Selecting the Patients Who Benefit the Most: Evidence from Marginal Patients in Health Checks

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February 16, 2024

Abstract

There is little evidence of the benefits of health checks. We study the effect of receiving a hyperlipidemia diagnosis from health checks on health and medical utilization using the administrative data from 6 million health checks in Taiwan. Our regression discontinuity design exploits the hyperlipidemia diagnostic threshold. We find that a diagnosis increases the likelihood of having related outpatient visits and drug prescriptions by 85.3 and 15.8 basis point (one in ten thousand) in the following year. The likelihood of having stroke hospitalizations decreases by 9.7 basis points. The causal forest estimator reveals substantial treatment effect heterogeneity: Compared to the average, the effect on stroke hospitalization is 16.0 times stronger for the top 20% quantile and 4.784 times stronger for the oldest 20%. A reference range based solely on cholesterol levels may result in unnecessary diagnoses or missed patients. Incorporating age into the diagnostic criteria could be beneficial.

Keywords: Health Checks, Hyperlipidemia, Causal Forest

Health checks provide an overall medical assessment to detect health conditions early on. They account for 44% of such spending in OECD countries (Gmeinder, Morgan and Mueller, 2017). However, the medical literature does not find associations between health checks and reduced risk of events such as strokes, heart attacks, or mortality (Liss et al., 2021). This gap between popularity and evidence makes the benefits of health checks an interesting policy topic.

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To inform the participants of their health, reports with the test results are usually provided after the check. However, as most laymen cannot recall nor interpret the exact measurements (Goldman et al., 2006), reference ranges are commonly included to categorize the continuous measurements as a binary diagnosis, normal or abnormal. The diagnosis is an important takeaway from the report and thus from the health checks.

Do diagnoses from health checks improve health? If they do, how well do the reference ranges target the participants whose health benefits outweigh medical expenses? We study these questions through the health and medical utilization effects of hyperlipidemia diagnosis from health checks. We find that the diagnosis increases medical utilization and also reduces short-term stroke risk. Cholesterol level alone does not fully capture the heterogeneity in treatment effect: diagnosis in the older population avoided more strokes without inducing additional cost. This suggests that a diagnostic rule including age can more precisely select the participants worth diagnosing.

We focus on hyperlipidemia diagnosis from health checks in Taiwan. Hyperlipidemia is prevalent in Taiwan with a 10% to 12% incidence rate. It also has serious complications like strokes and heart attacks. Furthermore, the widely utilized health check can be linked with medical claims from Taiwan's universal National Health Insurance. The 6 million sample size provides us with ample statistical power to detect effects on rare and major health events. We use a regression discontinuity design with the reference ranges of cholesterol to identify the effect of the hyperlipidemia diagnosis. The rich set of covariates from medical history and demographic information also allows us to employ causal forest estimators to uncover substantial heterogeneity in the treatment effects.

Our first finding is that the diagnosis increases related medical utilization and decreases major health events. The marginally diagnosed are -9.731 basis point less likely to experience a stroke-related hospitalization in the year after diagnosis, the effect is 2.055 times stronger for participants over 60 years old. This comes with increased medical utilization, the marginal patients are also 85.3 basis point more likely to pay some hyperlipidemia-related outpatient visits and 15.8 more likely basis point to receive drug prescriptions.

For the second question, we assess the precision of reference ranges by heterogeneity analysis implemented with causal forest estimators (Athey, Tibshirani and Wager, 2019). We argue that there is a negative relationship between the precision of the policy rule in selecting the beneficial participants and the variation of treatment effect unexplained by cholesterol level, the criteria variable. Empirically, we find that the effect on reduced strokes is 16.0 times stronger than average for the 20% population with the largest effect. Additionally, the oldest 20% population have 4.784 times the stroke effect while also incurring less medical expense. This suggests that including age in the reference range can make it diagnose participants who benefit most more precisely.

Our study is linked to the literature on medical diagnosis and discrete policy rules. Almond et al. (2010) pioneered the design of utilizing a continuous health measure against a discrete diagnosis rule with regression discontinuity. In the context of diagnosis, the design was first utilized to study the behavioral response to health information (Slade, 2012; Zhao, Konishi and Glewwe, 2013; Dahlberg et al., 2016; Dai et al., 2022). More recently, three similar studies examined the medical utilization and health effects of diagnosis in the view of policy evaluation. However, only indirect health effects were detected, such as improved blood sugar, BMI, and blood pressure among high-risk patients (Iizuka et al., 2021), short-term improvement of blood sugar (Alalouf, Miller and Wherry, 2023), or decreased waist size (Kim, Lee and Lim, 2019).

We contribute to this discussion by finding a major health effect and showing the policy relevance of treatment effect heterogeneity. Our empirical discovery is a piece of robust evidence supporting the effectiveness of popular yet under-examined health check programs. We also established the link between treatment heterogeneity unexplained by the criteria variable and the precision of targeting units worth treating. Such an approach can be applied in wider settings with discrete policy rules.

