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Who is responsible for your health: is it you, your doctor or the new technologies?

Vincenzo Atella[1] *and Francesco D'Amico*[1,2]

Abstract

The aim of the paper is to disentangle the roles that patients, physicians and technology can have on patient health outcomes. The analysis focuses on patients suffering from hypercholesterolemia. Using a large and detailed dataset of patients collected by the Italian College of General Practitioners (SIMG) over the period 2001–2006, we observe the existence of heterogeneity in the time needed to reach an optimal level of health stock. We firstly explore whether patients recovering faster exhibit lower hospitalization rates. Secondly, we study the determinants of the speed of recovery to a good health status. Results suggest that a 10 % increase in the speed of recovery reduces hospitalization rates by 1 % in the general sample and by 1.25 % in patients in primary prevention. Furthermore, we show that recovering to a good health status is a multifaceted phenomenon, with technology explaining from 54 to 68 % of the total effect.

1. Introduction

Patient health outcomes are complex phenomena and disentangling empirically their determinants is an ever more complex task arising from the interplays of three important factors: the patient, the physician and the available technologies. In fact, a valid diagnosis from a physician will not have the hoped for effect if effective treatments are not available. Similarly, the availability of effective treatments would not lead to a health improvement if physicians do not properly match diseases and treatments. Finally, patients should be compliant to physician recommendations in order to reach a good health outcome. Despite its importance from a policy perspective, no study to our knowledge has ever tried to disentangle and empirically measure the different roles that these actors jointly play on health outcomes.

In our view, what has prevented researchers to succeed in this task is the lack of a sufficient level of clinical and socio-demographic details when using "micro" data, even for those studies that adopt a disease-specific approach [1-3]. Furthermore, objective measures of health outcomes are needed. Finally, to be informative, the analyses should be conducted at population, or on samples representative of the population (such as those used in clinical trials). Clearly, this is a highly data demanding approach, requiring information on patient health profiles at the beginning of the observation period (initial conditions), on the treatments, on the events to which they have been exposed over time, and on the physician treatment strategies. Ideally, this implies adopting an investigation strategy similar to that used in randomized clinical trials, but extended to the population.

We try to fill this gap by disentangling and measuring the contribution that each of the above mentioned factors can have on the health outcomes of a large representative population of Italian patients suffering from hypercholesterolemia and treated with statins. While this research focuses on a particular health condition, the model we introduce in the following sections has the potential to be adapted to study other health problems and diseases for which there exists a measurable health target.

We decided to focus on hypercholesterolemia because it represents a particularly interesting condition to analyze, for at least three reasons. Firstly, over the last 10

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years there has been a growing public concern about high levels of cholesterol in the population that may have changed patient awareness about the problem, influencing their behavior (mainly through changes in compliance rates) over time. Secondly, although over the last 20 years the entire drug industry has witnessed a substantial technical advancement, statins represent a class of drugs which has shown a substantial improvement over time in its efficacy to lower cholesterol. Last but not least, new guidelines to treat cholesterol have been introduced in recent years, challenging doctors to continuously adapt their patient management strategies to the new evidence based medicine.

Compared to previous literature, we then further innovate by addressing a different and more important question for patient health status. Instead of exploring the determinants of patient health stock [4-8], we focus on the "time needed" to recover to an optimal level of health and on its determinants. Providing evidence on this issue has important policy implications beyond the specific case under investigation, given that a longer patient exposure to adverse health shocks (i.e., high levels of cholesterol) may results in future negative health outcomes, such as hospitalization, invalidity and death. Therefore, we will firstly explore whether patients with a faster recovery (i.e., lower exposure to high cholesterol levels) exhibit lower hospitalization rates for Cardio-Vascular Diseases (CVDs). Then, we will analyze the determinants of their speed of recovery.

The analysis is based on the Health Search Database [9], which is collected by GPs on a large sample of the Italian population. Unlike standard registry datasets, these data provide information on a richer set of patient characteristics that allows us to disentangle the beneficial effects of new technologies (more effective drugs) from *i)* patient compliance to medication, *ii)* physicians' ability to manage the disease ("process" innovation) and *iii)* standard confounding problems deriving from a patient's past clinical history.

The paper is organized into six sections. Section two presents some stylized facts about cholesterol trends. Section three introduces the methodology used to define and construct our objective health status indicator. Section four presents the data, the sample selection process and the steps followed to construct the variables of interest. Section five shows the main results and discusses the policy implications. In particular, we provide quantitative evidence on how the speed of recovery can affect hospitalization rates for CVDs and then we measure the role of each single factor on the speed of recovery. Finally, conclusions are drawn in section six.

2. Cholesterol trends and the role of statins: Some stylized facts and a puzzle.

Panel A in Figure 1 reports the trends in "Total" and "Low-Density Lipoprotein" (LDL) cholesterol levels for the patients included in Health Search, a nationally representative database managed by the Society of the Italian College of General Practitioners (SIMG). As we can see, both measures of cholesterol levels are decreasing. Furthermore, in panel B we observe the cholesterol level distributions over time, which show a movement toward the left (a reduction in average levels) as well as a shrinking of the distribution shape. This second aspect is important as it proves that in Italy not only the LDL average, but also its variability is reducing.

