HETEROGENEOUS RETURNS TO MEDICAL INNOVATIONS

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Abstract

This paper sets up a quasi-experiment to estimate the impact of medical innovations on the economic outcomes for the individual and their family based on the rich administrative data for Sweden covering 1 million persons. I find that an increase in medical innovations by one standard deviation raises family income by 15%. Medical innovations strongly influence not only own disposable and labour income and welfare payments but also a spouse's income. I also find that the economic effects are heterogeneous in relation to the insurance eligibility of the health shock. Results also suggest decreasing yet always positive returns to scale.

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

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

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Data Availability Statement: The individual-level data (SIP) used in this paper 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 https://www.scb.se/en/services/guidance-for-researchers-and-universities/. Researchers interested in obtaining this type of data could themselves apply for permission from the Ethical Review Board at https://www.epn.se/en/start/. 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 that I 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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I. Introduction

It is essential for society to know the welfare effects of medical innovations. Despite this, the most published research on this issue is difficult to generalize. An already vast literature has provided very different estimates for the aggregate productivity growth of medical care, yet none of them excludes the influence of factors other than medical care.[1] Several recent studies have used methods of causal inference to estimate the impact of specific medical innovations, such as pain-killing drugs, or specific diseases, such as breast and prostate cancer (Garthwaite, 2012; Bütikofer et al., 2018; Thirumurthy et al., 2008; Jeon and Pohl, 2019). The set of innovations as well as the outcomes studied in this literature has been scarce. Not only this, but previous studies have not accounted systematically for productivity effects in terms of the allocation of medical care. At the same time, the amount and the allocation of health investments are central policy choices because they influence not only current and future consumption and value added, but may also contribute to health inequalities.[2]

[1] At one extreme, Murphy and Topel (2006) found that returns to healthcare in 1970–2000 in the US amounted to a ratio of 3 to 1. At the other extreme, Bloom et al. (2020) reported that research productivity for medical research was negative in 1975–2006; for instance, research productivity for breast cancer declined annually by 6.8% using publications and 10.1% using clinical trials. Other studies found that the productivity rates lay within the range of these values (as reviewed, for instance, in Sheiner and Malinovskaya, 2016).

[2] Healthcare expenditures rise constantly in per capita terms or in relation to GDP among the OECD countries, and Sweden usually spends among the most, for instance, 5,447 USD PPP and 11% in 2018 respectively (OECD (2019)). R&D spending is among the largest in medicine and health care (Statistics Sweden, 2020). Not only in aggregate, healthcare usually challenges with ensuring proper and equal care for all patients (OECD, 2019). Even today, policy makers view healthcare as spending

This paper aims to fill in the gap by estimating the total and heterogeneous effects of medical innovations against the whole range of adult morbidities on the individual's economic outcomes. I have set up a quasi-experiment to obtain plausibly causal estimates by using rich data on both disease-specific medical innovations and individual-level longitudinal hospital admissions and economic outcomes for Sweden. More specifically, I have applied a difference-in-difference-in-differences (DDD) approach, and in doing so have estimated the impact of medical innovation on economic outcomes as an innovation-induced *reduction* in economic loss due to the onset of a specific disease. This analysis have been conducted in close connection to a theoretical framework of family health production by Grossman (1972, 2000), where the resources available for health production are family disposable income and its sources.

The results from my paper indicate that an increase in medical innovations by one standard deviation (SD) raises disposable family income by 14.8% (95% CI: 14.4%; 15.1%). Medical innovations appear to increase the income of both family members: by 5.99% (95%CI: 5.58%; 6.39%) of own disposable income and by 15.65% (95%CI: 14.15%; 17.16%) of a spouse's disposable income. The beneficial effects of medical innovations emerge through the increase in own labour supply at both its intensive and extensive margins. The effects of medical innovations vary extremely across diseases: they are strong for cancer (51.11%, 95%CI: 47.44%; 54.77%) and circulatory diseases (19.51%, 95%CI: 18.34%; 20.67%), are close to the mean aggregate effects for mental and nervous, infectious and respiratory diseases, and are absent or appear as losses for other health shocks. Results also

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rather than as investments and do not recognize the link between its allocation and health inequalities (Lundberg, 2018).

suggest decreasing returns to scale, yet far from reaching zeros by the end of the study period. Finally, the returns decline the higher the education level.

To obtain the causal estimates by means of the DDD approach, one should demonstrate that the assumption of "parallel trends" is likely to hold for all comparison groups involved in the estimation and that the estimation method provides an adequately weighted average treatment effect on the treated (ATET). These issues are solved in this paper by my discovery that individuals who experienced a health shock due to a specific disease compared to those who experienced the same shock in a very narrow time window are similar in pre-trends across the whole range of diseases. This discovery has allowed me to apply a DDD matching approach. Several previous studies on the returns to medical innovations inevitably failed to maintain the "parallel trends" assumption because they used healthy individuals as a counterfactual to the individuals who experienced a health shock (Glied and Lleras-Muney, 2008; Lichtenberg, 2019).[3] Additionally, many empirical studies that used two-way fixed-effects regressions to estimate the difference-in-differences (DD) effects with differential timing likely suffer from the weighting problem that may strongly bias these effects (Baker et al., 2021).

This paper contributes to several strands of literature in economics. First, it contributes to the applied microeconomic literature on the impact of single medical innovations on economic outcomes (e.g., Garthwaite, 2012; Bütikofer et al., 2018; Stephens and Toohey, 2018; Jeon and Pohl, 2019) by broadening the evidence to include almost all health conditions observable in the population. This evidence also adds to the growing literature on

[3] There are also studies that have examined a relationship between a broader set of medical innovations and health, though these rely on descriptive designs (e.g. Gross et al., 1999; Cutler et al., 2012).

the economic consequences of health shocks and their heterogeneity (e.g., García-Gómez et al., 2013; Lundborg et al., 2015; Dobkin et al., 2018) by assessing the value of the innovation-induced reduction in economic loss due to health shocks. My findings contribute to the empirical studies on the spousal labour supply responses to individuals' health and labour supply shocks (reviewed, e.g., in Fadlon and Nielsen, 2021) by establishing that the benefits of medical innovations accrue not only to the individual but also to the spouse.

Second, this paper contributes to the more general and diverse literature on the aggregate productivity of medical care (e.g., 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 showing plausibly causal gains of medical innovations based on a quasi-experimental design. My estimates of the impact of medical innovations on family income are ready-to-use to calibrate the value of health gains in terms of consumption. This strand of the literature has partially overlapped with the studies on the allocation of the productivity effects of medical innovations, which overwhelmingly covered the most common health conditions, such as cancer and heart disease (e.g. Berndt et al., 2002; Cutler et al., 2007; Cutler et al., 2012; Glied and Lleras-Muney, 2008). My paper adds to these studies by presenting findings on the causal heterogeneous economic returns to medical innovations across several theoretically driven dimensions – findings that are novel for the European context where the patterns can be different from the contexts with predominantly private health insurance.

II. Conceptual framework

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

$$(1)\ \partial W/\partial t = r \cdot W + \omega_m(H_m, E_{\omega,m}) \cdot h_{\omega,m} + \omega_f(H_f, E_{\omega,f}) \cdot h_{\omega,f} + B - p \cdot (M_m + M_f) - q \cdot X,$$

where r is the market interest rate, ω and h are the wage rates ('labour market earnings rate of return on human capital') and time spent at work respectively, these being functions of health (H) and level of education and on-the job training (E). B are transfers. p and q are the prices of medical care (M) and other goods (X) respectively.[4] The subscripts m and f denote husband and wife respectively. Hence, the individual's health affects market income in two ways: through its effect on the wage rate; and through its effect on the time a healthy individual is available for work. In this model, decreased health also decreases savings rates.

In turn, the development of stock of health for a husband (or wife) is in line with the following equation:

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

where $I_{m(f)}$ are gross investments in health and $\delta_{m(f)}$ is the rate of depreciation. That is, adverse health events are depreciations or negative investments in health that can be offset by positive investments. Health investments for a family member are a function of medical care ($M_{m(f)}$), own and another family member's time used in the production of health ($h_{H,m}$ and $h_{H,f}$), and productivity in health production ($E_{H,m}$ and $E_{H,f}$).

The time restrictions for each family member are

$$(3)\ \Omega_i = h_{\omega,i} + h_{X,i} + h_{H,m,i} + h_{H,f,i} + h_{S,i} \qquad i = m,f$$

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

where $h_{S,i}$ is duration of sickness $(h_{S,i} = h_{S,i}(H_i))$.

Equations 1 through 3 formulate that medical innovations (i.e. new drugs or medical procedures) are positive investments in health that reduce the decline in health capital through several channels. First, they directly reduce the negative consequences of a health shock, i.e. restore health. Second, they decrease time spent on health production that leads to an increase in time spent on market production and income. Finally, medical innovations affect the spouse's income. The effect of a health shock on the spouse's earnings is ambiguous: the spouse may compensate for the income loss of the individual by increasing their labour supply, or they may decrease their labour supply by increasing the time spent on the individual's health production.[5] Consequently, medical treatments of the individual reduce or increase income loss appeared on the spouse's side. In sum, the model suggests to consider both ultimate and provisional outcomes such as family income, own and partner's income, labour income, sickness and welfare payments and capital income.

The Grossman model explicitly formulates the way the individual's characteristics moderate the effects of a health shock. One important aspect is the severity of a health shock. In the 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 the spouse's labour supply and welfare uptake (e.g., McClellan, 1998). Another aspect is the type of returns to health investments over time, which the model suggests to be constant. An alternative model, with diminishing returns to scale, has been proposed in Galama et al. (2012; 2015). As a last aspect, productivity in health production of both family members affects the strength of a response to health

[5] In the context of Sweden, the subject of analysis in this study is generally not expected to remain attached to the labour market in the case of an adverse health event.

investments. As an illustration, individuals with a higher education level may be more efficient producers of health, and hence reap larger benefits from a medical innovation. In principle, a similar argument can justify gender differences in responses to health investments (Fuchs, 2004).

III. Empirical strategy

An ideal experiment of estimating the causal effects of medical innovations would assess to what extent medical innovations enable a reduction in the negative consequences of disease. In this study, in order to emulate such an experiment, I have applied a DDD approach and have estimated the impact of medical innovations on economic outcomes as an innovation-induced *reduction* in economic loss due to the onset of a specific disease. This can be thought of as the difference between the two DD estimators (see Goodman-Bacon, 2021, for details). To form the first DD estimator, the assumption is that one can compare the evolution of the economic outcomes of individuals who experienced a health shock due to a certain disease to those of valid counterparts. To form the second DD estimator, one needs to be sure that individuals also belong to either an affected group or an unaffected group. In my case, these differentially affected groups appear because the stock of medical innovations varies over time and across diseases.[6] To be able to obtain a triple-difference coefficient where one of the differences varies across the values of a continuous variable (i.e. medical innovations), I have estimated the following DDD specification:

[6] In 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 having access to different levels of innovations, regardless of whether they experienced a shock. The difference between these DD estimators (i.e. DDD) can be constructed because some individuals had already experienced a health shock and some had not done so yet.

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

where: 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 (treated) or that 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. DD_{idst} is an indicator for years during and after a health shock for individuals who experienced a negative health shock due to disease d in year s; $post_{ts}$ – are years during and after a health shock; M_{ds} denote a medical innovation available to treat disease d in year s; α_i – are individual fixed effects.[7,8]

The main identification assumptions of the DD framework is that potential outcomes and treatments of different groups are independent ("independent groups") and that the control group provides a valid counterfactual (the "parallel trends" assumption). These assumptions should hold for all DD comparisons that will eventually participate in the DDD estimation. If these assumptions are satisfied, the parameter of interest, β_3, represents the causal effect of a medical innovation on income and its sources, i.e. the innovation-induced difference in the ATET. The "independent groups" assumption is likely to hold in the setting given in this paper because the individual's probability of a health shock does not depend on the stock of medical innovations available in the country to treat disease. By contrast, there is the

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[7] A similar model was used by Jeon and Pohl (2019) who studied the impact of medical innovations for single diseases, such as breast and prostate cancer, and hence, medical innovations varied for them only between years.

[8] As I will show below, the control individuals are observed during the same years as the treated ones, so $post_{ts}$ and M_{ds} are defined for both groups. 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.

challenge of assuring that the "parallel trends" assumption holds for individuals who have and have not experienced a health shock. For instance, an observed health shock that is preceded by deteriorating health and, correspondingly, income, would violate this assumption.

I addressed the empirical challenge of obtaining plausibly valid counterfactuals in several ways. First, I extended an empirical approach previously suggested by Fadlon and Nielsen (2021) and matched individuals who experienced a health shock due to certain disease to those who experienced a shock due to the same disease within a few years of them, and stacked observations for the same years for cohorts with duplicates.[9] Second, to account for the remaining deviations from the "parallel trends" between treatment groups across all diseases observed in the population, I also matched on several pre-treatment characteristics of the individual that affect both the probability of a health shock and the outcome. Third, I included individual fixed effects in the main specification to partial out the influence of permanent factors specific to individuals that may affect the outcomes. Finally, to diminish the possibility of anticipation, I focused on individuals with no health shocks in the three preceding years. Conditional on no anticipation, I could perform a formal test for the absence of pre-trends (Novgorodsky and Setzler, 2019). In doing this, I followed Borusyak et al.

[9] Fadlon and Nielsen (2021) focused on heart attacks and strokes that are both sudden and severe, and 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. Similar to their paper, the research design in my paper is constructed to match individuals on the year of the shock occurring within sexes and the same cohorts, so this mechanically rules out calendar, sex and age effects.

(2021) and performed a *t*-test for the pre-trends in a fully dynamic specification (i.e. event-study) of the underlying DD models.[10]

As part of this study, in addition to measuring the total impact of medical innovations I have analyzed the allocation of this impact by estimating the heterogeneous DDD model:

(5) $Y_{itds} = \alpha_{\mathrm{i}} + \beta_1\, post_{idst}X_i + \beta_2\, DD_{idst}X_i + \beta_3\, DD_{idst}M_{ds}X_i + \beta_4\, post_{idst}M_{ds}X_i + u_{itds}$

where all terms are defined as in Eq.4, and X_i is the covariate of interest. Eq.5 is a model of Eq.4 fully interacted with the covariates of interest specified without a reference category in order to obtain the estimates across the whole range of the values of covariates (see Wooldridge, 2021, for discussion). I analyzed the heterogeneity of the impact of medical innovations on economic outcomes across different dimensions as suggested by the conceptual model, such as the aggregated groups of diseases and their severity, the years and ages at hospitalization, and education level.[11] I ran the analysis on all available realizations of the covariate to preclude the arbitrary choice of thresholds in the variable of interest for studying the heterogeneity. Last but not least, to be able to interpret the heterogeneous DDD coefficients as causal requires that the "parallel trends" assumption holds across the values of the covariate involved in Eq.5. To make it plausible, I match individuals within sex-by-

[10] Borusyak et al. (2021) state that the *t* and *F*-tests have a statistical power only to detect the non-linear pre-trends, so several distant pre-treatment event years should be used as reference categories. In this case, standard results about the tests' behaviour apply, and one can use conventional 5% critical values.

[11] Aggregated (broad) disease groups follow the ICD chapters, except for infectious and parasitic diseases that are grouped together due to small numbers.

disease groups and test for the pre-trends in a fully-dynamic specification for each of these groups.[12]

As a final important note, recent methodological literature has revealed that two-way fixed-effects regressions may not provide the ATET in the presence of heterogeneous effects due to a weighting problem, and this is true for both DD and event-study estimators (e.g., Callaway and Sant'Anna, 2020; Sun and Abraham, 2020). The solution proposed to solve this problem, to estimate the cohort-average treatment effects and appropriately aggregate them, is similar to the empirical approach applied in this paper. 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. 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 (see Chaisemartin and D'Haultfœuille, 2020, for details). Second, the availability of treatment pairs assured that differential treatment groups receive equal weights and contribute equally to the estimates in the two-way fixed-effects regression. In support of this statement, I estimated the aggregated ATETs following the approach by Callaway and Sant'Anna (2020) and received results nearly identical to those reported in the main body of the paper (available upon request).

IV. Data

a. Individual-level data

[12] This procedure will improve the plausibility of the identifying assumption primarily for broad and single disease-by-sex groups. Yet, since the matching procedure involves all covariates across which the heterogeneity is studied, this assumption is likely to hold for them as well.

The first piece of data needed to realize the empirical strategy presented above comes from the administrative longitudinal registers on the total Swedish population combined with the use of unique personal identifiers.[13] SIP includes, among others, data on demographic characteristics, income, labor market participation, education and health. I have selected from these data individuals aged 40–60 as the target population in order to capture the full economic impact of medical innovations. I have extracted information on these individuals over the period 1978–2006, as wide as the overlap between different registers has allowed me.

To define individuals who experienced a health shock due to a certain disease, I have utilized information on inpatient hospital admissions and their causes.[14] Inpatient hospital admissions involve considerable economic consequences, are identifiable, and guarantee access to the newest medical technologies including diagnostics, therapies and drugs (similar, for instance, to the studies by Dobkin et al., 2018; Lundborg et al., 2015). To minimize the possibility of obtaining anticipated health shocks, I have focused on first hospital admissions of individuals who had not been admitted recently; especially not in the three preceding

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

[14] Since 1987, the inpatient hospital register has covered all 24 counties in Sweden. Between 1977 and 1987, this coverage gradually increased by including 7 previously missing counties. Population of these counties for older cohorts is excluded from the analysis (4.51% of all observations). For the period under study, I have employed 3-digit ICD codes from revisions 8, 9, and 10.

years. I have also limited admissions to those individuals for which medical technology could be identified, and have hence excluded stays related to pregnancy, external causes and symptoms.

The data provide a rich set of variables for the individual's income and its sources. The main outcome variable is disposable family income in real terms that has been empirically regarded as an ultimate outcome of all economic consequences of a health shock (e.g. O'Donnell et al., 2015). This variable is calculated net of taxes that can be considered equivalent to a measure of efficiency, in the context of public health insurance and the absence of out-of-pocket expenses such as in Sweden.[15] Other important variables obtained from the data quantify the sources of family income, such as own and spouse's disposable income, labour income, capital income, and payments for sickness absence, unemployment and disability.[16] The results in this paper are insensitive to the functional form of the outcome. Yet, I have used the inverse hyperbolic sine (known henceforth as ihs) in order to limit the disproportionate influence of outliers and to ease interpretation and comparison to other studies.

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[15] SIP does not contain information on utilization, for instance, the consumption of drugs. To my knowledge, the acquisition of this statistical individual-level information is not granted with such a large pool of cohorts as used in this paper.

[16] Family income is a sum of income of the married or cohabiting persons that form a family, plus the income of children, which is a commonly absent part of family income. The components for family and own disposable income are the same throughout the period under analysis. To obtain the spouse's income, I subtract own income from the family income. There were several changes in the registration of welfare payments and its conditions in this period. This should not be problematic, as treated and control individuals are matched exactly on the calendar year.

b. Medical innovations

A second piece of data necessary for the empirical design is medical innovations by disease group and year. The main sources of these data are registries of the Swedish authorities responsible for the approval of medical innovations. I have created disease groups within which medical innovations are measured in a trade-off between clinically meaningful categories, as defined in Elixhauser et al. (2015), and the availability and consistency of the ICD codes for the causes of hospitalizations over the study period. The final list of disease groups, comprising 91 disease groups (see Appendix A Table), has been verified by the health experts (Lindström and Rosvall, 2019). Innovations in each disease group have been constructed on an annual basis over the study period.

One measure of medical innovations is the cumulative number of new molecular entities, a novel chemical compound that creates the basis for new drugs.[17] I have chosen it as my preferred measure because it captures the role of one component of innovations in medical care (see Kesselheim et al., 2013, for details). I have linked drugs to specific diseases in several steps. First, the Swedish Medical Products Agency (Läkemedelsverket) provides 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.[18] Second, each drug is also supplied with the information on the ATC code of the underlying molecular entity and therapeutic indications, and I have successfully matched their combinations with

[17] The term drug refers henceforth to a new molecular entity or an active substance.

[18] Available at https://www.lakemedelsverket.se/sv/sok-lakemedelsfakta?activeTab=1. Using as a basis the extract from this registry of all drugs approved for each year in 1950–2006, I have constructed cumulative series of active ingredients. Drugs disapproved during this period were excluded from this calculation.

the three-digit ICD codes available from the Theriaque database (Husson, 2008). Finally, to validate the series, I have cross-checked the appearance of the most important drugs with those in both the WHO Model List of Essential Medicines (WHO, 2019) and the relevant systematic assessments (Kesselheim and Avorn, 2013).

Another, and complementary, measure of medical innovations is patents granted for diagnostics and therapeutics and surgical treatment. I have obtained this information from the Swedish Patent Database run by the Swedish Patents and Registration Agency (Patent- och Registreringsverket) using a searching procedure practiced by advisory experts.[19] The database with its detailed information, such as the IPC code, and taken together with the patent in a searchable format, is a useful tool for finding technology and innovation within a certain field, their origin, and the dates in force. As a first step, I have limited the IPC codes to those covering surgery, electrotherapy, magnetotherapy, radiation therapy, ultrasound therapy, medical devices and diagnostics.[20] As a next step, based on the names of diseases in the corresponding ICD versions within each disease group, I have formulated combinations

[19] Available at https://tc.prv.se/spd/search?lang=sv&tab=1. The registry covers all patents granted, both in force and no longer in force, and I have constructed cumulative panels based on the extract listing these for each year in 1950–2006.

[20] They correspond to the subchapter in A61 “Medical or Veterinary Science; Hygiene” that 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”, A61N “Electrotherapy; Magnetotherapy; Radiation therapy; Ultrasound therapy”. I exclude patents granted for A61K “Preparations for medical, dental, or toilet purposes” that makes the variable measuring patents complementary to that for drug approvals.

of key words to be able to conduct inclusive yet independent searches (available upon request).[21] Based on these, I have conducted a search for the number of patents per disease group and year in the heading and in the text of patents.[22]

Figure 1 presents the resulting cumulative number of the drugs and patents together with their means aggregated to broader disease groups. The content and ranking of innovations based on the obtained series in general correspond to the categorizations provided by the 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 the lag of 1 year for each to capture the correct timing when the technology came in force as well as to take into account its exogenous nature. Previous literature has tended to choose the preferred lag length after examining the data that was the empirical exercise in itself, making any hypothesis testing irrelevant (e.g., Hirschauer et al., 2018).[23] In order to

[21] I have excluded cases in the groups of "other diseases" which could not be linked to independent groups.

[22] Namely patents defined the final year of treatment in this study: the obtained series end in 2006 because thereafter the law prohibited the granting of patents for surgical/therapeutic treatment and diagnostics.

[23] Gross et al. (1999) regressed current funding on research in medical sciences on current health measures. Cutler et al. (2012) related the current number of grants and publications to the decline in infant mortality by the end of the 15-year period to the current period. Lichtenberg (2015) found that lags of 10 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 wide use in healthcare, Jeon and Pohl (2019) used a 5-year lag of cumulative drug approvals and

compare this paper's findings with those in the previous studies, I have presented the results with a longer lag length in Section V.c.

[Figure 1 is about here]

c. Construction of the estimation sample

As mentioned in Section III, I extended an empirical approach previously suggested by Fadlon and Nielsen (2021) to all diseases observed in the Swedish population, and in this section I provide more details on the procedure and the results of the test for the pre-trends between the individuals who experienced a health shock and their matched counterparts in the initial estimation sample.

In a similar, data-driven, way, I observed that individuals from the same cohorts whose first hospitalization with the same disease was a few years apart from each other experienced a parallel development of economic outcomes prior to hospitalization. However, this applies not only to severe and sudden hospitalizations; I also observed that individuals shared similar pre-trends across a wide range of causes of hospitalization if they were hospitalized only several years apart. The probable reason for this is that, where there were a number of events preceding hospitalization such as an earlier diagnosis or job loss, both groups of individuals experienced a deterioration in economic outcomes resulting in similar pre-trends in a very narrow time window. I chose a group of individuals first hospitalized in year $t+2$ as a pool of potential control individuals. I then matched individuals first hospitalized in year t to individuals first hospitalized in year $t+2$ and found exactly the same calendar years for the

patent applications to measure their heterogeneous effect on employment reduction after cancer diagnosis.

control individuals in the window of [-3; +1] years for the treated individuals.[24] To account for the remaining differences in pre-trends, I also matched on linear measures of years of education, earnings (in ages 38–39) and year of birth within sex-by-disease groups.[25] This matching procedure was not particularly restrictive, as 97% of the individuals observed in the data were successfully matched.

As the empirical strategy required, I performed matching within each of the 91 disease x 2 sex groups for each year of first hospitalization (between 1980 and 2007). Across each of the 91 disease groups, I then performed a *t*-test for the pre-trends in a fully dynamic specification of the underlying DD model in Eq.4 by omitting t=-3 and t=-1 (see Borusyak et al., 2021, for details). Out of 91 disease groups at a 5% significance level I could not reject the null hypothesis of no effect in t=-2 in 89 groups but could reject it in a minor set of 2 groups (see Appendix B Table). The frequency of groups with significant pre-trends is 2.20%, which is close to random and supports my expectation of similarity in behaviour in a very narrow time window for individuals hospitalized currently and two years later across a very broad set of diseases. I also noticed that there are several disease groups where pre-

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[24] This is the smallest window possible: for the pre-treatment period, 3 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.