1 Background

Health checks are healthcare encounters with multiple lab tests and examinations. These checks aim to detect potential health conditions, such as hyperlipidemia, hypertension, and diabetes so that they can be treated before more serious complications occur. In 1996, Taiwan launched the Adult Preventive Health Services program via the National Health Insurance. The program provides free health checks for adults aged between 40 and 65 once every three years, and every year once they turn 65.[1] Similar government-sponsored health check programs can also be seen in the U.S. (NHS Health Check), and

[1] For people with poliomyelitis, the minimum age is 35. Indigenous people get yearly checks from 55.

Japan (Annual Health Check), and Korea (General Health Check-up).

Starting from 2011, Taiwan's health checks consist of surveys of health behaviors, physical examinations, and lab tests for measurements such as blood sugar, blood pressure, and cholesterol (National Health Insurance Administration, 2016). The check is widely utilized, our data shows that 51.6 percent of the eligible population have at least one visit.

After the health check, the attendants receive a report. The report includes two sections, a result section recording the measurements from the lab tests alongside reference ranges and a recommendations section based on the results. For example, people with cholesterol levels over 200 will see that their result is outside of the reference range, and also see an alert of hyperlipidemia risk and some advice to act accordingly.[2] After receiving the report, the patient with an abnormal mark may change their behavior or seek early medical help. Both reactions may improve their health.

Among the items in health checks, we focus on the cholesterol level and hyperlipidemia, a prevalent and dangerous condition. 10 percent of U.S. adults are found with severe hyperlipidemia (total cholesterol levels above 240 mg/dL) (Heart Association Council on Epidemiology and others, 2022), and in Taiwan, it is 12.5 percent for adult men and 10 percent for women (Pan et al., 2011). Hyperlipidemia is also a well-established risk factor for major health events like heart attacks and strokes (Alloubani, Nimer and Samara, 2021).

The complications of hyperlipidemia can be controlled with pharmaceuticals. Statins, a class of lipid-lowering medications, are capable of reducing the cardiovascular and stroke risk from hyperlipidemia (Brugts et al., 2009) and thus commonly prescribed. However, despite having effective treatment, many patients are unaware that they have hyperlipidemia. In Taiwan, 77 percent of participants with abnormal cholesterol values were previously unaware (Health Promotion Administration, 2023). These characteristics make hyperlipidemia an important issue in preventive care and a suitable setting for our study.

[2] All patients with cholesterol levels over 200 will get some suggestions, but the actual suggestion also depends on other risk factors and measurements Details of the report and recommendation are in the Appendix B.2.

Our other source of data is the medical claims from Taiwan's National Health Insurance (NHI). The NHI is compulsory for all citizens and covers outpatient visits, inpatient visits, as well as pharmaceuticals. Claims from hospitals, clinics, and pharmacies go to a single insurer, the National Health Insurance Administration. The expenditures from these claims consist of 52.9 percent of national health expenditures (Department of Statistics, 2022).[3]

2 Data

Data on all visits to the Adult Preventive Care Service is obtained from 2012 to 2020. For each visit, we observe the basic information, the health survey, and the health check results. For basic information, we have the ID of the attendant, the date of the visit, and the hospital that conducts the checks. The health survey asks about health behavior (drinking, smoking, exercising, and betelnut consumption) and self-reported disease history (stroke, heart disease, and chronic diseases). For the health check, we see body measurements like height, weight, waist size, and also lab results such as cholesterol level.

We observe claims to the NHI in the unit of visits. For each visit, we see the ID of the medical institution, the physician, and the patient. We also see the ICD code for the disease, the operation performed, the drug prescribed, and the amount of "dots" claimed for the visits. The dollar value of each dot fluctuates but is generally around 1 NTD (0.03 USD) per dot. [4] We also collect the death registry which contains the date of death, the cause of death, and the ID of the deceased. Finally, we use the enrollment registry for socioeconomic variables such as sex, birth year, and Salary Basis, a censored measure of salary.[5]

The sample construction process starts with the health check records. For each participant, we take the cholesterol value of their first check as the running variable. We then link it to the visits from medical claims and the death registry using the National ID. The visits can come from the outpatient, emergency department, inpatient, or pharmacy. We

[3]The national health expenditures include not only medical expenditures but also other health spending and capital investments.

[4]The NHI adopts a Global Budget Payment System. To control for the total spending, the value of a dot is calculated by dividing the pre-determined budget by the total amount of the dot in the quarter.