A more interesting phenomenon that emerges from these data is reported in Table 1 and in Figure 2, where LDL cholesterol level trends are split by patient cohorts according to their initial year of treatment. A number of interesting results emerge from the table:

1. The average starting level of LDL lowers across cohorts (Table 1, Panel

A). This is consistent with the update of cholesterol guidelines in Italy over time, progressively including patients with lower blood lipid levels in the treatment protocol, thus moving toward a more preventive approach to dyslipidemia;
2. The speed at which cholesterol levels reduce over time has increased (Table 1, Panel B);
3. Patients who started the therapy earlier are likely to converge to a "higher" level of cholesterol over a "longer" period of time. This phenomenon appears regularly throughout all cohorts in our sample (all trajectories intersect);
4. On average, older cohorts do not reach the LDL cholesterol target of 120 mg/dl.

While the first two results can be easily understood based on changes in guidelines over time, the last two results are somehow counter-intuitive, since we would expect that longer treatment periods would be conducive to better health outcomes. A possible explanation is that new and more effective chemical compounds (the so called "second-generation statins") have been marketed and prescribed in Italy over the period of our investigation, reducing cholesterol levels. Furthermore, the introduction in 2004 of larger pack-sizes (28-30 vs. 14 tablets per package), may have affected patient behavior by improving adherence to the treatment, thus leading to better cholesterol management. However, these two factors alone can hardly explain the different cohort patterns reported in Table 1-Panel B, given that new active ingredients and larger pack-sizes are supposed to be available to all patients, irrespective of the cohort to which they belong.

In our view, a plausible explanation for such cholesterol reduction patterns across cohorts may be found in physician behaviors in treating cholesterol. We believe that GPs who see their patients responding well to an existing therapy, could decide not to update it even when new protocols are available or newer compounds are introduced. If this was the case, it could be motivated by prudential attitudes, aimed to avoid any potential side-effects as a consequence of the adoption of newer drugs or of higher dosages. Symmetrically "newcomer" patients are more likely to be treated with the most recent drugs, in absence of a past treatment.

Under these assumptions, the presence of technical change (both in terms of process and products) could then contribute to create a gap in health outcomes for earlier and longer-lasting treated patients compared to "newcomer" patients.

3. The definition and measurement of the health indicator.

In this section we define our indicator of objective health status. One of the implications of the Grossman model [10] is that health is an inherited durable capital stock that depreciates over time. Therefore, investment in health can be seen as an activity where medical care is combined with other inputs in order to produce new health to partly counteract the natural deterioration of the health shocks. Thus, the demand for health care can be considered as a derived demand for goods and services to preserve the inherited stock of health $(HS_{i,t})$ and/or to further achieve a desired stock of health $(HS^{*}_{i,t})$. Following Grossman, the i-*th* patient's health status at time *t* can be represented by a partial adjustment model:

$$HS_{i,t} = HS_{i,t-1} + \lambda\,(HS^{*}_{i,t} - HS_{i,t-1}) - \delta_i HS_{i,t-1} \qquad (1)$$

where $\delta_i > 0$ is the health stock depreciation rate and $0 \leq \lambda_t \leq 1$ represents the "speed" at which individuals are able to achieve their target value. If patients reach their goal in one period then $\lambda=1$, while if their health status remains unchanged or even reduces, then $\lambda=0$ or it becomes negative.

In the empirical literature λ has always been considered as an "average" parameter to be estimated. Our aim in this research is to look at λ as a measurable variable and then to further understand its determinants. In order to achieve this goal, we make two simplifying assumptions that, without loss of generality, help designing the empirical procedure. We assume that health status for hypercholesterolemic patients is function of the LDL level alone ($HS_{i,t} = f(LDL_{i,t})$), with the first derivative being negative (i.e. $\partial HS_{i,t} / \partial LDL_{i,t} < 0$).

Based on these two assumptions, eq. (1) can be rewritten as:

$$f(LDL_{i,t}) = f(LDL_{i,t-1}) + \lambda[f(LDL^*_i) - f(LDL_{i,t-1})] - \delta_i f(LDL_{i,t-1}) \qquad (2)$$

with

$$LDL^*_i = f(r_i) \qquad (3)$$

The optimal level of LDL cholesterol (LDL^*_i) is patient specific, time-independent and is function of the individual cardiovascular risk-index (r_i).[3]

In order to derive an analytical formulation of λ, we solve the equation (2) to obtain:

$$\lambda_{i,t} = [\Delta f(LDL_{i,t}) + \delta_i f(LDL_{i,t-1})] / \Delta f(LDL^*_{i,t}) =$$

$$= \Delta' f(LDL_{i,t}) / \Delta f(LDL^*_{i,t}) \qquad (4)$$

where $\Delta f(LDL_{i,t}) = f(LDL_{i,t}) - f(LDL_{i,t-1})$ represents the difference between the current and the previous health status and $\Delta f(LDL^*_{i,t}) = f(LDL^*_{i,t}) - f(LDL_{i,t-1})$ is the health gap that still needs to be recovered at time t through medical treatment and healthy behaviors. From an empirical point of view the term $\Delta' f(LDL_{i,t})$ represents the absolute variation in the health stock expressed as a function of the LDL level.

