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

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THIS VERSION: 11 NOVEMBER 2022

ABSTRACT

This study provides new evidence regarding the extent to which medical care mitigates the economic consequences of various health shocks for the individual and a wider family. To obtain causal effects, I focus on the role of medical scientific discoveries and leverage the longitudinal dimension of unique administrative data for Sweden. The results indicate that medical innovations strongly mitigate the negative economic consequences of a health shock for the individual and create spillovers to relatives. Such mitigating effects are highly heterogeneous across prognoses. These results suggest that medical innovation substantially reduces the burden of welfare costs yet produces income inequalities.

JEL codes: I14; I18; J22; J24; J38; O31

Key words: medical innovation; health shock; family disposable income; income inequality; difference-in-differences-in-differences approach; machine learning

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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 (see Prinz et al. 2018 for a recent review). 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), 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 (Meyer and Mok 2019; Lundborg, Nilsson, and Vikström 2015).

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 adult 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-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 introduced and withdrawn new molecular entities (hereafter, NMEs) and patents for medical procedures in diagnostics, therapy, and surgery. They allow me to use variation of not few but 34 608 incepted and 5 860 withdrawn innovations. The study intends to establish the beneficial

[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, Zivin, and Goldstein 2008), and Cox-2 inhibitors for arthropathies (Bütikofer and Skira 2018; Garthwaite 2012).

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. It 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 welfare resources, for instance, to ensure that incomes are insulated from various 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, Meara, and Richards-Shubik 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. Appealingly, 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. In contrast to previous studies, I focus on both disapproved and approved NMEs and patents that allows me to eliminate a stochastic trend from a cumulative series and avoid the influence of this trend on results.

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 novel chemical substance 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%) and produce positive

spillovers for the partner's income (22%). Medical innovations return 65 606 SEK per year: equivalent to a fourth of the average annual family income in 2021. 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, *increases* the amount of 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 (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; Dobkin et al. 2018) by assessing the value of the innovation-induced reduction of economic losses due to health shocks. 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 spillover effects of medical innovations. Moreover, this study adds to the general economics literature on income profiles by introducing consumption of medical care as its important determinant (Meghir and Pistaferri 2011). Finally, this study allows for the analysis of the assumptions of the health capital theory and its extensions (Grossman 2000; Bolin, Jacobson, and Lindgren 2002) by looking at returns of medical care to scale and across disease severity.

This study also complements more general and diverse literature on the aggregate productivity of medical care (Murphy and Topel 2006; Bloom et al. 2020; 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 (Glied and Lleras-Muney 2008; Cutler, Meara, and Richards-Shubik 2012). 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 describes the data used in the analysis, including longitudinal individual-level data and a series of medical scientific discoveries. Section II presents the empirical strategy: the DDD and ML approaches. Section III 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. I conclude this section with robustness analyses. The final section presents my conclusions.

I. 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).[2] 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.

To identify individuals who had experienced health shocks due to certain diseases, I utilized

[2] I have used the database "Swedish Interdisciplinary Panel," which was hosted at the Centre for Economic Demography at Lund University (Statistics Sweden 1960-2021). 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.

information on inpatient hospital admissions.[3] 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, Nilsson, and Vikström 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, van Doorslaer, and van Ourti 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 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

[3] 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.

including the income of the partner and other household members.[4] 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, Steiner, and Palmer (2015)—and the availability and consistency of the ICD codes for hospitalization causes over the study period. The final list of 91 disease groups (see Appendix A Table A1) was verified by health experts (Lindström and Rosvall 2019). Innovations in each disease group were made annually during the study period.

The basis for a medical innovation measure used in this study is the list of approved and disapproved NMEs, which refer to novel chemical compounds. These chemical compounds capture the role of one component of innovation in medical care, in contrast to drugs that can be based on the same compound but marketed with different names (Kesselheim, Wang, and Avorn 2013). To compare, my database contains 6 743 drugs and only 1 939 NMEs, out of which 571 were disapproved in the period of study. I linked the NMEs to specific diseases in the following three steps. First, the Swedish Medical Products Agency was utilized to obtain a detailed registry of all drugs, their NMEs, and the dates of approval and disapproval to treat a particular disease in Sweden.[5] Second, as each drug also supplied information on the Anatomical Therapeutic Chemical

[4] 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. 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.

[5] 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.

code of the underlying NME 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 using a search procedure practiced by advisory experts.[6] 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 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.[7] 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 and lapsed 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. My final database contains 30 687 granted patents, out of which 3 921 were lapsed.

Figure 1 presents the series of NMEs and patents that were obtained and eventually used in the estimations, together with their means within year (see Appendix A Figure for the series of single diseases). I use a net series of approved and disapproved NMEs and granted and lapsed patents taken cumulatively 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

[6] 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.

[7] 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.

innovations based on the obtained series generally correspond to the categorizations provided by relevant benchmark studies for pharmaceutical (Kesselheim and Avorn 2013) and non-pharmaceutical innovations (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 (Lichtenberg 2015; Jeon and Pohl 2019) select the preferred lag length after examining the empirical exercise itself, thus making any hypothesis testing irrelevant. To compare the findings of this study with those of previous studies, I present the results with a longer lag length in Section III.e.

[Insert Figure 1 here]

II. 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, treatment groups are defined based on treatment status of their parents. I estimated the following equation:

$$(1)\ Y_{itds} = \alpha_i + \beta_1\, post_{idst} + \beta_2\, DD_{idst} + u_{itds}$$

In this equation, Y_{itds} is an outcome for an individual i in year t (family income and its sources), 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"). 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; and α_i represents individual fixed effects.

