effects are the greatest, include a combination of drugs and medical procedures. Appendix D presents the results of the ML analysis using approved drugs and granted patents, which include the years with the most powerful predictive effect of medical innovation, for which I identified single medical innovations from the database used to construct their cumulative series. These results indicate that the most efficient innovations in cancer treatment are "blockbuster" DNA-damaging drugs such as Paclitaxel, Gemcitabine hydrochloride, Etoposide, and

Fludarabine phosphate, supporting the idea that drugs with the greatest economic effects are those with well-known survival efficiencies against certain cancers (Chabner and Roberts, 2005; Lichtenberg, 2019). Meanwhile, the results using granted patents as a measure of innovation support the economic efficiency of computerized procedures, such as magnetic resonance imaging, laser treatment, application of devices for image-guided radiotherapy, and automated chemical diagnostics. These procedures result in better treatment outcomes and fewer side effects (Bradley, 2008). However, such treatments are often long term and involve substantial time investments for informal care from the partner, consistent with their negative labor market responses (cf. Yabroff and Kim, 2009).

A similar pattern was observed for mental disorders. As shown before, medical innovations reduce an individual's income loss but not that of the partner, including cases of mental and behavioral disorders due to drug and alcohol abuse, mood disorders, and mental retardation. The most efficient drugs to treat these diseases, which were identified with ML analysis, were Lorazepam, Zolopentixol Decanoate, and Acamprosate. These drugs require extensive therapy and commonly lead to side effects, such as fatigue and sleepiness, which, in turn, are linked to reduced household productivity (Duggan, 2005). As the analysis further shows, during the study period, there are no efficient medical procedures to treat mental disorders; the ones identified are related to the technological processes improving the preparation of the drugs. The lack of efficient innovations and formal care results in the partner spending increased time outside of work—caring for the affected individual.

Regarding circulatory diseases, the results reveal a pattern of positive economic effects for both the individual and his/her partner, and indicate that most innovations are highly efficient. The largest economic effects of medical innovations are related to thrombolytic drugs, including the coagulants Heparin, Streptokinase, and Argatroban. Additionally, the high economic efficiency of revascularization procedures is revealed, including electronic diagnostics, angioplasty, stent delivery, and advances in bypass surgery (e.g., high-capacity blood pumps or heart valve implants). Interestingly, for ischemic heart disease, the results suggest no single important drug; rather, each

drug and their combination has substantial mitigating effects, consistent with a series of continuous advances related to antihypertensive drugs, statins, and beta- and angiotensin blockers (Weisfeldt and Zieman, 2007). The commonality in these medical innovations is their capacity to save an individual's life and relatively quickly restore health to the pre-shock levels (Hoffmann et al., 2013).

The mitigating economic effects of medical innovations to treat HIV spill over to all family members and working-age children. The HIV patients in this study are likely those whose immune systems are strongly impaired by the infection: The health shocks caused by HIV often precipitate inpatient hospital admissions. This infectious disease causes strong negative income responses among both family members and adult children. The results of the ML analysis show that the most economically efficient drug is Nellfinavir and its combination with previous drugs that are free from severe side effects. These drugs almost fully restore the individual's capacity to work and form the core of antiretroviral therapy against HIV (Bhidé et al., 2020). As for medical procedures, results point to the efficacy of therapies that stimulate the immune system, such as electromagnetic radiotherapy. The identified medical innovations to treat HIV return individuals to a normal life, thus relieving close relatives of the burden of spending additional time on informal care.

e. ROBUSTNESS ANALYSIS

I have departed from the three standard assumptions of the DDD framework in the identification strategy: 1) There are no treatment effects prior to treatment realization ("no anticipation" effects). 2) The control group provides a valid counterfactual (the "parallel trends" assumption). 3) The potential outcomes and treatments of different groups are independent across underlying DD comparisons (the "independent groups" assumption). In this section, I provide evidence that these assumptions possibly hold true for the results of this study.

The "no anticipation" and "parallel trends" assumptions were addressed at the stage of constructing the estimation sample. As described before, the sample was constructed conditional on no anticipation, thus including only individuals who had not been hospitalized before and for whom

it was considered to be their first observed hospitalization in the age range of 40–70 years (see Section II.a). To obtain valid counterfactuals, I applied a matching technique that allowed me to deal with time-varying selection issues (see Section III.b). For the final estimation sample, both the visual analysis and formal tests by event year across the treated and control groups showed similar development in their pre-treatment outcomes. However, it is important to conduct a formal test for the absence of pre-trends for each DD comparison group participating in Eq.4. Therefore, I performed an *F*-test for the pre-trends in the event-year specification of Eq.4. by both disease and type of medical innovation (available upon request). In 89 of the 91 disease groups (98%), the results showed no significant pre-trends.