[25] Following Austin (2014), I used propensity score matching with a calliper of 0.2 standard deviations and no replacement as the most efficient matching procedure. 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 (at $t \in [-8; -4]$) and then as treated (at $t=0$) are considered and constructed as being independent of each other.

trends are detected at a 10% significance level and are influential in the final sample, pushing non-linearity in pre-treatment development of the outcomes. In sum, I observed that groups where the "parallel trends assumption" was likely to be violated are those heterogeneous disease groups that could not be split further due to the changes in the classification of diseases across the versions of the ICD. These groups have been omitted from the estimation sample.[26] Table 1 presents descriptive statistics for the final estimation sample.

[Table 1 is about here]

As a diagnostic for the "parallel trends" in the final estimation sample, I have plotted ihs family income by event years across DD groups that will further participate in the DDD estimation. As one way to look at these comparisons, Figure 2 presents the average family income by event years comparing treated and control groups of individuals in total and by the broad disease groups in the final estimation sample. The individual fixed components, α_i, were excluded from ihs family income to make the graphs compatible with the regression analysis in Eq.4.[27] It reveals remarkable similarity in the development of the outcome for

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[26] Disease groups with significant pre-trends detected at a 5% significance level, "Benign neoplasms" (#25) and "Diseases of oesophagus, stomach and duodenum" (#49), and those with significant pre-trends detected at a 10% significance level, "In situ neoplasms" (#24) and "Deforming dorsopathies, osteopathies and chondropathies. Disorders of muscles" (#59) have been dropped from the estimation sample. Probably, one could split these populous groups further so as to be able to match proper counterfactuals. For the hospital cases in this paper, changes in the classification of diseases across versions of the ICD impedes splitting. Excluding all disease groups where pre-trends are significant at a 10% level (an additional 4) marginally affects the main results.

[27] Development of family income as shown in the original series (α_i included) also demonstrates the similarity of pre-trends and is shown in Appendix B Figure B1.

both treated and control groups before the event year of $t = 0$, the year of hospitalization for treated individuals, across all groups of diseases. This observation applies both to severe and unanticipated diseases, such as cancers and circulatory, and to those usually understood as chronic and anticipated, such as mental/nervous and metabolic. During and after hospitalization, ihs family income declined rapidly for the treated individuals while there was no change for the control individuals. Figure B2 Appendix B shows similar patterns for the sources of family income as outcomes. Another way to look at the DD terms underlying the DDD specification is to compare the outcomes of both treated and control individuals assigned to different levels of medical innovations based on the year of hospitalization.[28] Figure B3 and B4 in Appendix B present the average family income by event years comparing individuals above and below the median of medical innovations, drugs and patents respectively. The outcomes of the comparison groups develop strictly parallel to each other.

V. Results

a. Main results

Table 2 presents the DDD estimates of the impact of medical innovations, such as the 1-year lags of the cumulative number of drug approvals and patents granted in diagnostics, therapy and surgery, on family income in total and by sex, obtained from Eq.4. As discussed above, these estimates are the innovation-induced *reduction* in economic loss due to hospitalization. The baseline economic loss, which is the impact of a health shock on family income when medical innovations are absent, is 36% using drugs and 28% using patents. In absolute terms, it equals to a substantial reduction in family income of 13 410 and 9 790 US dollars respectively per individual-year, these respective amounts having been adjusted for

[28] This implies the analysis of the groups underlying the $post_{idst}M_{ds}$ term.

inflation.[29] Results show that medical innovations significantly reduced these losses. It is easier to grasp the size of the DDD effect if it is interpreted in terms of one SD of the medical innovations. In these terms, the impact of medical innovations on family income amounts to 9.39% (95% CI: 9.01%; 9.76%) using drugs and to 5.38% (95% CI: 5.37%; 5.39%) using patents. Since both these measurements are independent and since constructed measures of medical innovations are complementary, I was able to calculate the sum of both effects to obtain the combined impact of medical innovations.[30] The combined income impact of medical innovations was calculated to be 14.76% (95% CI: 14.39%; 15.14%). In absolute terms, medical innovations reduced the economic loss by 5 353 inflation-adjusted US dollars per individual-year. The 95% confidence intervals for the combined effects for men and women overlap (they amount to 12.79% and 15.11% for men and 14.96% and 15.92% for women), suggesting no difference between them in the *ultimate* impact of medical innovations on family income.

[Table 2 is about here]

Table 3 presents the DDD estimates of the impact of medical innovations on the sources of family income, such as own and spouse's disposable income, own labour income, different welfare payments and own capital income. Medical innovations appear to increase the income of both family members: by 5.99% (95%CI: 5.58%; 6.39%) of own disposable

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[29] This is compared to the real family income among the counterfactuals (i.e. $DD_{idst} = 0$) that equals 36 245 inflation-adjusted US dollars per year (the base year is 2020).

[30] For independent measurements, as given in this paper, the standard error (*SE*) of the coefficient estimate in terms of one SD of the medical innovations can be obtained using the following formula:

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

income and by 15.65% (95%CI: 14.15%; 17.16%) of spouse's disposable income. I have also estimated the effects by sex separately (see Appendix C Table C1 for men and Table C2 for women). The beneficial effects of medical innovations on own income and welfare payments are almost twice as strong for men than for women, which could be linked to more severe health shocks being experienced by the former. In contrast, the combined impact of innovations on spouse's income is smaller for men than for women, and consistent with stronger responses on the part of women to the partner's health shock. The beneficial effects of medical innovations emerge through the increase in own labour supply at both its intensive and extensive margins. This is evident through the positive impact of innovations on labour income (10.83%, 95%CI: 9.50%; 12.16%), and their negative impact on payments of sickness absence (-37.64%, 95%CI: -39.36%; -35.73%) and unemployment benefits (-9.03%, 95%CI: -9.44%; -8.63%). The effects of medical innovations on disability pension are small in a DDD specification, although they can be detected in the last event year that reflects the long-term uptake of this form of insurance (see Section V.b).

[Table 3 is about here]

Figure 3 presents the heterogeneous DDD estimates of the impact of medical innovations on family, own and spouse's disposable income outcomes across broad disease groups estimated according to Eq.5.[31] Results show that medical innovations produce large positive effects on family income for individuals hospitalized due to cancer (51.11%, 95%CI: 47.44%; 54.77%) and circulatory diseases (19.51%, 95%CI: 18.34%; 20.67%). The estimates for own disposable and labour income show positive effects of medical innovations for nervous, respiratory and infectious diseases, the size of which are close to the mean effects

[31] The effect for each subgroup (heterogeneous DDD) is calculated as one SD of drug approvals/granted patents in this subgroup multiplied by the estimate of β_3 for this subgroup.

for the subsequent outcomes. It is worth noting that the effect of innovations in the case of hospitalizations due to mental disease is moderate (2.27%), albeit statistically insignificant.[32] Another notable finding for spouse's income (and for family income accordingly) is that the effects of innovations are negative for several chronic diseases, such as diseases of the digestive and blood-forming organs, and these counterbalance positive effects on own income for a few other chronic diseases. While spouse's income declines in response to a health shock for all these diseases, I suggest that it represents the family-level economic losses from shocks with low insurance eligibility.[33]

[Figure 3 is about here]

I further analyzed heterogeneous responses of household income to medical innovations following Grossman's theoretical formulations. First, bearing in mind the supposition that the depreciation rate of health capital increases with age, I found that the compensating effect of medical innovations on family income loss increases with age (see Panel (A) in Figure 4). For instance, for individuals admitted to hospital at the age of 43 (the youngest age observed) and at the ages of 58–60 (the oldest ages) the combined effect is equal to 7.04% (95%CI: 5.35%;

[32] By performing additional analyses, I found that it reaches 3.39% (95%CI: 0.75%; 6.03%) when using the 10-year lag of medical innovations instead of the 1-year lag. This may suggest a delay in the wide use of medical innovations for mental conditions after their appearance, in particular drugs, which should be taken into account.

[33] Here I rely on the effect of a health shock on the uptake of a disability pension that is no different from null after hospitalization due to a digestive, blood-forming or infectious disease. In contrast, the change in disability pension uptake is statistically and economically significant for other health conditions.

8.73%) and 31.5% (95%CI: 28.22%; 34.78%) respectively.[34] Second, the impact of medical innovations declines over time (i.e. across years of hospitalization), which suggests decreasing rather than constant returns to health inputs that are precluded by the theoretical model (see Panel (B) in Figure 4). That said, while these returns decline by more than two times (from 23.5%, 95%CI: 21.2%; 25.8%, in 1981/82 to 9.56%, 95%CI: 7.53%; 11.59%, in 2005/06), they are positive at any observed year, both by type of innovation and combined. Finally, I found that the effects of medical innovations decline the higher the education level that is contrary to the theoretical formulation (see Figure 5). These effects are equal to 22.92–24.78% (95%CI: 21.58%; 26.78%) for individuals whose completed their education at compulsory school, and drop by two-thirds for those with a higher education level (the mean effect for the latter being 7.33%).

[Figure 4 and 5 are about here]

b. Validity of the DDD design

As mentioned in Section III, the main identification assumptions of the DDD framework is that the control group provides a valid counterfactual (the "parallel trends" assumption) and that the potential outcomes and treatments of different groups are independent ("independent groups") across underlying DD comparisons. Both assumptions are essentially untestable, but in the following I provide suggestive evidence of their plausibility.

So far, to assure the plausibility of the "parallel trends" assumption, I have matched treated and not-yet-treated individuals within specific disease groups and gender and have

[34] I also estimated the heterogeneous effects of medical innovations with regard to severity of disease, and found that in general they increase the more nights that are spent in hospital (see Appendix D Figure). It can just be noted that the effects are disproportionately stronger for individuals discharged on the same day after admission, and this is driven by the larger share of circulatory cases.

tested the resulting groups for the absence of the pre-trends separately. One should bear in mind that the estimates for the coefficients and standard errors from these specifications may differ from those produced in the pooled sample due to a weighting problem (see Goodman-Bacon, 2021, for details). Even though the visual analysis by event years across different comparison groups showed a similar development in their outcomes, it is important to conduct a formal test. First, I performed the t-test for the pre-trends in the final estimation sample in total and by broad disease groups, comparing both treated and control groups (Appendix E Table E1) and groups across different levels of medical innovations (Table E2). Second, I ran the event study specification of Eq.4 for family income (Table E3) and its sources (Table E4). The results from the above tests show no differential pre-treatment trends (at t=-2) for either two-way or three-way differences. Finally, as suggested by Goodman-Bacon (2021), forthcoming, I included a more saturated set of fixed effects, namely disease group-by-sex-by-event year effects, in the event-study and DDD specification and received almost identical results (see Table 4 columns 1 and 2). In sum, results indicate that the "parallel trends" assumption is likely to hold.

[Table 4 is about here]

As I have previously mentioned, the "independent groups" assumption is likely to hold in the setting of this paper because the first-year lags of drug approvals and granted patents were plausibly exogenous to the decision of hospitalization. However, one may argue that the uptake of health insurance and care can induce medical innovation (e.g., Lleras-Muney and Lichtenberg, 2005; Acemoglu et al., 2006). Correlation between individuals treated in different years may also arise mechanically, because the levels of medical innovations have been constructed as cumulative series. I elaborated the plausibility of the "independent groups" assumption with several checks. I first detrended the panel of medical innovations within each disease group to obtain their white noise component and used the latter in the models (see Table 4 columns 3 and 4). I next estimated the models by looking at medical innovations of exclusively international origin that more likely approximated exogenous shocks (see Table 4 columns 5 and 6, cf. Papageorgiou et al., 2007).[35] I also estimated the models with the 5 and 10-year lags instead (and reported the latter), which should exacerbate the endogeneity problem, if any exists. As can be seen, the results from these three checks are very similar to the main ones.

The "independent groups" assumption should also hold for the event of a health shock, and this is likely because the individual's probability of becoming ill in the modern context should not be dependent on that of other individuals. However, the definition of a health shock in this study is based on inpatient hospitalizations that might be a decreasing function of the availability of hospital beds over the study period (Swift et al., 2018). Even though the way in which this paper's estimation sample is formed has partially ruled this out (i.e. by focusing on individuals who had not been recently hospitalized and who have been matched within 2 years of treatment of each other), I made several checks. First, I included individuals who experienced potentially similar health shocks but were left outside the estimation sample, at an accelerated rate over time, such as individuals treated in emergency units (see Table 4 columns 9 and 10) or outpatient care units (see Table 4 columns 11 and 12).[36]

[35] For the new molecular entities, these include only those related to the directly imported drugs. For patents, these include patents granted to non-Swedish applicants.

[36] To account for the hospitalizations in emergency units, I have included individuals who died due to one of the diagnoses specified in this analysis but who had not been treated in hospital prior to their death. In another check, I have added data on the outpatient care visits, available during the period 2000 to 2007. To achieve a fair benchmark, the estimates from the latter sample should be compared to the year-specific effects of medical innovations (cf. Panel B of Figure 4).

Second, I matched hospitalized individuals to the pool of those hospitalized due to symptoms or external causes in the future, which are potentially relevant matches for both acute and chronic diseases (see Table 4 columns 13 and 14).[37] In sum, the results presented in Table 4 for these models are similar to the main results, bearing in mind the magnitude of the baseline health shock (i.e. due to hospitalization).[38]

Finally, while the empirical approach of identifying the heterogeneous economic effects of medical innovations via interactions with theoretically motivated variables is absolutely correct, the estimation sample may hide important interactive effects of innovations across several individual variables. To carry out such a data-driven search for the valuable interactions, I implemented model-based recursive partitioning following Zeileis et al. (2008). This machine-learning algorithm adaptively partitions the estimation sample based on the fitted model (in this case the model is estimated according to Eq.4) with respect to the variables of interest (i.e., a broad group of diagnoses, the year of hospitalization, the age at hospitalization, education level and sex) using a greedy forward search.[39] Appendix G

[37] They include chapters XVIII (R00–R99), XIX (S00–T98), and XX (V01–Y98) in the ICD-10 and the equivalent chapters in earlier revisions. Construction of a control group is the same as in the main analysis (see Section III and Section IV.c).

[38] All the models included into Table 4 have successfully passed the tests for non-linear pre-treatment trends (see Appendix F Table).

[39] To apply a linear regression model equivalent to the model in the main analysis (Eq.4), I subtracted individual fixed effects (α_i) from all dependent and independent variables used in this equation. All partitioning variables were treated as categorical with categories identical to those used in the main analysis (unordered categories for broad groups of diagnoses and sex, and ordered categories for the year of hospitalization, the age at hospitalization, and years of schooling). To avoid overfitting with such a large dataset as mine, I applied both a p-value of 0.001 for detection of parameter instability

presents the resulting linear-regression trees for the impact of drug approvals and granted patents on disposable family income. Results support the presence of the main heterogeneity in the impact of medical innovations with regard to severity of disease as measured using a broad disease group (cancers, circulatory, and the rest) and completed education (compulsory/junior secondary education only or higher education levels).

c. Comparison to previous studies

A comparison of this paper's results to the previous findings is not easy if we are to understand the total effects of medical innovations. The main reason for this is the dominance of the cost-and-benefit analysis estimates for measuring productivity in healthcare – estimates that are far from being causal and tend to give extremely different results for different populations. Yet, the magnitudes of the effects in this paper are in annual terms compatible with the median positive productivity growth effects of healthcare expenditures found in these studies. I have presented the total (aggregate) effects of medical innovations in terms of one SD change (14.8%, 95% CI: 14.4%; 15.1%), which is roughly similar to the overall increase in medical innovations in 1981–2006. Hence, the row estimates for β_3 in percentage terms may approximate the annual impact of drugs and patents: their joint impact amounts to 0.69% (95% CI: 0.67%; 0.72%). This magnitude lies in a range of service-based and disease-based productivity measures reviewed, for instance, in Sneiner and Malinovskaya (2016).[40] Importantly, I found that the total effects of medical innovations are *positive*. This accords

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and post-pruning with the Bayes Information Criteria. To be able to grasp the decision rules of a tree, I also set up the depth of the tree to be not more than four, so that at its maximum the number of nodes would be roughly equivalent to the number of subgroups used in the main analysis.

[40] Since the main outcome is disposable income, the effects of medical innovations can be interpreted as productivity effects.

with Fonseca et al. (2021) and Cutler et al. (2021) who estimated the positive aggregate productivity growth of medical care to be 0.7% and 1.5% per year respectively. In contrast to the above studies, the total effect of medical innovations found in this paper can be seen as plausibly causal.

Regarding the heterogeneous effects of medical innovations, I was able first of all to compare these to the studies reporting heterogeneous effects by subsamples. While no study has examined the heterogeneous returns to medical innovations in the same level of detail as given in this paper, my findings align well with the studies that look at their different dimensions. The heterogeneity is large across disease groups, which is similar to findings in Cutler et al. (2021). In agreement with previous studies, total returns are positive yet decreasing over time (cf. Cutler, Rosen, Vijan, 2006), although they are negative for chronic diseases with low insurance eligibility (cf. Bloom et al., 2020). The only finding of note is that returns are larger for those with a lower education level, which is at odds with previous studies (e.g. Jeon and Pohl, 2019). In this paper, the treatments are defined through inpatient hospitalizations, not diagnoses, within the universally publicly insured population where efficiency in the consumption of medical care is likely to be less important in determining health outcomes.

Second, the amount of detail in the data made it easy for me to estimate the effects for single groups of diseases (in addition to broader groups reported in the main body) and compare these to the previous studies (see these estimates in Appendix H). In doing so, I was able to support previous findings from quasi-experimental studies for other contexts in that I found the positive effects of innovations in selected single disease groups, such as 19% (95%CI: 16%; 22%) for prostate cancer, 54% (95%CI: 44%; 64%) for breast cancer, 33% (95%CI: 31%; 36%) for ischemic heart disease, and 8% (95%CI: 2%; 15%) for treatment of infectious arthropathies. Additionally, I find causal effects for conditions for which previous studies were able to provide only the associations, such as 4% (95%CI: 1%; 8%) for hypertension, 9% (95%CI: 6%; 12%) for heart failure, 41% (95%CI: 36%; 46%) for cerebrovascular disease, and 11% (95%CI: 6%; 15%) for mental and behavioural disorders due to alcohol and other substance use.[41] Moreover, many other innovations against specific diseases, which were not previously studied, were efficient. They include the majority of cancers and nervous diseases, several diseases of digestive and urinary systems, the majority of respiratory diseases, certain metabolic diseases, and bacterial and viral diseases including tuberculosis (these estimates are available upon request).

VI. Conclusions

This paper provides novel evidence on the plausibly causal total and heterogeneous economic returns to medical innovations. The empirical strategy used in this paper made it possible to estimate the impact of medical innovation on economic outcomes as an innovation-induced *reduction* in economic loss due to the onset of a specific disease. I show

[41] For a comparison, studies found a statistically significant impact of single medical innovations or single diseases include the following (experimental or quasi-experimental studies are marked with asterisk): Jeon and Pohl* (2019) (the impact of drugs and therapies on economic outcomes of prostate and breast cancer survivors), Stephens and Toohey* (2018) (the impact of the multiple interventions aimed at reducing coronary heart disease on economic outcomes of the trial participants), Cutler, Landrum, Stewart (2006) (the impact of intensive medical care on disability reductions), Duggan (2005) (the impact of antipsychotic drugs on the prevalence of the extrapyramidal symptoms among the mentally ill), Cutler et al. (2007) (the impact of antihypertensive drugs on survival), Thirumurthy et al.* (2008) (the impact of the antiretroviral therapy, used to treat AIDS, on labour outcomes), Garthwaite* (2012) and Bütikofer et al.* (2018) (the impact of Cox-2 inhibitors, used to treat arthropathies, on labour outcomes), and Epstein et al. (2013) (the impact of minimally invasive surgery, used to treat cardiovascular disease and diseases of genital organs, on sickness absence).

that medical innovations, such as new molecular entities, therapies, surgeries and diagnostics against particular diseases in a set of around 90 groups, yield a relatively large positive impact on family disposable income, 15% in aggregate or 0.7% annually. Consistent with the theoretical model for family health production, medical innovations increase not only own income and labour supply at its extensive and intensive margins but also a spouse's income. The heterogeneity of returns to medical innovations is large and present with regard to severity of disease, year at hospitalization, and education level. While the returns to medical innovations are positive in aggregate throughout the period 1981–2006, they turn negative for several chronic diseases with low insurance eligibility.

In terms of policy implications, this research has important conclusions. First, this study shows that medical innovations can be regarded as investments with high (diminishing) returns. Since the growth in innovations in medical care surpasses the growth in health indicators or real income at the population level, any mere comparisons of the two would lead to the opposite, erroneous, conclusion (cf. Fuchs, 2004; Bloom et al., 2020). Second, the effects of medical innovations appear not only for the receiver of the treatment but also for the spouse. They emerge because the resources available for health production of the individual are not only own income but also total family income. However, the direction of the spouse's response to medical innovations differs with regard to the severity of individual's disease, suggestively due to the differences in insurance eligibility. This likely points to the weakness of the existing health insurance schemes to fully compensate for the negative consequences of less severe diseases (McClellan, 1998). Finally, the economic effects of medical innovations are not allocated equally across population groups. This has implications not only for the overall improvements in health and income but also for the equity (e.g., Cutler et al., 2012), a fact that the current policy makers have failed to fully recognize.

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Table 1. Descriptive statistics for the estimation sample

	Observations	Mean	SD
l1.drugs	6,110,797	16.3565	13.7442
l1.patents	6,110,797	324.4560	537.7418
post	6,110,797	0.4022	0.4903
post x l1.drugs	6,110,797	6.5729	11.8383
post x l1.patents	6,110,797	130.3870	376.0248
DD_{idst}	6,110,797	0.1997	0.3998
DD_{idst} x l1.drugs	6,110,797	3.2687	8.9762
DD_{idst} x l1.patents	6,110,797	64.8316	273.0323
ihs family disposable income	6,110,797	12.9713	1.2003
ihs own disposable income	6,110,797	12.4975	1.6273
ihs spouse's disposable income	6,110,797	9.0041	5.7642
ihs own labour income	6,110,797	11.7791	3.7679
ihs sickness absence payments	5,869,111	3.8184	4.9327
ihs unemployment benefits payments	6,110,797	0.2389	1.5051
ihs disability pension payments	5,869,111	0.9547	3.2587
ihs own capital income	6,110,797	-1.2053	8.0664
cancers	6,110,797	0.0955	0.2939
circulatory diseases	6,110,797	0.2431	0.4290
mental diseases	6,110,797	0.0742	0.2621
nervous diseases	6,110,797	0.0357	0.1855
digestive diseases	6,110,797	0.1836	0.3871
musculoskeletal diseases	6,110,797	0.0486	0.2150
urinary diseases	6,110,797	0.1024	0.3032
respiratory diseases	6,110,797	0.0698	0.2548
metabolic diseases	6,110,797	0.0434	0.2038
diseases of bloodforming organs	6,110,797	0.0069	0.0828
diseases of sense organs	6,110,797	0.0472	0.2121
diseases of skin	6,110,797	0.0147	0.1202
infectious/parasitic diseases	6,110,797	0.0348	0.1834

Table 2. DDD estimates: Impact of medical innovations in 1981–2006 on ihs family income in ages 40–60 Sweden

	Both Sexes	Both Sexes	Men	Men	Women	Women
	(1)	(2)	(3)	(4)	(5)	(6)
post	0.04124***	0.04933***	0.04391***	0.05401***	0.03790***	0.04422***
	(0.00127)	(0.00096)	(0.00194)	(0.00148)	(0.00157)	(0.00118)
post x l1.drugs	0.00044***		0.00039***		0.00051***	
	(0.00006)		(0.00010)		(0.00007)	
DD_{idst}	-0.35575***	-0.27581***	-0.37148***	-0.29744***	-0.33444***	-0.24980***
	(0.00344)	(0.00250)	(0.00496)	(0.00367)	(0.00472)	(0.00333)
DD_{idst} x l1.drugs	0.00683***		0.00668***		0.00683***	
	(0.00014)		(0.00022)		(0.00017)	
post x l1.patents		-0.00000		-0.00001***		0.00001***
		(0.00000)		(0.00000)		(0.00000)
DD_{idst} x l1.patents		0.00010***		0.00010***		0.00010***
		(0.00000)		(0.00001)		(0.00000)
Constant	13.13115***	13.13115***	13.10940***	13.10940***	13.15700***	13.15701***
	(0.00042)	(0.00042)	(0.00061)	(0.00061)	(0.00055)	(0.00055)
1 SD of l1.drugs /l1.patents	13.7442	537.7418	13.1586	516.0485	14.3734	562.4148
1 SD x effect x 100%	9.39%	5.38%	8.79%	5.16%	9.82%	5.62%
95% lower CI	9.01%	5.37%	8.22%	4.15%	9.34%	5.61%
95% upper CI	9.76%	5.39%	9.36%	6.17%	10.30%	5.63%
Individual (experimental) FEs	yes	yes	yes	yes	yes	yes
Observations	6,110,797	6,110,797	3,319,071	3,319,071	2,791,726	2,791,726
R-squared	0.00868	0.00741	0.00846	0.00748	0.00923	0.00756
Number of individuals	1,239,384	1,239,384	673,469	673,469	565,915	565,915

Note: Models are estimated according to Eq.4. Robust standard errors clustered at individual (experimental) level are in parentheses.

