Centre for Studies in Economics and Finance

WORKING PAPER NO. 440

Cost-Sharing and Use of Health Services in Italy: Evidence from a Fuzzy Regression Discontinuity Design

Michela Ponzo and Vincenzo Scoppa

April 2016

University of Naples Federico II

University of Salerno

Bocconi University, Milan

CSEF - Centre for Studies in Economics and Finance
DEPARTMENT OF ECONOMICS – UNIVERSITY OF NAPLES
80126 NAPLES - ITALY
Tel. and fax +39 081 675372 – e-mail: csef@unisa.it

Working Paper no. 440

Cost-Sharing and Use of Health Services in Italy: Evidence from a Fuzzy Regression Discontinuity Design

Michela Ponzo* and Vincenzo Scoppa**

Abstract
We use a Regression Discontinuity Design (RDD) to evaluate the impact of cost-sharing on the use of health services. In the Italian health system, individuals reaching age 65 and earning low incomes are given total exemption from cost-sharing for health services consumption. Since the probability of exemption changes discontinuously at age 65, we use a Fuzzy RDD in which the age threshold is used as an instrument for exemption. We find that prescription drug consumption, specialist visits and diagnostic checks remarkably increase with exemption. However, using several measures of health outcomes we do not find any change in individual health.

JEL classification: I10; I13, I11; I18; C26

Keywords: Health Insurance; Healthcare Demand; Cost-Sharing; Moral Hazard; Health Outcomes; Fuzzy Regression Discontinuity Design; Instrumental Variables

Acknowledgments: We would like to thank David Card, Vincenzo Carrieri, Guido de Blasio, Giuliana De Luca, Maria De Paola, Sabrina Giordano, Tullio Jappelli, Luca Mo Costabella, Marco Sisti, for useful comments and suggestions.

* Università di Napoli Federico II and CSEF. E-mail: michela.ponzo@unina.it.

** University of Calabria, and IZA (Bonn). E-mail: v.scoppa@unical.it.

Table of contents

1. Introduction

The problem of moral hazard in health insurance has a long tradition, starting from Arrow (1963), Zeckhauser (1970) and Feldstein (1973). When individuals are insured they tend to consume more of the health services than they would if they had to pay the whole price (“overconsumption”). Cost-sharing is the typical instrument used to tackle the problem of overconsumption, leading to a classical trade-off between appropriate incentives and risks borne by agents.

Estimating empirically the effect of insurance coverage and cost-sharing on medical utilization and on health outcomes is a thorny issue, since the extent of insurance coverage of individuals is not randomly assigned and typically in observational studies individuals with different coverage differ along observable and unobservable characteristics that also determine the demand for health services and their health outcomes.

To overcome these problems, in this paper we aim to provide evidence on the effects of cost-sharing on prescription drug consumption, specialist visits and diagnostic checks exploiting a discontinuity, based on age, for the access to exemption from cost-sharing in the Italian National Health System.

The National Health System in Italy provides universal, largely subsidized, health care coverage to all residents. To address individuals’ moral hazard some system of cost-sharing – in the form of copayment – is used for prescription drugs, specialist visits and diagnostic checks. However, individuals aged 65 or more, with an income below a threshold level, are entitled, for equity reasons, to complete exemption from cost-sharing. Therefore, to evaluate the extent of moral hazard problems in Italy we compare the demand of health services of individuals exempted from cost-sharing with individuals not exempted from cost-sharing and then we carry out the same comparison as regards some health outcomes. To avoid estimation biases arising from the possible correlation of the exemption status with some determinants of the demand of health services, we adopt an Instrumental Variables estimation strategy using as an instrument for exemption the threshold of 65 years that in Italy allow most individuals to be exempted. The estimation strategy corresponds to a Fuzzy Regression Discontinuity Design (Angrist and Pischke, 2009).

While in general individuals with different insurance coverage could differ for many characteristics, in our context individuals slightly above or below the age of 65 are very similar in terms of health and other characteristics and, therefore, any jump in the relationship linking utilization of health services and age close to the cutoff can be taken as evidence of a treatment effect. Along the same line, jumps in the relationship between health outcomes and age can be seen as the effect of exemption on health.

Our paper is related to a large body of research trying to evaluate, mainly for the US, how the demand for health care services is responsive to prices and then how different levels of health services are associated to health outcomes.

The most rigorous evidence comes from two very well-known experiments conducted in the US. The RAND Health Insurance Experiment (HIE) is a randomized experiment conducted in the mid-1970s. It involved almost 4,000 individuals and randomly assigned families to one of 14 different insurance plans that differed in cost sharing and out-of-pocket limit and provided convincing evidence that health care demand is sensitive to the price (with an elasticity of about –0.2) and that individuals' health does not improve when health care increases (Manning *et al.*, 1987; Newhouse, 1993).[1] In another famous and more recent experiment, carried out in Oregon in 2008, a group of uninsured low-income individuals were selected randomly and given public health insurance as Medicaid (Finkelstein *et al.*, 2012). The treatment group with access to public health insurance showed significantly higher health care utilization (emergency department visits, prescription drugs, hospitalization) than the control group. The greater utilization of health services led to marginally better self-reported physical health and considerably improved mental health for the treated.

A few natural experimental studies have tried to evaluate how demand for health care services depend on prices. Cherkin, Grothaus and Wagner (1989) analyze a natural experiment consisting in the introduction of a $5 copayment rate for state employees in Washington in the mid-1980s, while no change occurred for federal employees. The authors find a considerable reduction in primary and specialty care visits for treated. Similarly, Selby, Fireman and Swain (1996) find a significant drop (–15%) in the use of the emergency department after the introduction of a copayment for some employees relative to a control group of employees for whom the copayment did not increase. Goldman *et al.* (2004), Landsman *et al.* (2005) and Tamblyn *et al.* (2001) Gaynor, Li and Vogt (2007) find that prescription drug use is price sensitive, with elasticities ranging from –0.1 (for essential drugs or drugs related to chronic conditions) to –0.4.

Some studies have tried to verify the effects on health of a reduction in demand for health care: Hiesler *et al.* (2004) and Piette *et al.* (2004) show that health is worse for individuals using less prescription drugs because of their high costs, while Schoen *et al.* (2001) find that poor patients have better health thanks to the provision of free prescription drugs. Tamblyn *et al.* (2001) find that, after the introduction of cost-sharing, hospitalizations for the elderly increased significantly.

While many of previous studies focused on non-elderly, Chandra, Gruber, and McKnight (2010) study the effects of copayment increases for prescription drugs and physician visits on retired public employees in California and find a reduction in prescriptions and visits. However, an adverse effect emerged on the health of chronically ill individuals, with a subsequent rise in hospital care.[2]

---

[1] However, the small treatment groups make hard to statistically compare outcomes and the high number of drop-outs and large differences in attrition rates between groups undermine the internal validity of the experiment (Angrist and Pischke, 2015).