[5]the Salary Basis is used to determine the insurance fee for the NHI. For non-agricultural employees, it is the monthly payroll after rounding and top-censoring.

further categorize visits into 5 categories by their associated ICD codes, hyperlipidemia, Myocardial infarction (MI), Congestive Heart Failure (CHF), Peripheral vascular disease (PVD), and strokes. [6] We define a visit as related to complications if it falls into the latter four categories. Finally, we aggregate visits in a time frame into four groups of variables: a boolean of whether there are any visits, the visit counts, the total dot from the visits, and the total prescription or hospitalization days. These are our primary outcome variables.

For the main sample used in the following sections, we excluded some observations. We observe that some medical institutions have an extreme cholesterol distribution. Specifically, a few hospitals have more than half the observations in 200 and 206. We address this issue by removing observations from outlier institutions (outside the whisker of the distribution of relative density at 200 and 206 after shrinkage adjustments.) Finally, we exclude observations with invalid birthdays or cholesterol values. Data right on the cholesterol threshold (200) are also excluded to avoid the potential ambiguity that hospital staff and attendees face when interpreting the measurements on the threshold should be diagnosed (this is equivalent to using donut estimators). These criteria remove about 10 percent of the sample and leave us with a sample size of around 6 million. We discuss the context, procedures, and alternative criteria in detail in Appendix B.1,

Table 1 presents the summary statistics of the demographics, disease history, and medical utilization among the check participants and the population. In the main sample, about 43.6% is male, 30.2% holds a job, and 5.563% are previously diagnosed with hyperlipidemia. The average participants ages 58.5, spends 31,143.1 dot in NHI and pay 23.1 outpatient visits per year. The distribution of pre-determined variables is overall comparable among the population, the participants, and participants around the threshold.

[6] Hyperlipidemia is defined by disorders of lipid metabolism category in the Clinical Classification Software by the Agency of Healthcare and Research and Quality. For complications, we use the Charlson Comorbidity Index.

Table 1: Summary Statistics

Variable[a]	Population[b]	Check participants	[160, 200)[c]	[200, 240]
Count	500,000.0	6,063,300.0	1,554,500.0	1,341,248.0
Demographics				
Male (%)	48.1 (50.0)	43.6 (49.6)	44.0 (49.6)	40.7 (49.1)
Age at Health Check		58.5 (12.2)	58.0 (12.3)	57.9 (11.5)
Work (%)	36.9 (48.3)	30.2 (45.1)	31.7 (45.7)	31.4 (45.6)
Disease history[d]				
Salary	16,042.7 (26,973.9)	12,408.5 (23,143.1)	13,096.6 (23,674.7)	13,024.6 (23,730.4)
Hypertension (%)		21.7 (41.2)	21.6 (41.1)	20.5 (40.4)
Diabetes (%)		9.268 (29.0)	8.467 (27.8)	6.875 (25.3)
Hyperlipidemia (%)		5.563 (22.9)	4.784 (21.3)	5.597 (23.0)
Heart Disease History (%)		4.017 (19.6)	3.819 (19.2)	3.278 (17.8)
Stroke History (%)		0.948 (9.691)	0.814 (8.984)	0.666 (8.131)
Medical utilization				
Kidney Disease (%)		0.705 (8.367)	0.615 (7.817)	0.528 (7.245)
Expenditure from related visits	1,272.6 (23,385.8)	2,144.8 (20,063.3)	1,820.1 (18,266.1)	1,456.5 (14,749.5)
Total Medical Expenditure	35,369.1 (114,111.4)	31,143.1 (74,239.0)	28,967.3 (67,436.6)	26,311.2 (58,004.7)
Outpatient Visits	19.7 (19.6)	23.1 (20.4)	22.8 (20.1)	22.1 (19.6)
Hyperlipidemia outpatient visits	0.183 (1.212)	0.192 (1.196)	0.165 (1.142)	0.191 (1.171)
Drug Prescriptions	3.872 (7.081)	5.196 (8.282)	5.108 (8.119)	4.945 (7.988)
Hyperlipidemia drug prescriptions	0.055 (0.574)	0.064 (0.628)	0.055 (0.600)	0.061 (0.614)
Inhospitalizations	0.190 (0.862)	0.149 (0.695)	0.132 (0.629)	0.117 (0.574)

[a] All time-varying variables are measured in the year before the health check. Standard deviation are reported in parentheses

[b] Population is a 500k sample drawn from the total population, outcomes are measured in 2012.

[c] [160, 200) ([200, 240]) refers to the participants with cholesterol value between 160 and 200 (200 and 240) in the first check, outcomes are measured one year before the health check.

[d] Disease history comes from the self-reported status in the health survey.