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

Table 3. DDD estimates: Impact of medical innovations in 1981–2006 on the sources of ihs family income in ages 40–60 Sweden

	Ihs Own Disposable Income		Ihs Spouse's Disposable Income		Ihs Own Labour Income		Ihs Sickness Absence Payments		Ihs Unemployment Benefits Payments		Ihs Disability Pension Payments		Ihs Own Capital Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(14)	(15)
post	0.06186***	0.06416***	-0.16551***	-0.11185***	-0.14486***	-0.12495***	-0.25355***	-0.20297***	0.00173	0.00065	0.24661***	0.26002***	-0.42092***	-0.33744***
	(0.00218)	(0.00164)	(0.00534)	(0.00398)	(0.00412)	(0.00311)	(0.00736)	(0.00551)	(0.00198)	(0.00149)	(0.00314)	(0.00239)	(0.01008)	(0.00773)
post x l1.drugs	-0.00022**		0.00322***		0.00024		0.00432***		-0.00004		0.00186***		0.00778***	
	(0.00010)		(0.00026)		(0.00021)		(0.00034)		(0.00008)		(0.00015)		(0.00051)	
DD_{idst}	-0.08155***	-0.05750***	-0.50040***	-0.39166***	-0.18606***	-0.11664***	2.78908***	2.93590***	0.30461***	0.28513***	0.09449***	0.10075***	0.02875**	0.01883*
	(0.00341)	(0.00251)	(0.00870)	(0.00647)	(0.00618)	(0.00461)	(0.01163)	(0.00890)	(0.00366)	(0.00281)	(0.00469)	(0.00360)	(0.01420)	(0.01089)
DD_{idst} x l1.drugs	0.00240***		0.00826***		0.00553***		-0.00346***		-0.00305***		0.00012		-0.00061	
	(0.00015)		(0.00040)		(0.00030)		(0.00054)		(0.00015)		(0.00023)		(0.00072)	
post x l1.patents		-0.00002***		-0.00000		-0.00005***		0.00007***		0.00000		0.00005***		0.00014***
		(0.00000)		(0.00001)		(0.00001)		(0.00001)		(0.00000)		(0.00000)		(0.00001)
DD_{idst} x l1.patents		0.00005***		0.00008***		0.00006***		-0.00060***		-0.00009***		-0.00001**		-0.00000
		(0.00000)		(0.00001)		(0.00001)		(0.00001)		(0.00000)		(0.00001)		(0.00002)
Constant	12.48253***	12.48253***	9.12254***	9.12253***	11.85484***	11.85484***	3.32680***	3.32476***	0.18768***	0.18767***	0.81862***	0.81850***	-1.09088***	-1.09093***
	(0.00043)	(0.00043)	(0.00111)	(0.00111)	(0.00080)	(0.00080)	(0.00159)	(0.00159)	(0.00048)	(0.00048)	(0.00065)	(0.00065)	(0.00190)	(0.00190)
1 SD of l1.drugs /l1.patents	13.7442	537.7418	13.7442	537.7418	13.7442	537.7418	13.8578	545.7905	13.7442	537.7418	13.8578	545.7905	13.8578	545.7905
1 SD x effect x 100%	3.30%	2.69%	11.35%	4.30%	7.60%	3.23%	-4.79%	-32.75%	-4.19%	-4.84%	0.17%	-0.55%	-0.85%	0.00%
95% lower CI	2.89%	2.68%	10.28%	3.25%	6.79%	2.17%	-6.26%	-33.82%	-4.60%	-4.85%	-0.46%	-1.62%	-2.80%	-2.14%
95% upper CI	3.70%	2.70%	12.43%	5.36%	8.41%	4.28%	-3.33%	-31.68%	-3.79%	-4.83%	0.79%	0.52%	1.11%	2.14%
Individual (experimental) FEs	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	5,869,111	5,869,111	6,110,797	6,110,797	5,869,111	5,869,111	6,110,797	6,110,797
R-squared	0.00062	0.00054	0.00663	0.00601	0.00357	0.00333	0.06920	0.07010	0.00846	0.00854	0.02070	0.02069	0.00129	0.00121
Number of individuals	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,239,336	1,239,336	1,239,384	1,239,384	1,239,336	1,239,336	1,239,384	1,239,384

Note: Models are estimated according to Eq.4. Robust standard errors clustered at individual (experimental) level are in parentheses.

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

Table 4. DDD estimates: Robustness analyses of the impact of medical innovations in 1981–2006 on ihs family income in ages 40–60 Sweden

	Adding disease X sex X event-year FEs		Detrended Innovations		International Innovations Only		10-Year Lags of Innovations		Adding the Died to the Treated		Adding Outpatient Register (2000–2007)		Symptoms and External Causes as Controls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
post	1.04732	0.75594	0.04265***	0.04935***	0.04197***	0.04685***	0.04092***	0.04811***	0.04104***	0.04953***	0.06928***	0.07432***	0.04437***	0.04891***
	(.)	(.)	(0.00120)	(0.00095)	(0.00123)	(0.0009)	(0.00124)	(0.00093)	(0.00127)	(0.00097)	(0.00279)	(0.00186)	(0.00122)	(0.00092)
post x l1.drugs	0.00026*		0.00041***		0.00106***		0.00070***		0.00046***		0.00011		0.00051***	
	(0.00015)		(0.00006)		(0.00017)		(0.00009)		(0.00006)		(0.00008)		(0.00006)	
DD_{idst}	-0.36762***	-0.28407***	-0.34477***	-0.28301***	-0.36791***	-0.26412***	-0.37097***	-0.26923***	-0.35513***	-0.27554***	-0.06799***	-0.04985***	-0.36936***	-0.28226***
	(0.00339)	(0.00247)	(0.00326)	(0.00252)	(0.00352)	(0.00235)	(0.00348)	(0.0024)	(0.00344)	(0.0025)	(0.00453)	(0.00299)	(0.00324)	(0.00235)
DD_{idst} x l1.drugs	0.00716***		0.00703***		0.02010***		0.01166***		0.00681***		0.00102***		0.00694***	
	(0.00014)		(0.00014)		(0.00038)		(0.00021)		(0.00014)		(0.00013)		(0.00013)	
post x l1.patents		-0.00003***		-0.00000		0.00001***		0.00000		0.00000		0.00000		0.00001***
		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)
DD_{idst} x l1.patents		0.00010***		0.00012***		0.00015***		0.00016***		0.00010***		0.00002***		0.00008***
		(0.00000)		(0.00000)		(0.00001)		(0.00001)		(0.00000)		(0.00000)		(0.00000)
Constant	12.14490	12.44863	13.13112***	13.13113***	13.13114***	13.13116***	13.13114***	13.13115***	13.12893***	13.12893***	13.34204***	13.34204***	13.12792***	13.12793***
	(.)	(.)	(0.00042)	(0.00042)	(0.00042)	(0.00042)	(0.00042)	(0.00042)	(0.00042)	(0.00042)	(0.00045)	(0.00045)	(0.00039)	(0.00039)
1 SD of l1.drugs /l1.patents	13.7442	537.7418	13.39201	543.5962	5.0666	291.8543	9.4257	308.4032	13.7242	537.4985	17.3743	748.0260	13.8096	552.1995
1 SD x effect x 100%	9.84%	5.38%	9.41%	6.52%	10.18%	4.38%	10.99%	4.93%	9.35%	5.37%	1.77%	1.50%	9.58%	4.42%
95% lower CI	9.46%	5.37%	9.05%	6.52%	9.81%	3.81%	10.60%	4.33%	8.97%	5.36%	1.33%	1.49%	9.23%	4.41%
95% upper CI	10.22%	5.39%	9.78%	6.52%	10.56%	4.95%	11.38%	5.54%	9.72%	5.38%	2.21%	1.51%	9.94%	4.43%
Individual (experimental) FEs	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	6,149,619	6,149,619	2,731,000	2,731,000	7,112,891	7,112,891
R-squared	0.03939	0.03864	0.00867	0.00770	0.00894	0.00733	0.00930	0.00739	0.00862	0.00735	0.00191	0.00183	0.00917	0.00781
Number of individuals	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,249,051	1,249,051	553,349	553,349	1,442,305	1,442,305

Note: Models are estimated according to Eq.4 with modifications described in Section V.c. Robust standard errors clustered at individual (experimental) level are in parentheses.

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

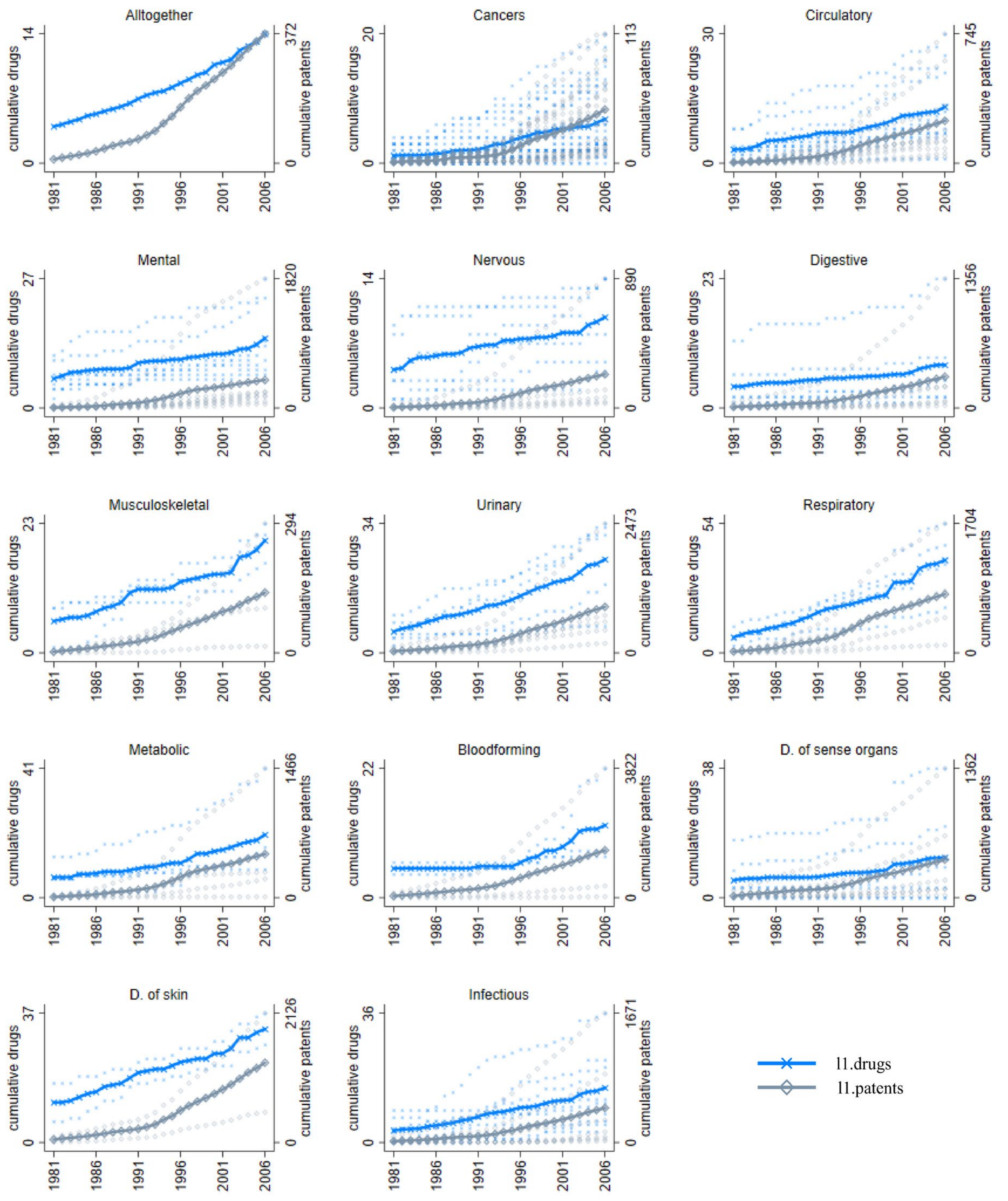

Figure 1. Development of medical innovations by disease and broad disease groups in 1981–2006 Sweden

Note: The connected lines denote the mean number of cumulative medical innovations in each broad disease group. The dotted lines denote the number of cumulative medical innovations in each single disease group.

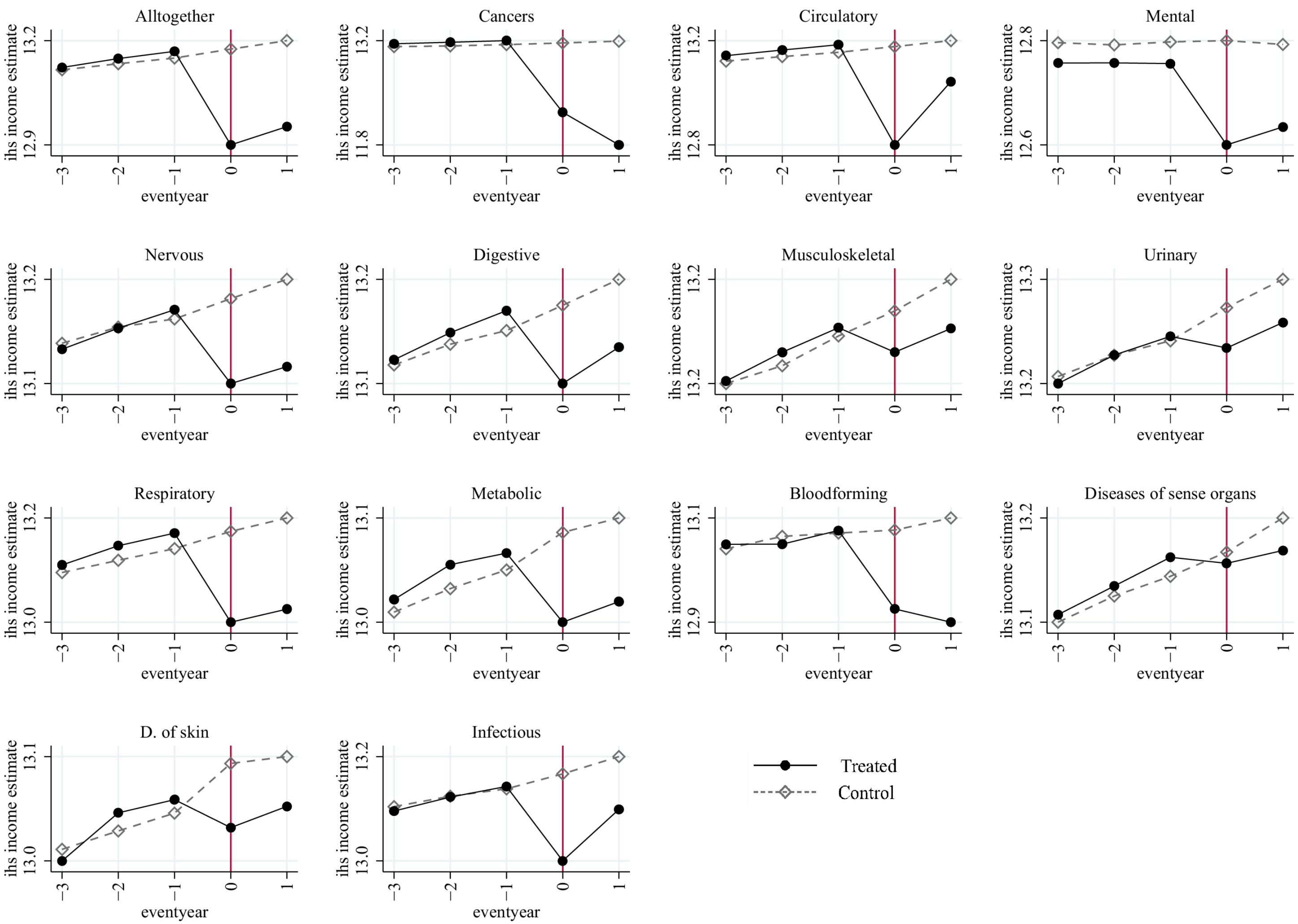

Figure 2. Development of ihs family income by event years for treated and control groups (without α_i), both sexes

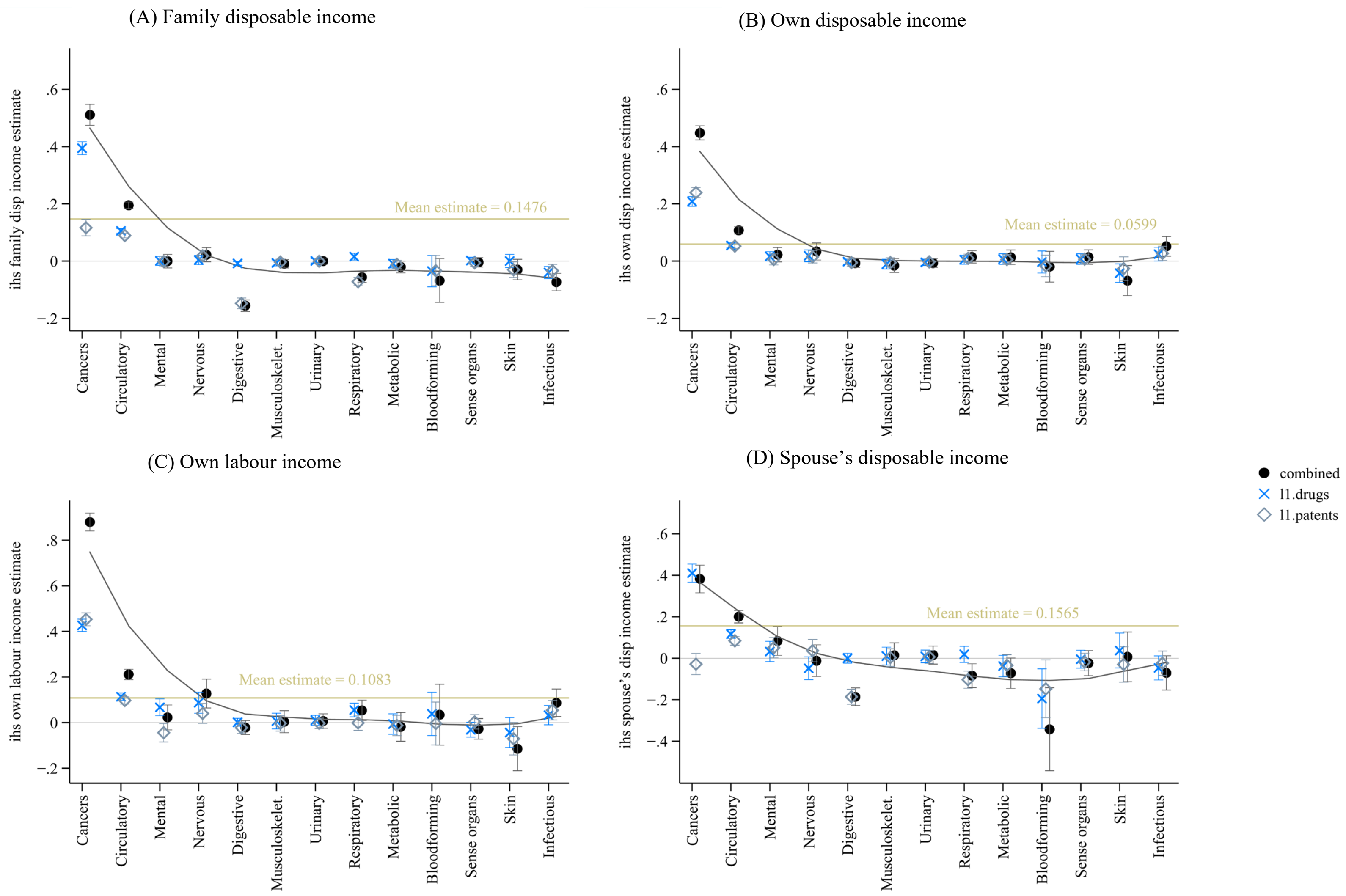

Figure 3. Heterogeneous DDD estimates: Impact of medical innovations on ihs family disposable income and its sources by cause of hospitalization (by broad groups)

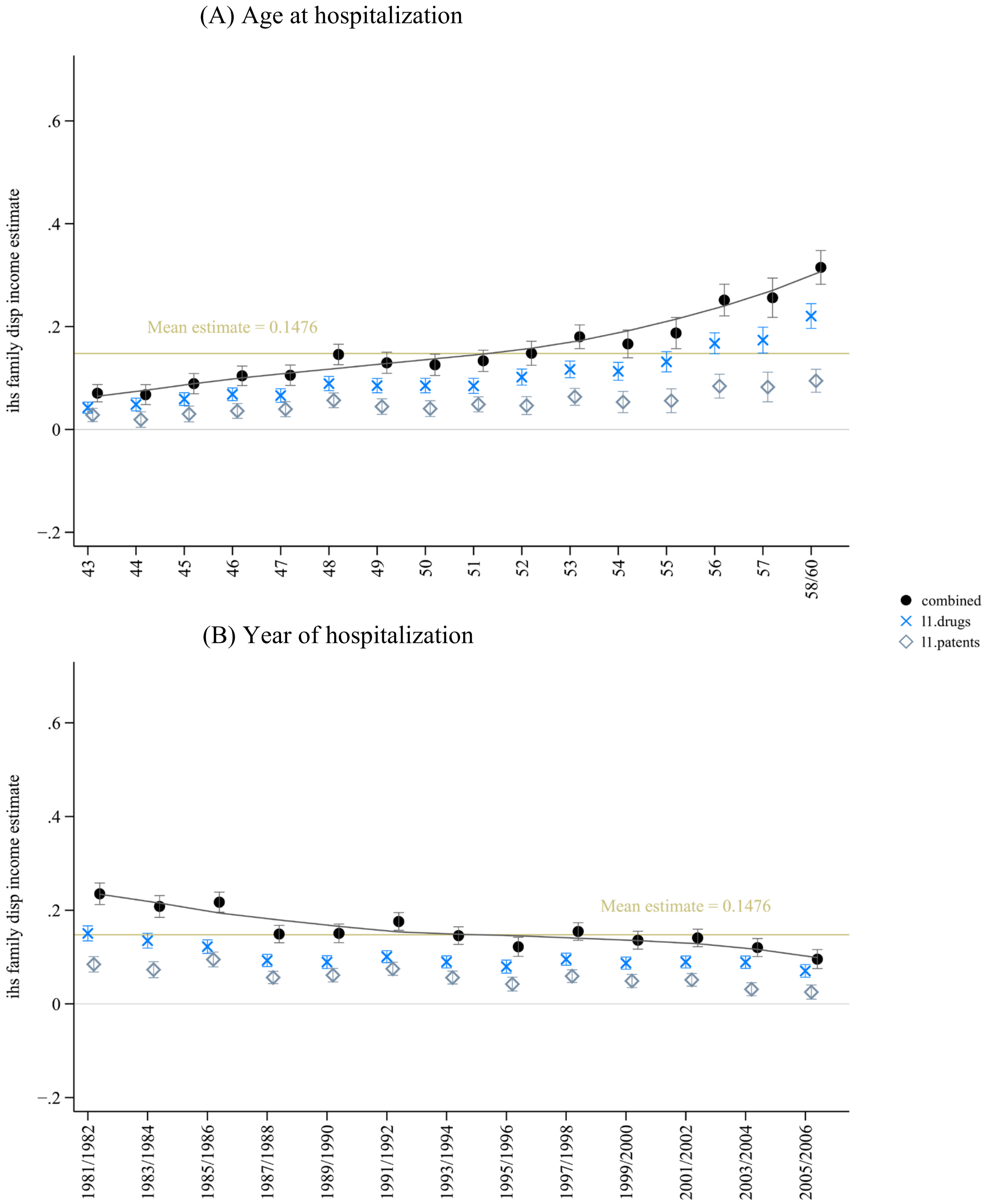

Figure 4. Heterogeneous DDD estimates: Impact of medical innovations on ihs family disposable income by age (at) and year of hospitalization

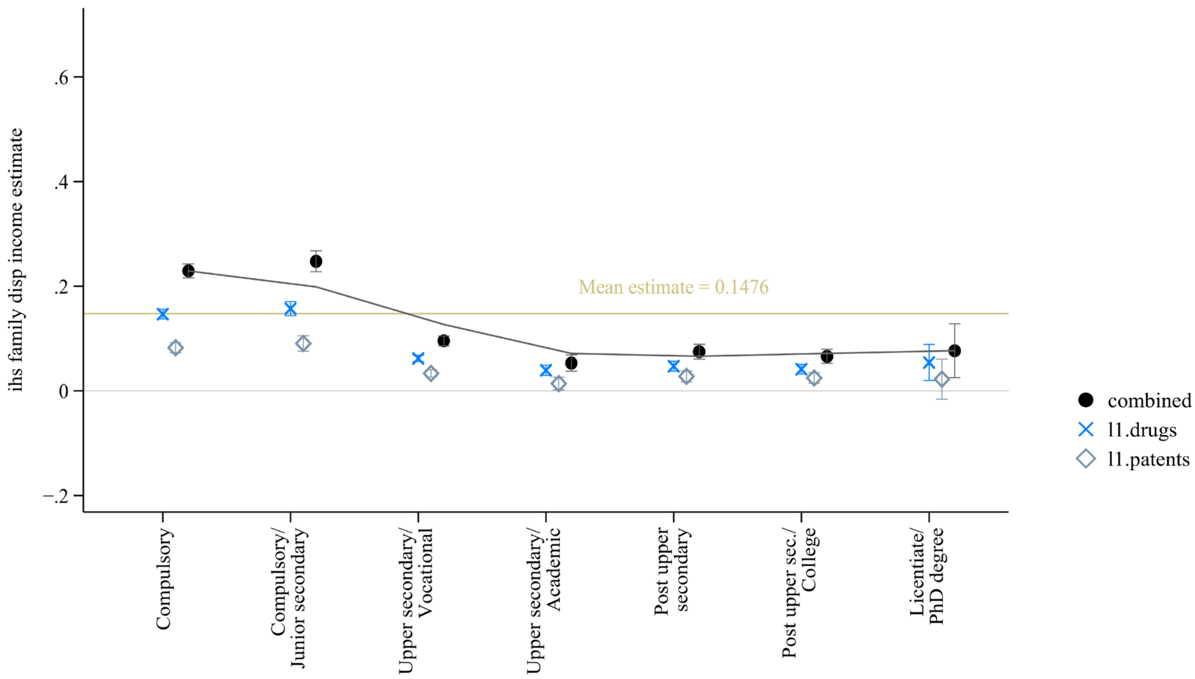

Figure 5. Heterogeneous DDD estimates: Impact of medical innovations on ihs family disposable income by education level