[2] The consumption of public and private health services for Italy in relation to their costs and substitutability have been examined in Fabbri and Monfardini (2009) and Atella and Deb (2008). Fabbri and Monfardini (2009) investigate the role of waiting times and charges on the consumption of public and private specialist visits. Although they find that waiting times and charges, respectively, reduce the demand for public and private specialist care, the cross-elasticities are not statistically significant and hence there is no substitution effect between the demand for public and private specialists. Charges only act as a deterrent to consumption in the

Recently, some studies use Regression Discontinuity Designs to estimate the impact of insurance coverage on the use of emergency departments and hospitals. Anderson, Dobkin and Gross (2012) exploit the threshold of individuals aged 19 "aging out" of their parents' insurance plans, while Anderson, Dobkin and Gross (2014) compare individuals just younger and older than 23, the threshold after which students are no longer eligible for their parents' health insurance. In both papers the authors find that the uninsured drastically reduce emergency department visits and hospital admissions.

Two recent papers of Card, Dobkin and Maestas (2008; 2009) – which are closely related to our work – carry out RD analyses for the US exploiting the fact that at age 65 people become eligible for Medicare. Insurance coverage jumps from 90% to 98% at age 65 for the population as a whole and people transit from private to public insurance. Card, Dobkin and Maestas (2008) analyze hospital admissions in three American states and find large increases in hospitalization rates at age 65 but with heterogeneous responses across socioeconomic groups and type of service. Doctor visits increase more for groups that previously lacked insurance, while hospital admissions for expensive procedures increase more for previously insured groups with supplementary coverage. Card, Dobkin and Maestas (2009) find that admission rates in hospitals and comorbidities of severely ill individuals below or above age 65 are similar, but patients older than 65 receive a significantly higher number of services in the hospital. Furthermore, the mortality rate of individuals aged 65 eligible for Medicare is also significantly lower.[3]

Almost all of the randomized and natural experimental studies have been conducted in the US while other health systems suffer from a lack of rigorous empirical evidence. The Italian National Health System is very different from the US system and it is interesting to analyze the effects of cost-sharing on healthcare demand in this context. In fact, while healthcare services are costly to patients even under Medicare (prescription drugs and routine checks were not exempted until recently), some categories of individuals in the Italian system are given complete exemption from health services costs. Therefore, we are able to investigate how the demand for several health services is affected by variations in the copayment, with no other change in the insurance status.

Using the described Fuzzy RDD, we find that individuals with exemption from cost-sharing – because they are just above the threshold of 65 – use significantly more health care services than individuals just below the threshold: specialist visits and diagnostic checks increase by more than 50 percent, while the use of prescription drugs raises of about 15-20 percent. However, we show that

---

private sector which is not substituted for more public care. Atella and Deb (2008) examine the relationships between health care visits to general practitioners or public and private sector specialists. General practitioners and public and private specialists are found to be substitute sources of medical care.

[3] Other works finding that Medicare leads to an increase in the use of health services are Dow (2004) – who compares changes in hospitalization rates from the period before the introduction of Medicare to the period after its introduction finding an increase among individuals older than 65 – and McWilliams et al. (2007) – who show an increase of hospitalizations and doctor visits among previously uninsured individuals with previous health problems. See Carrieri (2010) for a review of the literature.

health outcomes do not differ for people around the threshold in terms of the probability of incurring serious health problems, subjective perceived health and probability of going to the hospital.

The evidence on the high responsiveness of health services demand is relevant from a policy point of view to tackle the problem of an excessive growth of health spending, especially if the recent trends of increasing life expectancy, ageing population and supply of new pharmaceuticals and new tests will continue in the future.

The paper is organized as follows. In Section 2 we briefly describe the Italian National Health System and the dataset used in the empirical analysis. Section 3 presents the estimation strategy adopted and the estimation results for specialist visits and diagnostic checks. Section 4 examines the impact on prescription drug consumption, distinguishing the effects among regions applying the copayment and those not applying it. Section 5 presents the RD analysis to investigate the effects on health outcomes. Section 6 concludes.

2. The Italian National Health System and the Data

The Italian National Health system (NHS) provides universal and largely free health care coverage to all residents. Specifically, the NHS entitles residents to visit a General Practitioner (called "family doctor") and a pediatrician. This allows patients to undergo free outpatient and in-home medical examinations and to obtain prescriptions for drugs, specialist medical services and diagnostic tests. Residents are allowed to undergo free hospital accommodation and treatments (including tests, surgery and medication during hospitalization), and other services at a local health unit ("Consultorio"). The NHS is mostly under the control of the 20 regional governments, although the general framework is designed at the national level.

Drugs are strongly subsidized when prescribed by a General Practitioner (GP). Individuals are required to pay as a copayment only a small fraction of the price – the so called "Ticket". Currently, the cost to the patient is based on a rather complex structure and differ from one region to another. In most of the regions, the copayment is required for everyone except for those who are entitled to complete exemption, that is, patients with disabilities, chronic diseases, older than 65 years with low income, unemployed. The amount – which depends on the type of medicine and on clinical effectiveness – is on average 2€ for each prescription and 4€ for each drug package. In some other regions – which we call "Regions without Copayment" (Valle d'Aosta, Friuli Venezia Giulia, Emilia Romagna, Toscana, Marche, Umbria, Basilicata, Sardegna) – under the prescription of a GP drugs are completely free for all.

Specialist visits can be typically prescribed by a GP and require a copayment of around €36 for visit, applied in all the regions with small variations on the amount – except in the cases of exemption based on age, income and health status described above. The same mechanism is applied for diagnostic tests, for whom copayment depends on the type of test.

Surgeries and hospitalization provided by any public or private accredited hospitals are completely free of charge for everyone. Hospital admission occurs when prescribed by a GP. Patients are given free choice about the preferred structure. Emergency care expenses are also on charge of the NHS (a copayment is required for cases judged as not urgent).

Cost-sharing schemes – extensively applied since 1978 when the NHS was introduced – were aimed at introducing the principle of universality and equitable access to primary care to all residents, but at the same time they represent an instrument to protect against moral hazard and discourage overconsumption of health services and a way to raise public revenues.

The specific rule that we exploit for our empirical analysis is that as individuals get 65 or older and the (gross) income level of their family does not exceed 36,150 euros in the last year, they become exempted by the copayment for prescription drug consumption, specialist visits and diagnostic tests. It is worthwhile to note that the exemption is not a deterministic function of age, since from one hand individuals can be exempted before age 65 in case of permanent health problems or unemployment status and, on the other hand, are not entitled to the exemption after 65 if their family income is above the threshold level.