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.[8] To obtain a triple-difference coefficient, where

[8] 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,

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

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

In this equation, $DD_{idst}M_{ds}$ denotes the interaction between DD_{idst} and M_{ds} —lagged number of NMEs and patents (in separate models) available to treat disease d in year s; and other terms are defined as before.[9]

Eq.2 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.[10] Second, changes in the outcomes over time—similar to all individuals—are also mechanically ruled out due to the inclusion of the post-treatment dummy $post_{idst}$ and matching within the same observation years (see below). Finally, it excluded time-varying bias 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.

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 II.b for

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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. 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.

[9] In Eq.1 and 2, 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.

[10] 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.

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. Appendix A Table A2 presents the descriptive statistics of the final estimation sample.

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.[11] 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). Appendix B Figure B1 presents the results of this test for the study

[11] 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.

sample in total and for the ICD-chapter groups, 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.

Figure 2 presents the mean of economic outcomes under study by a comparison group across event years, while Appendix B contains information for specific disease groups. 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. As for the welfare outcomes, only for unemployment payments no pre-trends were detected (see Figure B6-B8); therefore, I focus on this outcome.

[Insert Figure 2 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, Jaravel, and Spiess'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 (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.

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. In the robustness analyses, I verify this with alternative estimators (see Section III.e).

In this study, I analyzed the inequalities in economic responses to medical innovation in two ways: 1) I estimated the heterogeneous DD and DDD effects across relevant individual's characteristics; 2) 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, Hothorn, and Hornik (2008), which relies on Eq.2, 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.

III. 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. In relation to the study cohorts, the magnitude of these responses is not known yet important to further understand the role of medical innovation.

Table 1 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—negative for the individual and ambiguous for household members (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.

[Insert Table 1 here]

Regarding the individual, Table 1 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, a reduction in wages is compensated by a large increase in the uptake of different welfare payments.[12] The responses by type of welfare payment

[12] Only the income outcomes are provided as net taxes; all other variables are gross and were partially subject

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 covering periods of short-term sickness. 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 1 presents the results for the effect of an individual's health shock on the economic outcomes of both the partner (or parents) and adult children. 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 (García-Gómez et al. 2013; Frimmel et al. 2020). In line with this evidence, my results show that 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 adult 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.

In Table 2 I present the impact of health shocks across individual's characteristics and herein analyze whether health shocks cause income inequalities. 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 create spillover effects for the partner even in generous welfare contexts (McClellan 1998; Fadlon and Nielsen 2021). My results show that differences in responses to health shocks are particularly large for married individuals (33%), individuals above age 60 (60%), and those diagnosed with cancer (93%). Importantly, reductions in the individual's wages and partner's incomes are universal yet extremely variable across prognoses. Presented in Table C2 and Figure C1-C4 in Appendix C, I find that in addition to cancer, less severe diagnoses requiring long-term treatment (e.g., mental and nervous diseases or diseases related to blood-forming organs) cause significant income losses for the partner, perhaps due to their decision to provide informal care or take charge of household work.

[Insert Table 2 about here]

to taxation. Therefore, the responses in welfare payments and self-insurance—and those in wages—do not equal the responses in income.

b. THE MITIGATING ECONOMIC IMPACT OF MEDICAL INNOVATIONS

In this section, I present the results of the mitigating impacts of medical care (i.e., β_2) on the economic outcomes of the individual and his/her close relatives. 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 remains underestimated in the context of different levels of medical care.

Table 3 presents the estimates for the mitigating impact of NMEs and patents on the economic outcomes of the individual and his/her close relatives that indicate three important findings. First, medical innovations significantly reduce individuals' and families' income losses. The mitigating impact of one standard deviation change in medical innovations on family income amounts to 12% (1.574 × 0.075 × 100%) using NMEs and 8% (0.335 × 0.243 × 100%) using patents. Referring to the latter magnitude of the overall decline in family income due to the health shock (32%, from Table 1), I find that medical discoveries moderated up between 25 and 38% of the family income loss. In absolute terms, medical innovations returned up to 65 606 SEK per individual year.

[Insert Table 3 about here]

Second, medical innovations have beneficial economic effects for both individuals and their partners. As for individual income, a one standard deviation change in medical innovation amounts to 4% using NMEs and 2% using patents. This result suggests that when medical innovations reduce an individual's net economic loss to zero. Additionally, there are large positive spillover effects of medical innovation on partner's income, up to 15%. However, in relative terms, the partner's income loss is mediated to a smaller extent, pointing to 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 (see also Table C4 Appendix C). In line with the absence of income responses to the parental health shock, there are no clear mitigating effects for adult children.

Even though my results are based on microdata, it is possible to juxtapose them with estimates for the aggregate productivity of medical care. 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). For compatibility, I multiply the annual change 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 is 0.4% using NMEs and 0.3% using patents. However, this is an estimate of the lower bound for two reasons. First, as the event-year estimates from Table 3 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 partners.

c. HETEROGENOUS MITIGATING EFFECTS OF MEDICAL INNOVATIONS

To understand how medical innovation influence income inequalities, I further present the results for the heterogeneous mitigating effects of medical innovations on the economic outcomes of both individuals and their close relatives. 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.