For Online Publication

Appendix to the paper

"Heterogeneous returns to medical innovations"

Volha Lazuka

Appendix A

Table – Disease groups used in the study

Group number	Group name	Broad group name
1	Malignant neoplasms of lip, oral cavity and pharynx	cancer
2	Malignant neoplasm of oesophagus	cancer
3	Malignant neoplasm of stomach	cancer
4	Malignant neoplasm of small intestine, colon, rectosigmoid junction, rectum, anus and anal canal	cancer
5	Malignant neoplasm of liver and intrahepatic bile ducts	cancer
6	Malignant neoplasm of gallbladder	cancer
7	Malignant neoplasm of pancreas	cancer
8	Malignant neoplasm of respiratory and intrathoracic organs	cancer
9	Malignant neoplasm of bone and articular cartilage	cancer
10	Melanoma and other malignant neoplasms of skin	cancer
11	Malignant neoplasms of mesothelial and soft tissue	cancer
12	Malignant neoplasm of breast	cancer
13	Malignant neoplasms of vulva, vagina, cervix uteri, corpus uteri and parts of uterus	cancer
14	Malignant neoplasms of ovary and placenta	cancer
15	Malignant neoplasms of penis, prostate, testis and other male genital organs	cancer
16	Malignant neoplasm of kidney, renal pelvis and ureter	cancer
17	Malignant neoplasm of bladder	cancer
18	Malignant neoplasms of eye and adnexa, meninges, brain, spinal cord, cranial nerves and other parts of central nervous system	cancer
19	Malignant neoplasms of thyroid gland, adrenal gland, and other endocrine glands	cancer
20	Hodgkin's disease	cancer
21	Non-Hodgkin's lymphoma	cancer
22	Malignant immunoproliferative diseases, multiple myeloma and malignant plasma cell neoplasms	cancer
23	Leukaemia	cancer
24	In situ neoplasms	cancer
25	Benign neoplasms	cancer
26	Acute rheumatic fever and chronic rheumatic heart diseases	circulatory diseases
27	Hypertensive diseases	circulatory diseases
28	Ischaemic heart diseases	circulatory diseases
29	Pulmonary heart disease and diseases of pulmonary circulation	circulatory diseases
30	Pericarditis	circulatory diseases
31	Endocarditis and myocarditis and cardiomyopathy	circulatory diseases
32	Cardiac arrhythmias and heart failure	circulatory diseases
33	Cerebrovascular diseases	circulatory diseases
34	Diseases of arteries, arterioles and capillaries	circulatory diseases
35	Diseases of veins, lymphatic vessels and lymph nodes, not elsewhere classified	circulatory diseases
36	Organic, including symptomatic, mental disorders and Alzheimer disease. Systemic atrophies.	mental diseases
37	Mental and behavioural disorders due to use of alcohol and other substances	mental diseases
38	Schizophrenia, schizotypal and delusional disorders	mental diseases
39	Mood (affective) disorders	mental diseases
40	Neurotic, stress-related and somatoform disorders	mental diseases
41	Disorders of adult personality and behaviour	mental diseases
42	Mental retardation. Disorders of psychological development, behavioral and emotional disorders	mental diseases
43	Inflammatory diseases of the central nervous system	nervous diseases
44	Demyelinating diseases of the central nervous system	nervous diseases
45	Epilepsy	nervous diseases
46	Migraine and other headache syndromes	nervous diseases
47	Sleep disorders	nervous diseases
48	Nerve, nerve root and plexus disorders, polyneuropathies and myneuropathies	nervous diseases
49	Diseases of oesophagus, stomach and duodenum	digestive diseases
50	Diseases of appendix	digestive diseases
51	Hernia	digestive diseases
52	Inflammatory bowel disease and other diseases of intestines	digestive diseases
53	Diseases of peritoneum	digestive diseases
54	Diseases of liver	digestive diseases
55	Diseases of gallbladder, biliary tract and pancreas	digestive diseases
56	Infectious arthropathies	musculoskeletal diseases
57	Rheumatoid and juvenile arthritis. Gout	musculoskeletal diseases
58	Arthrosis and systemic connective tissue disorders	musculoskeletal diseases

59	Deforming dorsopathies, osteopathies and chondropathies. Disorders of muscles	musculoskeletal diseases
60	Glomerular diseases and renal tubulo-interstitial diseases. Renal failure	urinary diseases
61	Urolithiasis	urinary diseases
62	Other diseases of the urinary system	urinary diseases
63	Diseases of male genital organs	urinary diseases
64	Diseases of female pelvic organs	urinary diseases
65	Diseases of upper respiratory tract	respiratory diseases
66	Pneumonia, other acute lower respiratory infections and diseases of pleura	respiratory diseases
67	Chronic obstructive pulmonary disease and chronic bronchitis	respiratory diseases
68	Asthma	respiratory diseases
69	Diabetes mellitus	metabolic diseases
70	Disorders of thyroid gland	metabolic diseases
71	Disorders of other endocrine glands	metabolic diseases
72	Obesity and other hyperalimentation, metabolic disorders	metabolic diseases
73	Nutritional anaemias	diseases of bloodforming organs
74	Haemolytic anaemias	diseases of bloodforming organs
75	Coagulation defects, purpura and other haemorrhagic conditions	diseases of bloodforming organs
76	Disorders of eyelid, lacrimal system and orbit, conjunctiva, sclera, cornea, iris, ciliary body, choroid and retina.	diseases of sense organs
77	Cataract, disorders of lens	diseases of sense organs
78	Glaucoma	diseases of sense organs
79	Disorders of globe, optical nerve and visual pathways, ocular muscles, accommodation and refraction, and blindness	diseases of sense organs
80	Diseases of external and middle ear	diseases of sense organs
81	Diseases of inner ear	diseases of sense organs
82	Infections of the skin	diseases of skin
83	Bullous disorders, dermatitis and eczema, urticaria and erythema	diseases of skin
84	Intestinal infectious diseases	infectious and parasitic diseases
85	Tuberculosis	infectious and parasitic diseases
86	Bacterial diseases. Erysipelas. Meningitis	infectious and parasitic diseases
87	Sexually transmitted diseases	infectious and parasitic diseases
88	Viral infections	infectious and parasitic diseases
89	Viral hepatitis	infectious and parasitic diseases
90	HIV	infectious and parasitic diseases
91	Protozoal diseases	infectious and parasitic diseases

Appendix B

Table – Results of the t-test on non-linear pre-trends in responses of ihs family income to a health shock by a disease group (β_2 is unrelated to future outcomes)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
event-year -2	0.02520	-0.00457	-0.00806	0.00466	0.04412	-0.05514	-0.00170	-0.00078	0.01786	-0.00419	-0.01174	-0.00752**	-0.01042	0.00061	-0.00094
	(0.02265)	(0.02328)	(0.02442)	(0.00794)	(0.03441)	(0.07470)	(0.02100)	(0.01267)	(0.02140)	(0.01027)	(0.02220)	(0.00374)	(0.00824)	(0.00648)	(0.00766)
event-year 0	0.08399***	-0.02042	0.05932**	0.02060**	0.05260*	0.02646	-0.00703	0.02828*	-0.04282	0.04087***	0.04394***	0.03341***	0.03896***	0.03058***	0.04017***
	(0.02097)	(0.06145)	(0.02309)	(0.00983)	(0.03164)	(0.02125)	(0.03110)	(0.01586)	(0.05046)	(0.01098)	(0.01452)	(0.00394)	(0.00793)	(0.00997)	(0.01032)
event-year 1	0.05492**	-0.01758	0.08362***	0.04821***	0.10414***	-0.00509	0.02942	0.08297***	-0.05395	0.05763***	0.05739***	0.06014***	0.05256***	0.04018***	0.08219***
	(0.02772)	(0.05180)	(0.02045)	(0.01050)	(0.03624)	(0.02663)	(0.02903)	(0.01392)	(0.05707)	(0.01583)	(0.01549)	(0.00433)	(0.00836)	(0.01199)	(0.01025)
event-year -2 x treated	0.00149	-0.00263	0.00551	-0.00914	-0.04147	0.06291	-0.02875	0.00648	0.01833	-0.00294	0.02506	0.00164	0.01517	-0.00773	-0.00267
	(0.03327)	(0.02915)	(0.02818)	(0.01171)	(0.03809)	(0.07601)	(0.03315)	(0.01811)	(0.04112)	(0.01389)	(0.03197)	(0.00495)	(0.01068)	(0.01171)	(0.01158)
event-year 0 x treated	-0.73653***	-3.31909***	-4.03894***	-1.26400***	-8.04393***	-6.63848***	-6.67887***	-4.14736***	-1.43776**	-0.61039***	-1.10626***	-0.17274***	-0.29028***	-0.73759***	-0.33897***
	(0.08846)	(0.32452)	(0.18601)	(0.05190)	(0.42741)	(0.47606)	(0.23049)	(0.10469)	(0.60996)	(0.05394)	(0.17181)	(0.01148)	(0.02879)	(0.06042)	(0.03723)
event-year 1 x treated	-1.55342***	-8.00268***	-5.86686***	-2.16355***	-9.31445***	-9.91839***	-10.16359***	-6.67137***	-2.87579***	-0.95737***	-1.92576***	-0.39720***	-0.73547***	-1.85194***	-0.72338***
	(0.12654)	(0.46035)	(0.25124)	(0.06580)	(0.79760)	(0.72999)	(0.34758)	(0.14291)	(0.81273)	(0.06578)	(0.22616)	(0.01582)	(0.04290)	(0.09103)	(0.05041)
Constant	13.04808***	13.07371***	13.14901***	13.20873***	13.10995***	13.00971***	13.16590***	13.06175***	13.06472***	13.17992***	13.24386***	13.23581***	13.10761***	13.15437***	13.37691***
	(0.01731)	(0.05097)	(0.02840)	(0.00890)	(0.05781)	(0.06578)	(0.03157)	(0.01604)	(0.10860)	(0.00956)	(0.03009)	(0.00226)	(0.00578)	(0.01152)	(0.00679)
Observations	12,998	3,097	10,346	59,328	2,064	1,721	7,885	33,405	494	28,732	4,693	217,867	52,720	26,061	38,471
R-squared	0.06535	0.42037	0.31669	0.10656	0.58853	0.55069	0.53798	0.34992	0.15892	0.04114	0.09364	0.01253	0.03041	0.0943	0.02619
Number of experimental IDs	2,656	643	2,177	12,121	448	370	1,695	7,012	102	5,871	962	43,888	10,668	5,294	7,792
t-test: event-year -2 x treated =0	*0.964*	*0.928*	*0.845*	*0.435*	*0.277*	*0.408*	*0.386*	*0.721*	*0.657*	*0.832*	*0.433*	*0.74*	*0.156*	*0.509*	*0.818*

	16	17	18	19	20	21	22	23	*24*	*25*	26	27	28	29	30
event-year -2	0.00280	-0.01770	0.00574	0.02863	0.01068	-0.02584**	-0.05437	-0.00504	0.00500	-0.00392*	0.00747	-0.00301	-0.00068	0.00827	-0.02188
	(0.01266)	(0.01509)	(0.01246)	(0.01774)	(0.01540)	(0.01210)	(0.04058)	(0.01912)	(0.00475)	(0.00214)	(0.01238)	(0.00644)	(0.00296)	(0.00761)	(0.01506)
event-year 0	0.02918	0.07541***	0.05296***	0.04394**	-0.01103	0.02017	0.04064	0.06342***	0.05022***	0.03773***	-0.05930	0.01964**	0.04144***	0.04745***	-0.00556
	(0.01950)	(0.01599)	(0.01955)	(0.02041)	(0.02573)	(0.01710)	(0.02650)	(0.01380)	(0.00549)	(0.00237)	(0.05424)	(0.00797)	(0.00334)	(0.01044)	(0.01717)
event-year 1	0.07004***	0.08437***	0.06667***	0.06520***	-0.00230	0.02750	0.07588**	0.05321***	0.05842***	0.05856***	0.01553	0.04613***	0.06009***	0.06725***	-0.00176
	(0.01615)	(0.02057)	(0.02022)	(0.02223)	(0.03401)	(0.02384)	(0.03254)	(0.01922)	(0.00661)	(0.00252)	(0.04128)	(0.00844)	(0.00377)	(0.01266)	(0.02053)
event-year -2 x treated	-0.00207	0.03554*	0.01636	-0.02085	-0.01458	0.03239	0.04342	0.03373	0.01215*	0.00816***	-0.04873	-0.00520	0.00409	-0.00781	0.00465
	(0.02154)	(0.01857)	(0.01937)	(0.01952)	(0.02182)	(0.02186)	(0.04468)	(0.02372)	(0.00641)	(0.00287)	(0.05695)	(0.00895)	(0.00410)	(0.01430)	(0.02294)
event-year 0 x treated	-1.77790***	-0.42553***	-2.21334***	-0.33604***	-0.20258	-0.92105***	-0.81948***	-1.79161***	-0.65461***	-0.02094***	-0.16125	-0.04866***	-0.42319***	-0.49801***	-0.15942***
	(0.11855)	(0.05379)	(0.14065)	(0.08764)	(0.16809)	(0.09155)	(0.15664)	(0.14127)	(0.02524)	(0.00395)	(0.11948)	(0.01376)	(0.01123)	(0.04520)	(0.04738)
event-year 1 x treated	-2.43352***	-0.77475***	-4.45151***	-0.27593***	-0.46965*	-1.63167***	-1.62889***	-3.04825***	-0.93350***	-0.02101***	-0.14599	-0.06880***	-0.18494***	-0.25111***	-0.13468***
	(0.13889)	(0.07013)	(0.19892)	(0.07783)	(0.24366)	(0.11965)	(0.21556)	(0.18643)	(0.02933)	(0.00410)	(0.09656)	(0.01452)	(0.00752)	(0.03128)	(0.04706)
Constant	13.17702***	13.14284***	13.23309***	13.21867***	13.19133***	13.18661***	13.22988***	13.21094***	13.16925***	13.22345***	12.93736***	13.09696***	13.13281***	13.20430***	13.25322***
	(0.01908)	(0.00993)	(0.02387)	(0.01422)	(0.03221)	(0.01607)	(0.02824)	(0.02387)	(0.00434)	(0.00079)	(0.01937)	(0.00268)	(0.00171)	(0.00674)	(0.00816)
Observations	14,673	21,378	12,248	5,603	1,106	14,229	4,576	9,931	135,735	536,388	3,200	103,021	502,948	34,342	15,413
R-squared	0.12975	0.028	0.22847	0.01434	0.02239	0.07878	0.07242	0.15935	0.04227	0.00212	0.00592	0.00058	0.01424	0.01833	0.00419
Number of experimental IDs	3,019	4,346	2,541	1,144	228	2,910	935	2,044	27,581	108,025	658	20,854	101,801	6,986	3,129
t-test: event-year -2 x treated =0	*0.924*	*0.0557*	*0.398*	*0.286*	*0.505*	*0.138*	*0.331*	*0.155*	*0.0581*	*0.00454*	*0.392*	*0.561*	*0.318*	*0.585*	*0.839*

	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
event-year -2	-0.00411	0.00003	0.00104	0.01056	-0.00200	0.01003	-0.00890	-0.00476	-0.00136	-0.01328	0.09709***	0.03840	0.02739	0.01003	-0.03824**
	(0.01129)	(0.00452)	(0.00415)	(0.00957)	(0.00333)	(0.01689)	(0.00758)	(0.00935)	(0.00723)	(0.00840)	(0.03642)	(0.04038)	(0.01989)	(0.00938)	(0.01568)
event-year 0	0.05357***	0.04755***	0.03659***	0.04812***	0.03706***	0.01002	-0.00712	-0.01386	0.02544***	0.01136	0.00185	0.03608	0.06756***	0.01886*	0.00764
	(0.01115)	(0.00490)	(0.00517)	(0.01122)	(0.00356)	(0.01738)	(0.00874)	(0.01284)	(0.00800)	(0.00911)	(0.05777)	(0.06319)	(0.02555)	(0.01054)	(0.01111)
event-year 1	0.07783***	0.07812***	0.06396***	0.07435***	0.05927***	0.00881	-0.02483**	0.00130	0.00396	0.02152**	-0.04110	0.04806	0.08585***	0.00605	0.02036
	(0.01220)	(0.00556)	(0.00556)	(0.01240)	(0.00380)	(0.02161)	(0.01025)	(0.01522)	(0.01084)	(0.00996)	(0.06458)	(0.06263)	(0.02641)	(0.01923)	(0.01402)
event-year -2 x treated	-0.00524	0.00187	-0.00168	-0.00593	0.00388	-0.02269	0.01015	-0.00085	0.01208	0.01381	-0.09983	-0.11323	0.00777	0.00525	0.03183*
	(0.01495)	(0.00615)	(0.00589)	(0.01266)	(0.00435)	(0.02227)	(0.01102)	(0.01373)	(0.01028)	(0.01174)	(0.06317)	(0.07336)	(0.02785)	(0.01454)	(0.01824)
event-year 0 x treated	-0.41423***	-0.23580***	-1.05637***	-0.58417***	-0.07083***	-0.49904***	-0.13915***	-0.09244***	-0.21783***	-0.17994***	-0.16068	-0.19997*	-0.51168***	-0.05979*	-0.24142***
	(0.03652)	(0.01379)	(0.02386)	(0.04047)	(0.00719)	(0.06650)	(0.01618)	(0.02414)	(0.01965)	(0.01872)	(0.10218)	(0.11676)	(0.08653)	(0.03303)	(0.03514)

event-year 1 x treated	-0.24799***	-0.15133***	-0.36842***	-0.28503***	-0.07005***	-0.64386***	-0.12450***	-0.02021	-0.11068***	-0.13544***	-0.04440	-0.11147	-0.34079***	-0.02618	-0.25963***
	(0.02870)	(0.01112)	(0.01264)	(0.02598)	(0.00689)	(0.07431)	(0.01709)	(0.02390)	(0.01729)	(0.01652)	(0.09975)	(0.10926)	(0.06861)	(0.03362)	(0.03658)
Constant	13.16978***	13.21002***	13.14763***	13.03875***	13.10451***	13.08650***	12.66890***	12.53469***	13.05938***	12.98482***	12.49749***	12.37911***	13.16485***	13.15320***	12.94399***
	(0.00580)	(0.00227)	(0.00332)	(0.00610)	(0.00134)	(0.01133)	(0.00321)	(0.00457)	(0.00342)	(0.00342)	(0.02061)	(0.02252)	(0.01382)	(0.00619)	(0.00632)
Observations	44,487	203,803	239,628	51,165	287,771	17,836	180,418	63,253	94,061	89,486	5,287	3,098	10,188	13,561	27,324
R-squared	0.01246	0.0056	0.05439	0.02267	0.00137	0.02613	0.00253	0.00119	0.00529	0.00451	0.00273	0.00274	0.01748	0.00078	0.01089
Number of experimental IDs	9,024	41,242	48,744	10,409	58,425	3,639	36,730	12,940	19,083	18,265	1,104	636	2,078	2,771	5,594
t-test: event-year -2 x treated =0	*0.726*	*0.761*	*0.775*	*0.639*	*0.373*	*0.309*	*0.357*	*0.951*	*0.24*	*0.24*	*0.114*	*0.123*	*0.78*	*0.718*	*0.081*

	46	47	48	*49*	50	51	52	53	54	55	56	57	58	*59*	60
event-year -2	0.01698**	-0.00158	0.00442	-0.00936*	-0.00490	0.00340	0.00835**	-0.02189	-0.00220	0.00289	-0.00730	-0.00480	-0.00548	-0.00202	0.00343
	(0.00663)	(0.01281)	(0.00666)	(0.00502)	(0.00527)	(0.00349)	(0.00382)	(0.02852)	(0.01252)	(0.00282)	(0.01626)	(0.00476)	(0.00423)	(0.00277)	(0.00704)
event-year 0	0.03869***	0.09472***	0.02447**	0.03037***	0.03781***	0.04228***	0.05103***	0.06013***	-0.02093	0.04212***	0.05294***	0.02794***	0.04452***	0.04226***	0.04335***
	(0.00746)	(0.01383)	(0.00965)	(0.00520)	(0.00602)	(0.00382)	(0.00447)	(0.01770)	(0.01705)	(0.00329)	(0.01189)	(0.00481)	(0.00477)	(0.00306)	(0.00835)
event-year 1	0.05797***	0.13231***	0.06074***	0.04897***	0.07762***	0.06394***	0.07255***	0.03912	-0.00713	0.06933***	0.07070***	0.03891***	0.08130***	0.06207***	0.04780***
	(0.00873)	(0.01470)	(0.00902)	(0.00585)	(0.00641)	(0.00444)	(0.00523)	(0.02683)	(0.01875)	(0.00357)	(0.01655)	(0.00522)	(0.00496)	(0.00352)	(0.01097)
event-year -2 x treated	-0.01343	0.00253	-0.01032	0.01452**	0.00289	0.00256	-0.00268	0.04619	-0.00755	-0.00209	0.01285	0.00847	0.00515	0.00704*	0.01371
	(0.00880)	(0.01672)	(0.01037)	(0.00656)	(0.00725)	(0.00470)	(0.00545)	(0.03252)	(0.01992)	(0.00386)	(0.02049)	(0.00592)	(0.00564)	(0.00373)	(0.00932)
event-year 0 x treated	-0.05307***	-0.05173**	-0.07745***	-0.07458***	-0.01715*	-0.02351***	-0.05795***	-0.31463***	-1.44466***	-0.07016***	-0.02525	-0.04019***	-0.03493***	-0.03316***	-0.12844***
	(0.01469)	(0.02180)	(0.01872)	(0.00997)	(0.00914)	(0.00638)	(0.00822)	(0.09730)	(0.07516)	(0.00652)	(0.02652)	(0.00842)	(0.00855)	(0.00511)	(0.01895)
event-year 1 x treated	-0.05759***	-0.06335***	-0.10801***	-0.09378***	-0.02714***	-0.02846***	-0.05804***	-0.23102***	-0.78331***	-0.09279***	-0.02787	-0.03793***	-0.04800***	-0.04135***	-0.11591***
	(0.01487)	(0.02457)	(0.01892)	(0.01080)	(0.00981)	(0.00670)	(0.00869)	(0.08073)	(0.05525)	(0.00684)	(0.03071)	(0.00869)	(0.00877)	(0.00554)	(0.02002)
Constant	13.15244***	13.28069***	13.10919***	13.05636***	13.21610***	13.09262***	13.17805***	13.20908***	12.99230***	13.18410***	13.22180***	13.11613***	13.23406***	13.18220***	13.14490***
	(0.00290)	(0.00480)	(0.00345)	(0.00195)	(0.00189)	(0.00132)	(0.00165)	(0.01532)	(0.01100)	(0.00126)	(0.00569)	(0.00166)	(0.00165)	(0.00107)	(0.00356)
Observations	75,929	31,834	59,322	206,881	157,152	265,276	250,891	4,700	31,888	411,905	17,837	121,618	157,521	466,556	71,363
R-squared	0.0008	0.00531	0.00135	0.00109	0.00216	0.00171	0.00123	0.01128	0.07587	0.00131	0.00211	0.00087	0.0026	0.00133	0.00216
Number of experimental IDs	15,418	6,419	12,075	41,929	31,796	53,767	50,666	962	6,559	83,057	3,620	24,581	31,807	94,240	14,503
t-test: event-year -2 x treated =0	*0.127*	*0.88*	*0.32*	*0.0269*	*0.691*	*0.586*	*0.623*	*0.156*	*0.705*	*0.588*	*0.531*	*0.153*	*0.361*	*0.059*	*0.141*