For specialist visits and diagnostic tests we run a standard Fuzzy RDD consisting in an IV analysis using as an instrument for the exemption status the 65 age threshold. To identify the effect of exemption from cost-sharing on prescription drug consumption, we exploit an additional characteristic of the Italian system: copayment is used in some regions but not in others. We carry out our RD analyses on the two sets of regions and we find that the threshold of age 65 for exemption – as expected – affects drug consumption in regions with copayment but has no effect in regions without copayment. This reassures us that the effect of age 65 is the result of exemption and is not related to some spurious correlation of age with some unobservable factor.

The dataset we use for our empirical analysis is the latest available wave (conducted between 2012 and 2013) of the Survey "Italian Health Conditions and Use of Health Services" provided by the Italian National Statistical Office (ISTAT). This survey is conducted on a nationally representative sample of 49,811 households for a total of 119,073 individuals and collects a wide range of information on individual demographic and socio-economic characteristics – age, gender, education, marital status, citizenship, main activity, region of residence, etc. – health conditions and use of health services.

We restrict our sample to individuals aged between 25 and 84 years. This leaves us with a sample of 87,685 observations. However, we estimate all our regressions on three symmetric windows across the threshold of age 65:

1) Window 1: age between 50 to 79 (43,934 obs.);
2) Window 2: age between 55 to 74 (29,618 obs.);
3) Window 3: age between 60 to 69 (15,004 obs.).

Our main variables are built as follows. *Age65* is a dummy equal to one if an individual is aged 65 or older. *Prescription Drug Consumption* is a dummy variable taking the value of one if an individual made use of prescription drugs in the latest two weeks prior to the interview and zero otherwise. *Specialist Visits* is a dummy variable taking the value of one if an individual undertook at least one specialist medical visit in the latest four weeks and zero otherwise.[4] *Diagnostic Tests* represents the number of laboratory diagnostic tests (blood tests, urine tests, pap tests, etc.) carried out in the latest four weeks.

Exemption is a dummy equal to one if an individual declares to have total exemption from the copayment or "Ticket" (no costs for health services).

Serious Health Problems is a dummy equal to one if an individual had some health problems that limited daily activities in the latest four weeks. *Health Status* is a variable taking values from 1 ("very bad") to 5 ("very good") indicating self-evaluated health status.

Descriptive statistics are reported in Table 1. About 18% of individuals in the main sample are completely exempted from cost-sharing; 56% used prescription drugs recently; 16% visited a specialist; 0.30 are the average diagnostic tests carried out. 12.6% had serious health problems; Health status has a mean of 3.7, almost 8% report to have a bad health while about 64% has a good or very good health.

Among individual characteristics, we take into account *Age* (52.9 is the average age; 26.8% are 65 or older), gender (females are 52%), *Education*[5] (10 years on average); *Married* (if the respondent is currently married or cohabiting, 65%); *Immigrant* (if foreign citizen, 5.6%); dummies for the main activity: *Employed*, *Unemployed*, *Retired*, *Other Non-Labor Force*; 20 dummies for region of residence (42% are from Northern regions; 18% from Center and 40% from South); *BMI* is the Body Mass Index (mean: 25.4); *Disability* is equal to one if the individual suffers for some disabilities (blindness, deafness, impaired mobility, and so on).

The dataset does not provide objective measures of family income but has a self-evaluation of economic resources on a four level scale (very good, adequate, poor, insufficient) and we control for the corresponding dummies. Finally, we control for quarterly dummies to take into account seasonal effects.

[4] The specialist visits that we consider are: cardiology; orthopedics; gastroenterology; otolaryngology; eye exam; geriatrics; endocrinology; psychiatry and psychotherapy; dermatological; venereology; obstetrics and gynecology; neurology; urology.

[5] Following a common practice, we use education as a discrete variable and recode education considering the years necessary to attain a given educational level. Education is set at zero for no educational qualification; 3 for some primary school; 5 for primary school; 8 for middle school; 11 for some High School; 13 for High School; 16 for First Level Degree, 18 for Second Level Degree and 21 for postgraduate qualification.

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs
Exemption	0.180	0.385	0	1	87685
Prescription Drug Consumption	0.560	0.496	0	1	87685
Specialist Visits	0.163	0.370	0	1	87685
Diagnostic Tests	0.302	0.854	0	5	87685
Serious Health Problems	0.126	0.332	0	1	87685
Health Status	3.693	0.848	1	5	87685
Age	52.928	15.723	25	84	87685
Age>=65	0.268	0.443	0	1	87685
Female	0.522	0.500	0	1	87685
Education	10.056	4.280	0	21	87685
Married	0.648	0.478	0	1	87685
Immigrant	0.055	0.227	0	1	87685
Employed	0.462	0.498	0	1	87685
Retired	0.246	0.431	0	1	87685
Unemployed	0.093	0.290	0	1	87685
Other Non-Labor Force	0.199	0.399	0	1	87685
BMI	25.365	4.424	12.457	163.966	87685
Disability	0.066	0.249	0	1	87685

Dataset: Survey “Italian Health Conditions and Use of Health Services” (2012-2013) ISTAT.

3. Cost-Sharing Exemption and the Demand for Healthcare Services

3.1. The Estimation Strategy

To deal with endogeneity problems, as is standard in the literature, we follow an Instrumental Variable estimation strategy. Thanks to the cutoff rule adopted in the NHS to give exemption from cost-sharing it is possible to evaluate the effects of exemption by using a Fuzzy Regression Discontinuity Design and by considering the dummy *Age65* as an instrument for the exemption. Therefore, in our framework the treatment status is probabilistically determined as a discontinuous function of age (Lee and Lemieux, 2010; Angrist and Pischke, 2009).

Following most of the papers in the literature, we use a parametric approach. Formally, we estimate the following model:

[1] $$Y_i = \beta_0 + \beta_1 Exemption_i + f\left(Age_i\right) + \beta_2 X_i + \varepsilon_i$$

[2] $$Exemption_i = \phi_0 + \phi_1 Age65_i + g\left(Age_i\right) + \phi_2 X_i + \upsilon_i$$

where Y_i is a measure of health services utilization (specialist visits, diagnostic checks, prescription drug consumption) of individual *i*; as explained above, $Exemption_i$ is a dummy variable representing complete exemption from cost-sharing; $f\left(Age_i\right)$ and $g\left(Age_i\right)$ are two flexible functional forms relating *Age*, respectively, to health services usage and $Exemption_i$; X_i is a vector of individual characteristics (gender, years of education, immigrant, marital status, region of residence, working conditions, subjective evaluations of economic resources, disabilities, etc.), that we use to increase the precision of estimates; ε_i and υ_i are random error terms.