Figure 4 presents the estimates of the mitigating income effects of medical innovation for the family and close relatives. The mitigating impacts of medical innovations on economic outcomes vary significantly across characteristics of the individual who experienced a health shock. Using, NMEs as a measure of innovation, for instance, these effects appear more significant for older adults (22%), and low (29%) versus highly educated individuals (9%). The impact on older adults is in line with more medical innovations developed for diseases that are common in older age (cf. Cutler et al. 2021). My finding on less educated individuals seems at odds with the previous studies (Jeon and Pohl 2019) but can be explained by the fact that health shocks under study here are sudden inpatient hospitalizations guaranteeing immediate access to innovative drugs and procedures that are not otherwise accessible. In general, for many subgroups medical innovations substantially reduce both absolute and relative economic consequences of health shocks.

[Insert Figure 4 here]

However, spillover effects of medical innovations for partners are not always positive. In principle, married individuals benefit more from medical care than do single individuals (12% versus no effect). While medical innovation reduces income loss on the part of the individual for any diagnosis, it induces the income loss on the part of the partner in case of many neoplasms, mental, respiratory, and blood-forming diseases (see Figure C5-C12 in Appendix C). Partners or other family members hence reduce their labor force participation due to increased consumption of medical care in the family and are not equally compensated. Therefore, medical innovations *induce* income inequalities between household members, suggestively revealing the lack of formal care and welfare compensation for the related parties accompanying the provision of more efficient medical treatments.

I also analyzed the mitigating effects of medical innovations in relation to scale and present results in Figure 5. While economic responses to medical innovation are predicted to either proportionally increase in relation to health inputs and disease severity increase (Grossman 2000), applied literature has not been able to prove it due to data limitations. This led some scholars to

argue that the growth in medical innovations yielded *negative* returns (cf. Bloom et al. 2020). My results suggest that these dynamics are not linear. In relation to severity of a health shock measured with longer stay at hospital, mitigating effects of medical innovation increase sharply but then decline and reduce to null. Results for the economic effects across cohorts demonstrate constant effects using NMEs and decreasing effects using patents. In sum, my results indicate that usual assumptions of theoretical models of health capital might be too restrictive.

[Insert Figure 5 here]

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, 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 differential effects of household members. 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.

The results for cancer, for which individual's mitigating effects are positive and partner's effects are negative, 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 NMEs with the greatest economic effects are those with well-known survival efficiencies against certain cancers (Lichtenberg 2019). Meanwhile, the results using patents 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).

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.

The mitigating economic effects of medical innovations to treat HIV spill over to all family members and adult children. The HIV patients in this study are likely those whose immune systems are strongly impaired by the infection, so 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, Datar, and Villa 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 the fixed-effects estimator is valid to estimate DDD effects and the assumptions possibly hold true.

In Section II.c I have argued that fixed-effects estimator is valid in a design-based DD and DDD framework due to the absence of weighting problem. I tested it empirically with two robustness checks and present results in Table 4. First, I checked whether compositional differences between treatment groups for different cohorts (i.e., levels of medical innovation) distort the results and added event-year-fixed effects interacted with ICD-chapter disease groups to Eq.2 (as suggested in Goodman-Bacon 2021). Second, following Callaway and Sant'Anna (2020), I used an alternative estimator which is based on estimation and aggregation of cohort-specific treatment effects. My results suggest that the fixed-effects estimator used in the main body of the paper produces ATET effects.

[Insert Table 4 here]

The "no anticipation" and "parallel trends" assumptions were addressed at the stage of constructing the estimation sample (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 II.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. In Appendix C Figures C5-C12, I have also demonstrated the absence of pre-trends for each DD comparison group participating in Eq.2. 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 measures of medical innovation are plausibly exogenous to the decision of hospitalization (see Section I.b). However, the uptake of health insurance and care arguably induces medical innovation (Lleras-Muney and Lichtenberg 2005; Acemoglu et al. 2006). I elaborated on the plausibility of the "independent groups" assumption through several checks. 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 with medical innovations of exclusively international origin that more likely approximated exogenous shocks, directly imported NMEs, and patents granted to non-Swedish applicants (cf. Papageorgiou, Savvides, and Zachariadis 2007). I also estimated the models with the 5- and 10-year lags, 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.

[Insert Table 4 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 and spillovers to their partners and adult children. To obtain the causal effects of medical care, I focused on the role of medical scientific discoveries and leveraged the longitudinal dimension of administrative microdata. This study reveals that medical innovations have sizable mitigating effects for the economic outcomes of individuals and their close relatives and that these effects are highly heterogeneous. Half of the family income loss is mitigated by medical innovations, which return 65 606 SEK per individual year, the sum equivalent to a fourth 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. While medical innovations are efficient concerning the individual for most diseases that cause a health shock, partners 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. Second, the effects of medical innovations appear to extend beyond the receivers of the treatment to their respective partners and adult children. 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, income profiles and economic repercussions of health shocks are poorly understood without focus on the family and medical care available to treat each disease.