	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75
event-year -2	0.00104	-0.00130	0.00491	0.00394	-0.00291	0.00111	-0.00067	0.00525	0.00090	0.00450	0.00313	-0.00788	0.00286	0.02061	0.01268
	(0.00547)	(0.00697)	(0.00554)	(0.00306)	(0.00472)	(0.00501)	(0.01160)	(0.00733)	(0.00714)	(0.00501)	(0.02182)	(0.01018)	(0.01213)	(0.02479)	(0.01177)
event-year 0	0.04710***	0.04808***	0.03585***	0.05301***	0.04712***	0.03893***	0.03651***	0.02401***	0.05567***	0.03348***	0.03582**	0.04034***	0.02438	0.02708	0.01562
	(0.00612)	(0.00625)	(0.00693)	(0.00419)	(0.00489)	(0.00584)	(0.01297)	(0.00926)	(0.00729)	(0.00617)	(0.01584)	(0.00862)	(0.01573)	(0.02392)	(0.02407)
event-year 1	0.07127***	0.06869***	0.05604***	0.09243***	0.06872***	0.05766***	0.03290**	0.04733***	0.05814***	0.05440***	0.06579***	0.04846***	0.04764**	0.04822	0.05688***
	(0.00656)	(0.00798)	(0.00760)	(0.00402)	(0.00530)	(0.00655)	(0.01546)	(0.01102)	(0.00848)	(0.00614)	(0.01937)	(0.01263)	(0.01872)	(0.02932)	(0.01986)
event-year -2 x treated	0.00594	0.00347	0.00056	-0.00469	0.00687	0.00336	0.01738	-0.00478	0.01706*	-0.00051	-0.00349	0.00434	-0.01833	-0.03062	-0.03070
	(0.00735)	(0.00850)	(0.00776)	(0.00426)	(0.00630)	(0.00694)	(0.01659)	(0.00985)	(0.00921)	(0.00683)	(0.02626)	(0.01401)	(0.01871)	(0.03158)	(0.02234)
event-year 0 x treated	-0.02587***	-0.04277***	-0.02289**	-0.01636***	-0.03175***	-0.25635***	-0.19146***	-0.10907***	-0.10300***	-0.03452***	-0.09942**	-0.10853***	-0.07853**	-0.32117***	-0.28926***
	(0.00970)	(0.01176)	(0.01129)	(0.00623)	(0.00786)	(0.01583)	(0.03538)	(0.02335)	(0.01419)	(0.01030)	(0.04268)	(0.02252)	(0.03085)	(0.07560)	(0.06898)
event-year 1 x treated	-0.03628***	-0.03925***	-0.02806**	-0.02027***	-0.03457***	-0.25815***	-0.19311***	-0.10831***	-0.10479***	-0.02791***	-0.08987**	-0.09192***	-0.15171***	-0.40743***	-0.27761***
	(0.01016)	(0.01293)	(0.01211)	(0.00624)	(0.00830)	(0.01559)	(0.03821)	(0.02240)	(0.01526)	(0.01008)	(0.03798)	(0.02238)	(0.04041)	(0.08533)	(0.05902)
Constant	13.15881***	13.27093***	13.14053***	13.31108***	13.19818***	13.11506***	12.93727***	13.03011***	12.97382***	13.17009***	13.13482***	13.12606***	13.01476***	13.05987***	13.14755***
	(0.00203)	(0.00239)	(0.00232)	(0.00127)	(0.00163)	(0.00277)	(0.00652)	(0.00411)	(0.00283)	(0.00206)	(0.00782)	(0.00422)	(0.00621)	(0.01346)	(0.01092)
Observations	147,713	82,259	101,713	222,832	178,285	178,166	27,068	43,132	119,552	92,183	13,127	40,420	23,436	9,730	9,032
R-squared	0.0016	0.0018	0.00105	0.00579	0.00189	0.00719	0.00502	0.00207	0.0014	0.00147	0.00151	0.00157	0.00164	0.01176	0.01183
Number of experimental IDs	29,952	16,620	20,595	44,790	36,078	36,124	5,518	8,800	24,307	18,727	2,676	8,221	4,766	1,991	1,845
t-test: event-year -2 x treated =0	*0.419*	*0.683*	*0.942*	*0.271*	*0.275*	*0.629*	*0.295*	*0.628*	*0.0641*	*0.94*	*0.894*	*0.757*	*0.327*	*0.332*	*0.17*

	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91
event-year -2	0.00440	0.01301	0.01915	0.02886**	0.00177	-0.01249*	0.00262	-0.00313	-0.00450	-0.02220	0.01220	0.00160	-0.02322*	0.02144	-0.04999	0.04265
	(0.00684)	(0.01183)	(0.01265)	(0.01145)	(0.00722)	(0.00687)	(0.01274)	(0.00836)	(0.00735)	(0.04005)	(0.00784)	(0.01168)	(0.01346)	(0.02877)	(0.07845)	(0.06944)
event-year 0	0.03172***	0.02856*	0.03277**	0.04644***	0.04353***	0.04966***	0.05881***	0.03358***	0.04175***	-0.09846*	0.03734***	0.02843	0.04752***	0.09667***	0.06379	-0.12957
	(0.00862)	(0.01520)	(0.01312)	(0.01434)	(0.00760)	(0.00668)	(0.01433)	(0.00866)	(0.00832)	(0.05390)	(0.00980)	(0.01801)	(0.01540)	(0.03171)	(0.04908)	(0.11004)
event-year 1	0.06877***	0.06790***	0.03835**	0.07793***	0.06540***	0.08006***	0.06542***	0.03654***	0.06823***	0.02271	0.05715***	0.03789**	0.08245***	0.14511***	0.45125	0.07057
	(0.00877)	(0.01979)	(0.01583)	(0.01615)	(0.00816)	(0.00753)	(0.01626)	(0.01031)	(0.00859)	(0.03980)	(0.01007)	(0.01880)	(0.01634)	(0.03926)	(0.41615)	(0.09945)
event-year -2 x treated	-0.01228	-0.01592	-0.01493	-0.02870*	0.00758	0.01261	0.01134	0.01271	-0.00073	0.01630	-0.00686	0.00907	0.01908	-0.01191	0.13496	0.08148

	(0.00937)	(0.02098)	(0.01484)	(0.01545)	(0.00916)	(0.00850)	(0.01681)	(0.01084)	(0.01083)	(0.05700)	(0.01092)	(0.01869)	(0.01841)	(0.03737)	(0.12870)	(0.11173)
event-year 0 x treated	-0.01430	0.00826	-0.01705	-0.04581*	-0.02368*	-0.02446**	-0.07743***	-0.01691	-0.05975***	0.14229	-0.24942***	-0.04782*	-0.08837***	-0.15228***	-3.83711***	0.03577
	(0.01188)	(0.02436)	(0.01849)	(0.02471)	(0.01211)	(0.01011)	(0.02458)	(0.01524)	(0.01532)	(0.10413)	(0.02444)	(0.02854)	(0.02912)	(0.05805)	(1.18031)	(0.17024)
event-year 1 x treated	-0.03454***	-0.03790	-0.04832*	-0.05991**	-0.04290***	-0.03503***	-0.05885**	-0.01416	-0.03907***	-0.15167	-0.11249***	-0.09384***	-0.04614*	-0.14861**	-1.93687**	-0.08150
	(0.01274)	(0.03357)	(0.02743)	(0.02706)	(0.01340)	(0.01096)	(0.02676)	(0.01672)	(0.01457)	(0.13010)	(0.01859)	(0.03308)	(0.02614)	(0.06001)	(0.91285)	(0.15736)
Constant	13.18173***	12.95165***	13.05045***	13.15974***	13.12386***	13.25635***	13.03690***	13.05110***	13.21741***	12.82511***	13.10734***	13.07019***	13.20781***	12.86963***	12.38742***	12.99260***
	(0.00247)	(0.00599)	(0.00495)	(0.00542)	(0.00264)	(0.00219)	(0.00516)	(0.00322)	(0.00291)	(0.02097)	(0.00407)	(0.00589)	(0.00527)	(0.01151)	(0.16396)	(0.03030)
Observations	91,118	12,240	13,188	21,063	70,495	80,305	38,006	51,630	65,583	3,683	80,996	21,695	27,198	11,621	255	1,921
R-squared	0.00147	0.00206	0.00117	0.00157	0.00163	0.00369	0.00096	0.00072	0.00162	0.00264	0.00531	0.00097	0.00236	0.00217	0.23675	0.00433
Number of experimental IDs	18,458	2,484	2,690	4,294	14,354	16,250	7,747	10,525	13,336	760	16,432	4,451	5,541	2,388	54	402
t-test: event-year -2 x treated =0	*0.19*	*0.448*	*0.314*	*0.0634*	*0.408*	*0.138*	*0.5*	*0.241*	*0.947*	*0.775*	*0.53*	*0.627*	*0.3*	*0.75*	*0.299*	*0.466*

Note: Additionally to the terms reported in the table, models include (experimental) individual fixed effects. Event-years -3 and -1 are reference categories. Disease groups that were excluded from the estimation sample – as those that have not passed the test – are in bold. Standard errors clustered at a (experimental) individual level are in parentheses.

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

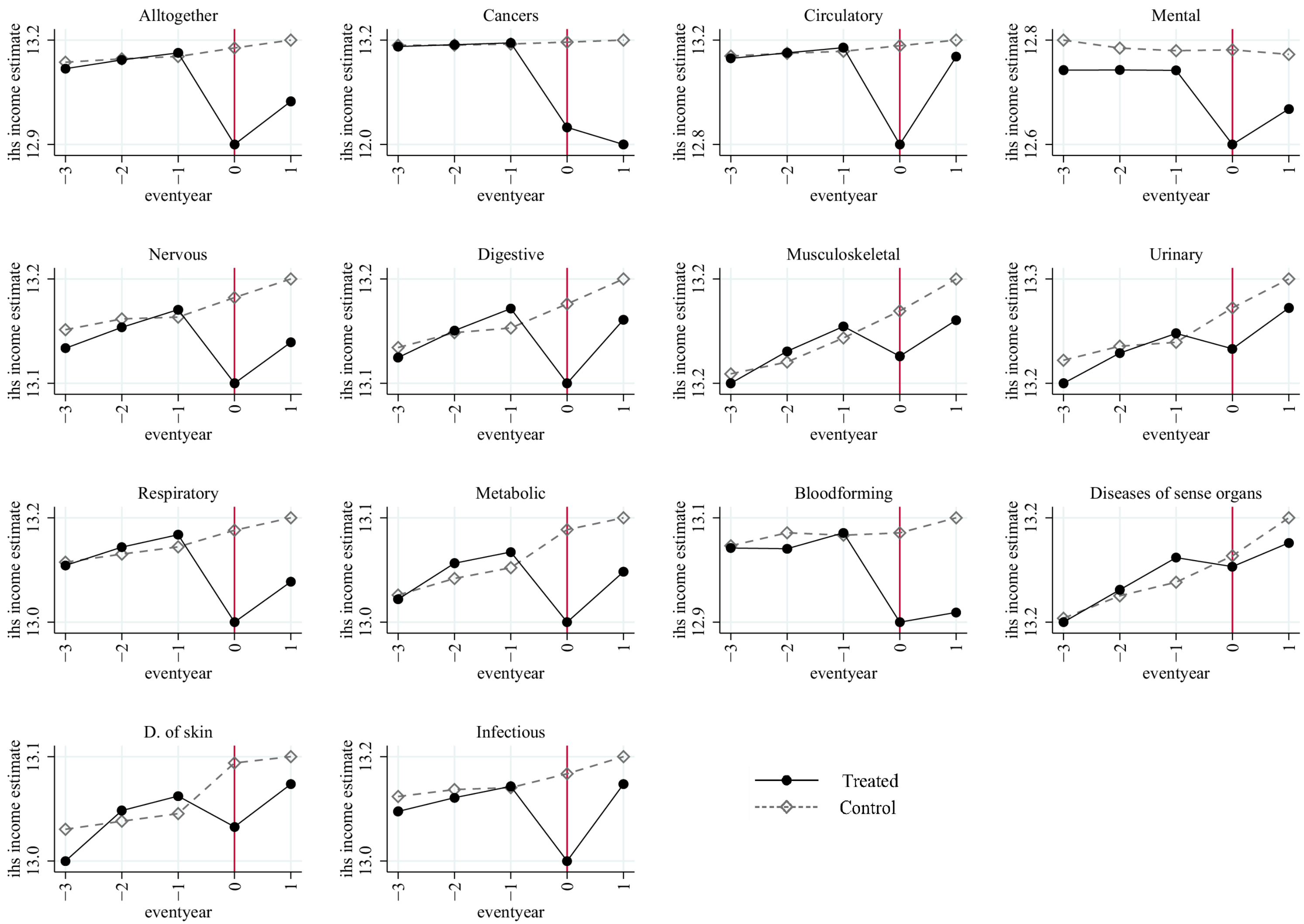

Figure B1 – Development of ihs family income by event years for treated and control groups (with α_i), both sexes

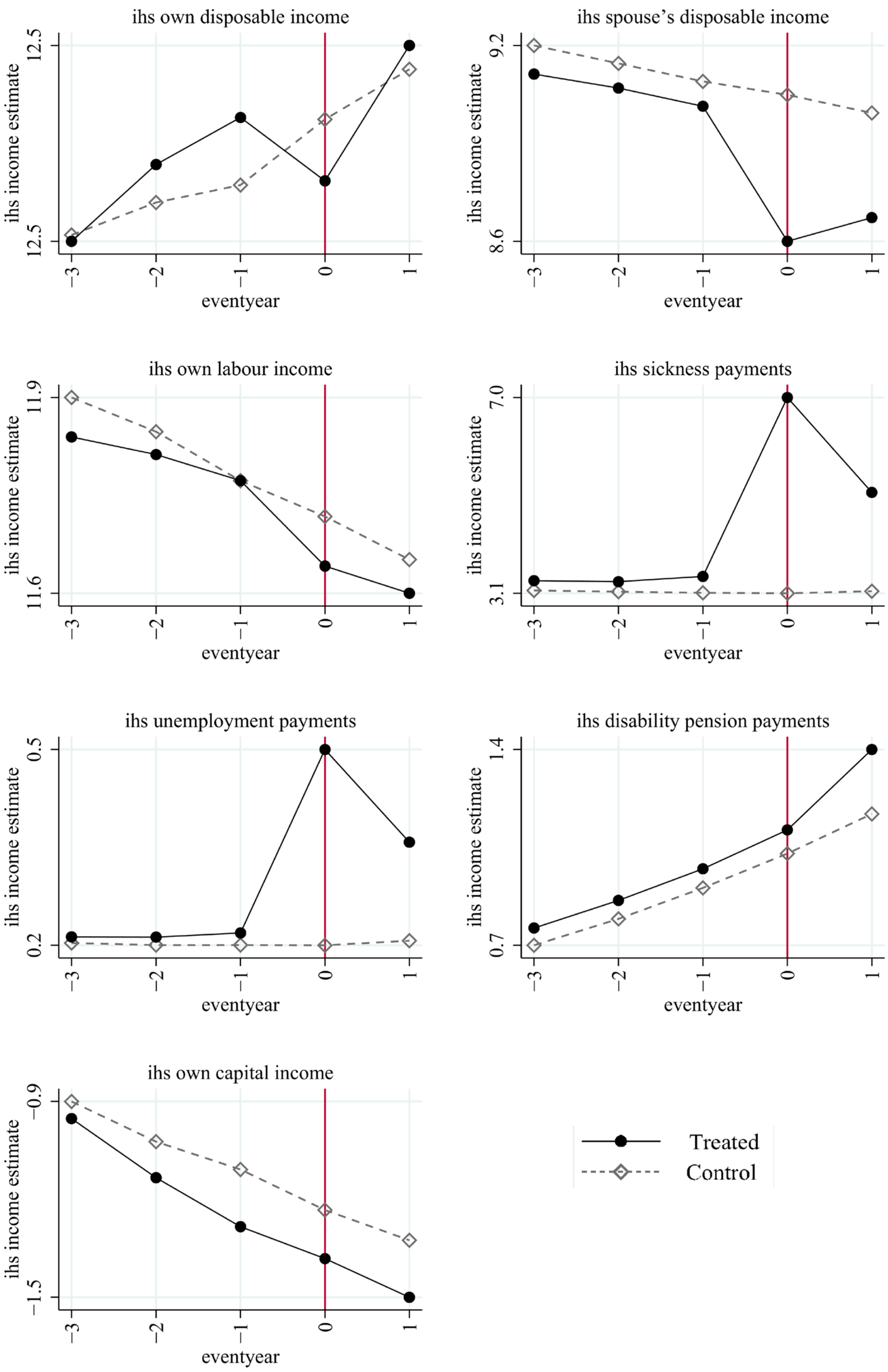

Figure B2 – Development of the sources of ihs family income by event years for treated and control groups (with α_i), both sexes

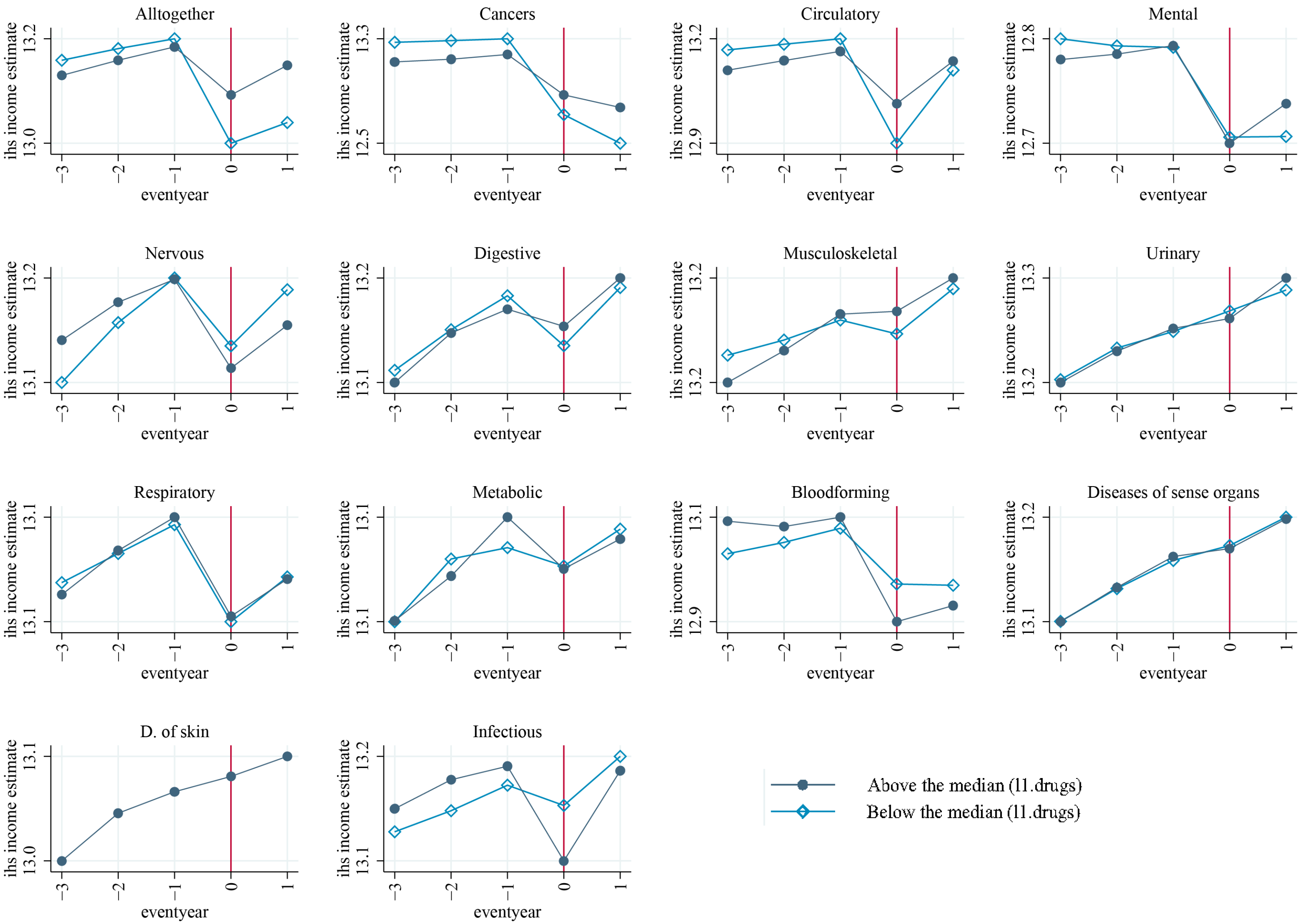

Figure B2 – Development of ihs family income by event years for groups by the level of l1.drugs (with α_i), both sexes

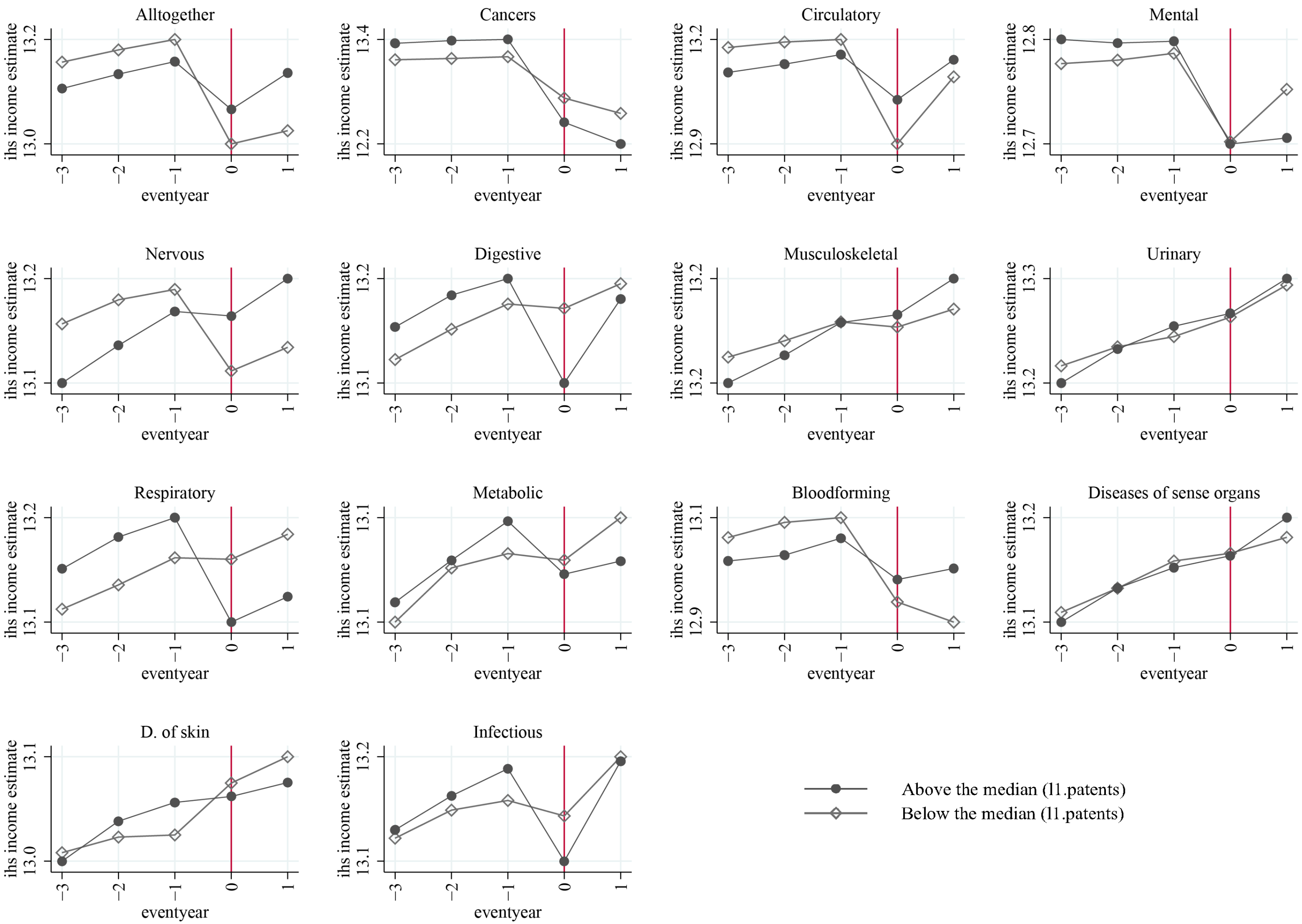

Figure B3 – Development of ihs family income by event years for groups by the level of l1.patents (with α_i), both sexes

Appendix C

Table C1 – DDD estimates: Impact of medical innovations in 1981–2006 on the sources of ihs family income *for men* in ages 40–60 Sweden

	Ihs Own Disposable Income		Ihs Spouse's Disposable Income		Ihs Own Labour Income		Ihs Sickness Absence Payments		Ihs Unemployment Benefits Payments		Ihs Disability Pension Payments		Ihs Own Capital Income	
post	0.04862***	0.05603***	-0.10280***	-0.04087***	-0.16652***	-0.13085***	-0.23665***	-0.21289***	0.00130	0.00081	0.20324***	0.20076***	-0.57490***	-0.44402***
	(0.00289)	(0.00219)	(0.00723)	(0.00538)	(0.00538)	(0.00411)	(0.00969)	(0.00731)	(0.00305)	(0.00233)	(0.00376)	(0.00295)	(0.01410)	(0.01083)
post x l1.drugs	0.00011		0.00294***		0.00075***		0.00204***		0.00005		0.00100***		0.01288***	
	(0.00016)		(0.00037)		(0.00029)		(0.00044)		(0.00014)		(0.00018)		(0.00075)	
DD_{idst}	-0.10646***	-0.07705***	-0.50652***	-0.40986***	-0.21009***	-0.13554***	2.92149***	3.11660***	0.38731***	0.37413***	0.09620***	0.10682***	0.05314***	0.03044**
	(0.00464)	(0.00344)	(0.01185)	(0.00884)	(0.00821)	(0.00620)	(0.01554)	(0.01200)	(0.00564)	(0.00439)	(0.00573)	(0.00452)	(0.01991)	(0.01528)
DD_{idst} x l1.drugs	0.00334***		0.00693***		0.00614***		-0.00362***		-0.00349***		0.00030		-0.00098	
	(0.00023)		(0.00057)		(0.00042)		(0.00074)		(0.00025)		(0.00028)		(0.00106)	
post x l1.patents		-0.00002***		-0.00005***		-0.00007***		0.00003**		0.00000		0.00006***		0.00023***
		(0.00000)		(0.00001)		(0.00001)		(0.00001)		(0.00000)		(0.00001)		(0.00002)
DD_{idst} x l1.patents		0.00007***		0.00004**		0.00007***		-0.00076***		-0.00013***		-0.00002**		0.00002
		(0.00001)		(0.00002)		(0.00001)		(0.00002)		(0.00001)		(0.00001)		(0.00003)
Constant	12.63420***	12.63420***	8.70217***	8.70215***	12.18627***	12.18626***	3.14804***	3.14582***	0.24087***	0.24086***	0.66272***	0.66278***	-1.55617***	-1.55625***
	(0.00059)	(0.00059)	(0.00151)	(0.00151)	(0.00108)	(0.00108)	(0.00213)	(0.00212)	(0.00074)	(0.00074)	(0.00080)	(0.00080)	(0.00265)	(0.00265)
Observations	3,319,071	3,319,071	3,319,071	3,319,071	3,319,071	3,319,071	3,184,765	3,184,765	3,319,071	3,319,071	3,184,765	3,184,765	3,319,071	3,319,071
R-squared	0.00059	0.00044	0.00574	0.00529	0.00459	0.00428	0.07537	0.07693	0.01100	0.01122	0.01703	0.01712	0.00202	0.00187
Number of individuals	673,469	673,469	673,469	673,469	673,469	673,469	673,437	673,437	673,469	673,469	673,437	673,437	673,469	673,469
Individual (experimental) FEs	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
1 SD of l1.drugs /l1.patents	13.1586	516.0485	13.1586	516.0485	13.1586	516.0485	13.2729	523.62	13.1586	516.0485	13.2729	523.62	13.1586	516.0485
1 SD x effect x 100%	4.39%	3.61%	9.12%	2.06%	8.08%	3.61%	-4.80%	-39.80%	-4.59%	-6.71%	0.40%	-1.05%	-1.29%	1.03%
1 SD combined effect x 100%		8.01%		11.18%		11.69%		-44.60%		-11.30%		-0.65%		-0.26%
1 SD combined SE x 100%		0.60%		1.28%		0.76%		1.44%		0.61%		0.64%		2.08%
CI lower 95%		6.83%		8.68%		10.21%		-47.41%		-12.50%		-1.91%		-4.34%
CI higher 95		9.18%		13.68%		13.17%		-41.79%		-10.10%		0.61%		3.83%

Note: Models are estimated according to Eq.4. Robust standard errors clustered at individual (experimental) level are in parentheses.