Equation [2] represents the first stage of the relationship between the probability of receiving exemption from cost-sharing and *Age*. The parameter ϕ_1 estimates the effect of *Age65* on the effective *Exemption*.

Equation [1] assumes that health services demand is related to *Age*, since individuals at different age tend to use different amounts of health services. However, the relationship between health services consumption and age can be estimated by using a smooth function. Under the assumption that the relationship between the outcome variables and *Age* is continuous in a neighborhood of the cutoff point, any jump in the dependent variable due to exemption in proximity to the cutoff point can be interpreted as evidence of a treatment effect. Therefore, the parameter β_1 measures the causal impact of *Exemption* on health care use.

3.2. Impact of Cost-Sharing Exemption on Specialist Visits

We first examine the impact of exemption on the probability of undertaking a specialist visit. As explained above, we use a parametric approach and run several IV regressions, controlling for different polynomial of age and for a number of variables that could affect the probability of health services usage.

In column (1) of Table 2 we control only for *Age*, while in columns (2) and (3) we control, respectively, for a quadratic and cubic polynomial of *Age*. Starting from column (4) we control for a number of variables that could be both correlated to the exemption status and affecting health services demand: in column (4) we control for *Female*, years of *Education, Married*, *Immigrant*. In addition, we include 20 regional dummies, to take into account regional differences in health and health services, and dummies for quarters to capture seasonal effects. In column (5) we add controls for employment condition (*Retired*, *Unemployed*, *Other Non-Labor Force*, leaving as reference category *Employed*) and three dummies for income levels, subjectively evaluated (the lowest category of income is the reference). Finally, in column (6) we add controls for *BMI* and for *Disability*.

In all the regressions we run Standard Errors are robust to heteroskedasticity and allowed for clustering at the *Age* level (Lee and Card, 2008). All the regressions are weighted by sampling weights.

First Stage Results

Let us consider First Stage results, reported in Panel B of Table 2. We show that reaching age 65 increases the probability of exemption of about 23 percentage points. The magnitude of the effect is remarkably stable across specifications. The instrument is highly relevant: the first-stage *F*-statistic is always 70 or higher, well above the threshold of 10 for non-weak instruments (Stock and Yogo, 2005).

Table 2. Fuzzy Regression Discontinuity Estimates of Cost-Sharing Exemption on Specialist Visits. TSLS Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Two-Stage Least Squares Estimates						
Exemption	0.150***	0.149***	0.127***	0.129***	0.100***	0.114***
	(0.016)	(0.037)	(0.029)	(0.030)	(0.033)	(0.032)
Age	0.001***	0.001	-0.012***	-0.016***	-0.012***	-0.016***
	(0.000)	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
Age^2		0.000	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age^3			-0.000***	-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Female				0.054***	0.059***	0.065***
				(0.004)	(0.004)	(0.005)
Education				0.004***	0.004***	0.005***
				(0.001)	(0.001)	(0.001)
Married				0.025***	0.024***	0.028***
				(0.003)	(0.003)	(0.003)
Immigrant				-0.038***	-0.041***	-0.037***
				(0.004)	(0.004)	(0.004)
Retired					0.028***	0.024***
					(0.006)	(0.006)
Unemployed					0.001	-0.002
					(0.006)	(0.006)
Other Non-Labor Force					-0.006	-0.014***
					(0.005)	(0.005)
Income 2					-0.010	-0.006
					(0.007)	(0.007)
Income 3					-0.019***	-0.012*
					(0.007)	(0.007)
Income 4					-0.015	-0.008
					(0.011)	(0.011)
BMI						0.001***
						(0.000)
Disability						0.121***
						(0.010)
Constant	0.068***	0.069**	0.282***	0.265***	0.218***	0.223***
	(0.008)	(0.030)	(0.066)	(0.066)	(0.069)	(0.069)
Observations	87685	87685	87685	87685	87685	87685
Panel B: First Stage						
Age>=65	0.345***	0.230***	0.239***	0.234***	0.230***	0.235***
	(0.028)	(0.031)	(0.027)	(0.026)	(0.027)	(0.028)
R-squared	0.245	0.254	0.255	0.280	0.296	0.311
First-Stage F-statistics	146.80	53.91	77.19	80.17	70.25	72.29
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Panel C: Intention To Treat Effects						
Age>=65	0.052***	0.034***	0.030***	0.030***	0.023**	0.027***
	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)

Notes: The Table reports IV estimates. The dependent variable is *Specialist Visits*. In regressions (4), (5) and (6) we control for 20 regional dummies and 4 quarterly dummies. Standard errors (reported in parentheses) are corrected for heteroskedasticity and allowing for clustering at *Age* level. The symbols ***, **, * indicate that coefficients are statistically significant, respectively, at the 1, 5, and 10 percent level. Sample weights are used.

In Figure 1 we show the estimated relationship between *Age* and the probability of exemption (the continuous line) based on a quadratic relationship while the red dots represent the effective rate of exemption by age levels (local averages). The vertical line shows the threshold of age 65. It is remarkable clear the jump of about 20 p.p. in the probability of being "treated" (i.e. obtaining exemption) at age 65.