The definition of $\lambda_{i,t}$ which stems from eq. (4) has an appealing clinical interpretation. In fact, although researchers cannot usually observe the single components that characterize the numerator in eq. (4), they can be interpreted as patient "good behavior" ($\Delta f(LDL_{i,t})$) and "bad behavior" ($\delta_i f(LDL_{i,t-1})$) in achieving the therapeutic goals. This interpretation can be better understood by looking at the graph in figure 3, where we observe two different hypothetical paths of LDL cholesterol towards the target (LDL^*). The blue line represents the behavior of a patient whose net investment is characterized only by "good behavior", while the black line represents the behavior of a patient who alternates periods of "good behavior" with periods of "bad behavior" (identified by those periods in which $\Delta LDL_{i,t} > 0$ and therefore $\Delta HS_{i,t} = HS_{i,t} - HS_{i,t-1} = \Delta f(LDL_{i,t}) \leq 0$). It is clear that the speed at which the first patient reaches

[3] The cardiovascular risk index represents the individual predicted risk at time t to incur in a CVD during the following 10 years on the basis of the assessed current health and life-style profile [10]. This index summarizes various patient characteristics including age, gender, smoking habits, clinical conditions, genetic factors and any previous experiences of CVD events.

the target is greater than the speed of the second patient.[4] In particular, individuals who diverge from full health will present a negative value of λ, while individuals who converge will show a positive value. For instance, let's assume that Patient A's optimal LDL level is 120 mg/dl and that their level at t-1 is 200 mg/dl. Let's also assume that Patient A's LDL level reduces to 180 mg/dl at time t. In this case, their λ value attained would be equal to (200-180)/(200-120)=0.25. The same formula would apply also if their LDL increases, leading however to a negative value of λ.

In this model we assume that $HS_{i,t}=f(LDL_{i,t})=1/LDL_{i,t}$, as it represents a simple functional form that produces an inverse relation between health and LDL. However, other functional specifications are equally suitable (e.g. $HS_{i,t} = -LDL_{i,t}$). In the empirical analysis we have run sensitivity tests using different specifications of the functional relationship and found that alternative functional forms do not alter our final results.

4. Data and descriptive statistics.

Our empirical analysis is based on data collected in the Health Search Database (HSD), a longitudinal observational database run by the Italian College of General Practitioners (SIMG – Società Italiana di Medicina Generale) since 1998. The HSD contains data from computer-based patient records from General Practitioners (GPs) throughout Italy. Participation is on a voluntary base, although the distribution of GPs tends to replicate the regional organization of the NHS [9].

Patient data are linked through a unique anonymous identifier to drug prescriptions, clinical events and diagnoses, hospital admissions and causes of death. It contains patient-level information on prescriptions such as dispensing date, drug information and the general practitioner recommended dosage (GPRD). It also includes hospitalization status by primary Diagnosis Related Groups, information on patients' clinical histories, on co-payment exemptions and a set of socio-demographic indicators.

Up to December 31st 2006, the dataset contained information collected by 796 GPs for a total of 1,532,357 patients. Our analysis is based on information gathered by those 400 GPs who guaranteed a high data quality according to a specific algorithm developed by the Health Search team [9, 13]. This algorithm selects GPs on the basis of their capacity to provide completeness of information in terms of patient clinical and vital characteristics (for instance smoking status, height, weight) and in terms of diagnostic tests results, diagnoses and other medical conditions.

From this sample we have extracted patient identifiers using two main inclusion criteria:

i) age between 39 and 70 at the time of their first appearance in the HSD (people using statins before their forties are often receiving them for reason other than hypercholesterolemia).

ii) received a prescription of statins at any point over the 2001-2006 period.

These criteria have produced a sub-sample of 42,140 patients. We have then dropped observations on the first quarter of 2001 (to avoid the risk of including non-incident patients) and those patients who started the treatment only in 2006 as their follow-up time would have been less than one year.

The original GP registry information has then been collapsed into quarterly statistics. The use of quarters as time unit seems reasonable in order to minimize the

[4] See Atella and D'Amico 2010 [12] for a more articulated discussion on the interpretation of Equation 4, reconciling the economic and the clinical perspective.

number of zero occurrences in drug consumption and to preserve the dynamic aspect of the model. More importantly, clinical evidence shows how statins may produce most of their effects simply after one quarter of use.

The final sample is a quarterly panel of individuals observed over the period 2002-2006. This dataset is balanced in terms of GPs (400), but unbalanced in terms of patients (4,290 patients, for a total of 21,188 observations). We compute the optimal LDL value for each patient as function of the individual's cardio-vascular risk ($r_{i,t}$) according to eq. 3. We define three different risk categories: low risk ($0\% \leq r_{i,t} \leq 5\%$ and no past CVD events), medium risk ($5\% \leq r_{i,t} \leq 10\%$ and no past CVD events) and high risk ($r_{i,t} > 10\%$, which includes all the individuals with any past CVD event)[5]. According to international guidelines, LDL needs to be lower than 120 mg/dl for low-risk patients, below 100 mg/dl for medium-risk patients, and under the level of 80 mg/dl for high-risk patients.

Table 2 reports the descriptive statistics. As we can see, the average value of $\lambda_{i,t}$ over the whole period is just above 0.1, meaning that patients take almost 10 quarters on average to reach the LDL* target.