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

Table C2 – DDD estimates: Impact of medical innovations in 1981–2006 on the sources of ihs family income *for women* in ages 40–60 Sweden

	Ihs Own Disposable Income		Ihs Spouse's Disposable Income		Ihs Own Labour Income		Ihs Sickness Absence Payments		Ihs Unemployment Benefits Payments		Ihs Disability Pension Payments		Ihs Own Capital Income	
post	0.07818***	0.07394***	-	-	-0.11812***	-0.11651***	-	-	0.00193	0.00030	0.30758**	0.33113**	-	-
	(0.00335)	(0.00249)	(0.00795)	(0.00593)	(0.00639)	(0.00476)	(0.01125)	(0.00835)	(0.00237)	(0.00177)	(0.00519)	(0.00387)	(0.01442)	(0.01100)
post x l1.drugs	-0.00061***		0.00395***		-0.00038		0.00644***		-0.00013		0.00227**		0.00211***	
	(0.00014)		(0.00037)		(0.00030)		(0.00051)		(0.00010)		(0.00024)		(0.00069)	
DD_{idst}	-0.05224***	-0.03542***	-	-	-0.15672***	-0.09422***	2.61465***	2.72813***	0.19711**	0.18031**	0.09126**	0.09345**	-0.00261	0.00318
	(0.00508)	(0.00369)	(0.01285)	(0.00950)	(0.00939)	(0.00692)	(0.01751)	(0.01327)	(0.00438)	(0.00331)	(0.00765)	(0.00575)	(0.02024)	(0.01547)
DD_{idst} x l1.drugs	0.00139***		0.00936***		0.00481***		-0.00227***		-0.00201***		-0.00002		-0.00008	
	(0.00020)		(0.00056)		(0.00043)		(0.00078)		(0.00018)		(0.00036)		(0.00097)	
post x l1.patents		-0.00002***		0.00005***		-0.00002***		0.00010***		-0.00000		0.00005**		0.00004**
		(0.00000)		(0.00001)		(0.00001)		(0.00001)		(0.00000)		(0.00001)		(0.00002)
DD_{idst} x l1.patents		0.00002***		0.00012***		0.00006***		-0.00044***		-0.00005***		-0.00001		-0.00002
		(0.00001)		(0.00001)		(0.00001)		(0.00002)		(0.00000)		(0.00001)		(0.00003)
Constant	12.30220**	12.30220**	9.62234***	9.62232***	11.46079**	11.46080**	3.53886***	3.53692***	0.12445**	0.12445**	1.00352**	1.00328**	-	-
	(0.00063)	(0.00063)	(0.00164)	(0.00164)	(0.00120)	(0.00120)	(0.00239)	(0.00239)	(0.00057)	(0.00057)	(0.00104)	(0.00104)	(0.00272)	(0.00272)
Observations	2,791,726	2,791,726	2,791,726	2,791,726	2,791,726	2,791,726	2,684,346	2,684,346	2,791,726	2,791,726	2,684,346	2,684,346	2,791,726	2,791,726
R-squared	0.00095	0.00093	0.00794	0.00720	0.00254	0.00239	0.06233	0.06264	0.00536	0.00536	0.02504	0.02497	0.00063	0.00062
Number of individuals	565,915	565,915	565,915	565,915	565,915	565,915	565,899	565,899	565,915	565,915	565,899	565,899	565,915	565,915
Individual (experimental)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
1 SD of l1.drugs /l1.patents	14.3734	562.4148	14.3734	562.4148	14.3734	562.4148	14.4856	570.7715	14.3734	562.4148	14.4856	570.7715	14.3734	562.4148
1 SD x effect x 100%	2.00%	1.12%	13.45%	6.75%	6.91%	3.37%	-3.29%	-25.11%	-2.89%	-2.81%	-0.03%	-0.57%	-0.11%	-1.12%
1 SD combined effect x		3.12%		20.20%		10.29%		-28.40%		-5.70%		-0.60%		-1.24%
1 SD combined SE x 100%		0.63%		0.98%		0.84%		1.61%		0.26%		0.77%		2.19%
CI lower 95%		1.88%		18.28%		8.65%		-31.55%		-6.21%		-2.12%		-5.53%
CI higher 95		4.36%		22.13%		11.93%		-25.25%		-5.19%		0.92%		3.05%

Note: Models are estimated according to Eq.4. Robust standard errors clustered at individual (experimental) level are in parentheses.

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

Appendix D

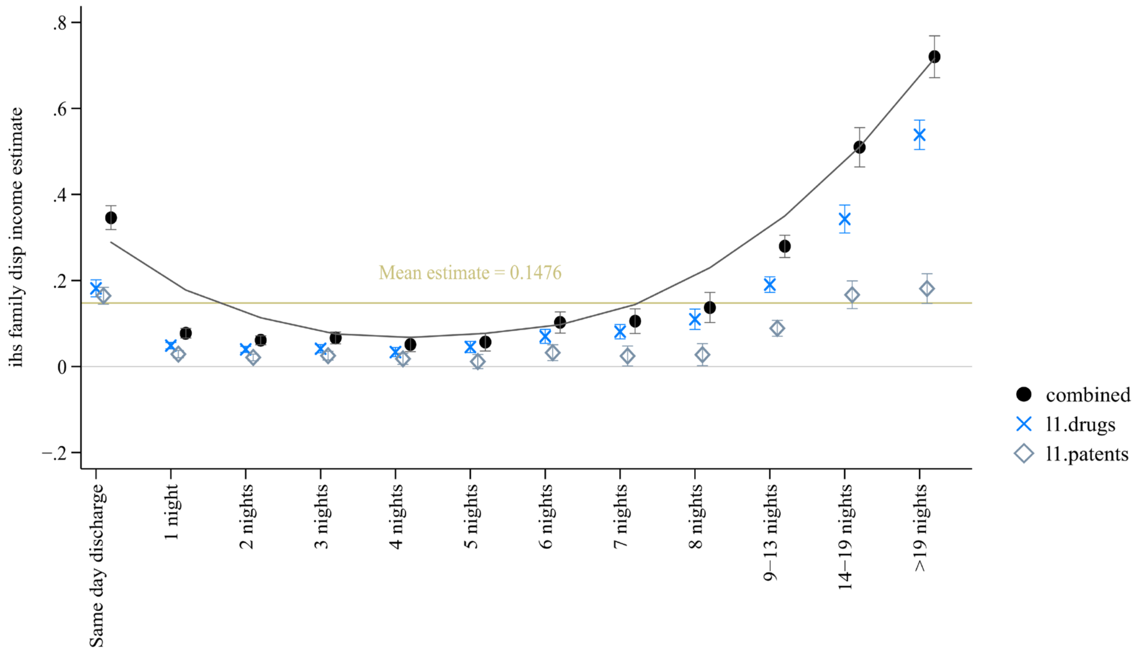

Figure – Heterogeneous DDD estimates: Impact of medical innovations on ihs family disposable income by the length to stay in a hospital

Appendix E

Table E1 – Results of the t-test on non-linear pre-trends in responses of ihs family income to a health shock by broad disease groups from a final estimation sample (β_2 is unrelated to future outcomes)

	Altogether	Cancers	Circulatory	Mental	Nervous	Digestive	Musculo-skeletal	Urinary	Respiratory	Metabolic	D. of bloodforming organs	D. of sense organs	D. of skin	Infectious
event-year -2	-0.00004	-0.00456*	-0.00043	-0.00536	0.00400	0.00290	-0.00531*	0.00266	-0.00030	0.00092	0.00906	0.00180	-0.00066	0.00162
	(0.00081)	(0.00239)	(0.00165)	(0.00406)	(0.00415)	(0.00178)	(0.00313)	(0.00226)	(0.00306)	(0.00412)	(0.00920)	(0.00357)	(0.00724)	(0.00466)
event-year 0	0.03785***	0.03589***	0.03918***	0.00341	0.03936***	0.04182***	0.03827***	0.04712***	0.04069***	0.04464***	0.02312**	0.04059***	0.04430***	0.03854***
	(0.00093)	(0.00270)	(0.00189)	(0.00473)	(0.00464)	(0.00206)	(0.00328)	(0.00268)	(0.00342)	(0.00421)	(0.01154)	(0.00403)	(0.00787)	(0.00570)
event-year 1	0.05913***	0.05972***	0.06253***	-0.00440	0.06304***	0.06762***	0.06333***	0.07332***	0.05966***	0.05575***	0.04976***	0.07031***	0.04880***	0.06667***
	(0.00103)	(0.00293)	(0.00209)	(0.00561)	(0.00509)	(0.00230)	(0.00354)	(0.00294)	(0.00382)	(0.00488)	(0.01310)	(0.00432)	(0.00910)	(0.00598)
event-year -2 x treated	0.00213*	0.00372	0.00115	0.00634	-0.00242	-0.00039	0.00698*	0.00187	0.00493	0.00799	-0.02388*	-0.00188	0.01210	0.00101
	(0.00112)	(0.00330)	(0.00228)	(0.00587)	(0.00557)	(0.00247)	(0.00404)	(0.00304)	(0.00418)	(0.00540)	(0.01357)	(0.00468)	(0.00948)	(0.00661)
event-year 0 x treated	-0.25361***	-0.98413***	-0.40943***	-0.17179***	-0.10540***	-0.08970***	-0.03655***	-0.03605***	-0.14357***	-0.07988***	-0.17991***	-0.02090***	-0.04258***	-0.13955***
	(0.00262)	(0.01468)	(0.00640)	(0.00959)	(0.01015)	(0.00429)	(0.00592)	(0.00454)	(0.00809)	(0.00836)	(0.02863)	(0.00598)	(0.01363)	(0.01223)
event-year 1 x treated	-0.23238***	-1.47194***	-0.18551***	-0.12736***	-0.10854***	-0.07950***	-0.04285***	-0.03866***	-0.14441***	-0.07523***	-0.23639***	-0.03934***	-0.03310**	-0.08387***
	(0.00245)	(0.01744)	(0.00424)	(0.00952)	(0.01008)	(0.00410)	(0.00614)	(0.00476)	(0.00805)	(0.00863)	(0.03229)	(0.00662)	(0.01487)	(0.01054)
Constant	13.13080***	13.20313***	13.13839***	12.80599***	13.13390***	13.16037***	13.18502***	13.22320***	13.12995***	13.07319***	13.05364***	13.17099***	13.04507***	13.13059***
	(0.00045)	(0.00247)	(0.00097)	(0.00181)	(0.00190)	(0.00079)	(0.00116)	(0.00092)	(0.00147)	(0.00164)	(0.00520)	(0.00129)	(0.00287)	(0.00216)
Observations	6,110,797	583,626	1,485,778	453,439	218,158	1,121,812	296,976	625,880	426,651	265,282	42,198	288,409	89,636	212,952
R-squared	0.00713	0.07139	0.01416	0.00334	0.00169	0.00142	0.00170	0.00186	0.00273	0.00109	0.00500	0.00187	0.00074	0.00211
Number of experimental IDs	1,239,384	118,866	301,272	92,397	44,355	226,807	60,008	126,460	86,520	53,931	8,602	58,530	18,272	43,364
t-test: event-year -2 x treated =0	*0.0559*	*0.260*	*0.614*	*0.280*	*0.663*	*0.875*	*0.0843*	*0.540*	*0.238*	*0.139*	*0.0783*	*0.688*	*0.202*	*0.878*

Note: Additionally to the terms reported in the table, models include (experimental) individual fixed effects. Event-years -3 and -1 are reference categories. Standard errors clustered at a (experimental) individual level are in parentheses.

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

Table E2 – Results of the t-test on non-linear pre-trends in responses of ihs family income to changes in medical innovations (drugs and patents) by broad disease groups from a final estimation sample (β_4 is unrelated to future outcomes)

	Altogether	Cancers	Circulatory	Mental	Nervous	Digestive	Musculo-skeletal	Urinary	Respiratory	Metabolic	D. of bloodforming organs	D. of sense organs	D. of skin	Infectious
(A) Drugs														
event-year -2	0.00090	0.00142	0.00116	-0.00338	0.00691	0.00129	-0.00253	0.00413	0.00067	0.01025***	0.00483	-0.00029	0.00863	-0.00456
	(0.00085)	(0.00270)	(0.00209)	(0.00557)	(0.00877)	(0.00154)	(0.00677)	(0.00320)	(0.00494)	(0.00356)	(0.01088)	(0.00312)	(0.01680)	(0.00679)
event-year 0	-0.14973***	-0.67605***	-0.30653***	-0.08816***	-0.00238	-0.00131	-0.00941	0.01854***	-0.07852***	0.00427	-0.03325	0.02940***	0.01083	0.02246**
	(0.00218)	(0.01314)	(0.00662)	(0.00882)	(0.01593)	(0.00250)	(0.00999)	(0.00446)	(0.01032)	(0.00557)	(0.03123)	(0.00399)	(0.02482)	(0.01139)
event-year 1	-0.12459***	-0.93418***	-0.09646***	-0.09502***	0.02970*	0.02548***	-0.00729	0.03096***	-0.06765***	0.01840***	-0.05396*	0.04490***	0.01068	0.04186***
	(0.00207)	(0.01469)	(0.00405)	(0.00866)	(0.01521)	(0.00250)	(0.01046)	(0.00466)	(0.01011)	(0.00570)	(0.03234)	(0.00446)	(0.02581)	(0.01077)
event-year -2 x l1.drugs	0.00001	-0.00044*	-0.00005	0.00008	-0.00038	0.00021	0.00004	-0.00002	0.00004	-0.00031*	-0.00080	0.00007	-0.00011	0.00033
	(0.00004)	(0.00024)	(0.00012)	(0.00029)	(0.00079)	(0.00016)	(0.00033)	(0.00011)	(0.00013)	(0.00016)	(0.00080)	(0.00017)	(0.00058)	(0.00031)
event-year 0 x l1.drugs	0.00364***	0.02544***	0.00867***	0.00029	-0.00109	-0.00031	0.00146***	0.00043***	0.00120***	-0.00001	-0.00356	0.00004	0.00041	-0.00271***
	(0.00009)	(0.00102)	(0.00030)	(0.00047)	(0.00141)	(0.00023)	(0.00049)	(0.00015)	(0.00024)	(0.00024)	(0.00302)	(0.00022)	(0.00084)	(0.00058)
event-year 1 x l1.drugs	0.00413***	0.03333***	0.00408***	0.00168***	-0.00198	0.00032	0.00247***	0.00095***	0.00141***	-0.00004	-0.00148	0.00037	0.00074	-0.00088*
	(0.00008)	(0.00113)	(0.00021)	(0.00044)	(0.00134)	(0.00024)	(0.00050)	(0.00016)	(0.00024)	(0.00026)	(0.00288)	(0.00023)	(0.00084)	(0.00050)
Constant	13.13137***	13.20603***	13.13911***	12.80648***	13.13421***	13.16052***	13.18510***	13.22327***	13.13031***	13.07340***	13.05428***	13.17107***	13.04519***	13.13089***
	(0.00045)	(0.00255)	(0.00098)	(0.00182)	(0.00191)	(0.00080)	(0.00116)	(0.00092)	(0.00148)	(0.00165)	(0.00526)	(0.00129)	(0.00288)	(0.00217)
Observations	6,110,797	583,626	1,485,778	453,439	218,158	1,121,812	296,976	625,880	426,651	265,282	42,198	288,409	89,636	212,952
R-squared	0.00301	0.03609	0.00703	0.00170	0.00015	0.00033	0.00141	0.00167	0.00050	0.00012	0.00160	0.00165	0.00046	0.00090
Number of experimental IDs	1,239,384	118,866	301,272	92,397	44,355	226,807	60,008	126,460	86,520	53,931	8,602	58,530	18,272	43,364
t-test: event-year -2 x l1.drugs =0	*0.740*	*0.0709*	*0.660*	*0.780*	*0.629*	*0.188*	*0.908*	*0.845*	*0.754*	*0.0628*	*0.317*	*0.660*	*0.855*	*0.278*
(B) Patents														
event-year -2	0.00129**	-0.00160	0.00119	0.00055	0.00512	0.00302**	-0.00135	0.00445**	0.00036	0.00769***	-0.00143	-0.00229	0.00648	-0.00140
	(0.00064)	(0.00272)	(0.00163)	(0.00354)	(0.00359)	(0.00145)	(0.00312)	(0.00199)	(0.00290)	(0.00298)	(0.00804)	(0.00272)	(0.00593)	(0.00489)
event-year 0	-0.10416***	-0.52523***	-0.24522***	-0.08000***	-0.02413***	0.04998***	0.00840*	0.02506***	0.00353	0.00722	-0.05415***	0.02790***	0.02552***	-0.00664
	(0.00158)	(0.01438)	(0.00496)	(0.00632)	(0.00688)	(0.00311)	(0.00447)	(0.00288)	(0.00474)	(0.00465)	(0.01680)	(0.00345)	(0.00828)	(0.00829)
event-year 1	-0.07315***	-0.77166***	-0.06375***	-0.04812***	-0.00277	0.05596***	0.01979***	0.04917***	0.02369***	0.02079***	-0.06503***	0.04561***	0.02760***	0.02777***
	(0.00148)	(0.01615)	(0.00316)	(0.00600)	(0.00679)	(0.00266)	(0.00472)	(0.00302)	(0.00481)	(0.00478)	(0.01965)	(0.00387)	(0.00926)	(0.00769)
event-year -2 x l1.patents	-0.00000	-0.00002	-0.00000	-0.00000	-0.00001	-0.00000	-0.00000	-0.00000	0.00000	-0.00001*	-0.00000	0.00002**	-0.00000	0.00000
	(0.00000)	(0.00005)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00001)
event-year 0 x l1.patents	0.00004***	0.00137***	0.00037***	-0.00000	0.00004**	-0.00046***	0.00006***	0.00001**	-0.00008***	-0.00001	-0.00002	0.00001	-0.00000	-0.00003***
	(0.00000)	(0.00025)	(0.00001)	(0.00001)	(0.00002)	(0.00003)	(0.00002)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
event-year 1 x l1.patents	0.00005***	0.00259***	0.00016***	-0.00003***	0.00004**	-0.00025***	0.00011***	0.00001***	-0.00008***	-0.00001	-0.00000	0.00003**	0.00000	-0.00000
	(0.00000)	(0.00028)	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Constant	13.13135***	13.20599***	13.13905***	12.80646***	13.13422***	13.16045***	13.18510***	13.22326***	13.13025***	13.07340***	13.05429***	13.17107***	13.04518***	13.13090***
	(0.00045)	(0.00255)	(0.00098)	(0.00182)	(0.00191)	(0.00079)	(0.00116)	(0.00092)	(0.00148)	(0.00165)	(0.00526)	(0.00129)	(0.00287)	(0.00217)
Observations	6,110,797	583,626	1,485,778	453,439	218,158	1,121,812	296,976	625,880	426,651	265,282	42,198	288,409	89,636	212,952
R-squared	0.00225	0.03232	0.00668	0.00173	0.00024	0.00483	0.00148	0.00159	0.00090	0.00012	0.00163	0.00167	0.00046	0.00077
Number of experimental IDs	1,239,384	118,866	301,272	92,397	44,355	226,807	60,008	126,460	86,520	53,931	8,602	58,530	18,272	43,364
t-test: event-year -2 x l1.patents =0	*0.654*	*0.743*	*0.467*	*0.375*	*0.386*	*0.730*	*0.864*	*0.548*	*0.443*	*0.0901*	*0.528*	*0.0374*	*0.867*	*0.378*

Note: Additionally to the terms reported in the table, models include (experimental) individual fixed effects. Event-years -3 and -1 are reference categories. Standard errors clustered at a (experimental) individual level are in parentheses.