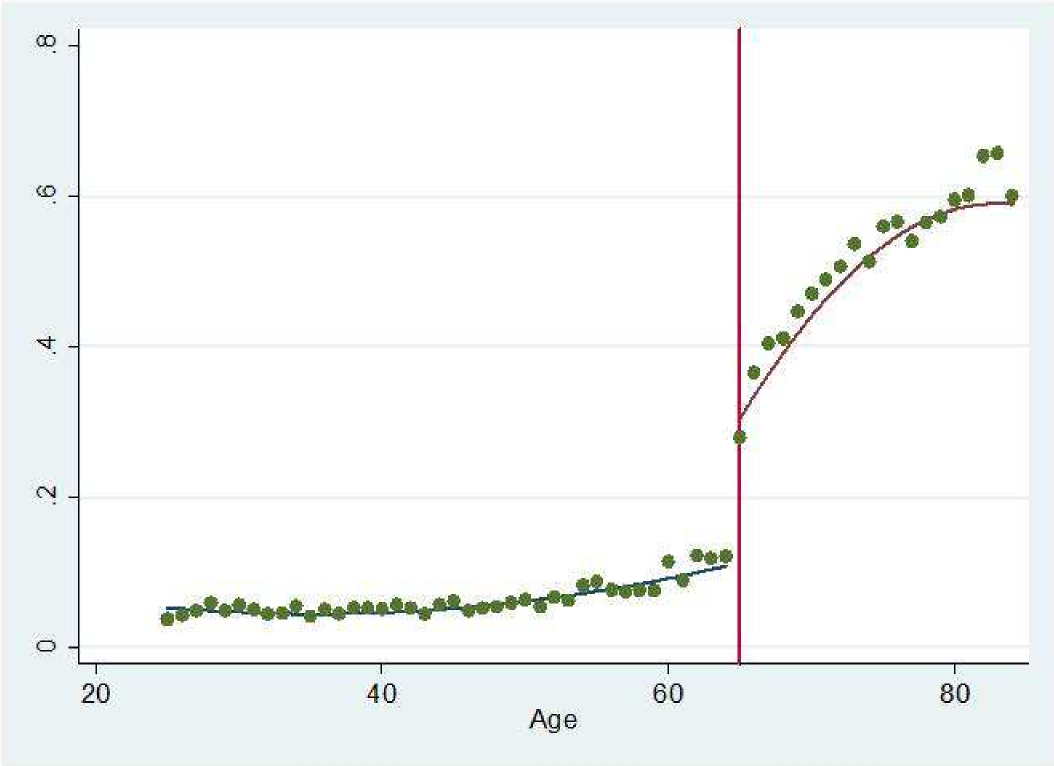

Figure 1. First Stage relationship: Cost-Sharing Exemption and Age

Second Stage Results

We now consider our Second Stage Estimates reported in Panel A of Table 2. In column (1), controlling only for *Age*, we find that the exemption due to the reaching of age 65 is causing an increase of the probability of undertaking a specialist visit of about 15 percentage points.

In the following specifications, with a number of control variables, we show that exemption is causing a jump in the probability of a specialist visit from 10 to 15 percentage points according to the specification (the coefficients are always highly statistically significant): this is a very strong impact ranging from 60% to almost 100%, considering that the average probability of a specialist visit is about 16%. As regards control variables, we find that females, more educated people, married and retired tend to undertake more visits, while immigrants do fewer.

In Panel C of Table 2 we report Intention-To-Treat (ITT) effects, that is, the coefficient on *Age65* of the reduced form of the model of equations (1)-(2). Reaching the age of 65 rises the probability of undertaking a specialist visit of about 3 p.p..

Discontinuity Samples (Local Linear Regressions)

Following Imbens and Lemieux (2008), we next consider only data in a neighborhood around the discontinuity. The comparison of average outcomes in a small enough neighborhood to the left and to the right of the threshold value should estimate our effect of interest in a way that does not depend on the correct specification of the model for the conditional expected function.

In Table 3 are reported estimation results obtained from our local linear regressions. In these specifications, *Age* is considered only in linear form. We experiment focusing on three different windows: the first considering 15 years before and after 65 (age from 50 to 79) (columns 1-3); the second considering 10 years before and after 65 (age from 55 to 74) (columns 4-6) and the last focusing on a window 5 years before and 5 years after the threshold (age from 60 to 69) (columns 7-9). In regressions (1), (4) and (7) we control only for *Age*. In regressions (2), (5) and (8) we control for *Age*, *Female*, *Education*, *Married*, *Immigrant*, 20 regional dummies and 4 quarterly dummies. In regressions (3), (6) and (9) we control for all the variables in column (6) of Table 2.

The first stage results for these local windows are shown in Panel B of Table 3: the impact of *Age65* on *Exemption* is quite strong also on these restricted samples, with an increase of 15-20 p.p. at the cutoff.

As regards second stage estimates, in all specifications, the exemption determines a strong increase of the probability of a specialist visit (from 10 to 16 p.p.) and the effect becomes even larger in magnitude as the window is shortened. The coefficients are in line with the estimates on the whole sample and are always highly statistically significant.

Table 3. Local Linear Regressions. Estimates of Cost-Sharing Exemption on Specialist Visits. TSLS Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel A: Two-Stage Least Squares Estimates				
Exemption	0.108***	0.115***	0.113***	0.115***	0.116***	0.126***	0.150***	0.141**	0.157**
	(0.032)	(0.034)	(0.034)	(0.043)	(0.043)	(0.044)	(0.054)	(0.059)	(0.062)
Window		50≤Age≤79			55≤Age≤74			60≤Age≤69	
Obs.	43934	43934	43934	29618	29618	29618	15004	15004	15004
					First Stage				
Age>=65	0.226***	0.218***	0.222***	0.191***	0.189***	0.194***	0.155**	0.154***	0.160***
	(0.042)	(0.039)	(0.039)	(0.045)	(0.044)	(0.044)	(0.048)	(0.046)	(0.047)

Notes: The Table reports IV estimates on specific windows (Local Linear Regressions). The dependent variable is *Specialist Visits*. In regressions (1), (4) and (7) we control only for *Age*. In regressions (2), (5) and (8) we control for *Age*, *Female*, *Education*, *Married*, *Immigrant*, 20 regional dummies and 4 quarterly dummies. In regressions (3), (6) and (9) we control for all the variables in column (6) of Table 2. Standard errors (reported in parentheses) are corrected for heteroskedasticity and allowing for clustering at *Age* level. The symbols ***, **, * indicate that coefficients are statistically significant, respectively, at the 1, 5, and 10 percent level. Sample weights are used.

As a robustness check, in order to avoid to impose any restriction on the underlying conditional form, we also include among controls an interaction term between *Age* and *Exemption* and use as instrumental variables *Age65* and the interactions between the latter and *Age*. This procedure corresponds to estimating separate functions on either side of the cutoff point. The impact of *Exemption* is substantially unchanged (not reported to save space).

To confirm the impact of exemption on specialist visits we consider a related outcome. In the Survey that we are using individuals are asked if they have given up undertaking a specialist visit for its costs. We build a dummy variable *Giving Up Specialist Visits* and we run the same IV regressions of Table 2 using as a dependent variable the latter dummy. We show that the probability of giving up visits reduces from 4 to 8 p.p. (the effects are highly statistically significant) when individuals are given exemption from cost-sharing because they turn 65 (estimates not reported). Similar effects of exemption are found when we focus on linear regressions on local windows.

3.3. Cost-Sharing and Diagnostic Tests

In this section we carry out the same analysis conducted above for specialist visits, investigating if the exemption from cost-sharing due to the reaching of the age 65 affects the number of diagnostic tests undertaken by individuals.

We run the same IV regressions of Table 2 and report the estimates in Table 4 (we report only the coefficient on *Exemption* to save space).[6] We find that the exemption increases by about 0.15-0.25 the number of diagnostic checks that corresponds to a rise of more than 50%, given that the average number of tests is 0.30.

Table 4. Fuzzy Regression Discontinuity Estimates of Cost-Sharing Exemption on Diagnostic Tests. TSLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Exemption	0.261***	0.248***	0.191***	0.193***	0.127**	0.156***
	(0.039)	(0.085)	(0.057)	(0.060)	(0.062)	(0.060)
Observations	87685	87685	87685	87685	87685	87685

Notes: The Table reports IV estimates. The dependent variable is *Diagnostic Tests*
See Notes of Table 2.