The sample is balanced in terms of gender with more than 70% of the individuals over 60 years old. Atorvastatin and Simvastatin determine more than 60% of the prescriptions, the average daily dosage prescribed being close to 27 mg. About 60% of the patients suffer from hypertension and 29% have diabetes. 9% are in secondary prevention, meaning that they have experienced at least one CVD in the past, as opposed to primary prevention, when the individual has not experienced any CVD related event. Most of our sample is made up of patients who started treatment in 2002. Treatment starting year for our purposes defines as a "cohort".

Table 3 shows descriptive statistics by cohort of treatment. Speed of recovery (λ) has sharply and monotonically increased by starting year, with the 2002 cohort recording the lowest value (11% or about 10 quarters) and the 2005 cohort reporting the highest value (38% or about 2.5 quarters).

5. Empirical results.

5.1 – The effect of the speed of recovery on hospitalization rates.

In this section we explore whether the speed of recovery (λ) has any impact on the CVD hospitalization probability by using a probit model. From a methodological perspective, we examine the probability of hospitalization over a two-year period starting from the first appearance of the patient in the dataset. A two-year time window is adequate as it allows us to observe a uniform time period for all cohorts, including patients who started treatment in 2005. We include in this analysis only those patients for whom a full set of information was available for at least two consecutive years since their first appearance. The final sample consists of 3,316 observations. We consider a two-year period an effective compromise: a longer span would have reduced too much the sample, while a smaller span would have been able only to find short-term effects, therefore not capturing effects on CVD hospitalization, that are thought to happen in the medium and long-term.

The Probit model adopts hospitalization as a dependent variable and speed of recovery (λ) plus a set of socio-economic and health characteristics as control variables. Between dependent variable and covariates there exists a one-year lag, to ensure that medium and long-term effects on hospitalization are captured. We repeat

[5] Individual cardiovascular risks indicators are computed according to the algorithm included in [11].

this analysis for the subset of patients in primary prevention in order to understand the impact on individuals who are using statins as a preventative therapy.

Results of these analyses are reported in Table 4. Looking at the elasticity column, we observe that a 10% increase in the speed of recovery ($\lambda_{i,t}$) is able to reduce the hospitalization rate by 1%. Less significant results are found in the other control variables, there being a small gender effect (men are slightly more likely to go to the hospital) but no significant geographical effects. As expected, patients in secondary prevention were more likely to be hospitalized. When looking at the primary prevention subset, we find slightly stronger and more significant results for hospitalization reduction (the elasticity effect being above 1.2%) with the other coefficients being similar to the previous specification, although gender and hypertension lose their significance. This finding is particularly important as it refers to a class of patients that could avoid or see delayed hospitalizations for CVDs, reducing social costs and financial costs for the NHS.

Based on these results, and given that the number of CVD-related admissions in Italy was about 1.2 million in 2006 [14], it then follows that the number of hospitalisations that could be saved following a minimum of 10% increase in λ would range between 12,000 and 15,000 cases per annum. Obviously, if we could double the value of λ (corresponding to a 100% increase),we could then save hospitalizations in a range of 120,000-150,000 per year, with a huge impact also on the health expenditure side.

5.2 The determinants of the speed of recovery

5.2.1. The empirical model

In order to analyze the determinants of the speed of recovery (λ) and to disentangle the specific role played by patients, physicians and technical innovation, we define the following empirical model where our dependent variable is regressed over a set of covariates:

$$\lambda_{i,t} = \varphi(LDL_{i,t-1}, HP_{i,t}, LS_{i,t}, SEC_{i,t}, TR_{i,j,t}, t_t, c_i) + \varepsilon_{i,t} \qquad (5)$$

where the lagged cholesterol level, $LDL_{i,t-1,}$ may help capturing faster convergence rates for cases with higher LDL level; $HP_{i,t}$ is a vector of variables defining the patient health profile; $LS_{i,t}$ is a vector of variables that refers to patient lifestyle; $SEC_{i,t}$ is a vector of patient demographic and socio-economic characteristics; $TR_{i,j,t}$ refers to the *j-th* active ingredient taken by the *i-th* patient; t_t is a time trend to capture improvements in the speed of recovery that are not otherwise captured by the other ariables; $c_{i,t}$ is a cohort dummy representing the year (cohort) in which patients have started the therapy with statins. Time and cohort variables represent residual effects, which are not captured by the other covariates and will capture doctors' input in terms of effort and ability, which is usually difficult to determine directly. Finally, $\varepsilon_{i,t}$ is a standard additive idiosyncratic error term normally distributed.

The first four variables in eq. (5) are intended to capture patient behaviour, while $TR_{i,j,t}$ and t_t account for exogenous technical change. Concerning patient health profiles, the $HP_{i,t}$ vector contains a dummy controlling for the presence of past CVD events (primary vs. secondary prevention) and additional dummy variables controlling for hypertension and diabetes. The vector $LS_{i,t}$ controls for smoking

behaviour, while the vector $SEC_{i,t}$ includes age, gender, region of residence and exemption typology. In this model we use a principal-agent framework, thus assuming that only physicians can decide what to prescribe and whether to switch patients to a new therapy; whereas patient decisions are limited to adhering or not to the proposed treatments and to adopt or not lifestyle advices. Patient decisions may be independent of the therapy suggested, but influenced by other individual-specific factors (i.e. economic variables such as disposable income $Yd_{i,t}$ and drug price p_t that negatively affect patient adherence to treatment).