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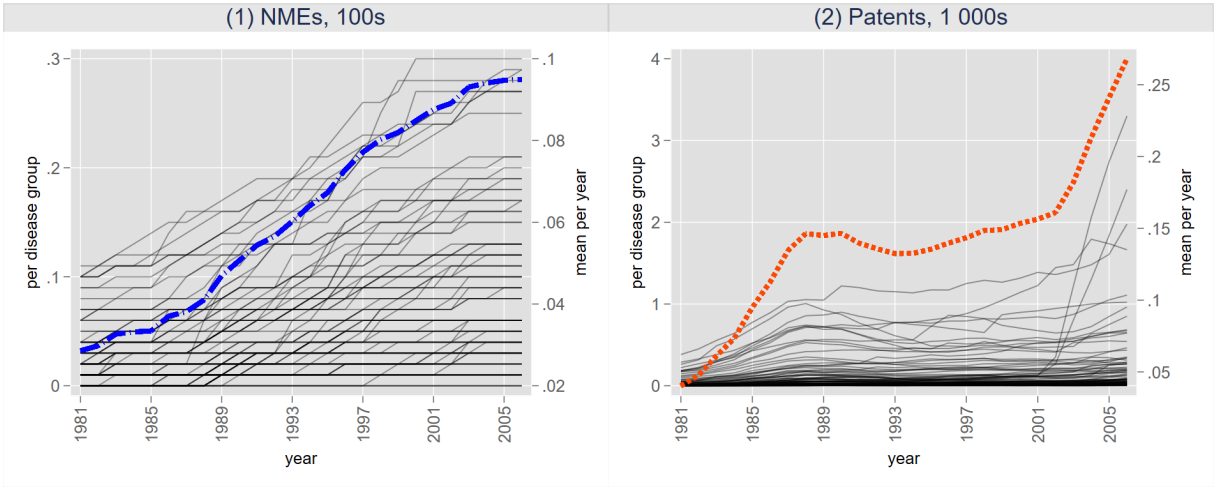

Figure 1. Development of medical innovations by disease over study period

Note: The lines denote the one-year lags of the number of cumulative medical innovations (approved and disapproved for NMEs and granted and lapsed for patents) in each disease group (91 in total). The bars denote the mean number of this series per year.

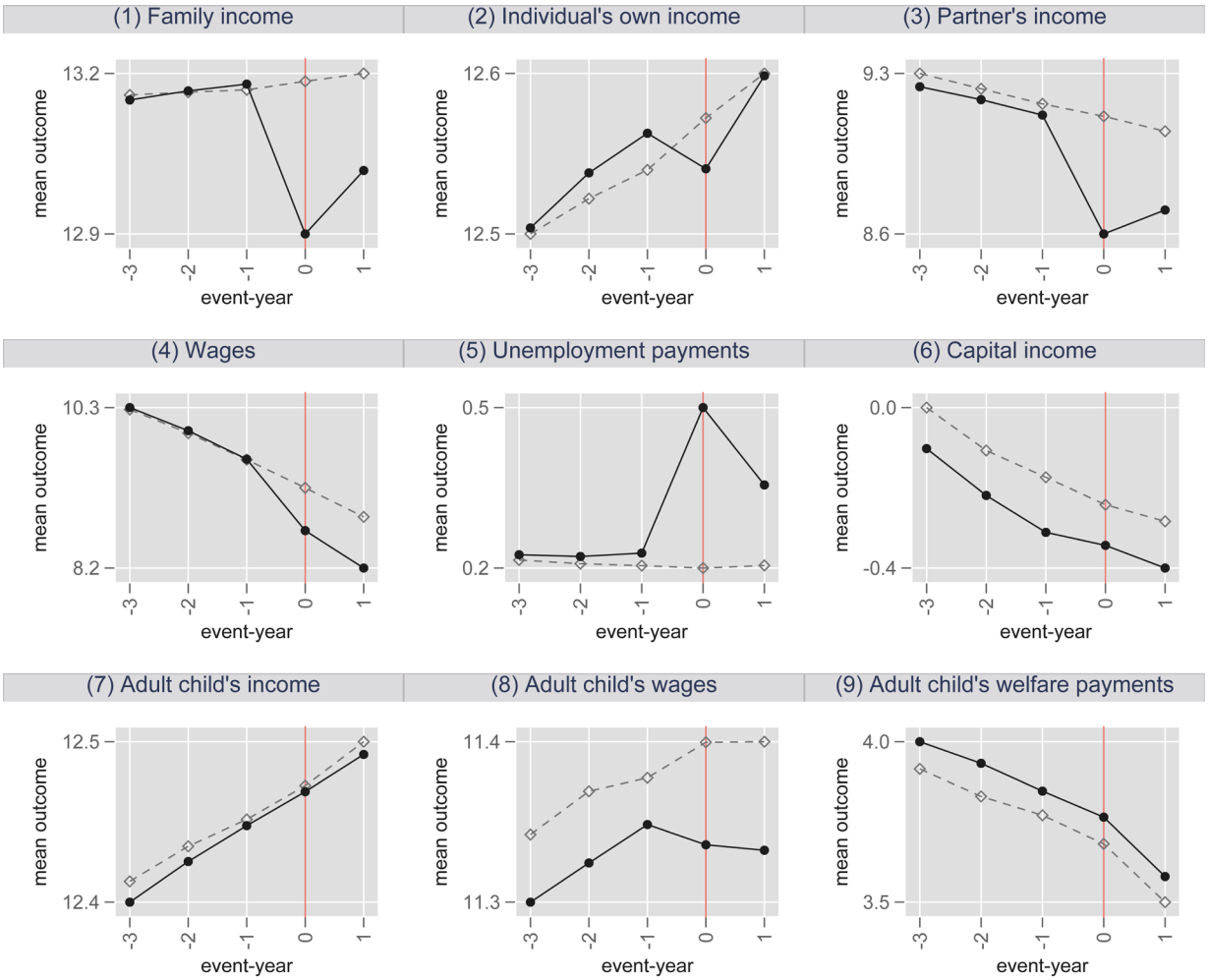

Figure 2. Development of economic outcomes by event-years for "ever-treated" and matched individuals in the estimation sample