Furthermore, we carry out linear regressions on local windows and the estimates are reported in Table 5. Our results are confirmed in the local window regressions: the exemption causes an increase of diagnostic tests of 0.14-0.22.

Table 5. Local Linear Regressions. Estimates of Cost-Sharing Exemption on Diagnostic Tests. Two-Stage Least Squares Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Window	50≤Age≤79			55≤Age≤74			60≤Age≤69		
Exemption	0.140**	0.148**	0.152**	0.164**	0.159**	0.178***	0.203**	0.194**	0.224**
	(0.060)	(0.062)	(0.060)	(0.070)	(0.070)	(0.067)	(0.086)	(0.091)	(0.088)
Obs.	43934	43934	43934	29618	29618	29618	15004	15004	15004

Notes: The Table reports IV estimates on specific windows (Local Linear Regressions). The dependent variable is *Diagnostic Tests*. See Notes of Table 3.

[6] The first stage estimates are the same of Table 2.

4. Cost-Sharing Exemption and Prescription Drug Consumption

In Section 3 we have shown the strong impact of exemption from cost-sharing on the probability of undertaking a specialist visit and on the number of diagnostic tests. In this Section we analyze the impact of exemption on the probability of consuming prescription drugs in the latest two weeks.

In this case, we can exploit an additional identification strategy since in some Italian regions the copayment ("Ticket") for buying prescription drugs is applied for individuals less than 65 but not for those older than 65 (similarly to the other health services such as specialist visits and diagnostic tests), whereas in the remaining regions no copayment is applied for anyone. Therefore, if the exemption status is really causing the increase of prescription drug consumption at age 65, using the same RD framework we should observe this effect for "Regions with copayment" but we should not find the same impact for "Regions without copayment".

We run separately our IV regressions for regions with and without copayment.[7] In Table 6 we show our TSLS estimates for regions with copayment (using the whole range of age), with about 60,000 observations. We run the same regressions as in Table 2 but we report only the coefficients on *Exemption*. We find that in these regions the exemption due to the turn of age 65 is causing an increase of the probability of prescription drug consumption from 5 to 20 percentage points, according to the specification.

Table 6. Fuzzy Regression Discontinuity Estimates of Cost-Sharing Exemption on Prescription Drug Consumption. Two-Stage Least Squares Estimates. Regions with copayment

	(1)	(2)	(3)	(4)	(5)	(6)
Exemption	0.224***	0.214**	0.117***	0.104**	0.055	0.077*
	(0.048)	(0.097)	(0.040)	(0.042)	(0.046)	(0.043)
Observations	60556	60556	60556	60556	60556	60556

Notes: The Table reports IV estimates. The dependent variable is *Prescription Drug Consumption*. See Notes of Table 2.

On the other hand, in Regions without copayment we find, as expected, no effect of exemption. Our TSLS are reported in Table 7. With the exception of column (1) in which we control only for Age, we find that the exemption due to the threshold of age 65 is not determining any increase in the consumption of prescription drugs: this is reasonable since in these regions no one, regardless of age, pays for prescription drugs.

The findings of a differential impact of age 65 in regions with or without copayment reassure us that the effect of the threshold of age 65 in regions with copayment is not due to some omitted factors affecting prescription drug consumption in coincidence with the age of 65, but is the causal effect of the exemption from cost-sharing.

[7] Preliminarily, in a simple regression with a bunch of controls (female, age, education, immigrant, married, income, occupational status, and so on) we find that individuals living in regions without copayment consume significantly more prescription drugs than individuals living in regions requiring the copayment. Obviously, this represents only a suggestive correlation and not a causal effect, since the compared regions could differ for a number of unobservable factors.

Table 7. Fuzzy Regression Discontinuity Estimates of Cost-Sharing Exemption on Prescription Drug Consumption. TSLS Estimates. Regions without copayment

	(1)	(2)	(3)	(4)	(5)	(6)
Exemption	0.172***	0.099	-0.008	-0.009	-0.045	-0.027
	(0.055)	(0.104)	(0.068)	(0.066)	(0.073)	(0.066)
Observations	27129	27129	27129	27129	27129	27129

Notes: The Table reports IV estimates. The dependent variable is *Prescription Drug Consumption*. See Notes of Table 2.

Next, as above, we run our regressions for drug consumption for the two sets of regions on limited local windows (age 50-79; 55-74: 60-69). In Table 8 we show that in regions with copayment there is a relevant effect of exemption (from 11 to 25 percentage points), although in some cases the effects are imprecisely estimated due to the low number of observations and several control variables used in the regressions.

Table 8. Local Linear Regressions. Estimates of Cost-Sharing Exemption on Prescription Drug Consumption. Two-Stage Least Squares Estimates. Regions with copayment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Window	50≤Age≤79			55≤Age≤74			60≤Age≤69		
Exemption	0.123	0.122	0.114*	0.190**	0.192**	0.190***	0.239	0.233	0.255*
	(0.082)	(0.079)	(0.064)	(0.079)	(0.077)	(0.066)	(0.150)	(0.155)	(0.134)
Obs.	30112	30112	30112	20354	20354	20354	10335	10335	10335

Notes: The Table reports IV estimates on specific windows (Local Linear Regressions). The dependent variable is *Prescription Drug Consumption*. See Notes of Table 3.

In Table 9 we run the same regressions as in Table 8 but for regions without copayment. In all the specifications, we find a null effect of exemption due to age 65.

Table 9. Local Linear Regressions. Estimates of Cost-Sharing Exemption on Prescription Drug Consumption. Two-Stage Least Squares Estimates. Regions without copayment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Window	50≤Age≤79			55≤Age≤74			60≤Age≤69		
Exemption	0.029	0.025	0.034	-0.014	-0.027	0.009	0.023	0.012	0.046
	(0.103)	(0.104)	(0.091)	(0.147)	(0.147)	(0.134)	(0.250)	(0.238)	(0.225)
Obs.	13822	13822	13822	9264	9264	9264	4669	4669	4669

Notes: The Table reports IV estimates on specific windows (Local Linear Regressions). The dependent variable is *Prescription Drug Consumption*. See Notes of Table 3.

5. Cost-Sharing Exemption and Health Outcomes

We have seen in the previous empirical analyses that the exemption from cost-sharing leads to a remarkable increase in specialist visits, diagnostic tests and consumption of prescription drugs. An important issue that we need to tackle is whether these rises in the use of health services determine an improvement in the health of individuals.

As measures of health outcomes a number of studies in the literature have focused on the mortality of people, on self-reported health status, or on specific indicators such as blood pressure or cholesterol. For example, Finkelstein (2007) find that the introduction of Medicare did not reduce the relative mortality of people over 65 and Card, Dobkin and Maestas (2008) show that the age profiles of self-reported health status are smooth around age 65. On the other hand, Card, Dobkin and Maestas (2009) show a reduction of mortality rates for people admitted to the hospital.