The "independent groups" assumption is likely to hold in this study setting because the first-year lags of drug approvals and granted patents were plausibly exogenous to the decision of hospitalization. However, the uptake of health insurance and care arguably induces medical innovation (Lleras-Muney and Lichtenberg, 2005; Acemoglu et al., 2006). The correlation between individuals treated in different years may also arise mechanically because the levels of medical innovations have been constructed as a cumulative series. I elaborated on the plausibility of the "independent groups" assumption through several checks (see Table 6). First, I detrended the panel of medical innovations within each disease group to obtain their white noise components and used the latter in the models. Next, I estimated the models by looking at medical innovations of exclusively international origin that more likely approximated exogenous shocks, directly imported drugs, and patents granted to non-Swedish applicants (cf. Papageorgiou et al., 2007). I also estimated the models with the 5- and 10-year lags (and reported the latter), which should exacerbate any existing endogeneity problem. I included individuals who experienced potentially similar health shocks but were left outside the estimation sample, such as individuals who were treated in emergency units and died. In sum, the results of the robustness models are similar to the main results of this study. Each model successfully passed the tests for non-linear pre-treatment trends (available upon request).

[Insert Table 6 here]

Conclusions

Despite growing evidence of the negative economic consequences of various health shocks and their heterogeneity in different treatment schemes, little is known about the extent to which these consequences can be mitigated by medical care. This study fills this gap in the literature by studying adults in Sweden aged from 40–70 years suffering with diseases of varying severity and progression, their partners, and their working-age children. To obtain the causal effects of medical care, I focused on the role of medical scientific discoveries and leveraged the longitudinal dimension of unique administrative data. This data allowed me to construct counterfactuals for diseased individuals who have similar pre-trends in economic outcomes for most diseases observed in the population. I studied the total mitigating effects of medical innovations and their heterogeneities, including the effects across relevant individuals' characteristics, single diseases, and single innovations.

This study reveals that medical innovations have sizable mitigating effects on the economic outcomes of individuals and their close relatives and that these effects are highly heterogeneous. An individual's health shock leads to negative economic consequences, including income loss for the whole family: the individual, partner, and other family members. Half of the family income loss is mitigated by medical innovations, which return 58 773 SEK per individual year, the sum equivalent to a fifth of the yearly family income in the study period. If medical care had been less efficient, the burden of welfare transfers would have been almost three times greater to fully compensate for the individual's capacity and income losses. The beneficial economic effect of medical innovations is 1.4% annually. Health shocks also produce substantial income inequalities— which were most pronounced when examining the disease and marital (cohabitation) status of the individual, as demonstrated by this study. Medical innovations also mitigate income inequality with a twofold reduction. The results establish the importance of examining a single disease to grasp the size of economic repercussions—generated by health shocks and mitigated by medical innovations. For certain diseases, mainly cancers, economic effects differ from the average. While medical innovations are efficient concerning the individual for most diseases, partners or other family members are relied

on to reduce the individual's work effort in the case of certain diseases due to the increased consumption of medical care in the family.

This study provides important policy implications. First, it shows that medical innovations can be regarded as investments with high returns. Since the growth in medical care innovations has surpassed the growth in health indicators or the real income at the population level, any mere comparison of the two would lead to the opposite, erroneous conclusion (cf. Fuchs, 2004; Bloom et al., 2020). Second, the effects of medical innovations appear to extend beyond the receivers of the treatment to their respective partners and working-age children. This result emerges because the resources available for an individual's health production are not only their personal income but also their total family income. However, the partner's response to medical innovations is heterogeneous in the individual's disease during the health shock, consistent with the efficiency of medical innovations being inversely related to the amount of extra informal care needed from the partner and working-age children. This highlights the weakness of the existing income insurance schemes in fully compensating for the economic repercussions of disease for the related parties. Finally, the mitigating economic effects of medical innovations are not equally distributed across population groups. This supports the idea that the existing welfare and public health systems do not sufficiently ensure equity and the absence of income loss after various health shocks. In summary, the economic repercussions of health shocks are neglected due to the lack of focus on the family and medical care available to treat each disease.

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