3 Main results

3.1 Regression discontinuity

The causal effect of hyperlipidemia diagnosis is identified with a regression discontinuity design. This strategy, first used in Almond et al. (2010), exploits the fact that medical workers often determine the use of certain treatments like incubators by a discrete threshold on continuous health measurements such as a newborn's weight. In our setting, the idea is that the attendees with cholesterol values just above the 200 threshold are almost identical to the attendees just below, but the former receives a diagnosis while the latter doesn't. Therefore, their differences after the health check are attributed to the effect of the diagnosis. Formally. as in Hahn, Todd and Van der Klaauw (2001), the causal effect of hyperlipidemia is identified by:

$$\tau = \lim_{x \to c^+} E[Y_i | X_i = x] - \lim_{x \to c^-} E[Y_i | X_i = x] \tag{1}$$

where Y_i is the outcome of interests, X_i is the cholesterol level, and c is the threshold that equals to 200. Assuming continuity of the conditional expectation of potential outcomes at the cutoff.

We estimate this equation by the procedures proposed by Cattaneo, Idrobo and Titiunik (2019). Two local polynomials on both sides of the threshold are estimated. Then, the difference of predictions at the threshold is taken as the estimate of the treatment effect. Specifically, we estimate linear regressions with a triangular kernel and use the optimal bandwidth that minimizes MSE (Calonico, Cattaneo and Farrell, 2019). The standard errors reported are estimated with the robust bias-corrected method (Calonico, Cattaneo and Titiunik, 2014). We discuss the robustness of our results to these specifications in Appendix A.2.

Our main source of confidence in the validity of the design comes from the empirical setting. There is little room for manipulation in the simple process that generates the observed cholesterol level. For the participants, it is biologically impossible to manipulate their underlying biological condition precisely. Neither the hospital nor the lab staff have the incentive to manipulate the results.

We formally check the validity of the identification assumption by testing the discontinuities in density and covariates. Using local polynomial density estimators (Cattaneo, Jansson and Ma, 2020), we fail to reject the hypothesis that the density is continuous at the threshold (p-value: 0.2636). We then use pre-determined variables as placebo outcomes such as demographics (age at check, sex, work dummy, salary) and medical utilization (previous visits and expenditures related to hyperlipidemia and complications). We fail to reject any hypothesis that the covariates are continuous at the threshold with a minimal p-value of 0.082. The full result is available in Appendix A.1.

3.2 Medical utilization and health effect

The diagnosis causes the patients to have more outpatient visits and drug prescriptions. Figure 1 and Table 2 report the effect of diagnosis in the calendar year of the health check. Participants receiving the marginal diagnosis are 85.3 basis point (one in ten thousand) more likely to pay some hyperlipidemia outpatient visits, and 15.8 basis point more receive some drug prescriptions. The average marginal patient pays 92.1 more related outpatient visits and receives 16.0 more drug prescriptions per ten thousand years. The extra visits cost 14.0 dots for outpatient visits and 2.568 for prescriptions (insignificant).

When we expand the time frame from 1 to 5 years, the total visits increased only from 92.1 to 139.3 and drug prescriptions from 16.0 to 30.0 per ten thousand years. suggesting that the effect fades away at least partially. Many estimates also turn insignificant. We focus on outcomes in the first year after the check in the following parts. The dynamics of the effect are explored in more detail in Appendix A.3.

The diagnosis effectively reduces adverse health events. The marginal Participants are -9.731 basis points less likely to experience a stroke-related hospitalization. However, we find no effect on other complications and mortality.

The older population is the main benefactor of the health effects. For the population over 60 years old when attending the check, the diagnosis makes them -22.2 basis point less likely to experience stroke-related hospitalizations, 2.055 times larger than the average effect. In comparison, there is barely any effect for the younger population. The older population also receives more care. They are 125.0 basis point more likely to have related outpatient visits (1.333 times larger than average treatment effect) and 26.4 basis point to receive prescriptions (1.500 times larger than average treatment effect). We examine this significant heterogeneity more systematically in the next section.