Using the same empirical strategies presented above, we investigate if the exemption from cost-sharing – through a rise in the use of health services – leads to better health outcomes looking at the probability of incurring some health problems limiting daily activities (*Serious Health Problems*) and considering a self-evaluated *Health Status* (on a scale from 1 to 5).

In this exercise we follow the existing literature but admittedly this evidence is only suggestive since health problems could take long periods of time to be solved when health services are used more intensely because of the exemption and the RDD strategy has difficulties in identifying an effect developing over time.

In Table 10 we run our IV regressions using as a dependent variable the dummy *Serious*

Table 10. Fuzzy Regression Discontinuity Estimates of Cost-Sharing Exemption on Serious Health Problems. TSLS Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Exemption	0.074***	-0.041	-0.013	-0.015	0.006	0.027
	(0.022)	(0.047)	(0.036)	(0.037)	(0.036)	(0.033)
Age	0.002***	-0.004***	0.012***	0.012***	0.010***	0.004*
	(0.000)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Age^2		0.000***	-0.000***	-0.000***	-0.000***	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age^3			0.000***	0.000***	0.000***	0.000**
			(0.000)	(0.000)	(0.000)	(0.000)
Female				0.040***	0.037***	0.043***
				(0.003)	(0.003)	(0.003)
Education				-0.002***	-0.001	0.000
				(0.001)	(0.001)	(0.000)
Married				-0.005	-0.000	0.006**
				(0.003)	(0.003)	(0.003)
Immigrant				-0.022***	-0.033***	-0.028***
				(0.005)	(0.005)	(0.005)
Retired					-0.014**	-0.020***
					(0.006)	(0.006)
Unemployed					-0.008	-0.011*
					(0.006)	(0.006)
Other Non-Labor Force					0.005	-0.007
					(0.006)	(0.005)
Income 2					-0.028***	-0.022***
					(0.006)	(0.006)
Income 3					-0.067***	-0.058***
					(0.006)	(0.006)
Income 4					-0.072***	-0.061***
					(0.011)	(0.011)
BMI						0.001***
						(0.000)
Disability						0.176***
						(0.009)
Constant	0.013	0.146***	0.000	-0.092*	-0.025	0.002
	(0.009)	(0.031)	(0.000)	(0.055)	(0.047)	(0.044)
Observations	87685	87685	87685	87685	87685	87685

Notes: The Table reports IV estimates. The dependent variable is *Serious Health Problems*. In regressions (4), (5) and (6) we control for 20 regional dummies and 4 quarterly dummies. Standard errors (reported in parentheses) are corrected for heteroskedasticity and allowing for clustering at *Age* level. The symbols ***, **, * indicate that coefficients are statistically significant, respectively, at the 1, 5, and 10 percent level. Sample weights are used.

Health Problems and instrumenting, as usual, *Exemption* with *Age65*. We find that *Exemption* (with the exception of the first column) has no impact on the probability of having health problems. The coefficient on *Exemption* is almost zero (sometimes even positive) and it is always far from being statistically significant.

In Table 11 we present the estimates of our linear regressions on local windows. Again, we find that the greater use of health services through exemption does not lead to a reduction of health problems.

Table 11. Local Linear Regressions. Estimates of Cost-Sharing Exemption on Serious Health Problems. Two-Stage Least Squares Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Window	50≤Age≤79			55≤Age≤74			60≤Age≤69		
Exemption	0.017	0.013	0.038	0.035	0.032	0.050	0.017	0.019	0.058
	(0.056)	(0.055)	(0.043)	(0.065)	(0.062)	(0.053)	(0.071)	(0.066)	(0.062)
Obs.	43934	43934	43934	29618	29618	29618	15004	15004	15004

Notes: The Table reports IV estimates on specific windows (Local Linear Regressions). The dependent variable is *Serious Health Problems*. See Notes of Table 3.

In Table 12 we analyze the impact of *Exemption* on subjectively evaluated *Health Status* (we rescaled the original variable from 1 to 5: in our setting 1 represents “Very Bad” and 5 is “Very Good”) running our main specifications. We do not find any significant impact of exemption on this measure of health. In Table 13 we run local linear regressions and we do not find positive effects of exemption on *Health Status* (in some specifications we tend to find negative effects).

Table 12. Fuzzy Regression Discontinuity Estimates of Cost-Sharing Exemption on Health Status. Two-Stage Least Squares Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Exemption	-0.214***	0.080	0.068	0.111	0.087	-0.008
	(0.043)	(0.072)	(0.069)	(0.070)	(0.075)	(0.060)
Observations	87685	87685	87685	87685	87685	87685

Notes: The Table reports IV estimates. The dependent variable is *Health Status*.
See Notes of Table 2.

Table 13. Local Linear Regressions. Estimates of Cost-Sharing Exemption on Health Status. Two-Stage Least Squares Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Window	50≤Age≤79			55≤Age≤74			60≤Age≤69		
Exemption	-0.142	-0.105	-0.177**	-0.150*	-0.131	-0.207**	-0.214	-0.195	-0.301*
	(0.099)	(0.089)	(0.070)	(0.086)	(0.085)	(0.081)	(0.148)	(0.168)	(0.169)
Obs.	43934	43934	43934	29618	29618	29618	15004	15004	15004

Notes: The Table reports IV estimates on specific windows (Local Linear Regressions). The dependent variable is *Health Status*. See Notes of Table 3.

Finally, we analyze the effect of *Exemption* on the probability of being admitted to the hospital: we do not find any effect of exemption on hospitalization (estimates not reported to save space).

6. Concluding Remarks

With increasing health spending in most advanced countries from a policy point of view it is important to evaluate how demand for healthcare services respond to cost-sharing in order to deal with the trade-off between moral hazard problems and risk-sharing. However, on this issue there is a lack of rigorous experimental evidence outside US.

In this paper we exploit a natural experiment based on the rule established in the Italian National Health System that individuals aged 65 or more with low incomes are completely exempted from cost-sharing for the use of a number of healthcare services.

We use the discontinuity in age to implement a Fuzzy Regression Discontinuity Design (since the probability of exemption changes discontinuously at age 65) – corresponding to an Instrumental Variables estimation strategy – and investigate the effects of cost-sharing on prescription drug consumption, specialist visits and diagnostic tests.

To avoid any estimation biases we control for a large number of variables that could affect the demand for health services and be correlated to the age threshold. We also use a number of polynomial forms for age. In addition, we estimate our regressions both on the whole range of age and on three restricted windows (age 50-79; 55-74: 60-69).