5.2.2 Results

Results are presented in Table 5 and are based on different empirical specifications of the model in eq. (5). All estimates are based on a random-effects model with the addition of group-means of the independent variables, according to the Mundlak specification [15].This specification allows us to use random-effects in a context where we cannot assume that covariates and individual effects are uncorrelated. At the same time, we cannot use a fixed-effects specification because it would imply dropping some of the time-invariant variables that are essential for our model, i.e. the cohort dummies[6]. In our model, the reference patient is a male, aged below 50 years, living in the Centre (i.e. the central regions of Italy), treated with Fluvastatin, non-smoker, not exempt from prescription charges, with no co-morbidities and in primary prevention.

As expected, speed of recovery is positively related with patient lagged cholesterol level, $LDL_{i,t-2}$. A higher past cholesterol level is associated with a quicker reduction of the health gap. Looking at the role of technical progress in terms of "product" innovation our results show that "second generation" statins (i.e. Atorvastatin and Rosuvastatin) are found to be more effective than the alternatives. A smaller, but still significant role is played by Simvastatin, which belongs to the "first generation" group and still holds an important share of the Italian market (around 30% in 2005, the last available year of our data, Table 6).

The role played by "process" innovation is captured by the cohort dummies. These parameters show an increase in the speed of recovery by cohort. Cohort dummies can be thought as "residual effects*" à la Solow*, in a model where we control for a variety of factors linked to patients or to technology, such as for instance individual characteristics and typology of treatment. Interpreting these "residual effects" as doctors' exogenous contribution is therefore a consequence of the covariates included in the specification, being aware that we do not have a direct measure of their "ability to treat", an effect that, in general, is problematic to measure.

By looking at the distribution of statin prescriptions by cohort (Table 6), we observe how there exist systematic differences between people belonging to different cohorts, within a common year of the sample. For instance, in 2005 the 2001 cohort received Simvastatin in about 35% of cases, while the 2005 cohort, in the same year, received Simvastatin in only 28% of cases. More importantly, Rosuvastatin (the most innovative product at the time) was prescribed to 9.5% of the 2001 cohort, while the 2005 cohort received the same active ingredient in 20% of the cases. This shows a

[6] In the estimation phase, we have tried two specifications, one adding individual-means covariates with within-variance greater than 33% and the other controlling for mean variables with within-variance greater than 40%, in order to avoid multi-collinearity problems. Results are consistent between the two specifications, but we decided to use the one with a 33% bar as it is less restrictive. Estimates have been produced using the command `mundlak` in STATA.

certain degree of conservativeness from doctors in treating patients who started the treatment with statins earlier, as they are kept using older generation and less effective statins. On the other side, later cohorts would be expected to receive a boost in terms of lowering LDL levels as they are using, on average, more advanced drugs.

Looking at patient behaviour, we see that persistence to the treatment is found to be consistently significant. We also find a strong positive association between speed of recovery and being in secondary prevention. It seems that patients who have experienced a serious cardiovascular event or are experiencing co-morbidities are, understandably, more careful, thus showing a faster recovery. Finally, a less significant but still positive association is found between speed of recovery and being hypertensive.

The impact of smoking on the speed of recovery is found to be negative but not significant. The sign direction is as expected, while the non-significance could be due to an extremely low rate of smokers in the sample.

The alternative specifications seem to confirm the results so far described. In model 2 we included as a further control the prescribed daily dosage (in terms of milligrams of active ingredient), in order to separate the compound effect from the dosage effect. This aspect is not entirely trivial, as physicians can use an older statin with an increased dosage, potentially getting the same effect of a newer compound at a reduced dosage. The results from this specification provide additional evidence of the positive effect that a higher dosage has on the speed of recovery. Looking at the active ingredient indicators, we observe that the "hierarchy" between the compounds' effectiveness remains unchanged and it is fairly stable in terms of proportions.

In model 3 we added the interaction terms between active ingredient and daily dosage. In this case the daily dosage loses part of its significance, while the size of the coefficient is almost unaltered, although Simvastatin loses its significance.

In model 4 we added the interactions between the cohort dummies and a linear time trend, introducing a set of parameters that could help replicate the patterns found in figure 2. For each cohort, each interaction term can be seen as a differential effect on the speed of recovery with respect to the treatment starting year. According to this interpretation, the sign and magnitude of all interaction parameters seem to replicate correctly the patterns of the unconditional means reported in Table 1 and Figure 2. In particular, the interactions for the 2002 and 2003 cohorts suggest an increasing trend, which make them benefit from having an additional effect with respect to the cohort standard effect. With regards to the 2004 cohort, such an increasing trend does not appear, but both cohort and interactions are significant at 1%. An exception is represented by the 2005 cohort, whose only time interaction variable is found to be high in magnitude but not significant.

As a robustness check, we have investigated the role of attrition in our sample and how it affects our estimates by re-weighting the observations according to their drop-out probability [16]. Overall, we found that our results are not affected by attrition (the estimates are available upon request to the authors).

5.3 – Who is responsible for your health? A quantitative assessment

We are now in a position to provide an answer to our initial question: who is responsible for your health. In order to achieve this goal we calculate the impact of the three factors (patients, doctors or technology) over the predicted values of lambda, the speed of recovery.

The role of patients is approximated using the persistency variable; the role of

doctors is captured by the cohort dummy parameters, while medical technology impact is represented by the active ingredient dummies.