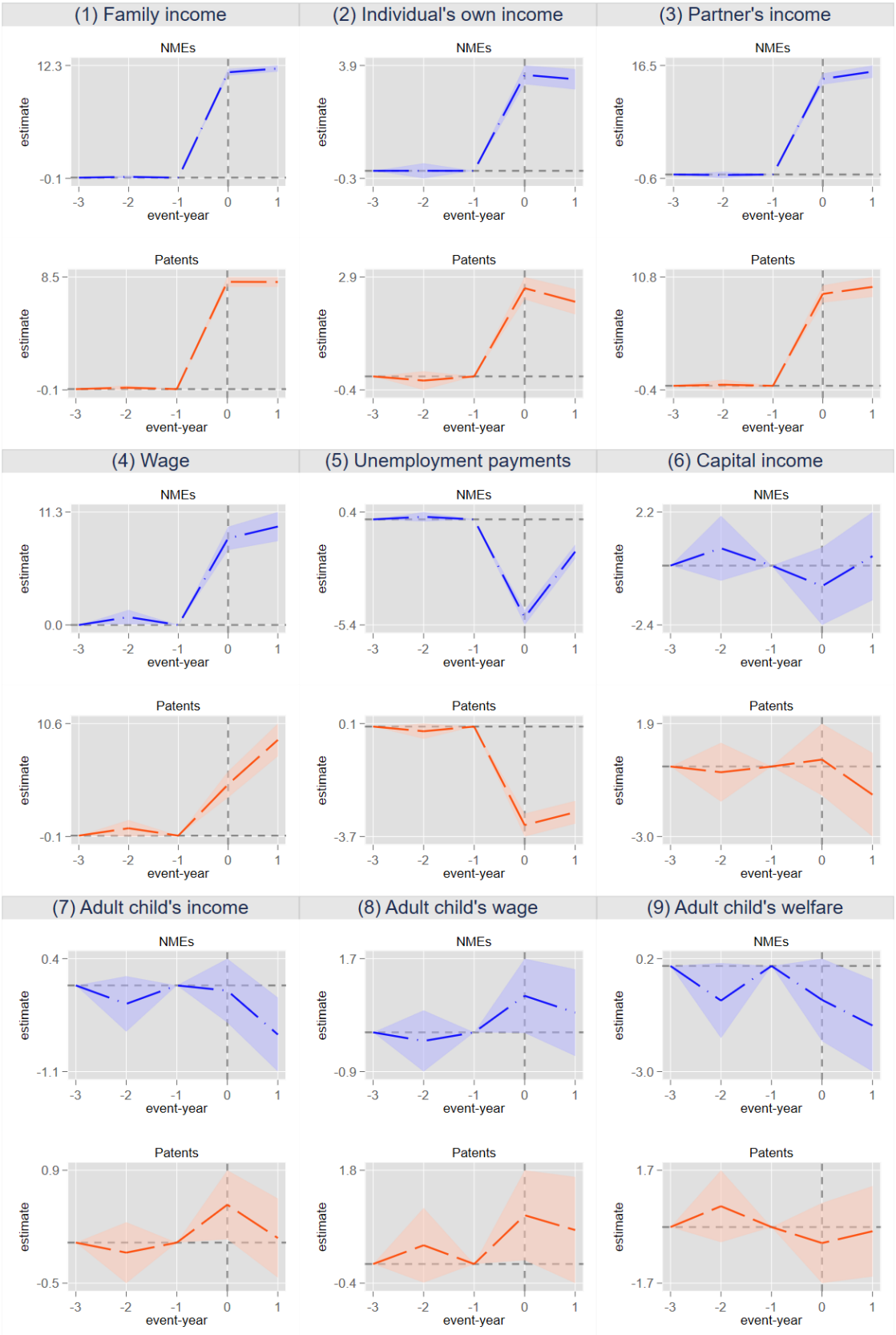

Figure 3. Estimates of the impact of medical innovations (L^1 NMEs and L^1 patents) and 95-% confidence intervals by event-years for the outcomes of "ever-treated" and matched individuals (one SD change x 100)