In all the specifications and samples used, we find that specialist visits and diagnostic tests increase a lot – approximately by more than 50% – when individuals are given exemption from cost-sharing because of the reaching of age 65. Similar effects are found for the consumption of prescription drugs, although the magnitude is more contained (around 20%). As regards prescription drugs, our findings are strengthened by the fact that the effect is found only in regions with copayment whereas no effect at all emerges in regions in which no copayment is applied. This reassures us that the uncovered effects are due to the age threshold rather than to some confounding variables related to age.

However, when we analyze the impact of the exemption on several measures of health status (the probability of having serious health problems or of going to the hospital, the individual's perceived health) using the same empirical strategy we do not find any effect of greater consumption of health services on health outcomes. The latter findings is suggestive evidence of an overuse of medical services but cannot be considered a rigorous proof that complete exemption gives rise to moral hazard – since the RDD strategy might not identify properly effects on health that takes time to develop.

Considering that in developed countries life expectancy continues to increase, population is ageing and technological progress will offer new drugs, new tests and new therapies, the evidence on the price response of the demand of healthcare services is particularly relevant for policy makers to face the risks of an explosion of health spending.

References

Anderson, M., Dobkin, C., and Gross, T. (2012), "The Effect of Health Insurance Coverage on the Use of Medical Services, *American Economic Journal: Economic Policy*, 4(1), 1-27.

Anderson, M., Dobkin, C., and Gross, T. (2014). "The effect of health insurance on emergency department visits: Evidence from an age-based eligibility threshold", *Review of Economics and Statistics*, 96(1), 189-195.

Angrist, J., Pischke, J., (2009), *Mostly Harmless Econometrics*, Princeton University Press.

Angrist, J., Pischke, J., (2015), *Mastering 'Metrics*, Princeton University Press.

Arrow, K. (1963), "Agency and the welfare economics of medical care", *American Economic Review*, 53(5), 941973.

Atella V. - Deb P. (2008), "Are Primary Care Physicians, Public and Private Sector Specialists Substitutes or Complements? Evidence from a Simultaneous Equations Model for Count Data", *Journal of Health Economics*, vol. 27, no. 3, pp. 770-785.

Card, D., Dobkin, C., and Maestas, N., (2008),. "The Impact of Nearly Universal Insurance Coverage on Health Care Utilization: Evidence from Medicare." *American Economic Review*, 98, 5, 2242–58.

Card, D., Dobkin, C., and Maestas, N., (2009), "Does Medicare Save Lives?" *Quarterly Journal of Economics*, 124, 2, 597–636.

Carrieri, V. (2010), "The Effects of Cost-Sharing in Health Care: What Do We Know from Empirical Evidence?", *Economia Politica*, 2.

Chandra, A., Gruber, J. and McKnight, R. (2010). "Patient Cost-Sharing and Hospitalization Offsets in the Elderly." *American Economic Review*, 100(1): 193–213.

Cherkin, D., Grothaus, L. and Wagner, E. (1989). "The Effect of Office Visit Copayments on Utilization in a Health Maintenance Organization," *Medical Care*, 27, 1036-1045.

Dow, W. (2004), "The Introduction of Medicare: Effects on Elderly Health. University of California", Berkeley, Unpublished Working Paper.

Fabbri D., Monfardini C. (2009), "Rationing the Public Provision of Healthcare in the Presence of Private Supplements: Evidence from the Italian NHS", *Journal of Health Economics*, vol. 28, no. 2, pp. 290-304.

Feldstein, M., (1973) "The Welfare Loss of Excess Health Insurance." *Journal of Political Economy*, 81 (March–April): 251–80.

Finkelstein *et al.*, 2012 , "The Oregon Health Insurance Experiment: Evidence from the First Year", *Quarterly Journal of Economics*, 127, 3, 1057-1106.

Finkelstein, A. (2007). "The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare." *Quarterly Journal of Economics*,122(1): 1–37.

Gaynor, M., Li, J., and Vogt, B. (2007), "Substitution, spending offsets, and prescription drug benefit design", in *Forum for Health Economics & Policy* (Vol. 10, No. 2).

Goldman, D. *et al.* (2004). "Pharmacy Benefits and the Use of Drugs by the Chronically Ill," *Journal of the American Medical Association*, 291, 2344-2350.

Hiesler, M. et al. (2004). "The Health Effects of Restricting Prescription Medication Use Because of Cost," Medical Care, 42, 626-634.

Imbens G., Lemieux T. (2008), "Regression Discontinuity designs: A guide to practice", *Journal of Econometrics* 142 (2): 615–635.

Landsman et al. (2005). "Impact of 3-Tier Pharmacy Benefit Design and Increased Consumer Cost-Sharing on Drug Utilization", *American Journal of Managed Care*, 11, 621-628.

Lee, D., and Card, D. (2008), "Regression discontinuity inference with specification error", *Journal of Econometrics*, 142, pp. 655-674.

Lee, D., and Lemieux, T., (2010), "Regression Discontinuity Designs in Economics", *Journal of Economic Literature*, 48(2), pp. 281-355.

Manning, G., Newhouse, P., Duan, N., Keeler, B., and Leibowitz, A. (1987). "Health insurance and the demand for medical care: evidence from a randomized experiment", *American Economic Review*, 251-277.

McWilliams, M.; Zaslavsky, A.; Ayanian, J. (2007), "Use of Health Services by Previously Uninsured Medicare Beneficiaries", *New England Journal of Medicine* 2007;357:143–153.

Newhouse, J. and the Insurance Experiment Group (1993), *Free For All? Lessons from the RAND Health Insurance Experiment*. Cambridge, MA: Harvard University Press.

Piette, J., Wagner, T. Potter, M. and Schillinger, D. (2004). "Health Insurance Status, Cost-Related Medication Underuse, and Outcomes Among Diabetes Patients in Three Systems of Care," *Medical Care*, 42, 102-109.

Schoen, M. *et al.* (2001). "Impact of the Cost of Prescription Drugs on Clinical Outcomes in Indigent Patients with Heart Disease," *Pharmacotherapy*, 12, 1455-1463.

Selby, J., Fireman F. and Swain, B. (1996). "Effect of a Copayment on use of the Emergency Department in a Health Maintenance Organization," *New England Journal of Medicine*, 334, 635-641.

Stock, J., and Yogo, M. (2005). "Testing for weak instruments in linear IV regression. Identification and inference for econometric models", Essays in honor of Thomas Rothenberg.

Tamblyn, R. *et al.* (2001). "Adverse Events Associated with Prescription Drug Cost-Sharing Among Poor and Elderly Persons," *Journal of the American Medical Association*, 285, 421-429.

Zeckhauser, R., (1970), "Medical insurance: a case study of the tradeoff between risk spreading and the appropriate incentives", *Journal of Economic Theory*, 2,10-26.