Results of this accounting exercise are presented in Table 7. In the first specification, where we are not controlling for the drug dosage, medical behaviour present a greater impact than technology (around 49% vs. 38%), while the role of patients appears to be minor. After controlling for drug dosages in specification 2 and 3, technology becomes by far the most important factor.

This result is also confirmed in the last two specifications, when interactions between cohorts and the time-trend are added. The effect of technology ranges between 54% and 68%. The role of doctors appears to be greater than the role of patients in all the specifications considered.

As a further check, separate computations of the effects for men and women (not reported here) have shown that gender issues do not significantly affect the relative importance of the three factors.

Our findings suggest that the use of drugs is the only effect, which prevails steadily. This is not surprising, as doctors and patients effort is to be thought as conditioned on the available pharmacological therapies. However, our estimates seem to prove that technology explains just above two-thirds (at best 68%) of the speed of recovery to a better health status, with its efficacy mediated by physician and, to a lesser extent, patient behaviours.

6. Conclusion

Focusing on patients suffering from hypercholesterolemia and treated with statin-based drugs, in this work we have analysed the determinants of a better health status, trying to disentangle the roles played by patients, physicians and technology, and how a faster recovery is reflected in terms of reduction in hospitalization rates. Our results show that the speed of recovery is capable of reducing future hospitalization rates: better-treated patients experience lower hospitalization rates for CVDs (from 1% for the general sample to more than 1.2% for patients in primary prevention).

More importantly, we found that treatments with newer drugs, even after controlling for dosage, leads to a faster recovery to better health conditions. However, this effect could be seriously undermined if patients are not persistent in the treatment. Finally, there is a suggestion that a reduced prescription of newer drugs from GPs to longer-lasting treated patients may have a role in their slower recovery. In this respect, we found some evidence of a certain degree of conservativeness in GPs, who tended to persist in the use of older statins for the long-term treated group.

From an accounting exercise, we observe that technology, although being the driving factor in increasing the speed of recovery, can explain at best 68% of the total effect, which reduces to 54% in the richer specification.

In conclusion, the evidence obtained from this work sheds light on the importance of technical progress (both in terms of product and process innovation) for a full and faster health recovery for patients suffering from hypercholesterolemia, which could be even more effective if this technical advancement was made immediately available to all patients.

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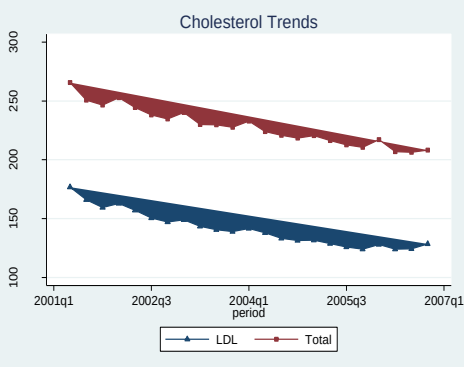
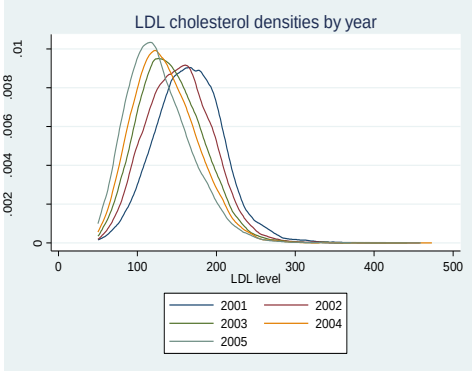
Figure 1
Trends and distributions of cholesterol levels in the Health Search population

Panel A	*Panel B*
	

Source: Our calculation, based on HSD data.