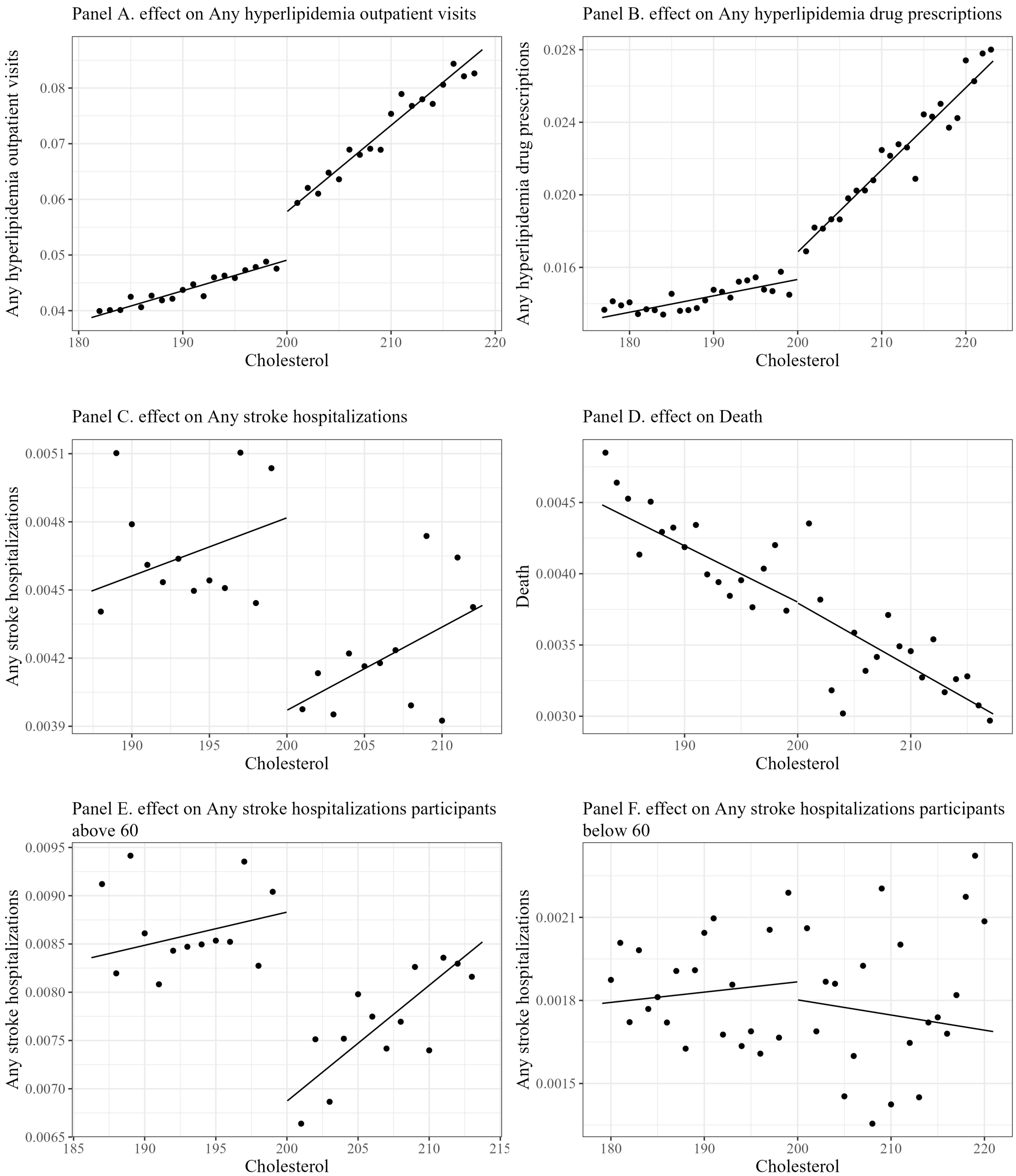

Figure 1: Effect of hyperlipidemia diagnosis

Note: This figure shows RD plots of the effect of the hyperlipidemia diagnosis on health and medical utilization. Dots are the mean of the outcome variable within bins with data-driven intervals (Calonico, Cattaneo and Titiunik, 2015). Solid lines are fitted values from a local linear regression with a triangular kernel and the same optimal bandwidth in the main results.

Table 2: Effect of the hyperlipidemia diagnosis

Outcome variable	All participant	Age < 60 [a]	Age ≥ 60
Medial utilization			
Any hyperlipidemia outpatient visits (‱)	85.3 [68.7, 101.9]	61.0 [42.4, 79.6]	125.0 [98.1, 151.9]
Any hyperlipidemia drug prescriptions (‱)	15.8 [7.575, 24.1]	8.432 [-0.845, 17.7]	26.4 [11.4, 41.3]
Hyperlipidemia outpatient visits (×10000)	92.1 [8.449, 175.7]	75.7 [-1.825, 153.2]	210.2 [77.3, 343.0]
Hyperlipidemia drug prescriptions (×10000)	16.0 [-22.9, 55.0]	-4.909 [-47.0, 37.2]	50.2 [-18.1, 118.6]
Any MI hospitalizations (‱)	-0.002 [-2.078, 2.073]	-0.342 [-2.191, 1.508]	0.803 [-3.087, 4.693]
Health effect			
Any PVD hospitalizations (‱)	-0.544 [-1.674, 0.587]	0.119 [-0.812, 1.050]	-1.351 [-3.511, 0.810]
Any CHF hospitalizations (‱)	-1.592 [-4.013, 0.829]	-0.008 [-1.589, 1.573]	-3.968 [-9.109, 1.173]
Any stroke hospitalizations (‱)	-9.731 [-15.4, -4.066]	-0.753 [-4.713, 3.206]	-22.2 [-33.1, -11.3]
Any complications hospitalizations (‱)	-10.4 [-17.3, -3.500]	-0.009 [-5.041, 5.023]	-26.0 [-40.1, -11.9]
Cerebrovascular death (‱)	0.278 [-0.856, 1.412]	-2.559e-04 [-0.638, 0.638]	0.917 [-1.482, 3.316]
Heart-related death (‱)	0.462 [-0.666, 1.590]	-0.188 [-0.776, 0.401]	1.521 [-0.762, 3.803]
Death (‱)	-0.482 [-5.263, 4.299]	-0.450 [-3.560, 2.660]	0.560 [-8.748, 9.868]
Expenditure from hyperlipidemia outpatient visits	14.0 [5.421, 22.6]	7.995 [0.207, 15.8]	24.1 [6.273, 41.8]
Medical cost			
Expenditure from hyperlipidemia drug prescriptions	2.568 [-0.775, 5.911]	0.154 [-3.290, 3.598]	6.264 [0.237, 12.3]
Expenditure from complications hospitalizations	-48.6 [-180.2, 83.0]	25.0 [-98.7, 148.7]	-139.5 [-380.4, 101.3]
Expenditure from related visits	-19.3 [-171.8, 133.1]	44.3 [-88.0, 176.6]	-86.1 [-365.2, 193.0]