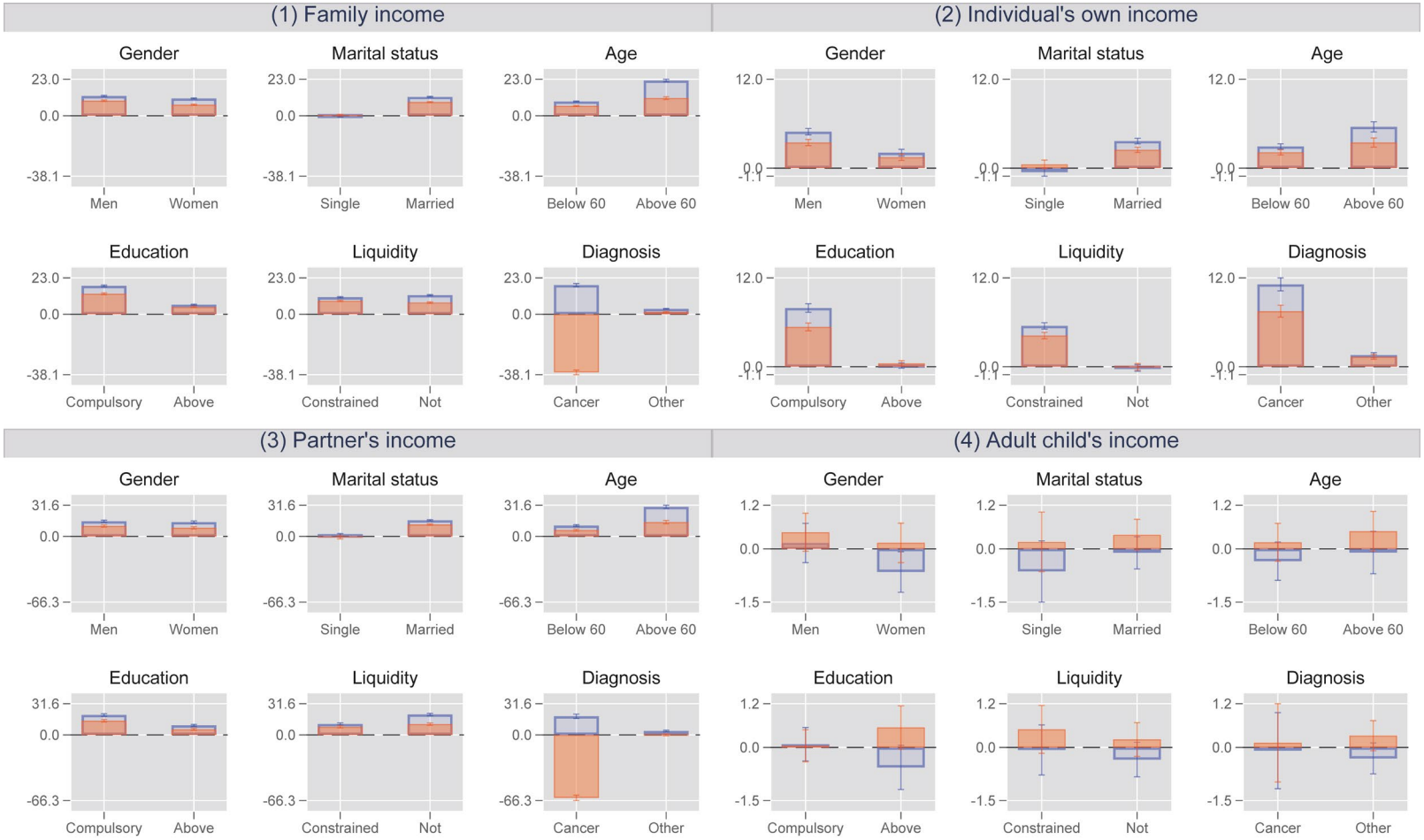

Figure 4. Heterogeneous mitigating effect of medical innovations (L^1 NMEs and L^1 patents) for incomes of the nuclear family, family members, and adult children (one SD change x 100)

Note: Estimates and 95-% confidence intervals are obtained according to Eq.1 by subsamples based on the characteristics of the individual experiencing a health shock. Blue lines/bars denote the impact of L^1 NMEs and orange lines/bars denote the impact of L^1 patents.