Figure 2
Mean LDL cholesterol by cohort

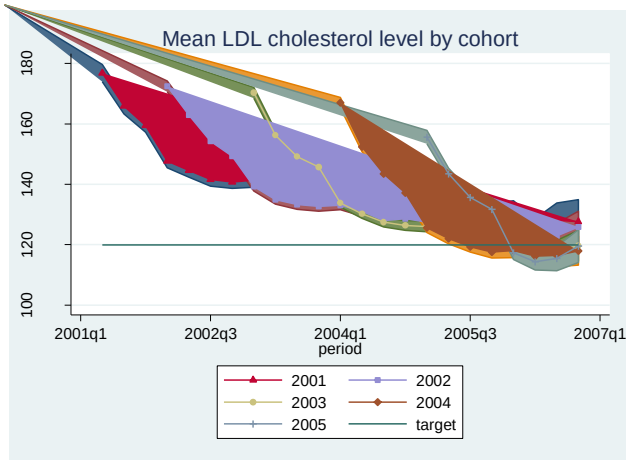


Figure 3
Possible patterns of cholesterol trends

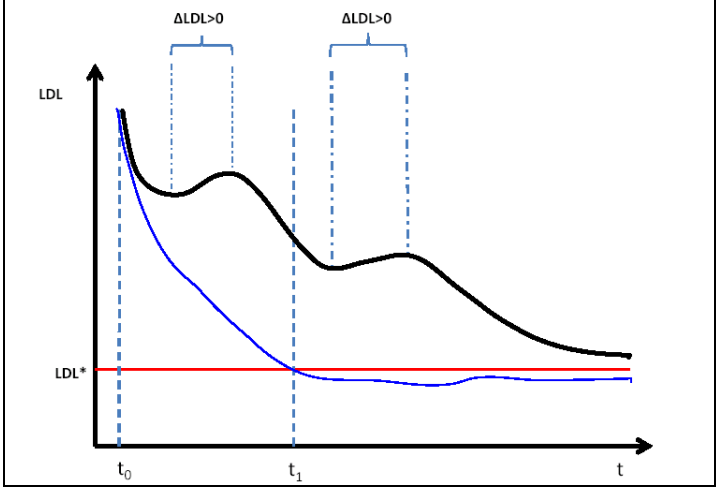


Table 1 – LDL statistics by cohort

Panel A
Average LDL levels by year

Year	**Cohort**				
	2001	2002	2003	2004	2005
2001	162.6	-	-	-	-
2002	139.3	153.2	-	-	-
2003	134.9	130.6	148.2	-	-
2004	132.0	126.3	125.4	143.2	-
2005	128.0	123.0	120.4	118.3	136.2
2006	127.0	123.6	118.7	114.4	114.6

Panel B
Changes in average LDL levels by year

Year	**Cohort**				
	2001	2002	2001	2004	2001
2001	-	-	-	-	-
2002	-14.3%	-	-	-	-
2003	-3.1%	-14.8%	-	-	-
2004	-2.2%	-3.3%	-15.4%	-	-
2005	-3.0%	-2.6%	-4.0%	-17.4%	-
2006	-0.8%	0.5%	-1.4%	-3.3%	-15.9%
Average %	-4,7%	-5,0%	-6,9%	-10,4%	-15,9%

Table 2 - Descriptive statistics for the full sample					
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
λ	21188	0.131	0.642	-3.6	4.0
Log LDL (t-2)	21188	4.972	0.244	4.0	6.1
Male	21188	0.509	0.500	0	1
Age Class 39-50	21188	0.049	0.215	0	1
Age Class 50-60	21188	0.230	0.421	0	1
Age Class 60-70	21188	0.484	0.500	0	1
Age Class 70+	21188	0.237	0.425	0	1
North-West	21188	0.247	0.431	0	1
North-East	21188	0.260	0.439	0	1
Centre	21188	0.147	0.354	0	1
South	21188	0.235	0.424	0	1
Islands	21188	0.112	0.315	0	1
Simvastatin	21188	0.319	0.466	0	1
Pravastatin	21188	0.164	0.370	0	1
Fluvastatin	21188	0.119	0.323	0	1
Atorvastatin	21188	0.310	0.463	0	1
Rosuvastatin	21188	0.088	0.284	0	1
Hypertensive	21188	0.594	0.491	0	1
Diabetes	21188	0.287	0.452	0	1
Secondary prevention	21188	0.094	0.291	0	1
Persistent	21188	0.702	0.457	0	1
Cohort 2001	21188	0.175	0.380	0	1
Cohort 2002	21188	0.410	0.492	0	1
Cohort 2003	21188	0.250	0.433	0	1
Cohort 2004	21188	0.135	0.342	0	1
Cohort 2005	21188	0.030	0.171	0	1
Smoker	21188	0.017	0.130	0	1
Drug milligrams	21188	27.449	20.088	0	1
Exemption: Age	21188	0.279	0.449	0	1
Exemption: CVD	21188	0.100	0.300	0	1
Exemption: Invalidity	21188	0.059	0.236	0	1
Exemption: Income	21188	0.048	0.213	0	1
Doctor is a female	21188	0.119	0.324	0	1
Doctor's age	21188	50.711	4.035	35	67
Year 2002	21188	0.084	0.277	0	1
Year 2003	21188	0.229	0.420	0	1
Year 2004	21188	0.309	0.462	0	1
Year 2005	21188	0.284	0.451	0	1
Year 2006	21188	0.094	0.291	0	1

Table 3 - Sample means by cohort for the full sample

Variable	Cohort				
	2001	**2002**	**2003**	**2004**	**2005**
λ	0.113	0.207	0.219	0.360	0.384
Initial LDL	166.0	170.1	170.4	167.6	161.8
Target LDL	102.0	102.2	101.1	99.1	98.5
LDL (t-1)	149.5	149.3	146.9	145.2	145.9
LDL (t-2)	150.6	152.5	152.1	153.0	156.0
Hospitalized	0.008	0.012	0.008	0.012	0.015
Patients reaching target	0.063	0.101	0.110	0.160	0.155
Male	0.483	0.468	0.473	0.512	0.507
Age	63.4	62.9	63.1	63.3	62.7
North-West	0.255	0.251	0.233	0.233	0.209
North-East	0.238	0.239	0.247	0.245	0.233
Centre	0.203	0.128	0.137	0.154	0.139
South	0.179	0.264	0.274	0.254	0.274
Islands	0.124	0.117	0.109	0.114	0.145
Hypertensive	0.493	0.571	0.594	0.637	0.675
Diabetes	0.227	0.232	0.255	0.321	0.400
Secondary prevention	0.066	0.107	0.079	0.098	0.131
Persistent	0.582	0.564	0.640	0.715	0.634
No. Patients	474	1396	1148	933	339