Note:

The table reports the estimates of effect of hyperlipidemia diagnosis on outcomes in the first year after the health check. Results are estimated using separate local linear regressions around the cutoff, with optimal bandwidth, triangular kernel and excluding observations on the cutoff. 95 percent confidence interval of the estimate calculated with the robust bias-corrected standard error are reported in brackets.

[a] Age < (>=) 60 reports the effect for subpopulation who are under (over) age 60 at the time of the health check.

[b] Variables with names that end with (‱) are reported in liklihood in basis point (one in ten thousand)

[c] Variables with names that end with (times 10000) are reported in average count per ten thousand years.

4 Extension: heterogeneity

4.1 Policy Rule and treatment effect heterogeneity

Our main results suggest that there is a trade-off between lowering the risk of stroke and incurring additional medical costs when diagnosing patients. It is reasonable to guess that diagnosing patients with high cholesterol would have a more substantial health impact compared to participants with low cholesterol levels. Then, the reference range is effectively a policy rule that determines who to diagnose by the treatment effect conditional on the cholesterol level.

Whether setting the cholesterol threshold at 200 is optimal is beyond our scope, since the policymaker's preferences are unknown. However, we can still assess the preciseness of selection on cholesterol levels by the variation of the treatment effect conditional on a cholesterol level. This happens to be what our regression discontinuity design identifies. If the treatment effect varies significantly at the threshold level of cholesterol, indicating that some individuals benefit more from treatment than others, then there may be missed opportunities or unnecessary treatments near this threshold, provided the treatment effect is somewhat consistent, assuming that the treatment effect does not change too abruptly.

In a first-best scenario, we can create a policy rule to treat every unit worth treating. However, since we cannot directly observe individual treatment effects, we can only rely on other observable variables. Adding a variable that captures the treatment effect heterogeneity can make the policy rule more effective at selecting those who would most benefit from diagnosis. In short, the treatment effect heterogeneity on the cholesterol threshold can help us assess the preciseness of the policy rule, and observables that capture that heterogeneity can be a good addition to the policy rule.

4.2 Causal Forest

To systematically examine the treatment effect heterogeneity of diagnosis, we employ the causal forest estimators (Wager and Athey, 2018). The causal forest utilizes random forest, a machine learning algorithm, to estimate the heterogeneity of the causal effects in the potential outcome framework with valid inference. Compared to traditional approaches, causal forest allows us to utilize the rich sets of covariates to reveal patterns that are not expected a priori. Specifically, we estimate a conditional linear model with the linear model forest (Athey, Tibshirani and Wager, 2019):

$$Y_i = \mu(X_i) + \beta(X_i)X_i^r + \tau(X_i)1\{X_i^r \geq c\}, \tag{2}$$

where X_i^r is the running variable and $\tau(X_i)$ is the conditional average treatment effect (CATE). X is the set of covariates.

We use two auxiliary tools to interpret the high-dimensional CATE. First, we can project the CATE onto a linear regression to assess the influence of individual variables. Another useful method is the Targeting Operation Characteristic curve. Given a prioritization rule, $S(X_i)$, the curve $T(q)$ compares the treatment effect of the top q fraction of units, to the overall average treatment effect.

Specifically, we focus on the heterogeneity of the effect on total related medical expenditure and stroke-related hospitalizations. We use a variety of covariates, such as demographics, pre-medical utilization, lab test results, disease history, and health behavior. Due to computation constraints, we only use a 500k sample and train 500 trees. After obtaining the CATE, we address the regularization bias and overfitting in Chernozhukov et al. (2018) by adjusting with the doubly robust score (Athey and Wager, 2021).