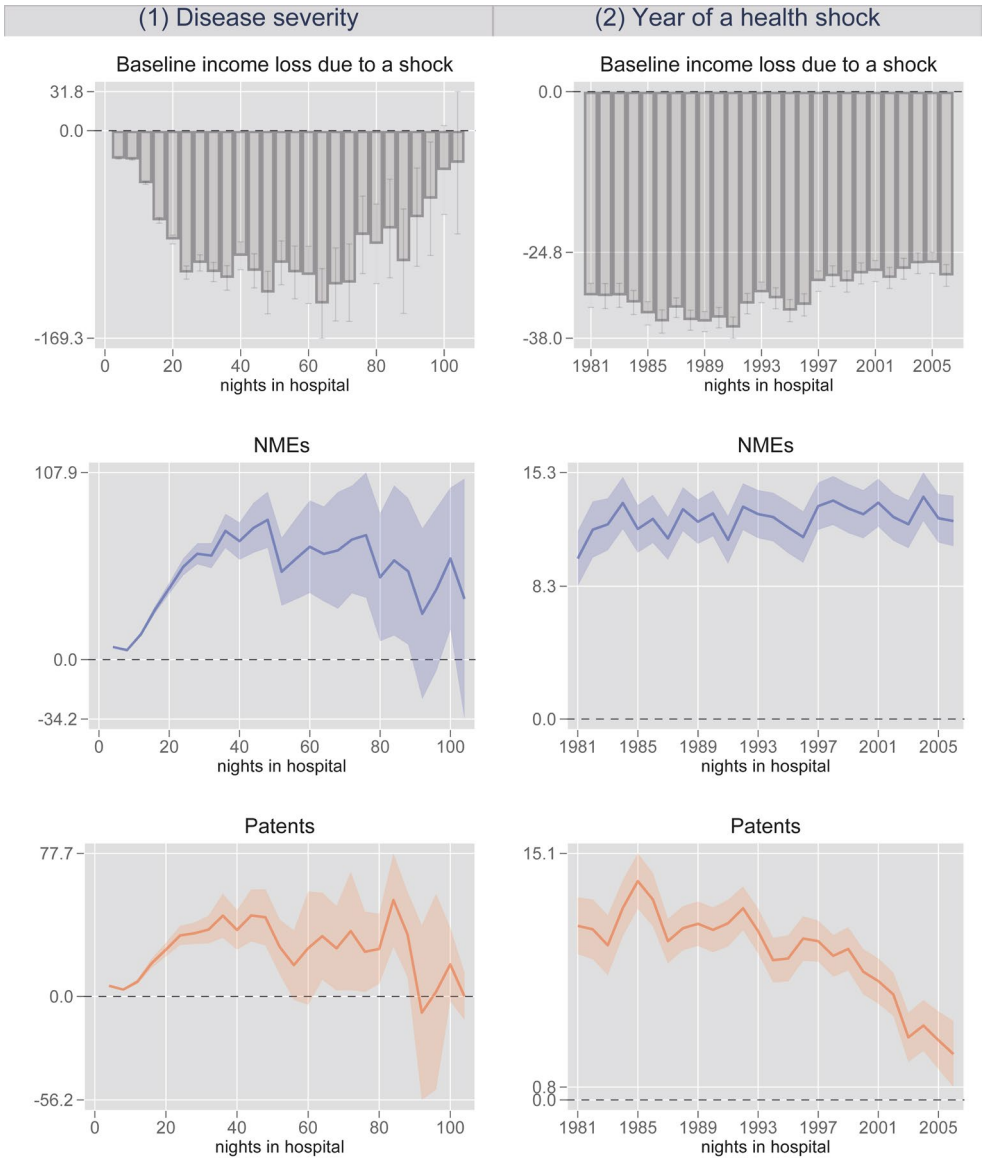

Figure 5. Mitigating effect of medical innovations (L^1 NMEs and L^1 patents) for family income by severity and year of a health shock

Note: Estimates and 95-% confidence intervals are obtained according to Eq.1 by subsamples based on the characteristics of the individual experiencing a health shock. Blue lines denote the impact of L^1 NMEs and orange lines denote the impact of L^1 patents.

Table 1. Impact of a health shock on economic outcomes of the nuclear family, family members, and adult children

	Family and family members						**Adult children**		
	Family income	Individual's own income	Partner's income	Wages	Unemploy-ment payments	Capital income	Income	Wages	Welfare payments
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DD_{idst}	-0.315***	-0.051***	-0.464***	-0.382***	0.246***	0.038***	0.002	-0.009**	0.031***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.002)	(0.007)	(0.002)	(0.004)	(0.006)
by event-year									
DD_{idst} X event-year 0	-0.327***	-0.054***	-0.474***	-0.254***	0.333***	0.028***	0.004*	-0.006	0.028***
	(0.002)	(0.002)	(0.005)	(0.004)	(0.002)	(0.008)	(0.002)	(0.004)	(0.006)
DD_{idst} X event-year 1	-0.304***	-0.049***	-0.455***	-0.303***	0.157***	0.048***	0.000	-0.012**	0.034***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.009)	(0.002)	(0.005)	(0.007)
Outcome for DD_{ids} =0, 10 000 SEK	32.803	18.909	13.894	21.751	0.036	0.506	16.090	17.938	0.785
Observations	11 032 884	11 032 884	11 032 884	11 032 884	11 032 884	11 032 884	9 763 843	9 763 843	9 497 515
Number of individuals	2 243 040	2 243 040	2 243 040	2 243 040	2 243 040	2 243 040	1 282 796	1 282 796	1 282 609

Note: Models were estimated according to Eq.1. Robust standard errors clustered at individual (experimental) level are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 2. Heterogeneous mitigating impact of medical innovations on income of the nuclear family, family members, and adult children

	Men	**Women**	**Single**	**Married**	**Below age 60**	**Above age 60**	**Compulsory education**	**Higher**	**Liquidity-constrained**	**Not-constrained**	**Cancer**	**Other than cancer**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(A) Family income												
DD_{idst}	-0.356***	-0.266***	0.004*	-0.328***	-0.231***	-0.591***	-0.474***	-0.206***	-0.343***	-0.274***	-0.928***	-0.190***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)
Outcome for DD_{ids}=0, 10 000 SEK	33.188	32.850	22.571	36.971	33.722	29.449	26.698	37.653	13.206	27.416	33.853	32.456
(B) Individual's own income												
DD_{idst}	-0.066***	-0.034***	0.007**	-0.055***	-0.039***	-0.082***	-0.107***	-0.012***	-0.084***	-0.006***	-0.151***	-0.030***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
Outcome for DD_{ids}=0, 10 000 SEK	21.600	16.409	19.518	19.184	19.256	18.055	15.308	21.952	16.197	12.79024	18.730	19.000
(C) Partner's income												
DD_{idst}	-0.532***	-0.388***	-0.035***	-0.522***	-0.357***	-0.834***	-0.640***	-0.346***	-0.451***	-0.479***	-1.311***	-0.295***
	(0.006)	(0.006)	(0.008)	(0.004)	(0.005)	(0.009)	(0.007)	(0.005)	(0.006)	(0.006)	(0.012)	(0.004)
Outcome for DD_{ids}=0, 10 000 SEK	11.588	16.440	3.052	17.787	14.465	11.393	11.390	15.701	9.766	11.219	15.122	13.455
(D) Adult child's income												
DD_{idst}	-0.001	0.004*	0.003	0.001	0.003	0.001	0.004	0.001	0.002	0.001	-0.001	0.002
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.005)	(0.002)
Outcome for DD_{ids}=0, 10 000 SEK	16.171	16.571	16.034	16.717	15.224	17.985	15.294	17.423	12.463	16.598	17.069	16.009