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

Table E3 – Results of the t-test on non-linear pre-trends in responses of ihs family income to a health shock across levels of medical innovations (drugs and patents) by broad disease groups (β_3 is unrelated to future outcomes) from a final estimation sample (an event-study specification of the DDD specification in the main body)

	Altogether	Cancers	Circulatory	Mental	Nervous	Digestive	Musculo-skeletal	Urinary	Respiratory	Metabolic	D. of bloodforming organs	D. of sense organs	D. of skin	Infectious
(A) Drugs														
event-year -2	0.00021	0.00073	-0.00054	-0.00779	0.00307	0.00036	-0.01412	0.00121	0.00772	0.00902*	0.02169*	-0.00081	0.02134	-0.00873
	(0.00124)	(0.00390)	(0.00305)	(0.00751)	(0.01349)	(0.00224)	(0.01056)	(0.00474)	(0.00700)	(0.00527)	(0.01318)	(0.00483)	(0.02503)	(0.00963)
event-year 0	0.03115***	0.02864***	0.02547***	-0.01265	0.06637***	0.03805***	-0.01196	0.03588***	0.01499*	0.04111***	0.01880	0.04122***	0.01686	0.03669***
	(0.00138)	(0.00427)	(0.00346)	(0.00871)	(0.01332)	(0.00256)	(0.01051)	(0.00535)	(0.00803)	(0.00548)	(0.02099)	(0.00517)	(0.02731)	(0.01139)
event-year 1	0.05147***	0.04384***	0.04332***	-0.01760*	0.07695***	0.06421***	0.01114	0.05164***	0.03112***	0.05355***	0.04780**	0.06460***	0.05817*	0.07124***
	(0.00154)	(0.00467)	(0.00377)	(0.01038)	(0.01567)	(0.00284)	(0.01111)	(0.00583)	(0.00926)	(0.00649)	(0.02312)	(0.00576)	(0.03080)	(0.01212)
event-year -2 x treated	0.00103	-0.00068	0.00256	0.00846	0.00727	0.00176	0.02258*	0.00564	-0.01450	0.00223	-0.03280	0.00101	-0.02522	0.00808
	(0.00170)	(0.00538)	(0.00418)	(0.01112)	(0.01760)	(0.00308)	(0.01360)	(0.00641)	(0.00987)	(0.00713)	(0.02158)	(0.00626)	(0.03367)	(0.01357)
event-year 0 x treated	-0.35758***	-1.39229***	-0.65778***	-0.14813***	-0.13600***	-0.07794***	0.00563	-0.03413***	-0.18344***	-0.07246***	-0.10101	-0.02320***	-0.01052	-0.02702
	(0.00431)	(0.02547)	(0.01303)	(0.01752)	(0.03163)	(0.00498)	(0.01992)	(0.00889)	(0.02044)	(0.01108)	(0.06175)	(0.00796)	(0.04942)	(0.02263)
event-year 1 x treated	-0.35255***	-2.05754***	-0.27676***	-0.15347***	-0.09357***	-0.07696***	-0.03609*	-0.04096***	-0.19555***	-0.06933***	-0.20145***	-0.03909***	-0.09369*	-0.05753***
	(0.00415)	(0.03010)	(0.00811)	(0.01730)	(0.03036)	(0.00500)	(0.02091)	(0.00931)	(0.02017)	(0.01139)	(0.06500)	(0.00891)	(0.05149)	(0.02149)
event-year -2 x l1.drugs	-0.00001	-0.00062*	0.00001	0.00015	0.00009	0.00037*	0.00044	0.00006	-0.00020	-0.00047*	-0.00128	0.00017	-0.00076	0.00051
	(0.00006)	(0.00036)	(0.00018)	(0.00038)	(0.00120)	(0.00022)	(0.00050)	(0.00017)	(0.00018)	(0.00025)	(0.00087)	(0.00025)	(0.00087)	(0.00043)
event-year 0 x l1.drugs	0.00041***	0.00085**	0.00085***	0.00102**	-0.00250**	0.00055**	0.00251***	0.00046**	0.00066***	0.00021	0.00044	-0.00004	0.00095	0.00009
	(0.00007)	(0.00038)	(0.00020)	(0.00045)	(0.00121)	(0.00026)	(0.00052)	(0.00019)	(0.00020)	(0.00020)	(0.00181)	(0.00032)	(0.00090)	(0.00055)
event-year 1 x l1.drugs	0.00047***	0.00187***	0.00119***	0.00084	-0.00129	0.00050*	0.00260***	0.00090***	0.00073***	0.00013	0.00020	0.00037	-0.00032	-0.00023
	(0.00008)	(0.00042)	(0.00023)	(0.00058)	(0.00139)	(0.00029)	(0.00057)	(0.00020)	(0.00023)	(0.00031)	(0.00197)	(0.00032)	(0.00103)	(0.00055)
event-year -2 x treated x l1.drugs	0.00007	0.00051	-0.00009	-0.00014	-0.00090	-0.00031	-0.00078	-0.00016	0.00050*	0.00033	0.00090	-0.00019	0.00129	-0.00035
	(0.00008)	(0.00048)	(0.00024)	(0.00057)	(0.00158)	(0.00031)	(0.00066)	(0.00022)	(0.00026)	(0.00033)	(0.00159)	(0.00034)	(0.00116)	(0.00061)
event-year 0 x treated x l1.drugs	0.00637***	0.04832***	0.01545***	-0.00151	0.00283	-0.00171***	-0.00210**	-0.00008	0.00103**	-0.00044	-0.00800	0.00015	-0.00111	-0.00560***
	(0.00017)	(0.00198)	(0.00060)	(0.00094)	(0.00280)	(0.00047)	(0.00097)	(0.00031)	(0.00047)	(0.00048)	(0.00598)	(0.00044)	(0.00167)	(0.00116)
event-year 1 x treated x l1.drugs	0.00733***	0.06768***	0.00566***	0.00167*	-0.00139	-0.00037	-0.00032	0.00010	0.00132***	-0.00035	-0.00355	-0.00001	0.00210	-0.00131
	(0.00017)	(0.00230)	(0.00042)	(0.00088)	(0.00267)	(0.00049)	(0.00100)	(0.00032)	(0.00047)	(0.00051)	(0.00582)	(0.00046)	(0.00168)	(0.00100)
Constant	13.13078***	13.20289***	13.13836***	12.80600***	13.13390***	13.16037***	13.18504***	13.22321***	13.12996***	13.07319***	13.05364***	13.17100***	13.04507***	13.13058***
	(0.00045)	(0.00246)	(0.00097)	(0.00181)	(0.00190)	(0.00079)	(0.00116)	(0.00092)	(0.00147)	(0.00164)	(0.00520)	(0.00129)	(0.00287)	(0.00216)
Observations	6,110,797	583,626	1,485,778	453,439	218,158	1,121,812	296,976	625,880	426,651	265,282	42,198	288,409	89,636	212,952
R-squared	0.00886	0.08012	0.01679	0.00342	0.00173	0.00144	0.00190	0.00197	0.00295	0.00112	0.00520	0.00189	0.00081	0.00271
Number of experimental IDs	1,239,384	118,866	301,272	92,397	44,355	226,807	60,008	126,460	86,520	53,931	8,602	58,530	18,272	43,364
t-test: event-year -2 x treated =0	*0.547*	*0.899*	*0.539*	*0.447*	*0.679*	*0.568*	*0.0969*	*0.378*	*0.142*	*0.754*	*0.129*	*0.872*	*0.454*	*0.551*
t-test: event-year -2 x l1.drugs =0	*0.810*	*0.0885*	*0.964*	*0.681*	*0.943*	*0.0897*	*0.381*	*0.714*	*0.268*	*0.0537*	*0.141*	*0.501*	*0.385*	*0.240*
t-test: event-year -2 x treated x l1.drugs =0	*0.420*	*0.292*	*0.713*	*0.812*	*0.571*	*0.319*	*0.239*	*0.474*	*0.0510*	*0.311*	*0.572*	*0.580*	*0.265*	*0.571*
(B) Patents														
event-year -2	0.00013	-0.00231	0.00008	-0.00297	-0.00066	0.00181	-0.00646	0.00496*	-0.00048	0.00455	0.01203	-0.00474	0.00261	-0.00513
	(0.00094)	(0.00387)	(0.00236)	(0.00485)	(0.00541)	(0.00201)	(0.00494)	(0.00301)	(0.00425)	(0.00451)	(0.01121)	(0.00427)	(0.00929)	(0.00682)
event-year 0	0.03769***	0.02600***	0.03132***	0.00932	0.03830***	0.04556***	0.02239***	0.04240***	0.03929***	0.04415***	0.02258*	0.03596***	0.02884***	0.03322***
	(0.00104)	(0.00429)	(0.00269)	(0.00582)	(0.00562)	(0.00249)	(0.00479)	(0.00339)	(0.00452)	(0.00482)	(0.01337)	(0.00460)	(0.00956)	(0.00819)
event-year 1	0.06106***	0.03964***	0.05128***	0.01300*	0.05390***	0.07180***	0.04110***	0.07003***	0.06161***	0.05651***	0.04901***	0.06202***	0.03628***	0.06409***
	(0.00117)	(0.00472)	(0.00294)	(0.00682)	(0.00654)	(0.00274)	(0.00518)	(0.00369)	(0.00506)	(0.00543)	(0.01570)	(0.00496)	(0.01090)	(0.00869)

event-year -2 x treated	0.00212*	-0.00015	0.00165	0.00672	0.01119	0.00235	0.00997	-0.00103	0.00159	0.00603	-0.02637	0.00478	0.00738	0.00721
	(0.00128)	(0.00542)	(0.00325)	(0.00707)	(0.00720)	(0.00290)	(0.00626)	(0.00400)	(0.00581)	(0.00598)	(0.01606)	(0.00547)	(0.01193)	(0.00976)
event-year 0 x treated	-0.28078***	-1.08752***	-0.54913***	-0.17592***	-0.12297***	0.00871	-0.02757***	-0.03431***	-0.07027***	-0.07276***	-0.15062***	-0.01581**	-0.00629	-0.07806***
	(0.00314)	(0.02789)	(0.00979)	(0.01254)	(0.01365)	(0.00609)	(0.00891)	(0.00575)	(0.00942)	(0.00924)	(0.03332)	(0.00689)	(0.01649)	(0.01645)
event-year 1 x treated	-0.26871***	-1.69400***	-0.22891***	-0.12049***	-0.11209***	-0.03043***	-0.04230***	-0.04149***	-0.07421***	-0.07068***	-0.22768***	-0.03267***	-0.01700	-0.07135***
	(0.00297)	(0.03331)	(0.00634)	(0.01198)	(0.01355)	(0.00539)	(0.00944)	(0.00603)	(0.00960)	(0.00954)	(0.03940)	(0.00774)	(0.01848)	(0.01534)
event-year -2 x l1.patents	-0.00000	-0.00005	-0.00000	-0.00000	0.00002	0.00001	0.00001	-0.00000	0.00000	-0.00001	-0.00000	0.00003***	-0.00000	0.00001
	(0.00000)	(0.00007)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00001)
event-year 0 x l1.patents	0.00000	0.00021***	0.00004***	-0.00001	0.00000	-0.00003**	0.00008***	0.00001**	0.00000	0.00000	0.00000	0.00002*	0.00002**	0.00001
	(0.00000)	(0.00008)	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
event-year 1 x l1.patents	-0.00001**	0.00042***	0.00005***	-0.00002***	0.00003**	-0.00004**	0.00011***	0.00000	-0.00000	-0.00000	0.00000	0.00004***	0.00001	0.00000
	(0.00000)	(0.00009)	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00001)	(0.00001)
event-year -2 x treated x l1.patents	0.00000	0.00008	-0.00000	-0.00000	-0.00005**	-0.00002	-0.00002	0.00000	0.00001	0.00001	0.00000	-0.00004**	0.00000	-0.00001
	(0.00000)	(0.00010)	(0.00001)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00002)	(0.00001)	(0.00001)
event-year 0 x treated x l1.patents	0.00008***	0.00219***	0.00066***	0.00001	0.00007*	-0.00085***	-0.00005	-0.00000	-0.00016***	-0.00002	-0.00004	-0.00003	-0.00004***	-0.00008***
	(0.00000)	(0.00049)	(0.00003)	(0.00001)	(0.00003)	(0.00006)	(0.00004)	(0.00000)	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00001)	(0.00002)
event-year 1 x treated x l1.patents	0.00011***	0.00468***	0.00020***	-0.00001	0.00001	-0.00043***	-0.00000	0.00000	-0.00016***	-0.00002	-0.00001	-0.00004	-0.00002	-0.00002
	(0.00000)	(0.00058)	(0.00002)	(0.00001)	(0.00004)	(0.00004)	(0.00004)	(0.00001)	(0.00002)	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00002)
Constant	13.13079***	13.20313***	13.13836***	12.80598***	13.13390***	13.16028***	13.18504***	13.22320***	13.12993***	13.07319***	13.05364***	13.17100***	13.04509***	13.13059***
	(0.00045)	(0.00247)	(0.00097)	(0.00181)	(0.00190)	(0.00079)	(0.00116)	(0.00092)	(0.00147)	(0.00164)	(0.00520)	(0.00129)	(0.00287)	(0.00216)
Observations	6,110,797	583,626	1,485,778	453,439	218,158	1,121,812	296,976	625,880	426,651	265,282	42,198	288,409	89,636	212,952
R-squared	0.00758	0.07240	0.01619	0.00343	0.00189	0.00965	0.00195	0.00189	0.00392	0.00113	0.00524	0.00193	0.00093	0.00251
Number of experimental IDs	1,239,384	118,866	301,272	92,397	44,355	226,807	60,008	126,460	86,520	53,931	8,602	58,530	18,272	43,364
t-test: event-year -2 x treated =0	*0.0971*	*0.978*	*0.613*	*0.342*	*0.120*	*0.419*	*0.112*	*0.797*	*0.784*	*0.313*	*0.101*	*0.382*	*0.536*	*0.460*
t-test: event-year -2 x l1.patents =0	*0.786*	*0.518*	*0.787*	*0.567*	*0.122*	*0.333*	*0.754*	*0.338*	*0.960*	*0.118*	*0.348*	*0.00598*	*0.716*	*0.230*
t-test: event-year -2 x treated x l1.patents =0	*0.982*	*0.424*	*0.832*	*0.948*	*0.0103*	*0.157*	*0.531*	*0.308*	*0.480*	*0.539*	*0.637*	*0.0281*	*0.667*	*0.446*

Note: Additionally to the terms reported in the table, models include (experimental) individual fixed effects. Event-years -3 and -1 are reference categories. Standard errors clustered at a (experimental) individual level are in parentheses.

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

Table E4 – Results of the t-test on non-linear pre-trends in responses of the sources of ihs family income to a health shock across levels of medical innovations (drugs and patents) by broad disease groups (β_3 is unrelated to future outcomes) from a final estimation sample (an event-study specification of the DDD specification in the main body)

Variables	Ihs Own Disposable Income		Ihs Spouse's Disposable Income		Ihs Own Labour Income		Ihs Sickness Absence Payments		Ihs Unemployment Payments		Ihs Disability Pension Payments		Ihs Own Capital Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
event-year -2	0.00321	0.00131	0.00360	0.00168	0.00563*	0.01062***	0.01557**	0.00641	-0.00002	-0.00175	-0.01385***	-0.01507***	0.02468***	0.00715
	(0.00210)	(0.00155)	(0.00388)	(0.00290)	(0.00327)	(0.00247)	(0.00752)	(0.00553)	(0.00203)	(0.00150)	(0.00160)	(0.00122)	(0.00877)	(0.00678)
event-year 0	0.05134***	0.05210***	-0.13231***	-0.08783***	-0.10410***	-0.08902***	-0.25142***	-0.21744***	-0.00356	-0.00440***	0.18009***	0.19142***	-0.31324***	-0.27164***
	(0.00236)	(0.00177)	(0.00523)	(0.00390)	(0.00424)	(0.00320)	(0.00824)	(0.00612)	(0.00224)	(0.00168)	(0.00278)	(0.00212)	(0.01078)	(0.00828)
event-year 1	0.07452***	0.07708***	-0.19632***	-0.13476***	-0.18189***	-0.15382***	-0.24538***	-0.18425***	0.00700***	0.00454**	0.30401***	0.31867***	-0.51213***	-0.39845***
	(0.00264)	(0.00200)	(0.00636)	(0.00473)	(0.00503)	(0.00379)	(0.00911)	(0.00684)	(0.00248)	(0.00188)	(0.00371)	(0.00283)	(0.01246)	(0.00955)
event-year -2 x treated	0.00399	0.00616***	0.00017	0.00280	-0.00414	-0.00520	-0.06327***	-0.06933***	-0.00532*	-0.00243	0.00241	0.00472***	-0.02817**	-0.01311
	(0.00286)	(0.00213)	(0.00545)	(0.00407)	(0.00460)	(0.00346)	(0.01060)	(0.00782)	(0.00287)	(0.00213)	(0.00226)	(0.00172)	(0.01217)	(0.00940)
event-year 0 x treated	-0.08811***	-0.06186***	-0.49074***	-0.38706***	-0.17165***	-0.10181***	3.74694***	3.88978***	0.41135***	0.37895***	0.01301***	0.01965***	0.01803	0.00108
	(0.00392)	(0.00285)	(0.00920)	(0.00685)	(0.00658)	(0.00489)	(0.01323)	(0.01004)	(0.00442)	(0.00333)	(0.00411)	(0.00314)	(0.01519)	(0.01167)
event-year 1 x treated	-0.07141***	-0.04825***	-0.51174***	-0.39551***	-0.20586***	-0.13692***	1.74219***	1.89676***	0.18950***	0.18599***	0.18454***	0.19095***	0.01654	0.02578*
	(0.00408)	(0.00302)	(0.01044)	(0.00773)	(0.00758)	(0.00564)	(0.01428)	(0.01091)	(0.00418)	(0.00321)	(0.00584)	(0.00455)	(0.01767)	(0.01355)
event-year -2 x l1.drugs	-0.00014		0.00004		0.00039**		-0.00075**		-0.00008		0.00004		-0.00160***	
	(0.00010)		(0.00019)		(0.00016)		(0.00032)		(0.00008)		(0.00008)		(0.00047)	
event-year 0 x l1.drugs	-0.00024**		0.00293***		0.00021		0.00297***		-0.00001		0.00158***		0.00376***	
	(0.00012)		(0.00025)		(0.00021)		(0.00037)		(0.00010)		(0.00014)		(0.00056)	
event-year 1 x l1.drugs	-0.00029**		0.00353***		0.00053**		0.00517***		-0.00014		0.00216***		0.01073***	
	(0.00013)		(0.00031)		(0.00025)		(0.00041)		(0.00011)		(0.00018)		(0.00063)	
event-year -2 x treated x l1.drugs	0.00007		0.00011		-0.00006		-0.00014		0.00015		0.00003		0.00095	
	(0.00014)		(0.00027)		(0.00023)		(0.00046)		(0.00012)		(0.00011)		(0.00065)	
event-year 0 x treated x l1.drugs	0.00260***		0.00734***		0.00564***		-0.00533***		-0.00433***		0.00068***		-0.00039	
	(0.00017)		(0.00041)		(0.00031)		(0.00062)		(0.00019)		(0.00020)		(0.00079)	
event-year 1 x treated x l1.drugs	0.00224***		0.00930***		0.00542***		-0.00104		-0.00158***		-0.00050*		-0.00006	
	(0.00019)		(0.00048)		(0.00037)		(0.00065)		(0.00018)		(0.00027)		(0.00089)	
event-year -2 x l1.patents		-0.00000		0.00001		0.00000		-0.00001		0.00000		0.00001**		-0.00003**
		(0.00000)		(0.00000)		(0.00000)		(0.00001)		(0.00000)		(0.00000)		(0.00001)
event-year 0 x l1.patents		-0.00001***		0.00001		-0.00004***		0.00005***		0.00000		0.00005***		0.00006***
		(0.00000)		(0.00001)		(0.00001)		(0.00001)		(0.00000)		(0.00000)		(0.00001)
event-year 1 x l1.patents		-0.00002***		-0.00001		-0.00006***		0.00008***		0.00000		0.00006***		0.00019***
		(0.00000)		(0.00001)		(0.00001)		(0.00001)		(0.00000)		(0.00001)		(0.00002)
event-year -2 x treated x l1.patents		-0.00000		-0.00000		0.00000		0.00001		-0.00000		-0.00001*		0.00000
		(0.00000)		(0.00001)		(0.00001)		(0.00001)		(0.00000)		(0.00000)		(0.00002)
event-year 0 x treated x l1.patents		0.00005***		0.00005***		0.00007***		-0.00069***		-0.00012***		0.00001***		0.00003
		(0.00000)		(0.00001)		(0.00001)		(0.00002)		(0.00000)		(0.00001)		(0.00002)
event-year 1 x treated x l1.patents		0.00004***		0.00011***		0.00006***		-0.00051***		-0.00007***		-0.00004***		-0.00003
		(0.00001)		(0.00001)		(0.00001)		(0.00002)		(0.00000)		(0.00001)		(0.00002)
Constant	12.48133***	12.48133***	9.12079***	9.12079***	11.85171***	11.85172***	3.33752***	3.33561***	0.18867***	0.18866***	0.82241***	0.82230***	-1.08819***	-1.08823***
	(0.00051)	(0.00051)	(0.00118)	(0.00118)	(0.00090)	(0.00090)	(0.00186)	(0.00186)	(0.00055)	(0.00055)	(0.00064)	(0.00064)	(0.00223)	(0.00223)
Observations	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	5,869,111	5,869,111	6,110,797	6,110,797	5,869,111	5,869,111	6,110,797	6,110,797

R-squared	0.00072	0.00065	0.00669	0.00606	0.00389	0.00366	0.08586	0.08676	0.01001	0.01006	0.02485	0.02486	0.00139	0.00127
Number of experimental IDs	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,239,336	1,239,336	1,239,384	1,239,384	1,239,336	1,239,336	1,239,384	1,239,384
t-test: event-year -2 x treated =0	0.163	0.00382	0.975	0.492	0.368	0.133	0	0	0.0640	0.253	0.284	0.00606	0.0207	0.163
t-test: event-year -2 x l1.drugs =0	0.183		0.818		0.0139		0.0214		0.332		0.613		0.000587	
t-test: event-year -2 x treated x l1.drugs =0	0.601		0.676		0.790		0.755		0.199		0.771		0.144	
t-test: event-year -2 x l1.patents =0		0.661		0.115		0.339		0.191		0.566		0.0120		0.0273
t-test: event-year -2 x treated x l1.patents =0		0.441		0.749		0.970		0.400		0.698		0.0902		0.900

Note: Additionally to the terms reported in the table, models include (experimental) individual fixed effects. Event-years -3 and -1 are reference categories. Standard errors clustered at a (experimental) individual level are in parentheses.

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

Appendix F

Table – Results of the t-test on non-linear pre-trends in the models for robustness analyses

Variables	Detrended Innovations		International Innovations Only		10-Year Lags of Innovations		Symptoms and External Causes as Controls		Adding the Died to the Treated		Adding Outpatient Register	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
event-year -2	0.00017	0.00006	0.00066	0.00003	-0.00042	0.00009	-0.00004	-0.00015	0.00056	0.00037	0.00066	0.00120
	(0.00117)	(0.00092)	(0.00120)	(0.00088)	(0.00121)	(0.00091)	(0.00118)	(0.00089)	(0.00124)	(0.00094)	(0.00252)	(0.00176)
event-year 0	0.03240***	0.03771***	0.03148***	0.03612***	0.03086***	0.03691***	0.03348***	0.03679***	0.03102***	0.03795***	0.05325***	0.05978***
	(0.00131)	(0.00103)	(0.00136)	(0.00098)	(0.00136)	(0.00102)	(0.00134)	(0.00102)	(0.00139)	(0.00105)	(0.00306)	(0.00207)
event-year 1	0.05301***	0.06103***	0.05290***	0.05758***	0.05069***	0.05938***	0.05524***	0.06092***	0.05143***	0.06134***	0.08574***	0.08966***
	(0.00146)	(0.00115)	(0.00149)	(0.00110)	(0.00150)	(0.00114)	(0.00147)	(0.00111)	(0.00155)	(0.00118)	(0.00344)	(0.00227)
event-year -2 x treated	0.00110	0.00215*	0.00043	0.00231*	0.00165	0.00211*	0.00188	0.00259**	0.00074	0.00200	0.00063	0.00437*
	(0.00161)	(0.00126)	(0.00165)	(0.00120)	(0.00166)	(0.00124)	(0.00161)	(0.00120)	(0.00170)	(0.00128)	(0.00352)	(0.00242)
event-year 0 x treated	-0.34701***	-0.28610***	-0.37046***	-0.27055***	-0.37291***	-0.27532***	-0.36759***	-0.28457***	-0.35707***	-0.28041***	-0.06319***	-0.04677***
	(0.00408)	(0.00316)	(0.00444)	(0.00295)	(0.00438)	(0.00301)	(0.00404)	(0.00294)	(0.00431)	(0.00314)	(0.00525)	(0.00349)
event-year 1 x treated	-0.34109***	-0.27787***	-0.36431***	-0.25543***	-0.36723***	-0.26100***	-0.36924***	-0.27744***	-0.35201***	-0.26862***	-0.07218***	-0.04988***
	(0.00394)	(0.00303)	(0.00423)	(0.00278)	(0.00420)	(0.00284)	(0.00391)	(0.00281)	(0.00415)	(0.00298)	(0.00551)	(0.00359)
event-year -2 x l1.drugs	-0.00001		-0.00011		0.00004		-0.00002		-0.00003		-0.00004	
	(0.00006)		(0.00016)		(0.00009)		(0.00006)		(0.00006)		(0.00008)	
event-year 0 x l1.drugs	0.00038***		0.00103***		0.00064***		0.00041***		0.00041***		0.00010	
	(0.00007)		(0.00018)		(0.00010)		(0.00007)		(0.00007)		(0.00009)	
event-year 1 x l1.drugs	0.00043***		0.00101***		0.00078***		0.00061***		0.00049***		0.00010	
	(0.00008)		(0.00020)		(0.00011)		(0.00007)		(0.00008)		(0.00010)	
event-year -2 x treated x l1.drugs	0.00007		0.00027		0.00004		0.00005		0.00008		0.00011	
	(0.00009)		(0.00022)		(0.00012)		(0.00008)		(0.00008)		(0.00011)	
event-year 0 x treated x l1.drugs	0.00654***		0.01902***		0.01100***		0.00651***		0.00637***		0.00101***	
	(0.00017)		(0.00047)		(0.00026)		(0.00016)		(0.00017)		(0.00015)	
event-year 1 x treated x l1.drugs	0.00757***		0.02136***		0.01236***		0.00742***		0.00729***		0.00110***	
	(0.00017)		(0.00045)		(0.00025)		(0.00016)		(0.00017)		(0.00016)	
event-year -2 x l1.patents		-0.00000		-0.00000		-0.00000		-0.00000		-0.00000		-0.00000
		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)
event-year 0 x l1.patents		0.00000		0.00001***		0.00001		0.00001***		-0.00000		-0.00001**
		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)
event-year 1 x l1.patents		-0.00001**		0.00001***		-0.00000		0.00001***		-0.00001**		-0.00000
		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)
event-year -2 x treated x l1.patents		-0.00000		-0.00000		0.00000		0.00000		0.00000		-0.00000
		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)		(0.00000)
event-year 0 x treated x l1.patents		0.00010***		0.00012***		0.00014***		0.00007***		0.00008***		0.00002***
		(0.00000)		(0.00001)		(0.00001)		(0.00000)		(0.00000)		(0.00000)
event-year 1 x treated x l1.patents		0.00014***		0.00017***		0.00018***		0.00009***		0.00011***		0.00001***
		(0.00000)		(0.00001)		(0.00001)		(0.00000)		(0.00000)		(0.00000)

Constant	13.13076***	13.13076***	13.13076***	13.13077***	13.13078***	13.13079***	13.12754***	13.12755***	13.12853***	13.12854***	13.34154***	13.34154***
	(0.00045)	(0.00045)	(0.00045)	(0.00045)	(0.00045)	(0.00045)	(0.00042)	(0.00042)	(0.00045)	(0.00045)	(0.00052)	(0.00052)
Observations	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	6,110,797	7,112,891	7,112,891	6,149,619	6,149,619	2,731,000	2,731,000
R-squared	0.00885	0.00789	0.00911	0.00750	0.00947	0.00756	0.00933	0.00797	0.00879	0.00752	0.00212	0.00204
Number of experimental IDs	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,239,384	1,442,305	1,442,305	1,249,051	1,249,051	553,349	553,349
t-test: event-year -2 x treated =0	0.495	0.0881	0.795	0.0552	0.320	0.0898	0.243	0.0310	0.665	0.117	0.858	0.0713
t-test: event-year -2 x l1.drugs =0	0.837		0.492		0.683		0.788		0.666		0.622	
t-test: event-year -2 x treated x l1.drugs =0	0.408		0.208		0.718		0.515		0.347		0.297	
t-test: event-year -2 x l1.patents =0		0.877		0.912		0.817		0.761		0.688		0.196
t-test: event-year -2 x treated x l1.patents =0		0.979		0.760		0.974		0.850		0.978		0.708

Note: Additionally to the terms reported in the table, models include (experimental) individual fixed effects. Event-years -3 and -1 are reference categories. Standard errors clustered at a (experimental) individual level are in parentheses.