4.3 Heterogeneity

The impact on medical expenditures and stroke reduction varies significantly, as shown in the Targeting Operating Characteristic (Figure 2). Among the top 20% of individuals with the highest reduction in strokes, there was a decrease of -170.5 in stroke-related hospital admissions per ten thousand years, which is 16.0 times the average effect. Similarly, for the 20% of individuals with the lowest induced medical expenditures, the costs changed by -2,972.8. From the cross Targeting Operating Characteristics, we can see that people with more stroke reduction also have lower medical expenses. This indicates that diagnosing certain individuals can be more advantageous than others.

Table 3 shows that aside from variables related to past hospitalization history, which are often not visible in a health check), age is the only notable factor in explaining the variation in the treatment effect. Conditional on other variables, each additional year in a participant's age is associated with an -1.909 variation in the impact on stroke hospitalizations, equivalent to 19.1 percent of the average effect. Treating the oldest part of the participants is particularly effective. The oldest 20 % experience -57.8 fewer stroke hospitalizations (4.784 times the average) and a change in related medical expenditures of -496.6. This shows that age carries the information that can improve the precision of the policy rule in assigning diagnoses.

Table 3: Best linear projection of the conditional average treatment effect

Dependent variable	Stroke hospitalizations (×10000)[a]	Expenditure from related visits
Male	-1.526 [-19.0, 15.9]	-123.6 [-436.1, 188.8]
Age at Health Check	-1.909 [-2.557, -1.262]	-16.3 [-27.9, -4.700]
Work	-2.035 [-27.3, 23.3]	-36.7 [-490.2, 416.7]
Salary	1.478e-04 [-3.299e-04, 6.256e-04]	0.005 [-0.003, 0.014]
Height	-0.668 [-1.355, 0.018]	1.053 [-11.2, 13.3]
Weight	0.108 [-0.558, 0.773]	-4.074 [-16.0, 7.854]
Waistline Measurement	0.094 [-0.185, 0.373]	0.147 [-4.859, 5.154]
Alcohol Consumption	-11.6 [-31.7, 8.464]	-190.4 [-550.5, 169.8]
Smoking	7.644 [-14.6, 29.9]	149.4 [-248.7, 547.5]
Exercise	7.321 [-6.109, 20.8]	-164.0 [-404.8, 76.8]
Intercept	189.4 [70.2, 308.5]	1,006.1 [-1,129.3, 3,141.5]

Note:

The table reports the best linear projection of the conditional average treatment effect on a subset of observable variables commonly avalible in health checks. 95 percent confidence interval are reported in brackets.

[a] Estimate are reported in effect on average visits per ten thousand years.