Note: Models are estimated according to Eq.1 by subsamples based on the characteristics of the individual experiencing a health shock. Robust standard errors clustered at individual (experimental) level are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 3. Mitigating impact of medical innovations on income and its sources of the nuclear family, family members, and adult children

	Family and family members						Adult children		
	Family income	Individual's own income	Partner's income	Wages	Unemploy-ment payments	Capital income	Income	Wages	Welfare payments
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(A) L^1 NMEs, 100s									
DD_{idst} x L^1 NMEs	1.574***	0.470***	2.009***	1.177***	-0.468***	-0.071	-0.036	0.097*	-0.152**
	(0.020)	(0.022)	(0.054)	(0.081)	(0.022)	(0.097)	(0.028)	(0.059)	(0.075)
By event-years									
DD_{idst} x L^1 NMEs x event-year 0	1.480***	0.457***	1.912***	2.036***	-0.685***	-0.151	0.002	0.126**	-0.089
	(0.021)	(0.022)	(0.055)	(0.081)	(0.026)	(0.101)	(0.030)	(0.061)	(0.078)
DD_{idst} x L^1 NMEs x event-year 1	1.667***	0.479***	2.115***	0.350***	-0.229***	0.029	-0.080**	0.072	-0.190**
	(0.021)	(0.023)	(0.058)	(0.090)	(0.025)	(0.108)	(0.035)	(0.071)	(0.091)
(B) L^1 patents, 1 000s									
DD_{idst} x L^1 patents	0.335***	0.100***	0.387***	0.270***	-0.126***	-0.015	0.014	0.029	-0.024
	(0.006)	(0.006)	(0.017)	(0.026)	(0.007)	(0.031)	(0.009)	(0.019)	(0.024)
By event-years									
DD_{idst} x L^1 patents x event-year 0	0.310***	0.101***	0.356***	0.464***	-0.134***	-0.011	0.022**	0.036*	-0.030
	(0.007)	(0.007)	(0.018)	(0.026)	(0.008)	(0.032)	(0.009)	(0.019)	(0.026)
DD_{idst} x L^1 patents x event-year 1	0.359***	0.099***	0.419***	0.082***	-0.116***	-0.020	0.004	0.023	-0.015
	(0.007)	(0.007)	(0.020)	(0.031)	(0.008)	(0.036)	(0.011)	(0.023)	(0.030)
Outcome for DD_{ids} =0, 10 000 SEK	32.803	18.909	13.894	21.751	0.036	0.506	16.090	17.938	0.785
Observations	11 032 884	11 032 884	11 032 884	11 032 884	10 665 937	11 032 884	9 763 843	9 763 843	9 497 515
Number of individuals	2 243 040	2 243 040	2 243 040	2 243 040	2 242 971	2 243 040	1 282 796	1 282 796	1 282 609

Note: Models are estimated according to Eq.2. Robust standard errors clustered at individual (experimental) level are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 4. Robustness analyses of the mitigating impact of medical innovations on family income

	Adding event-year X ICD - fixed effects	Using CATE estimator	Detrended Innovations	International Innovations	10-Year Lags of Innovations	Adding Data from Emergency Units
	(1)	(2)	(3)	(4)	(5)	(6)
			(A) L^1 NMEs, 100s			
DD_{idst} x L^1 NMEs	1.590***	1.705***	1.598***	2.733***	2.288***	1.574***
	(0.020)	(0.017)	(0.019)	(0.017)	(0.028)	(0.020)
By event-years						
DD_{idst} x L^1 NMEs x event-year 0	1.550***	1.620***	1.568***	2.612***	2.269***	1.482***
	(0.025)	(0.016)	(0.024)	(0.021)	(0.035)	(0.022)
DD_{idst} x L^1 NMEs x event-year 1	1.629***	1.709***	1.626***	2.851***	2.350***	1.661***
	(0.023)	(0.015)	(0.023)	(0.020)	(0.033)	(0.019)
1 SD L^1 NMEs	0.075	0.075	0.073	0.056	0.053	0.075
			(B) L^1 patents, 1 000s			
DD_{idst} x L^1 patents	0.338***	0.419***	0.333***	0.558***	0.411***	0.338***
	(0.006)	(0.005)	(0.006)	(0.005)	(0.008)	(0.006)
By event-years						
DD_{idst} x L^1 patents x event-year 0	0.335***	0.386***	0.332***	0.490***	0.404***	0.314***
	(0.007)	(0.003)	(0.007)	(0.005)	(0.010)	(0.009)
DD_{idst} x L^1 patents x event-year 1	0.340***	0.421***	0.333***	0.598***	0.416***	0.363***
	(0.008)	(0.005)	(0.007)	(0.001)	(0.010)	(0.003)
1 SD L^1 patents	0.243	0.243	0.241	0.154	0.175	0.243
Outcome for DD_{ids} =0, 10 000 SEK	32.803	32.803	32.803	32.803	32.803	32.796
Observations	11 032 884	11 032 884	11 032 884	11 032 884	11 032 884	11 033 065
Number of individuals	2 243 040	2 243 040	2 243 040	2 243 040	2 243 040	2 243 061

Note: Models are estimated according to Eq.1 and 2 with modifications described in Section III.e. Robust standard errors clustered at individual (experimental) level are in parentheses.

*** p<0.01, ** p<0.05, * p<0.1