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

Appendix G

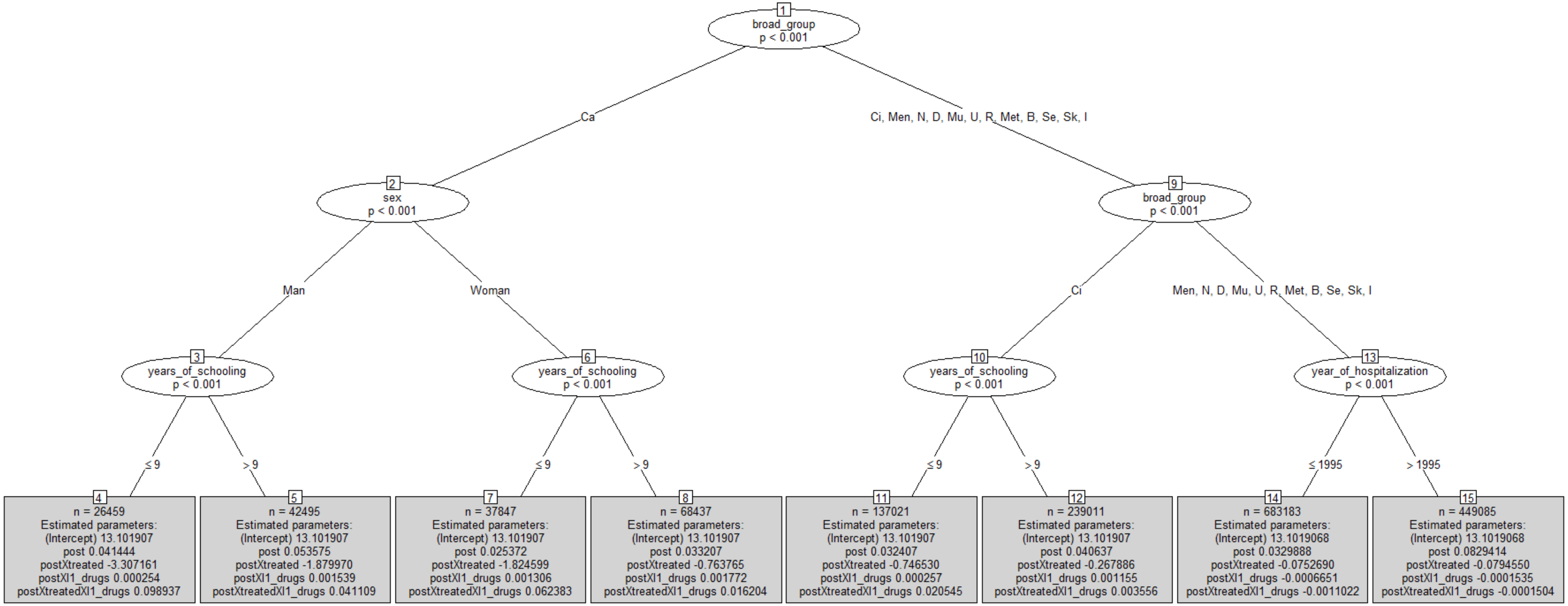

Figure G1 – Linear regression-based tree for the impact of medical innovations (l1.drugs) on ihs family disposable income.

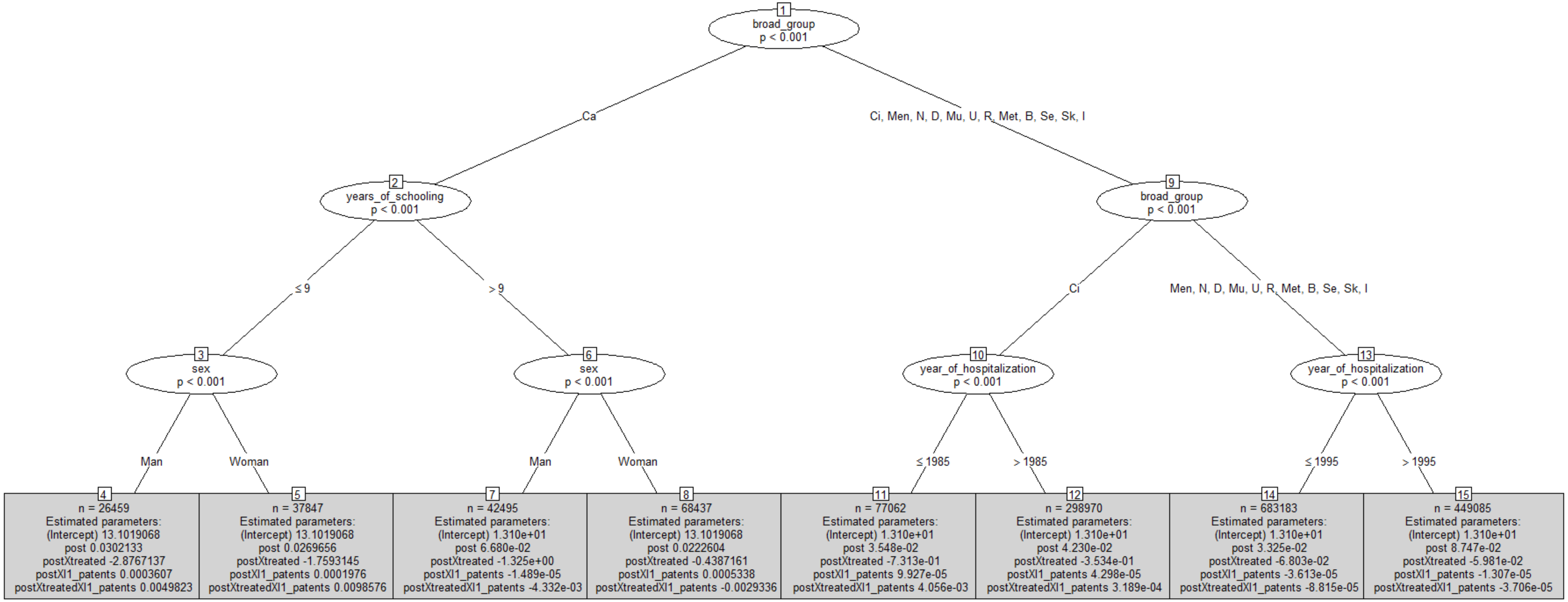

Figure G2 – Linear regression-based tree for the impact of medical innovations (l1.patents) on ihs family disposable income.

Appendix H

Table – DDD estimates for selected single diseases: Impact of medical innovations in 1981–2006 on the ihs family income in ages 40–60 Sweden

	Prostate Cancer				Breast Cancer				Hypertensive diseases				Ischaemic heart diseases			
	ihs family income		ihs own income		ihs family income		ihs own income		ihs family income		ihs own income		ihs family income		ihs own income	
post	0.00937	0.00985	0.09506***	0.09792***	0.02963	0.05281***	-0.01970	-0.00040	-0.01216	0.00435	-0.00386	0.05359	0.02300***	0.02421***	0.05911***	0.05378***
	(0.00724)	(0.00749)	(0.01838)	(0.01871)	(0.03753)	(0.01534)	(0.05678)	(0.02567)	(0.01761)	(0.01788)	(0.03048)	(0.03315)	(0.00776)	(0.00595)	(0.01258)	(0.00971)
post x l1.drugs	0.00320***		-0.00254*		0.00194		0.00403		0.00181***		0.00153		0.00144***		0.00004	
	(0.00058)		(0.00134)		(0.00232)		(0.00338)		(0.00068)		(0.00115)		(0.00043)		(0.00068)	
DD_{idst}	-0.47224***	-0.47515***	-0.14243***	-0.13907***	-1.73045***	-0.94086***	-0.91345***	-0.23122***	-0.11106***	-0.11696***	0.04901	0.04544	-0.75891***	-0.64987***	-0.51214***	-0.41933***
	(0.02647)	(0.02747)	(0.03048)	(0.03075)	(0.19074)	(0.07022)	(0.17044)	(0.05465)	(0.03144)	(0.03470)	(0.04526)	(0.05072)	(0.02700)	(0.02166)	(0.02662)	(0.02136)
DD_{idst} x l1.drugs	0.01512***		0.00790***		0.07345***		0.05167***		0.00214*		-0.00207		0.02314***		0.02080***	
	(0.00175)		(0.00207)		(0.01091)		(0.00974)		(0.00115)		(0.00167)		(0.00122)		(0.00125)	
post x l1.patents		0.00071***		-0.00062**		0.00024		0.00131**		0.00027		-0.00017		0.00025***		0.00006
		(0.00013)		(0.00030)		(0.00043)		(0.00054)		(0.00017)		(0.00030)		(0.00006)		(0.00009)
DD_{idst} x l1.patents		0.00343***		0.00170***		0.01157***		0.00463***		0.00055*		-0.00045		0.00325***		0.00297***
		(0.00041)		(0.00047)		(0.00145)		(0.00112)		(0.00030)		(0.00044)		(0.00017)		(0.00018)
Constant	13.23354***	13.23354***	12.36356***	12.36356***	13.37578***	13.37566***	12.86785***	12.86783***	13.09513***	13.09512***	12.41587***	12.41582***	13.13333***	13.13334***	12.55318***	12.55318***
	(0.00215)	(0.00215)	(0.00238)	(0.00238)	(0.00662)	(0.00661)	(0.00516)	(0.00518)	(0.00237)	(0.00236)	(0.00356)	(0.00356)	(0.00162)	(0.00162)	(0.00161)	(0.00161)
Observations	217,867	217,867	217,867	217,867	38,471	38,471	38,471	38,471	103,021	103,021	103,021	103,021	502,948	502,948	502,948	502,948
R-squared	0.01215	0.01191	0.00079	0.00075	0.02850	0.02952	0.00584	0.00338	0.00105	0.00083	0.00029	0.00034	0.01479	0.01497	0.00338	0.00358
Number of individuals	43,888	43,888	43,888	43,888	7,792	7,792	7,792	7,792	20,854	20,854	20,854	20,854	101,801	101,801	101,801	101,801
Individual (experimental) FEs	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
1 SD of l1.drugs /l1.patents	6.436942	27.05131	6.436942	27.05131	3.545197	24.24355	3.545197	24.24355	10.30004	40.7342	10.30004	40.7342	7.161477	51.14879	7.161477	51.14879
1 SD x effect x 100%	9.73%	9.28%	5.09%	4.60%	26.04%	28.05%	18.32%	11.22%	2.20%	2.24%	-2.13%	-1.83%	16.57%	16.62%	14.90%	15.19%
1 SD combined effect x 100%		19.01%		9.68%		54.09%		29.54%		4.44%		-3.97%		33.20%		30.09%
1 SD combined SE x 100%		1.58%		1.84%		5.23%		4.39%		1.70%		2.48%		1.23%		1.28%
CI lower 95%		15.91%		6.07%		43.85%		20.93%		1.11%		-8.83%		30.78%		27.57%
CI higher 95		22.11%		13.29%		64.33%		38.15%		7.78%		0.90%		35.61%		32.60%

Table G1 Cont'd

	Cardiac arrhythmias and heart failure				Cerebrovascular diseases				Diseases of arteries, arterioles and capillaries				Mental and behavioural disorders due to use of alcohol and other substances			
	ihs family income		ihs own income		ihs family income		ihs own income		ihs family income		ihs own income		ihs family income		ihs own income	
post	-0.02750	0.01809*	0.00336	0.02076	0.01261	0.02074**	0.05153***	0.05583***	0.06846***	0.07724***	0.05043	0.05292*	-0.02371	0.01210	0.01283	0.06143**
	(0.01764)	(0.01021)	(0.03059)	(0.01731)	(0.00995)	(0.01038)	(0.01803)	(0.01859)	(0.02595)	(0.01994)	(0.03597)	(0.02848)	(0.05898)	(0.02217)	(0.07324)	(0.02635)
post x l1.drugs	0.00315***		0.00205*		0.00388***		-0.00044		-0.00137		0.00050		0.00111		-0.00180	
	(0.00064)		(0.00108)		(0.00102)		(0.00186)		(0.00339)		(0.00438)		(0.00621)		(0.00771)	
DD_{idst}	-0.36692***	-0.28976***	-0.14254***	-0.08145***	-1.18349***	-1.21691***	-0.61881***	-0.68695***	-0.53963***	-0.50059***	-0.25572***	-0.23008***	-0.25071***	-0.17362***	-0.28695***	-0.12734***
	(0.04525)	(0.02563)	(0.04911)	(0.02801)	(0.04653)	(0.04677)	(0.04038)	(0.04318)	(0.07276)	(0.05672)	(0.06167)	(0.05444)	(0.09612)	(0.03845)	(0.10677)	(0.04198)
DD_{idst} x l1.drugs	0.00599***		0.00384**		0.04672***		0.05104***		0.01294		0.02374***		0.01186		0.03146***	
	(0.00152)		(0.00168)		(0.00419)		(0.00362)		(0.00871)		(0.00711)		(0.00996)		(0.01108)	
post x l1.patents		0.00014***		0.00013**		0.00021***		-0.00006		-0.00004		0.00000		-0.00002		-0.00004**
		(0.00003)		(0.00005)		(0.00007)		(0.00013)		(0.00005)		(0.00006)		(0.00001)		(0.00002)

DD$_{idst}$ x l1.patents		0.00029***		0.00015*		0.00340***		0.00393***		0.00014		0.00036***		0.00002		0.00010***
		(0.00007)		(0.00008)		(0.00028)		(0.00026)		(0.00011)		(0.00010)		(0.00002)		(0.00003)
Constant	13.21043***	13.21043***	12.59019***	12.59020***	13.14844***	13.14842***	12.47717***	12.47714***	13.04147***	13.04145***	12.45956***	12.45956***	12.66785***	12.66781***	12.28084***	12.28076***
	(0.00208)	(0.00208)	(0.00223)	(0.00223)	(0.00327)	(0.00327)	(0.00259)	(0.00259)	(0.00576)	(0.00576)	(0.00467)	(0.00467)	(0.00283)	(0.00283)	(0.00313)	(0.00313)
Observations	203,803	203,803	203,803	203,803	239,628	239,628	239,628	239,628	51,174	51,174	51,174	51,174	180,668	180,668	180,668	180,668
R-squared	0.00534	0.00535	0.00092	0.00095	0.04143	0.04187	0.00524	0.00655	0.01770	0.01760	0.00135	0.00161	0.00256	0.00253	0.00018	0.00015
Number of individuals	41,242	41,242	41,242	41,242	48,744	48,744	48,744	48,744	10,411	10,411	10,411	10,411	36,780	36,780	36,780	36,780
Individual (experimental) FEs	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
1 SD of l1.drugs /l1.patents	6.979301	151.1118	6.979301	151.1118	4.219155	62.80019	4.219155	62.80019	3.368879	256.7495	3.368879	256.7495	1.482522	588.1559	1.482522	588.1559
1 SD x effect x 100%	4.18%	4.38%	2.68%	2.27%	19.71%	21.35%	21.53%	24.68%	4.36%	3.59%	8.00%	9.24%	1.76%	1.18%	4.66%	5.88%
1 SD combined effect x 100%		8.56%		4.95%		41.06%		46.22%		7.95%		17.24%		2.93%		10.55%
1 SD combined SE x 100%		1.50%		1.68%		2.49%		2.24%		4.07%		3.51%		1.89%		2.41%
CI lower 95%		5.63%		1.65%		36.18%		41.83%		-0.03%		10.36%		-0.77%		5.82%
CI higher 95		11.50%		8.25%		45.95%		50.60%		15.94%		24.12%		6.63%		15.27%

Table G1 Cont'd

	Schizophrenia, schizotypal and delusional disorders				Mood (affective) disorders				Infectious arthropathies				Arthrosis and systemic connective tissue disorders			
	ihs family income		ihs own income		ihs family income		ihs own income		ihs family income		ihs own income		ihs family income		ihs own income	
post	0.02376	0.01130	0.30430**	0.09945***	-0.01460	-0.00769	0.01977	0.12035**	0.03724	0.04659	-0.13650	-0.10006	0.02222	0.03795***	0.14464***	0.12032***
	(0.10539)	(0.02691)	(0.14292)	(0.03771)	(0.01670)	(0.02129)	(0.02788)	(0.04771)	(0.05918)	(0.03020)	(0.11820)	(0.08717)	(0.01403)	(0.00861)	(0.02884)	(0.01822)
post x l1.drugs	-0.00130		-0.01357**		0.00102		0.00077		0.00188		0.01324*		0.00188***		-0.00296**	
	(0.00492)		(0.00661)		(0.00064)		(0.00092)		(0.00413)		(0.00795)		(0.00061)		(0.00123)	
DD$_{idst}$	0.04311	-0.03087	-0.09061	0.06521	-0.19044***	-0.16666***	-0.04630	-0.04939	-0.30809**	-0.12525	0.06718	0.09560	-0.03729	-0.03862**	0.05119	0.03274
	(0.17341)	(0.04611)	(0.21644)	(0.05779)	(0.03639)	(0.05302)	(0.04136)	(0.07567)	(0.13028)	(0.08058)	(0.17175)	(0.11875)	(0.02545)	(0.01576)	(0.04378)	(0.02780)
DD$_{idst}$ x l1.drugs	-0.00457		0.00946		0.00076		0.00201		0.01929**		-0.00441		-0.00027		-0.00191	
	(0.00801)		(0.00999)		(0.00122)		(0.00132)		(0.00873)		(0.01180)		(0.00107)		(0.00183)	
post x l1.patents		-0.00022		-0.00128**		0.00011		-0.00039*		0.00124		0.01087*		0.00009***		-0.00014***
		(0.00037)		(0.00051)		(0.00012)		(0.00023)		(0.00201)		(0.00591)		(0.00003)		(0.00005)
DD$_{idst}$ x l1.patents		-0.00036		0.00071		-0.00001		0.00031		0.00669		-0.00648		-0.00002		-0.00008
		(0.00062)		(0.00077)		(0.00026)		(0.00036)		(0.00525)		(0.00789)		(0.00005)		(0.00008)
Constant	12.53303***	12.53302***	12.09120***	12.09117***	13.06065***	13.06065***	12.44551***	12.44545***	13.22154***	13.22155***	12.61755***	12.61759***	13.23313***	13.23313***	12.54123***	12.54122***
	(0.00419)	(0.00419)	(0.00484)	(0.00484)	(0.00313)	(0.00313)	(0.00344)	(0.00344)	(0.00498)	(0.00499)	(0.00663)	(0.00663)	(0.00145)	(0.00145)	(0.00241)	(0.00241)
Observations	63,263	63,263	63,263	63,263	94,131	94,131	94,131	94,131	17,837	17,837	17,837	17,837	157,521	157,521	157,521	157,521
R-squared	0.00068	0.00072	0.00189	0.00198	0.00478	0.00465	0.00084	0.00071	0.00344	0.00245	0.00144	0.00150	0.00235	0.00237	0.00256	0.00259
Number of individuals	12,942	12,942	12,942	12,942	19,097	19,097	19,097	19,097	3,620	3,620	3,620	3,620	31,807	31,807	31,807	31,807
Individual (experimental) FEs	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
1 SD of l1.drugs /l1.patents	2.769833	34.78858	2.769833	34.78858	13.16524	57.06547	13.16524	57.06547	2.857023	4.200988	2.857023	4.200988	6.870148	159.2471	6.870148	159.2471
1 SD x effect x 100%	-1.27%	-1.25%	2.62%	2.47%	1.00%	-0.06%	2.65%	1.77%	5.51%	2.81%	-1.26%	-2.72%	-0.19%	-0.32%	-1.31%	-1.27%
1 SD combined effect x 100%		-2.52%		5.09%		0.94%		4.42%		8.32%		-3.98%		-0.50%		-2.59%
1 SD combined SE x 100%		3.09%		3.85%		2.19%		2.69%		3.33%		4.73%		1.08%		1.79%
CI lower 95%		-8.58%		-2.46%		-3.34%		-0.86%		1.80%		-13.25%		-2.63%		-6.09%
CI higher 95		3.55%		12.64%		5.23%		9.69%		14.85%		5.28%		1.62%		0.92%

Table G1 Cont'd

	Deforming dorsopathies, osteopathies and chondropathies				Diseases of male genital organs				Diseases of female pelvic organs				HIV			
	ihs family income		ihs own income		ihs family income		ihs own income		ihs family income		ihs own income		ihs family income		ihs own income	
post	0.01489**	0.02733***	0.05227***	0.06954***	0.02290	0.03493***	0.05909***	0.05876***	0.03497	0.04533***	0.04986	0.05712*	-0.43324	-0.70974	-0.37795	-0.64686
	(0.00624)	(0.00538)	(0.01030)	(0.00920)	(0.01461)	(0.00982)	(0.01963)	(0.01301)	(0.02276)	(0.01562)	(0.04365)	(0.03001)	(0.54844)	(0.84106)	(0.53885)	(0.83108)
post x l1.drugs	0.00145***		0.00032		0.00180		-0.00032		0.00098		0.00036		0.04497		0.04139	
	(0.00024)		(0.00039)		(0.00134)		(0.00175)		(0.00061)		(0.00115)		(0.04697)		(0.04657)	
DD_{idst}	-0.02875***	-0.02901***	0.01480	0.00975	-0.00593	-0.01540	0.00805	-0.00183	-0.04409	-0.03012	-0.00024	0.00471	-3.63504	-3.29495	0.44015	0.84992
	(0.01010)	(0.00883)	(0.01443)	(0.01293)	(0.02255)	(0.01580)	(0.02945)	(0.01971)	(0.03400)	(0.02337)	(0.05542)	(0.03810)	(2.95396)	(3.66706)	(0.64624)	(0.95363)
DD_{idst} x l1.drugs	-0.00041		-0.00080		-0.00167		-0.00105		0.00073		-0.00025		0.02767		-0.05009	
	(0.00038)		(0.00055)		(0.00199)		(0.00268)		(0.00090)		(0.00146)		(0.16659)		(0.05068)	
post x l1.patents		0.00002***		-0.00001		0.00008		-0.00003		0.00005*		0.00001		0.00447		0.00418
		(0.00000)		(0.00001)		(0.00009)		(0.00011)		(0.00003)		(0.00006)		(0.00469)		(0.00466)
DD_{idst} x l1.patents		-0.00001		-0.00001		-0.00009		-0.00002		0.00003		-0.00003		0.00043		-0.00545
		(0.00001)		(0.00001)		(0.00014)		(0.00018)		(0.00004)		(0.00007)		(0.01536)		(0.00503)
Constant	13.18272***	13.18272***	12.56455***	12.56454***	13.14229***	13.14228***	12.67301***	12.67301***	13.31162***	13.31162***	12.56104***	12.56104***	12.40196***	12.40215***	12.22417***	12.22419***
	(0.00090)	(0.00090)	(0.00130)	(0.00130)	(0.00195)	(0.00195)	(0.00250)	(0.00250)	(0.00107)	(0.00107)	(0.00187)	(0.00187)	(0.17507)	(0.17512)	(0.04956)	(0.04932)
Observations	466,576	466,576	466,576	466,576	101,713	101,713	101,713	101,713	222,832	222,832	222,832	222,832	255	255	255	255
R-squared	0.00143	0.00134	0.00122	0.00125	0.00097	0.00095	0.00118	0.00117	0.00513	0.00513	0.00141	0.00141	0.19866	0.19697	0.03443	0.03812
Number of individuals	94,244	94,244	94,244	94,244	20,595	20,595	20,595	20,595	44,790	44,790	44,790	44,790	54	54	54	54
Individual (experimental) FEs	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
1 SD of l1.drugs /l1.patents	12.24771	803.7869	12.24771	803.7869	5.271199	79.13483	5.271199	79.13483	5.978831	125.1056	5.978831	125.1056	2.730056	7.438911	2.730056	7.438911
1 SD x effect x 100%	-0.50%	-0.80%	-0.98%	-0.80%	-0.88%	-0.71%	-0.55%	-0.16%	0.44%	0.38%	-0.15%	-0.38%	7.55%	0.32%	-13.67%	-4.05%
1 SD combined effect x 100%		-1.31%		-1.78%		-1.59%		-0.71%		0.81%		-0.52%		7.87%		-17.73%
1 SD combined SE x 100%		0.93%		1.05%		1.53%		2.01%		0.73%		1.24%		46.89%		14.33%
CI lower 95%		-3.13%		-3.84%		-4.58%		-4.64%		-0.63%		-2.95%		-84.04%		-45.82%
CI higher 95		0.51%		0.27%		1.40%		3.22%		2.25%		1.90%		99.78%		10.36%

Note: Models are estimated according to Eq.4. Robust standard errors clustered at individual (experimental) level are in parentheses.

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