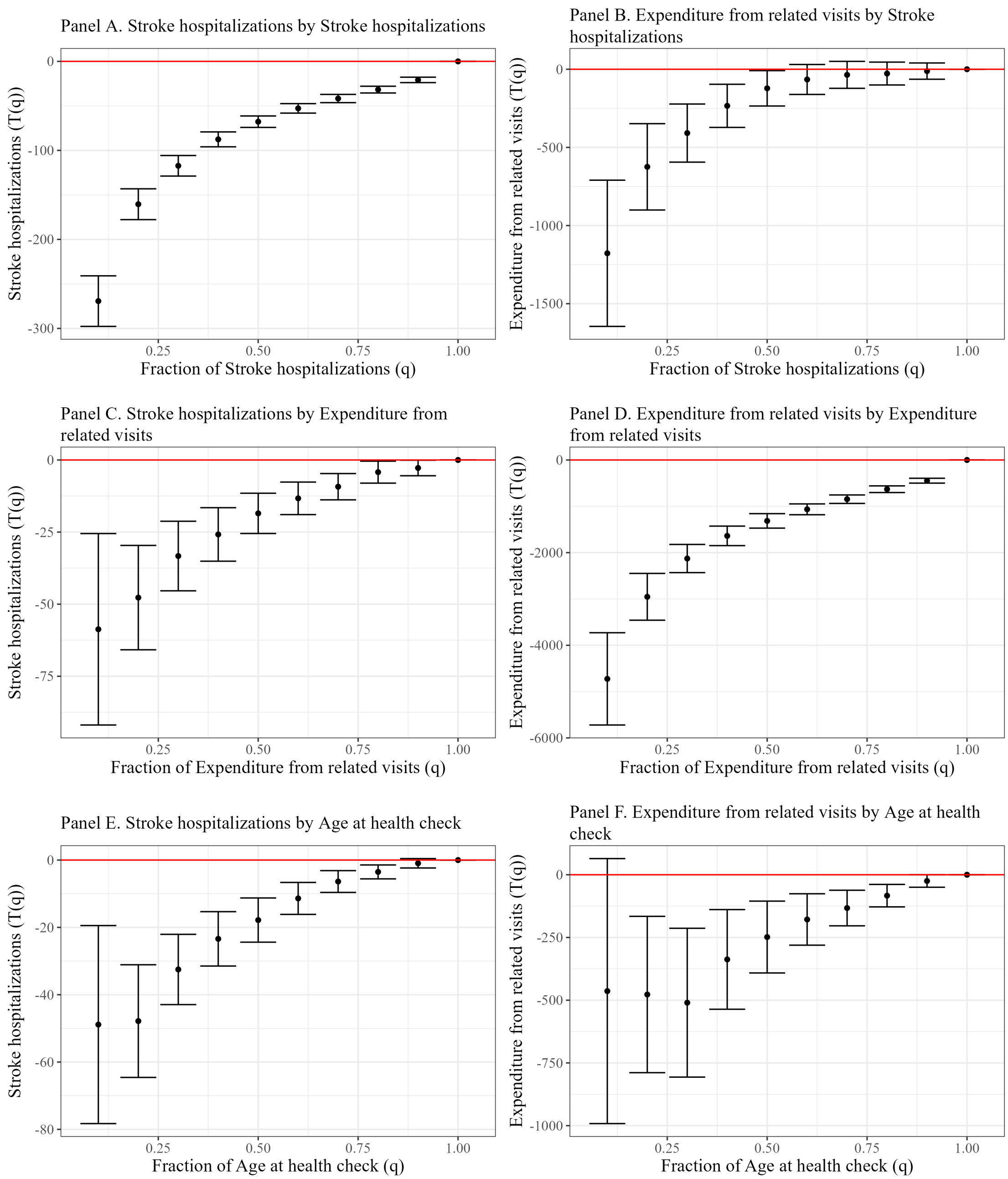

Figure 2: Target operating characteristic

Note: This figure plots the target operating characteristic curves. Each dot is the treatment effect relative to the average treatment effect (T(q)) for the quantile of units prioritized by a variable (q). For example, the second leftmost dot in Panel E shows that the difference between the stroke effect on the oldest 20 percent and the average population is -47.8 visits per ten thousand years. All stroke effects are visits per ten thousand years. The error bar reports the 95% confidence interval.

5 Discussion

In this paper, We study the impact of receiving a hyperlipidemia diagnosis on health and medical utilization. Based on data from Taiwanese health checks, we find that hyperlipidemia leads to an increase in outpatient visits and medication prescriptions, and also a decrease in stroke-related hospitalizations. We emphasize the policy relevance of the local average treatment effect identified by the regression discontinuity design in assessing discrete policy rules. Its heterogeneity is informative of the preciseness of the discrete threshold in selecting units that benefit more from the treatment. In our case, causal forest estimators show that the effect varies significantly. The older population has a much stronger effect on reduced strokes without incurring more costs. This suggests that reference ranges have some room for improvement as policy rules, and age can be a beneficial addition.

We interpret our findings with caution. The observed causal effect stems from multiple potential channels. Initially, upon receiving a diagnosis, the participants receive both information about their health condition and recommendations from the physicians. The response to the diagnosis can be behavioral and medical, both can contribute to the health effects. Therefore, rather than trying to dissect the causal mechanisms, we focus on the overall effect of the diagnosis and its policy implications. Furthermore, our results show that age could be a significant variable to include in diagnostic criteria. However, we have not estimated an optimal reference range that incorporates both age and cholesterol levels, nor its potential benefits. Such a task would require the treatment effect across different cholesterol levels, but our design identifies the treatment effect on the cutoff.

For health checks, the natural next step is to find optimal diagnostic rules if the treatment effect conditional on the cholesterol can be estimated. More broadly, we posit that the link between precision and treatment effect heterogeneity also applies to other discrete policy rules. This interpretation of the heterogeneity analysis could be extended to more contexts, including medical treatments (Almond et al., 2010) and regional policies based on population thresholds (Brollo et al., 2013).

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The appendices are still a work in progress.

Appendix A Additional result

A.1 Validity

A.2 Robustness

A.3 Extension

Appendix B Detail

B.1 Sample construction

We notice that some hospitals have an extreme distribution of cholesterol measurements. For example, certain hospitals have more than half of observations in the value of 206. We suspect that this comes from errors when keying the data, or problems with the lab equipment. In light of this, we remove observations from 1 percent of hospitals with the most extreme density in 206 and 200. Doing this removes about 5 percent of observations. We conduct formal tests to confirm that the distribution is continuous enough after removing these hospitals.

Therefore, the plausible sources of discontinuity is

malfunctioning equipment or data-entering mistakes

Then, for the lab equipment and the staff that record the results, there

We calculate the ratio of the count at 200 and 206, the point of problems, relative to the count around the neighborhood. We use a shrinkage estimator to avoid removing only small hospitals. Finally, we label hospitals with the top and bottom 5 percent as extreme.

The alternative solution is to use a donut estimator to avoid using these points with abnormal distribution,

B.2 The report