Table 4 - Hospitalization probability				
	Full Sample		**Primary prevention**	
Variable	**Coefficient**	**Elasticity**	**Coefficient**	**Elasticity**
λ_{t-1}	-0.271**	-0.098	-0.347***	-0.125
LDL *t-1*	-0.119	-1.507	-0.256	-3.314
Male	0.196*	0.245	0.169	0.210
Age class 50-60	-0.015	-0.010	0.036	0.023
Age class 60-70	0.074	0.096	0.137	0.182
Age class 70+	-0.015	-0.007	0.008	0.004
North-West	-0.012	-0.007	0.129	0.081
North-East	0.086	0.054	0.117	0.074
South	0.218	0.084	0.357	0.143
Islands	0.170	0.108	0.295	0.191
Hypertensive *t-1*	0.252**	0.352	0.208	0.295
Diabetes *t-1*	0.103	0.065	0.011	0.007
Secondary prevention *t-1*	0.609***	0.123	-	
Cohort 2001	-0.130	-0.111	-0.1524	-0.130
Cohort 2002	-0.071	-0.049	-0.049	-0.034
Cohort 2003	-0.022	-0.010	-0.093	-0.045
Cohort 2004	0.011	0.001	-0.089	-0.010
Constant	-1.926		-1.302	
No. Patients	3316		3052	

Table 5 -Mundlak Random-Effects panel estimates					
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Log LDL (t-2)	0.884***	0.885***	0.885***	0.961***	0.961***
Male	-0.01	-0.013	-0.013	-0.015	-0.016
Age class 50-60	-0.033	-0.033	-0.033	-0.038	-0.039
Age class 60-70	-0.015	-0.015	-0.014	-0.034	-0.034
Age class 70+	0.008	0.007	0.008	-0.029	-0.029
North-West	-0.023	-0.016	-0.014	-0.013	-0.012
North-East	-0.017	-0.009	-0.006	-0.006	-0.008
South	0.017	0.024	0.027	0.029	0.028
Islands	0.026	0.026	0.027	0.029	0.026
Simvastatin	0.051**	0.216***	0.128	0.121	0.121
Pravastatin	-0.037	0.113***	0.052	0.043	0.042
Atorvastatin	0.127***	0.325***	0.207**	0.192**	0.191**
Rosuvastatin	0.212***	0.430***	0.400***	0.365***	0.363***
Hypertensive	0.019	0.018	0.018	0.007	0.008
Diabetes	-0.054***	-0.056***	-0.056***	-0.063***	-0.064***
Secondary prevention	0.106***	0.101***	0.100***	0.087***	0.087***
Persistent	0.035*	0.035*	0.035*	0.039**	0.039**
Cohort 2002	0.080***	0.078***	0.078***	-0.009	-0.007
Cohort 2003	0.096***	0.092***	0.091***	0.007	0.007
Cohort 2004	0.178***	0.174***	0.174***	0.104***	0.103***
Cohort 2005	0.213***	0.211***	0.210***	0.205***	0.203***
Smoker	-0.019	-0.018	-0.018	-0.018	-0.018
Exemption: Age	-0.095***	-0.096***	-0.095***	-0.074***	-0.074***
Exemption: CVD	0.064**	0.061**	0.061**	0.052**	0.052**
Exemption: Invalidity	0.027	0.028	0.028	0.018	0.018
Exemption: Income	0.039	0.039	0.039	0.018	0.018
Drug milligrams		0.003***	0.002**	0.002*	0.002*
Simvastatin x mg			0.002	0.001	0.001
Pravastatin x mg			0.001	0.001	0.001
Atorvastatin x mg			0.004	0.004	0.004
Rosuvastatin x mg			-0.003	-0.004	-0.004
Cohort 02 x year 03				0.072***	0.071***
Cohort 02 x year 04				0.093***	0.091***
Cohort 02 x year 05				0.145***	0.141***
Cohort 02 x year 06				0.176***	0.171***
Cohort 03 x year 04				0.089***	0.087***
Cohort 03 x year 05				0.121***	0.118***
Cohort 03 x year 06				0.174***	0.170***
Cohort 04 x year 05				0.116***	0.115***
Cohort 04 x year 06				0.111***	0.109***
Cohort 05 x year 06				0.049	0.047
Doctor is female					0.003
Doctor's age					0.001
Constant	-0.159	-0.393	-0.311	-0.31	-0.373
No. Observations	21188	21188	21188	21188	21188
No. Patients	4290	4290	4290	4290	4290

Table 6 - Distribution of statins prescriptions by cohort (Sample Year 2005)					
Active Ingredient	**2001**	**2002**	**2003**	**2004**	**2005**
Simvastatin	34.5%	34.4%	32.4%	27.0%	27.8%
Pravastatin	17.8%	16.8%	18.8%	16.2%	12.7%
Fluvastatin	47%	8.5%	9.2%	7.0%	7.3%
Atorvastatin	33.5%	31.2%	30.6%	31.9%	31.8%
Rosuvastatin	9.5%	9.1%	9.1%	18.0%	20.5%
No. Observations	8735	19517	18703	22860	17861

Table 7 - Estimated importance of patients, technology and doctors in determining speed of recovery					
Model Specification	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Patient behaviour	13.6%	7.3%	9.5%	10.7%	10.8%
Technology	37.9%	67.5%	57.8%	53.8%	53.9%
Medical behaviour	48.5%	25.3%	32.7%	35.4%	35.3%